3
Literature Review of Refineries Planning under Uncertainty

The purpose of the present chapter is to present a survey of existing literature in the area of refinery planning models (strategic, tactical, and operational), with emphasis on the main techniques used to deal with optimization under uncertainty. The aim of the review is to identify the major literature gaps and the research opportunities in this area. The literature review considers only journal papers because of their academic relevance, the number of citations to them in other papers, and their search facility. The review considers papers published starting from the nineties as that is when the first work on optimization under uncertainty applied to the refinery planning (Liu and Sahinidis, 1996) was published. The review focuses on the midstream segment of refinery planning, but a few papers dealing with the other segments (upstream and downstream) are also included. Finally, production scheduling studies are beyond the scope of this thesis, and the interested reader can refer to the works by Joly *et al*. (2002), Grossmann *et al*. (2001), Pinto *et al*. (2000), and Verderame *et al*. (2010). Scheduling is concerned with detailed information about decisions such as task sequencing and task allocation to equipments in order to meet the goals set by planning and considers periods of time such as days or weeks (Magalhães *et al*., 1998).

The remainder of this chapter is organized as follows. Section 3.1 presents a possible classification of the refining planning problem. An overview of the main approaches to optimization under uncertainty is discussed in section 3.2. Next, section 3.3 presents a classification of uncertainty factors. The literature review is then presented in section 3.4. Section 3.5 offers the conclusions of the review.

3.1.
Problem classification

The refinery planning problem can be written as a nonlinear problem (NLP) as follows:

$$\underset{x}{Max}\{z(x)\} \text{ subject to } g_i(x) \leq 0,\ i = 1,...,m,\ x \in \Re^n \qquad \textbf{(3.1)}$$

Where the nonlinearities arise from the final product specification constraints. Product properties, such as octane number and vapor pressure, assume a nonlinear relationship with quantities at each blending component (Lasdon and Waren, 1983). The difficulties in solving NLP led to the development of specialized techniques to different kinds of handle nonlinearities. Many nonlinear features in refinery planning models can be readily linearized in order to gain computation speed. So, Model 3.1 can be rewritten as the following LP:

$$\underset{x}{Max}\{z(x) = c^T x\} \text{subject to } Ax \leq b,\ x \in \Re^n,\ c \in \Re^n,\ b \in \Re^m,\ A \in \Re^{m \times n} \qquad \textbf{(3.2)}$$

Two commonly used approaches in industry and commercial planning software to tackle this problem are linear blending indices and successive linear programming (SLP). Linear blending indices are dimensionless numerical figures that were developed to represent true physical properties of mixtures on either volume or weight average basis (Bodington and Baker, 1990). This approximation is adopted in many refineries because it can be used directly in the linear problem (LP) (Al-Qahtani and Elkamel, 2010a). Successive linear programming (SLP), on the other hand, is a more sophisticated method to linearize blending nonlinearities in the pooling problem. The idea of SLP was first introduced by Griffith and Stewart (1961) who utilized the concept of Taylor series expansion to remove nonlinearities in the objective function and constraints then solving the resulting linear model repeatedly. Every LP solution is used as an initial solution point for the next model iteration until a satisfying criterion is reached. Most commercial blending software and computational tools nowadays, such as RPMS and PIMS, are based on SLP. However, such commercial tools are not built to support studies on plants integration and stochastic modeling and analysis.

Additionally, discrete decisions such as minimum quantity of oil purchased and choice of an operational mode considering the requirement of a minimum quantity of material to be processed can also be imposed in refinery planning models. In this case, the models (1) and (2) are reformulated to include constraints of the form $g_i(x) \leq b\rho$ and $Ax \leq b\rho$ ($\rho \in \{0,1\}$), hence giving rise, respectively, to mixed-integer nonlinear models (MINLP) and mixed-integer linear models (MILP).

The approaches to optimization of the previously presented models when they are subject to uncertainties are discussed in the next section.

3.2.
Approaches to optimization under uncertainty

The main techniques for dealing with uncertainty in the refinery planning optimization problem are shown in Figure 5 and are detailed below.

