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New measures and procedures to manage financial risk with applications to the planning of gas commercialization in Asia

Ahmed Aseeri, Miguel J. Bagajewicz*

Department of Chemical Engineering, University of Oklahoma, 100 E. Boyd St., T-335, Norman, OK 73019, USA

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Abstract

This paper presents some new concepts and procedures for financial risk management. To complement the use of value at risk a new concept, upside potential or opportunity value as means to weigh opportunity loss versus risk reduction as well as an area ratio are introduced and discussed. Upper and lower bounds for risk curves corresponding to the optimal stochastic solution are developed, the application of the sampling average algorithm, one scenario at a time, is analyzed, and the relation between two-stage stochastic models that manage risk and the use of chance constraints is discussed. Finally, some anomalies arising from the use of value at risk and regret analysis are pointed out. These concepts are applied to the commercialization of gas and/or gas-derivatives (synthetic gasoline, methanol, and ammonia) in Asia. Results show that, given the set of costs chosen, the production of synthetic gasoline should be the investment of choice and that the use of contracts can increase expected profit. Other suboptimal cases are also revealed and it is shown how financial risk can be managed.

Keywords: Planning; Financial risk; Robust optimization

1. Introduction

A new approach to the management of financial risk was recently presented by Barbaro and Bagajewicz (2003, 2004a, 2004b). The methodology uses a well-known definition of risk based on cumulative probability distributions. A mathematical expression for risk at different aspiration levels was presented and connected to earlier definitions of downside risk (Eppen, Martin, & Schrage, 1989). Some elements of the risk manipulation, similar to the procedure developed by Barbaro and Bagajewicz (2003) have also been recently presented by Gupta and Maranas (2003), although these authors think of risk as a symmetric measure given by variability and believe that the risk definition given by Barbaro and Bagajewicz (2003, 2004a) is an approximation. In particular, Barbaro and Bagajewicz (2003, 2004a) showed that downside risk is the integral of the risk curve. They also proved that downside risk is not monotone with risk, that is, lower downside risk does not necessarily imply lower risk. All these were incorporated into a two-stage stochastic programming framework to manage risk through multiobjective programming. They also showed that a series of candidate Pareto optimal solutions that reduce risk at a cost of reducing expected profit can be obtained and downside risk instead of risk directly, reducing thus the number of binary variables needed (risk uses binary variables, while downside risk does not). Finally they made connections with value at risk (VaR) and suggested the use of a downside expected profit (DEP) as means of making risk-related decisions in a project.

In other related work, Cheng, Subrahmanian, and Westerberg (2003) suggest that risk should be managed directly in its downside risk form for a particular aspiration level together with other project attributes like expected profit and life cycle. They claim that a multiobjective framework, solvable with methodologies rooted in dynamic programming

* Corresponding author. Tel.: +1 405 3255458; fax: +1 405 3255813.
E-mail address: bagajewicz@ou.edu (M.J. Bagajewicz).

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methods is the correct procedure to craft a project. This use of risk as a point measure keen to risk-averse decision makers is in apparent contrast with the claim made by Barbaro and Bagajewicz (2003, 2004a) that risk should be looked at through the entire curve. Not looking at the entire curve was in part the reason why symmetric measures, like variance, were used to assess and manage risk in earlier work (Mulvey, Vanderbei, & Zenios, 1995). Recently, the same tendency is seen in the use of value at risk (Guldimann, 2000; Jorion, 2000). Looking at the entire curve is important because, even when one is a risk-averse decision maker, and consequently concerned with the profit distribution at low profit expectations, one can also assess the effect of risk-related decisions in the downside region of the profit distribution on the loss of profit potential at the other end of the spectrum. The difference with the approach proposed by Cheng, Subrahmanian, and Westerberg (2003) is, after all, not so fundamental because one can perfectly add to their approach more than one objective to address risk, much in the way as proposed by Barbaro and Bagajewicz (2003, 2004a) and also use any other risk measure (value at risk, risk, downside expected profit). The only point in which real differences persist are in that Barbaro and Bagajewicz (2003, 2004a) propose to visualize the entire set of curves before making a decision, while the method of Cheng, Subrahmanian, and Westerberg (2003) has to resort to constructing complicated Pareto optimal surfaces, which in higher dimensions are difficult to visualize. The differences, nonetheless, are likely to be secondary and we expect these two approaches to complement each other somehow.

Finally, to overcome the numerical difficulties associated with the use of large number of scenarios, Barbaro and Bagajewicz (2003, 2004a) discussed the use of the sampling average algorithm (SAA) (Verweij, Ahmed, Kleywegt, Nemhauser, & Shapiro, 2001) and compared it with the use of Benders decomposition (Benders, 1962; Geoffrion, 1972). Clearly, large problems including large number of scenarios remain elusive for regular desk computers.

In this paper we address new definitions necessary to properly manage financial risk. These definitions are: upside potential (UP) or opportunity value (OV) and the risk area ratio (RAR). The former is a point measure symmetrically opposite to value at risk, while the second is an integral measure that establishes a relation between the reduction in risk and the loss of profit potential at profit expectations above the expected value. Some intricacies related to the use of these measures are theoretically analyzed and illustrated in the example. We also show briefly that the use of chance constraints is a poor way of managing risk and we discuss and illustrate the shortcomings of the use of regret analysis, by itself or as a constraint of two-stage stochastic models, as proposed by Ierapetritou and Pistikopoulos (1994). Finally we also discuss the use of the sampling algorithm to determine upper and lower risk curves bounding the optimal solutions of the purely stochastic problem. All these concepts are illustrated solving the planning of gas commercialization in Asia.

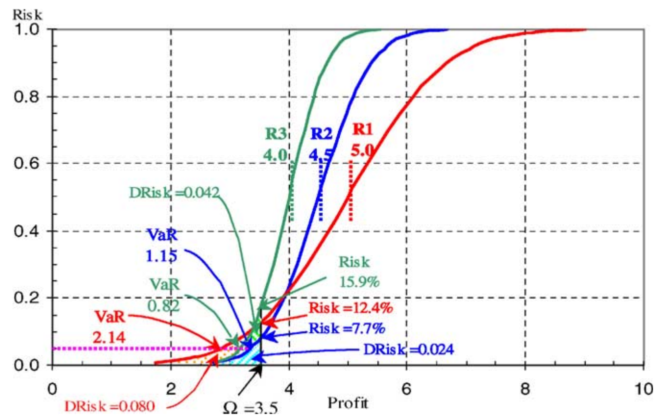

Fig. 1. Comparison of VaR to risk and downside risk.

2. Value at risk and upside potential

A widely used measure of risk in literature is the value at risk (Guldimann, 2000; Jorion, 2000) defined as the expected loss for a certain confidence level usually set at 5% (Linsmeier & Pearson, 2000). A more general definition of VaR is given by the difference between the mean value of the profit and the profit value corresponding to the p-quantile (value at p risk). VaR has been used as a point measure very similar to the variance. Moreover, it suffers from the same problem, that is, it either assumes a symmetric distribution, or it ignores the effect of reducing VaR on the optimistic scenarios.

VaR measures the deviation of the profit at 5% risk from the ENPV. To compare the performance of VaR to that of risk and downside risk as discussed by Barbaro and Bagajewicz (2003, 2004a), consider the hypothetical risk curves of Fig. 1. VaR, risk and downside risk values for the three solutions are compared in Table 1. Assume that R1 is the stochastic solution that maximizes the ENPV. If the investor is risk-averse and would prefer to have a more robust solution than R1 even if its ENPV is reasonably smaller, then R2 is obviously the best choice. R3 is dominated by R2. In other words, R2 and R3 do not intersect. Table 1 depicts the VaR, risk and downside risk of all three solutions. We also note that R3 would

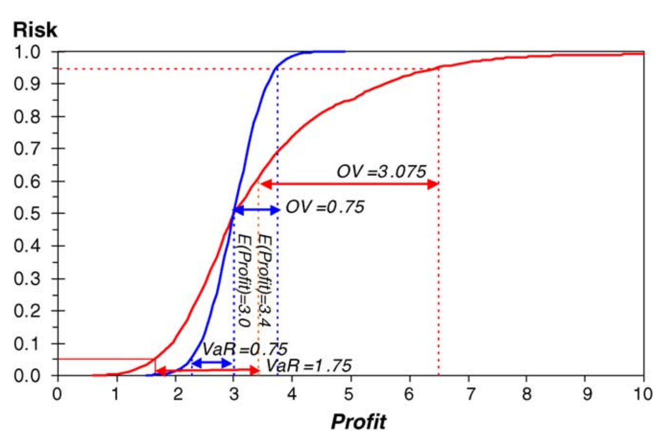

Fig. 2. Upside potential (UP) or opportunity value (OV) vs. VaR.

Table 1
VaR, risk and DRisk for the example in Fig. 1

Solution	ENPV	VaR (5%)		Risk @ 3.5		DRisk @ 3.5	
		VaR	Reduction from R1 (%)	Risk	Reduction from R1 (%)	DRisk	Reduction from R1 (%)
R1	5.0	2.14	–	0.124	–	0.080	–
R2	4.5	1.15	46.3	0.077	37.9	0.024	70
R3	4.0	0.82	61.7	0.159	−31.5	0.042	47.5

never be picked by a two-stage stochastic model that manages risk at expectations close to 3.5, but it can arise in using other approaches as an alternative.

Let us now see what VaR, risk and downside risk suggest to a risk-averse investor. R3 has a VaR that is considerably smaller than that of both R1 and R2 (Table 1). If VaR is used as the only means of evaluating the solutions R3 would be picked. However looking at both risk and downside risk at an aspiration level of 3.5 units one can see that R3 is less convenient than R2. As stated above, it only becomes a convenient choice at lower expectations than 3.5. The question then is how can a decision maker make a trade-off between risk and expected profit by just looking at these measures on the downside?

From this we see that the concept of value at risk can only be used as a measure of robustness, but not risk. It is, however, clear that investors do not use only VaR to make decisions. They look at both, VaR and ENPV, but it is unclear what systematic procedure captures the trade-offs. The example above illustrates the dangers of not looking closely at the upside region.

To ameliorate these difficulties, we propose that VaR be compared to a similar measure, the upside potential or opportunity value, defined in a similar way to VaR but at the other end of the risk curve with a quantile of $(1-p)$ as the difference between the net present value corresponding to a risk of $(1-p)$ and the expected value. Both concepts are illustrated in Fig. 2, where two projects are compared, one with expected profit of 3 (arbitrary units) and the other of 3.4. The former has a VaR of 0.75 while the latter has a VaR of 1.75. Conversely, the upside potential of these two projects is 0.75 and 3.075. We emphasize the need of the upside potential for a good evaluation of these two projects. Indeed, one might stop and think that a reduction in VaR has a large price in loss of upside potential and reject this risk-hedging solution in favor of looking for some other that would not reduce the upside potential so much.

3. Risk area ratio

VaR and UP (or OV) are point measures and do not represent the behavior of the entire curve. For this reason we propose the use of a method that compares the areas between two curves (Fig. 3). The proposed ratio, the risk area ratio between the design being evaluated and some reference design with better ENPV, can be simply calculated as the ratio of the opportunity area (O_Area), enclosed by the two curves above their intersection, to the risk area (R_Area), enclosed by the two curves below their intersection (Eq. (1) and Fig. 3). Note that this is only true if the second curve is minimizing risk in the downside region. If risk on the upside is to be minimized, then the relation is reversed (i.e. O_Area is below the intersection and R_Area is above it).

$$\mathrm{RAR} = \frac{\mathrm{O\_Area}}{\mathrm{R\_Area}} \tag{1}$$

The areas can be calculated by integrating the difference of risk between the two curves over NPVs as shown next:

$$\mathrm{RAR} = \frac{\mathrm{O\_Area}}{\mathrm{R\_Area}} = \frac{\int_{-\infty}^{\infty} \psi^{+}\,\mathrm{d}\xi}{\int_{-\infty}^{\infty} \psi^{-}\,\mathrm{d}\xi} \tag{2}$$

where

$$\psi^{+} = \left\{ \begin{array}{ll} \psi & \text{if } \psi \geq 0 \\ 0 & \text{otherwise} \end{array} \right\} \tag{3}$$

$$\psi^{-} = \left\{ \begin{array}{ll} -\psi & \text{if } \psi < 0 \\ 0 & \text{otherwise} \end{array} \right\} \tag{4}$$

$$\psi = \mathrm{Risk}(x_2, \mathrm{NPV}) - \mathrm{Risk}(x_1, \mathrm{NPV}) \tag{5}$$

where x_1 is the design with the best ENPV and x_2 is the design being compared to it (ξ is a dummy variable for NPV).

The closer is this ratio to one the better is the alternative solution. When $x_1 = x^*$, the optimal solution of the stochastic problem (not constrained by risk), this ratio cannot be less

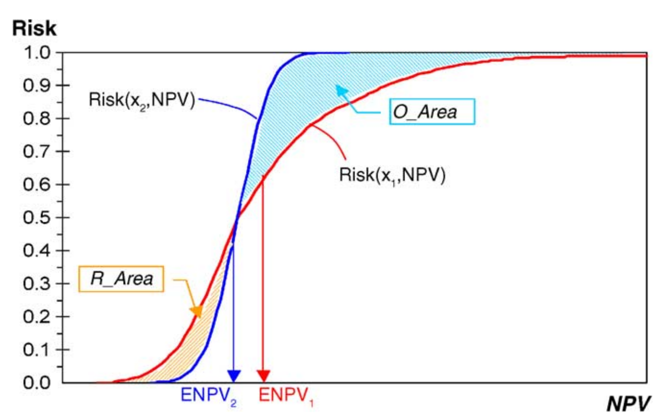

Fig. 3. Risk area ratio.

than one for any feasible design x_2 that one wish to consider. Indeed, if RAR is smaller than one, then:

$$\int_{-\infty}^{\mathrm{NPV}^{\times}} [\mathrm{Risk}(x^*, \xi) - \mathrm{Risk}(x_2, \xi)]\, \mathrm{d}\xi$$

$$> \int_{\mathrm{NPV}^{\times}}^{\infty} [\mathrm{Risk}(x_2, \xi) - \mathrm{Risk}(x^*, \xi)]\, \mathrm{d}\xi \tag{6}$$

where $\mathrm{NPV}^{\times}$ is the abscissa of the intersection of both curves. Rearranging we get

$$\int_{-\infty}^{\infty} [\mathrm{Risk}(x^*, \xi) - \mathrm{Risk}(x_2, \xi)]\, \mathrm{d}\xi = \mathrm{ENPV}_2 - \mathrm{ENPV}^* > 0 \tag{7}$$

which is a contradiction.

We propose to use this measure to assess the trade-off established between the gains from risk reductions and the opportunity loss. We claim that a good risk-reduced plan suitable for risk-averse decision makers is one that has the area ratio as close to one as possible. This is illustrated below through the example. Risk takers, instead, prefer solutions that have higher risk at low expectations with increased chances at high profit levels. Thus, for those cases, this area ratio does not apply and a new area ratio, as stated above, needs to be constructed.

Finally, it should be pointed out that RAR is neutral toward variance. Given the same maximum ENPV solution, there could be two candidate solutions, with different variance, but the same RAR. Risk-averse investors would prefer the one with smaller variance.

4. Use of the sampling algorithm to obtain optimal solutions

Consider the sampling average approximation method (SAA) (Verweij, Ahmed, Kleywegt, Nemhauser, & Shapiro, 2001), which was illustrated and discussed by Barbaro and Bagajewicz (2003, 2004a). In this method, a relatively small number of scenarios are generated and used to run the stochastic model. After these series of designs are obtained, the first stage variables of each one is used as fixed numbers in a new stochastic model containing a much larger number of scenarios. The claim is that this algorithm, run for a sufficiently large number of scenarios can *approximate* the optimal solution. In fact, it tends asymptotically to such optimum. The proof is outlined next.

Theorem I. *Given a sufficiently large number of scenarios, the sample algorithm, run using one scenario at a time to generate first stage variables, provides a solution that tends asymptotically to the stochastic model with an arbitrarily large number of scenarios.*

Proof. Let x^* be the first stage variables optimal solution of the stochastic problem (SP) and let z^* be the corresponding objective function value. Consider now the stochastic model for one scenario.

$$(\mathrm{SP1})\ \mathrm{Max}[q_1^{\mathrm{T}} - c^{\mathrm{T}} x] \tag{8}$$

s.t.

$$Ax = b \tag{9}$$

$$Tx + W\nu = h_1 \tag{10}$$

$$x \geq 0 \quad x \in X \tag{11}$$

$$\nu \geq 0 \tag{12}$$

In this model, ν represents the second stage decision variables, T is the technology matrix, W is the recourse matrix and h is the vector of second stage uncertain parameters. This nomenclature is the same as the one used by Barbaro and Bagajewicz (2004a). If one can prove that x^* is an optimal solution of (SP1) for some values of h_1 and q_1, then one can claim that successive sampling of h_1 and q_1 eventually render x^* as a solution. However, the objective function and the second stage variables of SP1 may in principle be different from z^* and any of the corresponding second stage values. In the particular case of the planning model of this paper, one can argue that there is always a demand level and a set of prices that render a specific net present value for a set of first stage variables. To show this in general, we first recognize that if, $h_1 = \sum_s p_s h_s$ then $(x^*, \sum_s p_s y_s^*)$ is a feasible solution of SP1, but not necessarily optimal. One recognizes also that in such case, the objective function of SP1 is equal to z^* if

$$q_1^{\mathrm{T}} \sum_s p_s y_s^* = \sum_s p_s q_s^{\mathrm{T}} y_s^* \tag{13}$$

or

$$q_1^{\mathrm{T}} = \frac{\sum_s p_s q_s^{\mathrm{T}} y_s^*}{\sum_s p_s y_s^*} \tag{14}$$

Thus x^* is a feasible solution of SP1 if $h_1 = \sum_s p_s h_s$ However, this does not mean that other values of h_1 for which x^* is feasible do not exist. In addition, $(x^*, \sum_s p_s y_s^*)$ has the same objective function value for a value of q_1 inside the sampling region. We now need to prove that for those value of q_1 and h_1 no better solution can be obtained than $(x^*, \sum_s p_s y_s^*)$. Suppose not, suppose that there exists $x' = x^* + \delta$ and $\nu' = \sum_s p_s y_s^* + \gamma$ that renders a better solution of SP1. We now write $\nu' = \sum_s p_s (y_s^* + \eta_s)$, where $\gamma = \sum_s p_s \eta_s$ Since ν' is feasible for SP1, then $(y_s^* + \eta_s)$ are also feasible solutions of SP, for a suitable choice of the values of η_s which can always be achieved. In such case, the new solution would be better also for SP, which is a contradiction. □

The above results proves that when stochastic solutions are asymmetrically distributed, that is, when certain scenarios are highly more profitable than others, the deterministic solution may render a solution that is far less advantageous than the stochastic one. This has been recently illustrated by Bonfill, Bagajewicz, Espuña, and Puigjaner (2003) and Romero, Badell, Bagajewicz, and Puigjaner (2003). It also proves that using proper values in the sampling algorithm, one can capture the stochastic solution.

