

# 12

## Integration of Process Systems Engineering and Business Decision Making Tools: Financial Risk Management and Other Emerging Procedures

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### 12.1 Introduction

Economics has always been part of engineering. So talking about its integration in our discipline seems rather odd. Moreover, many companies, especially those dealing with risky projects, employ advanced financial tools in their decision making. For example, the oil industry is relatively more sophisticated than other industries in their supply chain management tools and the associated finances. However, these are not widespread tools that all engineers employ and certainly not tools that are used in education or in academic papers. Indeed, only certain aspects of the tools that economists and financiers use, namely a few profitability measures, are fully integrated into our education and engineering academic circles. This has started to change in recent years, but many tools are still completely out of sight for mainstream chemical engineers.

This is not a review article, so not all the work that has been published on the matter will be cited or discussed. Rather, the intention is to discuss some of the more relevant and pressing issues and provide some direction for future work. It is also an article that is written targeting engineers as the audience.

As a motivating example, one could start with the following statement of a typical process design problem.

‘Design a plant to produce chemical X, with capacity Y’

This is the problem that many capstone design classes used to propose to students to solve (and some still do) for a long time. This is fairly well known. The answer is a flowsheet, optimized following certain economics criteria, with a given cash flow profile (costs and prices are given and are many times considered fixed throughout time), from which a net present value and a rate of return is obtained. In the 1980s environmental considerations started to be added, but these were mostly used as constraints that at the end usually increased costs. It is only recently that engineers started to talk about green engineering and sustainability, but in most cases, these are still considered as constraints of the above design problem, not as valid objectives.

Reality is, however, more complex than the assumptions used for the above problem: raw materials change quality and availability, demands may be lower than expected, and products may require different specifications through time, all of which should be accomplished with one plant. So in the 1980s engineers proposed to solve the following flexible design problem.

‘Design a flexible plant to produce chemical X, with capacity Y, capable of working in the given ranges of raw materials availability and quality and product specifications’

While the problem was a challenge to the community, it hardly incorporated any new economic considerations. The next step was to include uncertainty. Thus the revised version was:

‘Design a plant to produce chemical X, taking into account uncertain raw materials and product prices, process parameters, raw material availability and product demand, given the forecasts and determine when the plant should be built as well as what expansions are needed’

Substitute ‘plant’ by ‘network of processes’ or by ‘product’ and you have supply chain problems or product engineering.

This has been the typical problem of the 1990s. However, very few industries have embraced the tools and the procedures and only a few schools teach it at the undergraduate level. As noted, this was later extended to networks of plants and supply chains, a subject that is still somewhat foreign in undergraduate chemical engineering education. Notice first that the fixed capacity requirement and the flexibility ranges are no longer included. The engineer is expected to determine the right capacity and the level of flexibility that is appropriate for the design. In doing so, it maximizes expectation of profit. *The profit measures (net present value or rate of return), however, did not change and are the same as the one engineers have been using for years.* The novelty is the planning aspect and the incorporation of uncertainty.

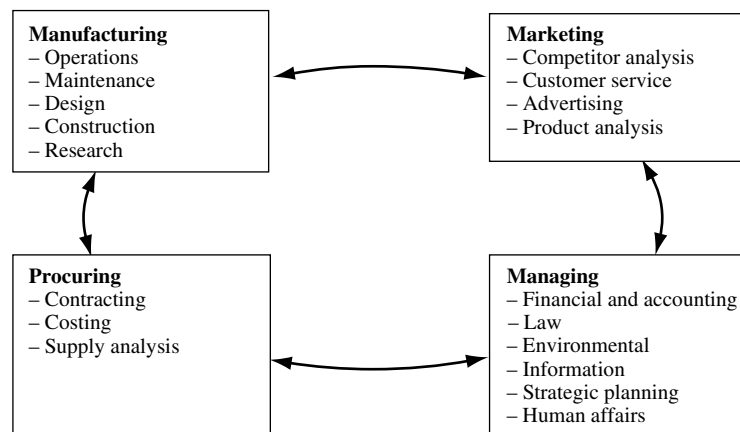
In addition, one has to realize that not all design projects are alike. Some are constrained by spending and some not, some are performed to comply with regulations and do not necessarily target profit, but rather cost. Thus, the type of economic analysis and the tools associated change.

*Where do the engineers go from here?* This chapter addresses some answers to this question. Many of the most obvious pending questions/issues, some of which intersect and others being already explored, are as follows:

- What is the financial risk involved in a project?
- What is the project impact in several indicators of the finance status of the company that is considering this project, namely,
  - liquidity ratios (assets to liabilities)?
  - cash position, debts, etc?
  - short-, medium-, and long-term shareholder value, or in the case of a private company the dividends, among others?
- How does the size of the company in relation to the capital involved in the project shape the decision maker's attitudes? It is not the same type of decision making one makes belonging to a big corporation than to a medium-size private company, even when the financial indicators are similar. In other words, the question at large is how the project impacts on company market value.
- How the decision making related to the project can reflect the strategic plans of the company and, most importantly, vice versa, that is, *how to take into account the strategic plan of the company at the level of project or investment decision making?*
- Can 'here and now' decisions and design parameters be managed in relation to targets or aspiration levels for the different indicators listed above?
- Can short- and long-term contracts and options be factored in at the decision making time, not afterwards as control actions, to increase profitability?
- When should projects be based on taking equity and be undertaken with no increment in profit because they are instrumental for other projects?
- Can one plan to alter the exogenous parameters, like prices, demands, to affect the expected profit and/or the aforementioned indicators?
- Should one consider advertisement as part of the decision making, or product presentation (form, color, etc.), that is, the psychology of the user?
- Should sociology/psychology/advertisement/etc. be incorporated into the decision making by modeling the different decisions vis-à-vis the possible response of the market? In other words, should one start considering the market demand as susceptible of being shaped, rather than using it as simple forecasted data?

The answer to the above list of questions (which is by no means exhaustive) is slowly and strongly emerging. The latest Eighth International Symposium on Process Systems Engineering held in China (PSE 2003) had many of the above issues as the central theme, but there is substantial earlier pioneering work. For example, in an article mostly devoted to prepare us for the information technology (IT) age (now in full development), and its impact on corporate management, Robertson *et al.* (1995) argued about the lack of proper communication in the corporate flow loop (Figure 12.1). They argue that the four major components of this loop (manufacturing, procuring, managing, and marketing) operate almost as separate entities with minimal data sharing.

Notwithstanding the lack of data sharing, which will (or is being) corrected, the real issue is that the different elements of the loop also start to share the same goals and methods, like Bunch and Iles (1998) argued. As in many examples illustrated in the following text, decisions at the level of manufacturing, for example the schedule of operations, are influenced by the company's cash position and are related to pricing, etc. This involves marketing, procuring, and manufacturing in the solution of the problem. Corporate management, procuring, and marketing should also work together to solve investment problems, etc. This is the nature of the challenge and the core of our



**Figure 12.1** Corporate information loop (following Robertson *et al.*, 1995)

analysis: chemical engineering methods and procedures, which were mostly related to manufacturing, are now increasingly involving/including the other components of the corporate loop in integrated models.

## 12.2 Project Evaluation as Chemical Engineers Know It

Engineers have all been likely to be educated with some exposure to the classic book on process design authored by Peters and Timmerhaus, which was recently updated (Peters *et al.*, 2003). Even in this last update, the part dealing with economics contains mostly the same chapter on profitability as earlier editions with small changes. Other available textbooks do not depart from this recipe. The recommended measures of profitability are:

- Internal rate of return
- Pay out time
- Net present value (NPV)
- Discounted cash flow rate of return.

For the most part, these methods consider that the plant is build at some point, time at which the whole capital investment is used, and that profits are somehow predictable throughout the time horizon. The methods respond to a project evaluation paradigm that was crafted years ago in the era when computers were not powerful enough and/or even available, and when uncertainty in modeling was manageable only for small problems.

Extensions of these measures to uncertain future conditions have been made, especially in the form of expected net present value. Another problem with all measures is the uncertainty of how long the plant will be in operation, at what point will preventive maintenance be intensified, or when some revamps will take place. In old days, all these difficulties were ignored because of the inability or, actually, the lack of knowledge of how to handle uncertainty beyond a simple and reduced set of scenarios. In other words, the model was simplified for two reasons: an engineer should be able to do calculations and uncertainty was too complex to handle. The excuse is not valid anymore.

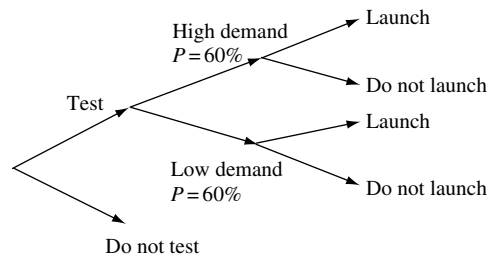


Figure 12.2 Example of a decision tree

Despite the aforementioned general tendency, uncertainty in project evaluations has been handled for years in various forms. Various branches of engineering still use decision models, trees, and payoff tables (McCray, 1975; Riggs, 1968; Gregory, 1988; Schuyler, 2001). Decision trees are good tools as long as decisions are discrete (e.g. to build a plant or not, to delay construction or not, etc.). A typical tree for investment decision making is illustrated next. Consider a company trying to decide if it wants to invest 5 million to test a product in the market, and if a test is positive, invest 50 million, or skip the test. A decision tree for this case is shown in Figure 12.2. In this decision tree, two types of nodes typically exist, those associated with decisions (test or not test) and the outcomes or external conditions (high/low demand), to which probabilities are associated.

Thus, to build a decision tree, one needs to *explicitly* enumerate all possible scenarios and the responses (decisions) to such scenarios. However, 'for some problems, . . . , a combinatorial explosion of branches makes calculations cumbersome or impractical' (Schuyler, 2001). One way that this problem is ameliorated (but not solved) is by introducing Monte Carlo simulations at each node of the decision tree. However, this does not address the problem of having to build the tree in the first place. In addition, trees are appropriate for the case where discrete decisions are made. Continuous decisions like for example the size of the investment, or more specifically, the size of a production plant, cannot be easily fit into decision trees without discretizing.

A separate paragraph needs to be devoted to dynamic programming (Bellman, 1957; Denardo, 1982). This technique is devoted to solve sequential decision making processes. It has been applied to resource allocation, inventory management, routing in networks, production control, etc. In many aspects this technique is equivalent to two-/multi-stage stochastic programming, with the added benefits that under certain conditions, some properties of the solutions (optimality conditions) are known and are helpful for the solution procedure. In fact, under certain conditions, one can obtain the solution recursively, moving backwards from the last node to the first. The technique can be applied to problems under uncertainty. There has been recently a revival of the usage of this technique in chemical engineering literature due fundamentally to the recent work of Professor Westerberg (Cheng *et al.*, 2003, 2004).

By the late 1980s the engineering community had started to introduce two-stage stochastic programming (Birge and Louveaux, 1997) in problems like planning, scheduling, etc. (Iyer and Grossmann, 1998a; Liu and Sahinidis, 1996; Gupta and Maranas, 2000, and many others). Two-stage stochastic programming is briefly outlined next using linear functions for simplicity. The dynamic programming approach is outlined briefly later.

### 12.2.1 Two-Stage Stochastic Programming

Two features characterize these problems: the uncertainty in the problem data and the sequence of decisions. Several model parameters, especially those related to future events, are considered random variables with a certain probability distribution. In turn, some decisions are taken at the planning stage, that is, before the uncertainty is revealed, while a number of other decisions can only be made after the uncertain data become known. The first decisions are called *first-stage decisions* and the decisions made after the uncertainty is unveiled are called *second-stage* or *recourse decisions*, and the corresponding period is called the second stage. Typically, first-stage decisions are structural and most of the time related to capital investment at the beginning of the project, while the second-stage decisions are often operational. However, some structural decisions corresponding to a future time can be considered as second-stage decisions. This kind of situation is formulated through the so-called multi-stage models, which are a natural extension of the two-stage case. Among the two-stage stochastic models, the expected value of the cost (or profit) resulting from optimally adapting the plan according to the realizations of uncertain parameters is referred to as the *recourse function*. Thus, a problem is said to have *complete recourse* if the recourse cost (or profit) for every possible uncertainty realization remains finite, independently of the nature of the first-stage decisions. In turn, if this statement is true only for the set of feasible first-stage decisions, the problem is said to have *relatively complete recourse* (Birge and Louveaux, 1997). This condition means that for every feasible first-stage decision, there is a way of adapting the plan to the realization of uncertain parameters. The following literature covers the technique in more detail: Infanger (1994), Kall and Wallace (1994), Higle and Sen (1996), Birge and Louveaux (1997), Marti and Kall (1998), and Uryasev and Pardalos (2001). In addition, Pistikopoulos and Ierapetritou (1995), Cheung and Powell (2000), Iyer and Grossmann (1998b), and Verweij *et al.* (2001) discuss solution techniques for these problems.

The general extensive form of a two-stage mixed-integer linear stochastic problem for a finite number of scenarios can be written as follows (Birge and Louveaux, 1997):

Model SP:

$$\text{Max} \quad E[\text{Profit}] = \sum_{s \in S} p_s q_s^T y_s - c^T x \quad (12.1)$$

s.t.

$$Ax = b \quad (12.2)$$

$$T_s x + W y_s = h_s \quad \forall s \in S \quad (12.3)$$

$$x \geq 0 \quad x \in X; \quad y_s \geq 0 \quad \forall s \in S \quad (12.4)$$

In the above model,  $x$  represents the first-stage mixed-integer decision variables and  $y_s$  are the second-stage variables corresponding to scenario  $s$ , which has occurrence probability  $p_s$ . The objective function is composed of the expectation of the profit generated from operations minus the cost of first-stage decisions (capital investment). The uncertain parameters in this model appear in the coefficients  $q_s$ , the technology matrix  $T_s$ , and in the independent term  $h_s$ . When  $W$ , the recourse matrix, is deterministic the problem is called to be of fixed *recourse*. Cases where  $W$  is not fixed are found for example in portfolio optimization when the interest rates are uncertain (Dupacova and Römisch, 1998).

It is worth noticing that decision trees are in fact a particular case of two-stage programming. In other words, one can code through rules (mathematical in this case) the same decisions one make in the tree explicitly, but in two-stage programming, one can also add logical constraints, if-the-else rules, etc., so there is no need for explicit enumeration of all options.

Aside from the issue of the plant life and the possible future upgrades, which complicate the modeling, there is yet another very important difficulty with these methods: the models are isolated from considering the size of the company, the health of its finances, even the temporary lack of liquidity or the abundance thereof as it was pointed out above. Take, for example, the simple question: Should the project be started this year, next year, or two years down the road? The answer relies on forecasting of course, and the choice can be modeled using current two-stage stochastic programming methods, but maximizing the above measures is not proper most of the time, as the answer is not the same if the project is undertaken by a big corporation or a small company.

One important point to make is that before any treatment of risk or uncertainty, a solid deterministic model needs to be developed.

*Summarizing:* Chemical engineers have understood uncertainty and flexibility and have incorporated it within a two (multi)-stage process decision optimization models. In doing so, Chemical Engineers are not embracing the use of decision trees, which, as claimed, are a particular case of the former. Integration of financial indicators other than financial risk as well as strategic planning as a whole has barely started.

### 12.3 Project Evaluation the Way Economists and Financiers Practice It

One learns from books on financial management (Keown *et al.*, 2002, Smart *et al.*, 2004) that maximization of shareholder wealth, that is, maximization of the price of the existing common stock, is the real goal of a firm, not just maximization of profit as engineers are trained to think. Some alternative form of maximizing dividends should be substituted if the company is non-publicly owned. They claim that such a goal also benefits society because 'scarce resources will be directed to their most productive use by businesses competing to create wealth'. Finance management also teaches that several other issues are of importance for that goal, namely:

- risk management, that is, its eventual reduction;
- risk diversification, that is, risky projects can be combined with other less risky ones in a balanced portfolio;
- cash flow management includes borrowing, raising investor's money, and also buying and selling securities;
- liquidity of the firm (ratio of assets to liabilities) and available cash, which affects investment and operating decisions;

among others. To deal with risk, they mostly measure it using variability (or volatility), which is incorrect in almost all engineering project cases, as it is explained later. They diversify by adding stocks to the portfolio.

