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Applications of Vose *ModelRisk* Software in Simulated Data

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Author's contribution

The sole author designed, analyzed and interpreted and prepared the manuscript.

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ABSTRACT

Statistical simulation is used in cases which there is not enough theoretical background about the method in hand. It is used to derive the performances of inferential methods like empirical estimation of sampling distributions, the power of statistical tests or robustness of methods. Simulation methods specially Monte Carlo methods are used frequently, in finance and in risk management. There are many powerful software to run the simulation in financial problems, like *@Risk* or *ModelRisk*. However, this software *(ModelRisk)* is applicable in many other statistical fields. The current paper is concerned with application of *ModelRisk* software in ten simulation cases. Applications are presented in the format of different examples, including change point analysis, rolling analysis, bootstrapping, Bayesian inference, numerical analysis and extreme value problems. Finally, a conclusion section is given.

Keywords: Bayesian; bootstrap; change point; copula; extreme value; geometric Brownian motion; ModelRisk of Vose; Monte Carlo; risk event; rolling; simulation.

1. INTRODUCTION

Using the statistical simulation approaches, there are a lot of opportunities to construct probabilities, confidence intervals and hypothesis testing, in cases at which there are a few theoretical background. There are many reasons for using the statistical simulation techniques

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such as simulation presents simple and important tools to solve problems. Second, simulation techniques help researcher to visualize and understand main statistical concepts. There are many useful software's to perform valid simulations. One of them is the *ModelRisk* of [1], an add-in to Microsoft Excel which is applied for professional quality risk analysis.

1.1 Problem Description

Financial applications of *ModelRisk* software has been received considerable attentions in literatures. For example, [2] proposed a comprehensive review about applications of this software. [3] applied the *ModelRisk* software to survey the assessment of risks that threaten a project. [4] applied this software to simulate the probabilistic time-specific risk load for PPP. [5] studied practical aspects of spreadsheet risk modeling for management. In this short note article, the applications of ModelRisk software in ten simulation cases has been shown. Applications are presented in the format of different examples.

2. METHODOLOGY

An important technique used in this paper is the Monte Carlo approach. It is a computerized mathematical methods used to compute the likelihood of various outcomes of a random experiment which are not predictable, analytically. It is used frequently in finance, project management, statistics, mathematics, numerical analysis and physics. It gives an opportunity to the decision-maker to see all possible consequences of a random experiment and their probabilities and distinguishing frequent and rare events.

The rest of paper is designed as follows. In section 2, experimental simulations containing ten examples including change point analysis, rolling analysis, bootstrapping, Bayesian inference, numerical analysis and extreme value problems are given. Results and discussions are given in section 4. Conclusions are presented in section 5.

3. EXPERIMENTAL SIMULATIONS

As follows, examples are presented and empirical results are also proposed.

Example 1. [6] approximated the law of the maximum partial sum of Normal deviates by a Chi-square distribution. Let $x_1, \ldots, x_n$ be a sequence of independent and identically Normally distributed (iid) random variables. Then, the maximum partial sum is given by

$$M = max_{1 \le k \le n} \sum_{i=1}^{k} (x_i - \bar{x}),$$

where $\bar{x}$ is the average of total x_i's, $i = 1, \ldots, n$. [6] fitted the distribution of $\frac{4}{n}M^2$ by a Chi-square distribution. Here, for a correlated sequence $x_1, \ldots, x_n$, precisely, for first order auto-regressive AR(1) in the presence of GARCH(1,1) errors $a_n M^2$ is approximated by Chi-squared with r_n degrees of freedom. The moment estimates of a_n and r_n are

$$a_n = \frac{2E(M^2)}{var(M^2)} \text{ and } r_n = a_n E(M^2).$$

The plot (Fig. 1) shows the histogram of M, for $n = 1000$.

The autoregressive parameter is $\alpha = 0.3$ and GARCH parameters are $w = 0.0005$ (constant term), $a_1 = 0.01$ (ARCH term) and $b_1 = 0.95$ (GARCH term). The following Table (Table 1) gives the standardized coefficient a_n and degrees of freedom r_n of M for various values of α. The sample size is $n = 1000$.

The scatter plot (Fig. 2) between α and r_n suggest a logarithmic relation which is given by

$$r_n = \exp(-5.028\alpha) \text{ and } a_n = \exp(0.233\alpha).$$

Table 1. The values of a_n and r_n

α	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45
r_n	0.675	0.742	0.664	0.79	0.515	0.52	0.58	0.339	0.377
a_n	1.313	1.4	1.098	1.004	0.638	0.666	0.592	0.285	0.285
α	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9
r_n	0.106	0.165	0.049	0.009	0.024	0.008	0.01	0.01	0.015
a_n	0.253	0.047	0.051	0.01	0.001	0	0	0	0

