USING STOCHASTIC MODEL FOR LOWER FINANCIAL RISK MANAGEMENT IN REFINERY OPERATIONS PLANNING

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ABSTRACT

Most Refineries historically models are deterministic, that is, they use nominal parameter values without taking into consideration the uncertainty in process, demands, refinery parameters, etc. And as a consequence, they are unable to perform risk management. In this paper a variety of methodologies for financial risk management in engineering decision have been already developed. We follow the approach presented by Barbaro and Bagajewicz (2004), who used two-stage stochastic programming model and you, can find all other approaches analyzed and discussed. The problem addressed here is that of determining the crude oil to purchase and decide on the production level of different products given predicts of demands. The profit is maximized taking into account revenues, crude oil costs, inventory costs, and lost demand costs. The model was tested using data from the Refinery owned by the State Oil Marketing Organization (SOMO) Company, Iraq. The results show that the stochastic model can forecast higher expected profit and lower risk compared to the deterministic model.

Keywords: refinery operations, petroleum, crude transportation, stochastic model.

INTRODUCTION

Previously Refineries have had to use a tool to determine the performance and economics of existing operating units and/or planned new units. Most commercial models (PIMS, RPMS, PETRO) perform refinery planning under deterministic conditions, that is, they do not consider uncertainty in process, refinery parameters, demands, etc. Aspen PIMS facilitates enterprise-wide planning through optimized feedstock evaluation, product slate optimization, plant design, and operational execution that enables refineries and petrochemical plants to run at maximum efficiency. The scalable single- or multi-user solution models linear and non-linear problems and interfaces to rigorous simulator models. Aspen PIMS is a core element of AspenTech's aspenONE® Planning and Scheduling applications. And as a result, they are unable to perform risk management. Aspen PIMS. (2004).

Although risk management is attractive to refinery planning operators, its development has been considered hard because it entails the extension of these deterministic models, complex as they are already, to present optimization under uncertainty and manage risk. The extension never posed conceptual problems, just possible computational problems (memory, running time, etc) and eventually business will to pursue this on the part of software vendors. We developed a model which is similar to several existing ones in the literature:

Lee et al. (1996), Jia et al. (2003), Wenkai et al. (2002) , Göthe- Lundgren et al. (2002), Moro et al. (1998), Pinto and Moro (2000), Pinto et al. (2000), Joly et al. (2002), Moro and Pinto (2004), Jia and Ierapetritou (2003), Zhang and Zhu (2000), among others. Stochastic cases have been considered by Bopp *et al.* (1996), Guldmann and Wang (1999), Escudero *et al.* (1999), Hsieh and Chiang (2001), Neiro and Pinto (2003), Lababidi *et al.* (2004). We use the two-stage stochastic programming approach for process planning under uncertainty (Liu and Sahinidis,1996). Barbaro and Bagajewicz (2003, 2004) presented a methodology for financial risk management in the framework of two-stage stochastic programming for planning under uncertainty, also they presented computational challenges and if implemented commercially would require changes in the available commercial code.

Based on this description, some of the theoretical expressions were developed, providing new insights on the trade-offs between risk and profitability. Therefore, the cumulative risk management curves were found to be very suitable to visualize the risk behaviour of different alternatives. Aseeri and Bagajewicz (2004) introduced new procedures and measures to manage financial risk. The concept of Value at Risk and Upside Potential as means to weigh opportunity loss versus risk reduction as well as an area ratio were used in this article and, in addition, upper and lower bounds for risk curves corresponding to the optimal stochastic solutions were developed. In the end, we introduced a new measure to evaluate risk. The method can be take advantage of the sampling average algorithm. The methodology that proposed by Aseeri and Bagajewicz (2004) was applied to refinery planning by Pongsadki et al.(2006), who used a linear programming model as the main deterministic planning solver.

In this paper, a model was developed for the production planning. We implement the strategy outlined by the aforementioned previous work using a commercial planner. PIMS used as engine to resolve the stochastic model and write computational routines to do it and manage financial risk. The results show that the procedure found solutions with very high expected value compared with those suggested by the deterministic model.

PROBLEM STATEMENT

The aim of the PIMS model is maximize the profit taking into account revenues, inventory costs and oil costs. The process units are modelled as vector - base, delta – base, mixers and splitters. Automatically the distillations units are modelled by sub models using crude oil assay data, and send directly the properties of the run products to the PIMS blending. The stochastic model formulated by using discrete scenarios. For the decision variables we consider are crude purchase decisions, process units internal flows and operation parameters, blending over time periods and inventory management. The uncertain parameters are: products demand, crude cost and prices. We assume that this information is a predict and it is available a probability density function.

