CHAPTER II
BACKGROUND AND LITERATURE SURVEY

2.1 Mathematical and Optimization Models

Nowadays, many applications in all areas of science and engineering employ mathematical models. According to Floudas (1995), a mathematical model of a system is a set of mathematical relationships (e.g., equalities, inequalities and logical conditions) which represent an abstraction of the real world system under consideration.

A mathematical model of a system consists of four key elements as follows:

1) Variables

Variables can be continuous integer or a mixed set of continuous integer. They have different values and their specifications defining different states of the system.

2) Parameters

Parameters are fixed to one or multiple specific values and each fixation defines a different model.

3) Constraints

Constraints are the prescribed bounds representing abstraction of the restrictions or confines in the real world system.

4) Mathematical relationships

Mathematical relationships can be algebraic, differential, integrodifferential, or a mixed set of algebraic and differential constraints, and can be linear on nonlinear.

2.1.1 Optimization Models

In the general terms, optimization is the way to find the best efficient solution from a collection of candidates for a problem by using numerical and mathematical methods. The optimization process lies at the root of engineering, since the classical function of the engineer is to design new, more efficient and less expensive plans, procedures or systems for the improved operation.

In order to apply the mathematical and numerical techniques of optimization to the real world engineering problems, good formulation problem is the key to succeed. The process of formulating the engineering optimization problem is to describe the boundaries of the system to be optimized, to select the system variables that will be used to characterize or identify candidates, and to define the performance criterion that will be used to rank the candidates and determine the "best" (Reklaitis, 1983).

The performance criterion is denoted as an objective function. It can be both the minimization of cost and the maximization of profit for instance. An optimization problem may contain one or multiple performance criteria.

2.1.2 Structure of Optimization Models

An optimization models generally can be stated as (Chapra, 2003):

Find x, which minimizes or maximizes $f(x,y)$

$$\begin{aligned} s.t. \quad & d_i(x, y) \leq a_i & i = 1,2,\dots, m \\ & e_i(x, y) = b_i & i = 1,2,\dots, p \\ & y \in Y \text{ integer} & \end{aligned} \tag{2.1}$$

Where x is an n-dimensional design vector, y is a vector of integer variables, $d_i(x,y)$ are inequality constraints, $e_i(x,y)$ are equality constraints, a_i and b_i are constants and $f(x,y)$ is the objective function.

Optimization problems can be classified by consideration or elimination of the problem elements:

- If the set of integer variables is empty and the objective function and constraints are linear, it is a linear programming (LP) problem.
- If the set of integer variables is empty, and there exist nonlinear terms in the objective function and/or constraints, then it becomes a nonlinear programming (NLP) problem.
- If the set of integer variables is not empty, the integer variables participate linearly and separately from the continuous, and the objective function

and constraints are linear, then it becomes a mixed-integer linear programming (MILP) problem.

- If the set of integer variables is not empty, and there exist nonlinear terms in the objective function and/or constraints, then it becomes a mixed-integer nonlinear programming (MINLP) problem.

2.1.3 Modeling Procedures

Modeling Procedures are composed of four phases: 1) problem definition and formulation, 2) preliminary and detailed analysis, 3) evaluation and 4) interpretation application. The modeling procedure is an iterative procedure (Edgar *et al.*, 2001). Figure 2.1 summarizes the activities of developing the optimization model.

- Problem definition and formulation phase

In this phase the problem is defined and the important elements that relate to the problem and its solution are identified. The degree of accuracy needed in the model and the model's potential uses is determined.

- Design phase

The design phase includes specification of the information content, general description of the programming logic and algorithms necessary to develop and employ a useful model, formulation of the mathematical description of such a model, and simulation of the model.

- Evaluation phase

This phase is intended as a final check of the model as a whole. Testing of individual model elements will be conducted during earlier phases. Evaluation of the model is carried out according to the evaluation criteria and test plan established in the problem definition phase. Next, sensitivity testing of the model inputs and parameters is carried out and determined if the apparent relationships are physically meaningful. This step is also referred to as diagnostic checking and may entail statistical analysis of the fitted parameters.