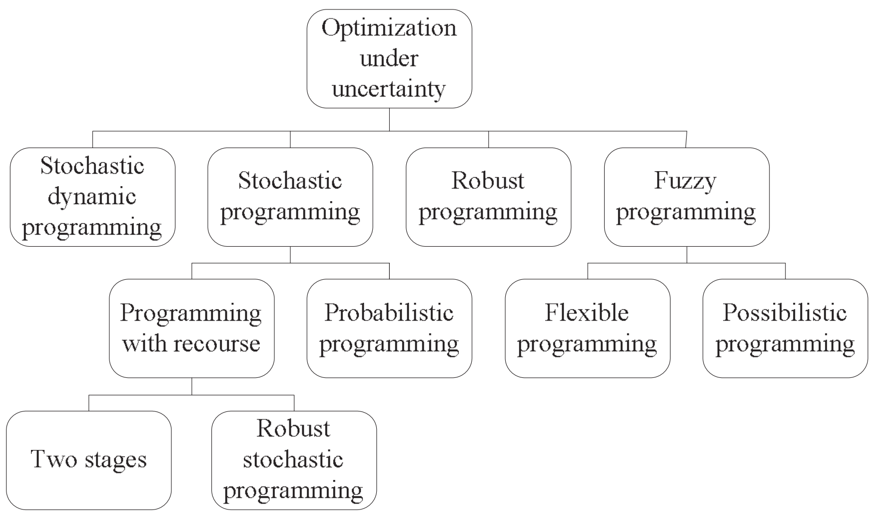

Figure 5. Approaches to optimization under uncertainty (based on Sahinidis, 2004 and Khor and Elkamel, 2008)

3.2.1
Stochastic programming

The stochastic programming approach deals with optimization problems with parameters that assume a discrete or continuous probability distribution and can be divided into recourse models and probabilistic models. The recourse models were originally proposed by Dantzig (1955) and Beale (1955) for *two-stage stochastic programming* problems and can be extended to the multistage case (*stochastic dynamic programming*). Recourse models use corrective actions to compensate the constraint violations after the realization of uncertainty. The probabilistic approach, also known as chance-constrained programming, was originally introduced by Charnes and Cooper (1959). In this approach, the infeasibilities in the second stage are allowed at a certain penalty.

Two-stage stochastic programming with recourse

In this approach, decision variables are cast into two groups, first- and second-stage variables (Dantzig, 1955; Beale, 1955). The first-stage variables are decided upon prior to the actual realization of the random parameters (*here-and-now decisions*). Once the uncertain events have unfolded, further operational adjustments can be made through values of the second stage.

Consider the classic linear problem (Model 3.2). The two-stage stochastic programming model can be formulated as:

$$\underset{x}{Max}\left\{z(x)=c^T x+E\left[Q(x,\xi)\right]\right\} \text{ subject to } Ax\leq b \quad \textbf{(3.3)}$$

Where $Q(x,\xi)$ is the optimal value of the second-stage problem:

$$\underset{y}{Max}\, q^T y \text{ subject to } Wy\leq h-Tx,\; y\geq 0 \quad \textbf{(3.4)}$$

Where $x\in R^n$ is the vector of first-stage decision variables, $y\in R^m$ is the vector of second-stage decision variables, and $\xi=(q,T,W,h)$ is the vector of data for the second-stage problem that can be represented by random variables with known probability distribution.

Robust stochastic programming with recourse

The two-stage stochastic programming provides a traditional risk-neutral approach to choose the best operational plan among a set of candidate periods. In this section, we introduce the risk-averse point of view using robust stochastic programming which was proposed by Mulvey *et al.* (1995). They defined two types of robustness: (a) a robust solution remains close to an optimal model solution for any scenario realization and (b) a robust model is almost feasible for any scenario realization. To get the risk notion in stochastic programming, Mulvey *et al.* (1995) proposed the following modification in Model (3.3):

$$\underset{x}{Max}\left\{z(x)=c^T x+E\left[Q(x,\xi)\right]-\lambda f(\xi,y)\right\} \quad \textbf{(3.5)}$$

Where f is a variability measure of the second-stage costs and λ is a non-negative scalar that represents the risk tolerance of the modeler. Large values of λ result in solutions that reduce variance, whereas small values of λ reduce expected costs (Sahinidis, 2004).

Probabilistic programming (chance-constrained programming)

The probabilistic models allow some second-stage constraints to be expressed in terms of probabilistic statements about the decisions of the first stage (Charnes and Cooper, 1959). Corrective actions for recourse models are avoided in this approach, since the second-stage constraints can be violated by incorporating a risk measure. The probabilistic models are particularly useful when the costs and benefits associated with the second-stage decisions are difficult to measure.