### 12.3.1 Profit Maximization

Capital budgeting, the process through which the company analyzes future cash inflows and outflows, is performed using concepts that are extensions of the tools engineers know.

The firm *cost of capital*, which is the hurdle rate that an investment must achieve before it increases shareholder value, is one key aspect of these decisions that the engineers have overlooked. Such cost of capital is measured typically by the firm's weighted average cost of capital (WACC) rate  $k_{WACC}$ . For example, a firm that uses only debt and common equity to finance its projects, this rate is given by:

$$k_{WACC} = [\text{After tax cost of debt}] \times \omega + [\text{Cost of equity}](1 - \omega) \quad (12.5)$$

where  $\omega$  is the portion of debt that one is financing, the cost of debt is that rate paid for borrowed money, and the cost of equity is the rate that shareholders expect to get from the cash retained in the business and used for this project. The latter rate is larger than the former, of course.

In practice  $k_{WACC}$  is more complex to calculate because there are several debts incurred at different times and they require common equity as well as preferred equity. In addition, new capital may be raised through new stock offerings. Finally, one is faced with the problem of calculating a return of a project that has multiple decisions at different times, with uneven and uncertain revenues. Clearly, this simple formula needs some expansion, to add the complexities of projects containing multiple first- and second-stage decisions through time.

Financial management also suggests the alternative that the appropriate discount rate to evaluate the NPV of a project is the weighted average cost of capital, based on one important assumption that the risk profile of the firm is constant over time. In addition, this is true only when the project carries the same risk as the whole firm. When that is not true, which is most of the time, finance management has more elaborate answers, like managerial decisions that 'shape' the risk.

They also manage projects for *market value added* (MVA). The free cash flow model provides the *firm value*:

$$\text{Firm value} = \sum_i \frac{\text{Free cash flow}(i)}{(1 + k_{WACC})^i} + \frac{\text{Terminal value}}{(1 + k_{WACC})^n} \quad (12.6)$$

where the summation is extended over the period of  $n$  periods of planning. This expression uses  $k_{WACC}$  and refers to the whole company. The *firm value* is used to get the *market value added* of the investment.

$$\text{Market value added} = \text{Firm value} - \text{Investment} \quad (12.7)$$

which is a formula very similar to the *net present value* engineers use for projects. In fact, the only difference is the value of the hurdle rate. Because the formula is a measure of the total wealth created by a firm at a given time, extending over a long time horizon, financial experts recommend the use of a shorter term measure, the *economic value added* (EVA) for period  $t$ .

$$\text{EVA}_t = \text{Net profit}_t - k_{WACC}[\text{Invested capital}] \quad (12.8)$$



where the net profit is computed after taxes. Thus, the MVA is the present value of all future EVA. Quite clearly, finance experts warn, managing for an increased EVA at any given time may lead to a non-optimal MVA.

In turn, the shareholder value can be obtained as follows: The *firm value* is the sum of *debt value* plus *equity value*. Then, if one knows the long-term interest-bearing liabilities, one has the *debt value*. Then one can obtain the shareholder value,

$$\text{Shareholder value} = \frac{\text{Equity value}}{\text{Number of shares}} = \frac{\text{Firm value} - \text{Debt value}}{\text{Number of shares}} \quad (12.9)$$

In principle, as noted above, the shareholder value is what one wants to maximize. This is what is true for the whole company and therefore implies one has to consider all projects at the same time. Thus, one can write

$$\text{Shareholder value} = \frac{\text{Equity value}}{\text{Number of shares}} = \frac{\sum_p [\text{Firm value}_p(x_p) - \text{Debt value}_p(x_p)]}{\text{Number of shares}} \quad (12.10)$$

where the summation is extended over different projects the firm is pursuing or considering pursuing and  $x_p$  is the vector of first-stage ('here and now') decisions to be made. Thus, if the projects are generating similar equity value, no simplification is possible and decisions have to be made simultaneously for all projects. Hopefully, procedures that will do this interactively, that is, change the decisions of all projects at the same time, will be developed.

However, which shareholder value does one want to maximize? The one corresponding to next quarter company report, or a combination of shareholder values in different points in the future? In other words, is there such thing as an optimal investment and operating strategy/path? This looks like an optimal control problem!

And then, there is the dividend policy. Is it possible that this should be decided *together with* and not *independently from* the specific project first-stage variables?

The 'here and now' decisions ( $x_p$ ) involve several technical choices of the processes themselves (catalysts, technologies, etc.) which require detailed modeling and also some other 'value drivers', like advertisement to increase sales, alliances to penetrate markets, investment in R&D, company acquisition, cost-control programs, inventory control, control of the customer paying cycles (a longer list is given by Keown *et al.*, 2002). Most of these 'knobs and controls' are called second-stage ('wait and see') decisions, but many are also first-stage decisions.

The literature on strategic planning (Hax and Majluf, 1984) has models that deal directly with shareholder value. They use different models (market to book values, profitability matrices, etc.) to obtain corporate market value, which take into account the company reinvestment policy, dividend payments, etc. One cannot help also mention some classic and highly mathematical models from game theory and other analytical approaches, some of which are discussed elegantly by Debreu (1959) and Danthine and Donaldson (2002).

A brief glance at the literature tells that economists are not yet so keen on using two-stage stochastic models. They understand, of course, the concept of options in projects, but many are still 'locked' to the use of point measures like NPV and decision trees (De Reyck *et al.*, 2001).

Finally, some of the financial ratios that are waiting to be embraced by engineering models are:

- Liquidity ratios
  - Current ratio = current assets/current liabilities
  - Acid test or quick ratio = (current asset inventories)/current liabilities
  - Average collection period: accounts receivable/daily credit sales
  - Accounts receivable turnover = credit sales/accounts receivable
  - Inventory turnover = costs of goods sold/inventory
- Operating profitability ratios
  - Operating income return on investment = income/total assets
  - Operating profit margin = income/sales
  - Total asset turnover = sales/ total assets
  - Accounts receivable turnover = sales/accounts receivable
  - Fixed assets turnover = sales/net fixed assets
- Financial ratios
  - Debt ratio = total debt/total assets
  - Times interests earned = operating income/interest expense
  - Return on equity = net income/common equity

While all these indicators focus on different aspects of the enterprise, they should be at least used as constraints in engineering models.

It is therefore imperative that engineers incorporate these measures and objectives in project evaluation, *when and if*, of course, *decisions at the technical level have an impact on the outcome*. In other words, how much of the project is financed by equity is a decision to make together with the technical decisions about size and timing of every project and the technical decisions of the project itself, like the selection of technologies, catalysts, etc. This last aspect is what makes the integration a must!

### 12.3.2 Risk Management

The other major component influencing business decisions is risk. First, one needs to distinguish business risk from financial risk.

Business risk is measured by the non-dimensional ratio of variability (standard deviation) to expected profit before taxes and interest (Keown *et al.*, 2002; Smart *et al.*, 2004). Thus the same variability associated with a larger profit represents less business risk. Thus, one can use this ratio to compare two investments, but when it comes to managing risk for one investment, the objective seems to be the usual, maximize profit and reduce variability. As it will be discussed later in greater detail, these are conflicting goals. Measures to reduce business risk include product diversification, reduction of fixed costs, managing competition, etc. More specifically, the change in product price and fixed costs is studied through the degree of operating leverage (DOL) defined in various forms, one being the ratio of revenue before fixed costs to earnings before interest and taxes (EBIT).

Engineers have not yet caught up in relating these concepts with their models. As usual, the mix includes some second-stage decisions, but most of them are first-stage 'here and now' decisions. Modeling through two-stage stochastic programming and including

technical decisions in this modeling is the right answer. Some of the aspects of this modeling are discussed below.

Financial risk is in some cases defined as the ‘additional variability in earnings . . . and the additional chance of insolvency . . . caused by the use of financial leverage’ (Keown *et al.*, 2002). In turn, the financial leverage is the amount of assets of the firm being financed by securities bearing a fixed or limited rate of return. Thus, the degree of financial leverage (DFL) is defined as the ratio of EBIT to the difference of EBIT and the total interest expense  $I$ , that is,

$$DFL = \frac{EBIT(x)}{EBIT(x) - I(x)} \quad (12.11)$$

In other words, business and financial risk differ fundamentally in that one considers interest paid and the other does not. Both are considered related to variability. As it is shown later, the claim is that this is the wrong concept to use in many cases.

Another very popular definition of risk is through the risk premium or *beta*. This is defined as the slope of the curve that gives market returns as a function of S&P 500 Index returns; in other words, comparing how the investment compares with the market. The concept of ‘beta’ (the slope of the curve) is part of the capital asset pricing model (CAPM) proposed by Lintner (1969) and Sharpe (1970), which intends to incorporate risk into valuation of portfolios and it can also be viewed as the increase in expected return in exchange for a given increase in variance. However, this concept seems to apply to building stock portfolios more than to technical projects within a company.

Financial risk is also assessed through point measures like risk-adjusted return of capital (RAROC), risk-adjusted net present value (RPV), Sharpe ratio (Sharpe, 1966). It is unclear if these point measures are proper ways of assessing risk, much less managing it, in engineering projects. This point is expanded below.

Economists also consider risk as ‘multidimensional’ (Dahl *et al.*, 1993). They have coined names for a variety of risks. Some of these, applied mostly to stocks, bonds, and other purely financial instruments, are market risk (related to the CAPM model and the above described parameter ‘beta’), volatility risk (applied to options, primarily), currency risk, credit risk, liquidity risk, residual risk, inventory risk, etc.

The managing of net working capital is used by finance experts to manage risk. The working capital is the total assets of the firm that can be converted to cash in a one-year period. In turn, the net working capital is the difference between assets and liabilities. Thus increasing the net working capital reduces the chance of low liquidity (lack of cash or ability to convert assets into cash to pay bills in time). This is considered as short-term risk. Several strategies are suggested to maintain an appropriate level of working capital (Finnerty, 1993).

A separate consideration needs to be made for inventory, which in principle is used to be able to uncouple procuring from manufacturing and sales. In this regard it is mostly considered as a risk hedging strategy that increases costs. Finally, contracts, especially option contracts and futures, are other risk hedging tools.

Recently, risk started to be defined in terms of another point measure introduced by J.P. Morgan, *value at risk* or VaR (Jorion, 2000). This is defined as the difference between the expected profit and the profit corresponding to 5% cumulative probability. Many other ‘mean-risk’ models use measures like tail value at risk, weighted mean

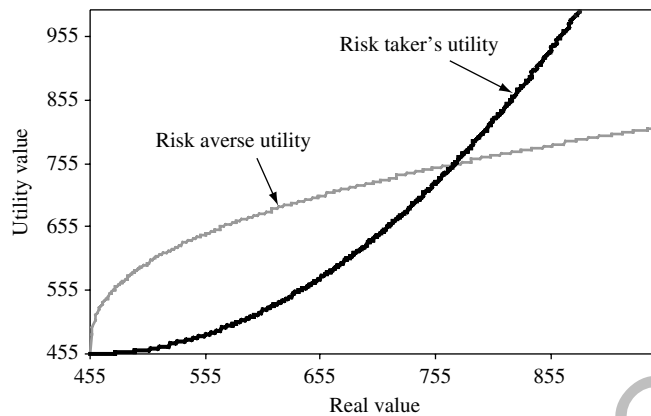


Figure 12.3 Utility functions

deviation from a quantile, and the tail Gini mean difference (reviewed by Ogryczak and Ruszcynski, 2002), to name a few.

More advanced material (Berger, 1980; Gregory, 1988; Danthine and Donaldson, 2002) proposes the use of *expected utility theory* to assess risks. This theory proposes to assign a value (different from money) to each economic outcome. Figure 12.3 illustrates the utility function of a risk-averse decision maker, who values (in relative terms) small outcomes more than large outcomes. It also shows the utility function of a risk taker who places more value in higher outcomes. In most cases, the utility curve is constructed in a somehow arbitrary manner, that is, taking two extreme outcomes and assigning a value of 0 to the less valued and the value of 1 to the most valued one. Then there are procedures that pick intermediate outcomes and assign a value to them until the curve is constructed.

This theory leads to the definition of loss functions as the negative utility values, which are used to define and manipulate risk (Berger, 1980). To do this, a decision rule must be defined. Thus, risk is defined as the expected loss for that particular decision rule. This, in turn, leads to the comparison of decision rules. Engineering literature contains some reference to this theory. As it is discussed below, expected utility has a lot of potential as decision making tool. All that is needed is to start putting it in the context of the emerging two-stage stochastic modeling.

The important thing one learns from the review of basic financing is as follows:

- 1) The majority of the tools proposed are deterministic, although some can be extended to expectations on profit distributions and therefore decision trees are presented as advanced material in introductory finance books. Quite clearly, one would benefit from using two-stage stochastic programming instead.
- 2) Risk is considered a univariate numerical measure like variability or value at risk (VaR), which is the difference between the project expected outcome and the profit corresponding to (typically) 5% cumulative probability. Opportunities at high profit levels are rarely discussed or considered.
- 3) Financiers only know how to evaluate a project. They can manipulate it on the financial side, but they cannot manipulate it in its technological details because they

need engineering expertise for it. This is the Achilles heel of their activity. Engineers, in turn, cannot easily take into account the complexity of finances. Both need each other more than ever.

## 12.4 Latest Progress of Chemical Engineering Models

Decision making is an old branch of management sciences, a discipline that has always had some overlap with engineering, especially industrial engineering. Some classical books on the subject (Riggs, 1968; Gregory, 1988; Bellman, 1957) review some of the different techniques, namely:

- resource allocation (assignment, transportation);
- scheduling (man-machine charts, Gantt charts, critical path scheduling, etc.);
- dynamic programming (Bellman, 1957; Denardo, 1982);
- risk (reviewed in more detail in the next section) through the use of decision trees, regret tables, and utility theory.

Notwithstanding the value of all these techniques, the new emerging procedures rely heavily on two-stage stochastic programming and some revival of dynamic programming. It is argued here that several techniques, like decision trees and utility theory, are special cases of two-stage stochastic programming. Others claim the same when advocating the dynamic programming approach (Cheng *et al.*, 2003, 2004). They proposed to model decision making as a multiobjective Markov decision process.

For example, in recent years, the integration of batch plant scheduling with economic activities belonging to procuring and marketing has been pioneered by the books by Puigjaner *et al.* (1999, 2000), which contain full chapters on financial management in batch plants where something similar to the corporate information loop (Figure 12.1), as viewed by engineers and economists, is discussed. They discuss the notion of enterprise wide resource management systems (ERM), one step above enterprise resource planning (ERP). They outline the cycle of operations involving cash flow and working capital, the management of liquidity, the relationships to business planning, etc. as it relates mostly to batch plants. They even raise the attention to the role of pricing theory and discuss the intertwining of these concepts with existing batch plant scheduling models. These summary descriptions of the role of cash and finances in the context of batch plants are the seeds of the mathematical models that have been proposed afterwards. Extensive work was also performed by many other authors in a variety of journal articles. A partial (clearly incomplete) list of recent work directly related to the integration of process systems engineering and economic/financial tools is the following:

- Investment planning (Sahinidis *et al.*, 1989; Liu and Sahinidis, 1996; McDonald and Karimi, 1997; Bok *et al.*, 1998; Iyer and Grossmann, 1998a; Ahmed and Sahinidis, 2000a, Cheng *et al.*, 2003, 2004).
- Operations planning (Ierapetritou *et al.*, 1994; Ierapetritou and Pistikopoulos, 1994; Pistikopoulos and Ierapetritou, 1995; Iyer and Grossmann, 1998a; Lee and Malone, 2001; Lin *et al.*, 2002; Mendez *et al.*, 2000; McDonald, 2002; Maravelias and Grossmann, 2003; Jackson and Grossmann, 2003; Mendez and Cerdá, 2003).

