İstatistikçiler Dergisi: İstatistik & Aktüerya

Journal of Statisticians: Statistics and Actuarial Sciences

IDIA 10, 2017, 1, 49-58

Geliş/Received:02.05.2017, Kabul/Accepted: 29.06.2017

www.istatistikciler.org

Araştırma Makalesi / Research Article

Optimal retention for profit maximizing under VaR levels constraints

Murat Büyükyazıcı

Hacettepe University, Faculty of Science,
Department of Actuarial Sciences, 06800
Beytepe, Ankara, Turkey.
E-mail: muratby@hacettepe.edu.tr

Abstract

We consider the problem of finding the optimal retention that maximizes the insurer's profit under different value-at-risk level constraints. We propose simulation optimization for the determination of optimal retention in stop-loss reinsurance using a package program which incorporates a simulation optimizer. Efficient frontier analysis is carried out to investigate maximum profit obtainable for a given risk level and minimum risk level obtainable for a given mean return under stop-loss reinsurance.

Keywords: *Stop-loss reinsurance, retention, profit maximization, expected value premium principle, standard deviation premium principle, value-at-risk (VaR), efficient frontier, simulation optimization.*

Öz

VaR seviyesi kısıtları altında karı maksimize eden optimal saklama payı

Farklı riske-maruz-değer (VaR) seviyesi kısıtları altında sigortacının karını maksimize eden optimal saklama payı problemi incelenmiştir. Toplam hasar fazlası reasürans anlaşmalarında optimal saklama payının belirlenmesinde, benzetim optimizasyonu içeren bir paket program kullanımı önerilmektedir. Toplam hasar fazlası reasürans anlaşması altında verilen bir risk seviyesi için elde edilebilecek maksimum kar ve verilen bir ortalama getiri için elde edilebilecek minimum risk seviyesi etkin sınır analizi ile belirlenmiştir.

Keywords: *Toplam hasar fazlası reasürans, saklama payı, kar maksimizasyonu, beklenen değer prim ilkesi, standart sapma prim ilkesi, riske-maruz-değer (VaR), etkin sınır, benzetim optimizasyonu.*

1. Introduction

Reinsurance is an effective risk management tool for an insurance company (insurer) to transfer risk to a reinsurance company (reinsurer). Stop-loss, excess-of-loss, quota-share and surplus reinsurance are examples of reinsurance contracts. The reinsurance contract is priced according to some premium calculation principles. One of the most commonly used principles is the expected value principle. Standard deviation principle, variance principle and mean value principle are a few of the many other principles that have been proposed by actuaries. For further reading about premium principles, please consult [1, 2].

When an insurer seeks reinsurance protection, the insurer is faced with the classic trade-off between the retained loss and the reinsurance premium. If the retention is small, then it is expected to be low retained loss to the insurer but higher premium payable to the reinsurer. On the other hand, if the retention is large, then it is expected to be large retained loss but lower cost of the reinsurance premium. This implies that the insurer is faced with a problem of determining the optimal retention. Thus, there have been many studies addressing the optimality of reinsurance depending on the optimality criterion and the chosen premium principle.

Borch [3] proved that stop-loss reinsurance minimizes the variance of the retained loss under the expected value principle. There have also been other researches which take into account the usual criteria and premium principles. For example, Denuit and Vermandele [4] derived results about the optimal reinsurance coverage for the insurer, when the optimality criterion consists of minimizing the retained loss with respect to the stop-loss order. Kaluszka [5] minimized the variance of the retained loss under premium principles based on the mean and variance of the insurer's share of the total claim amount. Taksar and Markussen [6] used stochastic optimal control theory to determine the optimal reinsurance policy which minimizes the ruin probability of the insurer. He, Hou and Liang [7] concerned with maximizing the expected present value of the dividend payout of the insurance company with proportional reinsurance policy under solvency constraints. Centeno and Guerra [8] concerned with the optimal form of reinsurance when the insurer seeks to maximize the adjustment coefficient of the retained risk. Hipp and Taksar [9] looked at minimization of ruin probabilities in the models in which the surplus process is a continuous diffusion process. They also focused on the case in which the surplus process is modelled via a classical Lundberg process, i.e. the claims process is compound process.