Assuming that the parameter $\boldsymbol{b}$ of Model (3.2) is an uncertain parameter with the cumulative distribution function Φ and assigning a confidence level α_i, the probabilistic program corresponding to the deterministic linear program can be stated as follows:

$$\mathrm{P}\left\{\sum_{j=1}^{m} A_{ij}x_i \leq b_i\right\} \geq \alpha_i \qquad i = 1,2,\ldots,n \qquad \textbf{(3.6)}$$

Where $\boldsymbol{P}$ is the probability measure. As α_i and Φ_i^{-1} are known, by applying the cumulative distribution function of $\boldsymbol{b}$, the probabilistic constraint can be written as an equivalent deterministic linear constraint:

$$\sum_{j=1}^{m} A_{ij}x_i \leq \Phi_i^{-1}(1-\alpha_i) \qquad i = 1,2,\ldots,n \qquad \textbf{(3.7)}$$

3.2.2
Stochastic dynamic programming

The stochastic dynamic models deal with multistage decision processes (Bellman, 1957). In a multistage model, the uncertain data $\xi_1, \xi_2 \ldots \xi_t$ is unfolded over $\boldsymbol{T}$ periods and decisions must be adapted to the process chronology. The decision vector x_t may depend on the information ξ_t available up to time t, but not on results of future observations. In addition, at a given stage t, the scenarios that have the same story ξ_t cannot be differentiated. These requirements are known as *nonanticipativity* constraints (Ruszczynski and Shapiro, 2009). The multistage model is formulated as follows:

$$\underset{x}{Max}\left\{z(x)=c^T x_1+E\left[Q(x_2,\xi_2)+...+E[Q(x_t,\xi_t)]\right]\right\} \text{ subject to } Ax_1 \leq b \qquad \textbf{(3.8)}$$

Where $Q(x_t,\xi_t)$ is the optimal value $\forall t=2,...T$:

$$\begin{aligned}\underset{y}{Max}\, q^T y_t(\xi_t) \text{ subject to } W_t(\xi_t)\, y_t(\xi_t) \leq h_t(\xi_t)-T_{t-1}(\xi_{t-1})\, x_{t-1}(\xi_{t-1}),\\ y_t(\xi_t)\geq 0\end{aligned} \qquad \textbf{(3.9)}$$

3.2.3 Robust programming

Robust optimization focuses on models that ensure solution feasibility for the possible outcomes of uncertain parameters. Under this approach, the decision-maker accepts a suboptimal solution to ensure that, when the data changes, the solution remains feasible and near optimal. On the other hand, this method assumes limited information about the distributions of the underlying uncertainties, such as the mean value and its range. Unlike in the approach of stochastic optimization, the specification of scenarios and corresponding probabilities are unnecessary in robust optimization, all of which can be often cumbersome to estimate.

Assume that the parameter ***A*** of Model (3.2) is subject to uncertainty and can take values in the range $[\bar{a}_{ij}-\hat{a}_{ij},\bar{a}_{ij}+\hat{a}_{ij}]$.

$$\text{Let } \Lambda=\left\{ \mathrm{A}\in\Re^{mxn} \left| a_{ij}\in[\bar{a}_{ij}-\hat{a}_{ij},\bar{a}_{ij}+\hat{a}_{ij}]\forall i,j, \sum_{(i,j)\in J}\frac{\left|a_{ij}-\bar{a}_{ij}\right|}{\hat{a}_{ij}}\leq\Gamma_i \right.\right\}.$$

According to Bertsimas and Thiele (2006), the robust problem is formulated as:

$$\underset{x}{Max}\left\{z(x)=c^T x\right\} \text{ subject to } Ax\leq b, \forall A\in\Lambda \qquad \textbf{(3.10)}$$

The first investigation based on the robust technique was reported by Soyster (1973), who proposed a conservative approach that assumed that all random parameters were equal to their worst-case values. Since then, several studies have extended the Soyster approach as can be seen in Beyer and Sendhoff

(2007). Ben-Tal and Nemirovski (1998, 1999, 2000), El-Ghaoui *et al*. (1998) and El-Ghaoui and Lebret (1997) presented robust methods that are less conservative, introducing a nonlinear term in the objective function. Bertsimas and Sim (2003, 2004) and Bertsimas *et al.* (2004) proposed a method that does not add complexity to the original problem, and the degree of conservatism is controlled by the decision-maker. In spite of these advantages, a limitation of the Bertsimas and Sim's approach is that the uncertain parameters are considered unknown but bounded and symmetric random variables. Other types of distributions are discussed by Ben Tal and Nemirovski (1999) for linear problems with bounded uncertainty as well as the extensions of Lin *et al*. (2004) (for MILP with bounded uncertainty) and Janak *et al*. (2007) (for MILP with known probability distributions). These works have further been studied and extended by Verderame and Floudas (2009, 2010a, and 2010b).