- Refinery operations planning (Shah, 1996; Lee *et al.*, 1996; Zhang *et al.*, 2001; Pinto *et al.*, 2000; Wenkai *et al.*, 2002; Julka *et al.*, 2002b; Jia *et al.*, 2003; Joly and Pinto, 2003; Reddy *et al.*, 2004; Lababidi *et al.*, 2004; Moro and Pinto, 2004).
- Design of batch plants under uncertainty (Subrahmanyam *et al.*, 1994; Petkov and Maranas, 1997).
- Integration of batch plant scheduling and planning and cash management models (Badell *et al.*, 2004; Badell and Puigjaner, 1998, 2001a,b; Romero *et al.*, 2003a,b).
- Integration of batch scheduling with pricing models (Guillén *et al.*, 2003a).
- Integration of batch plant scheduling and customer satisfaction goals (Guillén *et al.*, 2003b).
- Technology selection and management of R&D (Ahmed and Sahinidis, 2000b; Subramanian *et al.*, 2000).
- Supply chain design and operations (Wilkinson *et al.*, 1996; Shah, 1998; Bok *et al.*, 2000; Perea-Lopez *et al.*, 2000; Bose and Pekny, 2000; Gupta and Maranas, 2000; Gupta *et al.*, 2000; Tsiakis *et al.*, 2001; Julka *et al.*, 2002a,b; Singhvi and Shenoy, 2002; Perea-Lopez *et al.*, 2003; Mele *et al.*, 2003; Espuña *et al.*, 2003; Neiro and Pinto, 2003).
- Agent-based process systems engineering (Julka *et al.*, 2002a,b; Sirola *et al.*, 2003).
- Financial risk through the use of a variety of approaches and in several applications (Applequist *et al.*, 2000; Gupta and Maranas, 2003a; Mele *et al.*, 2003; Barbaro and Bagajewicz, 2003, 2004a,b; Wendt *et al.*, 2002; Orcun *et al.*, 2002).
- New product development (Schmidt and Grossmann, 1996; Blau and Sinclair, 2001; Blau *et al.*, 2000).
- Product portfolios in the pharmaceutical industry (Rotstein *et al.*, 1999).
- Options trading and real options (Rogers *et al.*, 2002, 2003; Gupta and Maranas, 2003b, 2004).
- Transfer prices in supply chain (Gjerdrum *et al.*, 2001).
- Oil drilling (Iyer *et al.*, 1998; Van den Heever *et al.*, 2000, 2001; Van den Heever and Grossmann, 2000; Ortiz-Gómez *et al.*, 2002).
- Supply chain in the pharmaceutical industry (Papageorgiou *et al.*, 2001; Levis and Papageorgiou, 2003).
- Process synthesis using value added as an objective function (Umeda, 2004). This chapter revisits dynamic programming approaches.

The rest of this chapter concentrates on discussing some aspects of the integration that have received attention by engineers, namely,

- financial risk
- effect of inventories
- regular, future, and option contracts
- budgeting
- pricing
- consumer satisfaction.

Some work calling for the integration of other disciplines and the role of the recent product engineering and the chemical supply chain key ideas in the integration with finances is also mentioned.

## 12.5 Financial Risk Management

### 12.5.1 Definition of Risk

There are various definitions of risk in the engineering literature, most of them rooted in the finance field, of course.

A good measure of risk has to take into account different risk preferences and therefore one may encounter different measures for different applications or attitudes toward risk. The second property that a risk measure should have is that when it focuses on particular outcomes, say low profit outcomes that want to be averted as in the figure above, one would like to also have information about the rest of the profit distribution. Particularly, when one compares one project to another, one would like to see what is that one loses in other portions of the spectrum as compared to what one gains averting risk.

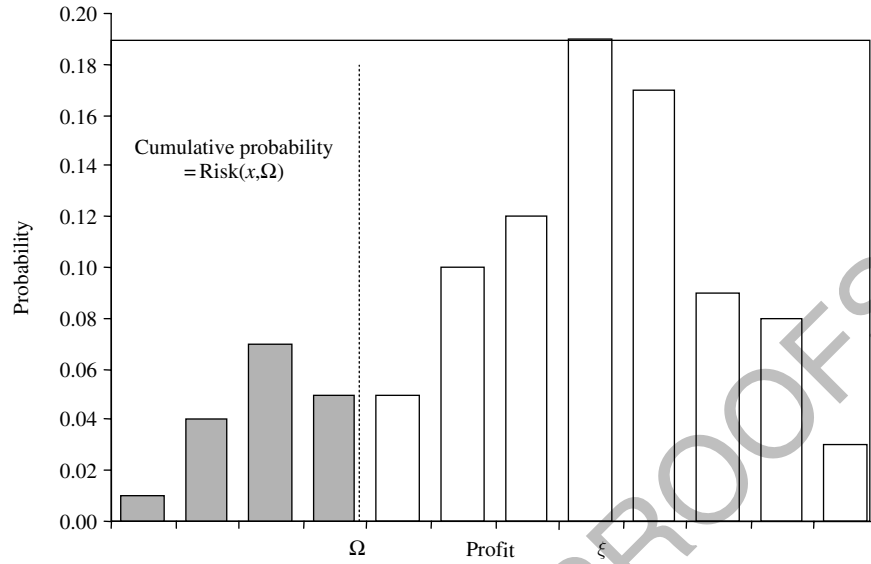
Some of these alternative measures that have been proposed are now reviewed:

- **Variability:** That is, standard deviation of the profit distribution. This is the most common assumption used in the non-specialized financial literature, where investment portfolios (stocks primarily) are considered. Mulvey *et al.* (1995) introduced the concept of *robustness* as the property of a solution for which the objective value for any realized scenario remains ‘close’ to the expected objective value over all possible scenarios and used the variance of the cost as a ‘measure’ of the robustness of the plan, i.e. less variance corresponds to higher robustness. It is obvious that the smaller the variability, the less negative deviation from the mean. But it also implies smaller variability on the optimistic side. Thus, either the distribution is symmetric (or this is assumed) or one does not care about the optimistic side. This is the specific assumption of stock portfolio optimization, but it is known not to be correct for other type of investments, especially multi-year ones (Smart *et al.*, 2004). Thus, the use of variability as a measure of risk is being slowly displaced by engineers (not necessarily by the finance community) in favor of other measures. Nonetheless, it is still being used. Tan (2002), for example, provides means to reduce variability by using capacity options in manufacturing. It has the added disadvantage that it is nonlinear.
- **Cumulative probability for a given aspiration level:** This is the correct way of defining risk when one wants to reduce its measure to a single number because unlike variance it deals with the pessimistic side of the distribution only. Consider a project defined by  $x$ . Risk is then defined by

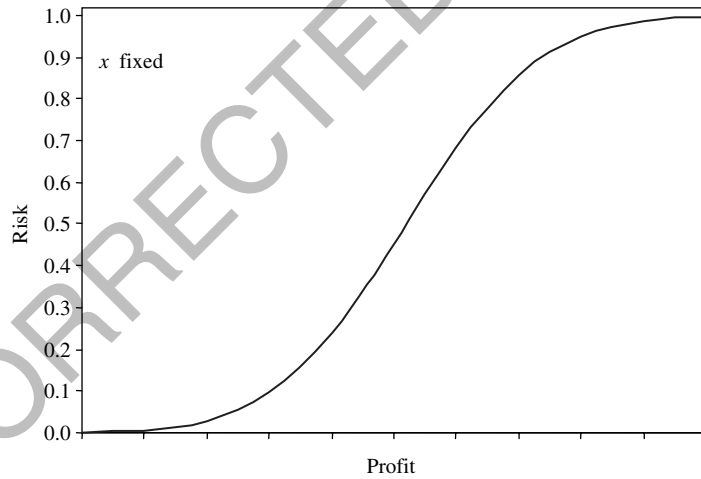
$$\text{Risk}(x, \Omega) = P\{\text{Profit}(x) \leq \Omega\} \quad (12.12)$$

where  $\text{Profit}(x)$  is the actual profit, showed in Figure 12.4 as the shaded area. This definition has been used by the petroleum industry for years (McCray, 1975). In the process systems literature this definition was used by Rodera and Bagajewicz (2000), Barbaro and Bagajewicz (2003, 2004a), and Gupta and Maranas (2003a). Figure 12.5 depicts a cumulative distribution curve, which also represents risk as a function of all aspiration levels. This is the preferred representation because, as it is discussed later, one can best manage risk using it.

- **Downside risk:** This measure, introduced by Eppen *et al.* (1989) in the framework of capacity planning for the automobile industry, is an alternative and useful way of



**Figure 12.4** Definition of risk. Discrete case

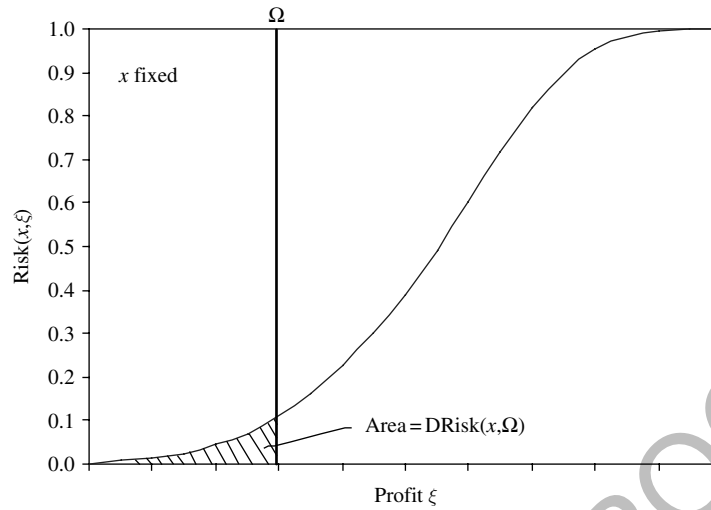


**Figure 12.5** Risk curve, continuous case

measuring risk using the concept of currency. Consider the positive deviation from a profit target  $\Omega$  for design  $x$ ,  $\delta(x, \Omega)$ , defined as follows:

$$\delta(x, \Omega) = \begin{cases} \Omega - \text{Profit}(x) & \text{If } \text{Profit}(x) < \Omega \\ 0 & \text{Otherwise} \end{cases} \quad (12.13)$$





**Figure 12.6** Interpretation of downside risk

Downside risk is then defined as the expectation of  $\delta(x, \Omega)$ , that is,  $\text{DRisk}(x, \Omega) = E[\delta(x, \Omega)]$ . This form has been very useful computationally to identify process alternatives with lower risk, as it is discussed below. Barbaro and Bagajewicz (2003, 2004a) proved that downside risk is just an integral of the risk curve, as shown in Figure 12.6. Moreover, they proved that downside risk is not monotone with risk, that is, two designs can have the same risk for some aspiration level, but different downside risk. Moreover, projects with higher risk than others can exhibit lower downside risk. Therefore, minimizing one does not imply minimizing the other. However, this measure has several computational advantages and was used to generate solutions where risk is managed using goal programming (Barbaro and Bagajewicz, 2003, 2004a). Gupta and Maranas (2003a) discuss these measures (risk and downside risk) as well.

- **Upper partial mean:** It is proposed by Ahmed and Sahinidis (1998). It is defined as the expectation of positive deviation from the mean, that is,  $\text{UPM}(x) = E[\Delta(x)]$ , where  $\Delta(x)$  is defined the same way as  $\delta(x, \Omega)$ , but using  $E[\text{Profit}(x)]$  instead. In other words, the UPM is defined as the expectation of the positive deviation of the second-stage profit. The UPM is a linear and asymmetric index since only profits that are below the expected value are measured. However, in the context of risk management at the design stage, this measure cannot be used because it can underestimate the second-stage profit by not choosing optimal second-stage policies. Indeed, because of the way the UPM is defined, a solution may falsely reduce its variability just by not choosing optimal second-stage decisions. This is discussed in detail by Takriti and Ahmed (2003), who present sufficient conditions for a measure of a robust optimization to assure that the solutions are optimal (i.e. not stochastically dominated by others). For these reasons, downside risk is preferred, simply because the expectation of positive deviation is done with respect to a fixed target ( $\Omega$ ) and not the changing profit expectation.
- **Value at risk (VaR):** It (discussed in detail by Jorion, 2000) was introduced by J.P. Morgan (Guldimann, 2000) and is defined as the expected loss for a certain

confidence level usually set at 5% (Linsmeier and 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. For instance, a portfolio that has a normal profit distribution with zero mean and variance  $\sigma$ , VaR is given by  $z_p\sigma$  where  $z_p$  is the number of standard deviations corresponding to the  $p$ -quantile of the profit distribution. Most of the uses of VaR are concentrated on applications where the profit probability distribution is assumed to follow a known symmetric distribution (usually the normal) so that it can be calculated analytically. The relationship between VaR and Risk is generalized as follows (Barbaro and Bagajewicz, 2004a):

$$\text{VaR}(x, p_\Omega) = E[\text{Profit}(x)] - \text{Risk}^{-1}(x, p_\Omega) \quad (12.14)$$

where  $p_\Omega$  is the confidence level related to profit  $\Omega$ , that is,  $p_\Omega = \text{Risk}(x, \Omega)$ . Notice that VaR requires the computation of the inverse function of Risk. Moreover, since Risk is a monotonically increasing function of  $\Omega$ , one can see from equation 12.14 that VaR is a monotonically decreasing function of  $p_\Omega$ .

While computing VaR as a post-optimization measure of risk is a simple task and does not require any assumptions on the profit distribution, it poses some difficulties when one attempts to use it in design models that manage risk. Given the computational shortcomings, it is more convenient to use VaR as a risk indicator, only because of its popularity in financial circles.

Finally, sometimes the risks of low liquidity measured by the cash flow at risk (CFAR) are more important than the *value at risk* (Shimko, 1998).

Companies that operate with risky projects identify VaR or similar measures directly with potential liability, and they would hold this amount of cash through the life of a project, or part of it.

- **Downside expected profit (DEP):** For a confidence level  $p_\Omega$  (Barbaro and Bagajewicz, 2004a), it is defined formally as the expectation of profit below a target corresponding to a certain level of risk  $p_\Omega$ , that is,  $\text{DEP}(x, p_\Omega) = E[\gamma(x, \Omega)]$ , where

$$\gamma(x, \Omega) = \begin{cases} \text{Profit}(x) & \text{If } \text{Profit}(x) \leq \Omega \\ 0 & \text{Otherwise} \end{cases} \quad (12.15)$$

and  $\Omega = \text{Risk}^{-1}(x, p_\Omega)$ . Plotting DEP as a function of the risk is revealing because at low risk values some feasible solutions may exhibit larger risk adjusted present value. The relationship between DEP, risk, and downside risk is

$$\text{DEP}(x, p_\Omega) = \int_{-\infty}^{\Omega} \xi f(x, \xi) d\xi = \Omega \text{Risk}(x, \Omega) - \text{DRisk}(x, \Omega) \quad (12.16)$$

where  $f(x, \xi)$  is the profit distribution.

- **Regret analysis** (Riggs, 1968): It is an old tool from decision theory that has been used in a variety of ways to assess and manage risk (Sengupta, 1972; Modiano, 1987). 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). The traditional way of doing 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 sampling average algorithm (Verweij *et al.*, 2001) to solve a deterministic design, scheduling and/or planning 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. The different criteria to choose the preferred solution are as follows:

- 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 suggests 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.
- The *maximin* criterion states that 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).

Aseeri and Bagajewicz (2004) showed that none of these strategies can guarantee the identification of the best risk-reduced solutions, although in many instances they can be used to identify promising and good solutions. For example, Bonfill *et al.* (2004) used the maximization of the worst case as means to obtain solutions that reduce risk at low expectations.

