Financial Risk Management with Product Pricing in the Planning of Refinery Operations

Hansa Lakkhanawat

The Petroleum and Petrochemical College, Chulalongkorn University, Bangkok 10330, Thailand

Miguel J. Bagajewicz*

School of Chemical, Biological and Materials Engineering, University of Oklahoma, Norman, Oklahoma, 73019

In this paper, the issue of uncertainty and financial risk in refinery operations planning is addressed. The problem is determining how much of each available crude one must purchase and decide on the anticipated production level of different products, given the forecasts of overall demands. We also include, as decision variables, the price of the products. The profit is maximized by taking into account revenues, crude oil costs, inventory costs, and the cost of unsatisfied demand. Data from the refinery that is owned by Bangchak Petroleum Public Company Limited, in Bangkok, Thailand, was used for the example. The results indicate the superiority of the stochastic model, as well as the incorporation of pricing in the decision making over the use of deterministic models. Moreover, we show that, without using pricing, which introduces a price-demand relationship—a feature that normally is not present in existing models—the results that one obtains are overly optimistic, proving that pricing is an essential ingredient of planning.

Introduction

The goal of planning and scheduling in refineries is to maximize the profitability by choosing the best feedstocks, operating conditions, and schedules, while fulfilling product quantity and quality objectives that are consistent with marketing commitments.[1]

Planning and scheduling in refineries occurs 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 one 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?".[2] The cascade of models used in operational planning and scheduling is depicted in Figure 1.

Linear and integer programming are heavily used in long-term planning models. With shorter time horizons, the models must be more detailed and accurate, which, in the past, prompted the use of successive linear programming. The greatest challenges lie with the transition from operational planning to detailed scheduling, where the assumptions that are implicit in linear programming (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, the planning and scheduling of oil refinery operations can be divided into three main parts (see Figure 2). 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. The third part covers the blending of the finished product, and the shipping of the product to the customer.[3]

The different modeling and solution of each of these problems will pave the way toward addressing the overall problem of scheduling of refinery operations. The lack of computational technology for production scheduling is the main obstacle for the integration of production objectives and process operations.[5]

Mathematical programming has been extensively studied and implemented for both long-term and short-term plantwide refinery planning. Commercial software, such as the Refinery and Petrochemical Modeling System (RPMS) and the Process Industry Modeling System (PIMS), among others, has been developed for refinery production planning.

In this paper, a model was developed for production planning in Bangchak Petroleum Public Company Limited, in Bangkok, Thailand. A recently developed stochastic model[6] that considers uncertainty and financial risk was expanded to consider the effect of pricing. Because several different fields converge into building this model (deterministic refinery planning, pricing, stochastic models, etc)., we discuss the background on each of them, and then we show results.

Deterministic Refinery Planning

In the last 20 years, several models have been developed to perform short-term scheduling and longer-term planning of batch plant production to maximize the economic objective.[7] Formal

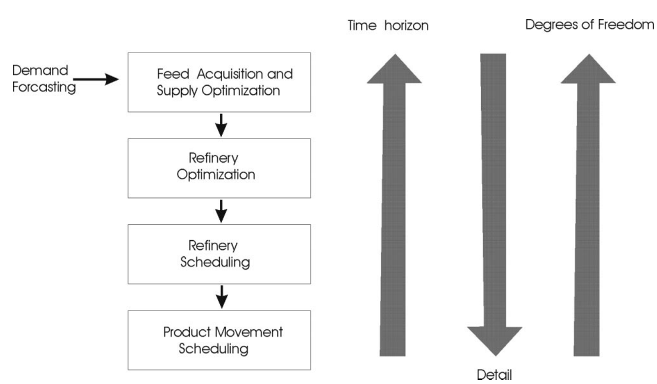

Figure 1. Planning and scheduling cascade in a refinery.[2]

* To whom correspondence should be addressed. Tel.: (405)325-5458. Fax: (405)325-5813. E-mail: bagajewicz@ou.edu.

10.1021/ie0710770 CCC: $40.75
Published on Web 07/03/2008

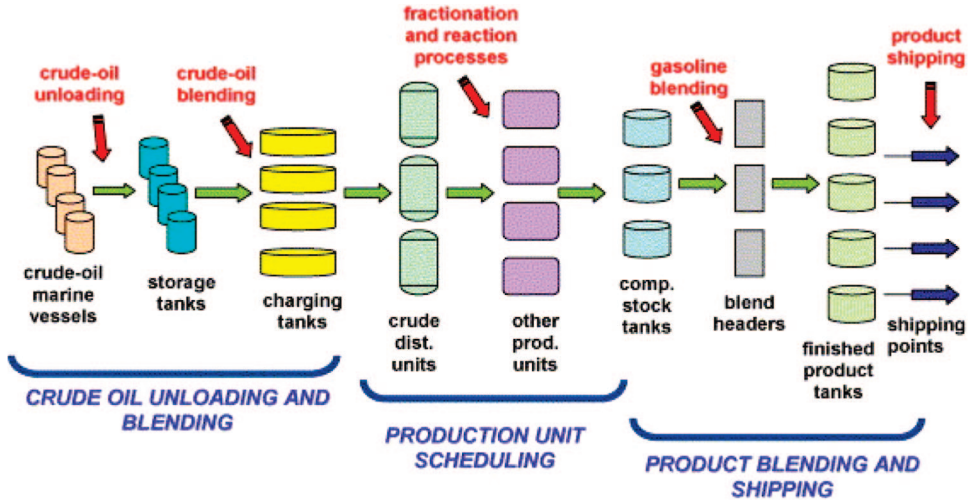

Figure 2. Overview picture of the oil refinery operations (following Méndez et al.[4])

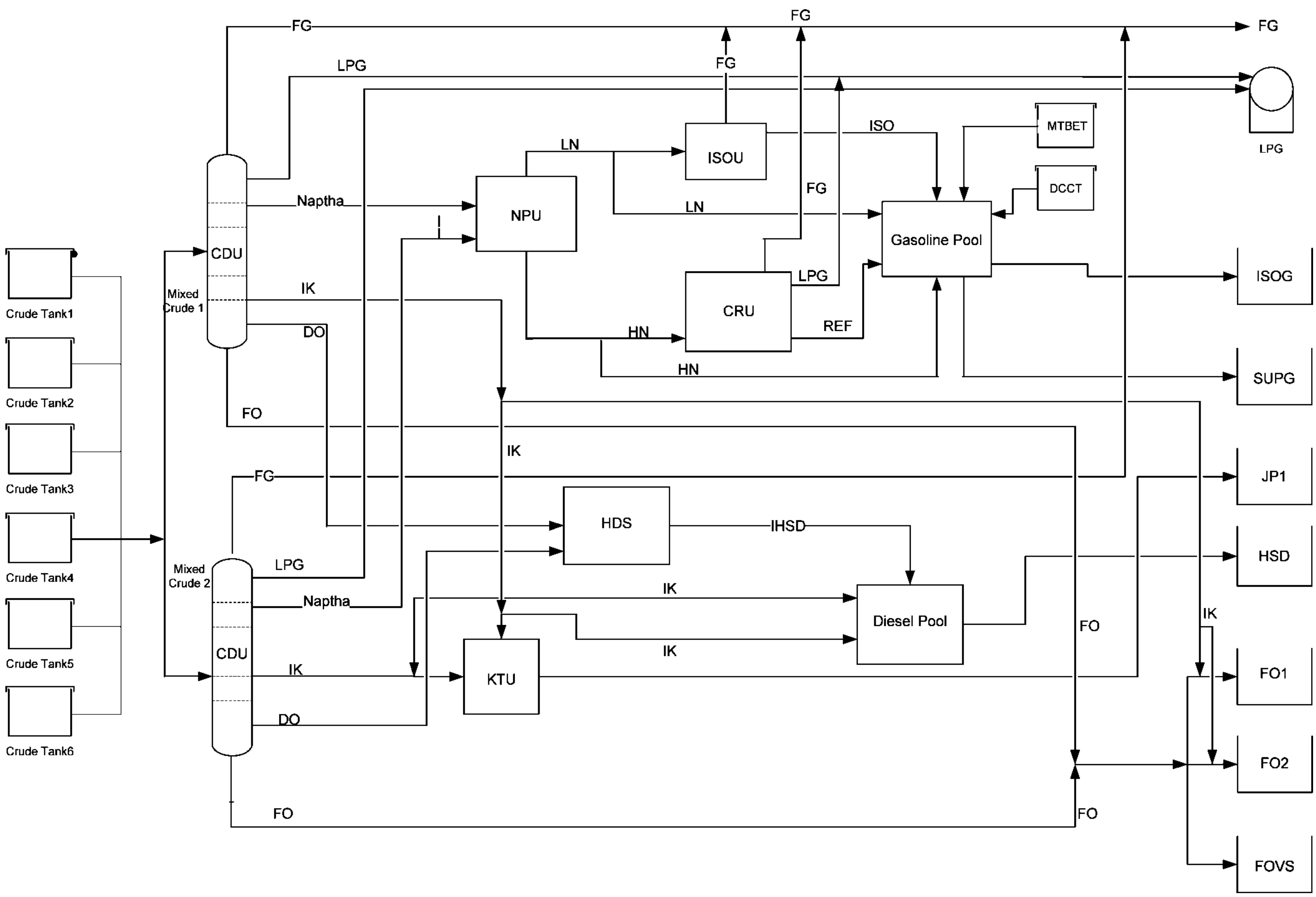

Figure 3. Refinery flow diagram.

mathematical programming techniques to the problem of scheduling the crude oil supply to a refinery was considered by Shah,[8] which includes the allocation of crude oils to refinery and portside tanks, the allocation 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 the 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: a downstream problem and an upstream problem. The downstream problem was solved first, and the upstream problem was solved subsequently.

In addition, optimization was applied for the refinery by Zhang et al.,[9] 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 they presented an approach on debottlenecking in refinery operation. Their objective was to shift bottlenecks from an expensive process to a less-expensive one by modifying networks such as the hydrogen network and the utility system. Other bottlenecks that could not be tackled by the network changes were retrofitted using detailed process models to achieve the required extra capacity. Zhang

Table 1. Crude Oil Cost and Available Quantity

crude oil	Cost ($/bbl)			max volume (m^3/month)
	time period 1	time period 2	time period 3	
Oman (OM)	56.38	64.16	58.03	no limit
Tapis (TP)	65.56	72.72	65.24	no limit
Labuan (LB)	62.31	65.73	63.24	95392.2
Seria light (SLEB)	62.31	65.73	63.24	95392.2
Phet (PHET)	58.03	63.65	58.12	57235.32
Murban (MB)	59.74	67.13	63.04	95392.2

Table 2. Product Demand and Price

product	Product Demand (m^3)			Product Price ($/bbl)		
	period 1	period 2	period 3	period 1	period 2	period 3
LPG	38020	42368	44185	32.64	31.49	30.8
SUPG	35365	37155	39093	71.87	83.76	62.63
ISOG	24173	22530	22063	73.74	85.75	64.53
JP-1	38693	35898	38373	80.63	88.68	80.54
HSD	160653	149210	147933	76.98	88.33	75.15
FO1	56823	54960	34503	55.21	56.35	47.47
FO2	56823	54960	34503	55.21	56.35	47.47
FOVS	56823	54960	34503	55.21	56.35	47.47

and Hua[10] also examined the energy consumption of the different units.

Moro et al.[11] developed a nonlinear planning model for diesel production. The resulting optimization model is solved with the generalized reduced gradient method. Pinto and Moro,[12] Pinto et al.,[5] and Joly et al.[13] focused on the refinery productions and 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 the short-term scheduling of a set of operation that includes receiving the product from processing units, storage, and inventory management in intermediate tanks, blending to meet oil specifications and demands, and transport sequencing in oil pipelines.

