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Improving risk assessment in financial feasibility of international engineering projects: A risk driver perspective

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Abstract

Major engineering projects characterized by intensive technologies and high investment are becoming more complex with increasing risks in a global market. Because incorrect investment decision-making can cause great losses to investors, quantitative risk assessment is widely used in establishing the financial feasibility of projects. However, existing methods focus on the impact of uncertain parameters, such as income, on decision variables of investment, neglecting assessing the impact of risk events, such as the sales of products falling short of expectations. In the context of international engineering projects from a risk driver perspective, this paper presents an improved quantitative risk assessment model to help risk managers identify the direct relationships between specific risk events and decision variables of investment. Stress testing is also introduced to assess the negative impact of extreme risks. The new model is applied to an on-going international petrochemical project to demonstrate its use and validate its applicability and effectiveness.

Keywords: Quantitative risk assessment; Investment decision-making; Risk driver perspective; Monte Carlo simulation; Stress testing

1. Introduction

The global operation of engineering companies has resulted in increasing foreign trade and investment. Due to the changing external environment and the complexity and high level of investment needed for projects, investment risks are becoming greater and more worrying for investors as wrong investment decisions, characterized by irreversibility and uncertainty, often exert a long-term impact, such as considerable financial losses and reputational damage (Kim et al., 2012; Alkaraan, 2015; Hallegatte et al., 2012). Consequently, it is considered vitally important to conduct a detailed risk assessment when making such investment decisions (Virlics, 2013).

Risk assessment is a systematic, evidence-based approach for assessing uncertain or risky future events. Here, uncertainty refers to a state where an exact numerical value cannot be given for an activity as some variation in values may occur due to unpredictable circumstances, while a risk event is defined as the probability that an event will occur and considers the impact on corresponding objectives when the event occurs (Samson et al., 2009). A widely used method for risk assessment of investment decisions for international engineering projects is Monte Carlo simulation. Practically, it is very common for individuals to evaluate the impact of uncertain parameters (such as costs, price of raw materials, sales price, construction period and productivity) on decision variables (Hacura et al., 2001; Ye and Tiong, 2000; Rezaie et al., 2007; Suslick et al., 2008). This commonly involves calculating the variation in net present value (NPV) and internal rate of return (IRR) under the condition that uncertain parameters vary within a specific range

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and then to obtain the probability distributions of NPV and IRR.

The values of the uncertain parameters involved vary with the occurrence of risk events. That is, it is the risk events rather than the uncertain parameters that are the root causes of the variation in the decision variables of investment. However, the traditional quantitative risk assessment model does not take into account the influence of risk events on decision variables and so no targeted measures are developed to prevent losses that might subsequently be incurred.

To overcome this defect, this paper presents an improved model to assess investment risks quantitatively for international engineering projects from a risk driver perspective. Stress testing is introduced to assess the negative impact of extreme risk events. The input and output information and specific processes of the model are firstly elaborated, followed by a case study to demonstrate its use and validate its applicability and effectiveness. Final remarks concern the potential of the model to provide more practical decision-making support for investment in international engineering projects as a means of reducing the prospects of investment failure.

2. The traditional quantitative risk assessment model

Risk assessment can be divided into qualitative and quantitative methods, with the traditional academic focus being on the latter (Tah and Carr, 2001). Quantitative risk assessment is inherently related to risk modelling (Taroun, 2013). Risk modelling has developed along with the shift of risk perception from an estimation variance initially (Edwards and Bowen, 1998; Taroun, 2013) to a project attribute later (Dikmen et al., 2007; Merna and Al-Thani, 2008). As a result, risk is mainly evaluated on two dimensions: the probability of occurrence and impact. Correspondingly, risk assessment tools have evolved from statistical methods based on probability theory (e.g., Edwards and Bowen, 1998) to analytical tools (e.g., Lazzerini and Mkrtchyan, 2011; Nieto-Morote and Ruz-Vila, 2011), such as the Analytical Hierarchy Process (AHP) and decision trees, and stochastic simulation (e.g., Choudhry et al., 2014)—used to simulate independent variables based on a set of random values to obtain probability distributions of the forecast variables, such as Monte Carlo simulation.

The most common quantitative risk assessment tools for investment decision-making are *decision trees* and *Monte Carlo simulation*. A *decision tree* model predicts target variables through a set of prediction rules that are arranged in a tree-like structure (Syachrani et al., 2012). It is used to represent different decision alternatives and their consequences. However, the analysis of decision trees is based on a single-value point estimate as an average outcome for the long run, which limits their real-life applications to a narrow scope of decision problems (Moussa et al., 2006). *Monte Carlo simulation*, on the other hand, is suitable for use with objects with probabilistic characteristics and is able to generate additional data (Shen et al., 2011) to produce probability distributions of possible outcome values and also indicate which inputs affect the outcome the most, which makes it the most common and applicable tool for quantifying investment risks in major engineering projects.