- *Chance constraints* (Charnes and Cooper, 1959): In essence, chance expressions are not other than risk, as defined above, but usually applied to outcomes other than cost or profit. Vice versa, financial risk can be thought of as a chance expression applied to profit. Many authors (Orcun *et al.*, 2002; Wendt *et al.*, 2002) use chance expressions by evaluating the probability that a design or a system can meet a certain uncertain parameter. Typical chance constraints have been used in scheduling of plant operations to assess the probabilities of meeting certain levels of demand. Aseeri and Bagajewicz (2004) showed that this approach is less efficient than straight risk curve analysis and is in fact a special case of it. For example, a chance constraint for the production, e.g.  $\text{Production} \leq \text{Demand}$ , should be replaced by  $\text{Production} \leq F^{-1}(1 - \alpha)$ , where  $F$  is the cumulative distribution for the demand and  $\alpha$  is the chosen confidence level. But a model with these types of constraints is just *one* instance of a sampling algorithm. Thus, the approach of using chance constraints is a subset of the sampling average algorithm discussed above.
- *The Sharpe ratio* (Sharpe, 1966): It is given by the expected excess return of investment over a risk-free return divided by the volatility, that is,

$$S = \frac{r - r_f}{\sigma} \quad (12.17)$$

where  $r$  and  $r_f$  are the expected return and the risk-free return, respectively, and  $\sigma$  is the volatility and can be used directly to assess risk in investments (Shimko, 1997).

- *Risk-adjusted return on capital (RAROC)*: It is the quotient of the difference between the expected profit of the project adjusted by risk and the capital (or value) at risk of an equivalent investment and the value at risk. This value is a multiple of the

Sharpe ratio in portfolio optimization, although this assertion is only valid for symmetric distributions. This particular measure has not been used in two-stage stochastic engineering models to manage risk. This is not preferred because, as explained below, it is better to depart from single valued measures looking at the whole risk curve behavior instead.

- *Certainty equivalent approach* (Keown *et al.*, 2002): In this approach a certainty equivalent is defined. This equivalent is the amount of cash required with certainty to make the decision maker indifferent between this sum and a particular uncertain or risky sum. This allows a new definition of net present value by replacing the uncertain cash flows by their certain equivalent and discounting them using a risk-free interest rate.
- *Risk premium*: Applequist *et al.* (2000) suggest benchmarking new investments against the historical risk premium mark. Thus, they propose a two-objective problem, where the expected net present value and the risk premium are both maximized. The technique relies on using the variance as a measure of variability and therefore it penalizes/rewards scenarios at both sides of the mean equally, which is the same limitation that is discussed above.
- *Risk-adjusted NPV (RPV)* (Keown *et al.*, 2001): This is defined as the net present value calculated using a risk-adjusted rate of return instead of the normal return rate required to approve a project. However, Shimko (2001) suggests a slightly different definition where the value of a project is made up of two parts, one from the part 'not at risk' discounted using the risk-free return rate, and the part 'at risk' discounted at the fully loaded cash plus risk cost.
- *Real option valuation (ROV)*: Recently, Gupta and Maranas (2004) revisited a real-option-based concept to project evaluation and risk management. This framework provides an entirely different approach to NPV-based models. The method relies on the arbitrage-free pricing principle and risk neutral valuation. Reconciliation between this approach and the above-described risk definitions is warranted.
- *Other advances theories*: Risk evaluation and its management continue to be an object of research. For example, Jia and Dyer (1995) propose a method to weigh risk (defined through the variance and assuming symmetry) against value. These models are consistent with expected utility theory.
- More generally, some define risk as just the probability of an adverse economic event and associate these adverse effects with something other than pessimistic profit levels (Blau and Sinclair, 2001). For example, Blau *et al.* (2000) when analyzing drug development define risk as the probability of having more candidates in the pipeline than available resources, which would result in delays in product launching. While all these are valid risk analyses, they are nonetheless, simplifications that one needs to remember one is doing. The ultimate risk analysis stems from the financial risk curve based on profit of the whole enterprise, as will be explored in more detail in the following text.

Fortunately, computers are available everywhere these days and tools to handle uncertainty and risk are also available: @Risk (Palisade <http://www.palisade.com>), Crystal Ball (Decision Engineering, <http://www.crystalball.com>), Risk Analyzer (Macro Systems, <http://www.macrosysinc.com/>), Risk+(C/S Solutions, <http://www.cs-solutions.com>) among many others. In other efforts, Byrd and Chung (1998) prepared a program for DOE to assess risk in petroleum exploration. They use decision trees. There are some

Excel templates used in chemical engineering classes (O'Donnel *et al.*, 2002). Therefore, there is no excuse anymore for not obtaining the expected net present value or other profitability measures and performing risk analysis by using these tools. Reports available from the web pages cited above indicate that the use of these tools is becoming popular. Its teaching in senior chemical engineering classes should be encouraged. All these Excel-based programs require that one builds the model, like in two-stage programming. Therefore, it is unclear how far one can go with these Excel-based modeling versus the use of two-stage stochastic programming.

#### Conclusions.

- The use of variance should be avoided because it incorporates information from the upside, when in fact one is targeting the downside profit.
- Point measures (VaR, RAROC, beta, etc.) are useful but incomplete. They do not depict what is taking place in the upside profit region and can lead to wrong conclusions.
- Regret analysis is potentially misleading and therefore should be used with caution.
- Chance values on specific constraints are weaker indicators of risk.
- The direct use of the probabilistic definition of risk (given by the cumulative distribution curve) or the closely related concept of downside risk as means of assessing risk is recommended.

#### 12.5.2 Risk Management at the Design Stage

Most of the strategies devoted to manage risk in projects at the design stage target variability. One very popular tool is known as 'six-sigma' (Pande and Holpp, 2001). Companies also make use of 'failure mode effects analysis' (Stamatis, 2003), which is a procedure originated at NASA in which potential failures are analyzed and measures to prevent it are discussed.

To manage risk while using two-stage stochastic models, one can use a constraint, restricting variability, risk itself, downside risk, VaR, etc., or incorporating chance constraints as well as regret functions as done by Ierapetrítou and Pistikopoulos (1994). Constraints including variability are nonlinear and, as discussed above, are not favored anymore. Others have not been attempted (VaR). Next, constraints using risk and downside risk for two-stage stochastic programming are discussed.

Since uncertainty in the two-stage formulation is represented through a finite number of independent and mutually exclusive scenarios, a risk constraint can be written as follows:

$$\text{Risk}(x, \Omega) = \sum_{s \in S} p_s z_s(x, \Omega) \leq R_\Omega \quad (12.18)$$

where  $z_s$  is a new binary variable defined for each scenario as follows:

$$z_s(x, \Omega) = \begin{cases} 1 & \text{If } q_s^T y_s > \Omega \\ 0 & \text{Otherwise} \end{cases} \quad \forall s \in S \quad (12.19)$$

and  $R_\Omega$  is the desired maximum risk at the aspiration level  $\Omega$ . A constraint to manage downside risk can be written in a similar fashion as follows:

$$\text{DRisk}(x, \Omega) = \sum_{s \in S} p_s \delta_s(x, \Omega) \leq \text{DR}_\Omega \quad (12.20)$$

where  $\delta_s(x, \Omega)$  is defined as in equation 12.13 for each scenario and  $DR_\Omega$  the upper bound of downside risk. Note that both expressions are linear. The former includes binary variables, while the latter does not. Since binary variables add computational burden, Barbaro and Bagajewicz (2004a) preferred and suggested the use of downside risk.

Thus, this representation of risk is favored and variability, upper partial mean, regret functions, chance constraints, VaR, and the risk premium are disregarded.

Now, adding the constraints is easy, but picking the aspiration levels is not. In fact, Barbaro and Bagajewicz (2003, 2004a) have suggested that the conceptual scheme is multiobjective in nature. Indeed, one wants to minimize risk at various aspiration levels at the same time as one wants to maximize the expected profit, which is equivalent to pushing the curve to the right. All this is summarized in Figure 12.7.

The (intuitive) fact that lowering the risk at low expectations is somehow incompatible with maximizing profit was formally proven in the engineering literature by Barbaro and Bagajewicz (2004a). In fact, the different solutions one can obtain using the multiobjective approach are depicted in Figure 12.8. Indeed, if only one objective at low aspirations is used ( $\Omega_1$ ), then the risk curve (curve 2) is lower than the one corresponding to maximum profit (SP). A similar thing can be said for curve 3, which corresponds to minimizing the risk at high aspiration levels. Curve 4 corresponds to an intermediate balanced answer. In all cases, one finds that the curves intersect the maximum profit solution (SP) at some point (they are not stochastically dominated by it) and they have (naturally) a lower expected profit.

To obtain all these curves, Barbaro and Bagajewicz (2004a) proposed to solve several goal programming problems penalizing downside risk with different weights, thus obtaining a spectrum of solutions from which the decision maker could choose. They also discuss the numerical problems associated with this technique. Gupta and Maranas (2003a) also suggested the use of this definition of risk, but did not pursue the idea thus

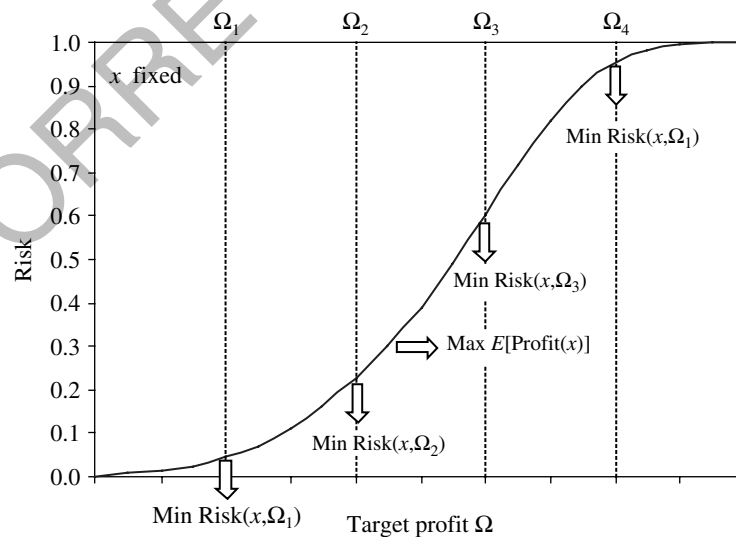
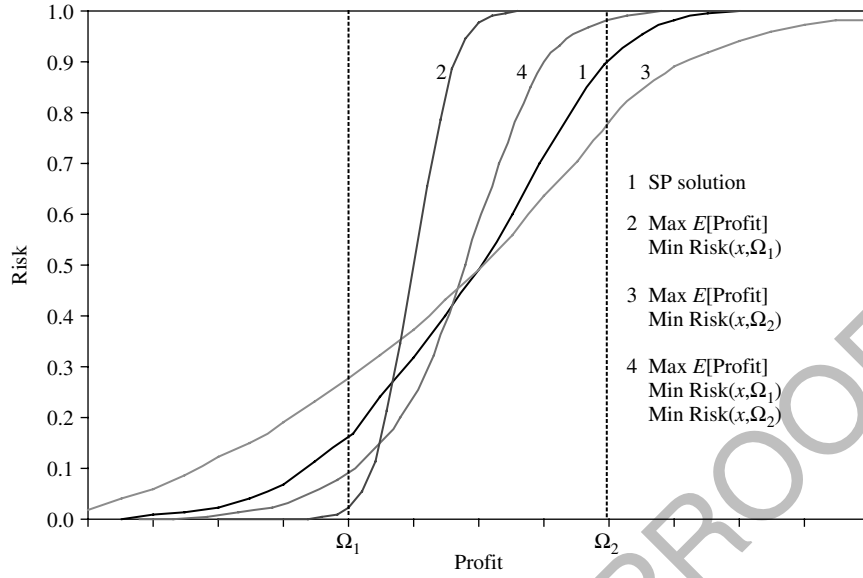


Figure 12.7 Multiobjective approach for risk management



**Figure 12.8** Spectrum of solutions obtainable using a multiobjective approach for risk management

far. Bonfill *et al.* (2004) also showed that maximizing the worst-case scenario outcome renders a single curve (not a spectrum) that has lower risk at low expectations. Conceivably, one can maximize the best-case scenario and obtain the optimistic curve like in case 3 (Figure 12.8).

In practice, after trying this approach in several problems, the technique was proven computationally cumbersome for some cases (too many scenarios were needed to get smooth risk curves) and the determination of a ‘complete’ (or at least representative) risk curve spectrum elusive, because too many aspiration levels need to be tried.

To ameliorate the computational burden of goal programming, an alternative way of decomposing the problem and generating a set of solutions was proposed (Aseeri and Bagajewicz, 2004). This decomposition procedure, which is a simple version of the sampling average algorithm (Verweij *et al.*, 2001), is the following:

- 1) Solve the full problem for each of the  $n_s$  scenarios at a time obtaining a solution  $(x_s, y_s)$ . The values of the first-stage variables  $x_s$  obtained are kept as representative of the ‘design’ variables for this scenario to be used in step c).
- 2) Use the profit of these  $n_s$  solutions to construct a (fictitious) risk curve. This curve is an upper bound to the problem.
- 3) Solve the full problem for all  $n_s$  scenarios,  $n_s$  times, fixing the first-stage variables  $x_s$  obtained in step a) in each case. This provides a set of  $n_s$  solutions  $(x_s, y_{s1}, y_{s2}, \dots, y_{s_{n_s}})$  that constitute the spectrum of solutions.
- 4) Identify the curve with largest expected profit and determine the gap between this curve and the one for the upper bound.
- 5) A (not so useful) lower bound curve can be identified by taking the largest value of all curves for each aspiration level.

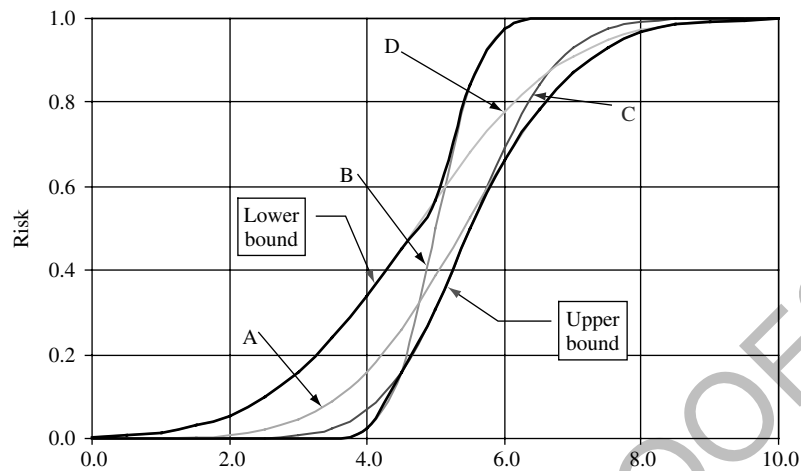


Figure 12.9 Upper bound curve and spectrum of solutions

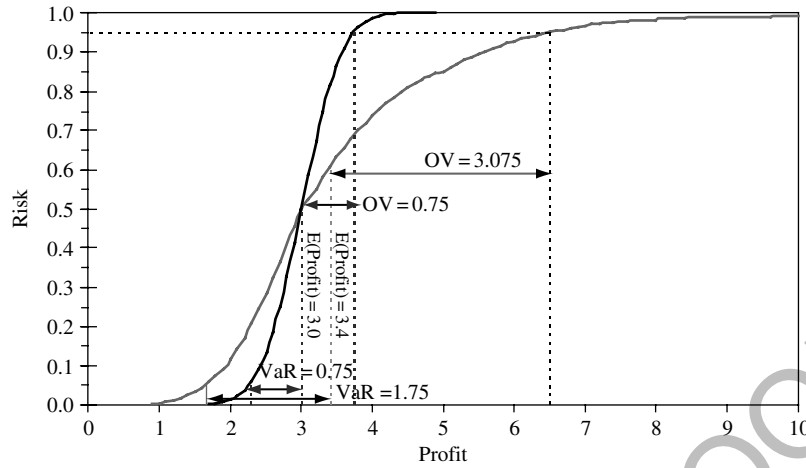
The assumption is that given a sufficiently large number of scenarios, one will be able to capture all possible (or significant) solutions, generating thus the entire spectrum. Figure 12.9 illustrates the procedure for four curves (A, B, C, and D). Design A contributes to the upside of the upper bound risk curve, while design B contributes to 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. One final warning needs to be added: upper bounds can be constructed only if the problems can be solved to rigorous global optimality.