Moro and Pinto[14] addressed the problem of crude oil inventory management of a refinery that receives several types of oil delivered through a pipeline. In regard to the blending process, Glismann and Gruhn[15] developed an integrated approach to coordinate the short-term scheduling of multiproduct blending facilities with nonlinear recipe optimization. Jia and Ierapetritou[3] introduced a mixed-integer linear programming (MILP) model that was based on continuous representation of the time domain for gasoline blending and distribution scheduling. Finally, a decomposition technique that is applied to overall refinery optimization was presented by Zhang and Zhu.[16]

Göthe-Lundgren et al.[17] described a production planning and scheduling problem in an oil refinery company. They focused on planning and scheduling to select the mode of operation to use to satisfy the demand while minimizing the production cost. The model considered changing operation modes and holding inventory. The model is formulated using a MILP model.

Rejowski and Pinto[18] considered a system that was composed of one petroleum refinery, one multiproduct 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 determined that the model was successfully able to avoid time periods of high-energy costs and, at the same time, manage to fulfill all product demands.

Neiro and Pinto[19] proposed a general framework for modeling petroleum supply chains after the model of processing units were developed by Pinto et al.[5] 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 that represent 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 mixed-integer nonlinear programming (MINLP) model. They then 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 a 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[20] 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 involves ensuring that it satisfies the given demand at the lowest cost. They suggested a shipment planning model that included considerations of production, by representing the production (process scheduling) with a LP model. The combined process scheduling and shipment planning problem is represented by a MILP model.

Méndez et al.[4] 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 objective was to determine the best way of mixing different intermediate products from the refinery to minimize the blending cost while meeting the quality and

Table 3. Oil Purchased from the Deterministic Model without Pricing

crude oil	available quantity	Period 1		Period 2		Period 3	
		volume (m^3)	percentage (%)	volume (m^3)	percentage (%)	volume (m^3)	percentage (%)
OM	no limit	176065	36.30	211937	37.03	117966	29.63
TP	no limit	0	0.00	17004	2.97	0	0.00
LB	95392	95392	19.67	95392	16.67	95392	23.96
SLEB	95392	60938	12.56	95392	16.67	95392	23.96
PHET	57235	57235	11.80	57235	10.00	57235	14.38
MB	95392	95392	19.67	95392	16.67	32158	8.08
total		485022	100.00	572353	100.00	398143	100.00
total (kbd)		101.69		120.00		83.47	
GRM				$9.574M US			

Table 4. Percentage of Crude Fed to Each CDU

crude oil	Period 1		Period 2		Period 3	
	CDU2	CDU3	CDU2	CDU3	CDU2	CDU3
OM	12.64	51.64	12.89	49.10	12.88	43.21
TP	0.00	0.00	7.11	0.90	0.00	0.00
LB	31.70	11.87	50.00	0.00	38.02	12.56
SLEB	25.66	4.07	0.00	25.00	16.99	29.61
PHET	30.00	0.00	30.00	0.00	32.11	0.00
MB	0.00	32.42	0.00	25.00	0.00	14.62
total	100	100	100	100	100	100
total (kbd)	40.00	61.69	40.00	80.00	37.37	46.11

Table 5. Standard Deviation of Demand and Price

product	demand (m^3)	price (US$/bbl)
LPG	3049	1.45
SUPG	2064	9.82
ISOG	1310	9.88
JP-1	2272	6.32
HSD	10267	8.11
FO1	11517	5.60
FO2	11517	5.60
FOVS	11517	5.60

demand requirements of the final products. An iterative procedure was proposed to effectively address nonlinear 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.

On the scheduling of crude oil unloading, Lee et al.[21] and Jia et al.[22] addressed the problem of inventory management of a refinery that imports several types of crude oil that are delivered by different vessels. Wenkai et al.[23] presented a solution algorithm and mathematical formulations for the short-term scheduling of crude oil unloading, storage, and processing with multiple oil types, multiple berths, and multiple processing units.

Pricing Decisions in Planning and Scheduling Models

Pricing decision is another important aspect for planning in a highly dynamic environment. Guillén et al.[24] integrated the pricing decision with the scheduling model for batch plants. Their integrated model can simultaneously provide 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[25] studied the business relationships within the supply chain and provided interesting opportunities for mutually increased benefit. They investigated the opportunities for suppliers and customers to collaborate on pricing, to establish mutually beneficial relationships. They demonstrated that this goal can only be attained when price is no longer regarded as a distributive parameter between market partners, but rather 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 discussed.

Karwan and Keblis[26] 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 called 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.

Refinery Planning and Scheduling under Uncertainty

One of the major problems of planning and scheduling is uncertainty. Bopp et al.[27] examined the management of natural gas purchases under uncertain demand and price. Guldmann and Wang[28] studied the problem of the optimal selection of natural gas supply contracts by local gas distribution utilities and presented a large MILP approximation and a much smaller NLP approximation that involved simulation and response surface estimation via regression analysis. Liu and Sahinidis[29] used a two-stage stochastic programming approach for process planning under uncertainty to address uncertainty effectively.

Multiperiod supply, transformation, and distribution (STD) has been studied by Escudero et al.,[30] who proposed a modeling framework for the optimization of an oil company that accounts for uncertainty on the product demand, spot supply cost, and spot selling price. Hsieh and Chiang[31] developed a manufacturing-to-sale planning system to address uncertain manufacturing factors. Neiro and Pinto[32] extended the single refinery model of Pinto et al.[5] to a corporate planning model that contained multiple refineries. They also examined different types of crude oil and product demand scenarios. The optimization model for the supply chain of a petrochemical company operating under uncertain operating and economic conditions was developed by Lababidi et al.[33] In this work, uncertainties were introduced in demand, market prices, raw material costs, and production yields. Finally, Liu and Sahinidis[34] presented an application of fuzzy programming to process planning of petrochemical complex.

Singh et al.[35] provided an improved formulation for the gasoline blending optimization problem that incorporates both the blend horizon and a stochastic model of disturbances into a real-time optimization (RTO) problem. The work starts with the examination of three different blending RTO strategies. Their suitability for use in blending optimization was examined.

Table 6. Oil Purchased from the Stochastic Model without Pricing

crude oil	available quantity	Period 1		Period 2		Period 3	
		volume (m^3)	percentage (%)	volume (m^3)	percentage (%)	volume (m^3)	percentage (%)
OM	no limit	211937	37.03	211937	37.03	126125	30.29
TP	no limit	17004.3	2.97	17004	2.97	0	0.00
LB	95392	95392	16.67	95392	16.67	95392	22.91
SLEB	95392	95392	16.67	95392	16.67	95392	22.91
PHET	57235	57235	10.00	57235	10.00	57235	13.75
MB	95392	95392	16.67	95392	16.67	42202	10.14
total		572353	100	572353	100	416347	100
total (kbd)		120		120		87.29	
GRM				$15.131M US			

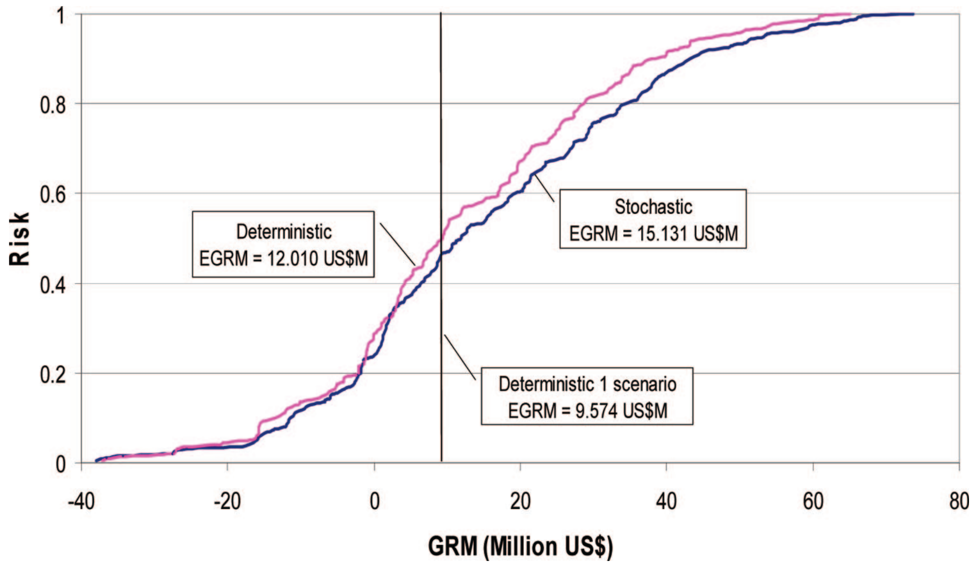

Figure 4. Risk curves of the deterministic and stochastic model solutions.

Table 7. Competition Product Price and Total Demand of Product

product	Competition Product Price ($/bbl)			Total Demand of Product (m^3)		
	period 1	period 2	period 3	period 1	period 2	period 3
LPG	32.64	31.49	30.8	76040	84735	88370
SUPG	71.87	83.76	62.63	70730	74310	78185
ISOG	73.74	85.75	64.53	48345	45060	44125
JP-1	80.63	88.68	80.54	77385	71795	76745
HSD	76.98	88.33	75.15	321305	298420	295865
FO1	55.21	56.35	47.47	113645	109920	69005
FO2	55.21	56.35	47.47	113645	109920	69005
FOVS	55.21	56.35	47.47	113645	109920	69005

Table 8. Consumer Budget in Time Period *t*

product	Consumer Budget ($)		
	period 1	period 2	period 3
LPG	15 610 000	16 783 000	17 119 000
SUPG	31 973 000	39 149 000	30 799 000
ISOG	22 422 000	24 303 000	17 909 000
JP-1	39 245 000	40 045 000	38 877 000
HSD	155 572 000	165 796 000	139 849 000
FO1	39 464 000	38 959 000	20 603 000
FO2	39 464 000	38 959 000	20 603 000
FOVS	39 464 000	38 959 000	20 603 000

Table 9. Standard Deviation of Total Demand and Consumer Budget

product	demand (m^3)	consumer budget (US$M)
LPG	24204	4.24
SUPG	18 891	8.20
ISOG	12 869	6.18
JP-1	20 377	9.15
HSD	61 181	34.55
FO1	33297	9.70
FO2	27 693	9.70
FOVS	36 254	9.70

Performance improvements were obtained using the time-horizon-based RTO (THRTO) approach system that considers the entire remaining blend horizon and incorporates 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.[36] presented the first complete continuous-time 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 a model that responded effectively and quickly 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.

Table 10. Prices and Demands Predicted by the Deterministic Model with Pricing

product	Product Price ($/bbl)			Demand of Product (m^3)		
	period 1	period 2	period 3	period 1	period 2	period 3
LPG	33.00	31.60	30.60	38 020.00	42 367.50	44 185.00
SUPG	71.00	83.60	62.30	35 365.00	37 155.00	39 092.50
ISOG	74.30	86.00	64.60	24 172.50	22 530.00	22 062.50
JP-1	79.70	87.70	79.70	38 692.50	35 897.50	38 372.50
HSD	77.00	89.00	75.70	160 652.50	149 210.00	147 932.50
FO1	55.60	57.00	47.70	56 822.50	54 960.00	34 502.50
FO2	54.60	56.30	47.70	56 822.50	54 960.00	34 502.50
FOVS	55.60	57.00	47.70	56 822.50	54 960.00	34 502.50

Some fundamental approaches for scheduling under uncertainty were determined and compared by Herroelen and Leus.[37] 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 a deterministic network evolution structure.