One may ask if the use of more than one scenario to generate designs (first stage variables) is of any advantage. Not necessarily. By using many scenarios the subproblems can get more computationally intensive. The same argument presented above can be made for the stochastic subproblems to show that, for a large enough number of scenarios, they can be represented by some of the solutions obtained by solving for each scenario. We leave the study of this trade-off to be performed elsewhere.

5. Use of the sampling algorithm to obtain Pareto optimal solutions of reduced risk

In a recent paper (Bonfill, Bagajewicz, Espuña, & Puigjaner, 2003), the idea of maximizing the worst-case scenario to identify solutions with smaller risk was introduced. One can prove using an argument almost identical to the above theorem, that it is also possible to capture this solution using the sample average solution algorithm. In practice, once all the designs have been generated, this is done by identifying the solution with the best worse-case performance. The same is true for solutions with minimum risk at a given aspiration level. This is illustrated at the end of the paper through the example of natural gas commercialization.

6. Chance constraints

Several authors have relied on the use of chance constraints to model and manage risk (Charnes & Cooper, 1959; Orcun, Joglekar, & Clark, 2002; Wendt, Li, & Wozny, 2002). We first note that chance constraints addressing risk directly are equivalent to the risk-constrained model (RR–SP–FR) (Barbaro & Bagajewicz, 2003, 2004a). Indeed, the planning model can be represented as follows:

Model SP

$$\text{Max } E[\text{Profit}] = \sum_{s\in S} p_s q_s^{\mathrm{T}} y_s - c^{\mathrm{T}} x \tag{15}$$

s.t.

$$Ax = b \tag{16}$$

$$T_s x + W y_s = h_s, \quad \forall s \in S \tag{17}$$

$$x \geq 0, \qquad x \in X \tag{18}$$

$$y_s \geq 0, \quad \forall s \in S \tag{19}$$

where x corresponds to first stage variables and y_s to second stage variables. A chance constraint involving risk can be written as follows:

$$P\{\text{Profit}(x) < \Omega\} \leq \varepsilon \tag{20}$$

where ε is some bound. But the above probability is nothing else than risk. Thus, the addition of the above chance constraint is equivalent to the risk-constrained model (RR–SP–FR) as formulated by Barbaro and Bagajewicz (2003, 2004a).

Model RR–SP–FR

$$\text{Max} \sum_{s\in S} p_s q_s^{\mathrm{T}} y_s - c^{\mathrm{T}} x \tag{21}$$

s.t.

$$Ax = b \tag{22}$$

$$T_s x + W y_s = h_s, \quad \forall s \in S \tag{23}$$

$$\sum_{s\in S} p_s z_{si} \leq \varepsilon_i, \quad \forall i \in I \tag{24}$$

$$q_s^{\mathrm{T}} y_s - c^{\mathrm{T}} x \geq \Omega_i - U_s z_{si}, \quad \forall s \in S, \ \forall i \in I \tag{25}$$

$$q_s^{\mathrm{T}} y_s - c^{\mathrm{T}} x \leq \Omega_i + U_s (1 - z_{si}), \quad \forall s \in S, \ \forall i \in I \tag{26}$$

$$z_{si} \in \{0, 1\}, \quad \forall s \in S, \ \forall i \in I \tag{27}$$

$$x \geq 0, \qquad x \in X \tag{28}$$

$$y_s \geq 0, \quad \forall s \in S \tag{29}$$

Interestingly, one would not be able to convert the above chance constraint to a deterministic one because the underlying distribution is not known. The use of other chance constraints, replacing those with stochastic parameters, like for example, chance constraint for the production, e.g. production $\leq$ demand, are also conducive to poor risk representation and management. Indeed, such chance constraint should be replaced by production $\leq F^{-1}(1-\alpha)$, where F is the cumulative distribution for the demand and α is the chosen confidence level. But a model with these types of constraints is just one instance of a sampling algorithm. In other words, these constraints do not add anything; moreover, they are inferior in all sense. We conclude that the use of chance constraints for risk management is a wrong choice However, one could conceivably keep changing the confidence level and obtain different solutions from which first stage design variables can be extracted. This offers an interesting alternative to sampling, the conceptual and numerical advantages of which are not explored here.

7. Connections to regret analysis

One type of criteria in decision making under uncertainty is the use of regret analysis (Riggs, 1968) to choose the

Table 2
Hypothetical profit matrix

	s_1 high	s_2 medium	s_3 low	Average
A	19	14	−3	10
B	16	7	4	9
C	20	8	−4	8
D	10	6	5	7
Max	20 (C)	14 (A)	5 (D)	10 (A)

Table 3
Regret matrix for profits in Table 2

	s_1 high	s_2 medium	s_3 low	Maximum regret
A	1	0	8	8
B	4	7	1	7
C	0	6	9	9
D	10	8	0	10

solution that is most appealing to the decision maker in terms of both profitability and risk level. Its use as a constraint in the context of optimization under uncertainty and aiming at the managing of financial risk has been suggested by Ierapetritou and Pistikopoulos (1994). We now concentrate on the simplest and traditional way of doing regret analysis. Regret analysis requires the presence of a table of profits for different designs under all possible scenarios. One way to generate such a table is to use the SAA to solve the model for several scenarios, one at a time or a certain number at a time, to obtain several designs (characterized by first stage variables). The next step is to fix these first stage variables to the values obtained and solve the model to obtain the profit of that design under every other scenario. We now describe the different approaches of regret analysis. These consist of different criteria to choose the preferred solution (there is no such thing as "optimal" solution in this context). To apply these criteria, a table of outcomes is constructed. In this table, each row corresponds to a design and each column to a scenario. Thus, if designs are obtained using only one scenario at a time, the numbers in the diagonal are the "wait and see" solutions, that is, the designs for each scenario. The rest of the numbers in that row are the realizations of that design under the rest of the scenarios.

The *maximum average* criterion states that one should choose the design that performs best as an average for all scenarios. This is equivalent to choosing the solution with best ENPV. The *maximax* criterion, suggest to choose the design that has the highest profit value in the profit table. This represents an *optimistic* decision in which all the bad scenarios are ignored in favor of a single good scenario. In the opposite approach, known as the *maximin* criterion, the design that performs best under the worst conditions is chosen. This is equivalent to identifying the worst-case value (minimum over all scenarios) for each design and choosing the design with the best worst-case value (or the maximum–minimum). We now show that none of these strategies can guarantee the identification of the best risk-reduced solutions.

Consider, for example, four designs (A, B, C and D) and three scenarios, depicted in Table 2. Under the maximum average criterion, scenario A would be chosen because it has the largest average value. The maximax criterion would suggest choosing design C, because it has the largest value in the whole table (20). Finally, the maximin criterion would suggest the use of design D. In this example, all designs perform the worst under scenario s_3, but design D is the one that has the highest minimum value of 5.

After uncertainties are unveiled, people usually evaluate the performance of their decisions based on what the correct decision should have been, based on the disclosure of reality; not based on the chosen criterion for decision making. To quantify this feeling, the *minimax regret* criterion is used. Regret is defined as the difference between the maximum profit under each scenario (or the profit from the design considering only that scenario) and the profit from each other design under that scenario. Table 3 shows a regret matrix for the hypothetical example in Table 2.

Using this criterion, the decision maker would look for the alternative that minimizes the maximum anticipated regret. Thus, in the example, design B would be chosen because it has the minimum of the maximum regrets. We now connect these concepts with risk and show that none of these criteria can be safely used and that the management of the whole risk curve is the only approach that can guarantee proper decision making.

The *maximin* criterion captures a design of low risk at aspiration levels smaller than the average. This does not necessarily mean that it captures the best design to reduce downside risk due to the fact that it considers only one point for each scenario (the worst), in a pessimistic manner. To compare the use of the maximin criterion to risk, consider the hypothetical example in Fig. 4.

Design A has the maximum ENPV of 3 units. Design B provides a significant reduction of risk at aspiration levels of 2 or less, with a small reduction of the ENPV from 3 to 2.8. Also design C reduces risk, albeit at lower aspiration levels than design B and with a large reduction of the ENPV from 3 to 1.7. The maximin criterion prefers design C over B since

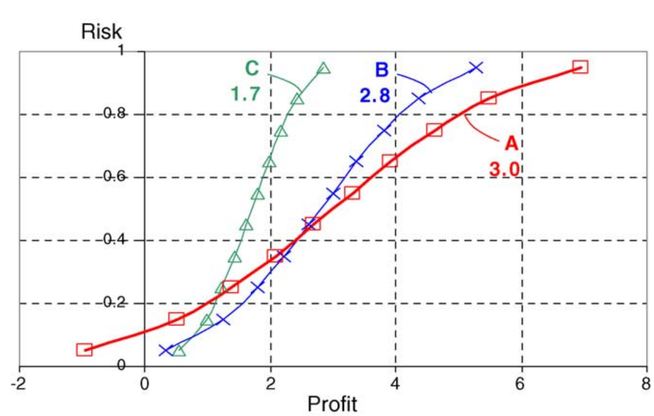

Fig. 4. Hypothetical example for comparing the maximin criterion with downside risk.

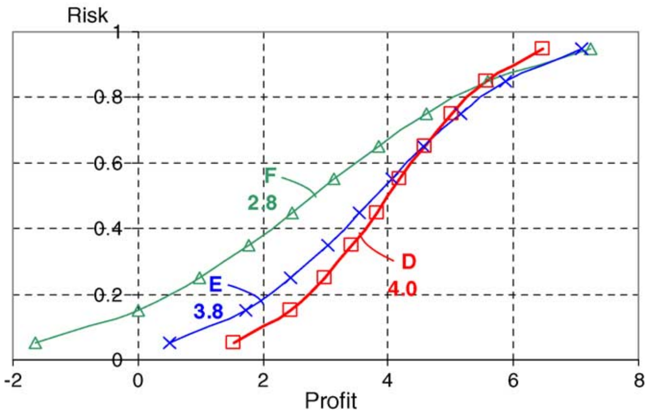

Fig. 5. Hypothetical example for comparing the maximax criterion with upside potential.

it has the highest minimum. This is not a good choice since it ignores the very high loss of profit in nine scenarios for a small gain in only one scenario. The case can be worse if more scenarios are used.

Likewise, the *maximax* criterion would capture a design of high upside potential. This does not necessarily mean that it captures the best design to increase upside potential due to the fact that it considers only one point for each scenario (the best), in an optimistic manner. To compare maximax criterion to upside potential, consider the hypothetical example in Fig. 5.

Design D has the maximum ENPV of 4 units. Design E gives significant increase in upside potential with a small reduction of the ENPV from 4 to 3.8. Also design F increases upside potential but with a large reduction of the ENPV from 4 to 2.8. The maximax criterion prefers design F over E since it has the highest maximum. This is not a good choice either, since it ignores the very high loss of profit in nine scenarios for a small gain in only one scenario. Moreover design F brings in the possibility of loosing.

When trying to make a choice that is neither too optimistic nor too pessimistic the *minimax regret* criterion would select a design that has the lowest maximum regret. To compare the minimax regret criterion to risk, consider the hypothetical example in Fig. 6.

Design G has the maximum ENPV of 4.3 units. Designs H provides a significant reduction of risk with small reduction of the ENPV from 4.3 to 4. Design I provides a significant increase of upside potential with small reduction of the ENPV from 4.3 to 4. Also design J slightly reduces risk but with a larger reduction of the ENPV from 4.3 to 3.9. For simplicity, we have assumed that the correspondence between scenarios and profit values follow the same order, that is, the lowest profit for all designs corresponds to the same scenario, the second lowest to another scenario, and so on. Thus, the regret for each design is the difference between the best (rightmost) value and the value for that design (indicated by a bracket in the figure). The maximum regret for designs G, I and J happen in the downside region where design H is the best. The

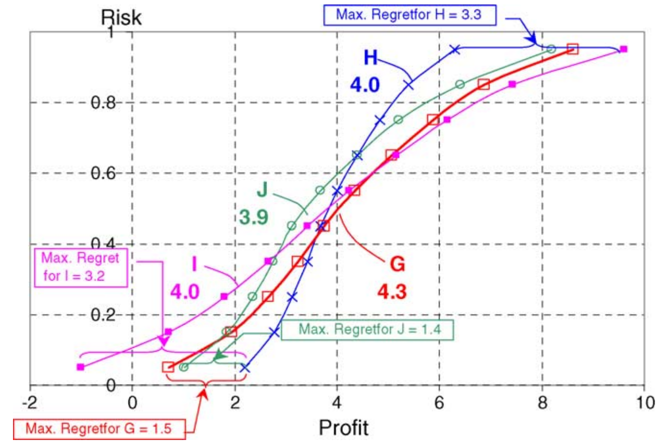

Fig. 6. Hypothetical example for comparing the minimax regret criterion with risk.

maximum regret for design H is at the upside region where design I is the best. The minimax regret criterion prefers design J over the others since it has the lowest maximum regret. Compared to design G which maximizes ENPV, design J is not a good choice since it ignores the loss of profit (and the increase in regret) in nine scenarios for a small reduction of regret in only one scenario.

To illustrate a case where the minimax regret criterion increases upside potential, consider the hypothetical example in Fig. 7.

Design K has the maximum ENPV of 4 units. Designs L gives a significant reduction of risk at low aspiration levels with a small reduction of the ENPV from 4 to 3.9. Designs M gives a significant increase of upside potential with small reduction of the ENPV from 4 to 3.9. Also design N slightly increases upside potential but with a larger reduction of the ENPV from 4 to 3.5. The maximum regret for designs M and N happen in the downside region where design L is the best. The maximum regret for designs K and L happen in the upside region where design M is the best. The minimax regret criterion prefers design N over the others since it has the lowest maximum regret. Compared to design K which

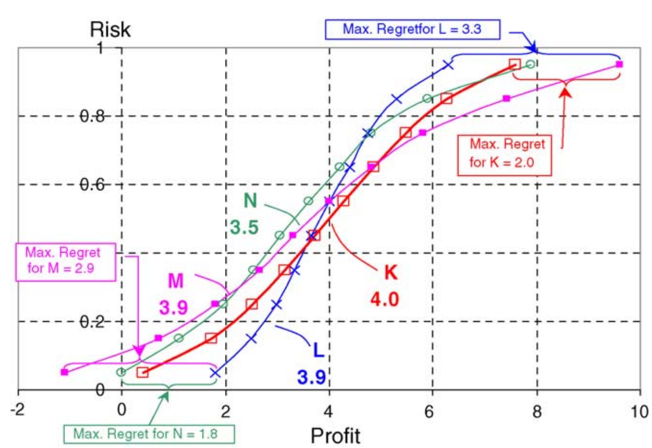

Fig. 7. Hypothetical example for comparing the minimax regret criterion with upside potential.

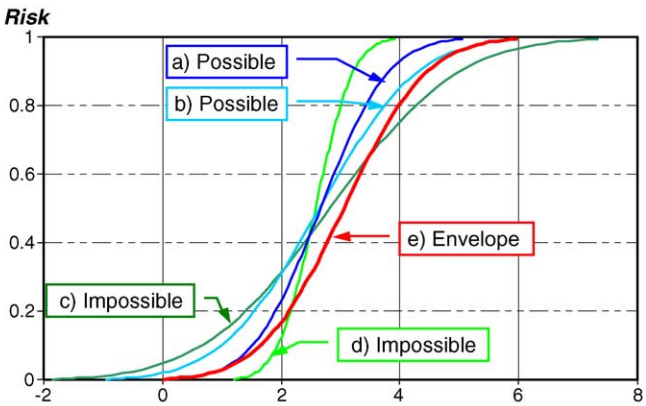

Fig. 8. Upper bound risk curve (or envelope).

maximizes ENPV, design N is not a good choice since it ignores the loss of profit (and the increase in regret) in nine scenarios for a small reduction of regret in only one scenario.

In conclusion, the minimax regret criterion does not always reduce risk at low aspiration levels, but reduces risk at one point in the entire curve, which could theoretically be anywhere. Thus, the decision maker has no choice regarding which risk level to reduce; it totally depends on the nature of the problem. The advantage of the minimax regret criterion over maximax and maximin criteria is that it does not render a design that has a relatively large loss at any single scenario. It can, however, render a design with significant loss in many scenarios as long as it has the minimum–maximum regret. We therefore advocate carefulness in the use of regret analysis directly or its incorporation as a constraint in stochastic optimization. Moreover, we think it should not be used.