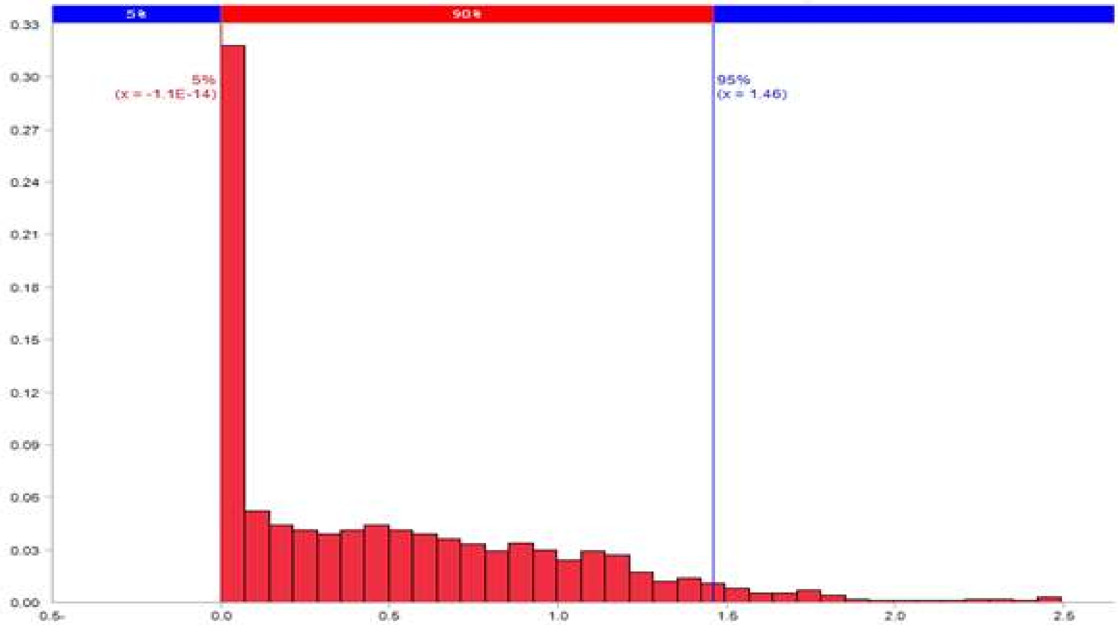

Fig. 1. Histogram of M

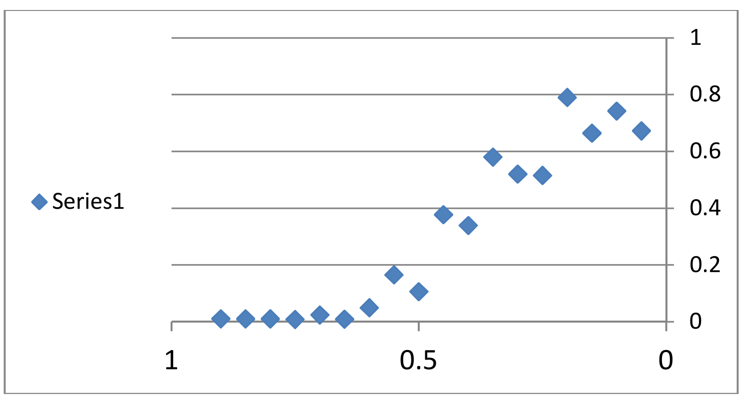

Fig. 2. Scatter plot between α and r_n

Also, the *stopsum* function used to show that the suitable sample size for Chi-square approximation for $a_n M^2$ is 150.

Example 2. Suppose that X_t and Y_t are two independent geometric Brownian motions with parameters μ_x , σ_x^2 and μ_y , σ_y^2 , respectively. Define $M = max_{0\le t\le T} X_t + max_{0\le t\le T} Y_t$. Here, first, the *Tornado* and *Spider* plots is applied to decompose the risk related to M. Then, X_t and Y_t are considered a sequence of iid random variables from an extreme value distributions. Next, it is possible to suppose that X_t and Y_t are two independent Markov processes and finally X_t and Y_t are considered correlated process having Franklin copula. Here, assume that 1000 samples are generated of both geometric Brownian motions where $\mu_x = 0.002$, $\sigma_x = 0.025$, $\mu_y = 0.001$ and $\sigma_y = 0.05$. The initial values of both time series is 1. The Fig. 3 shows the Tornado and Spider plots.

Example 3. Suppose that X_t, $t = 1,2, \ldots, n$ is a sequence of iid random variables where $E(X_t) = \mu_0$ for $t = 1, \ldots, t_0$ and $E(X_t) = \mu_1$ for $t = t_0 + 1, \ldots, n$. The t_0 is referred as change point. [7] showed that the bootstrapped samples X_t^* has a mixture distribution with mixing portion $\frac{t_0}{n}$. Another tool to detect the stability of a time series is the *rolling* analysis, see [8]. Suppose that 2000 samples are generated such that the first 1500 samples come from standard Normal distribution and the remaining are from Normal distribution with mean and variance one. The histogram (Fig. 4) is bootstrapped mean of the first 1500 observations.

