MODELLING AND SIMULATION OF VARIABILITY AND UNCERTAINTY IN SHIP INVESTMENTS: IMPLEMENTATION OF FUZZY MONTE-CARLO METHOD

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ABSTRACT

This paper investigates fuzzy Monte-Carlo simulation method for analysis of ship investment projects. Investment analysis has several approaches such as traditional net present value method, multi-criteria decision methods. The proposed method does not execute judgmental factors of investment, but it ensures decreasing uncertainty on variables. Income and cost variables are transformed to fuzzy sets and simulations are performed according to probabilities of fuzzy intervals. Probability of loss is assessed for several conditions. Empirical works are reported for Panamax size bulk carriers in different financing particulars. Results indicated effects of term length, loan size and different freight market conditions including historical simulation, optimistic and pessimistic scenarios.

Keywords: Fuzzy Monte-Carlo (FMC); Ship investment; Project default.

INTRODUCTION

Analysis of ship investments has several aspects including volatility in freight markets, cost of financing and cost of operating. All of these factors have an unstable nature which makes assessment of projects is particularly crucial. An investor or lender institution should consider both quantitative factors and qualitative factors originated from condition of political stress in a specified region or investing field. Investigation of qualitative factors is a specialised field which is mainly studied by decision making science. Quantitative factors of investment can be evaluated by various methods such as deterministic models or probabilistic methods.

Stochastic modelling is a method to estimate probability distributions of system outcomes by executing random variation of inputs and use of a parametric equation to generate outcome. Randomness of inputs is generally based on observed historical fluctuations in a specified period. Distribution of an outcome is derived by conducting large number of simulations. As a stochastic modelling tool, Monte-Carlo method was first applied by Ulam, Richtmyer and Neumann (1947) to solve neutron diffusion and multiplication problems in fission devices.

The Monte-Carlo method is a statistical sampling technique which is well established and applied in many problems. Monte-Carlo method is frequently applied to financial problems and it is used in mathematical finance to assess portfolios and investments under uncertainty in some degree. The importance of Monte-Carlo method is stemmed from the flexibility to increase number of variables. Therefore, it is very useful in complex problems. Hertz (1964) first applied Monte-Carlo method to a financial problem and later Boyle (1977) extended application field to derivatives market.

Many scholars suggested methods for analysis of stochastic systems in investment decisions. Monte-Carlo simulation methods are widely used and implemented for investment analysis purposes. It is briefly based on series of iterations of variables according to their assumed probability distributions. In many cases, a variable is assumed to be normally distributed and a combination of several revenue-debt distributions provides a final income distribution (i.e. net income, earnings before tax). The opinion of such a probabilistic simulation is very useful, but the structure and distributions are mostly judgmental. In financial markets, most of the variables have their own specific distributions and sometimes it is very difficult to fit a theoretical distribution function.

Time series clustering is a convenient method to bundle groups of data and simulate them according to their overall probability. Fuzzy time series is a method to cluster and structure time series data. Data is divided into groups in proper lengths and membership degree of a single point is defined by a fuzzy shape (triangle or trapezoidal in most cases). Fuzzy numbers can be executed by arithmetic operations and a final crisp value is derived by a predetermined formula (centre of gravity e.g.). In the assessment of ship investment, value of interest rate, operating income and operating cost are transformed to fuzzy time series and profit/loss calculations are all performed over fuzzy arithmetic. Final result is ratio of settlement default in a specific period. The intended method is a time-invariant model which does not take into account the recent levels of variables. For a short term analysis, instant conditions are substantial, but it can be omitted for long term. Since, our investment problem is based on a long lasting process, instant levels of variables are less important in highly volatile markets.

FUZZY SETS AND FUZZY MONTE-CARLO SIMULATION

Fuzzy extended Monte-Carlo simulation is designed to cluster data and simulate clusters according to their associated probabilities. Clustering process is proposed as it is conventionally used in fuzzy time-series approach.