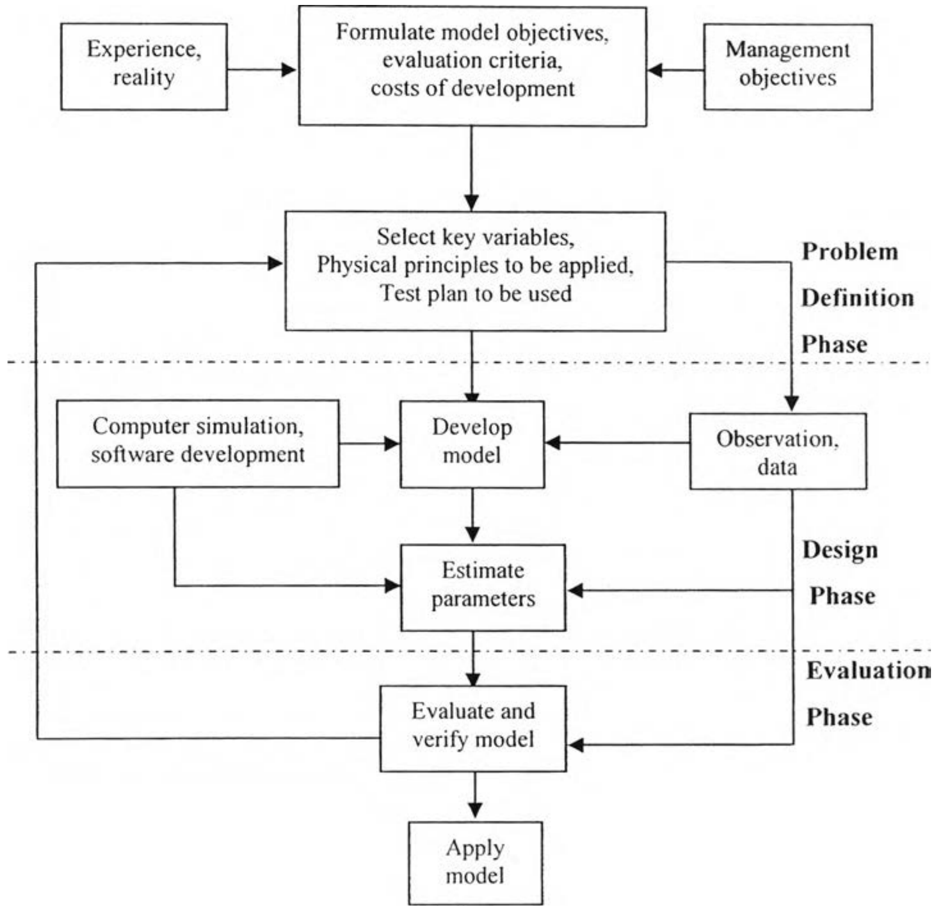

Figure 2.1 Major activities in model building prior to application (Edgar et al., 2001).

2.2 Mathematical Programming

Mathematical programming is the process of using mathematical models to help find good solutions to business problems. It provides a general framework for modeling the problem and organizing the data (Shimizu, 1997).

Much of the theory and most of the algorithms that exist for mathematical programming depend on the differentiability of the objective function and constraint functions defining the feasible region (Kendall *et al.*, 2005). When the data (parameters) are known number (without risk), assuming complete information about the problem to be solved and a static environment within which the schedule will be executed, the program is called the deterministic programming.

In reality, the deterministic schedule obtained may become infeasible because of the dynamic behavior of the real-world applications which involve data with uncertainties. To deal with such the problem, many approaches of scheduling have been proposed in the literature to take account of the presence of uncertainties (Kendall *et al.*, 2005). Reactive scheduling and stochastic programming are examples among these approaches.

Reactive scheduling involves revising or re-optimizing a schedule when an unexpected event occurs. Most efforts concentrate on ''repairing'' the existing predictive schedule to take account of the unexpected events that have come up (Herroelen and Leus, 2005). Stochastic programming is the model that enables the modeler to create a solution which is optimal over a set of scenarios. It takes advantage of the fact that probability distributions governing the data are known or can be estimated. The goal is to find some policy that is feasible for all (or almost all) the possible data instances and maximizes the expectation of some function of the decisions and the random variables. The most widely applied and studied stochastic programming models are two-stage linear programs (http://stoprog.org). Uncertainty planning and two-stage stochastic programming will be explained in detail in the next topic.

2.3 Refinery Operations Planning and Scheduling

The goal of planning and scheduling is to maximize the profitability of the entire refinery by choosing the best feedstocks, operating conditions and schedules, while fulfilling product quantity and quality objectives consistent with marketing commitments (Swift, 2000).

Planning and scheduling in refineries takes place over a hierarchy of time horizons. At the top level there is enterprise planning: this is concerned with a company's market position worldwide and allocating capital investment over a period of 5 years or more. Below this is operational planning over the time horizons between 1 week and 6 months; this is concerned with deciding which crudes to buy, how to process them and which products to sell. At the bottom there is detailed scheduling within the refinery, which answers the question "What am I going to do next?"

(Simon, 1997). The cascade of models used in operational planning and scheduling is shown in Figure 2.2.