Gajek and Zagrodny [10] considered more general risk measures like the absolute deviation and the truncated variance of the retained loss. Balbas, A., Balbas, B. and Heras [11] also considered a wide family of general risk measures including deviation measures, expectation bounded risk measures and coherent measures of risk. Zeng [12], on the other hand, considered the problem of minimizing the expected time to reach a goal for an insurance company whose reserve is relatively large compared to the size of the individual claim.

Using other well-known financial risk measures such as the value-at-risk (VaR), and the conditional-tail-expectation (CTE), Cai and Tan [13] calculated the optimal retention for stop-loss reinsurance under the expected value premium principle. They established the necessary and sufficient conditions for the existence of the nontrivial optimal retentions. They concluded that if the solution exists, both CTE-optimization and VaR-optimization yield the same optimal solution. Subsequently, Cai, Tan, Weng and Zhang [14] generalized these results by showing that the stop-loss contract is indeed the optimal one among the set of all convex increasing reinsurance strategies.

Tan, Chengguo and Zhang [15] extended Cai and Tan's [13] results in two directions. One is to expand the class of reinsurance contracts by considering the quota-share reinsurance, in addition to stop-loss reinsurance. The other is to examine the optimality of the stop-loss and the quota-share reinsurance under many other premium principles. The main results of the paper lie in establishing theorems for the existence of the optimal quota-share and the optimal stop-loss reinsurance under the general premium principle. For 17 premium principles, they effectively analyzed in detail the conditions for the optimal quota-share coefficient and optimal retention. As a result, they have expressed "Because of the complexity of the optimization problem for the stop-loss reinsurance, there are a few premium principles for which we are unable to determine analytically if the optimal reinsurance exist or not". One of these premium principles is standard deviation principle. Also, an insurer is not only concerned with reducing risk exposure, but also interested in maximizing the profit [15]. In [15], Tan, Chengguo and Zhang concluded that those desirable features could be incorporated into the optimal reinsurance models by explicitly introducing the profitability as a constraint in future research. We incorporated both of these goals into the optimal reinsurance models by maximizing profit under different VaR measure constraints for the standard deviation premium principle as well. We also obtained efficient frontier to describe the relationship between the insurer profit and the VaR of the insurer total cost. In such a complex optimization case, we propose practical solution for the determination of optimal retentions in stop-loss reinsurance under VaR risk measure using the Crystal Ball 11.1.2 [16] package program which incorporates OptQuest [17] simulation optimizer.

The remainder of the paper is organized as follows. In the next section, we provide a brief overview of VaR risk measure and simulation-optimization. Section 3 describes our simulation model. Numerical results are discussed in Section 4. Section 5 concludes this paper.

2. Relevant overviews

2.1. VaR risk measures

There are multiple ways to measure risk. The vast number of them can be broadly divided into two categories: 1) risk as the magnitude of deviations from a target, 2) risk as a capital (or premium) requirement. The value at risk (VaR) is a risk measure of the second kind [18].

VaR has many possible uses: 1) to set overall risk target, 2) to determine internal capital allocation, and capital requirements, 3) for reporting and disclosing purposes, 4) to assess the risks of different investment opportunities before decisions are made. For more on details see [19].

Let X be a non-negative random variable denoting the aggregate loss. The VaR of X at a confidence level $1-\alpha$, $0<\alpha<1$, is defined as

$$VaR_X(\alpha) = \inf\{x : P(X > x) \le \alpha\}$$

2.2. Simulation optimization

Most real-world systems are so complex that computing values of performance measures and finding optimal solutions analytically are extremely hard and sometimes impossible. Therefore, computer simulation is frequently used in evaluating complex systems and also in optimizing performance measures [20].