A fuzzy set is a group of data which has a grade of membership through the mentioned fuzzy set. Let U be the universe of discourse with $U=(u_1, u_2,\ldots,u_m)$ where u_i are linguistic variables.
Definition. $Y(x)$ (x =..., 0, 1, 2,…), is a subset of real numbers. Let $Y(x)$ be the universe of discourse defined by the fuzzy set $\tilde{A}$. If $F(x)$ consists of $\tilde{A}$, $F(x)$ is called a fuzzy time series on $Y(x)$.
Figure 1 illustrates a typical triangular fuzzy number. $\mu_A(x)$ is the membership degree on the fuzzy set $\tilde{A}$. '*a*' and '*b*' are lower and upper bounds respectively. '*m*' is the midpoint of fuzzy set. Crisp result of a fuzzy set can be defined by various methods. Centre of gravity method is the most used one which is calculated by averaging *a*, *m* and *b*.

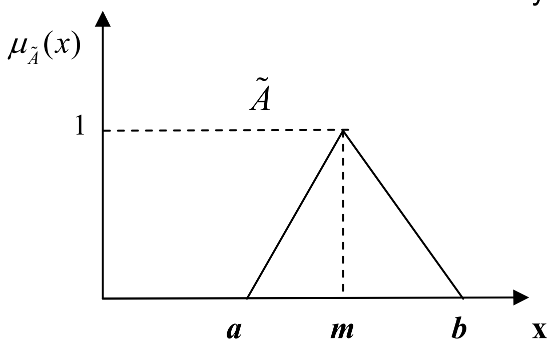

Figure 1 - Triangular fuzzy set.

Fuzzy Monte-Carlo simulation is designed in six steps (Fig. 2). The process is simply commencing with fuzzification of all simulation inputs, and then simulations are carried out. Finally, net results of financial period are calculated over fuzzy inputs and a fuzzy output will be produced for all iterations. Fuzzy output is transformed to a crisp result by calculating centre of gravity.

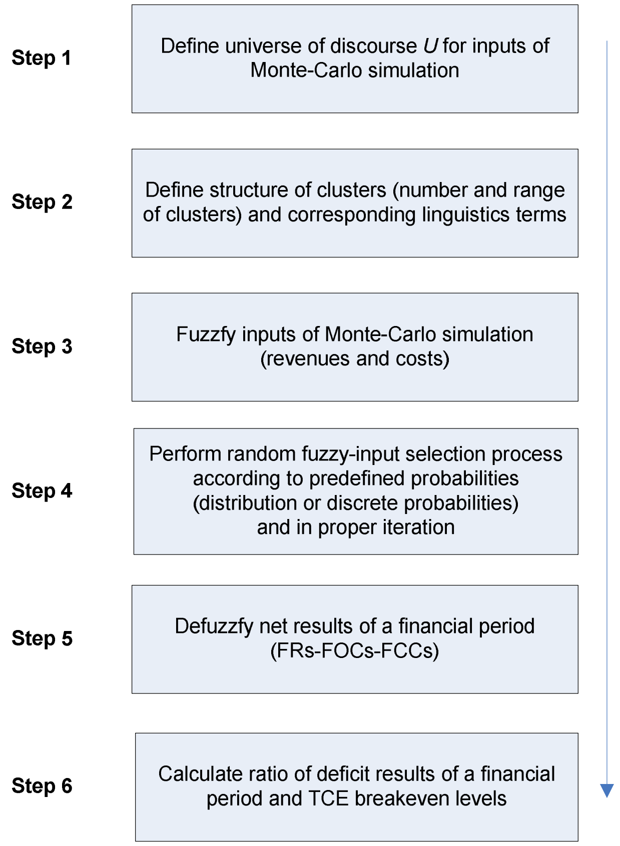

Figure 2 - The process of FMC simulation.