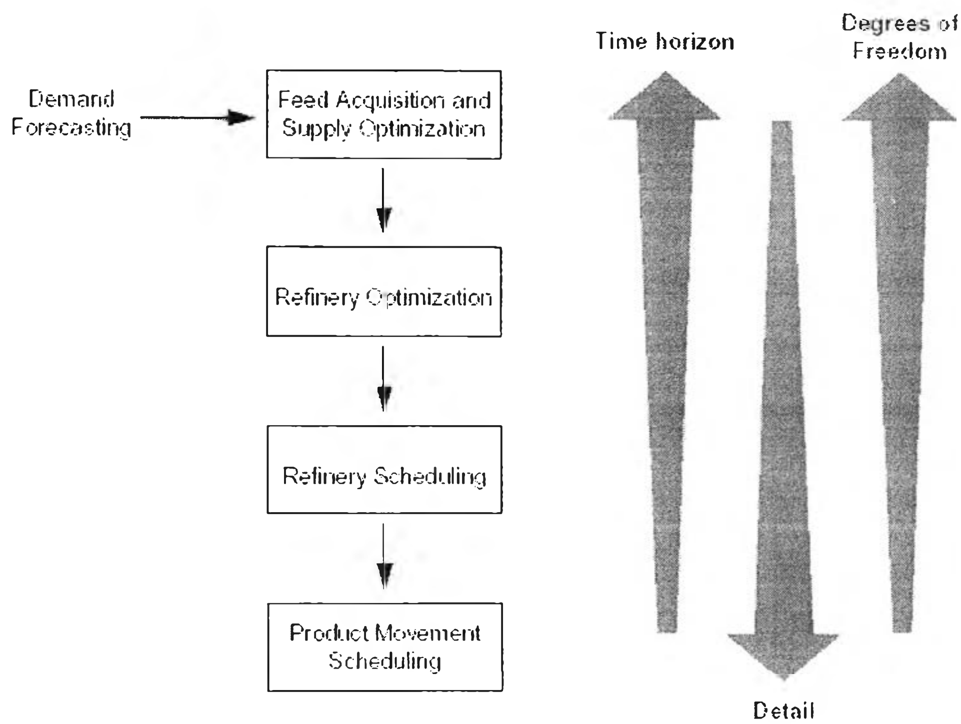

Figure 2.2 Planning and scheduling cascade in a refinery (Simons, 1997).

Linear and integer programming are heavily used in the long-term planning models. With shorter time horizons the models have to be more detailed and accurate and this leads to the use of Successive Linear Programming. The greatest challenges lie with the transition from operational planning to detailed scheduling, where the assumptions implicit in LP-based models break down. These are that operations can be broken down into a series of time periods, during each of which it suffices to model activities as continuous (or average) flows.

Generally, planning and scheduling of oil refinery operations can be divided into three main parts. The first part involves the crude-oil unloading, mixing and inventory control. The second part consists of the production unit scheduling, which includes both fractionation and reaction processes. Lastly, the third part covers blending of finished product, and shipping to the customer (Jia *et al.*, 2003). Figure 2.3 depicts the overall picture of oil refinery operations.

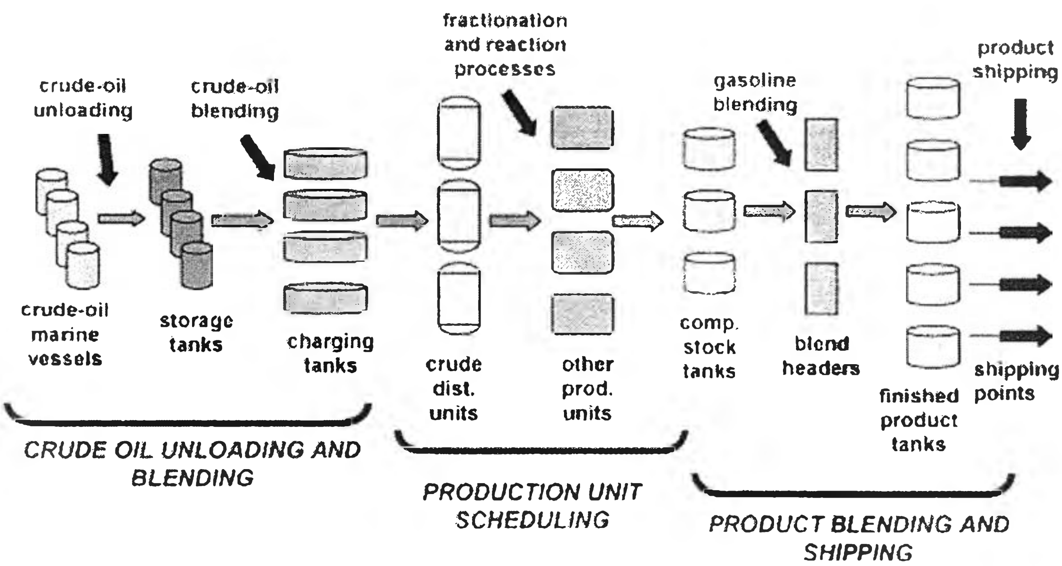

Figure 2.3 Overview picture of the oil refinery operations (Méndez *et al.*, 2006).

The different modeling and solution of each of these problems will pave the way toward addressing the overall problem of scheduling of refinery operations, a task that is currently prohibitively expensive to solve. The lack of computational technology for production scheduling is the main obstacle for the integration of production objectives and process operations (Pinto *et al.*, 2000).

2.3.1 Refinery Planning and Scheduling with Mathematical Programming Application

Mathematical programming has been extensively studied and implemented for both long-term and short-term plant-wide refinery planning. Some commercial software with linear programming (LP) models, such as RPMS (Refinery and Petrochemical Modeling System) and PIMS (Process Industry Modeling System), have been developed for refinery production planning. In this thesis, the mathematical model is implemented in the program called GAMS.

2.3.2 General Algebraic Modeling System (GAMS) and GAMS Data Exchange (GDX) facilities

GAMS is a software product of the GAMS Development Corporation. It includes the capability to solve linear programs and integer linear programs. It allows the formulation of models in many different classes of problem, including linear (LP), mixed integer linear (MIP), nonlinear (NLP), mixed integer nonlinear (MINLP), mathematical programs with equilibrium constraints (MPEC) and stochastic linear problems.

GDX facilities are binary files that are portable between different platforms. They are written using the byte ordering native to the hardware platform they are created on, but can be read on a platform using a different byte ordering. GDX facilities stores the values of one or more GAMS symbols such as sets, parameters variables and equations. They can be used to prepare data for a GAMS model, present results of a GAMS model, store results of the same model using different parameters etc.