Investors need to make decisions based on the likely values of the financial results of investment, using metrics such as NPV and IRR (Li and Sinha, 2009; Warszawski and Sacks, 2004; Hartman and Schafrick, 2004), and the use Monte Carlo simulation enables risk managers to determine their probability distributions by specifying influencing factors or independent variables (IVs), such as capital expenditure, operation costs, maintenance costs, productivity, product prices, prices of raw materials and inflation indices (Ye and Tiong, 2000; Davidson et al., 2006; Girmscheid, 2009; Hawas and Cifuentes, 2014), as probability distributions and calculating the results repeatedly, each time using a different set of random values from the probability functions. To do this necessitates risk managers defining the form of the IV probability distributions and their associated parameters. However, these parameters are themselves uncertain. Product price, price of raw materials and the inflation index, for example, are affected by risk events, such as the breakout of the global financial crisis.

In traditional quantitative risk assessment practice, the values of these uncertain IV parameters are estimated based on predictions and assumptions about the future. Investors cannot lower the possible losses incurred from the variation of uncertain parameters by making an increased effort. Nevertheless, investors still can lower or eliminate risk by further efforts. Most engineering project risk events, such as delays in the supply of raw materials, are knowledge-related and partly due to an inability to understand the project and its surrounding environment (Flage et al., 2013). Such risk events can be managed by risk reduction countermeasures as distinct from pure parameter estimation to bring about improved forecasts of NPV and IRR.

Stewart and Deng (2014) argue that risk managers generally pay insufficient attention to the probability of occurrence of risk events when conducting risk analysis. To overcome this, both the probability of occurrence *and* impact of risk events need to be defined as IVs. In addition, as extreme events occur that are characterized by low-probability and high-impact, the corresponding financial results are prone to deteriorate significantly. Investors therefore need to reserve enough risk provision or make corresponding risk countermeasures in advance or else, when extreme events do occur, they may suffer huge losses and even investment failure. To do this involves calculating the incurred loss when a risk has low-probability but high-impact—termed here as "stress testing"—to determine the negative impact of extreme risks on NPV and IRR.

In short, the traditional quantitative risk assessment model has two important drawbacks in failing to (1) define risk events that are the root causes of losses as IVs of decision variables of investment and (2) assess the negative impact of extreme risk events. An advanced quantitative risk assessment model is therefore presented to overcome these drawbacks by building up the direct relationships between risk events and decision variables of investment from a risk driver perspective and providing stress testing on the likely variation of the decision variables of investment.

3. Advanced quantitative risk assessment model

The processes of the new model are shown in Fig. 1. First, risk managers identify risk events and filter high- and medium-level risk events through a risk probability–impact matrix with reference to expert opinions. They then quantitatively assess the influence of the filtered risk events on the decision variables of investment (NPV and IRR in this case). The remainder of this section deals with the input needs and output possibilities of the model. These inputs are necessary for performing a risk analysis with a computer program. The outputs are chosen in support of investment decision-making and can be obtained from the program on completion of the analysis.

3.1. Inputs

3.1.1. Risk driver matrix

Given that risk events are root causes of losses, it is necessary to understand the influence of risk events on the decision variables of investment, namely to establish a risk driver matrix. The risk driver matrix shown in Table 1 lays the foundation for subsequent sensitivity analysis and Monte Carlo simulation in providing the probabilities and impact range of the filtered risk events. In the table, "1" represents a risk event that occurs, while "0" represents one that does not. The "Impact range" refers to the minimum (MIN), most likely (ML) and maximum (MAX) values of the impact of a specific risk event on the decision variables of investment. These three-point estimates are based on the impact value when the corresponding specific risk event does not occur. The probabilities and range of impact of the filtered risk events are all determined by experts' subjective opinions due to lack of historical and operational data (Goossens and Cooke, 1997).

Table 1
Risk driver matrix.

Risk events	Probability		Impact range		
	1	0	MIN	ML	MAX
Risk event 1					
Risk event 2					
Risk event 3					
……					

3.1.2. Determination of probability density functions

Prior to the Monte Carlo simulation, risk managers should determine the probability density functions (p.d.f.s) of the