Step 1 & 2. Inputs of the simulation are fuzzified according to defined fuzzy intervals. The number of clusters and their intervals are generally judgmental decisions which should be predetermined by practitioner. In the example of ship investment, three sample projects are used in empirical works. Samples are selected for a Panamax (75 000 DWT) bulk carrier with different financing characteristics. Table 1 shows particulars of projects which have different leverage ratios, but same risk premiums. For the cost inputs and revenues inputs (TCE), fuzzification maps are defined as in Fig. 2. Datasets are divided into five fuzzy intervals which have corresponding linguistic terms such as very low, low, moderate, high and very high.

Table I - Particulars of empirical ship investment projects.

Code of project	Ship type & size	Loan amount	Term Structure & Interest
P-1	Panamax (75 000 DWT) Bulk Carrier	20 000 000 USD	LIBOR base 1% Spread for risk premium Paid in 10 years, semi-annually
P-2	Panamax (75 000 DWT) Bulk Carrier	10 000 000 USD	LIBOR base 1% Spread for risk premium Paid in 10 years, semi-annually
P-3	Panamax (75 000 DWT) Bulk Carrier	5 000 000 USD	LIBOR base 1% Spread for risk premium Paid in 5 years, semi-annually

Step 3. Cost inputs, operating cost and LIBOR (London Interbank Offer Rate), and revenue inputs, TCE base income, are transformed to fuzzy sets. Operating cost (OPEX-Operating Expense) means fixed cost of ship which does not consists of cost of voyage (bunkers, port dues, commisions etc.). Since the income is based on TCE base, voyage costs are out of scope for the current study. Another important fixed cost is the capital cost which is arisen from project financing. One of the critical and volatile criterias of financial deal is the rate of interest (conventionally LIBOR rate and plus a risk premium based on risk perception of lender). According to LIBOR rate, capital cost of a financial period differs. As a cost input, LIBOR rate is also fuzzified and a predetermined spread of risk premium is applied over random selection of fuzzy-LIBOR rate.