In order to write data from GAMS to other application program, the user writes a GDX file and then to the program from the GDX file. The process to import data from an Excel file to GAMS is similar.

GAMS ----> GDX ----> Application Poogram
GAMS <---- GDX <---- Application Poogram

2.4 Pricing Theory

In marketing, pricing has the definition of "The evaluation of something in terms of its price, usually based on market demand and competition". The decisions related to the determination of prices begin with the available information on the fixed and variable costs, which are easily obtained from accounting and production registers. The relationship of demand and prices is also required as input data, and it is usually obtained by using historical data and, what is less usual, by direct experimentation over the consumer's response to different price levels in several consistent with the enterprise goals. The most widely used objective function when determining prices is the maximization of profit.

Economic theory of consumer behavior have been studied and proposed to see how consumers allocate their incomes and how this determines the demands for various goods and services. This will help us understand how changes in customer's income and product prices affect demands for goods and services and why the demands for some products are more sensitive to price and income changes than the others.

2.4.1 Consumer Behavior

Consumer behavior is best understood in three steps. The first step is to examine consumer preferences. Specifically, we need a practical way to describe how people might prefer one good to another. Second, we must account for the fact that consumers face budget constraints-they have limited incomes that restrict the quantities of goods that they can buy. The third step is to put consumer preferences and budget constraints together to determine consumer choices. In other words, given their preferences and limited incomes, what combinations of goods will consumers buy to maximize their satisfaction?

2.4.2 Utility Function

In economics, one way to describe the customer preference is using the concept of "utility". Utility is the measure of the relative level of satisfaction that a customer gets from consuming different bundles of goods and services. The demand function of the customer can be derived by considering a model of utility-maximizing behavior coupled with the economic constraints.

In the basic problem of preference maximization, the set of affordable alternatives is the set of all products that satisfy the consumer's budget constraint.

Let x be the customer consumption in bundle X, m be the fixed amount of money available to a consumer, and $p = (p_1, \ldots, p_k)$ be the vector of prices of $(goods_1, \ldots, goods_k)$. Now u is the utility function of the customer, and the budget set of the consumer, the set of affordable bundles, is given by

$$B = \{x \text{ in } X \ : \ px \leq m\} \tag{2.2}$$

The problem of preference maximization can then be written as:

$$\begin{aligned} & \max \quad u(\mathrm{x}) \\ \text{such that} \quad & px \leq m \\ \text{and} \quad & x \text{ is in } X. \end{aligned} \tag{2.3}$$

With this problem, we can characterize optimizing behavior by means of calculus, as long as the utility function is differentiable. The Lagrangian for the utility maximization problem can be written as

$$L = u(\mathrm{x}) - \lambda\,(\mathrm{px} - m) \tag{2.4}$$

where λ is the Lagrange multiplier. Differentiating the Lagrangian with respect to *x*, gives us the first-order conditions

$$\frac{\partial u(\mathrm{x})}{\partial \mathrm{x}_i} - \lambda \mathrm{p}_i = 0 \qquad \text{for} \quad \mathrm{i} = 1, \ldots, \mathrm{k}. \tag{2.5}$$

The demand function that maximize the consumer satisfaction are obtained from solving this equation.

In order to simplify calculations, various assumptions have been made of utility functions.

- CES (*constant elasticity of substitution*) utility is one with constant relative risk aversion
- quasilinear utility
- homothetic utility

2.4.3 Constant elasticity of substitution (CES) utility

The Constant Elasticity of Substitution (CES) utility function is the utility function that has a constant elasticity of substitution. It is useful because this class of utility functions can be used to model commodities that are either substitutes for one another, or complements of one another. The CES utility function for two commodities x and y can be written as:

$$u(\mathrm{x}, \mathrm{y}) = (a \cdot \mathrm{x}^{\rho} + b \cdot \mathrm{y}^{\rho})^{1/\rho} \tag{2.6}$$

For any values of $a > 0$ and $b > 0$.

2.5 Uncertainty and Risk

Uncertainty and risk are both referred to a situation wherein the possible future outcomes of a present decision are plural. But the classical distinction between risk and uncertainty is that: for risk, the dimensions and probabilities of the outcomes are known in advance while they cannot be objectively specified for uncertainty (Porterfield, 1995).

Most operations by business enterprises and many of their financing lie within the domain of uncertainty. One approach to avoid this dilemma is to convert the operation decision from an uncertainty situation to a quasi-risk situation, by projecting a subjective distribution of its possible outcomes and assigning subjective probabilities to each of them (Porterfield, 1995).

2.5.1 Uncertainty in Refinery Planning

For the refinery industry which has to deal with many sections from crude oil purchasing and processing to product distributing and selling, planning and scheduling may contain a lot of uncertainties. The uncertainties arise from crude cost, product price and demand etc. The effect of these uncertainties, for example, demand uncertainty, results in over- or under-production, with resultant excess inventories or/and inability to meet customer needs, respectively. Excess inventory incurs unnecessary holding costs, while the inability to meet the customer needs results in both losses of profits and potentially, the loss of customers. This trade-off between the profit maximization and the cost minimization of risk from safety stock leads to the formulation of a stochastic optimization.