### 12.5.3 Automatic Risk Evaluation and New Measures

All widely used measures of risk are related to the downside portion of the risk curve. In striving to minimize risk at low expectations, they rarely look at what happens on the upside. In other words, a risk averse decision maker will prefer curve 2 (Figure 12.8), while a risk taker will prefer curve 3. In reality, no decision maker is completely risk averse or completely risk taker. Therefore, some compromise like the one offered by curve 4 needs to be identified. Thus, some objective measure that will help identify this compromise is needed. If such a measure is constructed, the evaluation can be automated so that a decision maker does not have to consider and compare a large number of curves visually. Aseeri *et al.* (2004) discussed some and proposed other such measures:

- *Opportunity value* (or *upside potential*), which is defined the same way as VaR but on the upside. OV and VaR are illustrated in Figure 12.10 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, respectively. Considering a reduction in VaR without looking at the change in OV can lead to solutions that are too risk averse.
- The ratio of OV to VaR, which can be used in conjunction with the expected profit to sort solutions out.

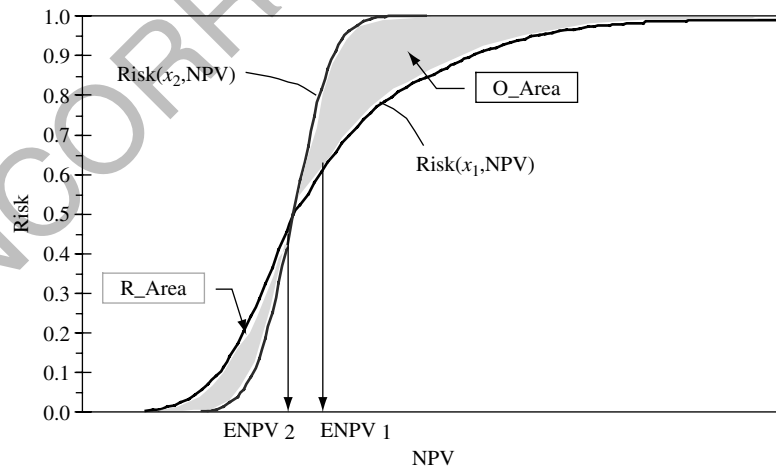




**Figure 12.10** Opportunity value (OV) or upside potential vs. VaR

- The *risk area ratio* (RAR), which is defined as the quotient of the areas between a solution and the maximum expected profit solution (SP). More specifically, it is given by 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 (Figure 12.11):

$$RAR = \frac{O\_Area}{R\_Area} \quad (12.21)$$



**Figure 12.11** Risk area ratio (RAR)

- By construction, the ratio cannot be smaller than 1, but the closer this ratio is to 1, the better is the compromise between upside and downside profit. Note also 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).

#### 12.5.4 Use of Expected Utility Theory

As discussed above, expected utility can be reconciled with the two-stage stochastic framework. For example, if one uses the nonlinear coordinate transformation of real value into utility value given by the utility function (Figure 12.3), one can modify the view of the risk curve, as shown in Figure 12.12. If such utility function can be constructed based more on quantitative relations to shareholder value, then one does not need to perform any risk management at all. One could speculate that it suffices to maximize utility value, but only if one has identified the ultimate objective function associated with the company's optimum financial path. It is worth noting that anything less, like the net present value, which can be considered a utility function too, will require the analysis of different curves before a final choice is made.

#### 12.5.5 Markov Decision Models and Dynamic Programming

This approach, recently suggested by Cheng *et al.* (2003), proposes to rely on a Markov decision process, modeling the design/production decisions at each epoch of the process as a two-stage stochastic program. The Markov decision process used is similar in nature to a multi-stage stochastic programming where structural decisions are considered also as possible recourse actions. Their solution procedure relies on dynamic programming techniques and is applicable only if the problems are separable and monotone. In addition, they propose to depart from single-objective paradigms, and use a multiobjective approach rightfully claiming that cost is not necessarily the only objective and that other objectives are usually also important, like social consequences, environmental impact, process sustainability. Among these other objectives, they include risk (measured by

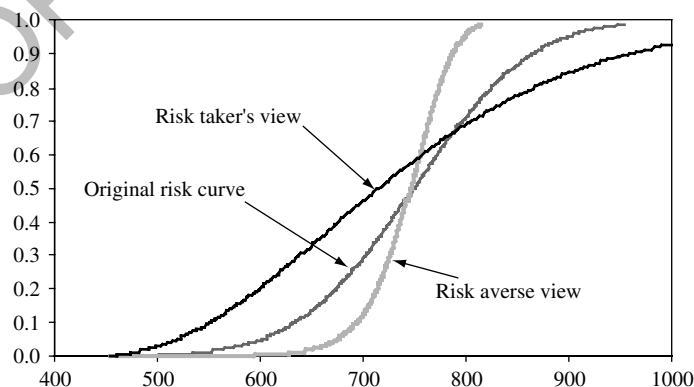


Figure 12.12 Risk curves based on utility functions

downside risk, as introduced by Eppen *et al.*, 1989) and, under the assumption that decision makers are risk averse, they claim it should be minimized. Aside from the fact that some level of risk could be tolerable at low profit aspirations in order to get larger gains at higher ones, thus promoting a risk-taking attitude, this assumption has some important additional limitations. Since downside risk is not only a function of the first-stage decisions but also of the aspiration or target profit level, minimizing downside risk at one level does not imply its minimization at another. Moreover, minimizing downside risk does not necessarily lead to minimizing financial risk for the specified target. Thus, treating financial risk as a single objective presents some limitations, and it is proposed that risk be managed over an entire range of aspiration levels as discussed above. This may present some problems for the dynamic programming approach making two-stage programming more appealing.

#### Conclusions.

- Models with chance or regret constraints are less efficient because they can only generate a subset of the spectrum solutions at best.
- The big difference between this engineering view and that of the economists is that they rely on point measures because they consider risk as the behavior of the distribution at low profit values, while the engineers try to strike a balance at all profit levels.
- Risk management can be best performed by the generation of the spectrum of solutions followed by the identification of the more desirable solutions, as opposed to penalization of stochastic solutions using any measure, including risk directly.
- Such spectrum can be obtained using goal programming, worst-case and best-case scenario maximization, and/or by a decomposition procedure based on the sampling average algorithm.
- The screening of solutions can be best made by looking at the area ratio.
- The use of utility functions, if they can be constructed in direct relation to shareholder value, would eliminate or reduce the need for risk management because the utility function already contains it.

#### 12.5.6 Case Studies

*Gas commercialization in Asia.* Aseeri and Bagajewicz (2004) considered the problem of investing in the distribution and use of gas in the region. Transportation through pipelines (whenever possible), LNG, and CNG ships was considered. The use of GTL technologies to produce gasoline, ammonia, and methanol were also considered. Many producers (Australia, Indonesia, Iran, Kazakhstan, Malaysia, Qatar, and Russia) and buyers in the region (Japan, China, India, South Korea, and Thailand) were considered. The scope of the project extends from the year 2005 to 2030 and the capital investment was limited. The planning model maximized the expected net present value and used the structure of classical planning models under uncertainty (Sahinidis *et al.*, 1989) and the risk analysis was performed using risk curve generation using the decomposition procedure based on the sample averaging method explained above. The solution to the problem included the number of ships that need to be purchased in each period of time, the number, location, and corresponding capacity of the plants to be built and the countries whose demand is to be partially (or fully) satisfied.

For an investment limit 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,

**Table 12.1** Results for stochastic model (200 scenarios). Gas commercialization in Asia

Time period	FCI	Processing facilities				Transportation to:				Avg. 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

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

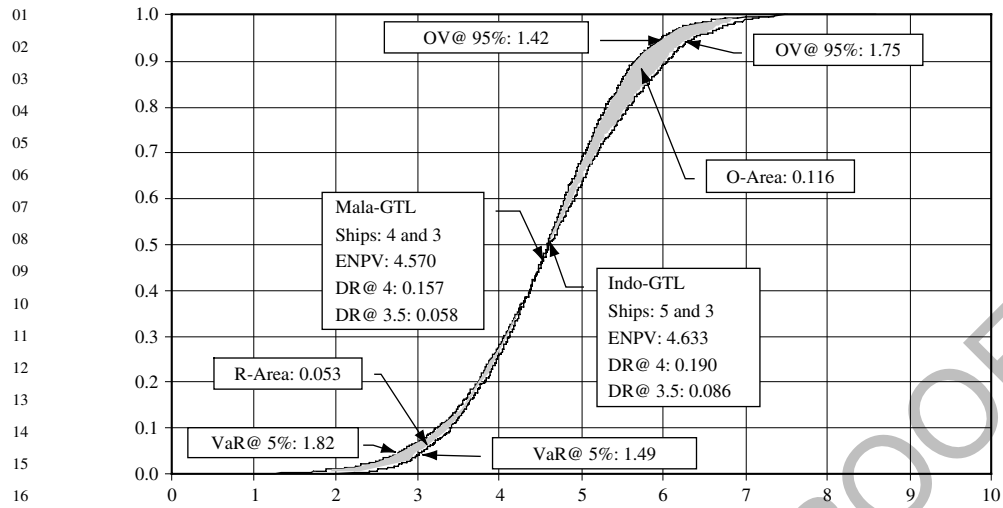
the model gave the results shown in Table 12.1. The first part of the table (processing facilities) shows the existing (available) capacities. The fixed capital investment (FCI) appears on the time period prior to capacity increases because of construction time (4 years). The required gas feed amounts are indicated on the 'Feed' column in billion SCF/year. Also the numbers of ships available for transportation are indicated in the 'Ships' column.

Thus, a GTL plant should be built in Indonesia in the first time period with a capacity of 4.43 million tons/year and five ships are to be built/purchased for the transportation of the GTL product. An expansion in the third time period to increase the capacity to 7.18 million tons/year as well as the purchase of three additional ships is suggested. The second part of the table (transportation) shows the number of ships that are assigned to transport products to different markets as well as the yearly flow of transported products (fractional ships should be understood as fractions of the year that each ship is allotted to a certain route). Not all the investment is utilized in the third period, which is explained by the fact that increased capacity leads to the need of more ships, money for which is not available.

When downside risk at 3.5 billion dollars is penalized, a design that reduces risk and does not have a large effect on ENPV was obtained. The design obtained is illustrated in Table 12.2. This result also suggests a GTL process, but at another supplier location

**Table 12.2** Results for stochastic model (200 scenarios) with downside risk at \$B 3.5 minimized. Gas commercialization in Asia

Time period	FCI	Processing facilities				Transportation to:				Avg. 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



**Figure 12.13** Comparison of risk curves for gas commercialization in Asia

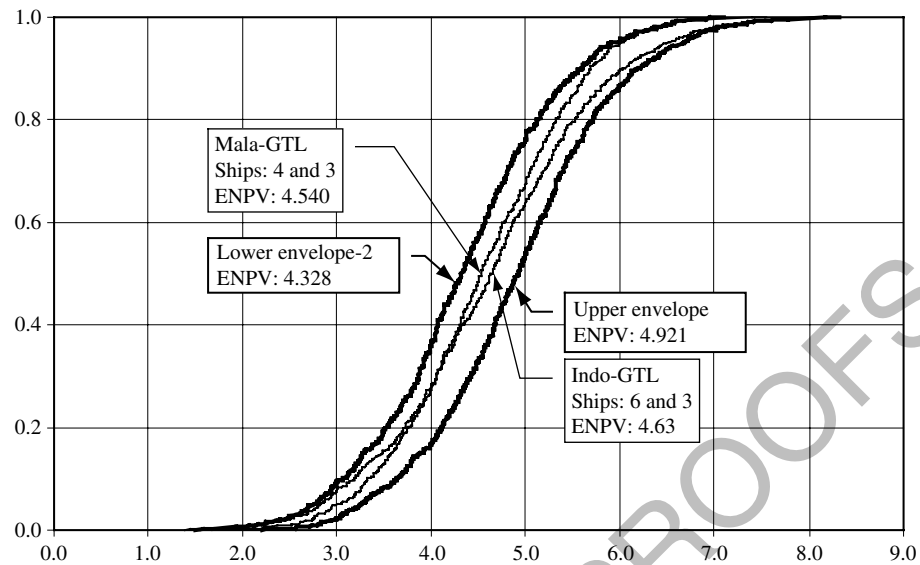
(Malaysia). Investment in Malaysia manages to reduce risk over that in Indonesia due to the lower volatility of natural gas prices in Malaysia. Figure 12.13 compares the risk curves and shows values of VaR and OV. Table 12.3 compares the risk indicators more closely. The VaR reduces from 18.1% but the OV (UP) reduces 18.9% and the risk area ratio (RAR) is equal to 2.2. This means that the loss in opportunity is more than twice the gain in risk reduction. The application of the decomposition procedure rendered similar solutions to those obtained using the full stochastic model. The use of regret analysis in this case produced similar but slightly less profitable answers.

Figure 12.14 shows the upper and lower bound risk curves 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 89.4% of its points were mainly contributed by one single bad design. When this design was excluded, a tighter and more practical lower bound risk curve was obtained, which is the one depicted.

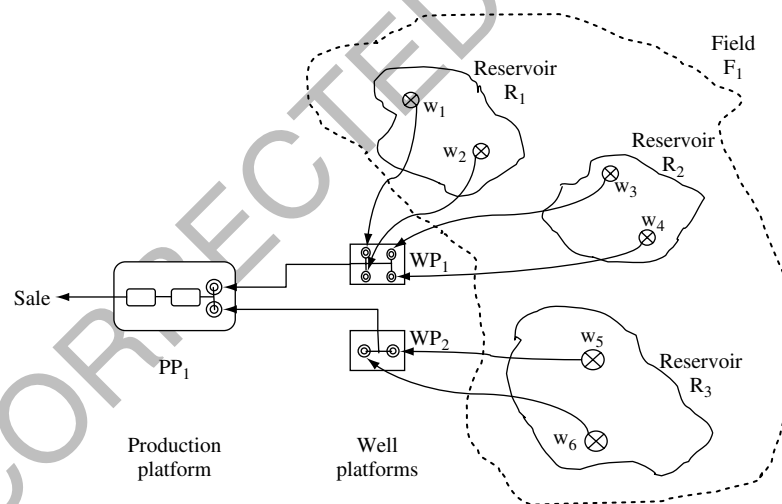
**Offshore oil drilling.** Aseeri *et al.* (2004) considered the problem of scheduling the drilling of wells in offshore reservoirs and planning their production using a basic model similar to that of Van den Heever *et al.* (2000). Uncertainties in reservoir parameters (productivity index) and oil price were considered. In addition, budgeting constraints tracing cash flow and debts were added. One field consisting of three reservoirs was assumed (Figure 12.15). In each reservoir two wells can be drilled for which estimates

**Table 12.3** Value at risk for the alternative solutions. Gas commercialization in Asia

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

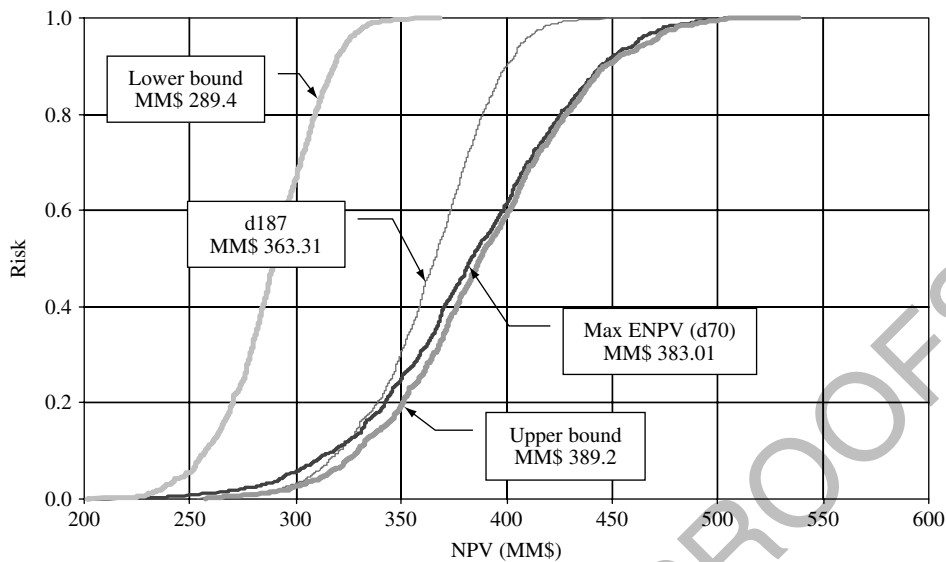


**Figure 12.14** Upper and lower bound risk curves for gas commercialization in Asia



**Figure 12.15** Offshore drilling superstructure

of the drilling cost as well as the expected productivity index are assumed to be known. The wells in reservoir  $R_1$  and  $R_2$  can be connected to a well platform  $WP_1$  and the wells in reservoir  $R_2$  can be connected to well platform  $WP_2$ . Both well platforms are to be connected to a production platform in which crude oil is processed to separate gas from oil and then oil is sent to customers. The objective of this problem is to maximize the net present value of the project. The decision variables in the model are reservoir choice,



**Figure 12.16** Solutions and bounds for the offshore drilling case study

candidate well sites, capacities of well and production platforms, and fluid production rates from wells. The problem is solved for a 6-year planning horizon with quarterly time periods (24 time periods).