The general optimization problem that minimizes objective function $J(\theta)$ is

$$\min_{\theta\in\Theta} J(\theta)$$

where $\theta\in\Theta$ represents the input variables, $J(\theta)$ is the objective function, and Θ is the constraint set. The most common form for J is an expectation, i.e,

$$J(\theta) = E\left[L(\theta,\varepsilon)\right]$$

where ε represents the stochastic effects of the system in a simulation replication and $L(\theta,\varepsilon)$ is the sample performance estimate obtained from the output of the simulation replication [21,22].

The main optimization approaches utilized in simulation optimization include random search, response surface methodology, gradient-based procedures, ranking and selection, sample path optimization, and metaheuristics including tabu search, genetic algorithms, and scatter search. For more information on simulation optimization approaches, advances, and applications, we refer readers to recent reviews [20, 21, 22].

Simulation optimization is an active research area in commercial software implementation. One of the well-known simulation optimization software packages is OptQuest. The OptQuest incorporates metaheuristics to guide its search algorithm toward better solutions. This approach remembers which solutions worked well and recombines them into new, better solutions [6]. In this approach metaheuristic optimizer chooses a set of values for *decision variables* (input parameters) and uses the responses generated by the simulation model to identify new scenario of the next trial solution [23]. Figure 1 shows the black box approach to simulation optimization favored by procedures based on metaheuristic methodology.

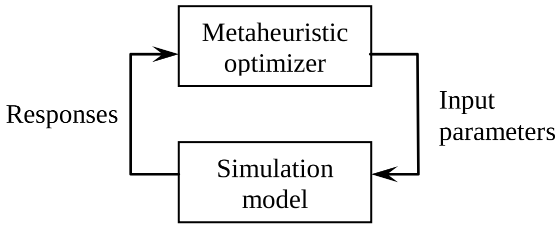


Figure 1. Black box approach to simulation optimization [23].

3. Model development

In this section, we set up the stochastic model of a non-life insurance company's total cost over one year period in a stop-loss reinsurance design and the simulation optimization model to find optimal retention limit.

3.1. Stochastic stop-loss reinsurance simulation model

Let X denotes the aggregate loss initially assumed by an insurer. The simulation model incorporates the stochastic nature of the aggregate loss by a non-negative random variable.

In a stop-loss reinsurance design, the insurer cedes part of its loss, say X_I and thus the reinsurer retains a loss $X_R = X - X_I$. The corresponding losses to the insurer and reinsurer are $X_I = \min\{x, d\}$ and $X_R = \max\{0, x - d\}$ respectively.

In exchange of undertaking the risk, the insurer incurs additional cost of reinsurance premium. It is expected that the higher the retained loss, the lower the reinsurance premium. Naturally, the reinsurance premium $\pi(d)$ is a decreasing function of d. Given that $\rho > 0$ is the safety loading, the expected value and the standard deviation premium principles are given as follows:

$$\pi_R(d) = (1+\rho)E(X_R)$$

$$\pi_R(d) = E(X_R) + \rho\sqrt{V(X_R)}$$

where $E(X_R)$ denotes the expected value of X_R and $V(X_R)$ denotes the variance of X_R.

The total cost of the insurer in stop-loss reinsurance comprises the retained loss and the reinsurance premium. That is:

$$T = X_I + \pi_R(d)$$

Let assume the loaded premium of insurer is calculated with the same safety loading ρ under the expected value principles; that is, $\pi_I = (1+\rho)E(X)$. So the profit of insurer, difference between the loaded premium of insurer and the total cost of the insurer, is:

$$S = \pi_I - T$$

3.2. Simulation optimization model

For comparing insurer's profits against different VaR_T (VaR of the insurer total cost) risk levels so that insurers can maximize their profit and minimize risk, an efficient frontier analysis can be carried out. This analysis starts by defining a range of values for a constraint bound for VaR_T risk levels. Then, it is relatively easy for a computer, with an efficient optimization engine, to try various combinations of profits and risk levels for any retention and locate the efficient frontier. Essentially, the optimization is run multiple times, each time with a different specified VaR_T risk level constraint. The optimization identifies the highest value of insurer's profit for each VaR_T risk level and the result is plotted. The curve obtained in this way defines the efficient frontier.