8. Upper and lower risk curve bounds

The upper bound risk curve is defined to be the curve constructed by plotting the set of net present values (NPV) for the best design under each scenario, that is by using all "wait and see" solutions. Fig. 8 shows the upper bound risk curve and curves corresponding to possible and impossible solutions.

We show next that such curve is indeed an upper bound.

Theorem II. *The risk curve for any feasible design is positioned entirely above* (*to the left of*) *the upper bound risk curve*.

Proof. The risk curve for any design is constructed by plotting its NPVs under all scenarios, sorted in an ascending order versus their cumulative probabilities. Consider two sets of NPVs, one for the upper bound risk curve (E) and the other for a feasible design (D), defined for n scenarios as illustrated in Table 4.

This table represents the NPVs in their raw form, before sorting them to obtain the risk curves. From the definition of the upper bound risk curve, each point in the table corresponds to the NPV of the best possible design under that scenario. That is:

Table 4
Raw NPVs

s	NPV_s^E	NPV_s^D
1	NPV_1^E	NPV_1^D
2	NPV_2^E	NPV_2^D
3	NPV_3^E	NPV_3^D
$\vdots$	$\vdots$	$\vdots$
n	NPV_n^E	NPV_n^D

$$\mathrm{NPV}_s^E \geq \mathrm{NPV}_s^D, \quad \forall s \tag{30}$$

We need to prove that this characteristic of the upper bound risk curve's NPVs continues to holds after sorting them, in order to prove that the risk curve for any feasible design is positioned entirely to the left of the upper bound risk curve. Consider the sorted NPVs with scenarios represented by s' (Table 5).

In this case the following relations hold:

$$\mathrm{NPV}_{s'}^E \geq \mathrm{NPV}_{s'+1}^E, \quad \forall s \tag{31}$$

$$\mathrm{NPV}_{s'}^D \geq \mathrm{NPV}_{s'+1}^D, \quad \forall s \tag{32}$$

$\mathrm{NPV}_{1'}^E$ is the minimum of the upper bound risk curve's NPVs and from relation (30) it must be greater than or equal to at least one of the design curve points, that is, $\mathrm{NPV}_{1'}^E \geq \mathrm{NPV}_{k'}^D$ for some k'. Since is the minimum of the design curve, we conclude that $\mathrm{NPV}_{1'}^E \geq \mathrm{NPV}_{1'}^D$.

For $\mathrm{NPV}_{2'}^E$, it also must be greater than or equal to at least one of the design curve points, that is $\mathrm{NPV}_{2'}^E > \mathrm{NPV}_{p'}^D$ for some p'. In addition, since, it must also be greater than or equal to. Therefore must be greater than or equal to at least two points in the design curve and since is the second minimum we conclude that.

A similar proof can be made for scenarios 3 through n and therefore the following is true

$$\mathrm{NPV}_{s'}^E > \mathrm{NPV}_{s'}^D, \quad \forall\, s \tag{33}$$

which is the mathematical representation of the claim of the theorem. □

In turn, the lower bound risk curve is defined to be the curve constructed by plotting the highest risk of the set of designs used to construct the upper bound risk curve at each

Table 5
Sorted NPVs

s'	$\mathrm{NPV}_{s'}^E$	$\mathrm{NPV}_{s'}^D$
$1'$	$\mathrm{NPV}_{1'}^E$	$\mathrm{NPV}_{1'}^D$
$2'$	$\mathrm{NPV}_{2'}^E$	$\mathrm{NPV}_{2'}^D$
$3'$	$\mathrm{NPV}_{3'}^E$	$\mathrm{NPV}_{3'}^D$
$\vdots$	$\vdots$	$\vdots$
n'	$\mathrm{NPV}_{n'}^E$	$\mathrm{NPV}_{n'}^D$

Table 6
Here and now NPVs

d	s				
	s_1	s_2	s_3	...	s_n
d_1	$NPV_{d1,\,s1}$	$NPV_{d2,\,s1}$	$NPV_{d3,\,s1}$	...	$NPV_{dn,\,s1}$
d_2	$NPV_{d1,\,s2}$	$NPV_{d2,\,s2}$	$NPV_{d3,\,s2}$	...	$NPV_{dn,\,s2}$
d_3	$NPV_{d1,\,s3}$	$NPV_{d2,\,s3}$	$NPV_{d3,\,s3}$	...	$NPV_{dn,\,s3}$
⋮	⋮	⋮	⋮		⋮
d_n	$NPV_{d1,\,sn}$	$NPV_{d2,\,sn}$	$NPV_{d3,\,sn}$	...	$NPV_{dn,\,sn}$
Min	NPV^{Min}_{s1}	NPV^{Min}_{s2}	NPV^{Min}_{s3}	...	NPV^{Min}_{sn}

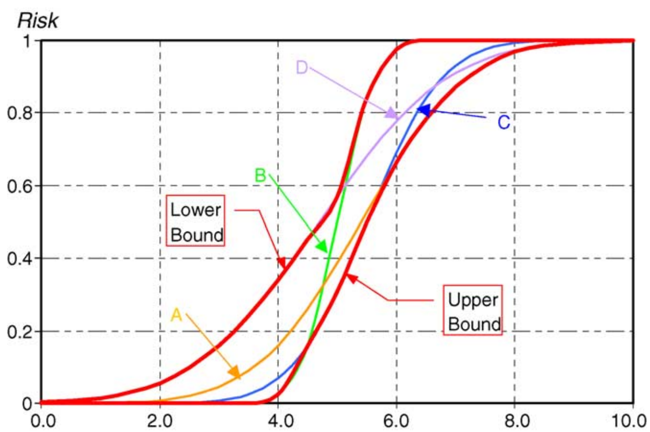

Fig. 9. Graphical representation of how the lower and upper bound risk curves are obtained.

net present value abscissa. The lower bound risk curve, unlike the upper bound risk curve, can be crossed by feasible solutions, but these would not be Pareto optimal solutions in the downside risk and expected net present value space. This curve is constructed after generating the table for all designs of individual scenarios. Table 6 illustrates a *here and now* table with the lower bound risk curve calculated as the NPV of the design with minimum NPV under that scenario, that is, the minimum of each column. In this table, the last row (labeled Min) represents the lower bound.

The upper bound risk curve can be also constructed from this table with the maximum NPVs instead of the minimum. Fig. 9 shows how lower and upper bound risk curves can be constructed. The upper and lower bound risk curves are combinations of points each having the maximum or the minimum value from the set of wait-and-see designs. Each wait-and-see design must be totally bounded be the two curves. Design A contributes the upside of the upper bound risk curve while design B contributes the downside of it. The middle portion of the upper bound risk curve is the contribution of design C. The lower bound risk curve is contributed from two designs B in the upside and D in the downside.

9. Example: gas commercialization in Asia

The main goal of this problem is to find the best system for distributing and using natural gas in Asia. Once the producers and buyers have been identified, their needs and transportation costs were modeled to determine the most efficient means of transporting the products. The scope of the project extends from the year 2005 to 2030, which is reasonable for any project that requires a substantial dollar investment.

Suppliers were chosen among those countries in Asia that have a large enough reserve to produce, at least 0.25 Tcf/year. This has been chosen based on the minimum recommended level taken from various sources (Eng & Patterson, 1998; USGS World Petroleum Assessment, 2000; USGS & Mineral Yearbook, 2002). From (USGS World Conventional Natural Gas Resources, by Basin, 1998) those seven countries have future potential to produce huge amount of natural gas: Australia, Indonesia, Iran, Kazakhstan, Malaysia, Qatar and Russia. Some countries with large reserves like Kuwait, Iraq, Saudi Arabia and UAE were excluded due to the fact that most of the gas reserve they hold are associated with oil and can only be produced as a byproduct with the production of oil. This presents a major restriction on the production of gas since the production of oil is limited by OPEC quotas. Furthermore, oil producing countries are interested more in exporting oil and using gas for domestic energy requirements since OPEC quotas are on production, not exports. Aseeri (2003) provides more details on gas availability in Asia.

Demand of natural gas, ammonia, gasoline, and methanol in the period from 2005 to 2020 for market countries were also estimated. The complete details are given by Aseeri (2003). Over the next two decades, global primary energy demand will increase by 2–3% annually, in line with expected economic growth. Two factors will ensure that during this period gas will increase its share of the total energy basket; one is economic, based upon the ever-increasing efficiency that new gas turbine technology is providing to power generation, while the other is environmental. The emerging economies in the Asian region are expected to grow at more than double the global rate. The market countries for natural gas selected for this study are the United States, Japan, China, India, South Korea, and Thailand. The total demand of natural gas and production rate of natural gas in each country are obtained from (EIA International Energy Outlook, 2002). Detail forecasted consumption on the selected countries is described by Aseeri (2003).

Processing natural gas should be preceded by the separation of some undesirable components such as water, acid gases (H_2S and CO_2) and heavy hydrocarbons (C_3^+). The next processing step depends on the transport system chosen. Natural gas can be commercialized in various forms: compressed natural gas (CNG) transported by pipelines or ships; liquefied natural gas (LNG), transported by ships; converted to chemicals (ammonia, methanol, FT liquid fuel (gasoline), etc.), and transported by ships. A detailed discussion of these three technologies can be found in the thesis by Aseeri (2003). In this reference a detailed analysis is performed regarding the investment involved. Appendix A summarizes the results of the capital and operating cost calculations performed. At this point we point out the large uncertainty associated in several of these estimations.

Traditionally GTL plants based on Fisher Tropsch Technology can be used to produce Diesel, Naphtha and Gasoline. We chose to use gasoline, but the model can be expanded to include the other choices. Gasoline is a consumer product that is available everywhere, and is always on high demand. Its consumption, in the United States for example, accounts for almost 45% of all oil use (EIA Annual Energy Outlook, 2003). It has been the most important oil product since the 1920s and maximizing gasoline production has been the main driver in the development of refinery technology and design. According to the Annual Energy Outlook by the Energy Information Administration, motor gasoline use is projected to increase by about 2% per year in the reference case, making up 59.2% of transportation energy demand.

In a special report on the 'impacts of increased diesel penetration in the transportation sector' (EIA, 1999), the Energy Information Administration showed that sharp decline in gasoline prices will only happen if the penetration reaches to 20% or more by 2010. In the reference case, which is based on the expected continuation of existing laws, regulations, and policies, a steady price increase is projected. Diesel prices, on the other hand, are expected to decline.

10. Planning model

This section introduces and explains the planning model used for the study of natural gas commercialization in Asia. The model is a mixed integer linear program (MILP) that maximizes the expected net present value (ENPV) of the project, over a certain number of scenarios, by varying transport process selection, expansion capacities and production rates. The model utilizes the two-stage stochastic formulation to account for future uncertainties in demand and prices. The first stage decision variables are whether or not to build production, transport, and receiving facilities in a specific time period and how much design capacity to assign to each facility. The second-stage variables, on the other hand, are the operating levels of these facilities when scenarios are unveiled. The details of model were commensurate with the quality of data used. Data was taken from public sources so it can be more accurate. Some economic calculations were also simplified. The reader is reminded that this article intends to show the validity of the concepts developed using a realistic problem and it is not our claim that the model captures *all* detailed aspects of the problem but rather the capabilities of the tool proposed.

The sets, parameters and variables used in the planning model are described next:

Sets and indices

Subscripts

i: set of countries that supply natural gas, referred as suppliers.
j: set of processes used to convert and/or transport gas.
m: set of countries where the various products can be sold.
c: set of chemicals or final products sold in markets.
t: set of time periods considered for design and/or operating variables.
s: set scenarios considered for modeling uncertainty.

Superscripts

I: a superscript denoting an initial or grass-root installation.
E: a superscript denoting an expansion.
1: a subscript denoting facilities at suppliers location.
2: a subscript denoting facilities on transit such as a pipeline or a ship.
3: a subscript denoting facilities at market location.

Parameters

Demand: demands in billion cubic feet per year (bcfy) for natural gas and million tons per year for converted products.
α: variable cost coefficient for capital investment.
β: fixed cost coefficient for capital investment.
δ: variable cost coefficient for operating cost per unit produced.
γ: fixed cost coefficient for operating cost per unit produced.
SalePrice: unit sale prices of the different finished products.
FeedCost: unit cost of natural gas feed.
MaxProdn: maximum natural gas production for each the supplier.
DF: discount factor for cash flow in different time period brought to year 2005 with annual interest rate of 7%.
Infl: inflation factor for fixed and operating costs in different time period brought up to each year from year 2005 with annual inflation rate of 3%.
Cvsn: a conversion factor from bcfy of natural gas to marketed product (bcfy or MMTY). For natural gas and CNG, the conversion factor is 1.
Dur: the duration of each time period in years.
CT: construction time requited to build facilities of a certain process.
ρ: goal programming weight.

Variables

Cap: design capacity of a facility.
Capacity: total installed capacity that can be utilized for operation.
Y: a binary variable for installation of a facility in a specific time period.
Z: a variable for the number of available installation in a specific time period.

FP: operating level of a processing facility at a specific time period.
FT: transportation flow at a specific time period.
FR: operating level of a receiving facility at a specific time period.
FChm: total flow rate of a certain chemical into a market.
NPV: the net present value for a specific scenario.
ENPV: the expected net present value over all scenarios.
p: the probability of a scenario's occurrence.

Stochastic model (NGC)

Objective function

$$\text{Maximize} \quad \text{ENPV} = \sum_{s=1}^{S}(P_S\,\text{NPV}_s) \tag{34}$$

Such that:

$$\begin{aligned}\text{NPV}_s =& \sum_{t=1}^{T}\left\{\text{DF}_t^*\left(\text{Sales}_{ts} - \text{Tax}_{ts} - \sum_{i=1}^{I}(\text{GasCost}_{its})\right.\right.\\ &- \sum_{i=1}^{I}(\text{FixedCost}_{it}^{P}) - \sum_{m=I}^{M}(\text{FixedCost}_{mt}^{R})\\ &\left.\left. - \sum_{i=I}^{I}(\text{OprCost}_{its}^{P}) - \sum_{m=I}^{I}(\text{OprCost}_{mts}^{R})\right)\right\}\end{aligned} \tag{35}$$

$$\text{Sales}_{ts} = \text{Dur}_t\sum_{C=1}^{C}\sum_{m=1}^{M}(\text{SalePrice}_{mcts}\text{FChm}_{mcts}) \tag{36}$$

$$\text{GasCost}_{its} = \text{Dur}_t\text{FeedCost}_{its}\sum_{j=1}^{J}(\text{Feed}_{ijts}) \tag{37}$$

$$\begin{aligned}\text{FixedCost}_{it}^{P} =& \text{Infl}_t\left\{\sum_{j=1}^{J}(\text{Cap}^{1I}\alpha_{ij}^{1I} + \beta_{ij}^{1I}Y_{ijt}^{1I}\right.\\ &+ \text{Cap}_{ijt}^{1E}\alpha_{ij}^{1E} + \beta_{ij}^{1E}Y_{ijt}^{1E})\\ &+ \sum_{j\in\{pip\}}\sum_{m=1}^{M}(\text{Cap}_{imjt}^{2I}\alpha_{imj}^{2} + \beta_{imt}^{2I}Y_{imjt}^{2I})\\ &\left.+ \sum_{j\notin\{pip\}}(\text{NewShips}_{ijt}\times\text{ShipCost}_j\right\}\end{aligned} \tag{38}$$

$$\begin{aligned}\text{FixedCost}_{mt}^{R} =& \text{Infl}_t\sum_{j=1}^{J}\sum_{m=1}^{M}(\text{Cap}_{mjt}^{3I}\alpha_{mj}^{3I} + \beta_{mj}^{3I}Y_{mjt}^{3I}\\ &+ \text{Cap}_{mjt}^{3E}\alpha_{mj}^{3E} + \beta_{mj}^{3E}Y_{mjt}^{3E})\end{aligned} \tag{39}$$

$$\begin{aligned}\text{OprCost}_{its}^{P} =& \text{Dur}_t\text{Infl}_t\left(\sum_{j=1}^{J}(\text{FP}_{ijts}\delta_{ijt}^{1} + \gamma_{ijt}^{1}Z_{ijt}^{1})\right.\\ &+ \sum_{j\in\{pip\}}^{J}\sum_{m=1}^{M}(\text{FT}_{imjts}\delta_{imjt}^{2} + \gamma_{imjt}^{2}Z_{imjt}^{2})\\ &\left.+ \sum_{j\notin\{pip\}}^{J}\sum_{m=1}^{M}(\text{TransShip}_{imjts}\text{OprShip}_j)\right)\end{aligned} \tag{40}$$

$$\text{OprCost}_{mts}^{R} = \text{Dur}_t\text{Infl}_t\sum_{j=1}^{J}(\text{FR}_{mjts}\delta_{imjt}^{3} + \gamma_{imjt}^{3}Z_{imjt}^{3}) \tag{41}$$

The Sales Eq. (36) calculate the total revenues in each time period from all processes at all markets. The gas cost equations calculate the total discounted cost of feed gas in each time period from all processes at all suppliers.

The fixed investment cost Eqs. (38) and (39) calculate the total FCI in each time period as the summation of the costs of investment of all new installations or expansions on supply, transport and receiving facilities. These costs are assumed to be linear. Similarly, the operating cost Eqs. (40) and (41) calculate the operating costs in each time period as the summation of the costs of operation on supply, transport and receiving facilities. These costs are also assumed to be linear.