Applying the decomposition procedure described above, the solutions and the corresponding bounds shown in Figure 12.16 were obtained. The gap between the optimal solution and the upper bound is less than 1.6%. The production rates and reservoir pressure profiles are, of course, different. The maximum profit solution opens production of wells w6, w5, none, w3, w4, w2, w1 in months three through nine, respectively. The alternative less risky design opens production of wells w3, w4, w1, w2, none, w6, w6 in the same months. Platforms are built in one time period before the wells are opened.

In the less risky solution, VaR reduced from 87.12 to 55.39 or 36.4% and OV reduced from 78.81 to 45.19 or 42.7%. The resulting RAR is 16.4. This is an indication of how significant the reduction in opportunity is compared to the small reduction in risk.

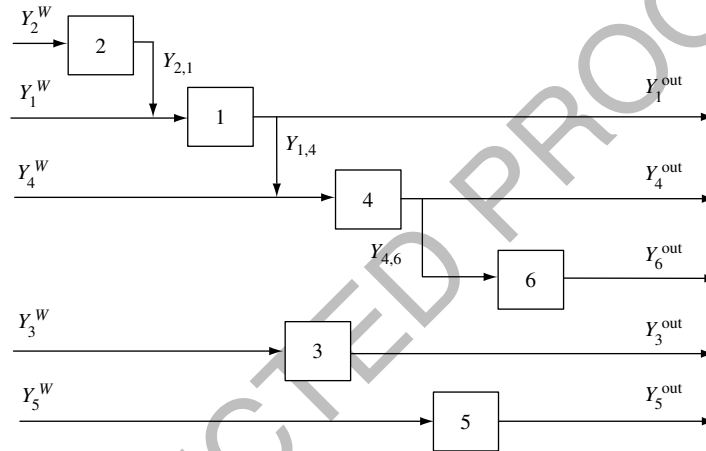
**Design of water networks.** Koppol and Bagajewicz (2003) considered the problem of designing water utilization networks. Water is used in many operations, mainly washing, or as direct steam in process plants. Water is put in contact with organic phases from which the contaminants are extracted. Such water utilization systems consist of networks of water reuse and partial regeneration, aimed at the reduction of cost. A review article by Bagajewicz (2000) offers a detailed description of the different reuse and regeneration schemes that have been proposed, as well as the variety of solution procedures proposed. In addition, Koppol *et al.* (2002) discuss zero liquid discharge cycles.

The problem consists of determining a network of interconnections of water streams among the processes so that the expected cost is minimized while processes receive water of adequate quality, with or without change of flows. Thus, one is allowed to reuse wastewaters from other processes, diluting it with fresh water if there is a need for it

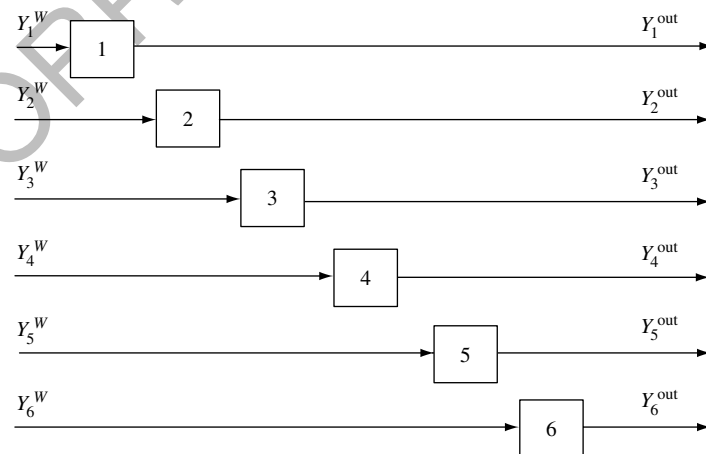
and eventually placing a treatment process between uses. The uncertainty in this case comes mainly from the contaminant loads that the water will pick up in each process.

One single-contaminant example involving six water using processes and solved by Koppol and Bagajewicz (2003) assumes 20% uncertainty for the contaminant loads and capital costs that are comparable to reductions in operation cost achieved by using reuse connections. The effects of financial risk considerations are illustrated by showing two results, one minimizing costs (Figure 12.17) and the other minimizing risk (Figure 12.18).

The corresponding risk curves are depicted in Figure 12.19. Note that the risk curves are inverted because this problem pursues minimization of cost and not maximization of profit. Second, the minimum cost solution reduces operating costs (consumes 107.5 ton/h of fresh water), while the risk reduced solution reduces capital cost of interconnection

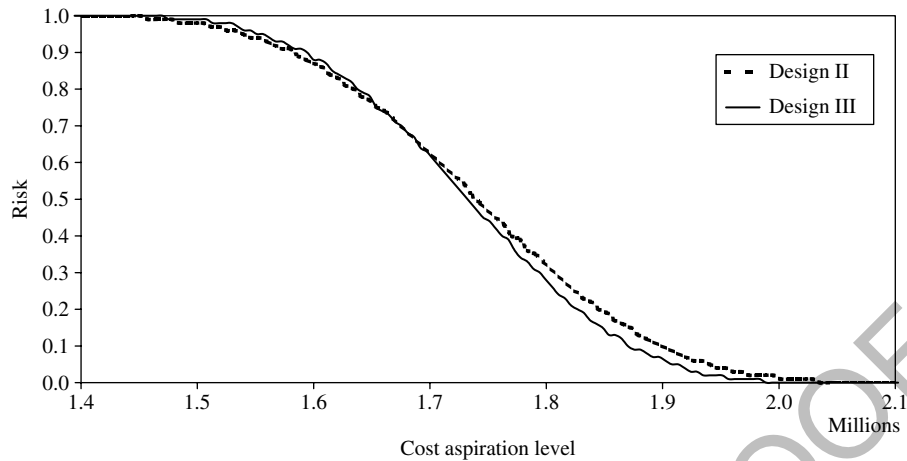


**Figure 12.17** Minimum expected cost water network



**Figure 12.18** Minimum risk water network





**Figure 12.19** Risk curves for water networks

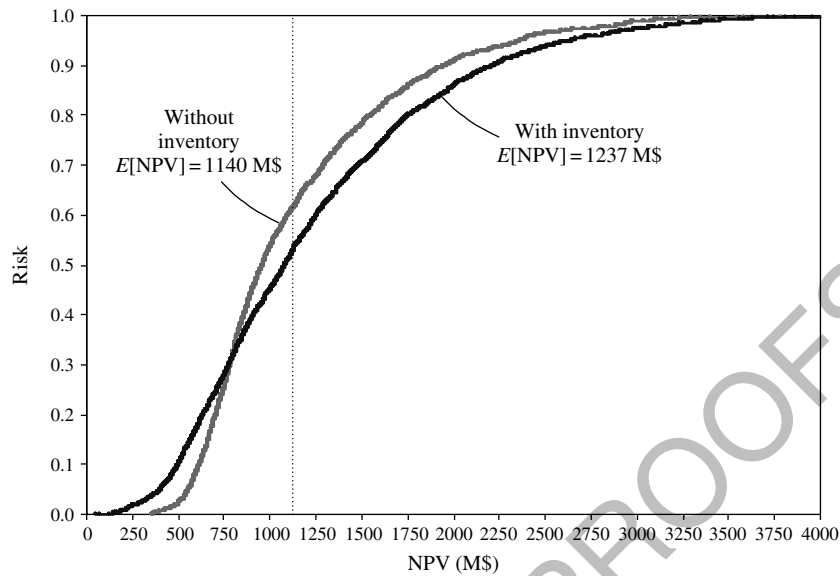
pipings and has a larger freshwater consumption (134.9 ton/h). The latter has a slightly higher cost (1.74 vs. 1.73 million dollars/year). One important thing to point out from these solutions is that the less risky solution makes no reuse of spent water, that is, it says one should not build any network of interconnections

*Planning of the retrofit of heat exchanger networks.* Barbaro and Bagajewicz (2003) considered the problem of adding area and heat exchangers between different plants to help save energy in the total site. This is a typical retrofit problem, with the exception that they also address how the placement of new units should be scheduled through time. The uncertainty considered is in the price of energy. The first-stage decisions are the schedule of additions of exchangers and the second-stage decisions consist of the energy consumption of the different units. The possibilities of reducing throughput because of the lack of installed capacity are taken into account. Results on small-scale examples show that financial risk considerations motivate changes in the decision making.

## 12.6 Effect of Inventories on Financial Risk

It is common accepted knowledge that inventory hedges from price, availability, and demand variations, and their impact on the profitability of the operations. It is also known that maintaining such inventory has a cost, both capital and operative. That risk is automatically reduced is not necessarily true unless risk is managed specifically as it is briefly shown next. Contrary to the assumption that operating at zero inventory (produce to order) always increases profit, it will be also shown that inventories do not represent a reduction in expected profit.

Barbaro and Bagajewicz (2004b) showed how the hedging effect of inventories can be better appreciated through the analysis of the risk curves. They presented an extension of the deterministic mixed-integer linear programming formulation introduced by Sahinidis *et al.* (1989) for planning under uncertainty. The model considers keeping inventories



**Figure 12.20** Solutions of investment planning in process networks (with and without inventory)

of raw materials, products, and intermediate commodities when uncertain prices and demands are considered. Details of the planning solution are omitted here, concentrating on the analysis of the risk curves. Figure 12.20 compares the solutions with and without the use of inventory. It is apparent from the figure that

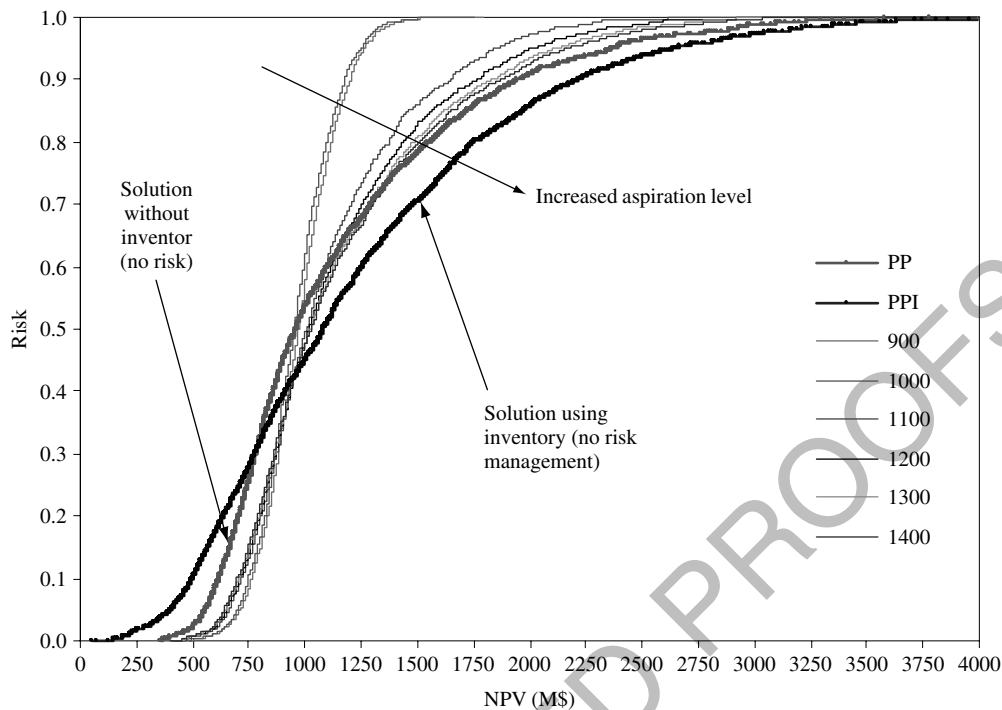
- the solution that makes use of inventory has higher expected profit, which is contrary to existing perceptions;
- risk exposure at low aspiration levels is higher when inventory is considered.

In turn, Figure 12.21 shows the spectrum of solutions obtained using downside risk through goal programming. In this spectrum, several solutions that reduce risk even compared to the solution not using inventory can be found. Thus:

- Solutions do not increase opportunities for high profit. The risk area ratio is expected to be large, more of a reason to watch the curve and not rely on point measure indicators.
- The usual perception that inventory helps reduce risk is confirmed, *but it requires risk to be specifically managed*.

Interestingly, many articles devoted to inventory risk, especially in management science, consider variance as a measure of risk (Gaur and Seshadri, 2004) and proceed consequently. While there are many other intricacies behind the relationship between inventories, risk hedging, and expected profit that engineers have not yet grasped, the use of variance constitutes the first head-on collision between both approaches.

In addition, by focusing on how external factors (product demand, prices, etc.) translate into changes in a company's assets through a two-stage stochastic programming approach, the decision maker can manage risk and also uncover several strategic options such as capacity integration (Gupta *et al.*, 2000).



**Figure 12.21** Spectrum of solutions of investment planning in process networks (with and without inventory)

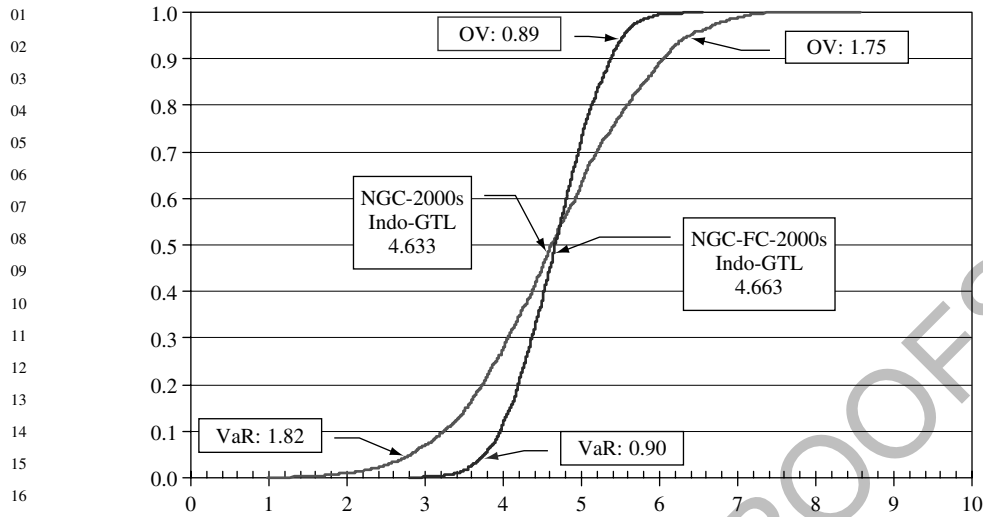
## 12.7 Effect of Contracts and Regulations in Project Planning

### 12.7.1 Regular Fixed 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 when prices are uncertain is to use long-term fixed-price contracts especially with raw material suppliers but also with consumers downstream of the supply chain. However, the risk arising if the spot market price for natural gas turns to be, in average, less than the fixed contract price cannot be avoided (Derivatives and Risk Management, EIA, 2002). This is addressed below by option contracts.

