CHAPTER II

BACKGROUND AND LITERATURE SURVEY

2.1 Mathematical and Optimization Models

According to Floudas (1995), a mathematical model of a system is a set of mathematical relationships (e.g., equalities, inequalities, logical conditions) which represent an abstraction of the real world system under consideration.

There are four key elements for a system of mathematical model:

1. Variables

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

2. Parameters

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

3. Constraints

   Constraints are fixed quantities by the model statement.

4. Mathematical relationships

   Mathematical model relations can be grouped as equalities, inequalities, and logical conditions. The model equalities are generally formulated from mass balances, energy balances, equilibrium relations, physical property calculations, and engineering design relations which describe the physical phenomena of the system. The model inequalities often consist of allowable operating regimes, specifications on qualities, feasibility of heat and mass transfer, performance requirements, and bounds on availabilities and demands. The logical conditions provide the connection between the continuous and integer variables.

The mathematical relationships can be algebraic, differential, integro-differential, or a mixed set of algebraic and differential constraints, and can be linear or nonlinear.

2.1.1 Optimization

Optimization is the use of specific methods to determine the most cost-effective and efficient solution to a problem or design for a process. This technique is one of the major quantitative tools in industrial decision making. A wide variety of problems in the design, construction, operation, and analysis of chemical plants (as well as many other industrial processes) can be resolved by optimization. A well-known approach to the principle of optimization was first scribbled centuries ago on the walls of an ancient Roman bathhouse in connection with a choice between two aspirants for emperor of Rome. It read "De doubus malis, minus est simper aligendum" – of two evil, always choose the lesser (Edgar *et al.*, 2001).

An optimization problem is a mathematical model which in addition to the aforementioned elements contains one or multiple performance criteria. The performance criterion is denoted as objective function, and it can be the minimization of cost, the maximization of profit or yield of a process for instance. If we have multiple performance criteria then the problem is classified as multi-objective optimization problem. A well defined optimization problem features a number of variables greater than the number of equality constraints, which implies that there exist degrees of freedom upon which we optimize. If the number of variables equals the number of equality constraints, then the optimization problem reduces to a solution of nonlinear systems of equations with additional inequality constraints.

2.1.2 Structure of Optimization Models

The structure of optimization models takes the following form (Floudas, 1995):

$$\begin{aligned} \min_{x,y} \ & f(x,y) \\ s.t. \ h(x,y) &= 0 \\ g(x,y) &\leq 0 \\ x &\in X \subseteq \Re^n \\ y &\in Y \text{ integer} \end{aligned} \qquad (2.1)$$

where $\boldsymbol{x}$ is a vector of $\boldsymbol{n}$ continuous variables, $\boldsymbol{y}$ is a vector of integer variables, $\boldsymbol{h(x,y)} = \boldsymbol{0}$ are m equality constraints, $\boldsymbol{g(x,y)} \leq \boldsymbol{0}$ are p inequality constraints, and $\boldsymbol{f(x,y)}$ is the objective function.

Equation (2.1) contains a number of classes of optimization problems, by appropriate consideration or elimination of its elements. If the set of integer variables is empty, and the objective function and constraints are linear, then Equation (2.1) becomes 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 Equation (2.1) becomes a nonlinear programming (NLP) problem. If the set of integer variables is nonempty, the integer variables participate linearly and separably from the continuous, and the objective function and constraints are linear, then Equation (2.1) becomes a mixed-integer linear programming (MILP) problem. If the set of integer variables is nonempty, and there exist nonlinear terms in the objective function and constraints, then Equation (2.1) is a mixed-integer nonlinear programming (MINLP) problem.

2.1.3 Modeling Procedures

There are four phases for building the model that is (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 to be performed.