The histogram (Fig. 5) presents the bootstrapped mean of whole 2000 observations. Clearly, it is a mixture distribution.

Example 4. The rolling estimate of a parameter θ based on sample window of length l is

$$\hat{\theta}_t = g(x_{t-l+1}, \dots, x_t).$$

[9] proved theoretically that $\hat{\theta}_t$ is a moving average process MA(l). This fact is tested via simulation. This correlation is fitted using the empirical copula and various types of copulas. Here, 1000 samples are derived of beta distribution with parameters 2,1. The length of rolling window l is 2 and function g is the standard deviation of x_{t-1} and x_t . The coefficients of MA(2) are simulated using Monte Carlo method. The histogram of the first coefficient is given in Fig. 6.

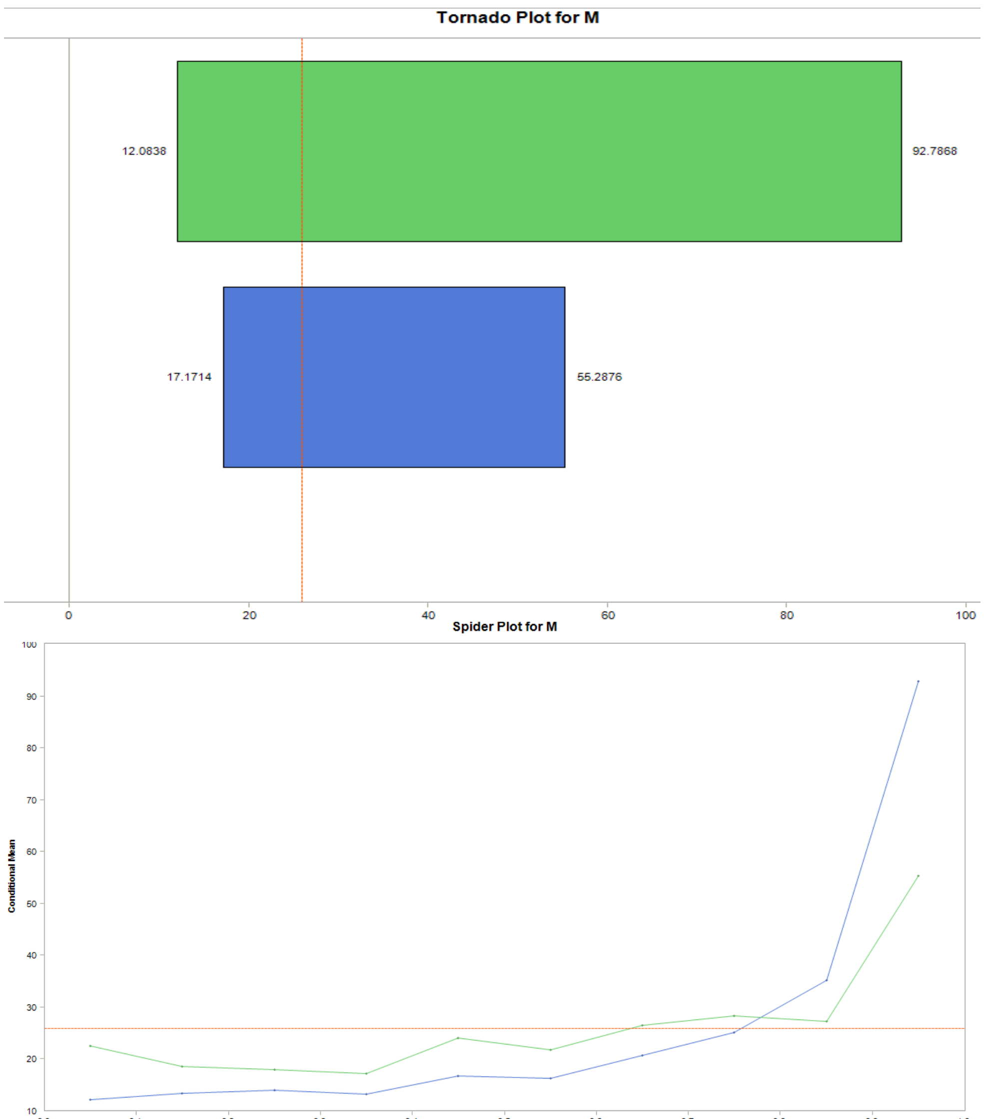

Fig. 3. Tornado and spider plot

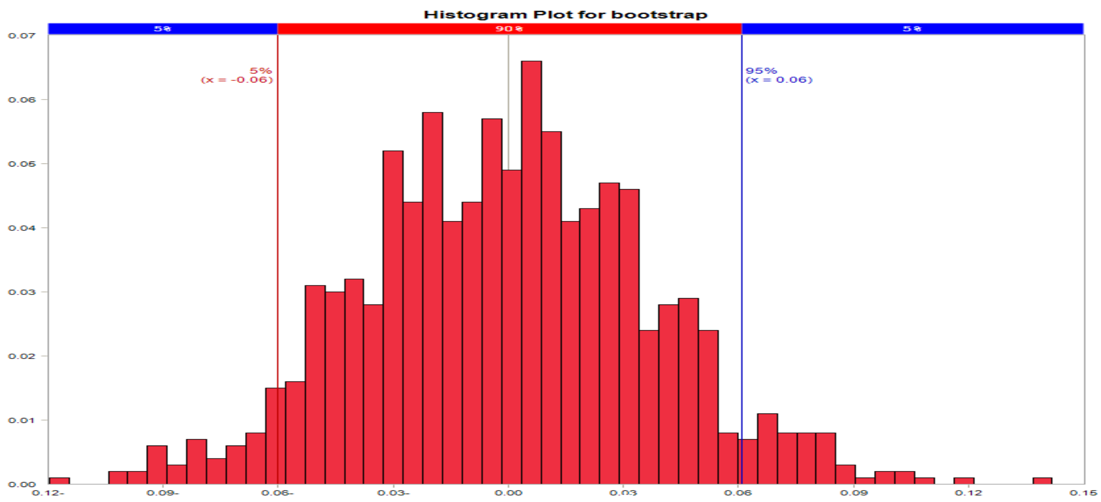

Fig. 4. Histogram under null hypothesis of no change

The Table 2 gives the summarize statistics about the second coefficient of MA(2) process.

Example 5. Here, in a risk event model, the Bayesian posterior is calculated using the Bayesian model averaging. An alternative option is to use the model tree models. Suppose that 1000 samples are generated from a risk event model with success probability 0.5 and the impact Beta distribution with parameters 3,4. Suppose that there is a prior knowledge about data such that i-th observation has weight $0.25(0.8^{\mathrm{i}}), \mathrm{i} = 1,2,\ldots$. The histogram (Fig. 7) is the posterior using Bayesian model averaging.

Example 6. The distribution of maximum and median of a combined and spliced distribution is approximated by empirical fit function. Suppose that 100 samples are generated of a splice distribution. The law distribution is Gamma with parameters 3, 8 and the second is a Pareto with parameters 4,6,3. The histogram of maximum is plotted in Fig. 8.