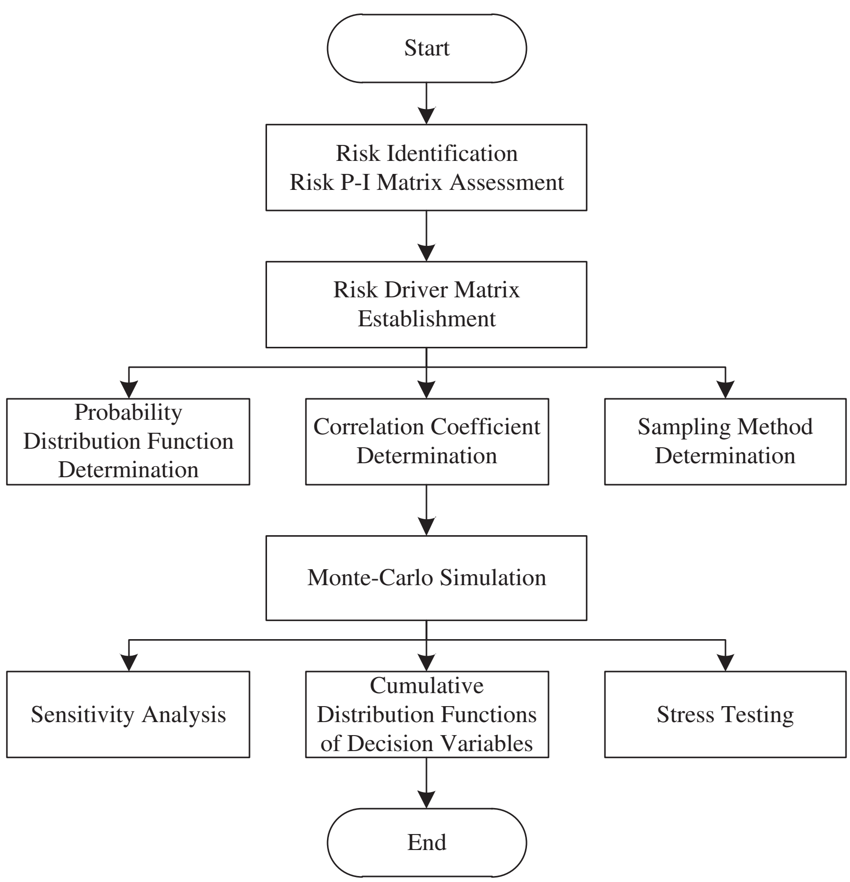

Fig. 1. Processes of the advanced quantitative risk assessment model.

filtered risk events and uncertain parameters (collectively referred to here as 'input variables'). Pritsker (1995) defines a p.d.f. as any rule that assigns a probability to all possible values of a random variable. In practice, risk managers should define the p.d.f.s of both the probabilities of occurrence of risk events and their impact on the decision variables of investment. However, considering the uncertain parameters fluctuate continuously due to the changing external environment, risk managers only need to determine the p.d.f.s of the parameters themselves.

Risk managers need to select the p.d.f.s of the input variables carefully, as the quality of the simulation results is strictly related to their accuracy. As an aid to doing this, Maio et al. (2000) has identified three approaches, namely *trace-driven simulation*, *empirical distribution* and a *theoretical distribution function*. *Trace-driven simulation* allows the use of real data in the simulation model, but has drawbacks in reproducing solely what has happened and in being time-consuming due to the need for large amounts of data (Law and Kelton, 1991). An *empirical distribution function* is obtained by grouping the data into a frequency histogram for use directly by the simulation model. This dampens extreme values however. In contrast, a *theoretical distribution function* using heuristic procedures or goodness-of-fit techniques will take extreme values into account, and represents the most compact and timesaving procedure in performing simulations (Maio et al., 2000). Consequently, most risk managers use this last method in defining the p.d.f.s involved.

In investment decision-making for international engineering projects, the theoretical p.d.f.s of the input variables most commonly used in the quantitative risk assessment model are the (1) uniform distribution, (2) triangular distribution, (3) normal distribution, (4) logarithmic normal distribution and (5) Bernoulli distribution. The p.d.f.s of the first four of these are

$$F(x) = \frac{1}{b-a}, a \le x \le b \tag{1}$$

$$F(x) = \begin{cases} \dfrac{2(x-a)}{(b-a)(c-a)}, a \le x \le c \\ \dfrac{2(b-x)}{(b-a)(b-c)}, c < x \le b \end{cases} \tag{2}$$

$$F(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{3}$$

$$F(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{[\ln(x)-\mu]^2}{2\sigma^2}\right) \tag{4}$$

where a, b and c in Eqs. (1) and (2) denote the minimum, maximum and most likely values of a random variable, and μ,σ^2 in Eqs. (3) and (4) the mean and variance. In general, risk managers mostly use three-point estimates, i.e., estimates of the minimum, most likely and maximum values, to determine the corresponding parameters of every p.d.f. In practice, risk analysts do not usually have access to sufficient objective information to determine the p.d.f.s of the input variables and therefore have to resort to information provided by experts, the imprecision of which is subject to the theory of possibility (Flage et al., 2013). Therefore, interviews with four experienced industrial experts were conducted to determine the p.d.f.s of the input variables. Three of these are from construction firms ranked in the Engineering News-Record (ENR) Top 250 International Contractors List in 2015 and have over 5 years working experience of quantitative risk assessment, while the other expert is from a risk management consulting firm. The probability of occurrence of risk events and their impact on the investment variables are empirically defined as Bernoulli and triangular p.d.f.s. The price of raw materials and products is usually defined as either normal or lognormal p.d.f.s depending on their coefficient of variation (cv), with cv < 30% for the former and cv > 30% for the latter.