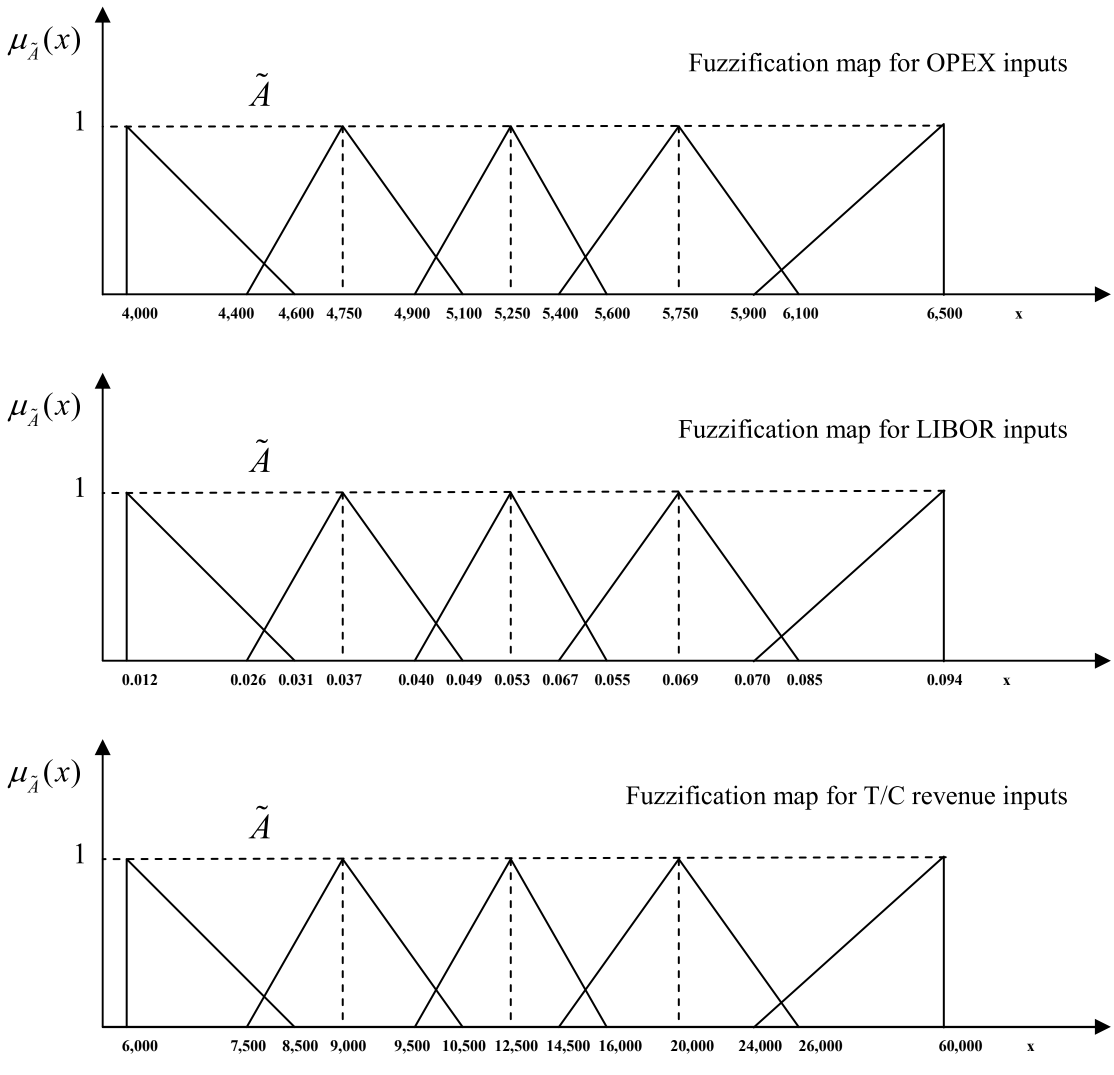

Figure 2 - Fuzzification maps of the FMC simulation inputs.

Step 4. Inputs of FMC simulation is selected randomly in a thousand iteration according to scenario characteristics. Scenarios are based on historical densities, Gaussian densities (normally distributed), lower case and higher case. Table 2 shows probability character of inputs based on historical record. OPEX data is collected from

Drewry Shipping Cost Annual reports for 2000-2009 term on annual average base. LIBOR rate series are including monthly averages between 1990 and 2009. T/C rates of a Panamax bulker are supplied from Clarkson Shipping Co. for 1987-2009 period. Probabilities that are presented on table 2 is calculated from historical probability distribution. For alternate scenarios, three additional fuzzy sets are defined as Gaussian distribution, lower case fuzzy set, which is exponentially decreasing probability distribution, and higher case fuzzy set, which is exponentially increasing probability distribution (table 3).

Table II - Historical probabilities of the FMC simulation inputs.

	OPEX	LIBOR	T/C Rate
U1	0.10	0.21	0.18
U2	0.35	0.20	0.18
U3	0.35	0.39	0.32
U4	0.15	0.15	0.14
U5	0.05	0.05	0.18

Table III - Probability table for Gaussian, lower case and higher case selections.

	Gaussian Distribution	Lower	Higher
U1	0.020	0.510	0.030
U2	0.110	0.260	0.067
U3	0.740	0.133	0.133
U4	0.110	0.067	0.260
U5	0.020	0.030	0.510

For every scenario, a thousand iteration of input is performed and result of output fuzzy sets is transformed to crisp numbers by calculating centre of gravity of triangle fuzzy numbers.

Step 5. Net result of a financial period (semi-annual in the present empirical work) is calculated by substracting Fuzzy-OPEX and Fuzzy-CAPEX (Capital Expense) from Fuzzy-TCE as follows:

$$\text{Profit/Loss} = \text{TCE} - \text{OPEX} - \text{CAPEX} \qquad \text{(eq. 1)}$$

CAPEX is based on straight line principals rather than straight line payments. Therefore, term payments decrease by the declining interest payment.

Substracting process is a fuzzy arithmetic operation which is proposed by Zadeh (1965). Selection of fuzzy sets depend on the objective scenario. Final crisp result is defined by calculating centre of gravity point on X-axis.