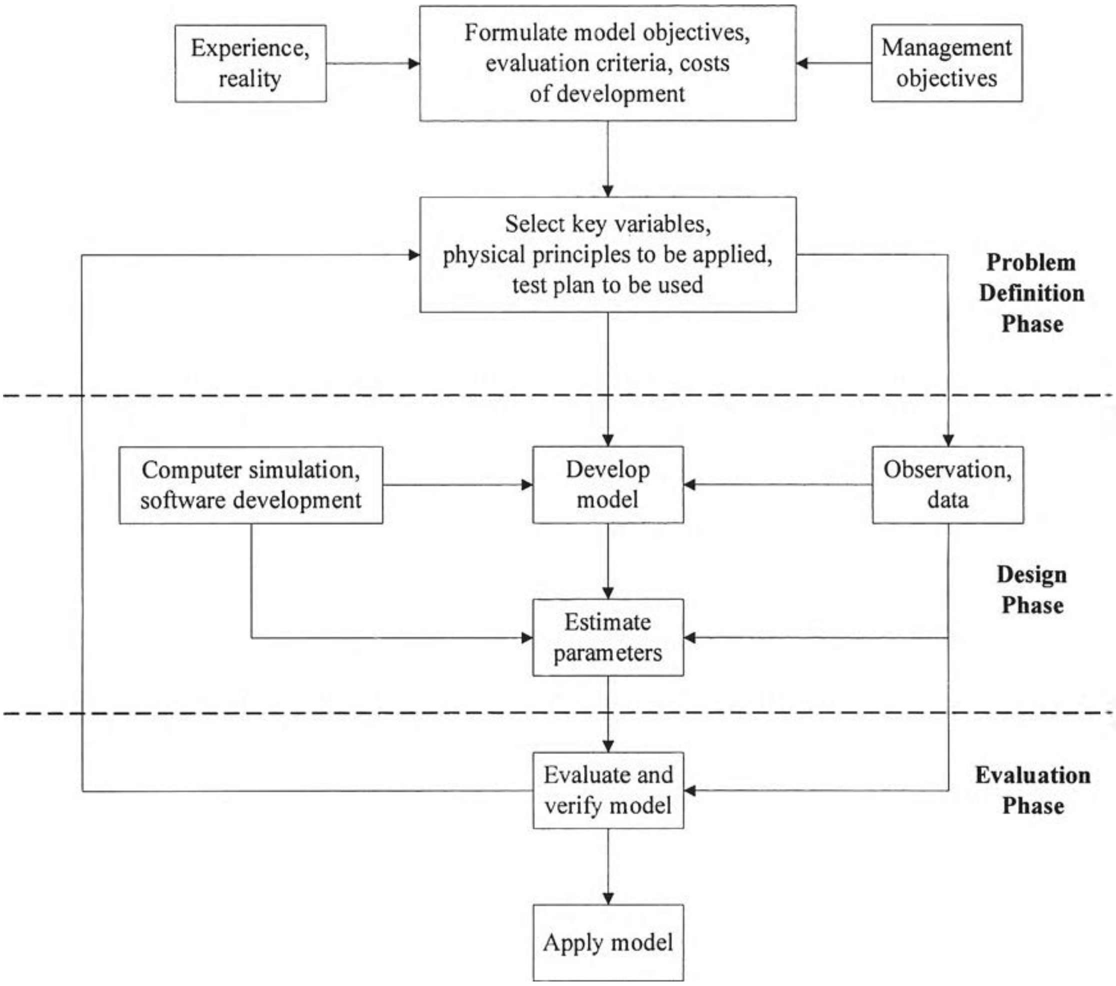

Figure 2.1 Major activities in model building prior to application (Edgar *et al.*, 2001).

- 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, carry out sensitivity testing of the model inputs and parameters, and determine 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.

2.2 Mathematical Programming

Mathematical programming is the process of using mathematical models to help find good solutions to business problems. Its key feature is that the mathematical model is optimized. This finds better solutions than other techniques and leads to greater understanding of the problem by rigorously challenging the model's assumptions (Simons, 1997).

2.2.1 Deterministic and Stochastic Programming

In deterministic mathematical programming the data (parameters) are known numbers (without risk). When some of the data incorporated into the objective or constraints is uncertain, the program is called stochastic programming. Uncertainty is usually characterized by a probability distribution on the parameters. Sensitivity analysis (SA) and Stochastic Programming (SP) formulations are the two major approaches used for dealing with uncertainty. SA is a post-optimality procedure with no power of influencing the solution. It is used to investigate the effects of the uncertainty on the model's recommendation. SP formulation, on the other hand, introduces probabilistic information about the problem data, though with the first moments (i.e. the expected values) of the distribution of the objective function with respect to the uncertainty (Arsham, 1996). SP is an attractive option for strategic planning because it allows the decision maker to analyze uncertainties and control risks explicitly (Lababidi *et al.*, 2004).