3.1.3. Determination of correlation coefficients

It is widely recognized that the correlation between uncertain parameters must be taken into consideration for engineering projects (e.g., Wang, 2002; Yang, 2006). The Pearson product–moment correlation coefficient measures the linear relationship between two continuous variables and is therefore generally unsuited to non-linearly correlated variables (Hauke and Kossowski, 2011). The Spearman's rank correlation, although less powerful, can deal with the correlation of variables that satisfy the monotonic relation without a strict requirement of linear correlation (Hauke and Kossowski, 2011; MacFarland and Yates, 2016). In the practice of quantitative risk assessment of investment decisions for international projects, if a coefficient is higher than 0.3, the coefficient is taken to be significant and supposed to be taken into account; while if a coefficient is higher than 0.6, the correlation needs to be considered.

3.1.4. Determination of the sampling method

In Monte Carlo simulation, generally, there are two sampling methods, namely Monte Carlo sampling and Latin Hypercube sampling. Monte Carlo sampling is used to generate valid numbers randomly based on pre-determined p.d.f.s. These numbers are completely independent, which means numbers in the sample will not have an effect on those of another sample. Adopting the method requires more samples to increase the statistical accuracy. In contrast, Latin Hypercube sampling generates random numbers from equally probable intervals. Sampling this way is more accurate than Monte Carlo sampling as it can provide a more complete picture of the p.d.f.s. In general, Monte Carlo sampling is better when attention has been paid to simulation of the practical application, while Latin Hypercube sampling is preferred when focusing on the statistical accuracy of the simulation.

Moreover, sampling will be setup to terminate only when the mean and variance of the forecast variables become stable, which can be achieved by use of risk analysis software.

3.2. Outputs

3.2.1. Sensitivity analysis

Sensitivity analysis is used to understand how the forecast variables can be qualitatively or quantitatively apportioned to different input variables (Saltelli, 2004). This has also been used in the past for model identification (Tang et al., 2007) and complexity reduction (Van Werkhoven et al., 2009). In practice, sensitivity analysis is used to estimate the likely variation in forecast variables when the input variables deviate from their expectations. Sensitivity analysis can be performed from a mathematical model defined by a series of equations and input variables. This can be conducted in quantitative risk assessment by risk assessment software after Monte Carlo simulation.

Considering the investment decision variables are calculated under uncertainty, a global (rather than local) sensitivity analysis method is chosen. The latter is carried out when one is interested in performing the analysis around a point of interest in the model input space (Borgonovo and Plischke, 2016). After sensitivity analysis, a rank of sensitivity can be obtained according to the impact of the input variables on the investment decision variables to determine the critical factors involved to develop specific control measures in response.

3.2.2. Cumulative distribution functions of decision variables

After establishing the functional relationship between the input variables and decision variables of investment, risk analysis tools such as @RISK can be used to obtain the c.d.f.s of the decision variables. These reflect not only all possible values but also their corresponding probabilities and enable a comparison to be made with pre-determined decision criteria to improve the accuracy of decisions.

3.2.3. Stress testing

Stress testing is used to calculate the possible loss involved when low-probability/high-impact risks occur. This is helpful in understanding the current risk exposure of a project. The method has been introduced into many fields, for example, financial risk management and software engineering (e.g., Dempster, 2002; Marciniak and Shumskas, 1994). However, it has had no application in risk assessment for investment decision-making of engineering projects. Once extreme risk events occur, investors can suffer huge losses, hence, it is necessary to undertake stress testing on low-probability but high-impact risk events.

In a Monte Carlo simulation, the scenarios generated on screen do not obviously reflect these low-probability scenarios and the p.d.f.s of input variables with a high impact on the decision variables need to be modified accordingly. This is especially the case for continuous distributions and discrete distributions without a well-defined maximum or minimum. To carry out stress testing, the selected range of probabilities is from at least P_{80} to P_{100}. This can enable investors to better understand their risk exposure, make investment decisions and devise targeted risk reduction countermeasures in advance.

4. Case study

4.1. Background

The project chosen for demonstrating the model is an actual oil refinery project in Brazil. The main raw materials of the oil refinery are crude oil, natural gas and methanol. Its products mainly comprise liquefied petroleum gas, naphtha, benzene, M8A, propylene, clean gasoline, jet fuel, diesel oil, low sulphur fuel oil, other fuel oil, petroleum coke, sulphur and liquid ammonia. The cash flow of the project is present in Table 2. In view of the project's complexity and its changing environment, a risk assessment model was needed for the detailed risk analysis to establish financial feasibility.

In consideration of risk level of projects in South America and experience and judgement of experts, the investor determined the decision criteria to be Prob(NPV > 0) ≥ 0.60 or Prob(IRR > 13%) ≥ 0.60 based on both its risk tolerance and international strategy.