Step 6. Finally, ratio of deficit results which named ‘loss probability’ among all iterations (a thousand results) is defined for investigation. The term ‘loss probability’ simply refers to percentage of results which give deficit account. It does not execute any company particular. Therefore, it is quite different than loss given default and probability of default terms.

RESULTS AND DISCUSSION

Loss Probability Results

FMC simulation is performed by thousand iterations and the default frequency is recorded for every case. Figure 3, 4 and 5 show time charter (TC) breakeven level and loss probability in the duration of projects. Because of decreasing capital cost, both TC breakeven and loss probability ratio have decreasing trend. Inputs are based on historical probabilities rather than smooth curves. Therefore, outputs do not lie on a smooth curve; they have irregularities, step-down patterns and changes in some periods. P-1 has 20 semi-annual repayments and loan size is 20 million USD. Figure 3 indicates results for P-1. Left hand side scale is for TC breakeven prices and right hand side scale is for percent of credit default without external funds. Until the ninth year, more than 50% of distribution has negative results (loss) and TC breakeven is over 12,500 USD per day. Figures indicate high risk of loss in any size which should be secured by collateralisation.

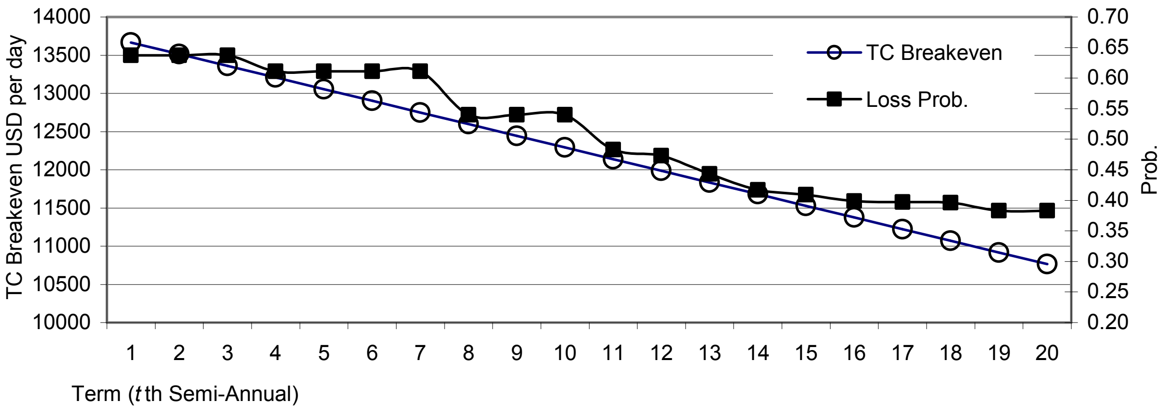

Figure 3 - Results of FMC simulations for Panamax size Bulk Carrier Project P-1.

Figure 4 shows results for P-2. Increasing owner's contribution and decreasing leverage conclude smaller loss probabilities. Rather than P-1, P-2 gained around 30% decline on loss probability in the first year. Spread between two loss probability data is around 20% in the last year of payments.