3.2.4 Fuzzy programming

The fuzzy programming approach was originally proposed by Bellmann and Zadeh (1970) and popularized by Zimmermann (1991). The main difference between the stochastic and fuzzy techniques is in the way the uncertainty is modeled. The stochastic programming models uncertainty as probability functions, while fuzzy programming models random parameters as fuzzy numbers and constraints as fuzzy sets. In addition, the objective function is modeled as a constraint with the bounds of these constraints defining the decision maker's expectations (Sahinidis, 2004).

Let the constraint $Ax \leq b$ of Model (3.2), assume that the parameter $\boldsymbol{b}$ can take values in the range $[b, b+\Delta b]$, $\Delta b \geq 0$. The membership function of this constraint can be defined as:

$$p(x) = \begin{cases} 1, & if \quad Ax \leq b \\ 1 - \dfrac{Ax-b}{\Delta b}, & if \quad b < Ax \leq b + \Delta b \\ 0, & if \quad b + \Delta b < Ax \end{cases} \qquad \textbf{(3.11)}$$

The fuzzy programming approach is further divided into flexible programming and possibilistic programming. Whereas the former deals with uncertainties in the soft constraints ($Ax \tilde{\leq} b \; Ax \tilde{\leq} b$), the latter recognizes the uncertainties in the objective function ($\tilde{c}^T x \; \tilde{c} x$) and the coefficient constraints ($\tilde{A}x \leq \tilde{b}$) (Sahinidis, 2004).

3.3.
Classification of uncertainty

Uncertainties can be categorized as short-term, mid-term, or long-term. Short-term uncertainties refer to unforeseen factors in internal processes such as operational variations and equipment failures (Subrahmanyam *et al*., 1994). Alternatively, long-term uncertainties represent external factors, such as supply, demand, and price fluctuations, that impact the planning process over a long period of time. Mid-term uncertainties include both short-term and long-term uncertainties (Gupta and Maranas, 2003).

Jonsbraten (1998) and Goel and Grossmann (2004) classified uncertainties as external (exogenous) uncertainties and internal (endogenous) uncertainties, according to the point-of-view of process operations. As indicated by the name, external uncertainties are exerted by outside factors that impact the process. The decisions at each stage are independent of the decisions taken in previous periods. On the other hand, internal uncertainties arise from deficiencies in the complete knowledge of the process. The decisions at each stage depend on decisions taken in previous periods.

Table 2 categorizes some examples of uncertainty factors according to the two criteria presented previously. Some of these examples can be seen in the stochastic programming applications detailed in the next section.

Table 2. Classification of uncertainty factors (based on Khor and Elkamel, 2008)

Time horizon	Process operations	
	External (exogenous)	***Internal (endogenous)***
Long-term	– Availability of sources of oil supply – Economic data on raw materials, finished products, utilities, etc. (prices, demands, and costs) – Location – Budgets on capital investments for capacity expansion and new equipment purchases or replacements – Investment costs of processes – Regulatory issues concerning laws, regulations, and standards – Technology obsolescence – Political issues	
Medium-term	– Economic data on raw materials, finished products, utilities, etc. (prices, demands, and costs) – Type of oil available	
Short-term		– Type of oil available – Properties of components – Product/process yields – Blending options – Process variations (flow rates and temperatures) – Machine availability

3.4.
Literature review of refinery planning

Table 3 presents a collection of works on refinery planning. The papers are classified according to the segment of the oil chain (upstream, midstream, or downstream), planning level (strategic, tactical, or operational), and problem type (LP, NLP, MILP, or MINLP). The works are also categorized as deterministic or stochastic, and it is indicated whether they present an actual application or not. It should be noted that the research focuses on midstream and few papers also consider the other segments. The most of the works that consider other segments present strategic or tactical planning models.