4.2. Inputs

The risk managers first identified the major risk events involved by consulting historical data and analysing characteristics of the project, and then assessed risk events by a probability–impact matrix. Based on the assessment results, they then filtered out the high- and medium-level risk events. After determining probabilities of occurrence of the risk events and their impact range on NPV and IRR, a risk driver matrix was constructed (Table 3).

Taking R14, labour risk, as an example, its probability of occurrence and non-occurrence is 0.70 and 0.30, respectively. The minimum, most likely and maximum impact values of 0.7, 1.1 and 1.3, respectively, of R_{14} are determined based on the condition that R_{14} does not occur. The variables affected by R_{14}

Table 2
Cash flow of the project.

Year	Cash flow before payment of taxes	Cash flow after payment of taxes	Year	Cash flow before payment of taxes	Cash flow after payment of taxes
1	−313,436	−313,436	16	1,674,610	1,369,049
2	−522,393	−522,393	17	1,765,039	1,442,978
3	−783,589	−783,589	18	1,860,251	1,520,899
4	−992,546	−992,546	19	1,960,810	1,603,028
5	283,668	141,462	20	2,429,290	1,821,967
6	900,665	720,076	21	2,560,471	1,773,246
7	1,009,249	818,908	22	2,698,737	2,024,053
8	1,099,484	898,865	23	2,844,469	2,133,351
9	1,158,856	947,403	24	2,998,070	2,248,552
10	1,221,434	998,563	25	3,159,966	2,369,974
11	1,287,392	1,052,485	26	3,330,604	2,497,953
12	1,356,911	1,109,320	27	3,510,456	2,632,842
13	1,430,184	1,169,223	28	3,700,021	2,775,016
14	1,507,414	1,232,361	29	3,899,822	2,924,867
15	1,588,814	1,298,908	30	6,150,054	5,122,450

Table 3
Risk driver matrix of the project.

Code	Risk events	Probability		Impact Range		
		1	0	MIN	ML	MAX
R_1	Supply risk of raw materials	0.75	0.25	0.8	1	1.3
R_2	Sales risk	0.75	0.25	0.7	1	1.3
R_3	Political changes	0.60	0.40	0.6	1.2	1.4
R_4	Economic changes in host country of the project	0.70	0.30	0.9	1	1.2
R_5	Price fluctuation of international oil and natural gas	0.50	0.50	0.9	1	1.2
R_6	Fluctuation in exchange and interest rates	0.60	0.40	0.9	1	1.2
R_7	Technological limitations	0.30	0.70	0.7	1	1.3
R_8	Force majeure or disasters not covered in the contract	0.25	0.75	0.9	1	1.1
R_9	Disputes arising from the process of signing and performing the contract	0.60	0.40	0.9	1	1.1
R_{10}	Regulatory changes in the host country of the project and contract modifications	0.50	0.50	0.9	1	1.1
R_{11}	Tax policy changes	0.60	0.40	0.9	1	1.2
R_{12}	Cost overrun	0.60	0.40	0.8	1	1.2
R_{13}	Schedule delay	0.60	0.40	0.8	1	1.2
R_{14}	Labour risk	0.70	0.30	0.7	1.1	1.3

include capital expenditure, interest incurred during construction, cash flow, NPV and IRR. Since the uncertain parameters are influenced by various risk events, their total impact values are a product of the impact values of related risk events. For example, capital expenditure is affected by R_3, R_8, R_{12}, R_{13} and R_{14}. Consequently, the minimum, most likely and maximum impact values of capital expenditure are $0.24 = (0.6 \times 0.9 \times 0.8 \times 0.8 \times 0.7)$, $1.32 = (1.2 \times 1 \times 1 \times 1 \times 1.1)$ and $2.88 = (1.4 \times 1.1 \times 1.2 \times 1.2 \times 1.3)$, respectively.

The next step was to define the p.d.f.s of the input variables. In this case, the probabilities of risk events occurring were defined as Bernoulli distributions, with the impact of the 14 risk events all defined as triangular distributions. In addition to defining capital expenditure as a BetaPERT distribution and defining both productivity and the inflation index as triangular distributions, the risk managers proposed to define the prices of natural gas, methanol and products as normal distributions and crude oil price as a lognormal distribution.

Before undertaking the simulation, the risk managers needed to determine the correlations between the uncertain parameters, especially those between the various prices of raw materials and products. For uncertain parameters with the same p.d.f., the correlation coefficients were obtained by direct calculation from the original data, while the correlation coefficients for the uncertain parameters with different p.d.f.s were determined with reference to expert opinions. For example, the correlation coefficient between prices of crude oil and naphtha was defined as 0.75.

Monte Carlo sampling was then adopted to obtain the c.d.f.s of NPV and IRR. In order to achieve mean and variance stability, the maximum number of iterations was set at 10,000.