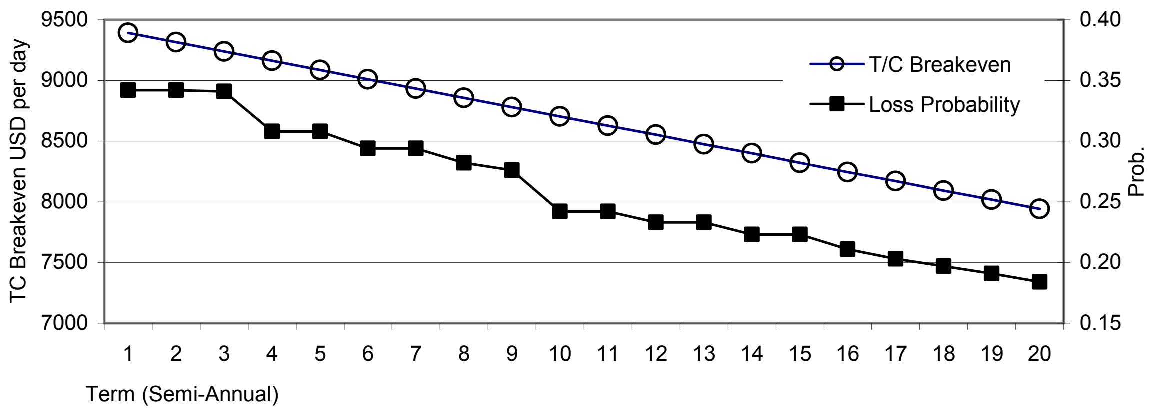

Figure 4 - Results of FMC simulations for Panamax size Bulk Carrier Project P-2.

P-3 has lesser loan leverage, but also term of payment is shorter (5 years). Both loss probability and TC breakeven have considerable declines. Maximum level of loss probability is 24%. Broadly risk of loss is declined (Fig. 5).

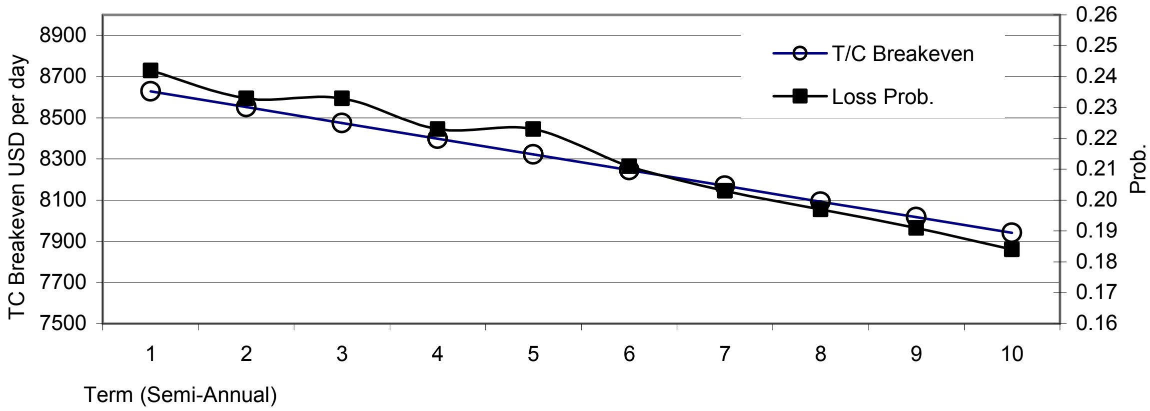

Figure 5 - Results of FMC simulations for Panamax size Bulk Carrier Project P-3.

Effects of loan size

FMC simulations are also carried out for different loan sizes in two project particulars. When all components are kept constant, loan amount is increased by 1 million USD steps and loss probability and TC breakeven is calculated. For instance, a Panamax ship project is selected as in P-1 in 20 years term and various loan sizes are displayed. In figure 6, loan size lies between 5 and 30 million USD which is assumed to be paid in 20 years contract and semi annual periods. Loss probability increases from 10% to 70% between two borders of interval. Two cycles are recorded between 5m-15m USD and 16m-30m USD. Rate of increase remains similar levels in general between 11m-15m USD and 24m-30m USD. These two cycles are caused by non uniform distributions of both cost and revenue inputs. FMC is based on fuzzy interval probabilities rather than smooth theoretical distributions. Therefore, such stepwise upswings are ordinary figures.