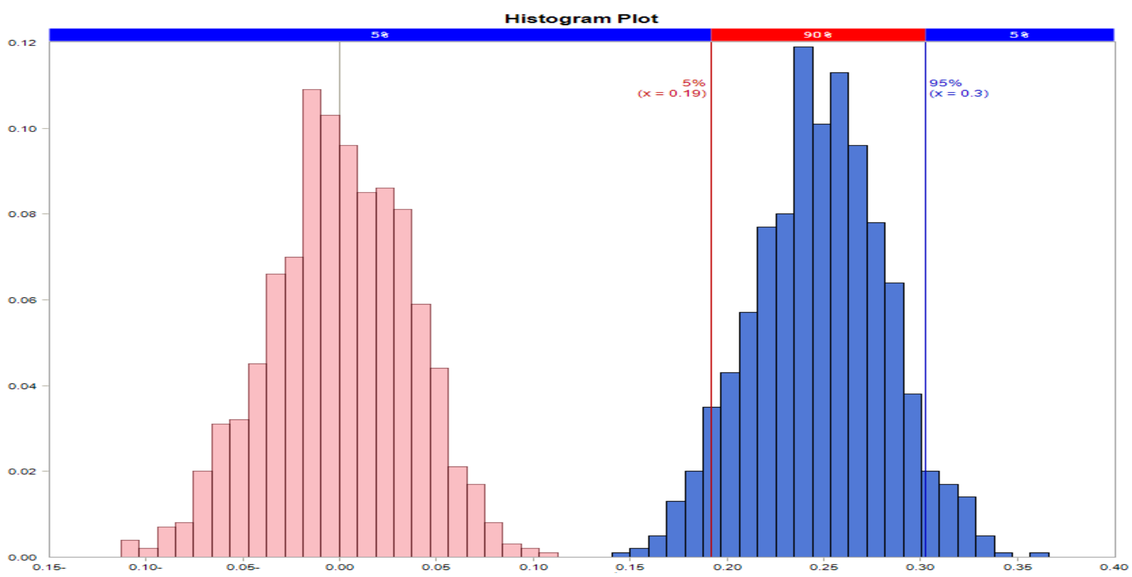

Fig. 5. Histogram under alternative hypothesis

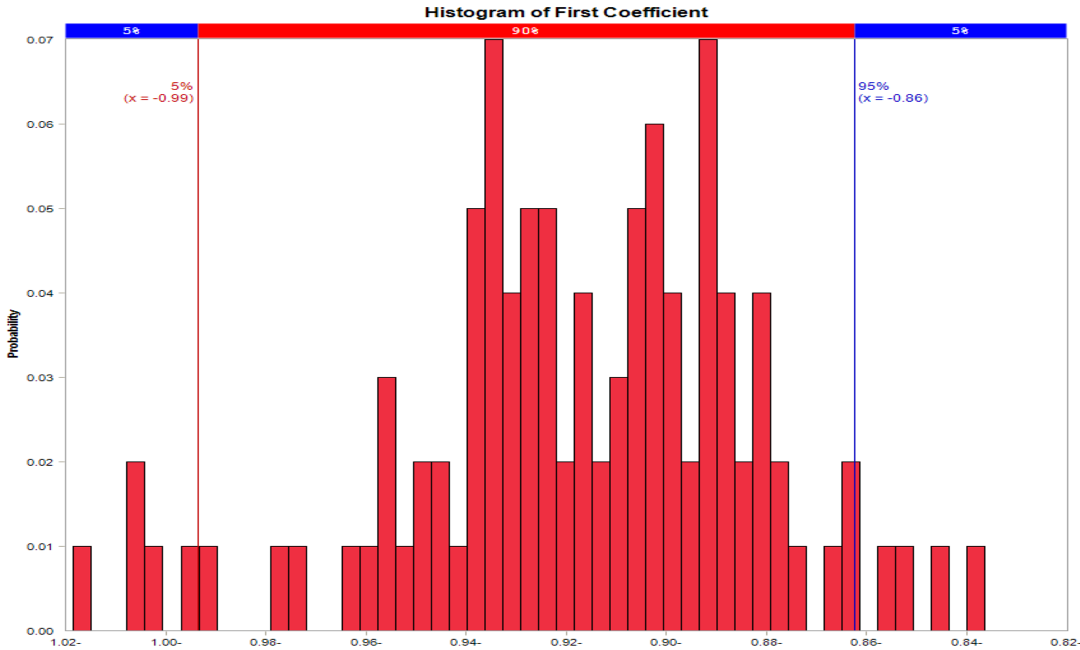

Fig. 6. Histogram of the first coefficient in MA(2)