Aseeri and Bagajewicz (2004) illustrated the effects of contracts using the problem of commercializing gas in Asia (outlined earlier). Natural gas prices were assumed to have fixed prices at the supplier location at their mean values. The risk curves are shown in Figure 12.22. We summarize the results as follows:

- For this case, the difference of expected profit is very small. Actually the plan that uses contracts is slightly higher profit (0.6%), but it is unclear if this is a real gain or just a numerical effect. The solution with contracts chooses the same locations as the one without contracts but different capacities.



**Figure 12.22** Effect of fixed price contracts on gas commercialization in Asia

- Risk is substantially reduced (about 50% reduction in VaR), but OV also reduces by roughly the same amount. Thus, contracts have a hedging effect from bad scenarios, but also prevents high profit to materialize in optimistic scenarios.
- Contracts have a larger risk reduction effect compared to plain risk management without using them. This can be seen by comparing with Figure 12.14.

### 12.7.2 Effect of Option Contracts

*Futures* and *option* contracts are often referred as *derivatives* (Hull, 1995). A futures contract is an agreement to buy or sell an asset at a certain time in the future for a certain price. In turn, there are two basic kinds of option contracts: calls and puts. A call option gives the holder the right to buy an asset by a certain date and for a certain price. On the other hand, a put option gives the holder the right to sell an asset by a certain date and for a certain price. These contracts are traded daily in many exchanges such as the Chicago Board of Trade (CBOT), the Chicago Mercantile Exchange (CMB), the New York Futures Exchange (NFE), and the New York Mercantile Exchange (NYMEX) among others. These derivatives are agreed and the option holder party pays a premium (option cost) to gain the privilege of exercising his/her options. 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 the case of gas commercialization in Asia the market price is the mean expected price of gas. If the two are equal then the intrinsic value is 0. 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).

Barbaro and Bagajewicz (2004b) introduced specific constraints that can be used in the context of two-stage stochastic investment planning models. Similarly to fixed contracts the usual assumption that option contracts hedge automatically risk at low profit levels is not always true. Specific risk management is required.

Aseeri and Bagajewicz (2004) showed that risk curve analysis can be also used to determine the right premium to pay depending on what side of the negotiation one is. Figure 12.23 shows the risk curves for the results of a stochastic model run using different premium 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, that is, it considerably increases the profit at almost all scenarios. The results with 4%, 6%, and 8% could be acceptable to the supplier since they have significant chance of success. Any price greater than 8% is not attractive to the buyer. They also run the model penalizing downside risk, showing that indeed, risk can be also managed. In fact, option contracts can produce a 38% reduction of VaR with a small reduction in risk area ratio (RAR), much smaller than the case of fixed contracts (although these last ones reduce VaR by 50%), all at the same value of expected profit. Thus,

- option contracts do not automatically reduce risk and require risk management;
- they are excellent tools to reduce risk at low profit expectations, maintaining upside potential (UP or OV).

Rogers *et al.* (2002, 2003) discuss the use of real options in pharmaceutical R&D projects, Gupta and Maranas (2003b) discuss the use of emission option contracts in the technology selection for pollution abatement, and Rico-Ramirez *et al.* (2003) use real options in batch distillation. Gupta and Maranas (2003b) recognize that variance cannot be used for risk management because of its symmetric nature, but we should give credit to Ahmed and Sahinidis (1998) for pointing this out first. Finally, the finance community has proposed means to manage risk through real options (Dixit and Pindyck, 1994; Trigeorgis, 1999).

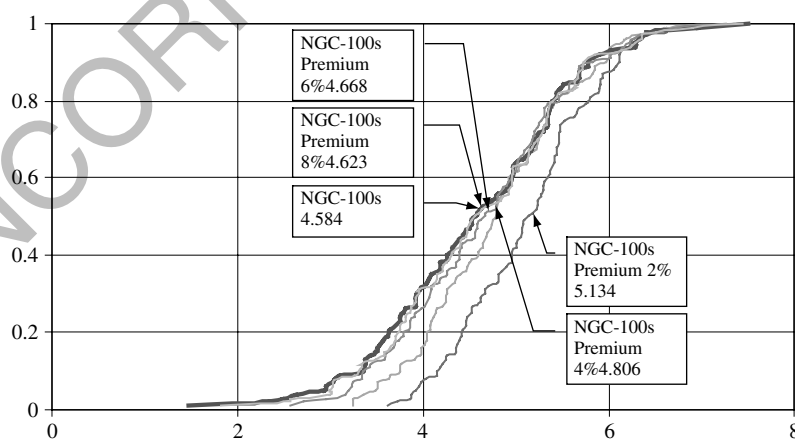


Figure 12.23 Effect of derivative premium on gas commercialization in Asia

### 12.7.3 Effect of Regulations

In a recent article Oh and Karimi (2004) explore the effect of regulations (bilateral and multilateral international trade agreements, import tariffs, corporate taxes in different countries, etc.) on the capacity expansion problem. They point out that barring the work of Papageorgiou *et al.* (2001), who explore the effect of corporate taxes in the optimization of a supply chain for a pharmaceutical industry, very little attempt has been made to incorporate other regulatory issues in the capacity expansion problem. However, they point out to other attempts in location-allocation problems and in production-distribution problems (Cohen *et al.*, 1989; Arntzen *et al.*, 1995; Goetschalckx *et al.*, 2002), which include tariffs, duty drawbacks, local content rules, etc. for a multinational corporation.

## 12.8 Integration of Operations Planning and Budgeting

Cash flow needs to be managed at the first stage, not at the second stage. This is contained in the pioneering work of Badell and Puigjaner (1998), Badell and Puigjaner (2001a,b), Romero *et al.* (2003a,b), and Badell *et al.* (2004). In these articles, the group of Professor Puigjaner establishes the links between procuring, financial management, and manufacturing, that is, proposes the use of models that break the walls existing between these three entities. Basically, deterministic cash flow is considered at the same time as scheduling of operations, batch plants in this case. The articles provide also some background on the literature of cash management models and the need to use and integrate them. More specifically, Romero *et al.* (2003a) propose the merging of scheduling and planning with cash management models (Charnes *et al.*, 1959; Robichek *et al.*, 1965; Orgler, 1970; Srinivasan, 1986). Their model shows that the profit increases by considering these activities together because procuring does not buy expensive raw materials too early in the process. The integrated approach, instead, proposes to rearrange the schedule to accumulate some cash to buy these expensive raw materials. The root of the difference is not only better cash management, but also a departure from Miller and Orr's (1966) model (Figure 12.24), where it is recommended to borrow or buy securities, only when a lower or upper bound is reached. A flat profile, like the one in Figure 12.25,

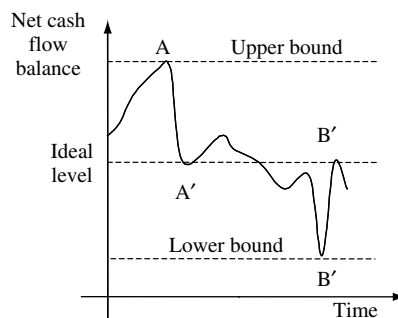


Figure 12.24 Miller and Orr's cash management model

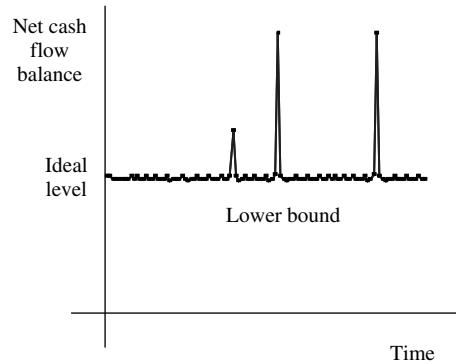


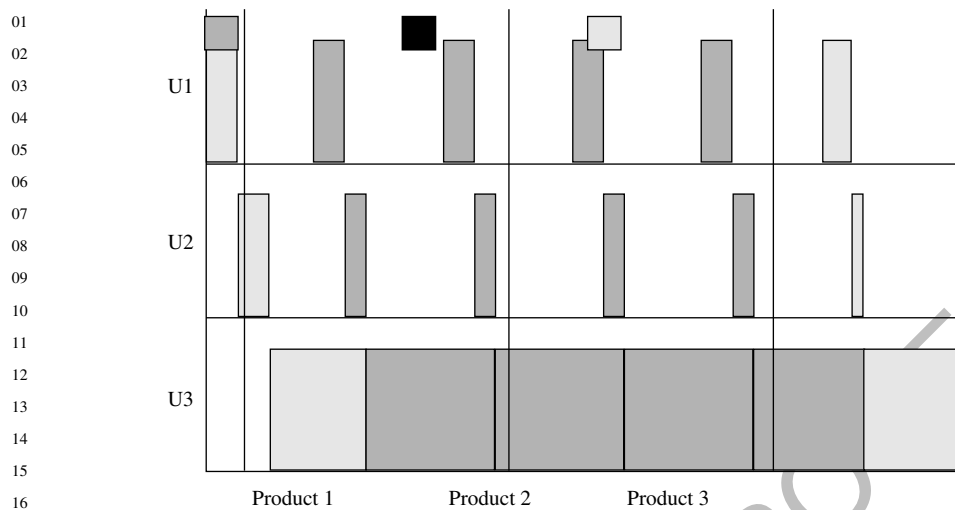
Figure 12.25 Ideal cash flow model

is desirable, and achievable only with the integrated model. In this flat profile, one only sees spikes due, for example, to the short span between the inflow of cash and the buying of securities. As one can see, no downward spikes are observed because the outflow of money can be planned.

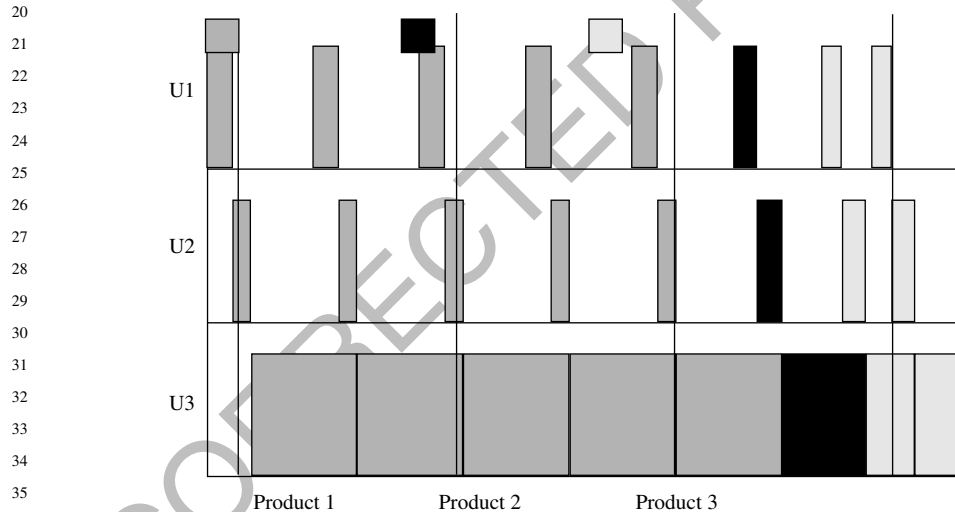
Romero *et al.* (2003a) also present preliminary work where the above ideas are also extended to consider uncertainty and financial risk. Some sort of budgeting, although not full cash management, was considered by Van den Heever *et al.* (2000) where royalty payments are taken into account in the offshore drilling problem. Although royalties were not included, full cash management with uncertainty was considered by Aseeri *et al.* (2004) for the same offshore oil drilling problem, results of which have been outlined above. Van den Heever and Grossmann (2000) proposed an aggregation/disaggregation method to solve the problem. The same group of researchers added tax and royalty calculations to the problem, which increased its numerical complexity (Van den Heever *et al.*, 2000) and studied the use of big-M constraints as well as disjunctive programming. Finally, Van den Heever *et al.* (2001) proposed a Lagrangean decomposition procedure.

## 12.9 Integration of Operations Planning and Pricing

Guillén *et al.* (2003a) suggested that pricing policies considered in an integrated manner with scheduling decisions (integration of manufacturing and marketing) increase profit. They discuss the existing models for pricing and point out that the supply curve, which is dependent on manufacturing costs, can be altered. In other words, altering the production schedule should and indeed does have an effect on the fixed costs per unit used in existing classical pricing models (Dorward, 1987; Mas-Collé *et al.*, 1995). They assumed an iterative model in which product prices are first fixed to obtain a schedule, which in turn can be used again in an iterative manner to obtain new product costs which enable the calculation of new process. They showed that this model not always converges. Moreover, an alternative model in which process and production schedules are obtained simultaneously is proposed. The integrated model, they show, produces different schedules and prices and allows larger profits. Indeed, for a case of three products, the iterative



**Figure 12.26** Gantt chart using the iterative method for scheduling and pricing

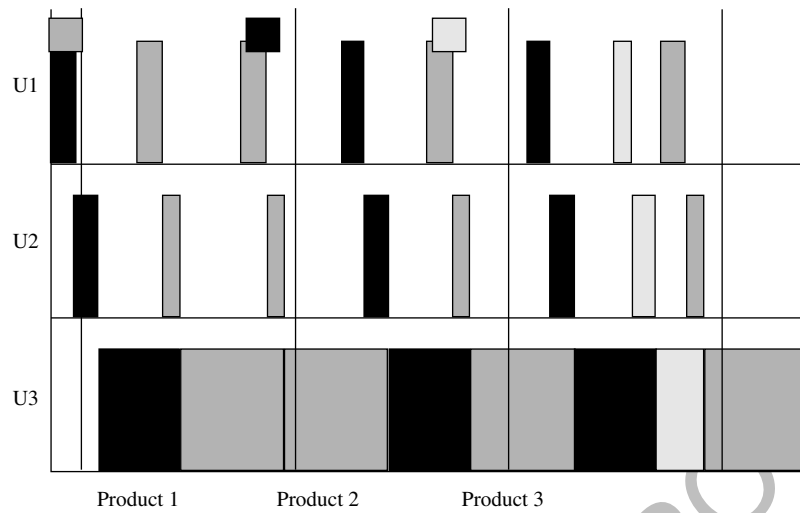


**Figure 12.27** Gantt chart using the integrated model for scheduling and pricing

model renders the Gantt diagram of Figure 12.26 and the integrated model renders the one in Figure 12.27, both choosing different process and the latter having almost twice the profit of the former. In these diagrams, the corresponding product produced in each stage is shown on top of each batch.