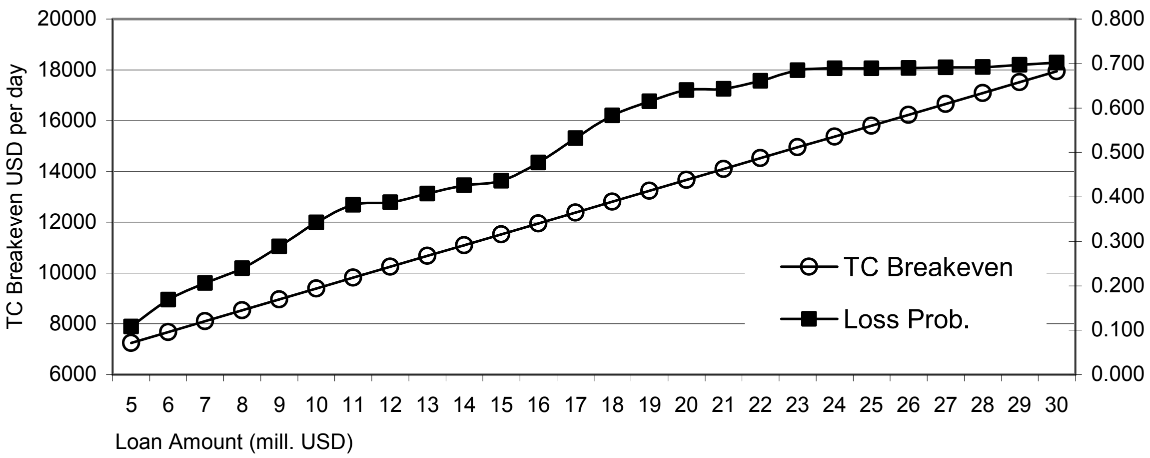

Figure 6 - Fluctuations of deficit ratio for Panamax project (20 years, semi-annually payments).

Cycles of loss probability are more intensive on figure 7. Configurations of P-1 are applied in different loan sizes. Loss probability has 10% increment at all, but number of step-up cycles is three. Because of decreasing loan term, period payments increased and effects of capital cost are deeper. Particularly after the levels of 10m USD, loss probability has enormous raise and on lender's side financing of project receives rapid increase on default risk. By reaching to 13m USD levels, loss probability is remaining on same rates broadly.

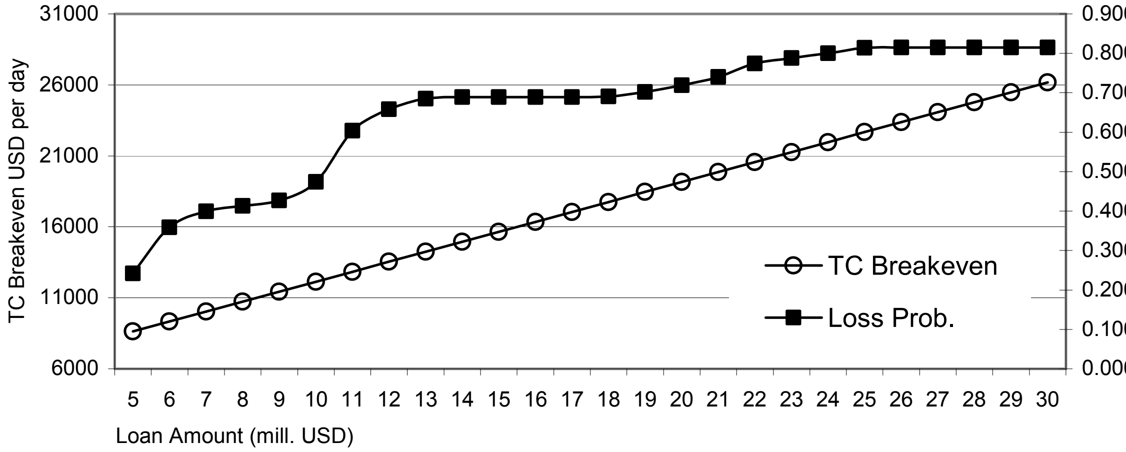

Figure 7 - Fluctuations of deficit ratio for Panamax project (10 years, semi-annually payments).

Normality assumption and differences

The final analysis is based on five different scenarios and their assumptions. 10 years Panamax ship project is selected with credit configurations of P-1 and loss probability is calculated between 1m-30m USD loan sizes. Five scenarios are designed as follows:

(1)Historical scenario : Inputs are based on historical distributions.
(2)Normal distribution : All inputs are normally distributed.
(3)Optimistic scenario : Higher TC, lower cost case.
(4)Pessimistic scenario : Lower TC, higher cost case.
(6)Mean of Optimistic and Pessimistic scenario.