CASE STUDY

The model PVOLSAMP was applied to the PIMS sample. PVOLSAMP model is a volume based multi-period refinery model and has the following process units: three operational modes units and two atmospheric distillation(CDU1 and CDU2), a naphtha hydrotreater (NHT) and one naphtha splitter (NSP), one kerosene (KHT) and a distillate, one low-press reformer (LPR) hydrotreater (DHT), one cat cracking unit (CCU), one butane isomerization (IS4), one sulfuric acid alkylation (SFA), one hydrocracker distillate, one delay coking (DLC), one delay coking multi path (DCX), one hydrogen plant (HYD), one plant fuel system (PFS), one amine sulfur removal unit (AMN), one sulfur recovery unit (SRU), one tail gas treater unit (TGT), one saturate gas plant (SGP), unsaturated gas plant (UGP), one utility generation unit and products blending. The goal of the refinery is make the following products: LPG, unleaded regular gasoline (URG), unleaded premium gasoline (UPR), leaded regular gasoline (LRG), kerosene/jet (JET), diesel (DSL), low sulfur fuel oil (LSF), high sulfur fuel oil (HSF), coke (coke) and crude atmospheric residue (ATB). The CDU1 and CDU2 can operate to obtain fuels, and the CDU2 is operates to get lube. The blended products specifications are shown in table 1.

Prefixes X and N refer to maximum and minimum values for the products qualities, respectively. The total capacity of the refinery is 100000 bbls/ day. The values of crude oil costs and product prices were taken from historical data published by the energy information administration webpage (http://www.eia.doe.gov/). The following data between parentheses indicate the maximum demand and standard deviation for products table 2.

Table 1: Blended Specifications.

	Property	URG	UPR	LRG	GSO	JET	DSL	LSF	HSF	CKE
XRVI	PVP Index	15.6	15.6	15.6						
NDON	Road ON	87.0	91.0	88.0						
NCNX	CNX ON			88.0						
XTEL	TEL gms/gal			0.1						
XLET	LET gms/gal			0.095						
NE16	Dist:%Evap@160F	15	15	15						
XE16	Dist:%Evap@160F	35	35	35						
XARO	Aromatics, LV%	50	50	100	30	24				
XBNZ	Benzene, LV%	2	2	100	5					
NE20	Dist:%Evap@200F	30	30	30						
XE20	Dist:%Evap@200F	70	70	70						
NE30	Dist:%Evap@300F	70	70	70						
NE40	Dist:%Evap@400F					10				
XSUL	Sulfur, WT%	0.05	0.05	0.10		0.30	0.50	1.00	3.00	9.00
XOLF	Olefins, LV%	25	25	100						
XOXY	Oxygen, WT%	3.7	3.7	100						
NSPG	Specific Gravity	0.7000	0.7000			0.7750	0.8160			
XSPG	Specific Gravity					0.8400	0.8760		0.9970	
NCTI	Cetane Index						46.2			
NLUM	Luminometer Number					40.0				
XPPI	Pour Point Index						1.61	42.52		
NVII	Visco Index @210F									
XVII	Visco Index @210F							1.86	1.86	
XVAN	Vanadium									1500

Table 2: Maximum Demand and Standard Deviation for Products.

product	LRG	URG	UPG	Kero/JET	diesel	HSF	ATB
maximum demand	5.00	45.00	200.00	10.00	22.00	5.50	1.20
standard deviation	0.34	3.09	8.00	1.31	2.88	0.33	0.07

RESULTS AND DISCUSSION

The deterministic optimization model (2281 constraints and 2317 variables) was run using mean values. Results show a gross refinery margin of 301 US$M per three months period with less than 30 seconds of execution time on a workstation M65 (Intel Core 2, 2GHz, 2 GB RAM). We then solved the stochastic model using our procedure. To compare, we then take the deterministic solution and evaluate its performance over the 600 scenario used. Figure 1 shows the risk curves for the best stochastic solution and the performance of the deterministic solution and Table 3 summarizes the results. Results indicate that the stochastic solution has an expected GRM of $411 million, a significant increase over the deterministic value. When the decisions of the deterministic model are evaluated over the uncertainty space, the expected GRM is $397 Million.