Csáji and Monostori[38] presented an approximate dynamic-programming-based stochastic reactive scheduler that could control the production process online, instead of generating an off-line rigid static plan. The stochastic scheduling problem was formulated as a special Markov decision process. Homogeneous multiagent systems were suggested, in which cooperative agents learn the optimal value function in a distributed way, using trial-based approximate dynamic programming (ADP) methods. After each trial, the agents asynchronously update the actual value function estimation. Finally, benchmark experimental results that illustrate the effectiveness of the ADP-based approach are shown.

Al-Redhwan et al.[39] 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

Table 11. Oil Purchased from the Deterministic Model with Pricing

crude oil	available quantity	Period 1		Period 2		Period 3	
		volume (m^3)	percentage (%)	volume (m^3)	percentage (%)	volume (m^3)	percentage (%)
OM	no limit	175 969	36.1235	211 937	37.0291	117 965	29.629
TP	no limit	0	0	17 004	2.97094	0	0
LB	95 392	63 144	12.9623	95 392	16.6667	95 392	23.9593
SLEB	95 392	95 392	19.5824	95 392	16.6667	95 392	23.9593
PHET	57 235	57 235	11.7494	57 235	10	57 235	14.3756
MB	95 392	95 392	19.5824	95 392	16.6667	32 157	8.07679
total		487 133	100	572 353	100	398 142	100
total (kbd)		102.13		120.00		83.47	
GRM				$10.712M US			

Table 12. Prices and Demands Predicted by the Stochastic Model with Pricing

product	Product Price ($/bbl)			Demand of Product (m^3)		
	period 1	period 2	period 3	period 1	period 2	period 3
LPG	33.00	31.00	30.60	32 958.00	51 390.00	44 127.00
SUPG	72.00	83.60	63.00	29 950.50	40 520.50	30 493.00
ISOG	73.60	86.00	64.60	15 167.50	26 655.00	21 017.50
JP-1	80.00	88.30	80.00	39 985.00	31 324.00	31 616.50
HSD	77.30	89.00	75.30	126 165.50	114 410.50	213 757.50
FO1	55.60	57.00	47.30	60 170.50	42 659.50	33 014.00
FO2	55.00	56.30	47.70	76 564.50	62 049.50	35 390.50
FOVS	55.60	55.60	47.30	56 895.50	66 667.50	46 406.50

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 the operating conditions. Finally, a stochastic formulation was developed, based on the scenario-analysis stochastic programming approach. The optimization models are nonlinear programming (NLP) problems that were effectively solved using GAMS. These models were tested on a typical refinery wastewater network.

Guillén et al.[24] considered the design and retrofit problem of a supply chain (SC) that consisted of several production plants, warehouses, and markets, and the associated distribution systems. A two-stage stochastic model was constructed to take into account 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[40] 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 increased. In addition, a multiobjective 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, which involved constraints of demand satisfaction and capacity.

Financial Risk Management

Risk management now has become a vital topic for planning and scheduling. Ierapetritou and Pistikopoulos[41] 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 to handle uncertainty while meeting production requirements and maximum regret. An algorithmic procedure was proposed for the estimation of such a combined metric, which involved the solution of two multiparametric LP subproblems for the evaluation of maximum regret. Analytical expressions of 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 has been illustrated with example problems.

Mulvey et al.[42] studied and discussed components of asset/liability management systems of three leading international firms in the United States: Towers Perrin, Frank Russell, and Falcon Asset Management. These companies applied asset/liability management to manage risk efficiently 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: (i) a multistage stochastic program for coordinating the asset/liability decisions, (ii) a scenario generation procedure for modeling the stochastic parameters, and (iii) solution algorithms for solving the resulting large-scale optimization problem.

Lowe et al.,[43] with regard to the financial risk problem, focused on maintaining an international sourcing/production

Table 13. Oil Purchased for Each Period from the Stochastic Model with Pricing

crude oil	available quantity	Period 1		Period 2		Period 3	
		volume (m^3)	percentage (%)	volume (m^3)	percentage (%)	volume (m^3)	percentage (%)
OM	no limit	207 796	37.40	211 937	37.03	105 350	26.41
TP	no limit	4 422	0.80	17 004	2.97	12 857	3.22
LB	95 392	95 392	17.17	95 392	16.67	95 392	23.92
SLEB	95 392	95 392	17.17	95 392	16.67	95 392	23.92
PHET	57 235	57 235	10.30	57 235	10.00	57 235	14.35
MB	95 392	95 392	17.17	95 392	16.67	32 601	8.17
total		555 630	100	572353	100	398 828	100
total (kbd)		116.49		120.00		83.62	
GRM				$8.049M US			

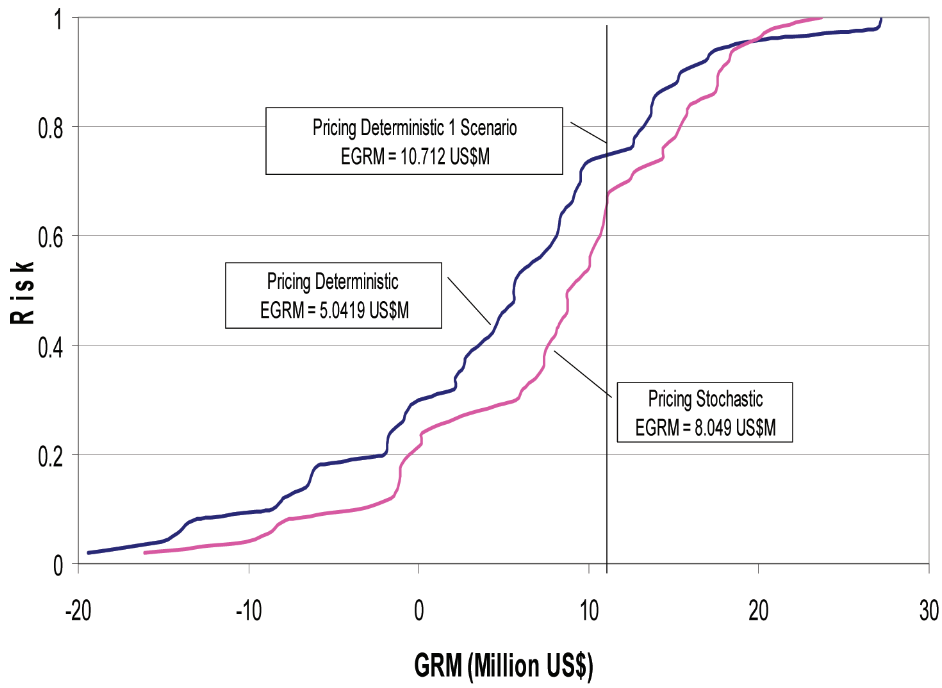

Figure 5. Risk curves of the deterministic and stochastic pricing model solutions.

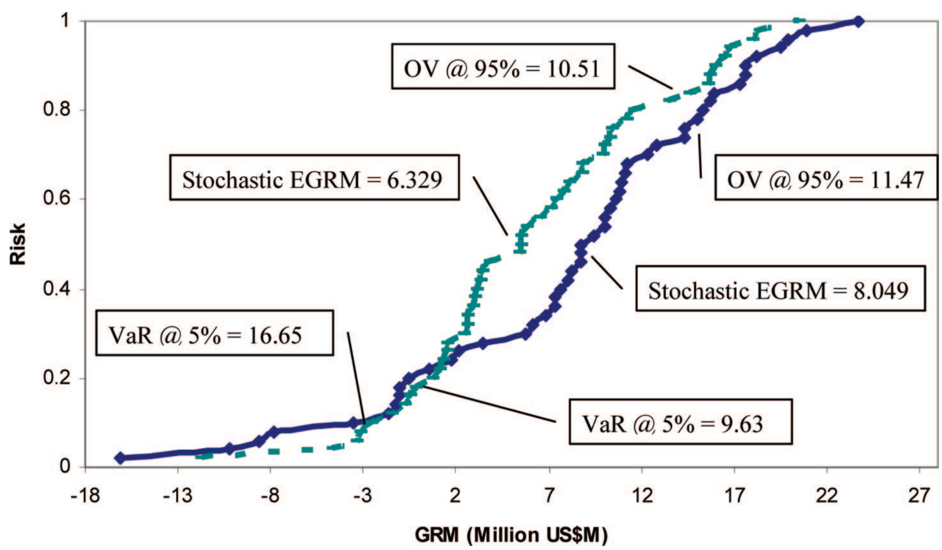

Figure 6. Risk curves of the stochastic pricing solution and one alternative (less risky) solution.

Table 14. Oil Purchased for Each Period from the Stochastic Model with Pricing for an Alternative (Less Risky) Solution

crude oil	available quantity	Period 1		Period 2		Period 3	
		volume (m^3)	percentage (%)	volume (m^3)	percentage (%)	volume (m^3)	percentage (%)
OM	no limit	169 801.15	36.31	211 937.01	37.03	132 318.95	35.44
TP	no limit	0.00	0.00	17 004.28	2.97	0.00	0.00
LB	95 392	95 392.20	20.40	95 392.20	16.67	22 752.17	6.09
SLEB	95 392	49 767.31	10.64	95 392.20	16.67	95 392.20	25.55
PHET	57 235	57 235.32	12.24	57 235.32	10.00	57 235.32	15.33
MB	95 392	95 392.20	20.40	95 392.20	16.67	65 678.77	17.59
total		467 588.18	100	572 353.21	100	373 377.41	100
total (kbd)		98.03		120.00		78.28	
GRM				$6.329 M US			

network. They proposed and illustrated a two-phase multi-screening approach that was used to help evaluate the strategy of having production facilities, using the Harvard Business School as a case study. 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. Ultimately, they illustrated how excess capacity could provide

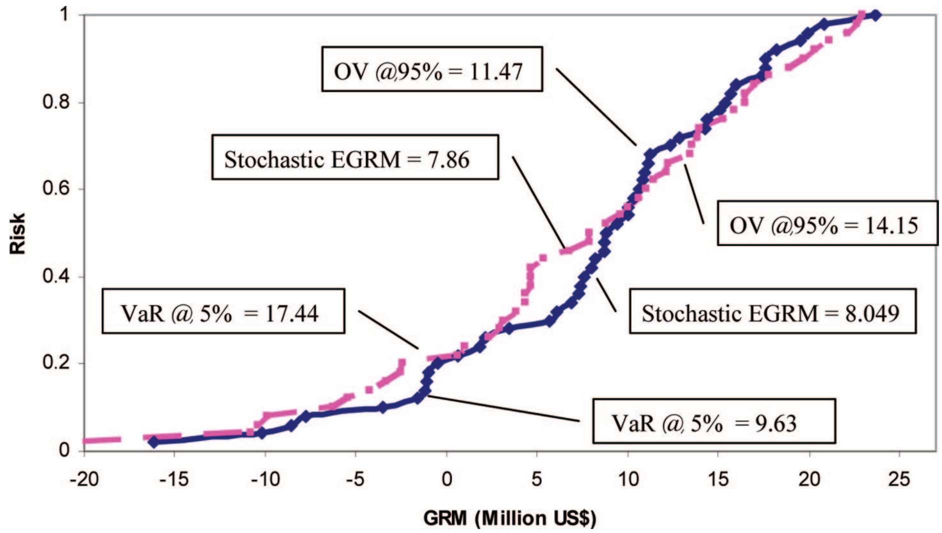

Figure 7. Risk curves of the stochastic pricing solution and the alternative solution with higher opportunity value (OV).

Table 15. Value at Risk and Opportunity Value for the Alternative Solution with Lower Risk

plan	value at risk, VaR (5%)	opportunity value, OV (95%)
stochastic solution	16.65	11.47
alternative solution	9.63	10.51

flexibility by allowing a global manufacturing firm to shift production between various production facilities as relative costs change over time.