Figure 8 shows the loss probability curves in various loan sizes. Normal distribution is assumed in many practical analyses and the figure indicates differences between assuming normality and some other conditions. Historical scenario is designed by real market prices in FMC and it has important disparities with normality assumption. Normal distribution scenario curve conceives a logistic plot as expected. Normality assumption indicates very low levels of loss probability till 16m USD loan size and it has substantial upswing later. However, historical records point out higher probability till 16m USD loan size and lesser later. Over 20m USD, historical FMC simulation has maximum 70% loss probability, but normality assumption reaches to 90% very quickly.

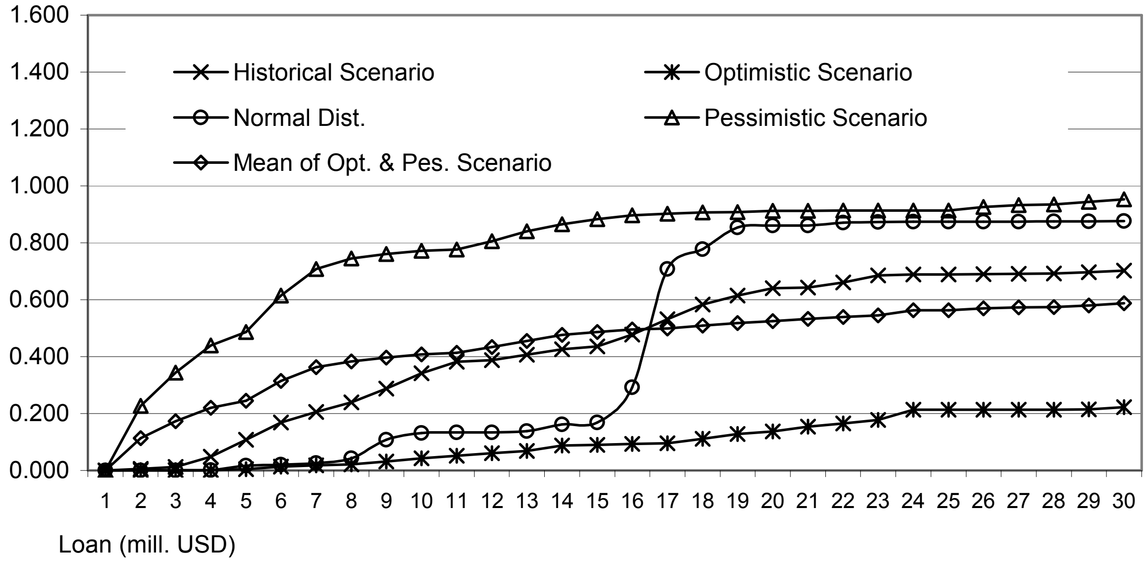

Figure 8 - Multiple scenarios for Panamax project (10 years, semi-annually payments).

By the evidences of analysis, risk is underestimated in half and overestimated on remaining. The rate of 50% is connection point for historical, normal and mean scenario curves. For the sample project, it is located on 16.5m USD loan size.

CONCLUSION

Probabilistic analysis of investment projects is a conventional practice in business management. Monte-Carlo simulations are well established and applied in project assessment task and it has several advantages beside disadvantages on assuming a theoretical curve. In actual records of many variables, there are several discontinuities and most of them can not be captured by a normal distribution. However, it is frequently used in practice as it is suggested by theories such as efficient market hypothesis.

Fuzzy Monte-Carlo method extends the recent literature by treatment of pattern recognition on probability distributions of investment appraisal. Probability curves are modelled by discrete frequencies on fuzzy intervals. The present paper indicated that assuming normality has various drawbacks such as over optimism and over pessimism in different particulars of credit issue.

Further research should be performed on analysis of credit issue experience in relation to loss probability and particularly due to records of credit defaults. Another gap lies on size of loss probability and collateralisation of potential default risks.

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