Tax relations

$$\text{Sales}_{its}^{\text{Tax}} = \text{Dur}_t\sum_{j=1}^{J}\sum_{m=1}^{M}\left(j\text{SalesPrice}_{mjts}\frac{\text{FT}_{imjts}}{s\text{Cvsn}_j}\right), \quad \forall i,\ t \text{ and } s \tag{42}$$

$$\text{Depr}_{it} = \sum_{\theta=t-3}^{t-1}\left(\frac{\text{FixedCost}_{i\theta}^{P}}{3}\right), \quad \forall i \text{ and } t \tag{43}$$

$$\begin{aligned}\text{Tax}_{ts} =& \sum_{i}^{I}\{\text{TaxRate}_i(\text{Sales}_{ist}^{\text{Tax}} - \text{GasCost}_{its}\\ &- \text{OprCost}_{its}^{P} - \text{Depr}_{it})\}, \quad \forall t, s\end{aligned} \tag{44}$$

The first set of Eq. (42) calculates the sales revenues associated with each supplier at any time period. This is used in the calculation of the taxes third set of equations. Unlike

SalePrice, used in Eq. (36), jSalePrice is the sale price per unit transported rather than unit of the commodity sold. The second set of Eq. (43) calculates the depreciation of the facilities to be exempted from the calculations of tax. Straight line depreciation is assumed over 12 operating years. Tax laws vary from country to country. Moreover, likely, the investment funds are from international sources, so a complicated scheme of taxation applies here. Should this model be expanded, this is certainly an area where improvements can be introduced.

Ship transportation

$$\text{NoShips}_{ijt} = \sum_{\theta=1}^{i-ct(j)} \text{NewShips}_{ij\theta}, \quad \forall, i,\ j \text{ and } t \tag{45}$$

$$\text{NoShips}_{ijt} \geq \sum_{m=1}^{M} \text{TransShips}_{ijtsm}, \quad \forall, i,\ j,\ t \text{ and } s \tag{46}$$

The first set of Eq. (45) calculates the number of available ships for transportation from any supplier as the sum of ships built before the beginning of that time period. The second set (46) assigns transportation ships from supplier to market and forces their sum to be less than or equal to the number of available ships.

Capacity limits

$$\text{MinCap}_j^i Y_{ijt}^{1I} \leq \text{Cap}_{ijt}^{1I} \leq \text{MaxCap}_{ijt}^{1I} Y_{ijt}^{1I}, \quad \forall i,\ j \text{ and } t \tag{47}$$

$$\text{MinCap}_j^2 Y_{ijt}^{1E} \leq \text{Cap}_{ijt}^{1E} \leq \text{MaxCap}_j^1 Y_{ijt}^{1E}, \quad \forall i,\ j \text{ and } t \tag{48}$$

$$\text{MinCap}_j^2 Y_{imjt}^{2I} \leq \text{Cap}_{imjt}^{2I} \leq \text{MaxCap}_j^2 Y_{imjt}^{2I}, \quad \forall i, m,\ j \in \{pip\} \text{ and } t \tag{49}$$

$$\text{MinCap}_j^3 Y_{mjt}^{3I} \leq \text{Cap}_{mjt}^{3I} \leq \text{MaxCap}_t^3 Y_{mjt}^{3I}, \quad \forall m,\ j \text{ and } t \tag{50}$$

$$\text{MinCap}_j^3 Y_{mjt}^{3E} \leq \text{Cap}_{mjt}^{3E} \leq \text{MaxCap}_j^3 Y_{mjt}^{3E}, \quad \forall m,\ j \text{ and } t \tag{51}$$

These equations force installation or expansion capacity to fall between a minimum and a maximum.

Material balance

$$\text{FP}_{ijts} = \sum_{m=1}^{M} \text{FT}_{imjts}, \quad \forall i,\ j,\ t \text{ and } s \tag{52}$$

$$\text{FR}_{jmts} = \sum_{i=1}^{I} \text{FT}_{imjts}, \quad \forall m,\ j,\ t \text{ and } s \tag{53}$$

These equations enforce material flow between different nodes to be balanced. The first set of Eq. (52) balance the flow from production facilities to transportation facilities while the second set (53) balances the flow from transportation facilities to receiving facilities.

Existing capacities

$$\text{Capacity}_{ijt}^1 = \sum_{\theta=1}^{t-CT(j)} (\text{Cap}_{ij\theta}^{1I} + \text{Cap}_{ij\theta}^{1E}), \quad \forall i,\ j \text{ and } t \tag{54}$$

$$\text{Capacity}_{imjt}^2 = \sum_{\theta=1}^{t-CT(j)} (\text{Cap}_{imj\theta}^{2I}), \quad \forall i, m, \quad j \in \{pip\} \text{ and } t \tag{55}$$

$$\text{Capacity}_{mjt}^3 = \sum_{\theta=1}^{t-CT(j)} (\text{Cap}_{mj\theta}^{3I} + \text{Cap}_{mj\theta}^{3E}), \quad \forall m,\ j \text{ and } t \tag{56}$$

These equations calculate the available capacities for production, transport and receiving facilities at each time period. The available capacity of a facility at any time period is the available capacity in the previous time period plus any additional capacity from a project for which construction time has elapsed.

Operating limits

$$\text{FP}_{ijts} \leq \text{Capacity}_{ijt}^1 \quad \forall i,\ j,\ t \text{ and } s \tag{57}$$

$$\text{FT}_{imjts} \leq \text{Capacity}_{imjt}^2, \quad \forall i, m,\ j \in \{pip\},\ t \text{ and } s \tag{58}$$

$$\text{FT}_{imjts} \leq \text{TransShips}_{imjts} \times \text{ShipyearlyCap}_{imj}, \quad \forall i, m,\ j \notin \{pip\},\ t \text{ and } s \tag{59}$$

$$\text{FT}_{jmts} \leq \text{Capacity}_{jmt}^1, \quad \forall i, m,\ j,\ t \text{ and } s \tag{60}$$

These equations limit the flow on each facility at all scenarios to be less than or equal to the existing capacity at that time period. The third set of Eq. (59) limits the ship transportation capacity to be less than the capacity that the transportation ships assigned to that route can deliver in 1 year.

Gas production limits

$$\mathrm{FP}_{ijts} = \mathrm{Feed}_{ijts}\mathrm{Cvsn}_j, \quad \forall i,\ j,\ t \text{ and } s \tag{61}$$

$$\sum_{j=1}^{J} \mathrm{Feed}_{ijts} \leq \mathrm{Max\_Production}, \quad \forall i,\ t \text{ and } s \tag{62}$$

These equations limit the total gas consumed from each supplier to be less than the maximum gas production allowed.

Existence of facilities

$$Z^1_{ijt} = Z^1_{ij(t-1)} + Y^1_{ij(t-CT_j)}, \quad \forall i,\ j \text{ and } t \tag{63}$$

$$Z^2_{imjt} = Z^2_{imj(t-1)} + Y^2_{imj(t-CT_j)}, \quad \forall i, m,\ j \in \{pip\} \text{ and } t] \tag{64}$$

$$Z^3_{mjt} = Z^3_{mj(t-1)} + Y^3_{mj(t-CT_j)}, \quad \forall m,\ j \text{ and } t \tag{65}$$

These equations represent the existence of each facility in operable condition. A facility is considered to exist if it existed in the previous time period or if installed before as many time periods as construction requires.

Expansions limit

$$Y^{1E}_{ijt} \leq Z^1_{ijt}, \quad \forall i,\ j \text{ and } t \tag{66}$$

$$Y^{3E}_{mjt} \leq Z^3_{mjt}, \quad \forall m,\ j \text{ and } t \tag{67}$$

$$Y^{3I}_{ijt} + Y^{3E}_{ijt} \leq 1, \quad \forall i,\ j \text{ and } t \tag{68}$$

$$Y^{3E}_{mjt} \leq Z^3_{mjt}, \quad \forall m,\ j \text{ and } t \tag{69}$$

The first two sets of Eqs. (66) and (67) prevent expansions from taking place if a facility does not exist. The second two sets of Eqs. (68) and (69) prevent new installations and expansions from taking place at the same time.

Logical relations

$$Y^{1I}_{ijt} + Y^{1E}_{ijt} \geq \sum_{m=1}^{M} Y^{2I}_{imjt}, \quad \forall i,\ j \in \{pip\} \text{ and } t \tag{70}$$

$$Y^{3I}_{mjt} + Y^{3E}_{mjt} \leq \sum_{m=1}^{I} Y^{3I}_{imjt}, \quad \forall i,\ j \in \{pip\} \text{ and } t \tag{71}$$

The above two sets of equations force a transport facility not to exist unless a production facility exists and forces a receiving facility not to exist unless a transport facility exists.

Limits on projects

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T}(Y^{1I}_{ijt} + Y^{1E}_{ijt}) \leq \mathrm{Max\_No\_of\_Projects}, \quad \forall t \tag{72}$$

$$\sum_{t}^{T} Y^{1I}_{ijt} \leq 1, \quad \forall i \text{ and } j \tag{73}$$

$$\sum_{t}^{T} Y^{1E}_{ijt} \leq 1, \quad \forall i \text{ and } j \tag{74}$$

$$\sum_{t}^{T} Y^{3I}_{ijt} \leq 1, \quad \forall i \text{ and } j \tag{75}$$

$$\sum_{t}^{T} Y^{3E}_{mjt} \leq 1, \quad \forall j \text{ and } m \tag{76}$$

The first set of Eq. (72) limit the number of projects at suppliers to be less than a certain limit. The remaining Eqs. (73)–(76) limit projects at any supplier to a maximum of one grass root installation and one expansion.

Flow conversion

$$\mathrm{FChm}_{mcts}|_{c=\mathrm{Gas}} = \sum_{j\in\{\mathrm{PIP,CNG,LNG}\}} (\mathrm{FR}_{mjts}\mathrm{Cvsn}_j), \quad \forall m, t \text{ and } s \tag{77}$$

$$\mathrm{FChm}_{mcts}|_{c=\mathrm{Ammonia}} = (\mathrm{FR}_{mjts})_{j=\mathrm{GTA}}, \quad \forall m, t \text{ and } s \tag{78}$$

$$\mathrm{FChm}_{mcts}|_{c=\mathrm{Methanol}} = (\mathrm{FR}_{mjts})_{j=\mathrm{GTM}}, \quad \forall m, t \text{ and } s \tag{79}$$

$$\mathrm{FChm}_{mcts}|_{c=\mathrm{Gasoline}} = (\mathrm{FR}_{mjts})_{j=\mathrm{GTL}}, \quad \forall m, t \text{ and } s \tag{80}$$

These equations convert the flow rate at receiving facilities to the flow rate of marketable commodities (gas, ammonia, methanol, and gasoline). Gas flow is equal to the sum of received gas from all gas transportation methods (pipe, CNG and LNG).

Demand limits

$$\mathrm{FChm}_{mcst} \leq \mathrm{CumDemand}_{mcst}, \quad \forall m, c, t \text{ and } s \tag{81}$$

$$\mathrm{CumDemand}_{mcst} = \mathrm{DemandIncr}_{mcs(t-1)} + \mathrm{DemandIncr}_{mcst}, \quad \forall m, c, t \text{ and } s \tag{82}$$

The above equations limit the flow of any commodity at a certain market to be less than the cumulative demand at each time period. The cumulative demand at a certain time period is defined to be the cumulative demand in the previous time period plus the increase in demand.

Cash flow limits

$$\text{FixedCost}_t \leq \text{InjCash}_t, \quad \forall t \tag{83}$$

This set of equations constrains the fixed investment at any time period to be less than the injected cash at that time period.

Stochastic model with downside risk management (NGC-DR)

To add downside risk management to model NGC the following equations are added:

$$\text{Delta}_s \geq \Omega - \text{NPV}_s, \quad \forall s \tag{84}$$

$$\text{Delta}_s \geq 0, \quad \forall s \tag{85}$$

$$\text{DRisk} = \sum_{s=1}^{S} (p_s \text{Delta}_s) \tag{86}$$

where Delta_s is the positive deviation of the net present values from the profit target Ω and DRisk is the downside risk. If risk management is performed, downside risk is penalized in the objective function (34) as follows:

$$\text{Maximize ENPV} = \sum_{s=1}^{S} p_s \text{NPV}_s - \rho \text{DRisk} \tag{87}$$

where ρ is a goal programming weight for penalizing risk. Barbaro and Bagajewicz (2004a) provided a detailed procedure for risk management using a multiobjective model where ρ is varied until an acceptable design is obtained.

11. Results

The MILP planning model was implemented in general algebraic modeling system (GAMS, GAMS Development Corp.) using CPLEX 7.5. A zero gap was specified. All optimization runs were made with investment limits of 3 billion dollars in the first time period and 2 billion dollars in the third time period with the other four time periods having no investments allowed.

11.1. Input data

The time horizon of this problem was divided into six equal time periods of 4 years. Data on Tables 7–10 are the mean values for demand used in the model runs. It was assumed that for a new project to be profitable, only increase in demand should be considered since existing demand will be already satisfied by others. Table 11 shows the standard deviations that were assumed for each commodity in each market. The model was run assuming project construction in periods T1 and T3 only.

The data on Table 12 are the estimated mean gas prices in year 2005 with the price trend mean value equal to their average (2.2 US$/MSCF). The average difference of each country form the mean is also shown, as well as the standard deviation

Table 7
Gas demand increases in selected markets (BCF per year)

	T1	T2	T3	T4	T5	T6
US	1800	1800	1471	1143	1143	1143
India	560	560	409	257	257	257
China	1000	1000	1014	1029	1029	1029
Thai	100	100	100	100	100	100
South Korea	280	280	269	257	257	257
Japan	120	120	203	286	286	286

Table 8
Methanol demand increases in selected markets (MM tonne per year)

	T1	T2	T3	T4	T5	T6
US	0	0	0	0	0	0
India	0.640	0.640	0.549	0.457	0.457	0.457
China	0	0	0	0	0	0
Thai	0.400	0.400	0.343	0.286	0.286	0.286
South Korea	0.800	0.800	0.686	0.571	0.571	0.571
Japan	0	0	0	0	0	0

Table 9
Ammonia demand increases in selected markets (MM tonne per year)

	T1	T2	T3	T4	T5	T6
US	1.080	1.080	1.240	1.400	1.400	1.400
India	0.100	0.100	0.090	0.080	0.080	0.080
China	0.184	0.184	0.205	0.226	0.226	0.226
Thai	0	0	0	0	0	0
South Korea	0.656	0.656	0.611	0.566	0.566	0.566
Japan	2.220	2.220	2.186	2.151	2.151	2.151

Table 10
Gasoline demand increases in selected markets (MM tonne per year)

	T1	T2	T3	T4	T5	T6
US	24.0	24.0	19.4	14.9	14.9	14.9
India	3.5	3.5	3.0	2.5	2.5	2.5
China	24.4	24.4	21.5	18.6	18.6	18.6
Thai	3.5	3.5	3.0	2.5	2.5	2.5
South Korea	1.7	1.7	1.2	0.7	0.7	0.7
Japan	24.4	24.4	21.5	18.6	18.6	18.6

Table 11
Standard deviations in each market

	US	India	China	Thai	South Korea	Japan
Gas	150	50	100	10	30	15
Methanol	0.00	0.10	0.00	0.05	0.15	0.00
Ammonia	0.15	0.02	0.04	0.00	0.10	0.50
Gasoline	3.00	0.40	3.50	0.50	0.20	3.00

Table 12
Mean feed gas prices forecast on year 2005 (US$/MSCF)

	Mean price	Difference from trend	Difference deviation
Iran	2.900	0.3	0.200
Russia	2.300	0.2	0.500
Kazakhstan	2.300	−0.7	0.100
Indonesia	1.500	−0.8	0.700
Malaysia	1.500	−0.7	0.100
Australia	3.000	0.7	0.400
Qatar	2.100	−0.1	0.100

Table 14
Estimated standard deviation of price deviation from the market trend (US$/MSCF for gas or US$/tones for others)

	US	India	China	Thai	South Korea	Japan
Gas	0.05	0.05	0.04	0.02	0.05	0.10
Methanol	0.20	0.10	0.10	0.20	0.30	0.10
Ammonia	0.30	0.10	0.20	0.20	0.10	0.20
Gasoline	0.60	0.50	0.50	0.50	0.50	0.70

of those differences. The same type of information for sales prices are shown on Tables 13 and 14. This price information was estimated from different sources that are publicly available (International Energy Agency, Energy Information Administration, The Institute of Energy Economics, Japan and others). Appendix B gives details about the sampling method used to generate price scenarios. The issue of following trends is of critical importance, but there is the additional one that should be taken into account in general, which is the correlation between prices and demands. This is left for future work.

11.2. Deterministic model results

Running the deterministic model using mean values, a solution was obtained with a NPV of 4.666 billion dollars with a few seconds of execution time in a computer having a 1.0 GHz processor and 512 memory. The results are shown in Table 15.

The first part of the table (processing facilities) shows the existing (available) capacities of the recommended project taking into account construction time which was assumed one time period (4 years). This is the reason why the fixed capital investment (FCI) appears on the time period prior to capacity increases. The required gas feed amounts are indicated on the “feed” column in billion SCF/year. Also the numbers of ships available for transportation are indicated in the “ships” column. The solution indicates that a GTL processing plant should be built in Indonesia in the first time period with a capacity of 4.43 million tonnes/year and that five ships are to be built/purchased for the transportation of the GTL product. It also suggests that an expansion of the same plant is needed in the third time period to increase the capacity to 7.18 million tonnes/year as well as the purchase of three additional ships. The second part of the table (transportation) shows the number of ships that will be assigned to transport products to different markets as well as the yearly flow of transported products. The first thing one notice is that not all the investment is utilized in the second period, which is explained by the fact that increased capacity leads to the need of more ships, money for which is not available. Notice also that the columns “ships” and “avrg. ships” under “transportation” are not necessarily integral values since they are second-stage decisions. These values represent the yearly utilization of ships for a specific route. A value of 4.34, for example, mean that four ships are fully dedicated to that route and one ship is only utilized 43% of the year time on that route, while the balance is either utilized for another route or not utilized due to demand constraints.

When the deterministic model was run with one time investment of 5 billion dollars allowed in the first time period, results in Table 16 were obtained. The NPV is 6.451 billion dollars, which is higher than the previous one.