2.2.2 Mathematical Programming in Refinery Planning

Mathematical programming has been extensively studied and implemented for both long-term and short-term plant-wide refinery planning. Some commercial software applied 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. Pelham and Pharris (1996) pointed out that this planning technology can be considered well developed, and startling further progress should not be expected. In this thesis, the mathematical model is implemented in the program called GAMS.

GAMS (General Algebraic Modeling System) is a software product of the GAMS Development Corporation which solves mathematical programs input in a way similar to how they are presented in books and research papers. It includes the capability to globally solve linear programs and integer linear programs, as well as to find local optima of nonlinear programs and integer nonlinear programs that have all nonlinearities in continuous variables. GAMS has an enormous number of features and options which allow it to support the most sophisticated mathematical programming and econometric applications. GAMS allows the formulation of models in many different problem classes, including linear (LP), mixed integer linear (MIP), nonlinear (NLP), mixed integer nonlinear (MINLP), mixed complementary (MCP), mathematical programs with equilibrium constraints (MPEC) and stochastic linear problems. GAMS can also handle constrained nonlinear systems (CNS). GAMS has been successfully used in both industry and academia since 1987 and has a user base of over 10,000 in 100 countries. More information can be found at www.gams.com.

2.3 Refinery Operations Planning and Scheduling

2.3.1 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. Typically, savings from improvements in these areas exceed $20 million per year for a world-scale refinery (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 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?" (Simons, 1997). The cascade of models used in operational planning and scheduling is shown in Figure 2.2.

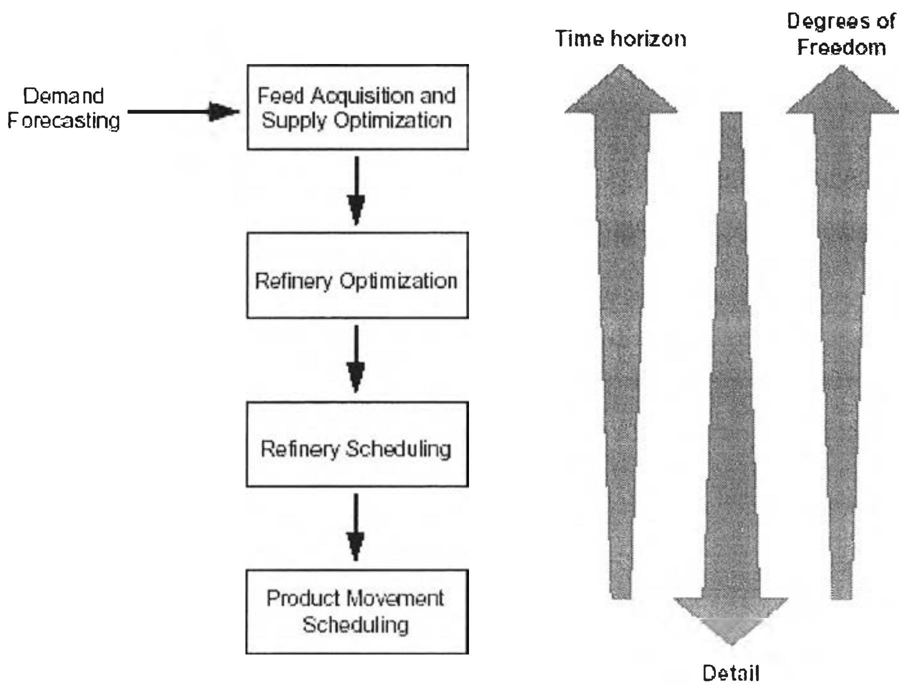

Figure 2.2 Planning and scheduling cascade in a refinery (Simons, 1997).

Linear and integer programming are heavily used in the longer-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 the finished product blending, and shipping to the customer (Jia *et al.*, 2003). Figure 2.3 depicts the overall picture of oil refinery operations.