4.3. Outputs

4.3.1. Sensitivity analysis

The sensitivity analysis results were obtained by use of relative functions of @RISK. As Table 4 shows, this indicated R_2-Impact, the price of country V's automobile diesel fuel, 93# and 97# clean gasoline, jet fuel, M8A and low sulphur fuel oil, R_9-Probability and productivity to have positive relationships with NPV. The table also shows the negative coefficients between NPV and some input variables, including crude oil price, the impact of R_1, R5, R_6, R_7, R_{12} and R_{13}, and the probabilities of R_5 and R_1, capital expenditure. Based on these results, the risk managers developed risk reduction response measures for specific high sensitivity risk events. For example, the investor was able to adopt a strategy of signing sales contracts in advance to reduce the sales risk to NPV.

4.3.2. c.d.f.s of NPV/IRR

The c.d.f.s of NPV and IRR in the case study are shown in Figs. 2 and 3. As Fig. 2 shows, the probabilities of NPV greater

Table 4
Sensitivity: NPV after payment of taxes.

No.	Input variables	Correlation value	Contribution to variance (%)
1	R_2-impact	0.56	41.2
2	Crude oil price	−0.45	25.8
3	R_1-impact	−0.35	16.1
4	Country V automobile diesel fuel	0.28	9.9
5	R_5-impact	−0.13	2.2
6	93# clean gasoline	0.10	1.3
7	R_5-prob.	−0.08	0.8
8	97# clean gasoline	0.07	0.7
9	R_1-prob.	−0.07	0.6
10	Jet fuel	0.04	0.2
11	M8a	0.04	0.2
12	R_9-prob.	0.03	0.1
13	Production load	0.02	0.1
14	R_{13}-impact	−0.02	0.1
15	R_{12}-impact	−0.02	0.1
16	Low sulphur fuel oil	0.02	0.1
17	Capital expenditure	−0.02	0.1
18	R_6-impact	−0.02	0.1

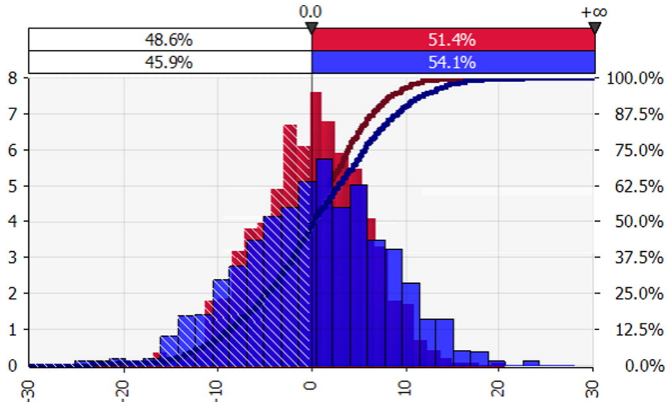

Fig. 2. Cumulative distribution functions of NPV.

than zero before and after payment of taxes are 54.1% and 51.4%, respectively, while, according to Fig. 3, the probabilities of IRR being greater than 13% before and after payment of taxes are 88.1% and 82.8%, respectively. Based on the pre-determined decision criteria of Prob(NPV > 0) ≥ 60% or Prob(IRR > 13%) ≥ 60%, therefore, the investors were able to confirm the feasibility of the project.

4.3.3. Stress testing

The three input variables with the most sensitivity were the impact of sales risk, crude oil price and the impact of supply risk of raw materials. Taking the impact of supply risk of raw material as an example, the risk managers changed the p.d.f. from P_{95} to P_{100}. The result is shown in Table 5, which indicates that, if the extreme case of the raw material supply risk occurred, NPV would be significantly reduced by approximately \$4.5 million, from a mean of \$318,714 to −\$4,183,494.

By comparatively analysing the standard deviation and coefficient of variation, it was concluded that NPV after stress testing was more concentrated than that before stress testing. Based on this analysis, the investor was able to both make the investment decision and take specific risk reduction measures in advance, including signing raw material supply contracts at an early stage.

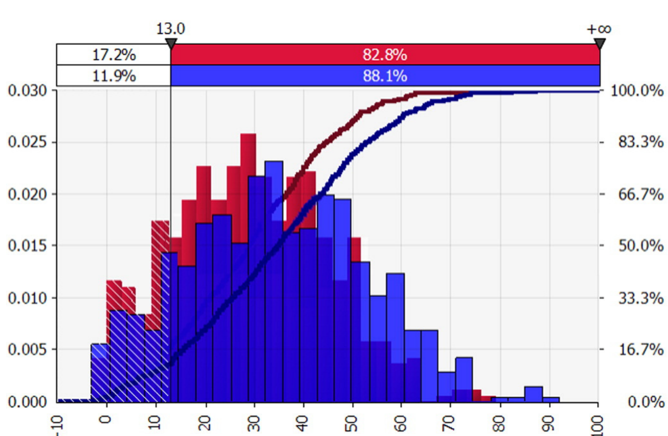

Fig. 3. Cumulative distribution functions of IRR.