Historically, refinery planning models for oil industry were based on LP and MILP. The computational and algorithmic complexity of NLP and MINLP inhibited the model development in this area. The first application of MINLP is the one of Liu and Sahinidis (1997); however, the applications of MINLP are still considered a challenge. In fact, LP represent $\frac{15}{40}$ and MILP also represent $\frac{15}{40}$ of the studies presented at Table 3, whereas NLP and MINLP reach $\frac{9}{40}$ and $\frac{8}{40}$, respectively. Note that some works present more than one model.

Table 3. Literature review of refinery planning

Author (year)	Segment			Decision level				Problem type				Deterministic	Stochastic	Actual
	Upstream	Midstream	Downstream	Strategic	Tactical	Operac.	Sched.	LP	NLP	MILP	MINLP			
Al-Qahtani & Elkamel (2010)		x	x	x						x			x	x
Park *et al.* (2010)		x				x		x					x	
Carneiro *et al*. (2010)	x	x	x	x				x					x	x
Leiras *et al*. (2010)		x				x		x					x	
Ribas *et al*. (2010)	x	x	x	x				x					x	x
Luo & Rong (2009)		x				x	x			x			x	
Khor & Nguyen (2009)		x				x			x				x	
Guyonnet *et al*. (2009)		x	x		x			x	x			x		
Alhajri *et al.* (2008)		x				x			x			x		
Al-Othman *et al*. (2008)	x	x	x		x					x			x	
Al-Qahtani & Elkamel (2008)		x	x	x						x		x		x
Elkamel *et al*. (2008)		x				x					x	x		
Gao *et al*. (2008)		x				x				x		x		x
Khor *et al*. (2008)		x			x			x					x	
Lakkahanawat & Bagajewicz (2008)		x				x		x					x	x
Li, Chufu *et al*. (2008)		x				x		x	x		x		x	x
Kim *et al*. (2008)		x	x		x	x			x	x		x		x
Zhang & Hua (2007)		x				x				x		x		x
Micheletto *et al*. (2007)		x				x				x		x		x
Pongsakdi *et al*. (2006)		x				x		x					x	x
Neiro & Pinto (2006)		x				x					x		x	x
Zhang and Zhu (2006)		x				x			x			x		
Neiro & Pinto (2005)		x				x					x		x	x
Li, Wenkai *et al*. (2005)		x				x			x			x		
Li, Wenkai *et al*. (2004)		x			x					x	x		x	x
Neiro & Pinto (2004)		x	x			x					x	x		x
Göthe-Lundgren *et al*. (2002)		x				x	x			x		x		x
Ponnambalam *et al*. (2002)		x				x		x				x		
Joly et al. (2002)		x				x	x		x	x		x		x
Hsieh & Chiang (2001)		x	x		x			x					x	x
Zhang *et al.* (2001)		x				x		x				x		
Dempster *et al*. (2000)		x	x		x			x				x	x	x
Pinto & Moro (2000)		x				x	x			x		x		x
Pinto *et al*. (2000)		x				x	x				x	x		x
Escudero *et al*. (1999)		x	x		x			x					x	
Moro *et al*. (1998)		x				x			x			x		x
Ahmed & Sahinidis (1998)		x		x						x			x	
Ravi & Reddy (1998)		x				x		x					x	
Liu & Sahinidis (1997)		x		x						x	x		x	
Liu & Sahinidis (1996)		x			x					x			x	

By analyzing the 40 studies presented in Table 3, it can be concluded that very few of them address strategic planning ($\frac{6}{40}$), whereas $\frac{26}{40}$ address operational planning. The emphasis on strategic models has increased over the past few years, as can be seen in the works by Al-Qahtani and Elkamel (2010b), Carneiro *et al.* (2010), Ribas *et al.* (2010), and Al-Qahtani and Elkamel (2008). The latter paper considers the problem of multisite integration and coordination strategies within a network of petroleum refineries. This work was extended by Al-Qahtani and Elkamel (2010b) to consider uncertainty using robust optimization techniques. Similarly, Ribas *et al.* (2010) developed a strategic planning model for the oil chain under uncertainty, considering investments in refining and logistic infrastructure. To deal with the uncertainties they proposed a two-stage stochastic model, a min-max regret robust model, and a max-min model. The models were applied to a Brazilian oil chain. Carneiro *et al.* (2010) extended this work by the incorporation of risk management. In spite of these contributions, the work by Liu and Sahinidis (1997) was the pioneer in the application of strategic models to the oil chain. Other contribution is the work by Ahmed and Sahinidis (1998) who proposed a robust stochastic programming model for the strategic planning problem.