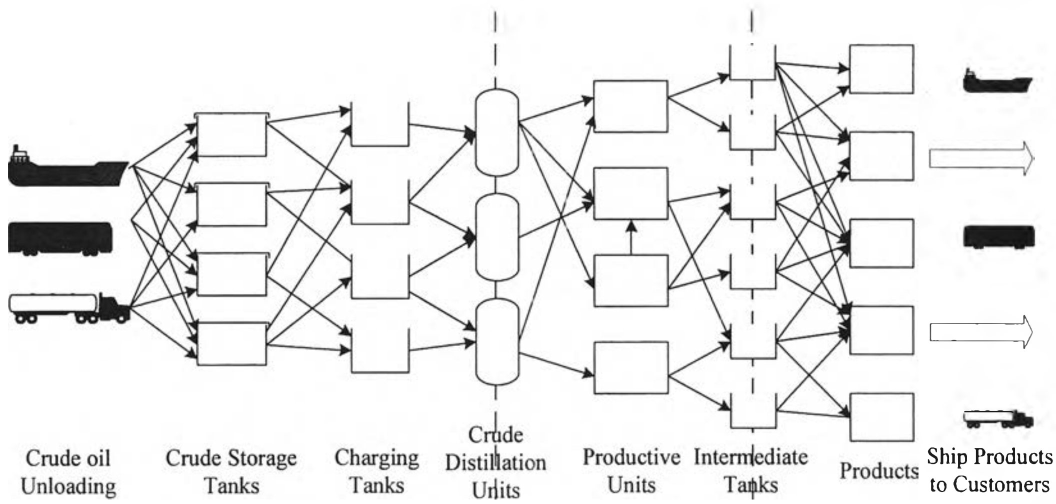

Figure 2.3 Overview picture of the oil refinery operations.

The efficient 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).

2.3.2 Blending

Crude oil consists of a vast range of hydrocarbon molecules. A crude distillation unit separates this mixture into components whose boiling points lie within certain ranges e.g. 0°C-78°C, 78°C-100°C, 100°C-145°C, etc. Other process units further refine these intermediate streams and chemically alter the hydrocarbon molecules, splitting them or removing sulfur, for instance. The resulting components have a wide range of physical properties: density, viscosity, octane, sulfur content, etc. On their own these components would not be suitable for commercial use, but blended together in various ways they form the products which we know as gasoline, diesel, heating oil, etc.

Blending is the combining of two or more materials to produce a new material. Since the final product of blending must meet certain specifications, it becomes necessary to be able to estimate priori certain properties of a proposed blend. Otherwise, a trial-and-error procedure could prove costly in time and materials. Also, because of the complexity of the problem, there may be an infinite number of blends that will meet a particular required specification. Usually there are several specifications to be met. Thus the problem becomes even more complicated. As a result, many refiners resort to a linear program to optimize their blends, particularly in the case of gasoline (Maples, 2000).

Since the blending operations offer such an enormous number of options, most refiners use LP models to aid them in their blending decisions. The blending operations may be modeled by on of two methods. The simplest method is to develop a number of recipes or blends which will meet the product specifications and then allow the LP model to select any combination of these blends to meet product demands. This method is most often used for modeling existing refineries where data on a number of feasible blends are available. Unfortunately, it has the disadvantage that a large number of blends may be required to adequately represent the flexibility of the blending operations and a completely new set of blends is required each time a specification value is changed, a new blend component is added, or the properties of the blend components change.

In the second method, the blend stock qualities and product specifications are used directly in the model which is allowed to select the optimum blend composition within the limits of these specifications. Although more flexible than the recipe technique, this method is more complex and requires more skill in preparing the property data and structuring the model. One of the major tasks is to put the property data into a form which can be blended linearly. In most models, blending is done to a quality specification (Simons, 1995).

Estimating a property becomes a problem when the particular property is not additive, which is usually the case. A property is considered additive if the property of a blend is the average of that same property of each of the components in the blend (averaged on a weight-, volume-, or mol-fraction basis). In other words, the property of a 50-50 blend would be the average of that property for the two components of the blend.