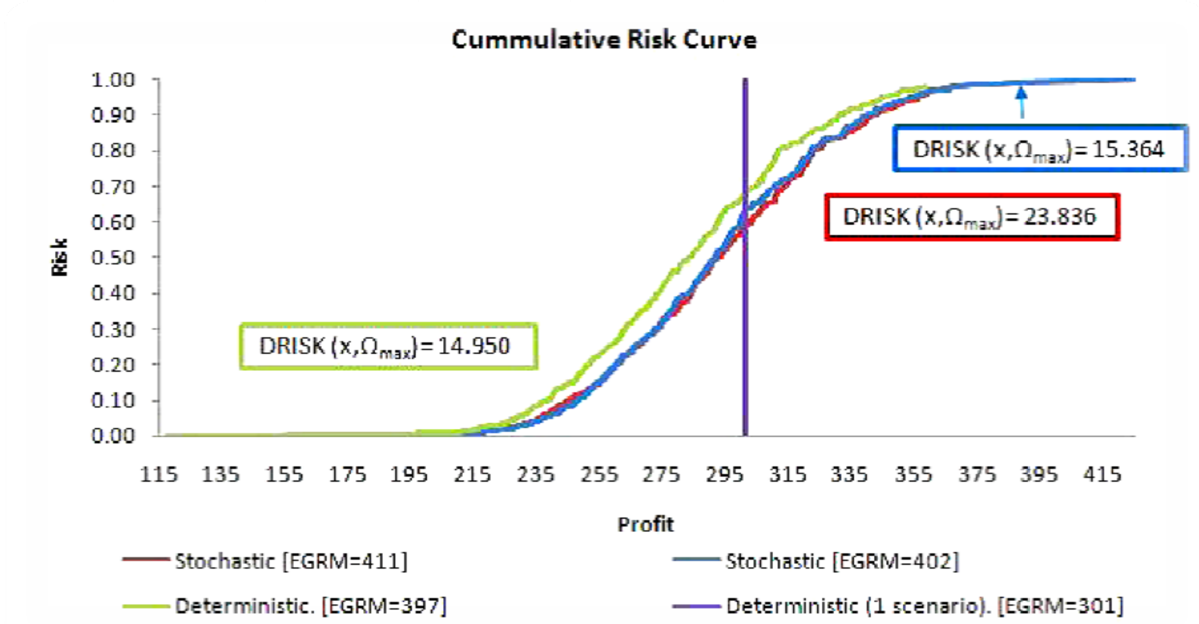
CONCLUSIONS

We successfully implemented a stochastic programming methodology to a refinery planning problem using a commercial planner. Our methodology can be seemingly migrated to other commercial planners. The two-stage stochastic programming approach is shown to be far superior to plans obtained using deterministic models fed by expected values of parameters (36.5% increases in expected GRM for our case study). Less risky solutions were also identified.

Table 3: Alternative Stochastic Solutions

EGRAM	VAR (5%)	OV (95%)	Drisk(X,Ω_{max})	EGRAM Reduction	VAR Reduction	OV Reduction	VAR Reduction	OV Reduction
				(From Stochastic solution)(%)				
411.369	175.342	55.710	15.364					
409.497	170.139	53.538	19.243	0.46%	2.97%	3.90%	2.97%	3.90%
406.167	172.139	52.912	16.588	1.26%	1.74%	5.02%	1.74%	5.02%
406.152	168.078	51.697	18.118	1.27%	4.14%	7.20%	4.14%	7.20%
404.032	164.181	51.676	21.363	1.78%	6.36%	7.24%	6.36%	7.24%
403.739	167.141	50.304	18.524	1.85%	4.68%	9.70%	4.68%	9.70%
403.689	166.270	48.971	22.525	1.87%	5.17%	12.10%	5.17%	12.10%
402.820	168.690	51.795	17.758	2.08%	3.79%	7.03%	3.79%	7.03%
402.479	165.873	47.308	23.594	2.16%	5.40%	15.08%	5.40%	15.08%
402.110	165.705	50.114	23.836	2.25%	5.50%	10.05%	5.50%	10.05%
400.696	165.266	50.719	20.057	2.59%	5.75%	8.96%	5.75%	8.96%
400.272	165.555	48.963	22.769	2.70%	5.58%	12.11%	5.58%	12.11%
399.555	164.583	49.428	23.195	2.87%	6.14%	11.28%	6.14%	11.28%
389.661	153.641	35.698	21.921	5.28%	12.38%	35.92%	12.38%	35.92%

Figure 1: Risk Curve



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