Table 2. Descriptive statistics of the second coefficient

mean	stdev	skew	kur	med	min	max
-0.919	0.038	0.168	2.91	-0.921	-1	-0.828

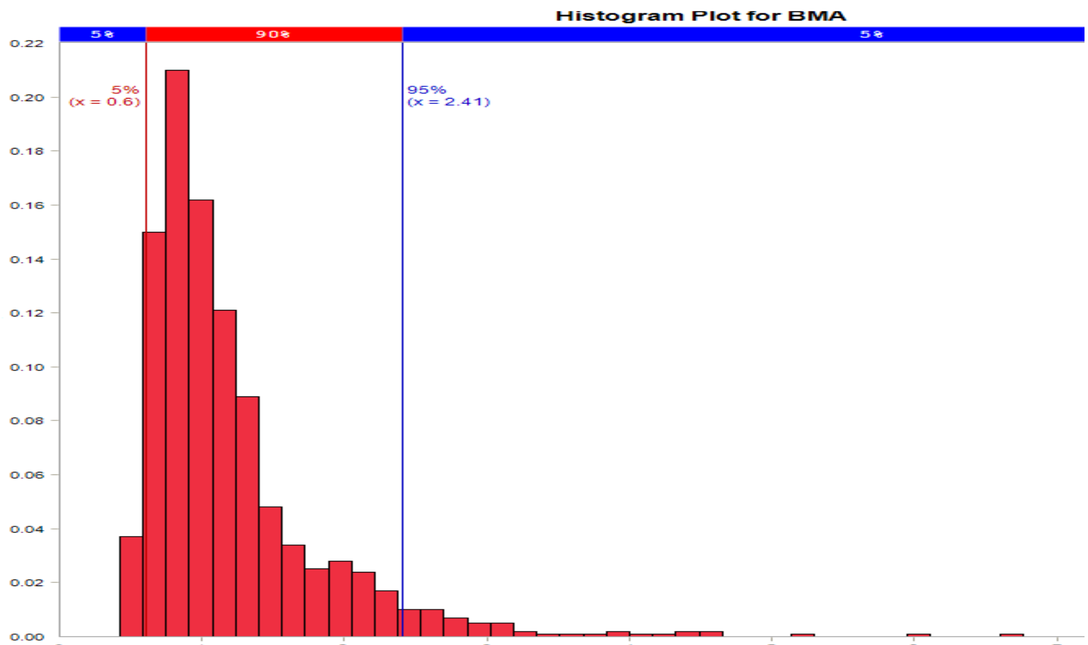

Fig. 7. Histogram of posterior distribution

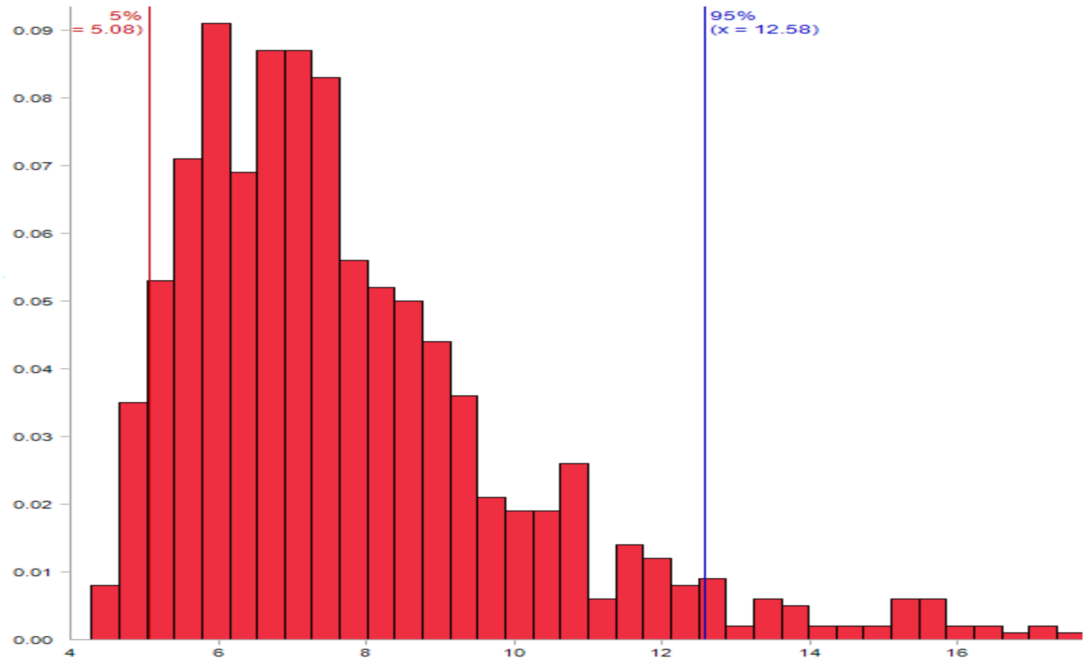

Fig. 8. Histogram of maximum of spliced distribution

A Chi-squared distribution is fitted to above distribution with 7.84 degree of freedom. For the median of combined distribution, the histogram (Fig. 9) is given as follows.

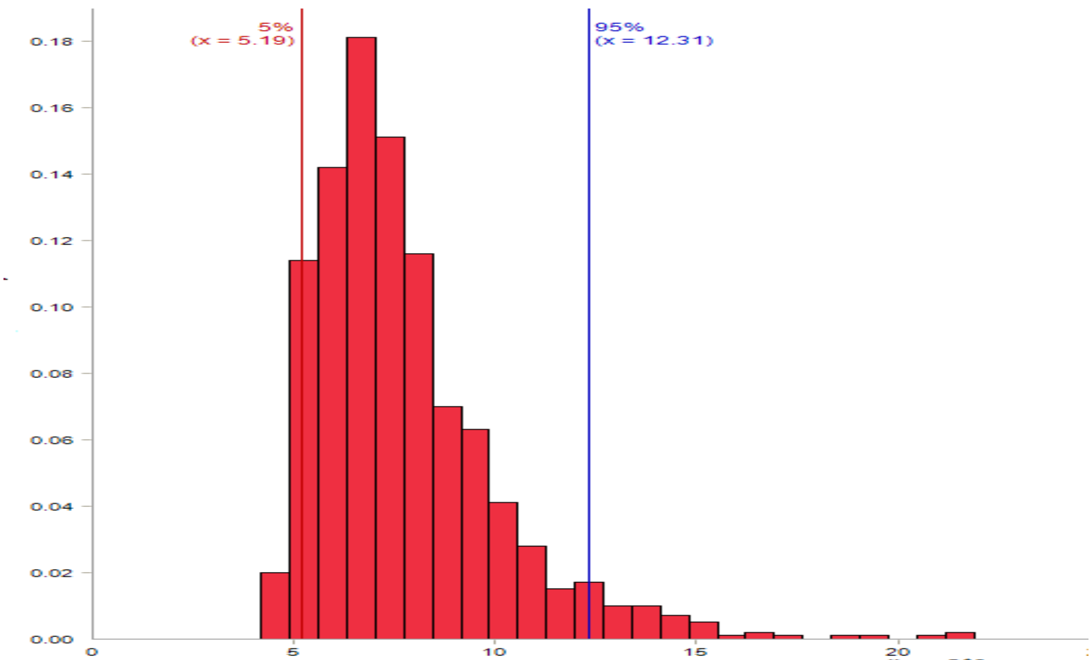

Fig. 9. Histogram of maximum of combined distribution

A Chi-squared distribution is fitted to above distribution with 1.93 degree of freedom.

Example 7. The expectation of a geometric Brownian motion is found by *ODE* and *Interpolate* functions. To calculate the mean, first the sample mean of 1000 samples of a GBM with $\mu = 0.01$, $\sigma = 0.025$ and the initial value 1 is computed. Then, μ changes from 0.01 to 0.05 with step size 0.01. Then, the numerical derivatives are obtained and the ODE is constructed. Table 3 gives the logarithm of mean values as follows.