The properties that are additive include:

- Boiling point based on values from a TBP distillation
- Vapor pressure on a mol percent basis
- Aniline point
- Sulfur content

The properties that are not additive on a volume basis include:

- Octane number
- Viscosity
- Flash temperature
- Pour point
- Reid vapor pressure (RVP)
- Smoke point

A property that is additive must be satisfied one of the following equations:

$$P_b = \sum W_i P_i \tag{2.2}$$

$$P_b = \sum V_i P_i \tag{2.3}$$

$$P_b = \sum X_i P_i \tag{2.4}$$

where:

P_b = property of total blend

P_i = property of component i

W_i = weight fraction of component i

V_i = volume fraction of component i

X_i = mole fraction of component i

When a property does not blend linearly (is not additive), one technique used is to substitute a blending number or blending index that does blend linearly. These functions, which are referred to as blending numbers, blending indices, or blending factors, must satisfy the following equations:

$$I_b = \sum W_i I_i \tag{2.5}$$

$$I_b = \sum V_i I_i \tag{2.6}$$

$$I_b = \sum X_i I_i \tag{2.7}$$

where:

I_b = blending index for total blend

I_i = blending index for component i

Note that the qualities blended in an LP model must be based on the same units, which is, weight, volume, mol-fraction. For instance, vapor pressures can be blended on a mol-fraction basis with good accuracy. In a model or in blending calculations based on volume flows, however, the vapor pressures must be converted to volume blending indices since the vapor pressures do not blend linearly on a volume basis. In the USA, most refinery LP models and blending calculations are based on volume units since these are the common units for the domestic petroleum business. However, in Europe and elsewhere, weight units are most often used.

Today most refineries use computer-controlled in-line blending for blending gasolines and other high-volume products. Inventories of blending stocks, together with cost and physical property data are maintained in the computer. The computer uses linear programming models to optimize the blending operations to select the blending components to produce the required volume of the specified product at the lowest cost. Moreover, with much improved continuous analyzers for octane and volatility coupled with computers, refiners can confidently blend directly to tankers and pipelines at considerable savings over batch blending due to reduced material in inventory, and closer approach to specifications (less quality give-away).

2.3.3 Uncertainties in Refinery Planning

Since the refinery industry is a tremendous business that has to deal with many sections from crude oil purchasing and processing to product distributing and selling, the refinery planning may contain a lot of uncertainties. The uncertainties can arise from crude cost, product price and demand etc. The effect of these uncertainties, for example, demand uncertainty, can result in over- or under-production, with resultant excess inventories or an 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 maximization of the profit and minimization the cost of risk from safety stock leads to the formulation of a stochastic optimization problem.

2.4 Two-Stage 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, 2003). Some model parameters are accounted as random variables with a certain probability distribution. In turn, some of these decisions must be made with incomplete 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.

Optimization this kind of 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):

$$\begin{aligned} Max\ \mathrm{E}\left[Profit\right] &= \sum_{s\in S} p_s q_s^{\mathrm{T}} y_s - c^{\mathrm{T}} x \\ \text{s.t.} \qquad Ax &= b \\ T_s x + W y_s &= h_s \qquad\qquad s \in S \\ x &\geq 0 \qquad\qquad x \in X \\ y_s &\geq 0 \qquad\qquad \forall s \in S \end{aligned} \tag{2.8}$$

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, $c^{\mathrm{T}}x$, and the expectation of the second-stage objective, $q_s^{\mathrm{T}}y_s$, taken over all realizations of the random event s. For a given realization of the random events, $s \in S$, the second-stage problem data q_s, h_s, and T_s become known, and then the second-stage decisions, y_s(x), must be made. In this thesis, the study was restricted to the cases where W, the recourse matrix, is fixed.

2.5 Financial Risk Management

According to Barbaro and Bagajewicz (2003), financial risk related with a planning project can be defined as the probability of not meeting a certain target profit (maximization) or cost (minimization) level.

2.5.1 Value at Risk and Upside Potential

Value at Risk (VaR) 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 (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 (2003) 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.

2.5.2 Risk Area Ratio

VaR and UP are point measures and do not represent the behavior of the entire curve (Aseeri and Bagajewicz, 2003). The use of a method that compares the areas between two curves was proposed. The proposed ratio, the Risk Area Ratio (RAR), can be calculated as the ratio of the Opportunity Area (O_Area), enclosed by the two curves above their intersection, to the Risk Area (R_Area), enclosed by the two curves below their intersection (Equation (2.9) and Figure 2.4).

$$RAR = \frac{O\_Area}{R\_Area} \tag{2.9}$$

Note that this is only true if the second curve is minimizing risk in the downside region. If risk on the upside is to be minimized, then the relation is reversed (i.e. O_Area is below the intersection and R_Area is above it).