2.5.2 Two-stages Stochastic Programming

This kind of problems is characterized by two essential features: the uncertainty in the problem data and the sequence of decisions (Barbaro and Bagajewicz, 2004). Some model parameters are accounted as random variables with a certain probability distribution. In turn, some of these decisions must be made with in-complete information about the future. Then, as some of the uncertainties are revealed, the remaining decisions will be made. A number of decisions that have to be made before the experiment are called first-stage decisions, and the period when these decisions are made is called the first stage. On the other hand, the decisions made after uncertainty is unveiled are called second-stage decisions and the corresponding period is called the second stage. 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. 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.

This Optimization model involves maximization or minimization of expected profits or expected cost, respectively, where the term "expected" refers to multiplying profits or costs associated with each scenario by its probability of occurrence (Lababidi et al., 2004).

The general form of a two-stage linear stochastic problem with fixed recourse and a finite number of scenarios can be defined as (Birge and Louveaux, 1997):

$$
\begin{aligned}
& Max\, \mathrm{E}[Profit] = \sum_{s \in S} p_s q_s^T y_s - c^T x \\
\text{s.t.} \quad & Ax = b \\
& T_s x + W y_s = h_s \qquad s \in S \qquad (2.7) \\
& x \geq 0 \qquad x \in X \\
& y_s \geq 0 \qquad \forall s \in S
\end{aligned}
$$

In the above equation, first-stage decisions are represented by variable x and second-stage decisions are represented by variable y_s, which has probability p_s. The objective function contains a deterministic term, $c^T x$, and the expectation of the second-stage objective, $q_s^T y_s$, taken over all realizations of the random events. For a given realization of the random events, $s \in S$, the second-stage problem data q_s, hs, and T_s become known, and then the second-stage decisions, $y_s(x)$, must be made.

2.5.3 Financial Risk

As previously mentioned, although the stochastic models can optimize the total expected performance measure, they usually do not provide any control of its variability over the different scenarios; i.e., the decision maker is assumed to be risk neutral. But different attitudes toward risk may be encountered.

The financial risk associated with a plan under uncertainty is defined as the probability of not meeting a certain target profit (maximization) or cost (minimization) level referred to as Ω (Barbaro and Bagajewicz, 2004). For the two-stage stochastic problem, the financial risk associated with a design x and target profit Ω is therefore expressed by the following probability:

$$Risk\,(x, \Omega) \;=\; P\,(Profit(x) \;<\; \Omega) \qquad (2.8)$$

Where $Profit(x)$ is the $Profit$ after the uncertainty has been unveiled and a scenario is realized.

According to Barbaro et al., the minimization of risk at some profit levels renders a trade-off with expected profit. A risk-averse decision maker will feel comfortable with low risk at low values of Ω, while a risk taker will prefer to lower the risk at high values of Ω. The trade-off lies in the fact that minimizing risk at low values of Ω (e.g., a loss) is in conflict with the minimization of risk at high values of Ω (e.g., large profits) and vice versa.

2.6 Financial Risk Management

Some measures to manage financial risk are as follows:

2.6.1 Value at risk and upside potential

Value at risk (or VaR) is a widely used measure of risk in literature (Guldimann, 2000). It is defined as the expected loss for a certain confidence level usually set at 5% (Linsmeier & Pearson, 2000). A more general definition of VaR is given by the difference between the mean value of the profit and the profit value corresponding to the p-quantile (value at p risk). VaR has been used as a point measure very similar to the variance. VaR measures the deviation of the profit at 5% risk from the expected value.

However, VaR can only be used as a measure of robustness, but not risk. To relieve these difficulties, Aseeri and Bagajewicz (2004) proposed that VaR be compared to a similar measure, the Upside Potential (UP) or Opportunity Value (OV), defined in a similar way to VaR but at the other end of the risk curve with a quantile of (1-*p*) as the difference between the value corresponding to a risk of (1-*p*) and the expected value. They discussed the need of the Upside Potential for a good evaluation of the project.

2.6.2 Use of Sampling Algorithm to Obtain Optimal Solution

In this method, a relatively small number of scenarios are generated and used to run the stochastic model. After the series of designs are obtained, the first stage variables of each one is used as fixed numbers in a new stochastic model containing a much larger number of scenarios. Aseeri and Bagajewicz (2004) proved that this algorithm, run for a sufficiently large number of scenarios can approximate the optimal solution.

2.6.3 Upper and Lower Risk Curve Bounds

The upper bound risk curve is defined as the curve constructed by plotting the set of net present value (NPV) for the best design under each scenario. Aseeri and Bagajewicz (2004) proved that any feasible solution cannot cross this curve. Figure 2.5 shows the upper bound risk curve and curves corresponding to possible and impossible solutions. The lower bound risk curve is defined as the curve constructed by plotting the highest risk of the set of designs used to construct the upper bound risk curve at each NPV abscissa. Unlike the upper bound risk curve, the lower bound risk curve can be crossed by feasible solutions.

The objective function value (ENPV) of any feasible solution is smaller than or equal to that of the upper bound risk curve (Aseeri and Bagajewicz, 2004). Therefore, the gap between any solution and the best possible integer solution will always be less than or equal to the gap between that solution and the upper bound risk curve.