4.4. Results

The results obtained by the use of the new advanced quantitative risk assessment model confirmed the financial feasibility of this project to the satisfaction of the investor—validating the applicability and effectiveness of the model.

5. Conclusions

The new advanced quantitative risk assessment model has shown its effectiveness in this Brazilian case. With the help of the model, investors and risk managers now can

1. Assess the influence of both probabilities of occurrence and the impact of specific risk events on decision variables of investment;
2. Quantify the possible loss incurred to the investment outcome in conditions where extreme adverse events can occur;
3. Provide more practical data support for investment decisions concerning international engineering projects.

From a risk driver perspective, the model supports the whole quantitative risk assessment process for engineering project investment decisions. With the use of the risk driver matrix, direct relationships are detected between risk events and the decision variables of investment. The probability of the occurrence of risk events is also taken into consideration. In addition, the introduction of stress testing helps to quantify the possible losses of investment results in the presence of low-probability but high-impact risk events.

Although the study produces some improvement compared with the traditional quantitative risk assessment model, it still suffers from some limitations. In practice, due to the lack of sufficient hard data for the input variables, individuals have to resort to expert judgements to determine the inputs, which causes some imprecision in the outputs. Furthermore, more trials are needed to further evaluate the applicability and validity of the new advanced quantitative risk assessment model.

Additional studies could also help extend the approach by, firstly, determining the p.d.f.s of the input variables more rationally and precisely. Secondly, by dividing the influencing factors of the decision variables of investment into: (1) external risk resulting from a changing macroeconomic environment and (2) risk resulting from the risk managers' limited cognitive ability and experience of the project. Distinguishing the different impacts of these two types of factors should contribute to further helping risk managers to adopt different strategies to reduce the current risks and uncertainties involved in their financial feasibility appraisals of major engineering projects in future.

Conflict of interest

The authors declare that there are no conflict of interests regarding the publication of this article.

Table 5
Simulation results: NPV after payment of taxes.

No.	Statistic	Before stress testing	After stress testing
1	Mean	318,714	−4,183,494
2	Median	499,418	−4,132,313
3	Standard Deviation	7,866,191	6,331,127
4	Skewness	−0.0887	−0.0721
5	Kurtosis	3.24	3.22
6	Coefficient of variation	24.68	−1.51
7	Minimum	−28,998,274	−30,099,513
8	Maximum	30,671,603	17,977,339

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References

Alkaraan, F., 2015. Strategic investment decision-making perspectives. Adv. Mergers Acquis. 14, 53–66.

Borgonovo, E., Plischke, E., 2016. Sensitivity analysis: a review of recent advances. Eur. J. Oper. Res. 248 (3), 869–887.

Choudhry, R.M., Aslam, M.A., Hinze, J.W., Arain, F.M., 2014. Cost and schedule risk analysis of bridge construction in Pakistan: establishing risk guidelines. J. Constr. Eng. Manag. 140 (7), 04014020.

Davidson, R.A., Lembo Jr., A.J., Ma, J., Nozick, L.K., O'Rourke, T.D., 2006. Optimization of investments in natural gas distribution networks. J. Energy Eng. 132 (2), 52–60.

Dempster, M.A.H. (Ed.), 2002. Risk Management: Value at Risk and Beyond. Cambridge University Press.

Dikmen, I., Birgonul, M.T., Gur, A.K., 2007. A case-based decision support tool for bid mark-up estimation of international construction projects. Autom. Constr. 17, 30–44.

Edwards, P.J., Bowen, P.A., 1998. Risk and risk management in construction: a review and future directions for research. Eng. Constr. Archit. Manag. 5 (4), 339–349.

Flage, R., Baraldi, P., Zio, E., Aven, T., 2013. Probability and possibility-based representations of uncertainty in fault tree analysis. Risk Anal. 33 (1), 121–133.

Girmscheid, G., 2009. NPV model for evaluating the economic efficiency of municipal street maintenance by private providers. J. Constr. Eng. Manag. 135 (8), 701–709.

Goossens, L.H.J., Cooke, R.M., 1997. Applications of some risk assessment techniques: formal expert judgement and accident sequence precursors. Saf. Sci. 26 (1), 35–47.

Hacura, A., Jadamus-Hacura, M., Kocot, A., 2001. Risk analysis in investment appraisal based on the Monte Carlo simulation technique. Eur. Phys. J. B Condens. Matter Complex Syst. 20 (4), 551–553.

Hallegatte, S., Shah, A., Brown, C., Lempert, R., Gill, S., 2012. Investment Decision Making under Deep Uncertainty—Application to Climate Change. World Bank Policy Research Working Paper (6193).

Hartman, J.C., Schafrick, I.C., 2004. The relevant internal rate of return. Eng. Econ. 49 (2), 139–158.

Hauke, J., Kossowski, T., 2011. Comparison of values of Pearson's and Spearman's correlation coefficients on the same sets of data. Quaest. Geogr. 30 (2), 87–93.