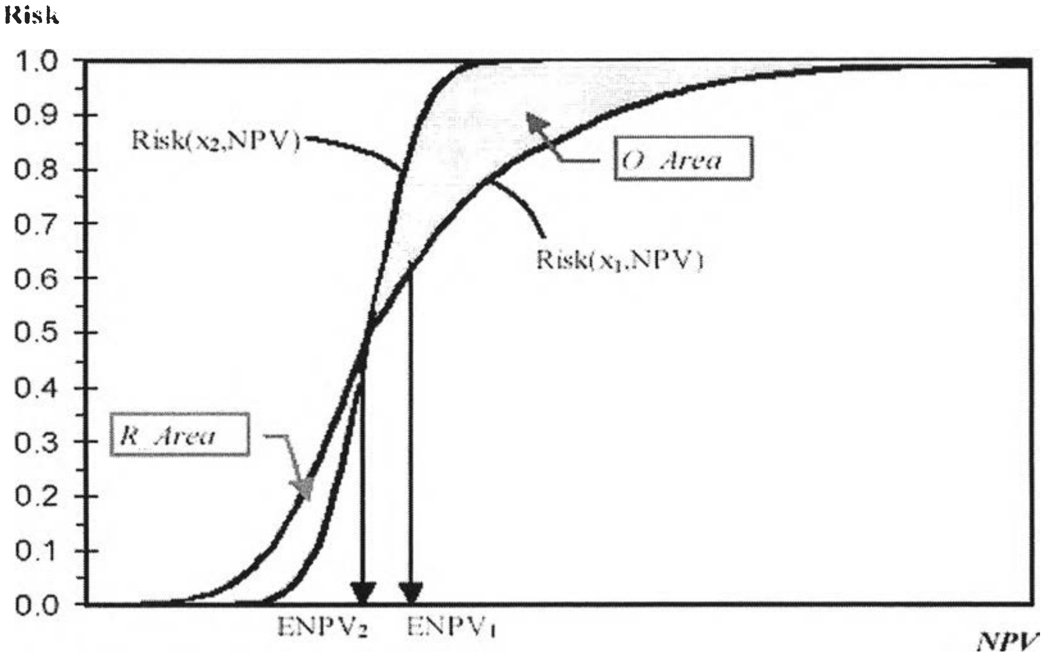

Figure 2.4 Risk Area Ratio (Aseeri and Bagajewicz, 2003).

2.5.3 Use of the 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 these series of designs are obtained, the first stage variables of each one is used as fixed numbers in a new stochastic model containing a much larger number of scenarios. The result tends asymptotically to such optimum which was proven by Aseeri and Bagajewicz (2003). In addition, using proper values in the sampling algorithm, one can capture the stochastic solution.

2.5.4 Upper Risk Curve Bounds

The upper bound risk curve is defined to be the curve constructed by plotting the set of net present values (NPV) for the best design under each scenario, that is by using all "wait and see" solutions. Figure 2.5 shows the upper bound risk curve and curves corresponding to possible and impossible solutions. The risk curve for any feasible design is positioned entirely above (to the left of) the upper bound risk curve (Aseeri and Bagajewicz, 2003).