Gupta and Maranas[44] developed a model to incorporate 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.[45] presented the method of risk management using the 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 multiperiod decision process, in which one makes decisions sequentially at each period. The objectives with which they were concerned are expected profit, expected downside risk, and process lifetime. The multiobjective Markov decision problem was finally decomposed, using a rigorous multiobjective stochastic dynamic programming algorithm, and the Pareto optimal design strategy was obtained.

In addition, various methods and tools are studied and introduced into optimizing and programming models to encounter the financial risk problem. The use of the value at risk was proposed by Guldimann[46] and Jorion.[47]

Barbaro and Bagajewicz[48] 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, which provided new insight into the tradeoffs between risk and profitability. Thus, cumulative risk curves were constructed 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[49] 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 the 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 relationship 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.

Pricing

Consumer behavior is best understood in three steps. The first step is to examine consumer preferences. Specifically, a mathematical description of how people might prefer one good to another is used. Second, one must account for the fact that consumers face budget constraints that restrict the quantities of goods that they 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?

In microeconomics, 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

Table 16. Oil Purchased for Each Period from the Alternative Solution with Higher Opportunity Value

crude oil	available quantity	Period 1		Period 2		Period 3	
		volume (m^3)	percentage (%)	volume (m^3)	percentage (%)	volume (m^3)	percentage (%)
OM	no limit	181 862.96	36.17	212 345.86	37.10	123 206.99	32.38
TP	no limit	0.00	0.00	16 595.42	2.90	0.00	0.00
LB	95 392	72 933.12	14.50	95 392.20	16.67	56 023.10	14.72
SLEB	95 392	95 392.20	18.97	95 392.20	16.67	95 392.20	25.07
PHET	57 235	57 235.32	11.38	57 235.32	10.00	57 235.32	15.04
MB	95 392	95 392.20	18.97	95 392.20	16.67	48 667.57	12.79
total		502 815.80	100	572 353.20	100	380 525.17	100
total (kbd)		105.42		120.00		79.78	
GRM				$7.863M US			

Table 17. Value at Risk and Opportunity Value for the Alternative Solution with Higher Opportunity Value

plan	value at risk (5%), VaR	opportunity value (95%), OV
stochastic solution	16.65	11.47
alternative solution	17.44	14.15

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 pricing decision, the price−demand model is first developed using microeconomic and mathematical methods. In developing the price−demand model, one solves the consumer problem, starting with the “utility function”. In microeconomics, the utility function is a measure of the satisfaction gained by consuming goods and services.

Considering the two products, with demands d_1 (for our products) and d_2 (for the competition products), we maximize the consumer utility (satisfaction), $u(d_1,d_2)$, subject to a budget limitation and a total demand limitation; that is,

$$\text{Max } u(d_1, d_2) \tag{1}$$

s.t.

$$p_1d_1 + p_2d_2 \le Yd_1 + d_2 \le D$$

where p_1 is our product’s selling price, p_2 the competitor’s product price, Y the consumer budget, and D the maximum possible demand.[50,51] From this expression, one can obtain the price−demand relationship.

A typical utility function has a constant elasticity of substitution (CES), on which we will focus in this work. The CES utility has the form of

$$u(d_1, d_2) = ({x_1}^{\rho} + {x_2}^{\rho})^{1/\rho} \tag{2}$$

where x is the function of demand, $x_i = x_i(d_i)$, which we can call “satisfaction functions”. The satisfaction functions are determined by considering the different in quality between products and the reaction of consumers to prices. We propose the following satisfaction functions:

$$x_1 = \alpha d_1 \tag{3a}$$

and

$$x_2 = \beta d_2 \tag{3b}$$

where β is a measure of how much a consumer prefers product 1 to product 2 and α is a measure of how much the consumer population is aware of the quality of product 1 (that is, our product). The solution to the consumer optimization problem when the budget constraint is binding (the usual case) is

$$p_1(d_1)^{1-\rho} = \left(\frac{\alpha}{\beta}\right)^{\rho} p_2\left[\frac{Y - p_1d_1}{p_2}\right]^{1-\rho} \tag{4}$$

When the budget constraint is not binding, the demand constraint is

$$(d_1)^{1-\rho} = \left(\frac{\beta}{\alpha}\right)^{\rho}(D - d_1)^{1-\rho} \tag{5}$$

Planning Model

This work addresses the planning of crude oil purchasing and its processing schedule to satisfy both specification and demand with the highest profit. The decision variables are crude oil supply purchase decisions, processing, inventory management, and blending over time periods. The length of time periods must be decided based on business cycles. The model represents a scheme of a refinery that includes product paths to each production unit. The product paths are recognized by the composition and some key properties, e.g., sulfur and aromatic content. Capacities and yields of several units are also taken into account. The optimization model is based on a discretization of the time horizon, and the model is linear. Many nonlinear features were reasonably simplified so that we could gain computation speed, which allowed us to explore the angle of uncertainty, financial risk, and pricing. It is based on the network structure proposed by Pinto et al.[5] and has been published earlier by Pongsakdi et al.[6] We summarize the model as briefly as possible in Appendix A, for the purpose of completeness. Next, we refer to some modifications that we introduce in this paper.

We now discuss the incorporation of the pricing equations into the model. The corresponding equations are nonlinear, so we made an effort to linearize them.

The Budget Case. We rearrange eq 4 as follows:

$$d_{1c,t}^{(Y)}(p_{1c,t})^{1/(1-\rho)}\left(\frac{\beta}{\alpha P_{2c,t}}\right)^{\rho/(1-\rho)} + p_{1c,t}d_{1c,t}^{(Y)} = Y \tag{6}$$

We now linearize this expression by discretizing the price term as follows:

$$p_{1c,t} = \sum z_{1_c}^{k} p_{1_c}^{k} \tag{7}$$

$$\sum z_{1_c}^{k} = 1 \tag{8}$$

where $z_{1_c}^{k}$ represent binary variables. The substitution of eq 7 into eq 6 renders

$$\sum z_{1_c}^k d_{1c,t}(Y)\varphi_{k,c,t} = Y \quad (9)$$

where

$$\varphi_{k,c,t} = \left[\left(\frac{\beta}{\alpha p_{2c,t}}\right)^{\rho/(1-\rho)} (p_{1,c,t}^k)^{1/1-\rho} + p_{1c,t}^k\right] \quad (10)$$

Equation 9 contains only products of the binary variables and continuous variables, for which the following well-known linearization trick is applied. We first let $\nu_{1c,t}^k = z_{1c}^k\ d_{1c,t}^{(Y)}$ and obtain the following final equations that contain big-M constraints:

$$\sum \upsilon_{1_c}^k \varphi_{k,c,t} = Y \quad (11)$$

$$\sum z_{1_c}^k = 1 \quad (12)$$

$$\upsilon_{1_c}^k - z_{1_c}^k \Omega \le 0 \quad (13)$$

$$\upsilon_{1_c}^k \ge 0 \quad (14)$$

$$(\mathrm{d}_{1c,t}^{(Y)} - \upsilon_{1_c}^k) - (1 - z_{1_c}^k)\Omega \le 0 \quad (15)$$

$$(d_{1c,t}^{(Y)} - \upsilon_{1_c}^k) \ge 0 \quad (16)$$

where Ω is a large number.

The Demand Case. Rearranging eq 5, we obtain

$$d_{1c,t}^{(D)} = \frac{(\beta/\alpha)^{\rho/(\rho-1)}D}{[1 + (\beta/\alpha)^{\rho/(\rho-1)}]} \quad (17)$$

which does not need further linearization.

To determine which constraint is actually active with regard to demand, we introduce a binary variable $w_{c,t}$ and write

$$d_{1c,t} = w_{c,t}d_{1c,t}^{(Y)} + (1 - w_{c,t})d_{1c,t}^{(D)} \quad (18)$$

and the real demand is either $d_{1c,t}^{(Y)}$ or $d_{1c,t}^{(D)}$, depending on the value of $w_{c,t}$. Finally, to obtain the value of $w_{c,t}$, we use the following two equations:

$$d_{1c,t}^{(Y)} + \left(\frac{Y - p_{1c,t}d_{1c,t}^{(Y)}}{p_{2c,t}}\right) - D + \Omega w_{c,t} > 0 \quad (19)$$

$$d_{2c,t} = w_{c,t}\left(\frac{Y - P_{1c,t}d_{1c,t}^{(Y)}}{P_{2c,t}}\right) + (1 - w_{c,t})(1 - d_{1c,t}^{(D)}) \quad (20)$$

where

$$d_{1c,t} + d_{2c,t} \le D \quad (21)$$

Thus, if $d_{1c,t}^{(Y)} + [(Y - P_{1c,t}d_{1c,t}^{(Y)})/P_{2c,t}] < D$, then eq 19 renders $w_{c,t} = 1$, making eq 20 the expression that defines the right competition demand and eq 21 is satisfied. However, if $d_{1c,t}^{(Y)} + [(Y - P_{1c,t}d_{1c,t}^{(Y)}/P_{2c,t}] > D$, $w_{c,t}$ is undefined by eq 19, but is forced to be zero by the combination of eqs 20 and 21. Equations 18−20 are further linearized using the standard trick of replacing the product of the binary variable and the continuous variable by a new continuous variable and adding a set of inequalities, as shown previously for the case of the budget constraint being binding.

Stochastic Formulation. Following Pongsadki et al.,[6] we use a two-stage stochastic program with fixed recourse. The uncertainty is introduced through the demand and product price parameter in the general planning model without pricing. For the planning model with a pricing decision, the uncertainty is introduced in the consumer budget (Y) and the total demand of products (D). The first-stage decisions are the amount of crude oil purchased ($\mathrm{AO}_{p,t}$) for every planning period, and the second-stage decisions are the amount of product produced ($\mathrm{MANU}_{p,t}^s$), the amount of product stock ($\mathrm{AS}_{p,t}^s$), the amount of intermediate purchased ($\mathrm{AI}_{p,t}^s$), the amount of product that cannot satisfy demand ($\mathrm{AL}_{p,t}^s$), and the amount of discount sales ($\mathrm{Ad}_{p,t}^s$). These second-stage scenarios are denoted by the index s and are assumed to occur with individual probabilities p_s. It is assumed that the random events that occur at the second stage are finite and independent from the first-stage decisions.

The stochastic results are obtained using a sampling algorithm method that was discussed by Aseeri and Bagajewicz.[49] In this method, a full deterministic model is run for each scenario and then, after that scenario is solved, the first-stage variables (a commitment to buy certain sets of crudes) are fixed and the model is run for the remaining scenarios. After that, the highest expected gross refinery margin (GRM) risk curves and non-dominated curves are selected and analyzed.

Results and Discussion

The planning model was implemented in GAMS using CPLEX 9.0 as a solver and run on a Pentium IV/2.4 GHz PC platform. The time horizon of this problem was divided into three equal time periods.

The model was applied and tested using the data from the Bangchak Refinery. Figure 3 shows a simplified scheme of the refinery. It has two atmospheric distillation units (CDU2 and CDU3), two naphtha pretreating units (NPU2 and NPU3), one light naphtha isomerization unit (ISOU), two catalytic reforming units (CRU2 and CRU3), one kerosene treating unit (KTU), one gas oil hydrodesulfurization (GO-HDS), and one deep gas oil hydrodesulfurization (DGO-HDS). The commercial products from the refinery are liquefied petroleum gas (LPG), gasoline RON 91 (SUPG), gasoline RON 95 (ISOG), jet fuel (JP-1), high-speed diesel (HSD), fuel oil 1 (FO1), fuel oil 2 (FO2), and low-sulfur fuel oil (FOVS). Fuel gas (FG) and some amount of FOVS produced from the process are used as an energy source for the plant. There are three product pools for blending products: a gasoline pool (GSP), a diesel pool (DSP), and a fuel oil pool (FOP).