Our objective is to maximize the profit of insurer for obtaining efficient frontier to describe the relationship between the insurer profit and the VaR_T risk measure. Under the stop-loss reinsurance model, with different VaR_T risk level constraints, the optimal retention d^* is the solution to the following optimization problem:

$$\max_{d\in[0,\infty)} E[S(d,\varepsilon)] \quad (1)$$

In efficient frontier analysis, a suitable lowest bound of VaR_T is needed to be determined by solving the following optimization problem:

$$\min_{d\in[0,\infty)} E[VaR_T(d,\alpha,\varepsilon)] \quad (2)$$

The resulting optimal retention d^* ensures that VaR_T is minimized for a given confidence level $1-\alpha$.

4. Simulation results

We obtained practical solutions for the determination of optimal retentions in the stop-loss reinsurance using the Crystal Ball 11.1.2 package program which incorporates a simulation optimizer, OptQuest. A simulation calculates numerous times the stochastic model by repeatedly picking values from the probability distribution of the aggregate loss.

In our stochastic model of a non-life insurance company's profit, the stochastic nature of the aggregate loss X is incorporated by a non-negative random variable. Exponential distribution, Pareto distribution and lognormal distribution are used for aggregate loss. In calculation of reinsurance premium, the expected value and the standard deviation premium principles are used. Thus, we obtain results for 6 case studies. In optimization process of each case study, we set Crystal Ball run preferences with 5000 simulations and 2000 trials, that's the optimal solution search process continues until OptQuest reaches 5000 simulations each one has 2000 trials.

The minimum values of VaR_T used in efficient frontier analysis for 6 case studies which are calculated by solving (2) with simulation optimization are given in Table 1. Note that these values are not the exact ones but approximate solutions obtained by simulation optimization.

Table 1. VaR_T optimization values with simulation optimization.

	Aggregate Loss (X) Distribution	Premium Principle	optimal retention (d*)	VaR_T
Case Study 1	Exponential	Expected Value	184,00	1182,85
Case Study 2	Exponential	Standard Deviation	000,00	1200,00
Case Study 3	Pareto	Expected Value	632,00	1079,84
Case Study 4	Pareto	Standard Deviation	194,72	1202,03
Case Study 5	Lognormal	Expected Value	316,00	1156,98
Case Study 6	Lognormal	Standard Deviation	044,00	1199,99

The lowest bounds of VaR_T in the following subsections are chosen by taking into account the values in Table 1. On the other hand, the highest bounds of VaR_T are chosen so that VaR_T and optimal retention are less than 2000.

4.1. Case Studies

In Case Study 1 and Case Study 2, we assume that the aggregate loss random variable X has exponential distribution with mean $E(X)=1000$.

In Case Study 3 and Case Study 4, we assume that the aggregate loss random variable X has Pareto distribution. Parameter values of the distribution are selected so that the aggregate losses in all Case Studies have the same mean and standard deviation. Thus, the shape parameter and the location parameter are calculated as 2.41 and 585.79 respectively by solving the system of two nonlinear equations.

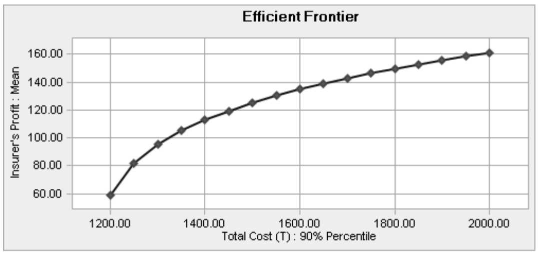
In Case Study 5 and Case Study 6, we assume that the aggregate loss random variable X has lognormal distribution with mean $E(X)=1000$, and standard deviation $SD(X)=1000$.

We simulate our stochastic model with the expected value premium principle for Case Study 1, Case Study 3 and Case Study 5 and with standard deviation premium principle for other Case Studies. We also assume $\alpha=0.1$ and $\rho=0.2$ for all Case Studies.