In addition, they consider uncertainty in the demand–price relation parameters. Thus, they build a stochastic model, in which processes are first-stage decisions, not parameters as it is common in batch scheduling models, and sales are second-stage variables. The model renders different schedules and prices (Figure 12.28). The resulting schedule

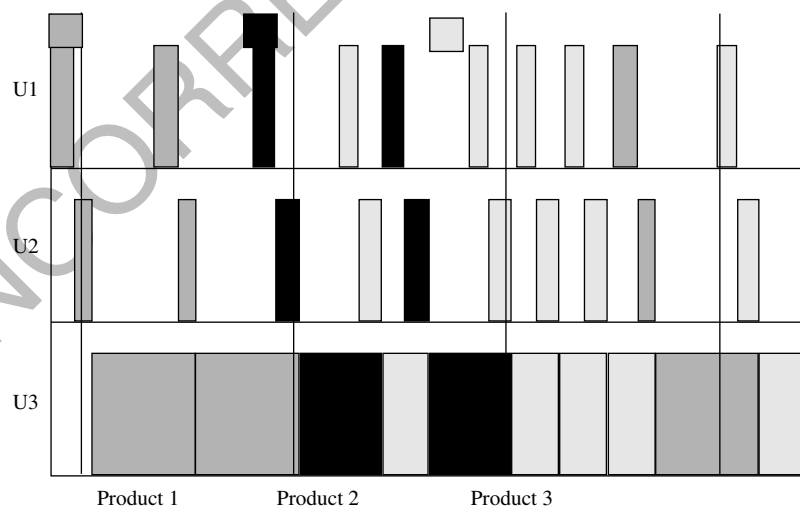




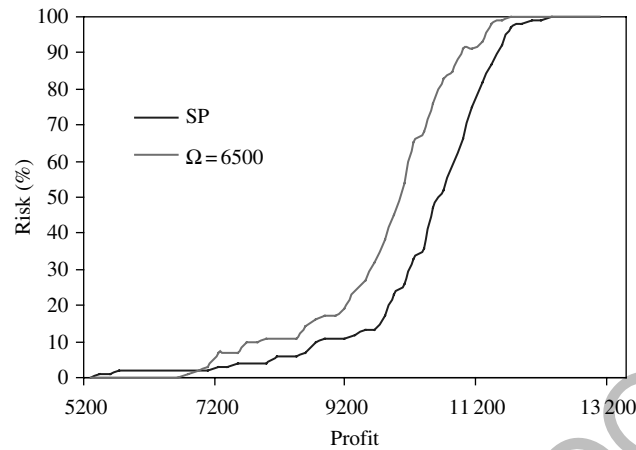
**Figure 12.28** Gantt chart for the stochastic case for scheduling and pricing

implies a mixed product campaign and not a single product campaign as occurred in the deterministic case. This schedule seems to be more robust.

In order to show the capability of the proposed formulation of risk management, the problem is modified so as to reduce the risk associated at low targets. The Gantt chart corresponding to one solution with lower risk and consequently lower expected profit is shown in Figure 12.29. The risk curves of both the stochastic solution (SP) and the one with lower risk are shown in Figure 12.30. The risk at low expectations (profits under a target of \$6500) was reduced to 0.



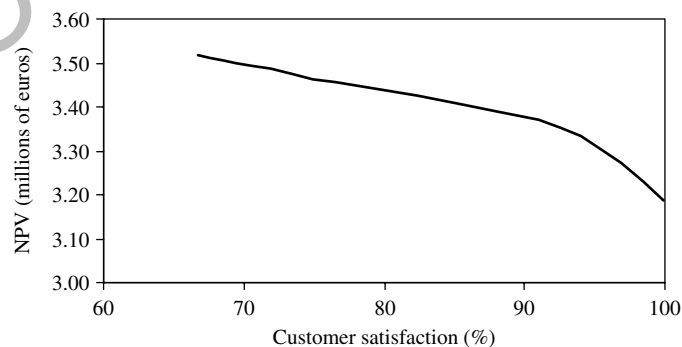
**Figure 12.29** Gantt chart for the risk managing solution for scheduling and pricing



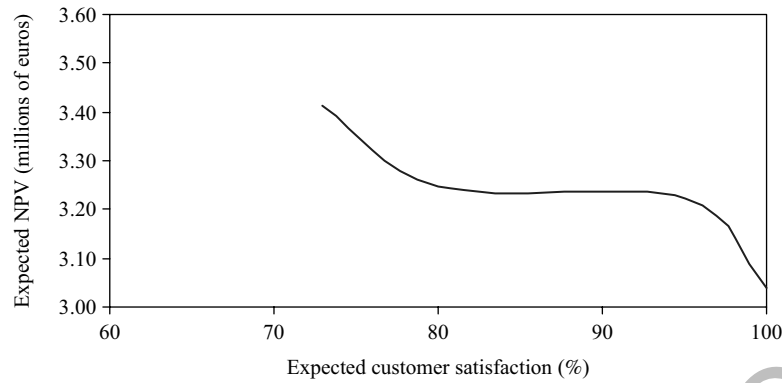
**Figure 12.30** Risk curves for scheduling and pricing

## 12.10 Consumer Satisfaction

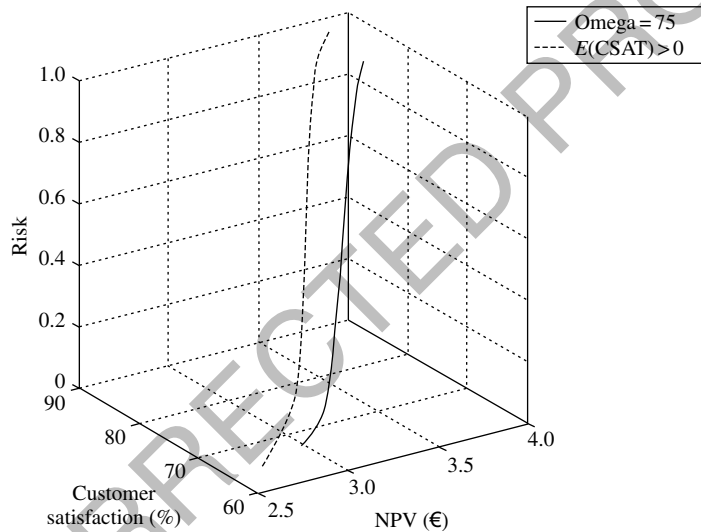
Consumer satisfaction was considered in conjunction with supply chain management by Tsiakis *et al.* (2001). They measure it using the quotient between sales and demand. Guillén *et al.* (2003b) study a similar problem, a supply chain with warehouses, markets, and distribution centers. Instead of constraining the customer satisfaction, they assume a multiobjective model and construct a Pareto surface. They also solve a stochastic model where demands are uncertain, the opening of plants/warehouses is first-stage variables and the sales are second-stage variables. The two resulting Pareto curves are different (Figures 12.31 and 12.32) revealing the need for stochastic models. Moreover, they define customer satisfaction risk and discuss the interrelation between three different objectives: NPV, customer satisfaction, and financial risk. Finally, they define compounded risk and evaluate it through composite curves (Figure 12.33).



**Figure 12.31** Deterministic Pareto curve profit–customer satisfaction



**Figure 12.32** Stochastic Pareto curve profit–customer satisfaction



**Figure 12.33** Composite financial and consumer satisfaction risk curves

## 12.11 Product Engineering and Process Engineering

In recent years, several authors advocated that process system engineers should pay increased attention to a new paradigm, that of product design, one eventually (and apparently) opposed to process design (Westerberg and Subramanian, 2000; Cussler and Moggridge, 2001). The suggestion, although implicit, is that process engineering is a mature field, while product design is a relatively virgin field, at least virgin from the use of tools and methods of the PSE community. One good example of efforts following the suggested path is the article by Wibowo and Ng (2001), who analyze the issues associated with the fabrication of creams and pastes. We already mentioned in the preceding text several articles dealing with drug development, which are in fact product

**Table 12.4** Process design versus product design  
(taken from Cussler, 2003)

Process design	Product design
1. Batch vs. continuous	1. Customer need
2. Input/Output	2. Idea generation
3. Recycles	3. Selection
4. Separation/Heat	4. Manufacture

design. Following the same trend, Cussler (2003) illustrates some of the differences between the two paradigms (Table 12.4). To do the comparison he uses the so-called conceptual design paradigm (Douglas, 1988), which is very similar to the onion model (Smith and Linnhoff, 1988; Smith, 1995), and is widely used. This is the order that many books on process and product design follow (Seider *et al.*, 2004). There are of course other approaches to process design, like the reducible superstructure approach (best represented by the book of Biegler *et al.*, 1997). The table, nonetheless, has a couple of interesting features.

- 1) Makes product design the center.
- 2) Suggests *ad hoc* idea generation and selection steps that presumably vary from product to product, for which a systematic search is not available or has to be constructed case by case (Cussler and Moggridge, 2001). We have seen examples on searches driven by functionalities (refrigerants, drugs, etc.) like those performed by Camarda and Maranas (1999) and Sahinidis and Tawarlamani (2000) and also described by Achenie *et al.* (2002).
- 3) In fact, some who advocate product design (Cussler and Moggridge, 2001) only call it chemical product design, which rules out mechanical and electronic and electromechanical devices, etc. In fact, it is only a matter of time until this expands to all products. Evans (2003), for example, has recently emphasized the upcoming integration between the process industries as providers of commodities and the discrete industries the providers of package goods, devices, appliances, automobiles, etc.
- 4) Its title suggests that these are somehow opposite and to an extent excluding activities.

Recently, Stephanopoulos (2003) reemphasized the idea of product design and suggested that manufacturing is indeed migrating from process (commodity)-centric to product-centric, all this judged by the performance of the companies in the stock market. He suggests that a company should maximize value-addition through the supply chain and that while the process-centered industry focuses on commodities, the product-centered industry focuses on identification of customer needs as a driving force. He asks whether 'Process Systems Engineering is prepared to engineer (design and manufacture) products, or someone else should do it?' One must wonder whether he refers to the role of chemical engineers in all end-user products, not only chemical products.

In parallel to this push for extending the borders of chemical process systems engineering to areas that have been traditional to industrial engineers, a new concept of supply chemical chain was recently discussed in detail by Grossmann and Westerberg (2000), and in the United States National Academies report by Breslow and Tirrell (2003). The chemical supply chain extends from the molecule level to the whole enterprise. Breslow and Tirrell (2003) suggest that

Another important aspect in the modeling and optimization of the chemical supply chain is the description of the dynamics of the information and material flow through the chain. This will require a better understanding of the integration of R&D, process design, process operation, **and business logistics**. The challenge will be to develop quantitative models that can be used to better coordinate and optimize the chemical enterprise. Progress will be facilitated by new advances in information technology, particularly through advances in the Internet and by new methods and mathematical concepts. Advances in computer technology will play a central role. Fulfilling the goal of effectively integrating the various functions (R&D, design, production, logistics) in the chemical supply chain will help to **better meet customer demands**, and effectively adapt in the new world of e-commerce. Concepts related to planning, scheduling, and control that have not been widely adopted by chemical engineers should play a prominent role in the modeling part of this problem. Concepts and tools of computer science and operations research will play an even greater role in terms of impacting the implementation of solutions for this problem. (The bold and underline was added)

The report cites the need of 'integration of several parts of the chemical supply chain', which 'will give rise to a number of challenges, such as multi-scale modeling for molecular dynamics, integration of planning, scheduling and control (including Internet based), and integration of measurements, control, and information systems', but falls short of discussing the full integration with economics management and business.

It is here suggested that:

- 1) Process engineering, which is mistakenly associated with the production of commodities, is an integral part of product design. Product design cannot exist without process design. So there is no antagonism of any sort.
- 2) When the chemical supply chain is considered in the context of process design, one realizes that the chemical supply chain contains many of the elements of product design. Indeed, it deals with the chemistry, the selection, the manufacturing, and the supply chain of entire enterprises, single- or multi-company, as in the alliances that Stephanopoulos (2003) suggested, that deliver the product to the customer.

Thus, product design, the newly proposed paradigm, can be constructed by putting marketing (idea generation and other tools) in front of the chemical supply chain, recognizing that process systems engineering is an essential tool used in the chemical supply chain and putting the customer and the market at both ends of the supply chain, upfront as an object of study for its needs and potential responses, and at the other end as the entity that shapes the demand and provides the feedback (Figure 12.34). Or perhaps, the chemical supply chain box needs to be broken apart into smaller pieces, each of one interacting with the rest in different forms.

Some elements addressing how one might address all these decision-making processes are described by Pekny (2002) who explores the role of different algorithm architectures in large-scale engineering problems.

We notice that in the figure the interactions are in both directions, suggesting that there is no sequential approach, as Cussler would suggest, but rather the notion that, since all activities influence each other, we ought to consider them simultaneously. We have also added some dotted line boxes to indicate that integrated models already exist between the different segments. Noticeably, the upfront identification of customer needs is not yet integrated with the rest of the activities. There is therefore a need for modeling in this area.

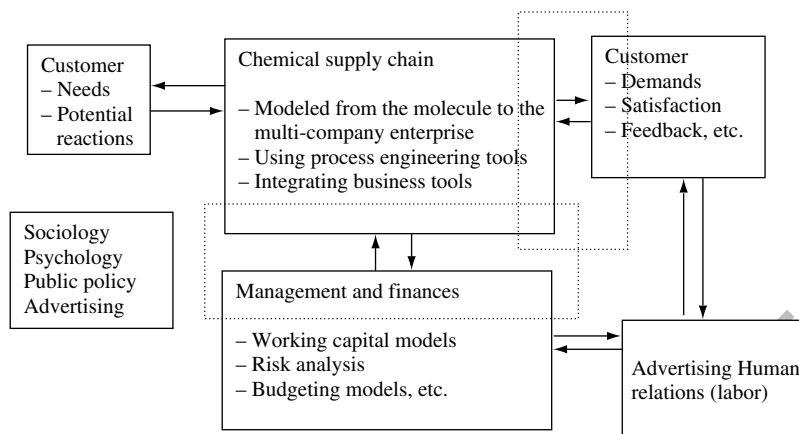


Figure 12.34 Product development and delivery supply chain

## 12.12 Retrofit

While most engineering assumes grass-roots activities, the issue of revamping the existing infrastructure of a company is sometimes even more challenging and it certainly involves the integration with finances. We leave specifically for some other discussion the retrofit activity of the existing industry.

## 12.13 The Environment

A lot was discussed in late years about sustainability and the global life cycle assessment of processes and products (Nebel and Wright, 2002). While some authors have started to incorporate this as constraints in process design, others have opted to leave sustainability (or some equivalent measure) as an alternative objective to be considered together with profitability and perhaps financial risk in Pareto surfaces (Cheng *et al.*, 2003). Grossmann (2003) discusses some of what he calls 'timid' efforts by the process systems engineering community in assessing sustainability (Marquardt *et al.*, 2000) and there are already work on industrial ecology performed by chemical engineers (Bakshi, 2000; Bakshi and Fiskel, 2003). Batterham (2003) provides an insightful analysis of sustainability emphasizing the fact that sustainability is no longer a *constraint* that comes from regulations and it is becoming a genuine objective of corporations in such a way that 'both companies and society can benefit'. Time will tell how genuine these efforts are. It is claimed here that sustainability is both a constraint and an alternative objective, leaving the analysis for future work.

## 12.14 Conclusions

This is not a review of the large number of developments concerning the integration of business tools with process and product engineering. Rather, some tools that help the integration, which has been recently proposed and used, are pointed out. The article

focuses on financial risk and proposes that the proper paradigm is through handling of risk curves, especially if they are immersed in a two- (or multi-) stage stochastic model. It also proposed to stress out the connections to shareholder value.

Full integration of several disciplines – management, finances, industrial engineering, and chemical engineering, among others – is slowly taking place. The result is this beginning to end modeling of the product research/development and delivery supply chain. In turn, more interactions with other disciplines (public policy, psychology, etc.) will come. At some point, with powerful computers and adequate modeling, one can dream of a full integration of the whole process in one single model. Then, one can start to ask if with so much access to information and with so many tools to respond optimally, we will reach a state where competition will cease to have a meaning.

## Acknowledgements

After we presented our first article on risk management in the 1999 AIChE Meeting (Rodera and Bagajewicz, 2000), we got busy developing the theory first (Barbaro and Bagajewicz, 2003, 2004a,b), and worked on applications of our theory to several problems. Some of these experiences are summarized in this chapter. I thank deeply my students who were instrumental in helping me articulate the vision. A fruitful sabbatical stay with the group of Dr Lluís Puigjaner at the Polytechnic of Catalunya (UPC) taught me invaluable lessons through many passionately argued ideas and discussions with students and professors.

My thanks also go to the following persons who read my original manuscript and were instrumental in improving it: Arthur Westerberg and Ignacio Grossmann (Carnegie Mellon University), Anshuman Gupta and Costas Maranas (Pennsylvania State University), Frank Zhu and Gavin Towler (UOP), Larry Evans (Aspentech), Jeffrey Siirola (Eastman), and Jesus Salas (University of Oklahoma).

Finally, I thank the organizers of this symposium for the financial support and the opportunity to think out loud.

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