In regard of tactical models, Liu and Sahinidis (1996) developed a two-stage stochastic model and a fuzzy model for process planning under uncertainty. A method was proposed for comparing the two approaches. Overall, the comparison favored stochastic programming. Escudero *et al.* (1999) worked in the supply, transformation, and distribution planning problem that accounted for uncertainties in demands, supply costs, and product prices. As the deterministic treatment for the problem provided unsatisfactory results, they applied the two-stage scenario analysis based on a partial recourse approach. Dempster *et al.* (2000) formulated the tactical planning problem for an oil consortium as a dynamic recourse problem. A deterministic multi-period linear model was used as basis for implementing the stochastic programming formulation. Hsieh and Chiang (2001) developed a manufacturing-to-sale planning system and adopted fuzzy theory for dealing with demand and cost uncertainties. Li *et al.* (2004) proposed a probabilistic programming model to deal with demand and supply uncertainties in the tactical problem. Kim *et al.* (2008) worked on the collaboration among refineries manufacturing multiple fuel products at different locations. Khor *et al.* (2008) treated the problem of medium-term planning of a refinery operation by using stochastic programming (a two-stage model) and stochastic robust programming. Al-Othman *et al.* (2008) have proposed a two-stage stochastic model for multiple time periods to optimize the supply chain of an oil company installed in a country that produces crude oil. Finally, Guyonnet *et al.* (2009) considered oil uploading and product distribution problems in their tactical formulation.

In the literature, many operational planning models have been tested in real refineries around the world. In fact, actual applications represent $\frac{22}{40}$ of the studies presented in Table 3 and $\frac{15}{22}$ about operational models. For example, Gao *et al.* (2008) developed a MILP to address the production planning problem of a large-scale fuel oil-lubricant plant in China. The authors considered the choice of operational modes at each processing unit as the main optimization decision of the model. The MILP proposed by Micheletto *et al.* (2007) optimizes the operation of a refinery plant in Brazil by considering mass and energy balances, operational mode of each unit, and demand satisfaction over multiple periods of time. Moro *et al.* (1998) also employed their model for studying a refinery in Brazil. They developed a nonlinear planning model, which was applied to the particular case of diesel production to maximize the profit of the refinery. Other applications in Brazil can be found in Neiro and Pinto (2004, 2005). In their early work (Neiro and Pinto, 2004), these authors developed a general framework for the modeling of petroleum supply chains. The resulting multi-period MINLP was tested in a supply chain consisting of four Brazilian refineries. A nonlinear integer programming application associated with uncertainty was investigated in the work by Neiro and Pinto (2005). They formulated a stochastic multi-period model for which the uncertainty is related to the prices of petroleum and product as well as to the product demand.

Pongsakdi *et al.* (2006) treated the uncertainty and financial risk in the planning of operations for a refinery in Thailand using a two-stage linear stochastic model. The problem consists in determining how much of each crude oil had to be purchased and the anticipated production level of different products based on demand forecasts. The uncertainty was introduced by means of the demand and product price parameters. The first-stage decisions were represented by the amount of crude oil purchased for each period. Lakkhanawat and Bagajewicz (2008) extended the work of Pongsakdi *et al.* (2006) by incorporating the product pricing in their study.

The understanding of the integration benefits of the different planning levels has also attracted attention in the refining planning area. The first contributions in this area were the works of Pinto *et al.* (2000) and Joly *et al.* (2002) who proposed deterministic models for integrated operational planning and scheduling of refineries. Luo and Rong (2009) also treated the integrated operational planning and scheduling of refineries but they dealt with uncertainty using the robust approach proposed by Janak *et al.* (2007).

The stochastic models represent $\frac{22}{40}$ of the studies presented in Table 3. These works are detailed in Table 4 according to the modeling technique used to account for uncertainty and to the uncertainty factors considered.