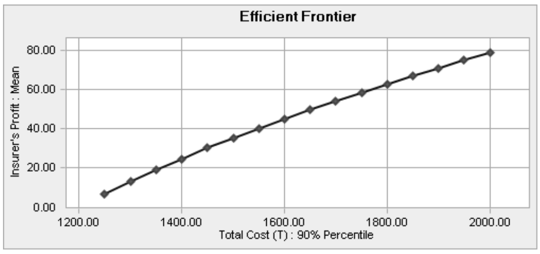
The objective is to maximize the insurer's profit given in (1). After 5000 solutions are evaluated, an efficient frontier is constructed for the test points varying the bound from the lowest value of VaR_T to the highest value of VaR_T in steps of 50 as seen in Figure 2. The tested constraints are that the $VaR_T(0.10)$, namely the 90% percentile of total cost, must be less than or equal to test points. Optimal retentions maximizing insurer's profit for each test points are given in Table 2.

The efficient frontiers in Figure 2 display plots of the insurer's profit against the VaR_T risk level that is being tested for each Case Study. For any given mean profit, there is a stop-loss reinsurance that has the possible smallest VaR_T risk level. Similarly, for any given VaR_T risk level, there is a stop-loss reinsurance that has the highest mean profit obtainable.

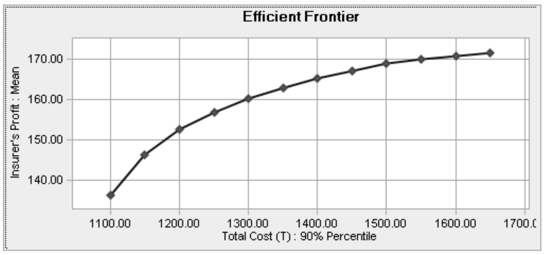
As seen in Figure 2, as the VaR_T risk level constraint is relaxed, the additional risk undertaken provides less incremental value in the insurer's profit compared to lower risk levels. Except Case Study 2, the slope of the curve encompassing the higher risk levels is flatter because the incremental profit is not quite as high. Thus, there is a declining incremental profit in the value obtained with each additional increment of risk. However, in Case Study 2, there is a considerable incremental profit in the value obtained with each additional increment of risk.



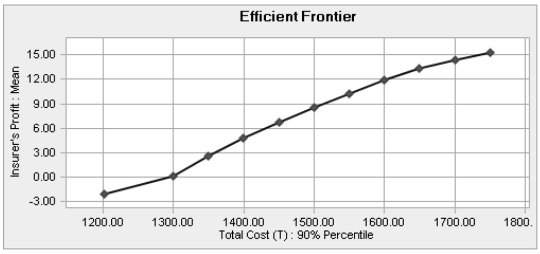
a) Case Study 1



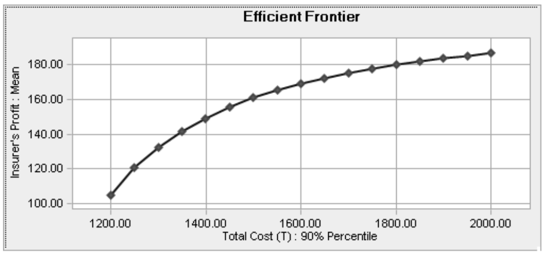
b) Case Study 2



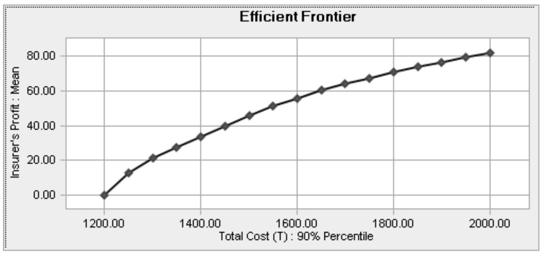
c) Case Study 3



d) Case Study 4



e) Case Study 5



f) Case Study 6

Figure 2. Efficient frontier of six case studies.