There are six crude oil types for feeding the refinery: Oman, Tapis, Labuan, Seria light, Phet, and Murban. The refinery produces eight commercial products (LPG, SUPG, ISOG, JP-1, HSD, FO1, FO2, and FOVS), using two crude distillation units (CDU2 and CDU3) and six productive units (NPU2, NPU3, CRU2, CRU3, ISOU, GO-HDS, DGO-HDS, KTU). Data of all units and commodities (crude oils, intermediates, products), the production yields, and the unit capacity can be found can be found in Appendix B. The maximum plant production capacity is 120 kbd.

In applying the case study, there are some specific restrictions of the refinery:

(1) PHET crude must be fed to CDU2 only, because of the limitations of the unit;

(2) The amount of MTBE in the gasoline must not be >10%; and

(3) The recipe used in blending FO1 and FO2 with IK is 7% of the FO1 volume and 2.5% of the FO2 volume.

Demand in each period was considered to be satisfied by the production. Uncertainty was introduced in market demand and price for the general stochastic model without pricing. For the model with the pricing decision added, uncertainty was taken into account in the consumer budget and the total demand of each product.

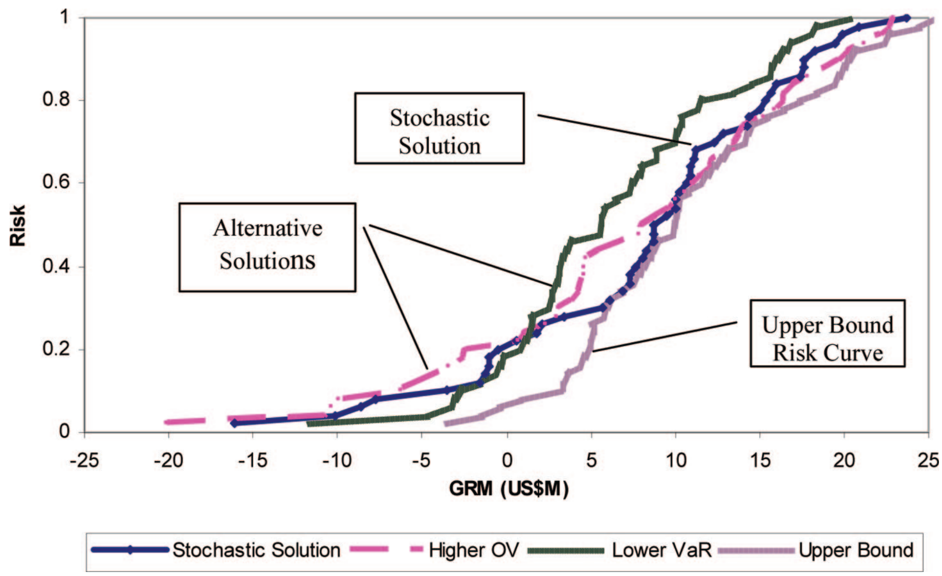

Figure 8. Upper-bound risk curve for the stochastic and alternative solution.

Deterministic Model Results. First, the general deterministic linear programming model was solved to obtain the results, including the amount and type of crude oil used, the amount and properties of the product that is refined, the amount of product stored, and profit. Table 1 gives the value of crude oil cost and available quantity. The mean values of the demand and price for all products are shown in Table 2. All of these values were estimated or taken from historical data given by the website of the Energy Policy and Planning Office, Ministry of Energy.[52]

Optimization results of the general deterministic model using mean values show a GRM of $9.574M US, using 754 variables and 655 constraints. The amount of the crude oil purchased is shown in Table 3, and the percentage of the crude oil fed to each CDU is shown in Table 4.

From the general deterministic model result, the Labuan, Phet, and Murban crudes are purchased at the maximum available quantity. Crude Phet is fed to the CDU2 unit only, because of the limitations of the unit. In addition, Phet is not suitable for the production of FO1 and FO2 (low-pour-point fuel oil) from the CDU3 unit, because it has a high pour point and a low viscosity factor @50 °C (V50) in the fuel oil portion. From Table 4, we learn that Oman crude is the major supply for the CDU3 unit, because it gives the best properties needed for low-pour-point fuel oil (FO1 and FO2) production in the CDU3 unit. The smallest amount of crude oil used is that of Tapis crude, because of its highest cost. It is chosen in time period 2, because of the higher product price in this period.

Stochastic Model Results. The general stochastic model takes into account the uncertainty in demand and the price of products. The model was solved using 200 scenarios. The demand and price were randomly generated independently by sampling from a normal distribution with mean values and standard deviations as shown in Tables 2 and 5.

The methodology used is the same as that suggested by Aseeri and Bagajewicz[49] and used by Pongsadki et al.[6] First, the deterministic model is run for each of the 200 scenarios with all of the first- and second-stage variables free. The first-stage variables obtained are then fixed and then the same model is run again under different scenarios to observe the results of the second-stage variables. The results are shown in Table 6.

Figure 4 shows the risk curves of the stochastic solution and the deterministic solution. The stochastic solution has the highest expected GRM (EGRM) of all the solutions obtained. The deterministic risk curve is constructed by running the stochastic model under each scenario with the first-stage variable fixed to that of the deterministic model result. The EGRM obtained from the deterministic model under 200 scenarios of uncertain parameters is different from that of the deterministic model using mean values. This is an indication of the nonsymmetric nature of the distributions obtained. Finally, the deterministic solution provides a lower EGRM than the stochastic solution but a slightly higher risk.

Results of the Deterministic Planning Model with Pricing. We first discuss the options for the parameters. In this paper, we use $\alpha = 1$ (that is, perfect knowledge). In addition, we also use $\beta = 1$ (that is, no preference for the refinery product over the competition, based on product characteristics). However, the pricing model will establish the demand, based on the price. In this work, we also chose an elasticity of substitution value of $\sigma_{ES} = -1$, which leads to equal demands for equal prices. In fact, our formula simplifies to the very well-known $p_1d_1 = p_2d_2$. Other values of ρ can be used if the elasticity is better determined. For example, it is a well-known fact that different motor fuels have different degrees of elasticity. This should change the results of our example, slightly without altering the main message (that message being that pricing has a big influence in planning).

Table 7 shows the competition product price and the total demand of product. The consumer budget is shown in Table 8, and the standard deviation of the total demand and consumer budget is shown in Table 9.

Optimization results of the deterministic model with pricing suggest a higher GRM than that of the general deterministic model. The EGRM obtained from this pricing model is $10.712M US, using 159 discrete variables. Table 10 shows the product demand and price predicted and suggested by the deterministic model with pricing. The amount of crude oil that was purchased corresponded to the predicted demand, as shown in Table 11.

The results of the deterministic pricing model suggest a highest EGRM of $10.712M US, which is similar to the results of the general deterministic model.

Results of the Stochastic Model with Pricing. The stochastic model takes into account the fact that the total demand of products and the consumer budget are uncertain. The product demands predicted by the model and the product price suggested by the model are shown in Table 12. The volume of petroleum purchased for this model is shown in Table 13.

The solutions shown in Table 13 suggest that a greater amount of crude oil was purchased in time period 1. The types of crude oil purchased from the stochastic pricing model are the same as those from the deterministic pricing model. From the results, Tapis crude is selected in time periods 1 and 3, because of the higher demand of fuel oil in time period 1 and high-speed diesel in time period 3. This is because Tapis crude gives a high fraction of fuel oil and diesel oil intermediates.

For comparison purposes, the solution obtained by the deterministic model using the mean values of total demand of product and consumer budget is evaluated against the same scenarios of the stochastic model by fixing the first-stage variables (amount of crude oil purchased) and computing the second-stage variables with the stochastic formulation. The risk curve of the deterministic pricing model against all scenarios is compared with the risk curve of the stochastic pricing model, as shown in Figure 5. This plot shows that the stochastic solution provides a higher EGRM than the deterministic solution. In addition, the stochastic model provides a solution with a lower risk of negative margin.

The EGRM suggested by the stochastic planning model with pricing is lower than that of the stochastic model without pricing. This is because of the difference in how the demand and price of product are generated. In the general stochastic model, the demand and price of product are generated independently for each scenario as the uncertain parameters and usually are considered independent. However, in the stochastic model with pricing, the demand and price are model variables that are related.

Financial Risk Management. Although stochastic models optimize the total EGRM, they do not provide any control of their variability over the different scenarios; i.e., they assume that the decision maker is risk neutral. Actually, different attitudes toward risk may be encountered. In this section, an approach to manage financial risk is applied to compare the results.

An alternative plan that can reduce risk was considered. Figure 6 shows the risk curves of this plan, compared to the stochastic solution. This plan suggests a smaller amount of crude oil purchased in time periods 1 and 3, as shown in Table 14.

From the above figure, decreasing the crude oil purchased resulted in lower risk at low targets but with a lower chance to make a higher profit. The value at risk (at 5%) (denoted as VaR) and the opportunity value (at 95%) (denoted as OV) for the two curves in Figure 6 are shown in Table 15. The value at risk of the alternative plan reduces from VaR = 16.65 for the stochastic solution to VaR = 9.63 (or 42%), but the opportunity value is also reduced, from OV = 11.47 to OV = 10.51 (or 8%). Therefore, this plan may be preferred by a risk-averse decision maker.

An alternative plan that suggests a higher opportunity value was also considered. Figure 7 shows the risk curves of the alternative plan with a higher opportunity of profit, compared to the stochastic solution. The amount of crude oil purchased that corresponds to this alternative plan is shown in Table 16.

The alternative plan has an opportunity value of OV = 14.15, which is much higher than the opportunity value for the stochastic solution with pricing (OV = 11.47). It increases by ~23%. The value at risk of the alternative design also increases from VaR = 16.65 to VaR = 17.44 (or 4.7%). The value at risk and opportunity value for this alternative plan are shown in Table 17. This alternative solution, with a higher opportunity of profit, may be preferred by the risk-taking decision makers who prefer a higher chance of getting greater profit.

Finally, Figure 8 shows the upper bond risk curve, compared to the risk curves of the stochastic solution and the two alternative plans. The stochastic solution curve and both alternative curves are entirely positioned on the left side of the upper bond risk curve, as expected. The position of the upper bound also indicates that there could be room for solutions with smaller VaR values, but so much room for solutions with higher OV values.

Conclusions

In this article, an optimization model for refinery planning with integrated pricing decisions was introduced. First, the planning model was developed using a deterministic approach. The relationship between product prices and demand then was modeled using the microeconomic concept of the "utility function". The price−demand model was integrated into a developed model to determine the prices and the optimal schedule simultaneously. After that, the model was adjusted by applying the stochastic technique to consider the uncertainty among the total demand of product and consumer budget.

The models were tested using data from Bangchak Petroleum Public Company Limited. Optimization results from the planning model without pricing are more optimistic than those of the pricing one. This is because the price and demand of the planning model without pricing were generated randomly and independently, instead of predicted from the price−demand relation, as in the planning model with pricing.

The deterministic model results are also compared with the stochastic model results. The results show that, when the uncertainty was considered, the risk curves of the deterministic solutions provided a lower expected gross refinery margin (GRM) and higher risk than those of the stochastic solutions. Some concepts of financial risk management were presented, including the upper-bound risk curve, the opportunity value (OV), and the value at risk (VaR), to compare the best stochastic result with the other alternative solutions.

All planning results showed that the Oman, Seria light, and Phet crudes were the first choice in purchasing, because of their high margin (which was due to lower costs).