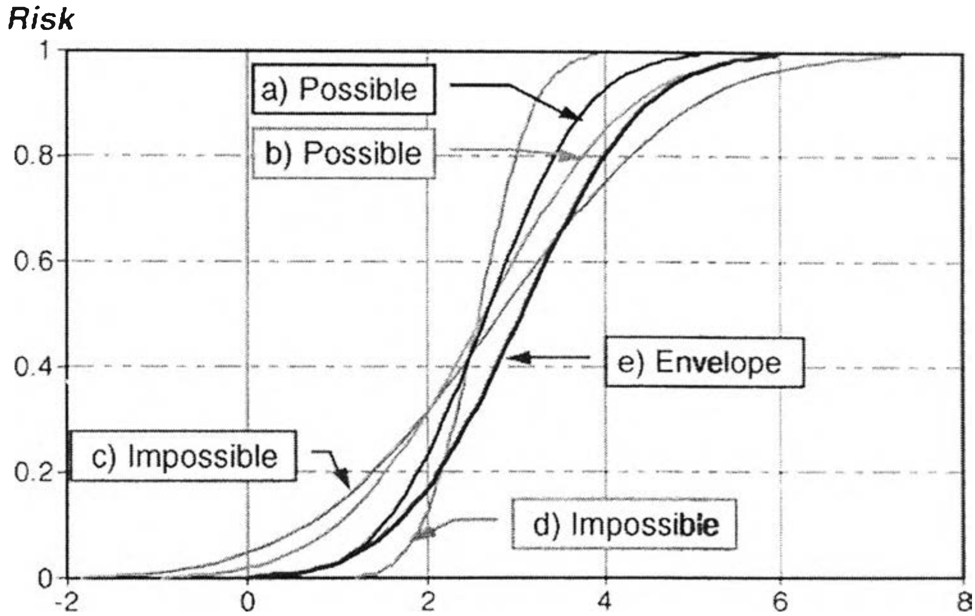

Figure 2.4 Upper bound risk curve, or envelope (Aseeri and Bagajewicz, 2004).

2.7. Literature Survey

2.7.1 Refinery Operation Planning and Scheduling

In the last 20 years, a number of models have been developed to perform short term scheduling and longer term planning of batch plant production to maximize economic objective (Shah, 1998). The application of formal, mathematical programming techniques to the problem of scheduling the crude oil supply to a refinery was considered by Shah (1996). The consideration includes the allocation of crude oils to refinery and portside tanks, the connection of refinery tanks to crude distillation units (CDUs), the sequence and amounts of crude pumped from the ports to the refineries, and the details related to discharging of tankers at the portside. The mathematical programming model is based on a discretization of the time horizon into intervals of equal duration. The problem was decomposed into two smaller ones: downstream and upstream problems. The downstream problem was solved first and the upstream problem was solved subsequently.

In addition, optimization was applied for refinery by Zhang *et al.* (2001) to integrate the hydrogen network and the utility system with the material processing system. They considered the optimization of refinery liquid flow, hydrogen flows, and steam and power flows simultaneously and presented the approach on debottlenecking in refinery operation. Their aim was to shift bottlenecks from an expensive process to a cheaper one by modifying networks such as the hydrogen network and the utility system. Other bottlenecks which could not be tackled by the network changes were retrofitted by using detailed process models to achieve the required extra capacity.

Moro *et al.* (1998) developed a nonlinear planning model for diesel production. The resulting optimization model is solved with the generalized reduced gradient method. Pinto and Moro (2000); Pinto et al. (2000) and Joly et al. (2002) focused on the refinery productions. The model are composed of a representation of the refinery processing units and their interconnections and involve equations to represent the performance of such units as well as the mixing of process streams. The work also addressed scheduling problems in oil refineries that are formulated as mixed integer optimization models and rely on both continuous and discrete time representations. The problems involve the optimal operation of crude oil unloading from pipelines, transfer to storage tanks and the charging schedule for each crude oil distillation unit. Moreover, they discussed the development and solution of optimization models for short term scheduling of a set of operation that includes product receiving from processing units, storage, and inventory management in intermediate tanks, blending in order to attend oil specifications and demands, and transport sequencing in oil pipelines.

Göthe-Lundgren *et al.* (2002) described a production planning and scheduling problem in oil refinery company. They focused on planning and scheduling to select mode of operation to use in order to satisfy the demand while minimizing the production cost. The model is formulated using a mixed-integer linear programming (MILP).

Rejowski and Pinto (2003) considered the system composed by one petroleum refinery, one multi product pipeline and several depots that are connected to local consumer markets. MILP models were proposed for the simultaneous optimization of systems with multiple depots. Key decisions of the model involve loading and unloading operations of tanks and of the pipeline. Several operating constraints were incorporated in the model and the model for a large-scale example that contains pipeline segments of similar size were solved. Finally, they found that the model was successfully able in avoiding time periods of high-energy costs and at the same time managed to fulfill all product demands.

Neiroa and Pinto (2004) proposed a general framework for modeling petroleum supply chains after the model of processing units were developed by Pinto *et al.* (2000). They also introduced the particular frameworks to storage tanks and pipelines. By considering nodes of the chain as grouped elementary entities that were interconnected by intermediate streams, they built the complex topology by connecting the nodes representing refineries terminals and pipeline networks. Their decision variables include stream flow rates, properties, operational variables, inventory and facilities assignment. The resulting multiperiod model is a large-scale MINLP. Then they applied the proposed model to a real-world corporation and showed the model performance by analyzing different scenarios. Their results have demonstrated the potential of problem petroleum supply chain to real-world petroleum supply chains and how it can be used to help in the decision making process of the production planning.