The model utilizes the whole investment to install a 7.33 million tonnes/year GTL plant in Malaysia with 10 ships to transport gasoline to both China and Thailand. We notice here that as demand of gasoline in Thailand builds up, transportation to China is phased out. This is due to the fact that Thailand is nearer to Indonesia and hence has lower transportation cost.

11.3. Stochastic model results

The stochastic model was run considering that the feed cost, the sale prices and the demands for the marketable commodities are uncertain. The sampling method used is discussed in Appendix B. The model was solved for different number scenarios (10, 50, 100 and 200) to illustrate the effect of number of scenarios. Two hundred (200) was the maximum

Table 13
Mean sales prices forecast for year 2005 (US$/MSCF for gas or US$/tones for others)

	Trend price	Trend deviation	Market differences from the trend					
			US	India	China	Thai	South Korea	Japan
Gas	3.5	0.5	−0.4	0.7	0.5	0	1	1.5
Methanol	150	30	0	0	0	0	0	0
Ammonia	160	30	0	0	0	0	0	0
Gasoline	400	40	1	0	0	0	0	0

Table 15
Results for deterministic model

Time period	FCI	Processing facilities				Transportation to				Avrg. ships
		Indo (GTL)				China		Thai		
		Cap	Flow	Feed	Ships	Ships	Flow	Ships	Flow	
T1	3.00									
T2		4.43	4.25	283.2	5.0	1.12	0.77	3.88	3.48	5.00
T3	1.90	4.43	4.43	295.5	5.0			4.94	4.43	4.94
T4		7.18	7.12	474.7	8.0	0.30	0.20	7.70	6.92	8.00
T5		7.18	7.18	479.0	8.0			8.00	7.18	8.00
T6		7.18	7.18	479.0	8.0			8.00	7.18	8.00

Capacities and flow are in million tons per year and feed gas flow is in billion standard cubic feet per year.

Table 16
Results for deterministic model with US$ 5 billion allowed in the first time period

Time period	FCI	Processing facilities				Transportation to				Avrg. ships
		Mala (GTL)				China		Thai		
		Cap	Flow	Feed	Ships	Ships	Flow	Ships	Flow	
T1	5.00									
T2		7.33	7.33	488.5	10.0	5.64	3.85	3.88	3.48	9.52
T3		7.33	7.33	488.5	10.0	1.27	0.87	7.20	6.46	8.47
T4		7.33	7.33	488.5	10.0			8.16	7.33	8.16
T5		7.33	7.33	488.5	10.0			8.16	7.33	8.16
T6		7.33	7.33	488.5	10.0			8.16	7.33	8.16

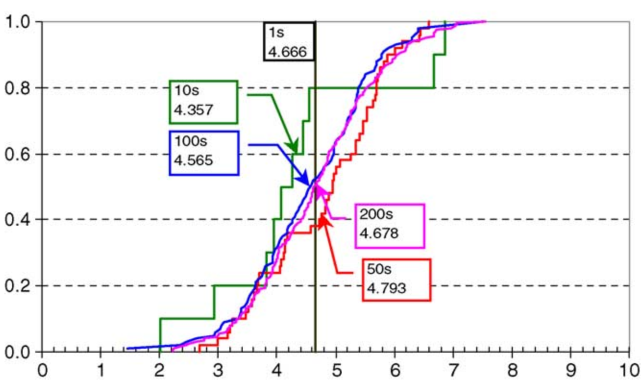

Fig. 10. Risk curves for obtained solutions of the stochastic model under different number of scenarios.

number of scenarios for which GAMS could run the model on the available computation resources (2.1 GHz processor and 2 GB RAM running a Linux operating system). The 200 scenario model run completes in about 3 h. More than 200 scenarios run the computer out of memory. Fig. 10 shows the risk curves for the solutions obtained under different number of scenarios in comparison to the deterministic solution.

The risk curves of the stochastic solutions are fairly stretched around the NPV of the deterministic solution. Tables 17–20 illustrate the obtained solutions. The columns “flow” and “feed” under “processing facilities” as well as “ships” and “flow” under “transportation” are the averages over scenarios. The column “avrg. ships” shows the average total utilization of ships. The solutions on the tables below suggest two possible designs. Both designs are to utilize natural gas from either Malaysia or Indonesia to produce

Table 17
Results for stochastic model (10 scenarios)

Time period	FCI	Processing facilities				Transportation to						Avrg. ships
		Mala (GTL)				China		Thai		India		
		Cap	Flow	Feed	Ships	Ships	Flow	Ships	Flow	Ships	Flow	
T1	3.00											
T2		4.29	4.29	286.1	6.0	1.22	0.83	3.43	3.08	0.59	0.38	5.24
T3	1.88	4.29	4.29	286.1	6.0			4.78	4.29			4.78
T4		7.18	7.07	471.6	8.0	0.51	0.35	7.49	6.73			8.00
T5		7.18	7.18	479.0	8.0			8.00	7.18			8.00
T6		7.18	7.18	479.0	8.0			8.00	7.18			8.00

Table 18
Results for stochastic model (50 scenarios)

Time period	FCI	Processing facilities				Transportation to				Avrg. ships
		Indo (GTL)				China		Thai		
		Cap	Flow	Feed	Ships	Ships	Flow	Ships	Flow	
T1	3.00									
T2		4.43	4.27	284.4	5.0	1.01	0.69	3.98	3.57	4.99
T3	1.90	4.43	4.43	295.5	5.0			4.93	4.43	4.93
T4		7.18	7.10	473.6	8.0	0.37	0.25	7.63	6.85	8.00
T5		7.18	7.18	479.0	8.0			8.00	7.18	8.00
T6		7.18	7.18	479.0	8.0			8.00	7.18	8.00

Table 19
Results for stochastic model (100 scenarios)

Time period	FCI	Processing facilities				Transportation to				Avrg. ships
		Indo (GTL)				China		Thai		
		Cap	Flow	Feed	Ships	Ships	Flow	Ships	Flow	
T1	3.00									
T2		4.43	4.23	282.2	5.0	1.18	0.81	3.81	3.42	4.99
T3	1.90	4.43	4.43	295.5	5.0	0.01	0.01	4.93	4.43	4.94
T4		7.18	7.10	473.1	8.0	0.41	0.28	7.59	6.82	8.00
T5		7.18	7.18	479.0	8.0			8.00	7.18	8.00
T6		7.18	7.18	479.0	8.0			8.00	7.18	8.00

Table 20
Results for stochastic model (200 scenarios)

Time period	FCI	Processing facilities				Transportation to				Avrg. ships
		Indo (GTL)				China		Thai		
		Cap	Flow	Feed	Ships	Ships	Flow	Ships	Flow	
T1	3.00									
T2		4.43	4.25	283.1	5.0	1.12	0.76	3.88	3.48	5.00
T3	1.90	4.43	4.43	295.5	5.0			4.94	4.43	4.94
T4		7.18	7.09	472.6	8.0	0.44	0.30	7.56	6.79	8.00
T5		7.18	7.18	479.0	8.0			8.00	7.18	8.00
T6		7.18	7.18	479.0	8.0			8.00	7.18	8.00

gasoline through GTL process. The solution for 10 scenarios suggests buying six ships on the first time period and two additional ships in the third time period while the solution for 50, 100, and 200 scenarios suggests buying five ships on the first time period and three additional ships in the third time period.

11.4. Risk management

The stochastic model was run for 200 scenarios with a penalty for the downside risk at 3.5 billion dollars. A design that reduces risk and does not have a large effect on ENPV was obtained. The design obtained is illustrated in Table 21.

This result also suggests a GTL process, but at another supplier location (Malaysia). Fig. 11 shows the risk curve of the solution of the downside risk and the stochastic models.

Investment in Malaysia manages to reduce risk over that in Indonesia due to the lower volatility of natural gas prices in Malaysia. The model was run with a penalty for the downside risk at 4 billion dollars instead of 3.5 billion dollars and the same solution was obtained.

To increase the accuracy of the risk curves first stage variables were fixed and NPVs were obtained for 2000 scenarios.

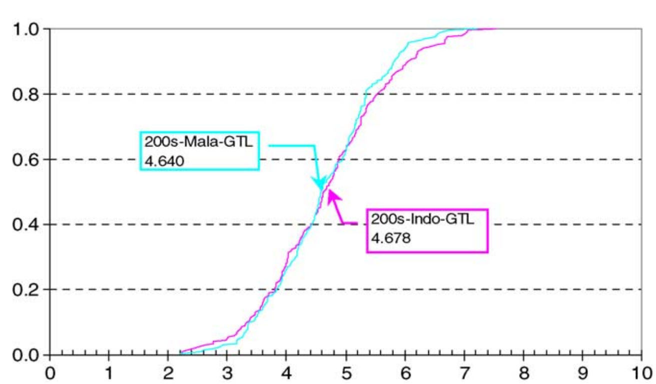

Fig. 11. Risk curves for the downside risk model solution vs. that of the stochastic model solution.

Table 21
Results for stochastic model (200 scenarios) with downside risk at 3.5 billion dollars minimized

Time period	FCI	Processing facilities				Transportation to				Avrg. ships
		Mala (GTL)				China		Thai		
		Cap	Flow	Feed	Ships	Ships	Flow	Ships	Flow	
T1	3.00									
T2		4.57	4.47	297.9	4.0	1.16	0.98	2.79	3.49	3.95
T3	1.89	4.57	4.57	304.9	4.0			3.66	4.57	3.66
T4		7.49	7.32	488.2	6.0	0.42	0.35	5.58	6.97	6.00
T5		7.49	7.49	499.6	6.0			6.00	7.49	6.00
T6		7.49	7.49	499.6	6.0			6.00	7.49	6.00

This was done twice for model NGC with different random samples. The results are 4.613 and 4.633 billion dollars (a difference of 0.5%). Fig. 12 shows the risk curves for the designs obtained for model NGC and NGC-DR with 2000 scenarios.

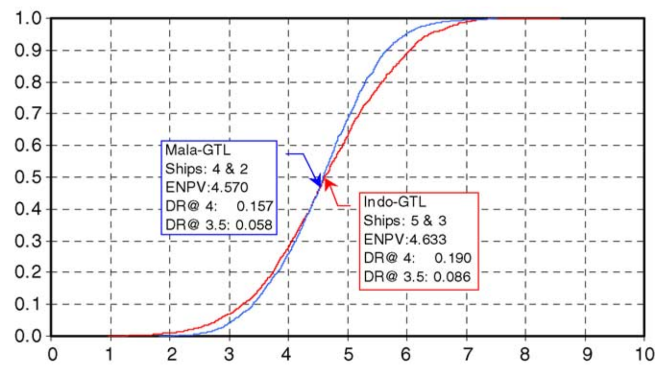

Fig. 12. Comparison of the results of models NGC and NGC-DR under 2000 scenarios.

11.5. Use of the sampling average algorithm (SAA)

After running the model for 100 scenarios to obtain first stage solutions, 12 different designs were obtained, some of which were repeated several times. All these designs suggest utilizing natural gas from either Indonesia or Malaysia with different capacities. Designs very similar to those obtained by the stochastic model with 200 scenarios were obtained 28 times. Also, designs very similar to those obtained by the downside risk model were obtained 15 times. Thus, those two good solutions were repeated in 43% of the designs obtained by this method. Also, the other designs obtained are very close to these in expected net present value and can be good candidate for optimality when run for a larger number of scenarios. This illustrates the claims made above regarding the use of the sampling algorithm. The risk curves for all these designs were obtained using 2000 scenarios by fixing all the first stage variables. It was noticed that the result of the model NGC shows better performance under 2000 scenarios than the other designs. Also the solution of the model NGC-DR shows better performance in terms of managing risk under 2000 scenarios than the other designs. This indicates that the noise on the solutions obtained with 200 scenarios did not have a significant effect on the first stage decisions. This means that 200 scenarios are sufficient for this case study, but not necessarily for all other problems. Fig. 12 shows the risk curves for these two designs with 2000 scenarios and Fig. 13 shows the distributions. Contrasting with other work (Barbaro & Bagajewicz, 2004b) they are very close to being symmetric.

11.6. Regret analysis

Applying the maximax analysis to the 100 × 100 table generated using the SAA renders the same results suggested by maximizing the average expected profit. On the other hand, the maximin method suggests the results obtained by minimizing downside risk. The minimax regret analysis suggests GTL processes in Malaysia with a slightly lower ENPV than that of model NGC-DR. It suggests buying five ships in the first time period and one in the third time period (the downside risk solutions suggests 4 and 2). These two solutions were run for 1000 scenarios and compared. The NPV obtained are 4.479 and 4.537 billion dollars, remarkably close. Thus, the minimax regret method provides good answers for this problem.

11.7. Value at risk and upside potential

Both concepts are illustrated in Fig. 14. The VaR (at 5% percentile or 0.05 quantile) and the UP (at 95%) for the two

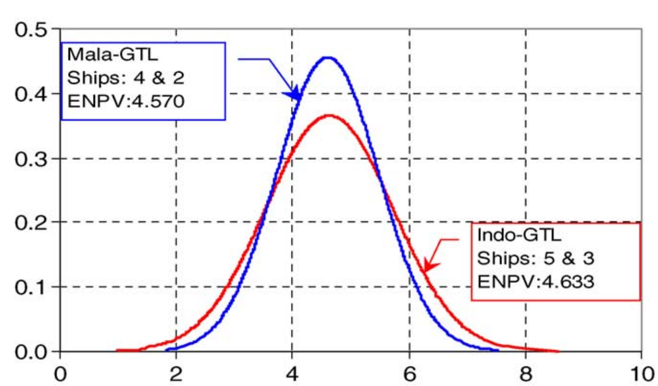

Fig. 13. Distributions for the solutions of models NGC and NGC-DR.

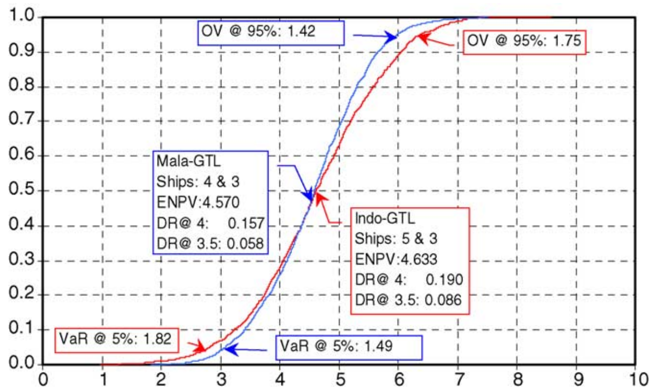

Fig. 14. VaR and OV for the results of models NGC and NGC-DR.

Table 22
Value at risk for the alternative solutions

Solution	VaR (5%)	UP (95%)	Risk @ 3.5 (%)	DRisk @ 3.5
NGC	1.82	1.75	14.4	0.086
NGC-DR	1.49	1.42	12.0	0.058

curves in Fig. 14 are shown Table 22. The VaR reduces from 1.82 to 1.49 or 18.1% in the result of model NGC-DR versus that of model NGC. For the curves in Fig. 14 the UP is reduced from 1.75 and 1.42 or 18.9% which when compared to a reduction of 18.1% in VaR looks reasonable.

Another measure of risk that that was proposed by Barbaro and Bagajewicz (2004a) is the downside expected profit (DEP) for a confidence level p, defined formally as follows:

$$\mathrm{DEP}(x, p_{\Omega}) = \int_{-\infty}^{\Omega} \xi f(x, \xi)\,\mathrm{d}\xi = \Omega \mathrm{Risk}(x, \Omega) - \mathrm{DRisk}(x, \Omega) \qquad (88)$$

The DEP is shown in Fig. 15 for the solution of model NGC and NGC-DR.

The NGC solution has by definition the highest value of DEP(x, 100%). At low levels of confidence (from 0% up to about 83%) the solution for NGC-DR has a higher downside expected profit (Fig. 16).

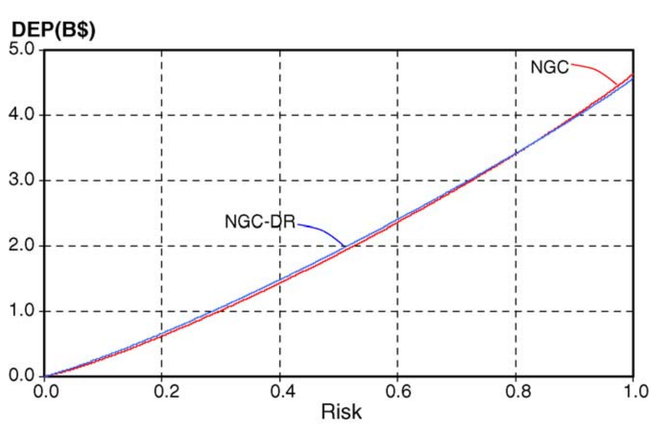

Fig. 15. Downside expected profit.

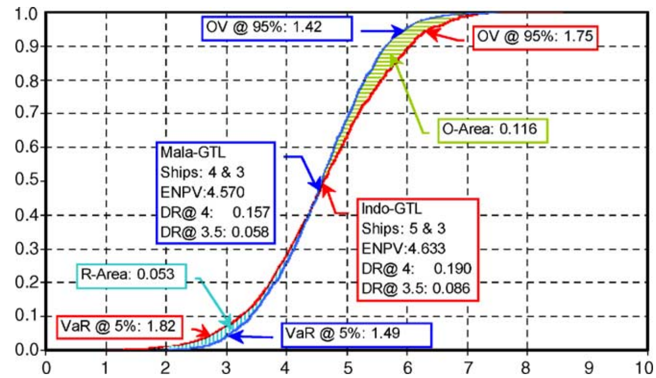

Fig. 16. Risk/upside potential loss ratio.