Hawas, F., Cifuentes, A., 2014. Valuation of projects with stochastic cash flows and intertemporal correlations: practical modeling guidelines. J. Constr. Eng. Manag. 140 (6), 06014003.

Kim, D.Y., Ashuri, B., Han, S.H., 2012. Financial valuation of investments in international construction markets: real-options approach for market-entry decisions. J. Manag. Eng. 29 (4), 355–368.

Law, A.M., Kelton, W.D., 1991. Simulation Modeling and Analysis. McGraw-Hill, New York.

Lazzerini, B., Mkrtchyan, L., 2011. Analyzing risk impact factors using extended fuzzy cognitive maps. IEEE Syst. J. 5 (2), 288–297.

Li, Z.Z., Sinha, K.C., 2009. Application of Shackle's model and system optimization for highway investment decision making under uncertainty. J. Transp. Eng. 135 (3), 129–139.

MacFarland, T.W., Yates, J.M., 2016. Introduction to Nonparametric Statistics for the Biological Sciences Using R. Springer.

Maio, C., Schexnayder, C., Knutson, K., 2000. Probability distribution functions for construction simulation. J. Constr. Eng. Manag. 126 (4), 285–292.

Marciniak, J.J., Shumskas, A., 1994. Acceptance Testing. John Wiley & Sons, Inc.

Merna, T., Al-Thani, F.F., 2008. Corporate Risk Management. John Wiley & Sons Inc.

Moussa, M., Ruwanpura, J., Jergeas, G., 2006. Decision tree modeling using integrated multilevel stochastic networks. J. Constr. Eng. Manag. 132 (12), 1254–1266.

Nieto-Morote, A., Ruz-Vila, F., 2011. A fuzzy approach to construction project risk assessment. Int. J. Proj. Manag. 29 (2), 220–231.

Pritsker, A.A.B., 1995. Introduction to Simulation and SLAM II. fourth ed. Wiley, New York.

Rezaie, K., Amalnik, M.S., Gereie, A., Ostadi, B., Shakhseniaee, M., 2007. Using extended Monte Carlo simulation method for the improvement of risk management: consideration of relationships between uncertainties. Appl. Math. Comput. 190 (2), 1492–1501.

Saltelli, A., et al., 2004. Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models. Wiley, New York.

Samson, S., Reneke, J.A., Wiecek, M.M., 2009. A review of different perspectives on uncertainty and risk and an alternative modelling paradigm. Reliab. Eng. Syst. Saf. 94 (2), 558–567.

Shen, L., Lu, W., Peng, Y., Jiang, S., 2011. Critical assessment indicators for measuring benefits of rural infrastructure investment in China. J. Infrastruct. Syst. 17 (4), 176–183.

Stewart, M.G., Deng, X., 2014. Climate impact risks and climate adaptation engineering for built infrastructure. ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civil Eng. http://dx.doi.org/10.1061/AJRUA6.0000809.

Suslick, S.B., Schiozer, D., Rodriguez, M.R., 2008. Uncertainty and risk analysis in petroleum exploration and production. Terræ 6 (1), 30–41.

Syachrani, S., Jeong, H.S.D., Chung, C.S., 2012. Decision tree-based deterioration model for buried wastewater pipelines. J. Perform. Constr. Facil. 27 (5), 633–645.

Tah, J., Carr, V., 2001. Knowledge-based approach to construction project risk management. J. Comput. Civ. Eng. 15 (3), 170–177.

Tang, T., Reed, P., Wagener, T., Van Werkhoven, K., 2007. Comparing sensitivity analysis methods to advance lumped watershed model identification and evaluation. Hydrol. Earth Syst. Sci. Discuss. 11 (2), 793–817.

Taroun, A., 2013. Towards a better modeling and assessment of construction risk: insights from a literature review. Int. J. Proj. Manag. 32 (1), 101–115.

Van Werkhoven, K., Wagener, T., Reed, P., Tang, Y., 2009. Sensitivity-guided reduction of parametric dimensionality for multi-objective calibration of watershed models. Adv. Water Resour. 32 (8), 1154–1169.

Virlics, A., 2013. Investment decision making and risk. Procedia Econ. Financ. 6, 169–177.

Wang, W.C., 2002. Simulation-facilitated model for assessing cost correlations. Comput. Aided Civ. Inf. Eng. 17 (5), 368–380.

Warszawski, A., Sacks, R., 2004. Practical multifactor approach to evaluating risk of investment in engineering projects. J. Constr. Eng. Manag. 130 (3), 357–367.

Yang, I.T., 2006. Using Gaussian couple to simulate repetitive projects. Constr. Manag. Econ. 24 (9), 899–909.

Ye, S.D., Tiong, R.L.K., 2000. NPV-at-risk method in infrastructure project investment evaluation. J. Constr. Eng. Manag. 126 (3), 227–233.