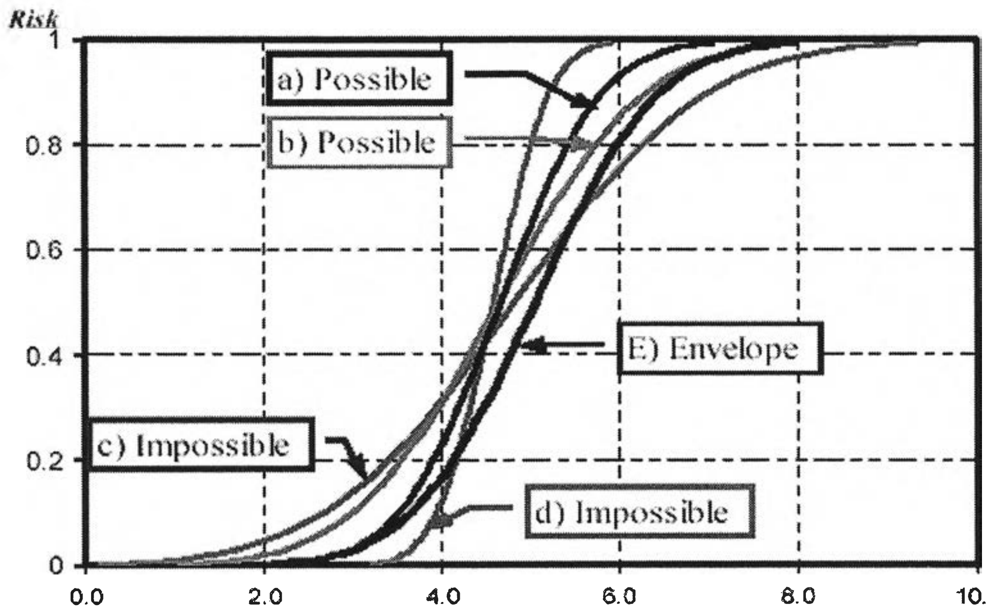

Figure 2.5 Upper bound risk curve (Aseeri and Bagajewicz, 2003).

2.6 Literature Survey

2.6.1 Refinery Operations 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 objectives (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 discretisation of the time horizon into intervals of equal duration. The problem was decomposed into two smaller ones: a downstream problem and an upstream problem. The downstream problem was solved first and the upstream problem was solved subsequently.

On the scheduling of crude oil unloading, Lee *et al.* (1996) addressed the problem of inventory management of a refinery that imports several types of crude oil which are delivered by different vessels. The problem is formulated as a mixed-integer linear program (MILP) that involves bilinear equations due to mixing operations. Nevertheless, the linearity is maintained by replacing bilinear terms with individual component flows. The LP based branch and bound method is applied to solve the model with several techniques to reduce the computation time.

Zhang *et al.* (2001) proposed a method for overall refinery optimization through integration of the hydrogen network and the utility system with the material processing system. This method considers the optimization of refinery liquid flows, hydrogen flows, and steam and power flows simultaneously. They also presented the approach on debottlenecking in refinery operation. The aim of the debottlenecking is to shift bottlenecks from an expensive process to a cheaper process by modifying networks such as the hydrogen network and the utility system. Other bottlenecks which cannot be tackled by the network changes are retrofitted by using detailed process models to achieve the required extra capacity.

Wenkai *et al.* (2002) presented a solution algorithm and mathematical formulations for short term scheduling of crude oil unloading, storage, and processing with multiple oil types, multiple berths, and multiple processing units. They suggest solving mixed-integer nonlinear programming (MINLP) model by iteratively solving two MILP models and a nonlinear programming (NLP) model.

Göthe-Lundgren *et al.* (2002) described a production planning and scheduling problem in an oil refinery company. In the production planning, the focus is on the production cost of changing mode and holding inventory. The model is formulated as a MILP.

Jia *et al.* (2003) addressed the problem of crude oil short term scheduling. The scheduling involves the optimal operation of crude oil unloading from vessels, its transfer to storage tanks, and the charging schedule for each crude oil mixture to the distillation units. The model is developed based on a continuous time representation and results in a MILP problem.

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 models 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 to represent 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. In their work, mathematical programming models are based on mixed integer optimization algorithms. They showed that these problems could be formulated as large-scale MIP optimization models. Continuous time models were found to avoid the difficulty originated by the relevant differences in processing time of the several operations involved while optimal results were obtained in reasonable time through discretization of scheduling horizon. The LP based branch and bound method is used to solve MILP models whereas NLP is solved by generalized reduced gradient method. The solution of the MINLP non-convex model presented for the fuel oil production problem can in principle be accomplished with the augmented penalty version of the outer-approximation method implemented in DICOPT++. However, it is computationally infeasible to obtain global optimal solutions due to the highly combinatorial features of the MIP formulations. These numerical problems of the model need to address.

On the blending process, Glismann and Gruhn (2001) developed an integrated approach to coordinate short term scheduling of multi-product blending facilities with nonlinear recipe optimization. The recipe optimization problem is treated as a NLP and its results are forwarded to the scheduling problem. The scheduling problem is formulated as a MILP based on a resource-task network (RTN) representation.

Jia and Ierapetritou (2003) introduced a MILP model based on continuous representation of the time domain for gasoline blending and distribution scheduling. The problem involves the optimal operation of gasoline blending, the transfer to product stock tanks, and the delivering schedule to satisfy all of the orders.