11.8. Risk area ratio

The risk area ratio is equal to 2.2. This means that the loss in opportunity is more than twice the gain in risk reduction. The closer is this number to one the better is the alternative solution. What this means is that for any two alternatives, both compared to the solution that maximizes ENPV, the alternative with RAR closer to one is preferable.

11.9. Upper and lower risk curve bounds

Fig. 17 shows the upper and lower bound risk curves for the NGC problem as well as the solution that maximizes ENPV and the one that minimizes risk.

It was noticed during the construction of the lower bound risk curve that its points were mainly contributed by one single bad design that happened to maximize profit at a single scenario. Points (89.4%) of the lower bound risk curve were from this bad design and the rest were from the other designs. When this design was excluded, a tighter and more practical lower bound risk curve was obtained (Fig. 18).

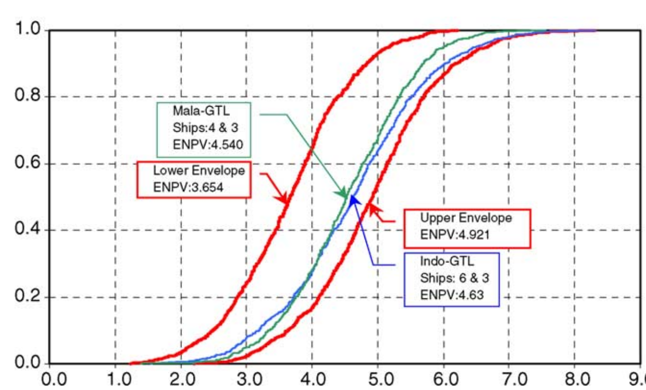

Fig. 17. Upper and lower bound risk curves for the NGC problem.

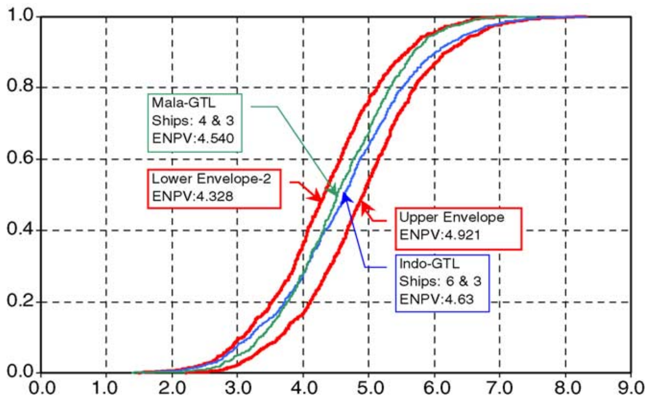

Fig. 18. Upper and lower bound risk curves for the NGC problem excluding the bad design.

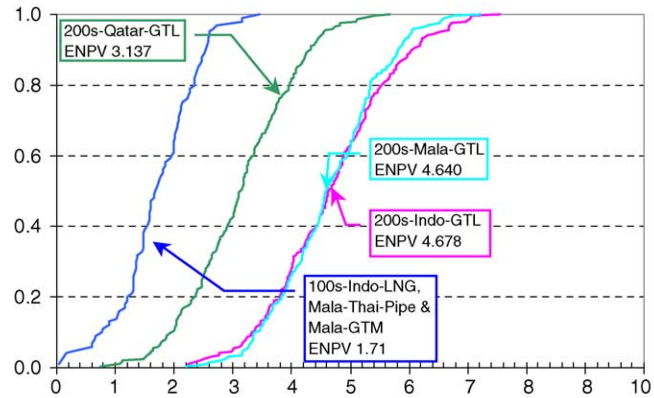

Fig. 19. Risk curves for suboptimal solutions.

11.10. Suboptimal solutions

The two best solutions that can be obtained from this problem as discussed in the earlier sections are: GTL from Indonesia with an expansion in the third time period, and GTL from Malaysia with an expansion in the third time period. To illustrate some other feasible solutions than these two, the model was run by excluding the best solutions, one by one. This is done by forcing the integer values of the excluded solution to be zero. This can be repeated until a reasonable number of good solutions are generated for comparison by the decision maker. The risk curves for the results are plotted in Fig. 19 and the solutions are illustrated in Tables 23 and 24. The third best solution (Table 23) is to construct a GTL plant in Qatar and to expand it in the third time period with an ENPV of 3.137 billion dollars. The fourth best solution (Table 24), suggests three simultaneous projects in the first time period with no expansions: a pipeline form Malaysia to Thailand, LNG transportation facilities from Indonesia to Japan with two ships and a GTM facility in Malaysia with two ships. The ENPV for the three projects is 1.71 billion dollars.

11.11. Effect of regular fixed contracts on the supply side

Financial risk can be managed (reduced) by utilizing contracts. A contract is a binding agreement which obligates the seller to provide the specified product and obligates the buyer to pay for it under specific terms and conditions. One method of managing the risk created by fluctuating prices is to use

Table 23
Results for NGC (200 scenarios) excluding GTL in Indonesia and Malaysia

Time period	FCI	Processing facilities				Transportation to				Avrg. ships
		Qatar (GTL)				China		Thai		
		Cap	Flow	Feed	Ships	Ships	Flow	Ships	Flow	
T1	3.00									
T2	0.00	4.29	4.11	274.0	6.0	1.96	0.64	3.93	3.47	5.89
T3	2.00	4.29	4.29	286.1	6.0			4.87	4.29	4.87
T4	0.00	7.23	7.12	474.8	9.0	1.13	0.37	7.66	6.75	8.79
T5	0.00	7.23	7.23	481.7	9.0			8.20	7.23	8.20
T6	0.00	7.23	7.23	481.7	9.0			8.20	7.23	8.20

Table 24
Results for NGC (100 scenarios) excluding all GTL processes

Time period	FCI	Pipeline		LNG facilities				GTM facilities				Methanol transportation to						Avrg. ships
		Mala-Thai		Indo-Japan				Mala				India		Thai		South Korea		
		Cap	Flow	Cap	Flow	Feed	Ships	Cap	Flow	Feed	Ships	Ships	Flow	Ships	Flow	Ships	Flow	
T1	3.00																	
T2		207.6	99.2	1.92	1.91	95.6	2.0	1.77	1.47	38.8	2.0	0.83	0.63	0.32	0.40	0.83	0.44	1.98
T3		207.6	195.4	1.92	1.90	95.0	2.0	1.77	1.76	46.4	2.0	1.34	1.00	0.59	0.74	0.03	0.03	1.96
T4		207.6	206.6	1.92	1.90	95.0	2.0	1.77	1.77	46.5	2.0	0.99	0.74	0.82	1.02			1.81
T5		207.6	205.9	1.92	1.90	95.0	2.0	1.77	1.77	46.5	2.0	0.60	0.45	1.05	1.31			1.65
T6		207.6	205.6	1.92	1.92	95.9	2.0	1.77	1.77	46.7	2.0	0.24	0.18	0.18	1.59			1.51

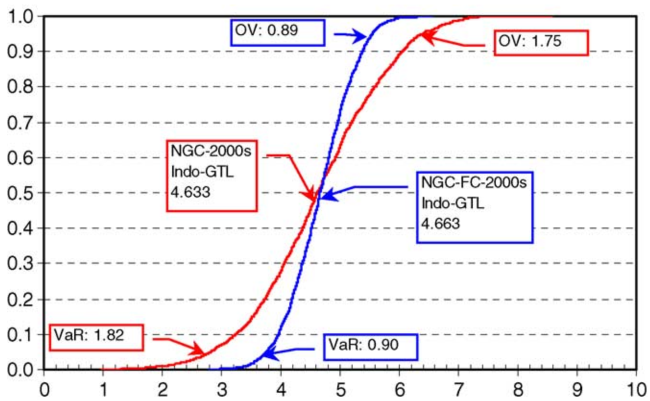

Fig. 20. Risk curve for model NGC-FC result.

long-term fixed-price contracts with gas suppliers. However, this would still leave some risk if the spot market price for natural gas turns to be, in average, less than the fixed contract price (derivatives and risk management, EIA, 2002a).

To run the model NGC with fixed contracts (NGC-FC), natural gas prices were assumed to have fixed prices at the supplier location. This is a practical contract in countries that do not have deregulated market for natural gas. The actual price of gas under a contract of this type would be a result of negotiation process between both parties. We assumed to have been contracted at their mean values. The model was run for 200 scenarios and the solution on Table 25 was obtained. Fig. 20 shows the risk curves for result of model NGC-FC (run for 2000 scenarios) compared to that of model NGC. The different values of VaR and OV, as well as risk area ratio for these solutions are depicted in Table 26.

Fixed contracts introduce a substantial reduction in risk from a value at risk of 1.82 to 0.90 or 50.5% reduction. In addition, it reduces the opportunity value from 1.75 to 0.89 or 49.1%. The risk area ratio is 0.87. This means that the loss in opportunity is less than the gain in risk reduction which is a result of the increase in ENPV. It might seem that this contradicts the earlier claim that this ratio cannot be less than one. However, the claim is only for solutions of the same problem while we are now solving a different problem; the introduction of contracts made it different. Using RAR in these circumstances may still add some useful information, as in this case. The ENPV increases by 0.6% when contracts are introduced which can be partially attributed to the noise in the solutions. For example, it was reported above that an error of 0.5% can happen in a 2000 scenario run using different random samples, so it is not clear in this case whether this is a real gain or a numerical effect. For problems that are markedly non-symmetric, the increase or decrease in expected profit for a contract at the mean prices can be more significant. We can see this effect very clear in a later section when we forbid GTL process and LNG and pipeline become the candidates for optimality.

Comparing this to the solution obtained earlier for model NGC-DR which suggested a GTL plant in Malaysia to reduce risk, we see that the reduction in risk obtained by the introduction of fixed contracts is significantly higher (see Fig. 21). Also we notice from this figure that the a fixed contract of gas price with Malaysia at its mean value is not as good as that with Indonesia since its risk curve is positioned almost entirely below it.

11.12. Effect of option contracts

Option contracts (or derivatives) are efficient tools for reducing financial risk. An option contract is an agreement between the buyer and the seller giving the option holder (the buyer for call option and the seller for a put option)

Table 25
Results for NGC-FC (200 scenarios)

Time period	FCI	Processing facilities				Transportation to				Avrg. ships
		Indo (GTL)				China		Thai		
		Cap	Flow	Feed	Ships	Ships	Flow	Ships	Flow	
T1	3.00									
T2		4.43	4.25	283.1	5.0	1.12	0.76	3.88	3.48	5.00
T3	1.90	4.43	4.43	295.5	5.0			4.94	4.43	4.94
T4		7.18	7.09	472.6	8.0	0.44	0.30	7.56	6.79	8.00
T5		7.18	7.18	479.0	8.0			8.00	7.18	8.00
T6		7.18	7.18	479.0	8.0			8.00	7.18	8.00

Table 26
Value at risk for the alternative solutions

Model	ENPV	VaR (5%)		UP (95%)		Risk area ratio (RAR) to NGC	Risk @ 3.5 (%)	DRisk @ 3.5
		VaR	Reduction from NGC (%)	UP	Reduction from NGC (%)			
NGC	4.633	1.82	–	1.75	–	–	14.4	0.086
NGC-DR	4.540	1.49	18.1	1.42	18.1	2.2	12.0	0.058
NGC-FC	4.663	0.90	50.5	0.89	49.1	0.87	1.6	0.003

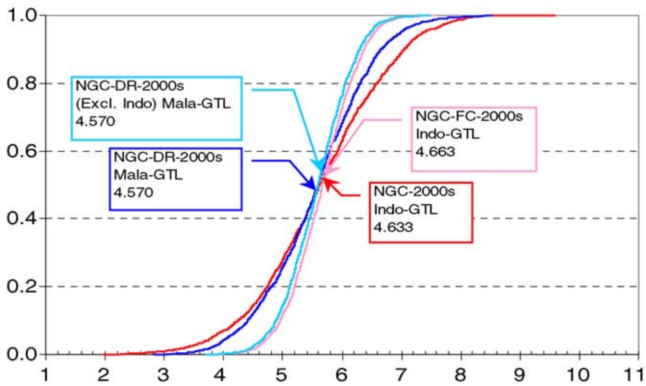

Fig. 21. Risk curve for model NGC results with and without fixed contracts.

the right to decide whether or not to enforce a purchase/sale at the specified price "strike price" for an underlying asset. Therefore, option contracts gain their value from that option of practicing the purchase or sale and hence the option holder has to pay a premium (option cost) to gain this privilege. If, during the specified timeframe for the option, the strike price happens to be more profitable (less than the market price for a call option and the reverse for a put option) than the market price, the option holder can exercise the option. On the other hand, if the market price is more profitable, the option holder will not be obligated to buy/sell at the option price (derivatives and risk management, EIA, 2002).

Option premium is the price the option holder should pay to the option writer in order to sign the option contract. It consists of two components, an intrinsic value and a time value. The intrinsic value is measured as the difference between the strike price and the market price, in this case the mean expected price of gas. If the two are equal then the intrinsic value is zero. The time value is the extra amount which the option buyer is willing to pay to reduce the risk that the price may become worse than the mean values during the time of the option. The time value is affected by two elements: the length of the time period for the option and the anticipated volatility of prices during that time (SCORE, 1998).

To introduce option contracts to this problem, the following modifications to the model NGC are needed (Barbaro & Bagajewicz 2004a):

- Add a new additional feed variable (FeedCO_{ijts}) that represents the amount of feed that is purchased using the option contract at the strike price for the feed gas (FeedCostCO_{its}) to Eq. (37) so that it will read:

$$\text{GasCost}_{its} = \text{Dur}_t\left[\text{FeedCost}_{its}\sum_{j=1}^{J}(\text{Feed}_{ijts}) + \text{FeedCost}_{its}\sum_{j=1}^{J}(\text{FeedCo}_{ijts})\right], \quad \forall\, i, s \text{ and } t \tag{89}$$

- Add the cost of the option contract (premium) to Eq. (38) to read:

$$\begin{aligned}\text{FixedCost}_{it}^{P} = \text{Infl}_t\Bigg\{&\sum_{j=1}^{J}(\text{Cap}_{ijt}^{1I}\alpha_{ij}^{1I}+\beta_{ij}^{1I}Y_{ijt}^{1I} + \text{Cap}_{ijt}^{1E}\alpha_{ij}^{1E}+\beta_{ij}^{1E}Y_{ijt}^{1E})\\ &+\sum_{j\in\{pip\}}\sum_{m=1}^{M}(\text{Cap}_{imjt}^{2I}\alpha_{imj}^{2}+\beta_{imj}^{2I}Y_{imj}^{2I})\\ &+\sum_{j\notin\{pip\}}(\text{NewShips}_{ijt}\times\text{ShipCost}_j)\Bigg\}\\ &+\text{Prem}_{it}, \quad \forall i \text{ and } t\end{aligned} \tag{90}$$

- Add a new set of equations to define the premium for each investment time period (t_1 and t_3):

$$\text{Prem}_{it} = \sum_{\theta=\left\{\begin{matrix}1,2,3\ fot\ t_1\\ 4,5,6\ fot\ t_3\end{matrix}\right\}}[\text{Dur}_\theta\text{ContCost}_{i\theta}\text{MaxCO}_{i\theta}], \quad \forall i \text{ and } t \tag{91}$$

where $\text{ContCost}_{i\theta}$ represents the unit cost for obtaining the option contract for a maximum amount of the option $\text{MaxCO}_{i\theta}$.

- Add a new set of equations to limit the feed obtained by practicing the option contract to be less than the maximum allowed by the contract:

$$\sum_{j=1}^{J}\text{FeedCO}_{ijts} \le \text{MaxCO}_{it}, \quad \forall i, s \text{ and } t \tag{92}$$

- To include the option contract feed into the material balance, change Eq. (61) to read:

$$\text{FP}_{ijts} = (\text{Feed}_{ijts}+\text{FeedCO}_{ijts})\text{Cvsn}_j, \quad \forall i, j, s \text{ and } t \tag{93}$$

- Also change Eq. (62) to read:

$$\sum_{j=1}^{J}[\text{Feed}_{ijts}+\text{FeedCO}_{ijts}] \le \text{Max\_Production}_{it} \quad \forall \text{i, s and t} \tag{94}$$

In practice, the premium for obtaining an option contract is a result of extensive negotiations. To estimate the premium in this problem, a unit cost is assumed as a percentage of the mean gas price. The model NGC-CO was run for 100 scenarios with the premium unit cost calculated at 2, 4, 6 and 8% of the mean gas prices. The histogram in Fig. 22 shows the risk curves for these runs in comparison to that obtained for model NGC.

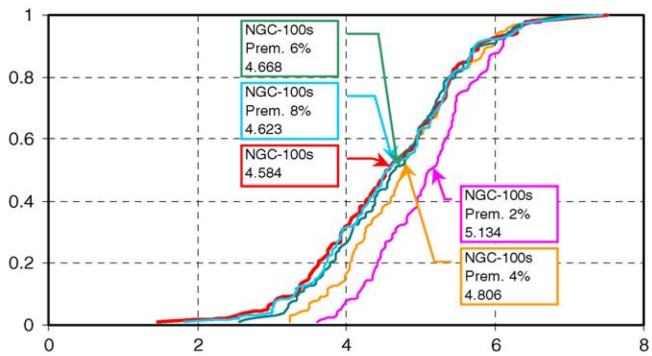

Fig. 22. Results of model NGC-CO at different premium unit costs.

We notice that with a premium unit cost of 2% of the mean value the option contract shifts the risk curve substantially to the right of that of model NGC, that is, it considerably increases the ENPV at almost all scenarios. Even though this is very appealing to the buyer of the contract (the holder), it is almost impossible to obtain since no supplier (writer) is willing to accept a contract that has no chance of success from his standpoint.