Persson and Göthe-Lundgren (2005) suggested an optimization model and a solution method for a shipment planning problem. They considered shipment planning of bitumen products from a set of refineries to a set of depots. The planning is about making sure that it satisfies the given demand at lowest cost. They suggested a shipment planning model that includes considerations of production, by representing the production (process scheduling) by a linear programming (LP) model. The combined process scheduling and shipment planning problem is represented by a mixed-integer linear programming (MILP) model.

Méndez *et al.* (2006) presented a novel MILP-based method that addresses the simultaneous optimization of the off-line blending and the short-term scheduling problem in oil-refinery applications. His main purpose was to find the best way of mixing different intermediate products from the refinery in order to minimize the blending cost while meeting the quality and demand requirements of the final products. An iterative procedure was proposed to effectively deal with non-linear gasoline properties and variable recipes for different product grades. The solution of a very complex MINLP formulation was replaced by a sequential MILP. Several examples representative of real world problems were presented to illustrate the flexibility and efficiency of the proposed models and solution technique.

2.7.2 Pricing Decisions in Planning and Scheduling Model

Pricing decision is another one important aspect for planning in a highly dynamic environment. Some studies have been done concerning this issue.

Guillén *et al.* (2005) integrated pricing decision with the scheduling model for batch plants. Their integrated model can simultaneously provides the optimal prices and operation schedule as opposed to earlier models where prices are usually considered as input data. The model was also developed to be able to handle the uncertainty associated to the demand curve. Finally, financial risk management is discussed.

Voeth and Herbst (2006) studied the business relationships within the supply chain provide interesting opportunities for mutually increased benefit. They investigated the opportunities for suppliers and customers to collaborate on pricing in order to establish mutually beneficial relationships. They demonstrated that this goal can only be attained when price is no longer regarded as an exante distributive parameter between market partners, but as a joint tool for outcome optimization within the overall supply chain process. A calculation example is clarified and the managerial implications for practical implementation. is pointed out.

Karwan and Keblis (2007) considered the plant operation problem in the industrial gas industry where the price of the primary production input changes hour to hour, which is often referred to as real time pricing. The purpose of their work is to present an optimization based planning approach that rigorously takes into account the realities of this problem. Their work seeks to identify the conditions under which real time pricing is most appealing vis-a-vis other electricity pricing schemes.

2.7.3 Planning and Scheduling under Uncertainty

One of major problems against planning and scheduling is uncertainty. Confronting this problem, different strategies have been studied and proposed.

Singh *et al.* (2000) provided an improved formulation for the gasoline blending optimization problem that incorporates both the blend horizon and a stochastic model of disturbances into the real-time optimization (RTO) problem. The work starts with examining three different blending RTO strategies. Their suitability for use in blending optimization was examined. Performance improvements were obtained using the time-horizon based RTO (THRTO) approach system that considers the entire remaining blend horizon and incorporated a prediction of future stochastic disturbances. Finally, an automotive gasoline blending case-study was used to illustrate the superior performance of this new RTO method.

Reddy *et al.* (2004) presented the first complete continuous-time mixed integer linear programming (MILP) formulation for the short-term scheduling of operations in a refinery that receives crude from very large crude carriers via a high-volume single buoy mooring pipeline. Their objective was to develop the model that respond effectively and speedily to uncertain oil markets while maintaining reliable operations. An iterative algorithm was used to eliminate the crude composition discrepancy. The algorithm uses MILP solutions and obtains maximum-profit schedules for industrial problems with up to 7 days of scheduling horizon.

Some fundamental approaches for scheduling under uncertainty were determined and compared by Herroelen and Leus (2005). The various approaches consist of reactive scheduling, stochastic project scheduling, fuzzy project scheduling, robust (proactive) scheduling and sensitivity analysis. They discussed the potentials of these approaches for scheduling under uncertainty projects with deterministic network evolution structure.

Csáji and Monostori (2005) presented an approximate dynamic programming based stochastic reactive scheduler that can control the production process on-line, instead of generating an off-line rigid static plan. The stochastic scheduling problem was formulated as a special Markov Decision Process. Homogeneous multi-agent systems were suggested, in which cooperative agents learn the optimal value function in a distributed way by using trial-based Approximate Dynamic Programming (ADP) methods. After each trial, the agents asynchronously update the actual value function estimation. Finally, benchmark experimental results which illustrate the effectiveness of the ADP based approach are shown.

Al-Redhwan *et al.* (2005) addressed the problem of uncertainty in optimizing water networks in process industries to be able to accommodate the changes of wastewater flow rates and level of contaminants. A three-step methodology was developed. First, they generated a deterministic optimization model. This model searches for the network configuration with minimum freshwater use and optimal wastewater reuse or regeneration-reuse. The second step involved a sensitivity analysis in which uncertainty was introduced as maximum and minimum ranges in operating conditions. Finally, a stochastic formulation was developed, based on the scenario-analysis stochastic programming approach. The optimization models are NLP problems which were effectively solved using GAMS. These models were tested on a typical refinery wastewater network.

Guillén *et al.* (2005) considered the design and retrofit problem of a supply chain (SC) consisting of several production plants, warehouses and markets, and the associated distribution systems. A two-stage stochastic model was constructed in order to take account of the effects of the uncertainty in the production scenario. The problem objective, i.e., SC performance, is assessed by taking into account both the profit over the time horizon and the resulting demand satisfaction. Finally, the SC configurations obtained by means of deterministic mathematical programming were compared with those determined by different stochastic scenarios representing different approaches to face uncertainty.