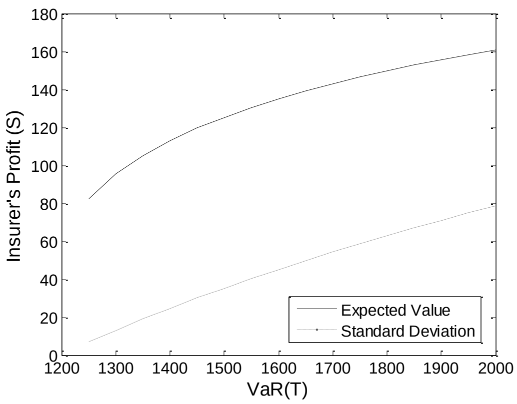
4.2. Comparison of the results

In Table 2, for three distributions, we give the stop-loss reinsurance retention levels which maximize the insurer's profit subject to the constraint that the $VaR_T(0.10)$, namely the 90% percentile of total cost, must be less than or equal to some test points. Table 2 also involves the corresponding maximum insurer's profit for each case study and each VaR_T level.

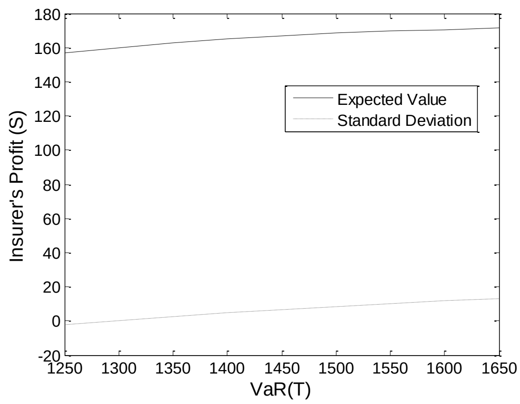
Table 2. Optimal retentions for each efficient frontier test points.

	Exponential				Pareto				Lognormal			
	Expected Value		Standard Deviation		Expected Value		Standard Deviation		Expected Value		Standard Deviation	
	Case Study 1		Case Study 2		Case Study 3		Case Study 4		Case Study 5		Case Study 6	
VaR_T	d*	S	d*	S	d*	S	d*	S	d*	S	d*	S
1100	-	-	-	-	744.2	136.4	-	-	-	-	-	-
1150	-	-	-	-	859.0	146.4	-	-	-	-	-	-
1200	372.2	59.3	-	-	945.5	152.5	-	-	590.7	105.1	66.1	0.0
1250	572.9	82.2	362.3	7.0	1021.6	156.8	194.2	-2.0	730.6	121.0	481.5	12.9
1300	708.8	95.4	526.8	13.1	1091.8	160.1	865.2	0.1	839.3	132.2	628.1	21.2
1350	822.0	105.2	654.8	19.1	1158.3	162.8	945.4	2.6	934.2	141.6	742.5	27.3
1400	922.2	113.0	765.6	24.7	1222.1	165.1	1018.3	4.8	1020.1	149.2	841.9	33.6
1450	1014.0	119.5	866.1	30.2	1284.0	167.1	1087.3	6.7	1100.6	155.6	931.9	40.0
1500	1099.7	125.3	958.9	35.2	1344.2	168.7	1152.7	8.5	1176.2	160.9	1015.6	45.9
1550	1180.7	130.4	1046.1	40.0	1403.3	169.8	1216.2	10.3	1249.0	165.6	1094.5	51.2
1600	1258.0	135.1	1129.0	44.9	1461.4	170.6	1277.8	11.9	1318.9	169.2	1169.9	56.0
1650	1332.4	139.3	1208.2	49.7	1518.6	171.4	1338.0	13.3	1386.5	172.3	1242.4	60.5
1700	1404.3	142.9	1284.6	54.3	-	-	1397.1	14.4	1452.4	175.1	1312.3	64.2
1750	1474.2	146.4	1358.6	58.7	-	-	1455.2	15.2	1516.9	177.6	1380.7	67.7
1800	1542.4	149.7	1430.5	62.8	-	-	-	-	1580.0	179.9	1447.1	70.9
1850	1609.1	152.7	1500.6	66.9	-	-	-	-	1642.0	181.8	1512.4	73.9
1900	1674.4	155.6	1569.2	71.0	-	-	-	-	1703.0	183.5	1576.3	76.8
1950	1738.5	158.3	1636.5	74.8	-	-	-	-	1763.2	185.1	1638.4	79.5
2000	1801.5	160.7	1702.5	78.7	-	-	-	-	1822.5	186.5	1701.2	81.9