Nomenclature

Indices

t = set of time periods
c = set of all commodities
o = set of crude oils
p = set of products
i = set of intermediates
u = set of productive units
q = set of properties
s = set of scenarios
k = set of discrete prices
Y = set of demands from budget constraint
D = set of demands from total demand constraint

Parameters

$\mathrm{pro}_{u,c,q}$ = property q of commodity c from unit u
$\mathrm{px}_{p,q}$ = maximum property q of product p
$\mathrm{pn}_{p,q}$ = minimum property q of product p
$\mathrm{cyield}_{o,c}$ = percent of component c in crude oil o (%)
$\mathrm{yield}_{u,c}$ = percent yield of commodity c from unit u (%)

$\text{dem}_{p,t}$ = demand of product p in time period t (m^3)
ux_u = maximum capacity of unit u (m^3)
un_u = minimum capacity of unit u (m^3)
ox_o = maximum monthly purchase of crude oil o (m^3)
on_o = minimum monthly purchase of crude oil o (m^3)
stox_p = maximum storage capacity of product p (m^3)
$\text{cp}_{p,t}$ = unit sale price of product p in time period t ($/$m^3$)
$\text{co}_{o,t}$ = unit sale price of crude oil o in time period t ($/$m^3$)
$\text{ci}_{i,t}$ = unit purchase price of intermediate I in time period t ($/$m^3$)
$\text{cl}_{p,t}$ = unit cost of lost demand penalty for product p in time period t ($/$m^3$)
density_u = density of feed to unit u (ton/m^3)
fuel_u = percent energy consumption for unit u based on tFOE (%)
disk = percent discount from normal price (%)
u = consumer utility function
Y = consumer budget ($)
D = total product demand (m^3)
ρ = price−demand relation parameter
α, β = product inferiority and superiority parameters

Variables

$\text{PO}_{u,c,q,t}$ = property q of commodity c from unit u in time period t
$\text{AF}_{u,t}$ = amount of feed to unit u in time period t (m^3)
$\text{AO}_{u,c,t}$ = amount of outlet commodity c from unit u in time period t (m^3)
$\text{A}_{u,t,u,t}$ = amount of commodity c flow between unit u and unit u in time period t (m^3)
$\text{MANU}_{p,t}$ = amount of product p produced in time period t (m^3)
$\text{AC}_{o,t}$ = amount of crude oil o refined in time period t (m^3)
$\text{AI}_{i,t}$ = amount of intermediate i added in time period t (m^3)
$\text{AS}_{p,t}$ = amount of product p stored in time period t (m^3)
$\text{AL}_{p,t}$ = amount of lost demand for product p in time period t (m^3)
$\text{AD}_{p,t}$ = amount of discount product sold in time period t (m^3)
$\text{Burned}_{p,t}$ = amount of product p burned in time period t (m^3)
Used_t = amount of fuel used in time period t (tFOE)
$\text{TP}_{p,t}$ = income from selling product p in time period t ($)
$\text{TO}_{o,t}$ = expense from purchasing crude oil o in time period t ($)
$\text{TI}_{i,t}$ = expense from purchasing intermediate in time period t ($)
$\text{TS}_{p,t}$ = expense from storage product p in time period t ($)
$\text{TL}_{p,t}$ = expense from lost demand of product p in time period t ($)
$\text{TD}_{p,t}$ = expense from discount sales of product p in time period t ($)
$\text{Sales}_{p,t}$ = sales of product p in time period t (m^3)
p_1 = price of product 1 ($/$m^3$)
p_2 = price of competition product 2 ($/$m^3$)
d_1 = demand of product 1 (m^3)
d_2 = demand of competition product 2 (m^3)

Appendix A

In Figure A1, commodity c_1 from unit $u'1$ is sent to unit u at flow rate $A_{u1',c1,u,t}$ in period t. The same unit u'_1 may send different commodities c (c_2, c_3,..., c_n) to unit u. In addition, u' ($u'2$, $u'3$,..., $u'n$) can feed commodities c (c_1, c_2,..., c_n) to unit u. The summation of feed for unit u is represented by $\text{AF}_{u,t}$. Parameters $\text{PO}_{u1',c1,q}$ denote properties q of commodity c_1 flow from $u'1$. Variables $\text{AO}_{u,c,t}$ represents the outlet flow rate of commodity c from unit u in time period t. A splitter is represented at every outlet stream because a product stream can be sent to more than one unit for further processing or storage.

The balance equations are described as follows. The balance of feeds to unit u is represented by

$$\text{AF}_{u,t} = \sum_{(u',c)\in \text{UC}_u} A_{u',c,u,t} \qquad \forall\, u \in \text{U}, t \in \text{T} \qquad \text{(A-1)}$$

The balance of products from the splitter is represented by

$$\text{AO}_{u,c,t} = \sum_{u'\in \text{UO}_{u,c}} A_{u,c,u',t} \qquad \forall\, c \in \text{CO}_u, u \in \text{U}, t \in \text{T} \qquad \text{(A-2)}$$

The balance of products from unit u is represented in two ways: through yields,

$$\text{AO}_{u,c,t} = \text{AF}_{u,t} \times \text{yield}_{u,c} \qquad \forall\, c \in \text{CO}_u, u \in \text{U}, t \in \text{T} \qquad \text{(A-3)}$$

and through percent yields,

$$AO_{u,c,t} = \sum_{u'\in \text{ctank}} \sum_{c'\in \text{C}_\text{O}} (A_{u',c',u,t} \times \text{cyield}_{c',c}) \qquad \forall\, c \in \text{CO}_u, u \in \text{CDU} \qquad \text{(A-4)}$$

The product properties leaving unit u are calculated by the sum of the flow fraction times the properties of each flow, as shown in the following equation (these are called blending equations):

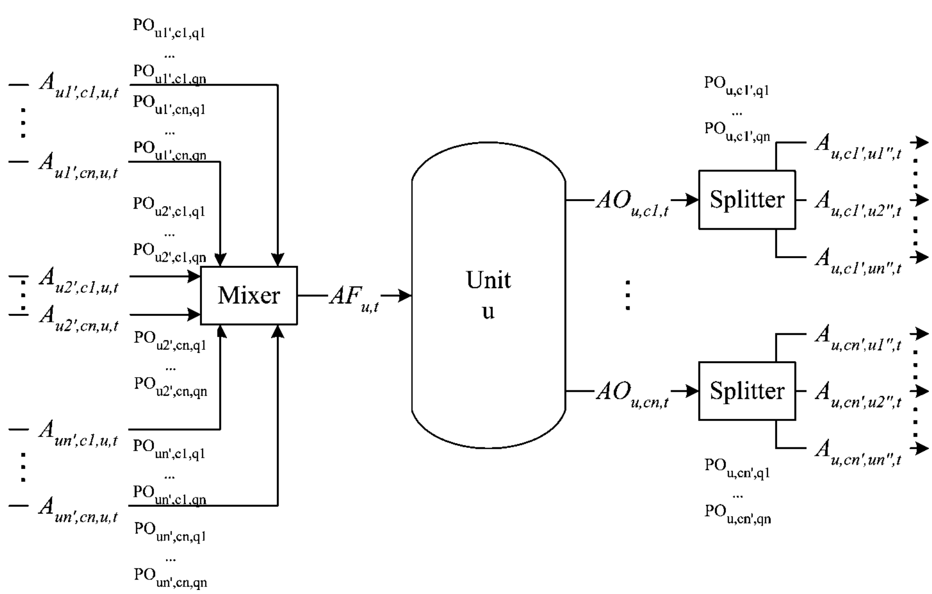

Figure A1. Balancing of a typical unit.

$$\mathrm{PO}_{u,c,q,t} = \frac{\sum_{u'\in \mathrm{U}'} \sum_{c'\in \mathrm{CO}_{u'}} (A_{u',c',u,t} \times \mathrm{pro}_{u',c,q})}{\sum_{u'\in \mathrm{U}'} \sum_{c'\in \mathrm{CO}_{u'}} A_{u',c',u,t}} \qquad \forall\, c \in \mathrm{CO}_u, u \in \mathrm{U} \tag{A-5}$$

The equation is nonlinear. To render it linear, we use it in a form of inequalities, to put bounds on the property, as described below. However, some product properties are fixed (e.g., isomerate from the isomerization unit and reformate from the reformer unit):

$$\mathrm{PO}_{u,c,q,t} = \mathrm{pro}_{u,c,q} \qquad \forall\, c \in \mathrm{CO}_u, q \in \mathrm{QO}_{u,c}, u \in \mathrm{U}, t \in \mathrm{T} \tag{A-6}$$

Bounds on the flow rates, the amount of oil refined, the amount stored, and the quality of certain products are imposed:

$$\mathrm{ux}_u \geq \mathrm{AF}_{u,t} \geq un_u \qquad \forall\, u \in \mathrm{U}, t \in \mathrm{T} \tag{A-7}$$

$$\mathrm{ox}_c \geq \mathrm{AC}_{c,t} \geq on_c \qquad \forall\, c \in \mathrm{C_O}, t \in \mathrm{T} \tag{A-8}$$

$$\mathrm{stox}_c \geq \mathrm{AS}_{c,t} \qquad \forall\, c \in \mathrm{C_P}, t \in \mathrm{T} \tag{A-9}$$

$$\mathrm{px}_{c,q} \geq \mathrm{PO}_{u,c,q,t} \geq \mathrm{pn}_{c,q} \qquad \forall\, c \in \mathrm{CO}_u, q \in \mathrm{QO}_{u,c}, u \in \mathrm{U}, t \in \mathrm{T} \tag{A-10}$$

The last inequality is substituted into eq A-5, rendering a linear expression.

The objective function in this model is profit, which is obtained by the product sales minus crude oil costs, intermediate costs, storage costs, expenses from lost demand, and expenses from discounted product. This is shown by the following equation:

$$\begin{aligned}\text{Max Profit} = {} & \sum_{t\in \mathrm{T}} \sum_{c\in \mathrm{C_P}} \mathrm{MANU}_{c,t} \times \mathrm{cp}_{c,t} - \sum_{t\in \mathrm{T}} \sum_{c\in \mathrm{C_O}} \mathrm{AC}_{c,t} \times \mathrm{co}_{c,t} - \\ & \sum_{t\in \mathrm{T}} \sum_{c\in \mathrm{C_{IA}}} \mathrm{AI}_{c,t} \times \mathrm{ci}_{c,t} - \sum_{t\in \mathrm{T}} \sum_{c\in \mathrm{C_P}} \left(\frac{\mathrm{AS}_{c,t} + \mathrm{AS}_{c,t-1}}{2}\right) \times \mathrm{cp}_{c,t} \times \mathrm{int} - \\ & \sum_{t\in \mathrm{T}} \sum_{c\in \mathrm{C_P}} \mathrm{AL}_{c,t} \times \mathrm{cl}_{c,t} - \sum_{t\in \mathrm{T}} \sum_{c\in \mathrm{C_P}} \mathrm{AD}_{c,t} \times \mathrm{cp}_{c,t} \times \mathrm{disc}\end{aligned} \tag{A-11}$$

$\mathrm{MANU}_{c,t}$ is equal to the amount of product produced in that time period:

$$\mathrm{MANU}_{c,t} = \sum_{u\in \mathrm{U}_c} \mathrm{AO}_{u,c,t} \qquad \forall\, c \in \mathrm{C_P}, t \in \mathrm{T} \tag{A-12}$$

where $\mathrm{AO}_{u,c,t}$ is the amount of product flow outward from the production unit in each time period. In turn, $\mathrm{AC}_{c,t}$ is the amount of crude oil refined in that time period:

$$\mathrm{AC}_{c,t} = \sum_{u\in \mathrm{U}_c} \mathrm{AO}_{u,c,t} \qquad \forall\, c \in \mathrm{C_O}, t \in \mathrm{T} \tag{A-13}$$

where $\mathrm{AO}_{u,c,t}$ is the amount of crude oil flow outward from the crude oil storage tank in each time period. Finally, $\mathrm{AI}_{c,t}$ is equal to the amount of purchased intermediate added in that time period:

$$\mathrm{AI}_{c,t} = \sum_{u\in U_c} \mathrm{AO}_{u,c,t} \qquad \forall\, c \in \mathrm{C_{IA}}, t \in \mathrm{T} \tag{A-14}$$

where $\mathrm{AO}_{u,c,t}$ is the amount of MTBE and DCC flow outward from their storage tank in each time period.