Table 3. Logarithm of mean values

μ	0.01	0.02	0.03	0.04	0.05
Ln(mean)	7.24	16.98	26.94	38.7	45.77

By fitting a regression between Ln(mean) and μ, it is seen that $Ln(mean) = 913.013\mu \approx 1000\mu$, which corresponds to famous formula of $E(S_T) = S_0 e^{\mu T}$.

Example 8. The individual risk model for total claim of insurer portfolio is

$$S = X_1 + \cdots + X_n,$$

where X_i is the i-th risk factor $i = 1, \ldots, n$. The *Aggregate* options like *FFT, Panjer, MC*, and *De Prill* are useful to this end. The *ruin* function calculates the possibility of ruin of insurer portfolio. Suppose that 1000 samples are generated from three risk event models with success probability 0.5 and the impact Beta distribution with parameters 3,4. The output is the sum of three random samples. The histogram is plotted in Fig. 10.

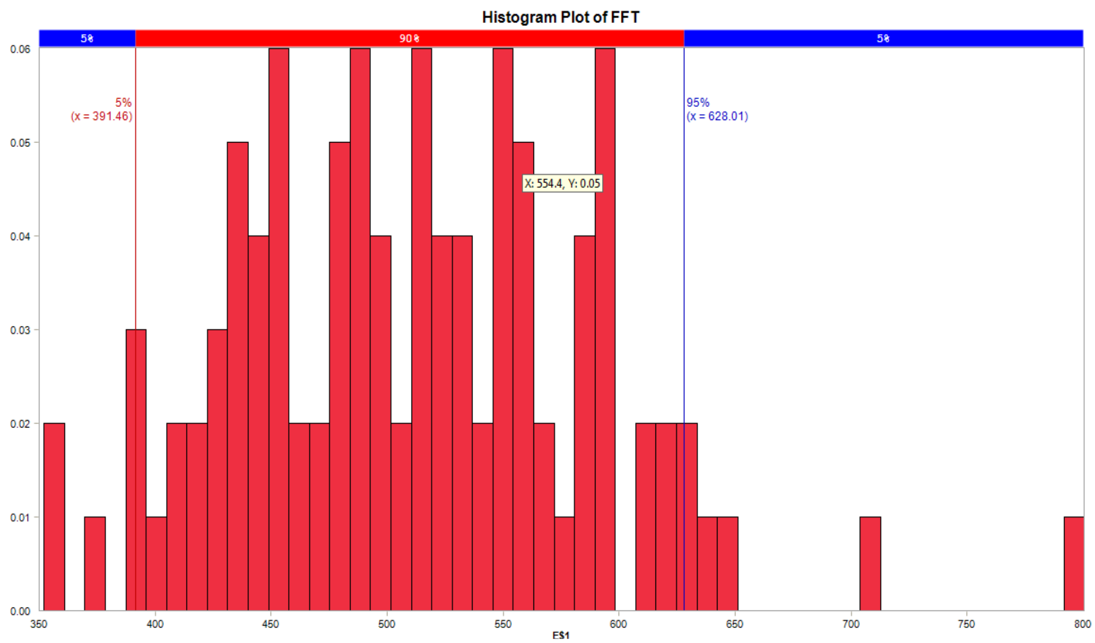

Fig. 10. Histogram plot of FFT

Example 9. A distribution is fitted for maximum of each random series of *Wilkie* models. *VoseTimeWilkie* is a function that generates random values from each of Wilkie's time series models. One of them is price inflation series produced by *VoseTimePriceInflation.* Its histogram (Fig. 11) and descriptive statistics (Table 4) are given as follows.