The result with 4, 6 and 8% could be acceptable to the supplier since they have significant chance of success. Any price greater 8% is not attractive to the buyer. Therefore, the expected price for the option contract can be negotiable between both parties in the range of 4–8% of the gas mean price. The model was also run with the downside risk penalized and the resulting curves were recalculated for 2000 scenarios after fixing first stage variables. Figs. 23–25 show the risk curves for model NGC-CO and NGC-CO-DR for premium unit prices of 4, 6 and 8% of gas mean prices, respectively. For comparison the risk curves for models NGC and NGC-FC are added also. The details of these six solutions are depicted in Tables 27–32. The different values of VaR and OV, as well as risk area ratio for these solutions are depicted in Table 33.

We see from Tables 27–32 that when the model is run with downside risk penalized, it asks for higher amounts of option

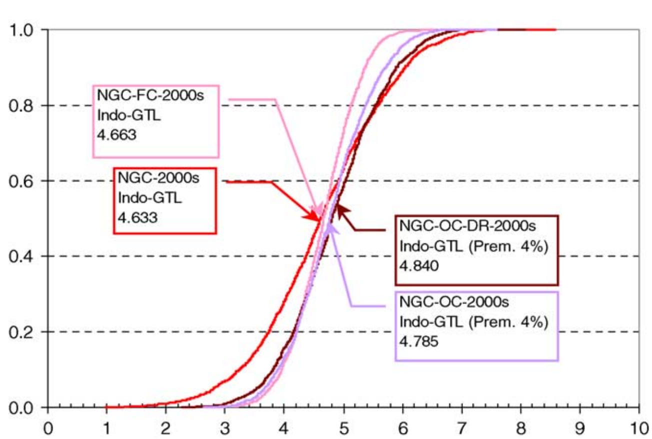

Fig. 23. Results of model NGC-CO and NGC-CO-DR for premium unit prices of 4%.

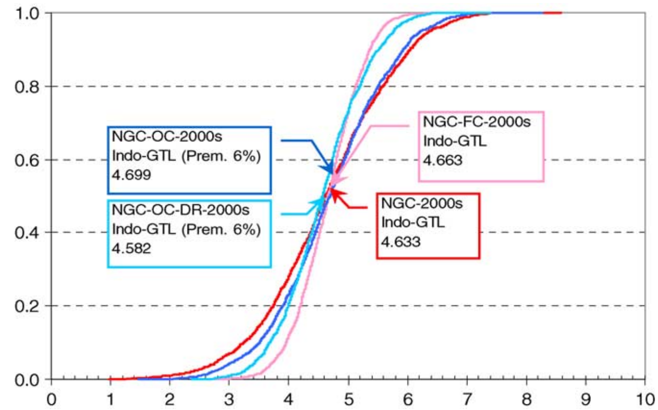

Fig. 24. Results of model NGC-CO and NGC-CO-DR for premium unit prices of 6%.

to be secured (shown on the tables under column OC). This has a trade-off with the capacities installed since the premium paid to get the option takes some of the available investment. For example, in the case when the unit premium cost is 6% (Tables 29 and 30), it reduces the expansion capacity from 4.37 to 4.08 million tonnes per year in the first time period and from 2.57 to 2.21 in the third time period. It also reduces the number of ships to be purchased in the third time period from 3 to 2. On the other hand, it asks for more contract amounts to be secured in all time periods.

None of the curves of the option contracts shown above perform better than the risk curve of the fixed contract solution in the downside region. However when considering the other side of the curve (the upside potential), the attractive feature of the option contracts can be seen. The curve with premium unit cost of 8% is not very appealing to an investor since neither the downside nor the upside risk are significantly reduced. Its risk area ratio is 3.81, which is very high. On the other hand, the curve with 4% is very attractive to the investor since it reduces both risks greatly. Its area risk ratio is 0.38, which is very low. Also the curve of 6% is reasonably acceptable with a risk area ratio of 1.39. Therefore, it would be expected for the negotiation on such a project to come into

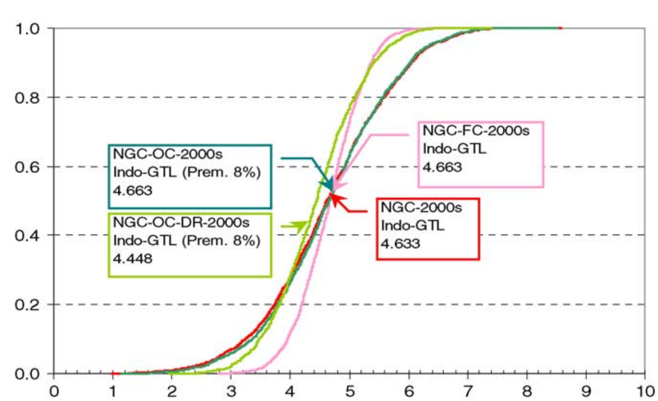

Fig. 25. Results of model NGC-CO and NGC-CO-DR for premium unit prices of 8%.

Table 27
Results for NGC-OC (100 scenarios) with premium cost of 4% of the mean gas cost

Time period	FCI	Processing facilities					Transportation to						Avrg. ships
		Indo (GTL)					India		China		Thai		
		Cap	Flow	Feed	O C	Ships	Ships	Flow	Ships	Flow	Ships	Flow	
T 1	3.00												
T 2		4.19	4.17	146.3	274.5	5.0	0.04	0.03	1.05	0.72	3.81	3.42	4.90
T 3	2.00	4.19	4.19	144.2	250.3	5.0					4.66	4.19	4.66
T 4		6.87	6.86	247.0	457.7	8.0	0.02	0.01	0.44	0.30	7.30	6.55	7.76
T 5		6.87	6.87	442.7	31.3	8.0					7.65	6.87	7.65
T 6		6.87	6.87	457.7	0.0	8.0					7.65	6.87	7.65

Table 28
Results for NGC-OC-DR (100 scenarios) with premium cost of 4% of the mean gas cost

Time period	FCI	Processing facilities					Transportation to						Avrg. ships
		Indo (GTL)					India		China		Thai		
		Cap	Flow	Feed	O C	Ships	Ships	Flow	Ships	Flow	Ships	Flow	
T1	3.00												
T2		4.18	4.16	144.3	278.3	5.0	0.05	0.03	1.03	0.70	3.81	3.42	4.89
T3	1.84	4.18	4.18	128.0	278.3	5.0					4.65	4.17	4.65
T4		6.29	6.27	225.6	419.1	7.0			0.08	0.05	6.92	6.21	7.00
T5		6.29	6.29	213.7	419.1	7.0					7.00	6.29	7.00
T6		6.29	6.29	209.5	419.1	7.0					7.00	6.29	7.00

Table 29
Results for NGC-OC (100 scenarios) with premium cost of 6% of the mean gas cost

Time period	FCI	Processing facilities					Transportation to						Avrg. ships
		Indo (GTL)					India		China		Thai		
		Cap	Flow	Feed	OC	Ships	Ships	Flow	Ships	Flow	Ships	Flow	
T1	3.00												
T2		4.37	4.23	233.9	100.0	5.0			1.12	0.76	3.88	3.48	5.00
T3	1.90	4.37	4.37	291.0		5.0					4.94	4.43	4.94
T4		6.94	6.93	251.5	457.9	8.0			0.44	0.30	7.56	6.79	8.00
T5		6.94	6.94	462.5		8.0					8.00	7.18	8.00
T6		6.94	6.94	462.5		8.0					8.00	7.18	8.00

Table 30
Results for NGC-OC-DR (100 scenarios) with premium cost of 6% of the mean gas cost

Time period	FCI	Processing facilities					Transportation to						Avrg. ships
		Indo (GTL)					India		China		Thai		
		Cap	Flow	Feed	OC	Ships	Ships	Flow	Ships	Flow	Ships	Flow	
T1	3.00												
T2		4.08	4.07	141.3	271.8	5.0	0.07	0.04	0.91	0.62	3.80	3.41	4.78
T3	2.00	4.08	4.08	144.1	241.0	5.0					4.54	4.08	4.54
T4		6.29	6.26	225.4	419.1	7.0			0.11	0.08	6.89	6.19	7.00
T5		6.29	6.29	213.7	419.1	7.0					7.00	6.29	7.00
T6		6.29	6.29	289.0	260.2	7.0					7.00	6.29	7.00

an agreement around 4% with which both parties can be reasonably satisfied. One interesting thing to note from Table 33 is the unexpected increase of VaR for the solution with 4% compared to that with 6%. Bear in mind that this does not necessarily reflect a decrease in profit at 5% risk. The profit at 5% risk is 3.46 billion dollars for the solution with 6% premium cost and 3.66 billion dollars for the solution with 4% premium cost. The increase in VaR is a result of the increase in ENPV.

11.13. Effect of uncertainty in cost parameters

It appears from the results of this model that it favors GTL processes over LNG. This, however, is contrary to the fact

Table 31
Results for NGC-OC (100 scenarios) with premium cost of 8% of the mean gas cost

Time period	FCI	Processing facilities					Transportation to						Avrg. ships
		Indo (GTL)					India		China		Thai		
		Cap	Flow	Feed	OC	Ships	Ships	Flow	Ships	Flow	Ships	Flow	
T1													
T2	3.00	4.43	4.23	282.2		5.0			1.12	0.76	3.88	3.48	5.00
T3		4.43	4.43	295.5		5.0					4.94	4.43	4.94
T4	2.00	7.16	7.09	383.4	193.8	8.0			0.44	0.30	7.56	6.79	8.00
T5		7.16	7.16	477.5		8.0					8.00	7.18	8.00
T6		7.16	7.16	477.5		8.0					8.00	7.18	8.00

Table 32
Results for NGC-OC-DR (100 scenarios) with premium cost of 8% of the mean gas cost

Time period	FCI	Processing facilities					Transportation to						Avrg. ships
		Indo (GTL)					India		China		Thai		
		Cap	Flow	Feed	OC	Ships	Ships	Flow	Ships	Flow	Ships	Flow	
T1	3.00												
T2		4.07	4.07	141.9	270.1	5.0	0.07	0.04	0.90	0.62	3.80	3.41	4.77
T3	2.00	4.07	4.07	207.0	121.9	5.0					4.54	4.07	4.54
T4		6.29	6.26	225.4	419.1	7.0			0.11	0.08	6.89	6.18	7.00
T5		6.29	6.29	217.9	419.1	7.0					7.00	6.29	7.00
T6		6.29	6.29	419.1		7.0					7.00	6.29	7.00

Table 33
Value at risk for the alternative solutions

Model	ENPV	VaR (5%)		UP (95%)		Area ratio to NGC	Risk @ 3.5 (%)	DRisk @ 3.5
		VaR	Reduction from NGC (%)	UP	Reduction from NGC (%)			
NGC	4.633	1.82	–	1.75	–	–	14.4	0.086
NGC-DR	4.540	1.49	18.1	1.42	18.1	2.2	12.0	0.058
NGC-FC	4.663	0.90	50.5	0.89	49.1	0.87	1.6	0.003
NGC-OC-DR-4%	4.785	1.13	38.3	1.17	33.3	0.38	2.5	0.006
NGC-OC-DR-6%	4.582	1.12	38.4	1.18	32.6	1.39	5.7	0.015
NGC-OC-DR-8%	4.448	1.23	32.6	1.23	29.5	3.81	10.5	0.033

that more LNG projects have been constructed than GTL. We explain this as follows:

(a) Uncertainty in cost data: construction cost factors used for this study are significantly uncertain. This is true for both LNG and GTL processes as well as others. The cost information is obtained from historical construction data that have high degree of fluctuation. In such historical data, there are undisclosed factors that could have affected the fluctuation in project costs such as location difficulties and infrastructure requirements. Also the effect of advances in technologies on reducing construction cost is absent from such historical data. In practice, accurate cost estimates cannot be obtained only from historical data but should also include a profound study of technology advancements, individual location requirements and market trends. Some factors that also contribute in favoring LNG are the enhanced engineering knowledge and project execution techniques, the advances in technology (e.g. gas turbines instead of steam turbines and improved equipment configurations), and the integration of LNG terminals with power plants.

(b) Technology risk: GTL processes, on the other hand, did not receive as much attention in the past as LNG. Both GTL construction costs and liquid fuel yields are uncertain. This technological risk has long contributed to the lag of GTL constructions. Technological advancements have evolved on GTL processes but are still considered risky since they have not been practiced on large scale. Two main factors can drive more attention to GTL process constructions: high oil prices yielding higher refinery products cost and more stringent environmental regulations on sulphur content in petroleum products.

One very important reason for GTL process to be favored over LNG is its market flexibility. A GTL product ship can practically sell its content to any customer that offer the highest price. LNG ship, on the other hand, can only sell its products in locations where special receiving facilities exist and cannot sell more than the maximum throughput of that re-

Table 34
Results with fixed contracts (GTL excluded)

	T1	T3
LNG from Indonesia to Japan		
Capacity (MM tonne/year)	2.40	3.26
Number of ships added	3	3
Pipeline from Malaysia to Thailand		
Capacity (BSCFY)	268.7	–

Table 35
Results with fixed contracts (GTL excluded and LNG cost reduced)

	T1	T3
LNG from Indonesia to Japan		
Capacity (MM tonne/year)	5.38	3.26
Number of ships added	6	3

ceiving facility. For this reason LNG projects are usually secured by long-term contracts (typically 20 years) with stringent take-or-pay requirements locking the prices and volumes and hence ships are fully dedicated to projects.

Addressing the issues above without significantly improved data is somewhat pointless. However, to obtain an idea about data uncertainty, we proceeded as follows. If one forbid all GTL Processes and run the model with the assumption that demand, feed prices and sale prices are fixed with contracts at their mean values we get the solution on Table 34 with a NPV of 2.01 billion dollars. This shows a significant increase in profit from the stochastic run shown in Fig. 19, which has an ENPV of 1.71 billion dollars. This clearly shows that contracts can increase the expected profit.

To illustrate the effect uncertainty of installation and operation costs on the results, we assumed lower costs of construction for LNG liquefaction facilities by eliminating the two highest construction cost data points from Fig. 30 in Appendix A and recalculating the fixed cost parameters. Also the demand limit for gas in Japan was increased assuming that the contract will allow carrying the increase in demand from one time period to the other. The results obtained with this new run gave the solution shown in Table 35 with an ENPV of 2.98 billion dollars.

From this we see that the uncertainty in data has a significant effect on the results. Using any of the cost data, GTL still shows to be more profitable than LNG. Since the objective of this work is to introduce, discuss and illustrate new concepts, we leave the discussion of the uncertainty of data and the technological risks to be done elsewhere.

12. Conclusions

In this paper some new concepts and procedures for financial risk management were presented including the upper and lower bound risk curves, the upside potential or opportunity value as well as a new area ratio as means to weigh opportunity loss versus risk reduction. The use of the sampling average algorithm was studied and the relation between two-stage stochastic models that manage risk as well as the use of chance constraints and regret analysis was discussed.

To illustrate the concepts, a stochastic planning model was introduced to optimize natural gas commercialization in Asia, under uncertainty. The commercialization of gas and/or gas-derivatives (synthetic gasoline, methanol, or ammonia) was considered for a set of gas producing and consuming countries. The effect of contracts (fixed and option) was examined.

Results were obtained for the model under different conditions. They showed that, by far, the production of synthetic gasoline should be the investment of choice and that gas supply should come from Indonesia for maximum profitability or from Malaysia for minimum risk. By having a close look at the geographic locations of those two countries, one can see that they are conveniently centered among markets. This allows for more products at different scenarios to be sent to markets that are in demand with a relatively small transportation cost, and hence the choice. Other suboptimal cases were also shown and some methodologies were discussed to help filter good solutions. The use of contracts was found to increase expected profit and reduce financial risk. Option contracts were found to have a potential for reducing downside risk with reasonably low effect on the upside potential. Fixed contracts would, however, be the only practical means for managing risk in countries that do not have deregulated market for gas.

Acknowledgements

We are grateful to the University of Oklahoma Supercomputing Center for Education and Research (OSCER) for allowing us to make many of our runs.

Appendix A

In this appendix we summarize the data used to construct cost correlations for the models. The data and the figures were extracted from Aseeri (2003). The main intention is for the reader to visualize the level of dispersion of the data used.

A.1. Pipelines

Fig. 26 shows the estimated cost of pipelines. This was constructed with the use of pipeline and compressors installed cost data from the *Oil & Gas Journal* special report on Pipeline Economics (2001). This estimate is reasonable with about 40% accuracy due to the high uncertainty in pipeline and compressor costs. Finally, a linear approximation to be used in the model was obtained (see Fig. 26) assuming that no project will be constructed with a capacity lower than 50 BSCFY. Operating costs per pipeline mile versus capacity were calculated using approximate factors from Peters and Timmerhaus (1991) (Fig. 27).

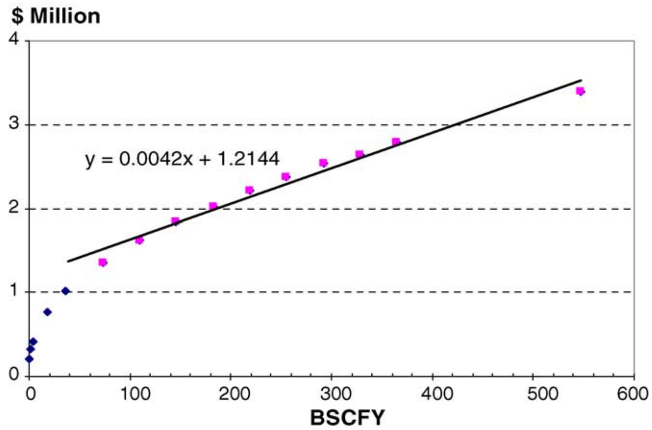

Fig. 26. Pipeline per mile fixed cost vs. annual capacity.