$\mathrm{AL}_{c,t}$ is the product volume that cannot satisfy its demand. The demand of each product must be equal to the volume of that product sale plus the volume of lost demand of that product:

$$\mathrm{dem}_{c,t} = \mathrm{sales}_{c,t} + \mathrm{AL}_{c,t} \qquad \forall\, c \in \mathrm{C_P}, t \in \mathrm{T} \tag{A-15}$$

The volume of the lost demand is taken into account as the opportunity cost if that production cannot satisfy the demand.

$\mathrm{AS}_{c,t}$ represents the closing stock, $\mathrm{AS}_{c,t-1}$ represents the opening stock, and int represents the average rate of interest payable in that period. In the equation, the financial cost incurred relates to the average stock level over a specified time period. Unless the stock levels are known, the average stock level is assumed to be equal to the arithmetic mean of the opening and closing stock.[53] The balance of product storage can be found in the following equation:

$$\mathrm{AS}_{c,t} = \mathrm{AS}_{c,t-1} + \mathrm{MANU}_{c,t} - \mathrm{sales}_{c,t} - \mathrm{AD}_{c,t} \qquad \forall\, c \in \mathrm{C_P}, t \in \mathrm{T} \tag{A-16}$$

Finally, sometimes production exceeds demand, and, therefore, production needs to be sold at a less-expensive discounted price. Thus, $\mathrm{AD}_{c,t}$ is the product volume that exceeds demand which will be sold at a less-expensive price.

The refinery balance is completed by

$$\mathrm{AO}_{u,c,t} - \mathrm{Burned}_{c,t} = \mathrm{MANU}_{c,t} \qquad \forall\, t \in \mathrm{T} \tag{A-17}$$

where $\mathrm{Burned}_{c,t}$ is equal to the amount burned.

$$\mathrm{Used}_t = \sum_{u\in \mathrm{U}} (\mathrm{AF}_{u,t} \times \mathrm{density}_u \times \mathrm{fuel}_u) \qquad \forall\, t \in \mathrm{T} \tag{A-18}$$

This completes the model. Detailed equations, unit by unit, are described in the reported work of Pongsadki et al.[6]

Appendix B

The properties of the crudes and the specifications of the units are summarized in this appendix. Table B1 lists the fuels used in the processing unit. The crude oil specifications and composite fractions for Oman crude are given in Tables B2 and B3. The crude oil specifications and composite fractions for Tapis crude are given in Tables B4 and B5. The crude oil specifications and composite fractions for Labuan crude are given in Tables B6 and B7. The crude oil specifications and composite fractions for Seris light crude are given in Tables B8 and B9. The crude oil specifications and composite fractions for Phet crude are given in Tables B10 and B11, respectively. The crude oil

Table B1. Fuel Used in Processing Unit (Fuel Oil Equivalence)[a]

unit	fuel used (wt %)
CDU2	1.8
CDU3	1.8
NPU2	2
NPU3	2
ISOU	4
CRU2	2.5
CRU3	2.5
KTU	2
GO-HDS	2
DGO-HDS	2

[a] Data taken from ref 53.

Table B2. Oman Crude Specification Properties

property	API gravity	Amount					
		sulfur	methane	ethane	propane	isobutane	*N*-butane
value	34.80	1.16 wt %	0.00 vol %	0.02 vol %	0.33 vol %	0.30 vol %	0.92 vol %

Table B3. Oman Crude Component Fractions

description	Component Fraction (vol %)							
	FG	LPG	LN	MN	HN	IK	DO+GO	FO
volumetric yield (lv %)	0.02	1.55	5.33	2.70	6.30	13.80	22.40	46.30
aromatics (lv %)			1.20	4.25	8.24	11.94	20.94	
cetane index					30.10	46.40	54.10	
freeze point (°C)				−85.50	−74.60	−53.50	−8.80	
RONC			69.50	49.20	40.60	27.60		
RVP (kg/cm^2)			0.70	0.16	0.04	0.00		
specific gravity			0.6517	0.7119	0.7385	0.7844	0.8447	0.9367
sulfur (wt %)			0.012	0.027	0.03	0.108	0.687	1.938
viscosity (cSt)								
@50 °C				0.41	0.54	1.01	3.64	609.0
@100 °C				0.34	0.40	0.62	1.66	52.22
pour point (°C)						−77.90		7.00

Table B4. Tapis Crude Specifications

property	API gravity	Amount					
		sulfur	methane	ethane	propane	isobutane	*N*-butane
value	44.50	0.025 wt %	0.00 vol %	0.54 vol %	0.66 vol %	0.82 vol %	1.21 vol %

Table B5. Tapis Crude Component Fractions

description	Component Fraction (vol %)							
	FG	LPG	LN	MN	HN	IK	DO+GO	FO
volumetric yield (lv %)	0.54	2.69	3.27	5.70	10.70	21.90	30.40	21.50
aromatics (lv %)			1.78	5.11	13.09	16.82	17.41	
cetane index					20.90	45.10	59.30	33.30
freeze point (°C)					−83.50	−51.10	6.00	
RONC			81.70	76.00	68.20	60.30		
RVP (kg/cm^2)			0.66	0.15	0.05	0.00		
specific gravity			0.6713	0.7247	0.7557	0.7857	0.8271	0.9175
sulfur content (wt %)			0.000	0.000	0.001	0.004	0.034	0.056
viscosity (cSt)								
@50 °C				0.43	0.55	0.96	2.88	15.26
@100 °C				0.31	0.37	0.58	1.37	4.59
pour point (°C)						−63.40		58.40

Table B6. Labuan Crude Specifications

property	API gravity	Amount					
		sulfur	methane	ethane	propane	isobutane	*N*-butane
value	31.80	0.080 wt %	0.00 vol %	0.02 vol %	0.22 vol %	0.18 vol %	0.36 vol %

Table B7. Labuan Crude Component Fractions

description	Component Fraction (vol %)							
	FG	LPG	LN	MN	HN	IK	DO+GO	FO
volumetric yield (lv %)	0.02	0.76	2.42	3.20	9.00	20.30	42.70	20.70
aromatics (lv %)			7.05	0.64	16.13	26.36	41.67	
cetane index					11.30	30.20	39.20	
freeze point (°C)						−67.80	−8.10	
RONC			83.20	76.40	73.60	50.20		
RVP (kg/cm^2)			0.64	0.16	0.04	0.00		
specific gravity			0.6898	0.7402	0.7759	0.8280	0.8911	0.9530
sulfur content (wt %)			0.001	0.001	0.002	0.017	0.083	0.175
viscosity (cSt)								
@50 °C				0.53	0.62	1.04	3.11	132.07
@100 °C				0.35	0.41	0.63	1.46	14.50
pour point (°C)						−86.50		45.10

Table B8. Seria Light Crude Specifications

property	API gravity	Amount					
		sulfur	methane	ethane	propane	isobutane	*N*-butane
value	35.80	0.068 wt %	0.00 vol %	0.00 vol %	0.25 vol %	0.26 vol %	0.62 vol %

Table B9. Seria Crude Component Fractions

description	Component Fraction (vol %)							
	FG	LPG	LN	MN	HN	IK	DO+GO	FO
volumetric yield (lv %)	0.00	1.33	4.77	4.00	11.3	23.1	35.0	19.50
aromatics (lv %)			2.65	8.19	15.88	24,28	53.56	
cetane index			-	-	12.8	31.6	43.0	
freeze point (°C)						−59.6	−6.40	
RONC			79.5	68.0	60.7	49.6		
RVP (kg/cm^2)			0.69	0.16	0.04	0.00		
specific gravity			0.6798	0.7415	0.7696	0.8200	0.8781	0.9506
sulfur content (wt %)			0.000	0.001	0.003	0.020	0.080	0.155
viscosity (cSt)								
@50 °C				0.21	0.21	0.21	0.34	132.96
@100 °C				0.21	0.21	0.21	0.27	16.87
pour point (°C)						−65.80		35.90

Table B10. Phet Crude Specifications

property	API gravity	Amount					
		sulfur	methane	ethane	propane	isobutane	*N*-butane
value	40.70	0.050 wt %	0.00 vol %	0.07 vol %	0.37 vol %	0.37 vol %	1.04 vol %

Table B11. Phet Crude Component Fractions

description	Component Fraction (vol %)							
	FG	LPG	LN	MN	HN	IK	DO+GO	FO
volumetric yield (lv %)	0.07	1.78	3.05	3.70	8.50	15.00	28.10	38.00
aromatics (lv %)			1.05	5.93	12.15	14.42	14.58	
cetane index					22.60	45.60	61.40	
freeze point (°C)					−88.80	−48.90	13.40	
RONC			70.00	61.40	53.50	41.60		
RVP (kg/cm^2)			0.71	0.16	0.04	0.00		
specific gravity			0.6662	0.7200	0.7502	0.7840	0.8236	0.8941
sulfur content (wt %)			0.000	0.000	0.001	0.006	0.047	0.087
viscosity (cSt)								
@50 °C				0.35	0.48	0.94	3.12	39.72
@100 °C				0.22	0.26	0.52	1.50	10.59
pour point (°C)						−51.50		55.90

Table B12. Murban Crude Specifications

API gravity	Amount					
	sulfur	methane	ethane	propane	isobutane	*N*-butane
40.80	0.867 wt %	0.00 vol %	0.07 vol %	0.52 vol %	0.45 vol %	1.32 vol %

Table B13. Murban Crude Component Fractions

description	Component Fraction (vol %)							
	FG	LPG	LN	MN	HN	IK	DO+GO	FO
volumetric yield (lv %)	0.07	2.29	5.94	3.30	10.1	20.4	25.9	29.7
aromatics (lv %)			1.76	0.41	12.41	20.48	25.48	
cetane index					27.90	43.50	53.20	
freeze point (°C)					−90.20	−56.10	−2.60	
RONC			76.0	72.2	70.1	56.3		
RVP (kg/cm^2)			0.75	0.16	0.04	0.00		
specific gravity			0.6609	0.7145	0.7438	0.7883	0.8455	0.9268
sulfur content (wt %)			0.000	0.000	0.000	0.107	1.051	1.688
viscosity (cSt)								
@50 °C				0.39	0.52	0.93	3.09	88.41
@100 °C				0.28	0.35	0.57	1.42	13.84
pour point (°C)						−73.00		33.40

Table B14. Product Specifications[a]

description	LPG	SUPG	ISOG	JP-1	HSD	FO #1	FO #2	FOVS
maximum RON		91	95					
maximum RVP @ 37.8 °C(KPA)		62	62					
maximum aromatics content (vol %)		35	35	25				
maximum freezing point (°C)				−47				
minimum cetane index					47			
viscosity (cSt)								
@50 °C						7−80	7−180	
@100 °C								3−30
maximum sulfur content (wt %)					0.05	2	2	0.5
maximum pour point (°C)						24	24	57

[a] Product specifications are based on rules from the Ministry of Commerce (MOC) of Thailand.