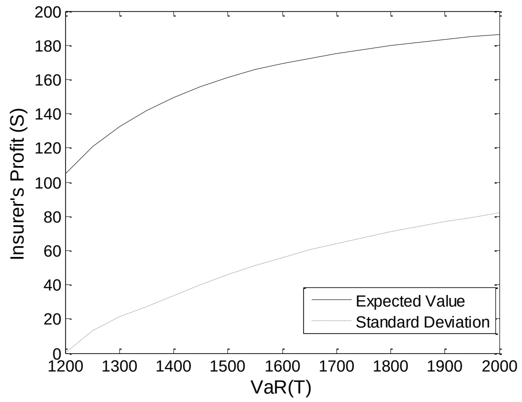
We compare premium principles for three distributions with respect to the insurer's profit for the same risk level. As seen in Figure 3, in all distributions expected value premium principle results in higher profit for each risk level.



a) Exponential distribution



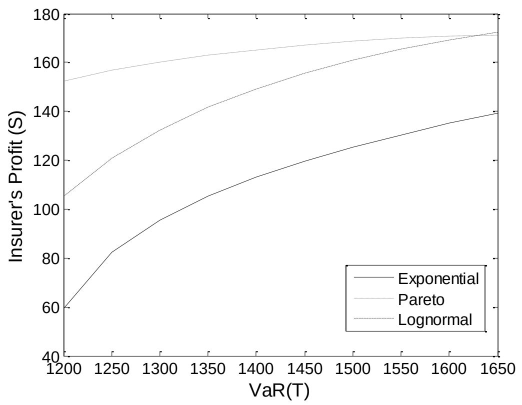
b) Pareto distribution



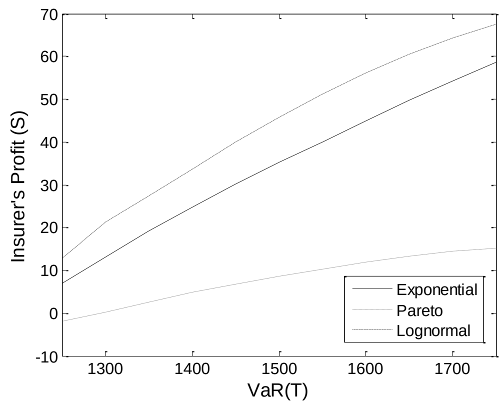
c) Lognormal distribution

Figure 3. Comparison of premium principles for three aggregate loss distributions.

We also compare the distributions for two premium principles with respect to the insurer's profit for the same risk level. Under expected value premium principle, for almost all risk levels Pareto distribution gives the highest profit and exponential distribution gives the lowest. As the risk level increases profits for exponential and lognormal distributions increase more rapidly than that for Pareto as seen in Figure 4-a. Under standard deviation premium principle, for each risk level lognormal distribution gives the highest profit and Pareto distribution gives the lowest. As the risk level increases profits for exponential and lognormal distributions increase more rapidly than that for Pareto as seen in Figure 4-b.



a) Expected value premium principle



b) Standard deviation premium principle

Figure 4. Comparison of distributions for two premium principles.

5. Conclusions

In this research, we apply the simulation optimization approach to the problem of finding the optimal retention in stop-loss reinsurance. In practice, an insurer is not only interested in maximizing the profit, but also concerned with reducing risk exposure while determining the retention limit. Therefore, we maximize the insurer's profit under different VaR risk level constraints. Computational results show that the assumed loss model and premium principle used are effective factors for determining optimal retention limit, so the insurer's expected profit. Finding analytically optimal solution to some complex real-world problems is extremely hard and even sometimes impossible. Therefore, simulation optimization approach can be used to find optimal retention limit for better profit with their acceptable VaR_T risk level.

References

[1] M. J. Goovaerts, F. De Vylder, J. Haezendonck, *Insurance Premiums: Theory and Applications*, North Holland, Amsterdam, 1984.