Table 4. Summarize statistics

mean	min	max	sd	skew	kur	med
0.078	0.04	0.286	0.024	20.26	13.67	0.07

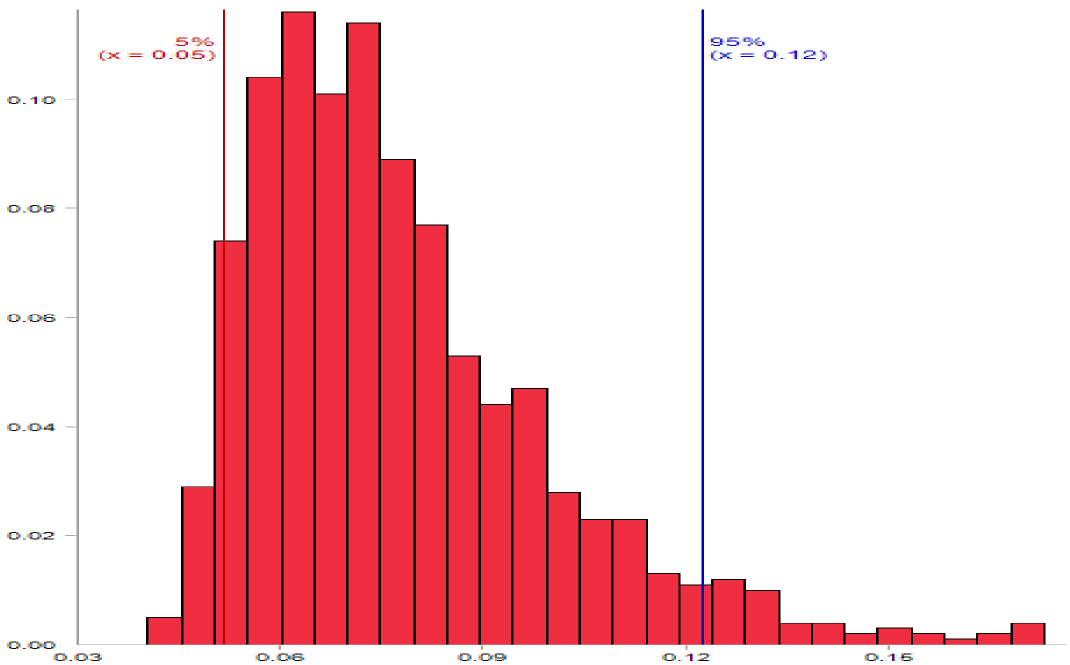

Fig. 11. Histogram plot

Example 10. Example 3 studies the change point analysis. However, the *ModelRisk six sigma* function presents the standard plots to detect shift in parameters of model. Suppose that 200 samples are generated such that the first 100 samples come from *t-student* distribution with 2 degrees of freedom and the remaining are from *t-student* distribution with 3 degrees of freedom. The cumulative sum (Fig. 12) is plot designed for detection of shift in parameters. It is seen that a change has occurred in time series.

Example 11. The Basel Accord sets limitation on exposures of bank. *ModelRisk* may be used the losses and Value at Risk (VaR's) under different scenarios. Consider a bank that has a portfolio of 100 loans. The volume of loans varies from 2,000 to 20000 dollars with different probability of default. The Table 5 presents the VaR under different scenarios (S).

Table 5. VaR under different scenarios

Scenarios	S	S	S_3
Expected loss	14503	14668	17655
VaR(0.95)	43736	43775	52554
VaR(0.975)	55775	55988	96888
VaR(0.99)	51154	52257	122442
VaR(0.995)	74776	75136	168332

Example 12. The *OptQuest* icon of *ModelRisk* performs stochastic optimization. Consider a portfolio contains 132 risky assets with Lognormal, PERT, Normal, ModPERT and Triangle distributions. The maximized value at risk (CVaR) for some significance level α are given as follows (V_0 is the initial value of portfolio) is given in Table 6.

Table 6. Maximized $\mathbf{CVaR}$

α	0.005	0.01	0.05	0.1
VaR	$0.58V_0$	$0.62V_0$	$0.83V_0$	$0.94V_0$

4. RESULTS AND DISCUSSION

In this paper, the application of *ModelRisk* software in statistical simulation problems are seen. Although, there are many other applications about this software. This paper can be considered as a starting point for many other similar research on this software. The main focus of this software is the application of Monte Carlo methods, distribution fitting, dependence analysis (copula fitting) and time series analysis in financial problems. However, in this short not, the ability of this software in financial management is used for many other important problems proposed in statistics.

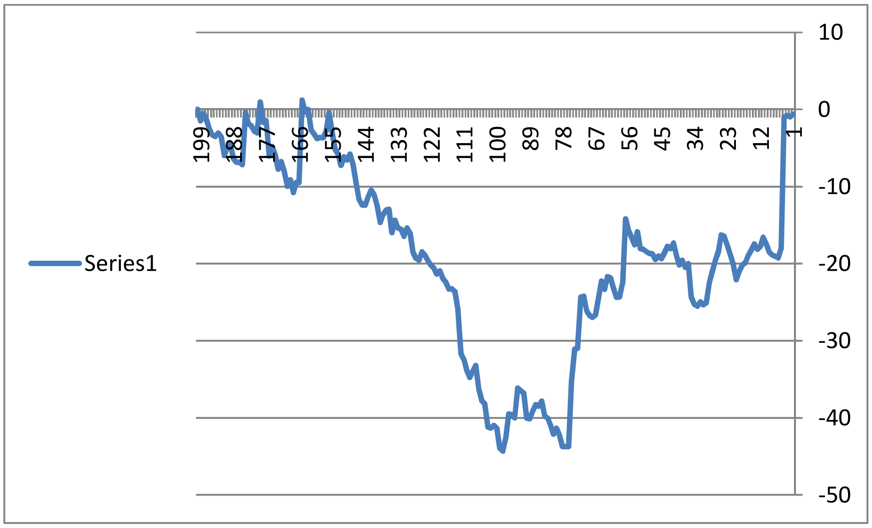

Fig. 12. Cumulative sum plot

5. CONCLUSIONS

This short note studies the application of *ModelRisk* software in simulated data. The main focus of this short note is on ability of *ModelRisk* software in implementing of statistical simulations which is shown by 12 examples. This note is extending by author.

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COMPETING INTERESTS

Author has declared that no competing interests exist.

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