A decomposition technique that is applied to overall refinery optimization was presented by Zhang and Zhu (2000). They decomposed the overall plant model into two levels, namely a site level (master model), and a process level (submodels). The master model determines common issues among processes such as allocation of raw materials and utilities. With these common issues determined, submodels then optimize individual processes. The results from submodel optimization are fed back to the master model for further optimization.

Moro and Pinto (2004) addressed the problem of crude oil inventory management of a refinery that receives several types of oil delivered through a pipeline. The short-term scheduling in this problem is modeled as mixed-integer programming models based on a continuous-time formulation.

2.6.2 Planning of Petroleum Supply Chain under Uncertainty

Bopp *et al.* (1996) described the problem of managing natural gas purchases under conditions of uncertain demand and frequent price change. In their paper, they presented a stochastic optimization model to solve this problem. Unlike other models, this model explicitly considers deliverability, the rate at which gas can be added to and withdrawn from a storage facility, as a variable, and considers its role in ensuring a secure supply of gas. Similarly, Guldmann and Wang (1999) presented a large MILP and a much smaller NLP approximation of the MILP, involving simulation and response surface estimation via regression analysis to solve the problem of the optimal selection of natural gas supply contracts by local gas distribution utilities. The model minimizes the total cost of gas supply and market curtailment, and thus determines the size of the interruptible market. The demand for various gas market segments is driven by using weather variability as the basic stochastic factor.

Liu and Sahinidis (1996) developed a two-stage stochastic programming approach for process planning under uncertainty. They extended a deterministic MILP formulation to account for the presence of discrete random parameters. A decomposition algorithm for the solution of the stochastic model was also introduced. A method was proposed to compare the stochastic and fuzzy programming approaches. The problems were solved using a combination of Bender decomposition with Monte Carlo sampling.

The optimization of a multiperiod Supply, Transformation, and Distribution (STD) can be found in literatures. Escudero *et al.* (1999) proposed a modeling framework for STD optimization of an oil company that accounts for uncertainty on the product demand, spot supply cost, and spot selling price. They used a two-stage scenario analysis based on a partial recourse approach. Tsiakis *et al.* (2001) introduced the design of multiproduct, multi-echelon supply chain networks. The networks include a number of manufacturing sites at fixed locations, a number of warehouses, and distribution centers of unknown locations which would be selected from a set of potential locations, and lastly a number of customer zones at fixed locations. Neiro and Pinto (2003) extended the single refinery model of Pinto *et al.* (2000) to a corporate planning model that contains multiple refineries. The model is optimized along a planning horizon resulting in a large scale MINLP that non-linearity arises from blending equations and physical properties. They also examined for different types of crude oil and product demand scenarios.

Using the fuzzy theory, Liu and Sahinidis (1997) presented an application of fuzzy programming to process planning of petrochemical complex. A global optimization algorithm is developed for the solution of nonlinear case.

Hsieh and Chiang (2001) developed a manufacturing-to-sale planning system to deal with uncertain manufacturing factors. The problem of the uncertain nature faced by the Chinese Petroleum Corporation (CPC) is the major objective of this study. A linear programming was suggested for developing the optimal strategy for use in production plans. Fuzzy theory was used to deal with demand and cost uncertainties.

The optimization model for the supply chain of a petrochemical company operating under uncertain operating and economic conditions was developed by Lababidi *et al.* (2004). In this work, a deterministic model was developed first and then uncertainties in key parameters were introduced. The model was tested on a typical petrochemical company, manufacturing different grades of polymer products. Uncertainties were introduced in demands, market prices, raw material costs, and production yields.

2.6.3 Financial Risk Management

Barbaro and Bagajewicz (2003) presented a methodology to include financial risk management in the framework of two-stage stochastic programming for planning under uncertainty. A known probabilistic definition of financial risk is adapted to be used in the framework of two-stage stochastic programming and its relation to downside risk is analyzed. 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 insights 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.

New measures and procedures to manage financial risk were introduced by Aseeri and Bagajewicz (2003). The concept of Value at Risk and Upside Potential as means to weigh opportunity loss versus risk reduction as well as an area ratio are introduced and discussed. Upper and lower bounds for risk curves corresponding to the optimal stochastic solutions were developed, the application of the sampling average algorithm, was analyzed, and the relation between two-stage stochastic models that manage risk and the use of chance constraints was discussed. These concepts are applied to the commercialization of gas in Asia.