Table 4. Main approaches to deal with uncertainty in refinery planning

Author (year)	Modeling technique						Uncertainty factor					
	Two stage	Robust Stoc.	Probabilistic	Dynam. Stoc.	Robust	Fuzzy	Demand	Supply	Price	Cost	Yield	Other
Al-Qahtani & Elkamel (2010)		x					x		x	x		
Park *et al.* (2010)		x							x			
Carneiro *et al*. (2010)		x					x	x	x			
Leiras *et al*. (2010)					x		x		x	x	x	
Ribas *et al*. (2010)	x				x		x	x	x			
Luo & Rong (2009)					x		x					x
Khor & Nguyen (2009)		x					x		x	x	x	
Al-Othman *et al*. (2008)	x						x		x			
Khor *et al*. (2008)	x	x					x		x		x	
Lakkahanawat & Bagajewicz (2008)		x					x		x	x		
Li, Chufu *et al*. (2008)			x				x					
Pongsakdi *et al*. (2006)		x					x		x			
Neiro & Pinto (2006)				x			x		x			
Neiro & Pinto (2005)				x			x		x			
Li, Wenkai *et al*. (2004)			x				x	x				
Hsieh & Chiang (2001)						x	x			x		
Dempster *et al*. (2000)				x			x		x	x		
Escudero *et al*. (1999)	x						x		x	x		
Ahmed & Sahinidis (1998)		x					x	x	x	x		
Ravi & Reddy (1998)						x						x
Liu & Sahinidis (1997)						x	x	x	x	x	x	
Liu & Sahinidis (1996)	x					x	x	x	x			

According to Table 4, the robust stochastic programming method is the most common approach used to deal with optimization under uncertainty in refinery planning $\left(\frac{8}{22}\right)$. Different risk measures can be used in the robust programming technique. Khor *et al*. (2008) applied Markowitz's mean variance (MV) and the mean absolute deviation (MAD) to handle randomness. Al-Qahtani and Elkamel (2010b) also considered variance as the risk factor. Khor and Nguyen (2009) adopted the MAD and the conditional value-at-risk (CVaR). CVarR was also used in the work of Carneiro *et al*. (2010). In Pongsakdi *et al*. (2006) and Lakkhanawat and Bagajewicz (2008), value-at-risk (VaR) measure and ratio area risk (RAR) measures, respectively, were used to study financial risk. Upper partial mean (UPM) and downside risk were used in the works of Ahmed and Sahinidis (1998) and Park *et al*. (2010).

Almost all papers presented in Table 4 show the demand as an uncertainty factor, and most of them also consider the product price variation. On the other hand, yield uncertainty, available unit capacity, and property of components have been rarely explored in the literature. Unit capacity was considered the uncertainty factor in the work of Ravi and Reddy (1998), whereas the uncertainty in property for components entering blending units was included in the paper of Luo and Rong (2009).

3.5.
Chapter conclusions

This chapter presented a literature review of refinery planning models with emphasis on the main techniques used to deal with uncertainties. Forty papers were classified according to the segment of the oil chain, planning level, and problem type that they present. Actual applications were also highlighted in the review. The works based on stochastic programming were detailed according to the modeling technique used to account for uncertainty and to the uncertainty factors considered.

Refinery planning aims not only to achieve economic optimization but also to provide planning solutions that remains near optimal when the stochastic parameters change. Thus, robust optimization appears to be a suitable alternative for this type of planning. Moreover, as the complexity of the MINLP models in refinery planning is considered a challenge; the application of stochastic MINLP models to actual refining instances is a difficult task. In this regard, the robust methodology of Bertsimas and Sim (2003) may be a viable alternative to consider uncertainty, since it does not add computational complexity to the original model. In addition, there is a predominance of studies that consider exogenous uncertainties such as price and demand. Thus, it is clear that dealing with endogenous uncertainty is also a challenge and an opportunity for research in the area.

The probabilistic programming, robust programming, and stochastic dynamic programming are techniques little explored to account for uncertainty in the refinery planning problem. The integration of different planning levels is also a rarely subject studied in the oil supply chain. So, further works may point out one of these approaches as promising areas when compared with the currently techniques in use.

In this thesis the classical two-stage stochastic programming with recourse is used to deal with uncertainty in the refinery planning problem. As the purpose of the model is to set production targets to meet a given market demand over a given time horizon, the two-stage model is more adequate. This finding is because the two-stage model represents a single plan that allows the decision-makers to identify the best oil purchase decisions which can change in time. The demand for refined products, oil prices, and product prices contain mid-term uncertainties which are incorporated in the tactical planning (medium-term), whereas oil supply and process capacity unit address the short-term uncertainties in the operational planning (short-term).