[2] V.R. Young, Premium Principles, in: B. Sundt, J. Teugels, J. (Eds), *Encyclopedia of Actuarial Science,* New York: John Wiley & Sons, Ltd. 2004.

[3] K. Borch, An attempt to determine the optimum amount of stop-loss reinsurance, in: Transactions of the 16th International Congress of Actuaries, 1960, pp. 597-610.

[4] M. Denuit, C. Vermandele, Optimal reinsurance and stop-loss order, *Insurance: Math. Econ*. 22 (1998), 229-233.

[5] M. Kaluszka, Optimal reinsurance under mean-variance premium principles, *Insurance: Math. Econ.* 28 (2001), 61-67.

[6] M. Taksar, C. Markussen, Optimal dynamic reinsurance policies for large insurance portfolios. *Finance and Stoch*. 7 (2003), 97-121.

[7] L. He, P. Hou, Z. Liang, Optimal control of the insurance company with proportional reinsurance policy under solvency constraints, *Insurance: Math. Econ.* 43 (2008), 474-479.

[8] M.L. Centeno, M. Guerra, The optimal reinsurance strategy - the individual claim case, *Insurance: Math. Econ*. 46 (2010), 450-460.

[9] C. Hipp, M. Taksar, Optimal non-proportional reinsurance control, *Insurance: Mathematics and Economics*, 47 (2010), 246-254.

[10] L. Gajek, D. Zagrodny, Optimal reinsurance under general risk measures, *Insurance: Math. Econ.*, 34 (2004), 227-240.

[11] A. Balbas, B. Balbas, A. Heras, Optimal reinsurance with general risk measures, *Insurance: Math. Econ*. 44 (2009), 374-384.

[12] X. Zeng, Optimal reinsurance with a rescuing procedure, *Insurance: Math. Econ*. 46 (2010), 397-405.

[13] J. Cai, S.K. Tan, Optimal retention for a stop-loss reinsurance under the VaR and CTE risk measures, *ASTIN Bull.* 37 (1) (2007), 93-112.

[14] J. Cai, S.K. Tan, C. Weng, Y. Zhang, Optimal reinsurance under VaR and CTE risk measures, *Insurance: Math. Econ*. 43 (2008), 185-196.

[15] K. S. Tan, W. Chengguo, Y. Zhang, VaR and CTE criteria for optimal quota-share and stop-loss reinsurance, *North Amer. Actuarial J*. 13 (4) (2009), 459-482.

[16] Oracle, Crystal Ball 11.1.2 trial version, <http://www.oracle.com> [Accessed December 2011].

[17] OptTek Systems Inc., The OptQuest Engine documentation. Available at: <http://www.opttek.com/Products/Documentation.html> [Accessed December 2011].

[18] P. Albrecht, Risk measures, in: B. Sundt, J. Teugels, (Eds), *Encyclopedia of Actuarial Science*, New York: John Wiley & Sons, Ltd., 2004.

[19] K. Dowd, Value-at-risk, in: B Sundt, J. Teugels, (Eds), *Encyclopedia of Actuarial Science*, New York: John Wiley & Sons, Ltd., 2004.

[20] E. Tekin, I. Sabuncuoglu, Simulation optimization: A comprehensive review on theory and applications. *IIE Transactions*, 36 (2004), 1067–1081.

[21] M.C. Fu, F.W. Glover, J. April, Simulation optimization: a review, new developments, and applications, in: M.E. Kuhl, N.M. Steiger, J.A. Joines (Eds), Proceedings of the 2005 winter simulation conference, 2005.

[22] M.C. Fu, C.H. Chen, L. Shi, Some topics for simulation optimization, in: S. J. Mason, R. R. Hill, L. Mönch, O. Rose, T. Jefferson, J.W. Fowler, (Eds), Proceedings of the 2008 winter simulation conference, 2008.

[23] J. April, M. Better, F. Glover, J.P. Kelly, M. Laguna, Enhancing Business Process Management with Simulation Optimization, in: Proceedings of the 38th conference on winter simulation, 2005.