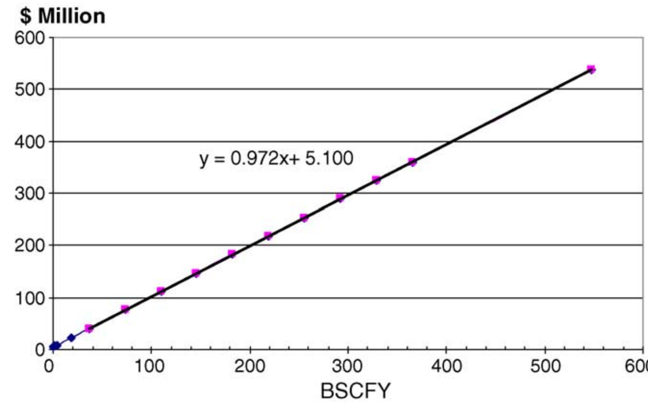

Fig. 28. Compression facility fixed cost vs. capacity.

A.2. Compressed natural gas ships

Calculations were based on the assumption that gas is received at a temperature of 120 °F and a pressure 300 psia and for flow rates ranging from 1 to 1500 MMSCFD. The fixed capital investment was then calculated as the total installed cost of all required compressors (Fig. 28). Operating costs for compression facilities were estimated using approximate factors from Peters and Timmerhaus (1991) and are plotted in Fig. 29.

The unit costs of CNG shipment are based on figures provided by Cran and Stenning (1998). The gas is transferred to a CNG vessel, which brings the CNG to a receiving terminal. The CNG vessels are each estimated to hold about 320 MMSCF of gas, and are estimated to cost US$ 125 million. These ships travel at approximately 21 knots. The fixed cost for shipping facilities is proportional to the number of ships needed. The number of ships needed is a function of the capacity and is calculated using the following equations.

$$\text{TimeRoundTrip (days)} = 2 \times (\text{distance\_knot\_miles}) \times \left(\frac{\text{h}}{\text{speed}}\right)\left(\frac{\text{days}}{24\,\text{h}}\right) + \text{extra\_days} \quad (95)$$

$$\text{Trips/year/ship} = \frac{365}{\text{TimeRoundTrip}} \quad (96)$$

$$\text{ShipYearlyCap(MMCF/year/ship)} = \text{ship\_size(MMCF/trip)(trips/year/ship)} \quad (97)$$

Three extra days are added into the round-trip time for each CNG ship to complete a voyage to account for mooring, loading, unloading, and downtime. Operating cost for CNG ships is assumed to be 10% of their FCI[22], if operated at full capacity and proportional to operating capacity if less than that.

A.3. Liquefied natural gas

An LNG system includes a liquefaction/storage facility that processes and liquefies the gas and transfers it to LNG

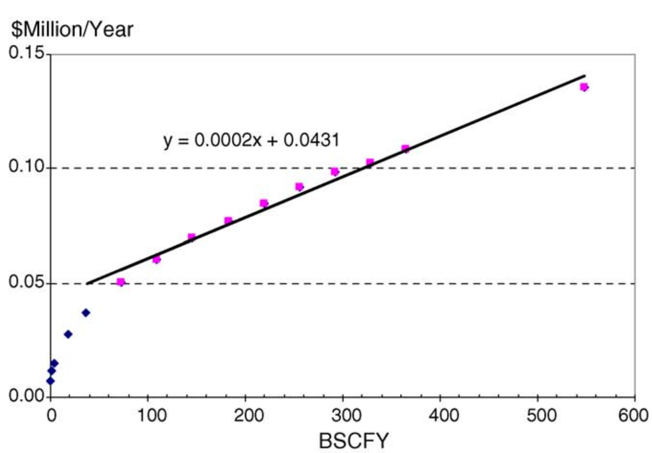

Fig. 27. Pipeline per mile annual operating cost vs. capacity.

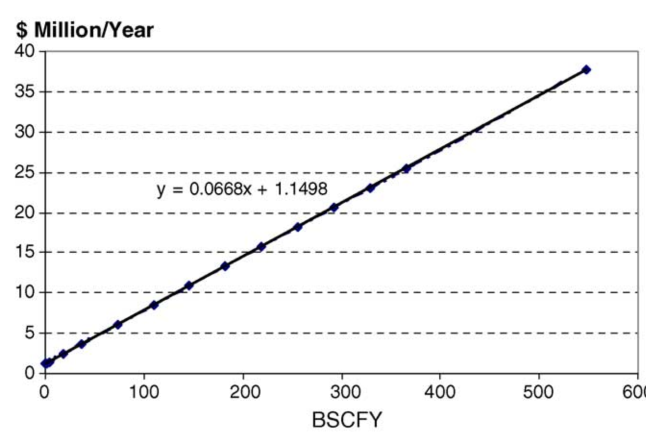

Fig. 29. Compression facility annual operating cost vs. capacity.

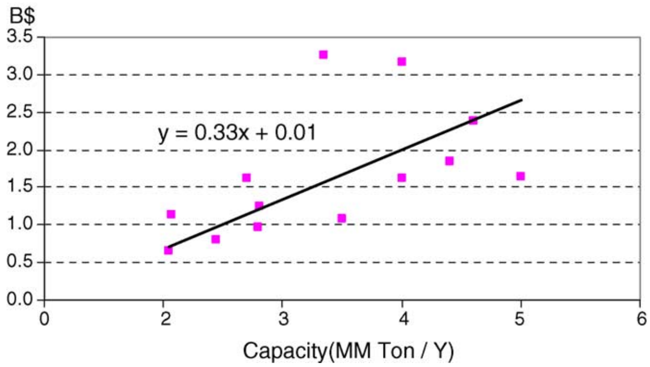

Fig. 30. LNG liquefaction facility cost vs. capacity.

carriers. Historical LNG liquefaction and regasification cost data were obtained from the *Oil* & *Gas Journal* report on Worldwide Gas Construction (2002). The fixed capital investments LNG liquefaction plants versus plant capacity in (million tonne/year) are plotted in Fig. 30. The fixed capital investment of LNG regasification plants versus plant capacity in (million tonne/year) are also plotted in Fig. 31. All cost figures are updated to 2005 dollars using Marshal and Swift cost indexes (Marshall, 1992, 1997, 2003). The correlations displayed in these figures have errors of ±60% for liquefaction facilities and 40% for regasification facilities.

The unit costs of LNG shipment are based on figures from Imperial Venture Corp (1998). The LNG vessels are each estimated to hold about 4.4 MMcf of LNG (or 56,633 tonne) which is equivalent to 2.854 BSCF of gas, and are estimated to cost US$ 170 million each. These ships travel at approximately 17.5 knots. Ship yearly capacities are calculated using Eqs. (95)–(97). Six extra days are added into the round-trip time for each LNG ship to complete a voyage to account for mooring, loading, unloading, and downtime. Operating cost for LNG Liquefaction and regasification facilities and LNG ships are assumed to be 10% of their FCI, if operated at full capacity and proportional to operating capacity if less than that.

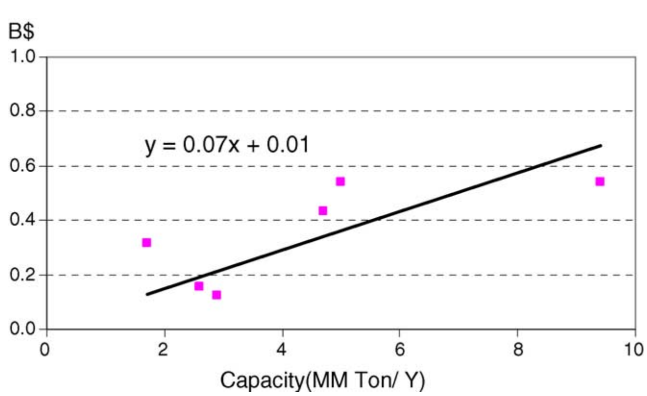

Fig. 31. LNG regasification facility cost vs. capacity.

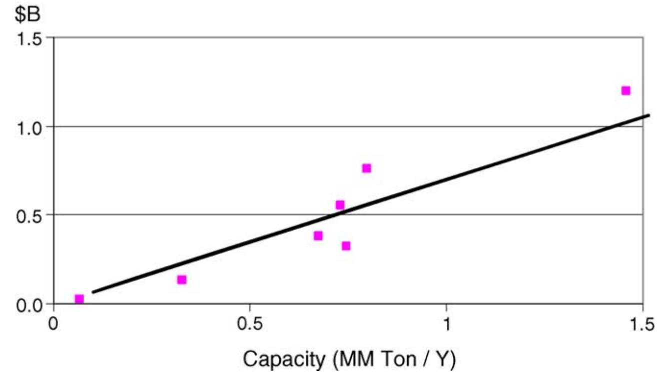

Fig. 32. GTA facility cost vs. capacity.

A.4. Ammonia plants

Historical GTA plant cost data were obtained from the *Oil* & *Gas Journal* report on Worldwide Petrochemical Construction, 25 November 2002. Fixed capital investments versus plant capacity in (million tonne/year) are plotted in Fig. 32. All cost figures are updated to 2005 dollars using Marshal and Swift cost indexes (Marshall, 1992, 1997, 2003). The correlation has an error of ±40% of the fixed capital investment. Operating cost was calculated using approximate factors from Peters and Timmerhaus (1991) and was found to be about 8% of the FCI.

The cost of ammonia shipment is based on an LPG carrier with a capacity of 8400 m^3 (or 5700 metric tonnes) and a cost of 21 million dollars (Marine Log, 2000). These ships travel at approximately 15 knots. Ship yearly capacities are calculated using Eqs. (95)–(97). Three extra days are added into the round-trip time for each ammonia ship to complete a voyage to account for mooring, loading, unloading, and downtime. Operating cost for the Ammonia ships are assumed to be 10% of their FCI, if operated at full capacity and proportional to operating capacity if less than that.

A.5. Methanol plants

Historical GTM plant cost data were obtained from the *Oil* & *Gas Journal* report on Worldwide Petrochemical Construction, 25 November 2002. Fixed capital investments versus plant capacity in (million tonne/year) are plotted in Fig. 33. All cost figures are updated to 2005 dollars using Marshal and Swift cost indexes (Marshall, 1992, 1997, 2003). The correlation has an error of ±40% of the fixed capital investment.

Operating costs for methanol plants are similar to those of ammonia plants and are about 8% of the FCI. The unit cost of methanol shipping is based on a chemical carrier with a capacity of 25,000 tonne and cost of 75 million dollars. These ships travel at approximately 15 knots.

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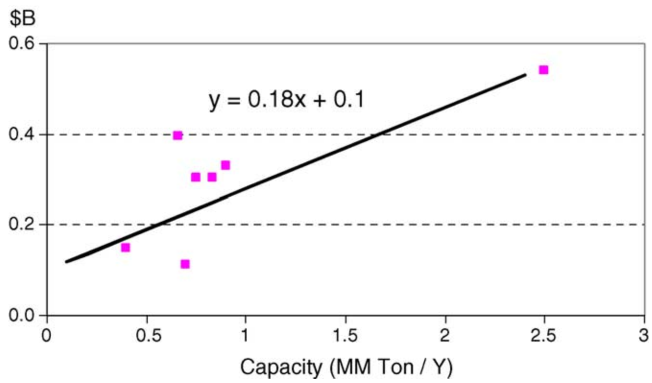

Fig. 33. GTM facility cost vs. capacity.

The fixed cost is proportional to the number of ships needed. Ship yearly capacities are calculated using Eqs. (95)–(97). Three extra days are added into the round-trip time for each methanol ship to complete a voyage to account for mooring, loading, unloading, and downtime. Operating cost for the methanol ships are assumed to be 10% of their FCI, if operated at full capacity and proportional to operating capacity if less than that.

A.6. Gas to liquid (GTL) plant

Historical GTL plant cost data were obtained from the *Oil & Gas Journal* report on Worldwide Gas Processing Construction (2002). Fixed capital investments versus plant capacity in (million tonne/year) are plotted in Fig. 34. All cost figures are updated to 2005 dollars using Marshal and Swift cost indexes (Marshall, 1992, 1997, 2003). The correlation has an error of ±50% of the fixed capital investment. Operating cost calculations for GTL plants were estimated using factors provided in Peters and Timmerhaus (1991).

The unit cost of gasoline shipping, similar to methanol shipping, is based on chemical carrier with a capacity of 25,000 tonne and cost of 75 million dollars. These ships travel at approximately 15 knots. Ship yearly capacities are calculated using Eqs. (95)–(97). Three extra days are added into the round-trip time for each ammonia ship to complete a voyage to account for mooring, loading, unloading, and downtime.

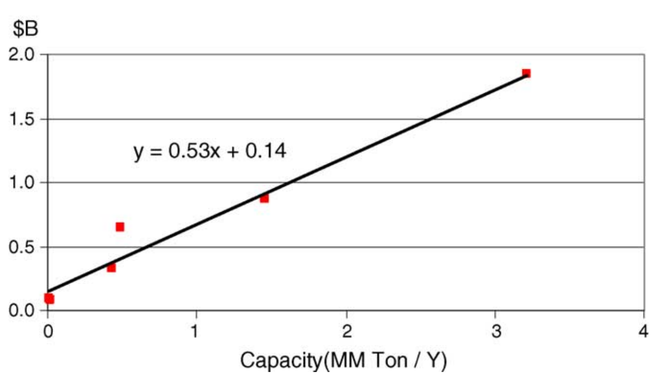

Fig. 34. GTM facility cost vs. capacity.

Operating cost for the gasoline ships are assumed to be 10% of their FCI, if operated at full capacity and proportional to operating capacity if less than that.

Appendix B. Sampling methodology

The distribution of the stochastic parameters is assumed to be normal. The demand of each commodity in each market was assumed independent from other markets and hence normally distributed around the mean of that market. However, this assumption cannot be applied to prices of either feed gas or marketable commodities for two reasons. First, in the real world markets, prices follow some general trend and do not vary independently. This means that the price of any product, gasoline for example, cannot be relatively very high in one market and relatively very low in the other market at the same time. This is true even though the price in one country, like Japan for example, may be always higher than the others.

When the model was solved with the assumption that prices are independently distributed, some unrealistic results were obtained. These results were showing that the ENPV obtained from the stochastic model is much higher than that obtained from the deterministic one as illustrated in Fig. 35. The ENPV of the stochastic solutions keeps increasing as the number of scenarios increases. The reason for this is that the random nature of the sampling assigns independent prices for each country under each scenario. It is very highly probable that at least one of market countries has a very high price under each scenario. The model will automatically select that country as the market for that scenario and will end up having high sale prices for a majority of the scenarios resulting in the curve shifting misleadingly to the right.

Due to this reason the gas feed cost and more importantly the sale prices cannot be assumed independent. A methodology was therefore developed to obtain price samples that are normally scattered around a price trend that follows a normal distribution. Fig. 36 shows the trend for some hypothetical price trend with country prices normally scattered around it.

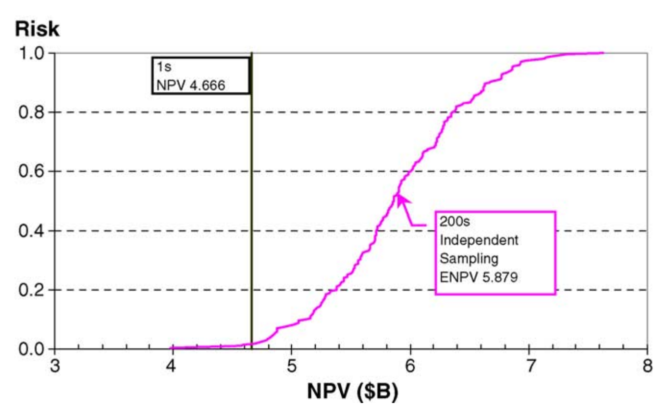

Fig. 35. Results with the assumption that prices in different countries are independent.

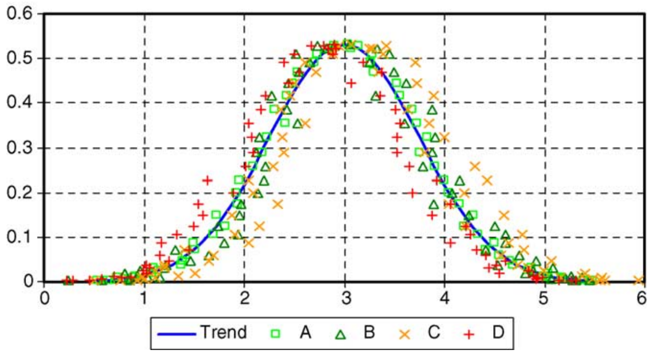

Fig. 36. Price trend with price samples scattered around it.

From this figure we see that some markets (A) have less deviation from the trend while some others (B) have larger deviation. Also some countries (C and D) could have a distribution that is generally deviated from the trend either in the positive or negative direction. To maintain these characteristics the following procedure was developed and utilized for sampling prices:

1. Estimate the general trend of price for each product, i.e. its mean and standard deviation. That is done either by a profound study of the markets and there average trend or approximated by analyzing historical data.
2. Estimate the average difference of each country from the trend as well as standard deviation of these average differences. That is done also by either a profound study of the markets or approximated by analyzing historical data.
3. When sampling for the model, use the mean and standard deviation of the trend to generate normally distributed samples for all the considered scenarios, TREND_{jts}. Where j, t and s represent products, time periods and scenarios, respectively.
4. For each scenario the price differences from the trend in individual countries are sampled with normal distribution around the average differences with the corresponding standard deviations, DIFF_{jtsm}. Where the subscript m represent market countries. The price samples are then calculated using the following relation:

$$\mathrm{PRICE}_{jtsm} = \mathrm{TREND}_{jts} + \mathrm{DIFF}_{jtsm} \tag{98}$$

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