Liao and Rittscher (2006) developed a measurement of supplier flexibility with consideration of demand quantity and timing reduction uncertainties. The measurement was extended to consider the uncertainty when the demand quantity is randomly raised. In addition, a multi-objective supplier selection model under stochastic demand conditions was developed. The model was determined with simultaneous consideration of the total cost, the quality rejection rate, the late delivery rate and the flexibility rate, involving constraints of demand satisfaction and capacity.

2.7.4 Financial Risk Management

Risk management now has become a vital topic for planning and scheduling. Some work in various fields of business and industry has been concerned about this subject and started turning to face this subject.

For example, Ierapetritou and Pistikopoulos (1994) introduced integrated metric and estimated future plan feasibility together with the potential economic risk for two-period linear planning models. The metric is based on the concepts of flexibility, the ability of handling uncertainty while meeting production requirements and maximum regret. An algorithmic procedure was proposed for the estimation of such a combined metric involving the solution of two multi-parametric linear programming sub-problems for the evaluation of maximum regret. Then the analytical expressions of the regret as a function of the uncertain parameters and the plan were obtained. These expressions were incorporated in a mixed-integer index programming formulation. The incorporation of these analytical tools into an overall planning framework was shown and illustrated with example problems.

Mulvey *et al.* (1997) studied and discussed components of asset/liability management systems of three leading international firms in USA as Towers Perrin, Frank Russell, and Falcon Asset Management. These companies applied asset/liability management for efficiently managing risk over extended time periods by dynamically balancing the firm's asset and liabilities to achieve their objectives. Three components of asset/liability management were compared and described: 1) a multi-stage stochastic program for coordinating the asset/liability decisions; 2) a scenario generation procedure for modeling the stochastic parameters; and 3) solution algorithms for solving the resulting large-scale optimization problem.

Lowe *et al.* (2002), concerning the financial risk problem, paid attention to maintain an international sourcing/production network. They proposed and illustrated a two-phase multi-screening approach which was used to help evaluate the strategy of having production facilities, using a Harvard Business School as a study case. Their approach involves a relatively simple one-year-ahead analysis in Phase 1, followed by a more detailed analysis in Phase 2. Afterward, new criteria of stochastic comparison: namely, Pareto optimality, near-Pareto optimality, maximum regret, mean–variance efficiency, and stochastic dominance were introduced. At last, they illustrated how excess capacity could provide flexibility by allowing a global manufacturing firm to shift production between various production facilities as relative costs change over time.

Gupta and Maranas (2003) developed a model for incorporating market-based pollution abatement instruments in the technology selection decision of a firm. Multistage stochastic programming is used to model emission and market uncertainties while accounting for the availability of derivative instruments. The instruments help minimize total pollution abatement costs and predict the environmental liability. The model quantifies the benefits of the flexibility offered by these instruments. Management of environmental and financial risks was addressed by linking the optimization model with basic statistical and probabilistic techniques.

Cheng et al. (2003) presented the method of risk management using Markov decision process with recourse that considers decision making throughout the process life cycle and at different hierarchical levels. The formulation integrates design decisions and future planning by constructing a multi-period decision process in which one makes decisions sequentially at each period. The objectives they concerned with are expected profit, expected downside risk, and process lifetime. The multi-objective Markov decision problem was finally decomposed, employing rigorous multi-objective stochastic dynamic programming algorithm, and the Pareto optimal design strategy was obtained.

In addition, various methods and tools are studied and introduced in to optimizing and programming models to encounter the financial risk problem. The use of value at risk were proposed by Guldimann (2000) and Jorion (2000). Other approaches to the management of financial risk was recently presented by Barbaro and Bagajewicz (2004), and Aseeri and Bagajewicz (2004).

Barbaro and Bagajewicz (2004) presented a methodology to include financial risk management in the framework of two-stage stochastic programming for planning under uncertainty. They adapted a known probabilistic definition of financial risk to use in the framework and analyzed its relation to downside risk. Their method is compared with the methods that intend to manage risk by controlling the second-stage variability. One of the major contributions of their work to the field of planning under uncertainty is the formal definition of financial risk as applied to these problems. Based on this definition, several theoretical expressions were developed, providing new insight on the trade-offs between risk and profitability. Thus, the cumulative risk curves were constructed to be very appropriate to visualize the risk behavior of different alternatives. Moreover, they examined the concept of downside risk and a close relationship with financial risk was discovered. Consequently, they suggested that downside risk be used to measure financial risk, considering that in that way there is no need to introduce new binary variables that increase the computational burden.

Aseeri and Bagajewicz (2004) presented some new concepts and procedures for financial risk management. Upside potential (UP) or opportunity value (OV) as means to weigh opportunity loss versus risk reduction as well as an area ratio (RAR) are introduced and discussed to complement the use of value at risk. Upper and lower bounds for risk curves corresponding to the optimal stochastic solutions were developed, the use of the sampling average algorithm was studied, and the relation between two-stage stochastic models that manage risk as well as the use of chance constraints and regret analysis was discussed. These concepts are illustrated by introducing a stochastic planning model to optimize natural gas commercialization in Asia, under uncertainty.