Table B15. Product Storage Data

description	LPG	SUPG	ISOG	JP-1	HSD	FO #1	FO #2	FOVS
initial product (m^3)	1500	14100	8400	15400	54000			
storage capacity (m^3)	5000	16000	14000	28000	80000	5000	15000	35000

Table B16. Property Constraints of Products Leaving from Both Crude Distillation Units (CDUs)

product and property	Constraint	
	CDU 2	CDU 3
IK		
ARO (lv %)	25 (max)	25 (max)
FPI	11.8 (max)	11.8 (max)
DO		
CI	47 (min)	47 (min)
FO		
sulfur content (wt %)	0.5 (max)	2.0 (max)
viscosity @ 50 °C (cSt)		300 (max)
viscosity @ 100 °C (cSt)	3−30	
pour point, PP (°C)	57 (max)	24 (max)

specifications and composite fractions for Murban crude are given in Tables B12 and B13, respectively. Product specifications are given in Table B14, and product storage data are listed in Table B15. The property constraints of the products that are leaving both crude distillation units (CDUs) are given in Table B16.

Acknowledgment

We gratefully acknowledge the Bangchak Petroleum Public Company Limited and Ms. Usakanok Thamnijkul for providing useful information and recommendations regarding this work and Kitipat Siemanond for his help.

Literature Cited

(1) Swift, A. O. Control and optimization. In *Modern Petroleum Technology: Volume 2, Downstream*, 6th Edition; Lucas, A. G., Ed.; Wiley: Chichester, U.K., 2000.

(2) Simons, R. MIMI brings OR tools together. *MP in Action—The Newsletter of Mathematical Programming in Industry and Commerce* **1997**, (December).

(3) Jia, Z.; Ierapetritou, M. Mixed-integer linear programming model for gasoline blending and distribution scheduling. *Ind. Eng. Chem. Res.* **2003**, *42*, 825–835.

(4) Méndez, C. A.; Grossmann, I. E.; Harjunkoski, I.; Kaboré, P. A simultaneous optimization approach for off-line blending and scheduling of oil-refinery operations. *Comput. Chem. Eng.* **2006**, *30* (4), 614–634.

(5) Pinto, J. M.; Joly, M.; Moro, L. F. L. Planning and scheduling models for refinery operations. *Comput. Chem. Eng.* **2000**, *24*, 2259–2276.

(6) Pongsakdi, A.; Siemanond, K.; Rangsunvigit, P.; Bagajewicz, M. Financial Risk Management in Refinery Operations Planning under Uncertainty. *Int. J. Prod. Econ.* **2006**, *103* (1), 64–86.

(7) Shah, N. Single-and multisite planning and scheduling: Current status and future challenges. In *Foundations of Computer Aided Process Operations*; Blau, G. E., Carnahan, B., Eds.; AIChE Symposium Series 320; American Institute of Chemical Engineers: New York, 1998; pp 75−90.

(8) Shah, N. Mathematical programming techniques for crude oil scheduling. *Comput. Chem. Eng.* **1996**, *20* (Suppl.), S1227–S1232.

(9) Zhang, J.; Zhu, X. X.; Towler, G. P. A level-by-level debottlenecking approach in refinery operation. *Ind. Eng. Chem. Res.* **2001**, *40*, 1528–1540.

(10) Zhang, B. J.; Hua, B. Effective MILP model for oil refinery-wide production planning and better energy utilization. *J. Cleaner Prod.* **2007**, *15* (5), 439–448.

(11) Moro, L. F. L.; Zanin, A. C.; Pinto, J. M. A planning model for refinery diesel production. *Comput. Chem. Eng.* **1998**, *22* (Suppl.), S1039–S1042.

(12) Pinto, J. M.; Moro, L. F. L. A planning model for petroleum refineries. *Braz. J. Chem. Eng.* **2000**, *17* (4−7), 575–586.

(13) Joly, M.; Moro, L. F. L.; Pinto, J. M. Planning and scheduling for petroleum refineries using mathematical programming. *Braz. J. Chem. Eng.* **2002**, *19* (2), 207–228.

(14) Moro, L. F. L.; Pinto, J. M. Mixed-integer programming approach for short-term crude oil scheduling. *Ind. Eng. Chem. Res.* **2004**, *43*, 85–94.

(15) Glismann, K.; Gruhn, G. Short-term scheduling and recipe optimization of blending processes. *Comput. Chem. Eng.* **2001**, *25*, 627–634.

(16) Zhang, N.; Zhu, X. X. A novel modeling and decomposition strategy for overall refinery optimization. *Comput. Chem. Eng.* **2000**, *24*, 1543–1548.

(17) Göthe-Lundgren, M.; Lundgren, J. T.; Persson, J. A. An optimization model for refinery production scheduling. *Int. J. Prod. Econ.* **2002**, *78*, 255–270.

(18) Rejowski, R.Jr.;.; Pinto, J. M. Scheduling of a multiproduct pipeline system. *Comput. Chem. Eng.* **2003**, *27* (8−9), 1229–1246.

(19) Neiro, S. M. S.; Pinto, J. M. A general modeling framework for the operational planning of petroleum supply chains. *Comput. Chem. Eng.* **2004**, *28* (6−7), 871–896.

(20) Persson, J. A.; Göthe-Lundgren, M. Shipment planning at oil refineries using column generation and valid inequalities. *Eur. J. Oper. Res.* **2005**, *163* (3), 631–652.

(21) Lee, H.; Pinto, J. M.; Grossmann, I. E.; Park, S. Mixed-integer linear programming model for refinery short-term scheduling of crude oil unloading with inventory management. *Ind. Eng. Chem. Res.* **1996**, *35*, 1630–1641.

(22) Jia, Z.; Ierapetritou, M.; Kelly, J. D. Refinery short-term scheduling using continuous time formulation: crude-oil operations. *Ind. Eng. Chem. Res.* **2003**, *42*, 3085–3097.

(23) Wenkai, L.; Hui, C. W.; Hua, B.; Tong, Z. Scheduling crude oil unloading, storage, and processing. *Ind. Eng. Chem. Res.* **2002**, *41*, 6723–6734.

(24) Guillén, G.; Mele, F. D.; Bagajewicz, M. J.; Espuña, A.; Puigjaner, L. Multiobjective supply chain design under uncertainty. *Chem. Eng. Sci.* **2005**, *60*, 1535–1553.

(25) Voeth, M.; Herbst, U. Supply-chain pricing-A new perspective on pricing in industrial markets. *Ind. Market. Manage.* **2006**, *35* (1), 83–90.

(26) Karwan, M. H.; Keblis, M. F. Operations planning with real time pricing of a primary input. *Comput. Oper. Res.* **2007**, *34* (3), 848–867.

(27) Bopp, A. E.; Kannan, V. R.; Palocsay, S. W.; Stevens, S. P. An optimization model for planning natural gas purchases, transportation, storage and deliverability. *Omega* **1996**, *24* (5), 511–522.

(28) Guldmann, J. M.; Wang, F. Optimizing the natural gas supply mix of local distribution utilities. *Eur. J. Oper. Res.* **1999**, *112*, 598–612.

(29) Liu, M. L.; Sahinidis, N. V. Optimization in process planning under uncertainty. *Ind. Eng. Chem. Res.* **1996**, *35*, 4154–4165.

(30) Escudero, L. F.; Quintana, F. J.; Salmerón, J. CORO, a modeling and an algorithmic framework for oil supply, transformation and distribution optimization under uncertainty. *Eur. J. Oper. Res.* **1999**, *114*, 638–656.

(31) Hsieh, S.; Chiang, C. C. Manufacturing-to-sale planning model for fuel oil production. *Adv. Manuf. Technol.* **2001**, *18*, 303–311.

(32) Neiro, S. M. S.; Pinto, J. M. Supply chain optimization of petroleum refinery complexes. In *FOCAPO 2003, Fourth International Conference on Foundations of Computer-Aided Process Operations*, Coral Springs, FL, January 12−15, 2003; pp 59−72.

(33) Lababidi, H. M. S.; Ahmed, M. A.; Alatiqi, I. M.; Al-Enzi, A. F. Optimizing the supply chain of a petrochemical company under uncertain operating and economic conditions. *Ind. Eng. Chem. Res.* **2004**, *43*, 63–73.

(34) Liu, M. L.; Sahinidis, N. V. Process planning in a fuzzy environment. *Eur. J. Oper. Res.* **1997**, *100*, 142–169.

(35) Singh, A.; Forbes, J. F.; Vermeer, P. J.; Woo, S. S. Model-based real-time optimization of automotive gasoline blending operations. *J. Process Control* **2000**, *10* (1), 43–58.

(36) Reddy, P. C. P.; Karimi, I. A.; Srinivasan, R. A new continuous-time formulation for scheduling crude oil operations. *Chem. Eng. Sci.* **2004**, *59* (6), 1325–1341.

(37) Herroelen, W.; Leus, R. Project scheduling under uncertainty: Survey and research potentials. *Eur. J. Oper. Res.* **2005**, *165*, 289–306.

(38) Csáji, B.; Monostori, L. Stochastic Reactive Production Scheduling by Multi-Agent Based Asynchronous Approximate Dynamic Programming. In *Multi-Agent Systems and Applications IV (CEEMAS 2005)*; Lecture Notes in Artificial Intelligence 3690; Springer: Berlin, Germany, 2005; pp 388−397.

(39) Al-Redhwan, S. A.; Crittenden, B. D.; Lababidi, H. M. S. Wastewater minimization under uncertain operational conditions. *Comput. Chem. Eng.* **2005**, *29* (5), 1009–1021.

(40) Liao, Z.; Rittscher, J. A multi-objective supplier selection model under stochastic demand conditions. *Int. J. Prod. Econ.* **2007**, *105*, 150–159.

(41) Ierapetritou, M. G.; Pistikopoulos, E. N. Simultaneous incorporation of flexibility and economic risk in operational planning under uncertainty. *Comput. Chem. Eng.* **1994**, *18* (3), 163–189.

(42) Mulvey, J. M.; Rosenbaum, D. P.; Shetty, B. Strategic financial risk management and operations research. *Eur. J. Oper. Res.* **1997**, *97* (1), 1–16.

(43) Lowe, T. J.; Wendell, R. E.; Hu, G. Screening location strategies to reduce exchange rate risk. *Eur. J. Oper. Res.* **2002**, *136* (3), 573–590.

(44) Gupta, A.; Maranas, C. Market-based pollution abatement strategies: Risk management using emission option contracts. *Ind. Eng. Chem. Res.* **2003**, *42*, 802–810.

(45) Cheng, L.; Subrahmanian, E.; Westerberg, A. W. Design and planning under uncertainty: Issues on problem formulation and solution. *Comput. Chem. Eng.* **2003**, *27* (6), 781–801.

(46) Guldimann, T. The story of risk metrics. *Risk* **2000**, *13* (1), 56–58.

(47) Jorion, P. *Value at Risk, The New Benchmark for Managing Financial Risk*, 2nd Edition; McGraw−Hill: New York, 2000.

(48) Barbaro, A.; Bagajewicz, M. J. Managing financial risk in planning under uncertainty. *AIChE J.* **2004**, *50* (5), 963–989.

(49) Aseeri, A.; Bagajewicz, M. J. New measures and procedures to manage financial risk with applications to the planning of gas commercialization in Asia. *Comput. Chem. Eng.* **2004**, *28*, 2791–2821.

(50) Hirshleifer, J.; Glazer, A. *Price Theory and Applications*; Prentice Hall: Englewood Cliffs, NJ, 1998.

(51) Varian, H. R. *Microeconomic Analysis*, 3rd Edition; Norton: New York, 1992.

(52) EPPO, Energy Data Notebook Quarterly Report, Energy Policy and Planning Office, Ministry of Energy, Thailand, 2003.

(53) Favennec, J. P., Ed. *Refinery Operation and Management*; Petroleum Refining Vol. 5; Editions Technip: Paris, 2001.

Received for review August 7, 2007
Revised manuscript received November 26, 2007
Accepted December 17, 2007

IE0710770