FINANCIAL RISK MANAGEMENT IN REFINERY OPERATIONS PLANNING USING COMMERCIAL SOFTWARE

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1. INTRODUCTION

Most commercial models (PIMS, RPMS, PETRO) perform refinery planning under deterministic conditions, that is, they do not consider uncertainty in process, demands, refinery parameters, etc. and as a consequence, they are unable to perform risk management. 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 perform optimization under uncertainty and manage risk. The extension never posed conceptual problems, just possible computational problems (running time, memory, etc) and eventually business will to pursue this on the part of software vendors.

A variety of methodologies for risk management in engineering decision have been already developed. We follow the approach presented by Barbaro and Bagajewicz [1], who used two-stage stochastic programming and where the reader can find all other approaches analyzed and discussed. All of them, including the one by Barbaro and Bagajewicz [1], presented computational challenges and if implemented commercially would require changes in the available commercial code.

To deal with the aforementioned computational difficulties, Aseeri and Bagajewicz [2] proposed a methodology that is capable of performing risk management using a deterministic model repeatedly. The methodology is conceptually rigorous and practically sound. It removes the need to alter existing code. Only new code needs to be generated.

The methodology proposed by Aseeri and Bagajewicz [2] was applied to refinery planning by Pongsadki et al. [3], who used a linear model as the core deterministic planning solver.

In this work we implement the strategy outlined by the aforementioned previous work using a commercial planner. We use PIMS as engine to solve the stochastic model and write computational routines to do it and manage financial risk. The results show that the procedure found solutions with higher expected value than those suggested by the deterministic model. We present more details now and cover some computational issues later.

2. PROBLEM STATEMENT

The objective of the PIMS model is maximize the profit taking into account revenues, crude oil costs and inventory costs. The process units are modeled as vector - base, delta – base, mixers and splitters. The distillations units are modeled automatically by submodels using crude assay data, and transmit the properties of the straight run products to the PIMS blending and other submodel sections [4]. We formulate the stochastic model using discrete scenarios.

The decision variables we consider are crude oil purchase decisions, process units operation parameters and internal flows, inventory management and blending over time periods.
The uncertain parameters are: crude oil cost, products demand and prices. We assume that this information is a forecast and it is available a probability density function.

After implementing the procedure, the downside risk and VaR (@5%) are computed.

3. CASE STUDY

The procedure was applied to the PIMS sample model PVOLSAMP. This model it is a volume based multi-period refinery model and has the following process units: two atmospheric distillation units (CDU1 and CDU2) and three operational modes, one naphtha splitter (NSP) and a naphtha hydrotreater (NHT), one low-press reformer (LPR), one kerosene (KHT) and a distillate 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 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 parenthesis indicate the maximum demand and standard deviation for products: LRG (5.00, 0.34), URG (45.00, 3.09), UPG (200.00, 8.00), Kero/JET (10.00, 1.31), diesel (22.00, 2.88), HSF (5.50, 0.33) and ATB (1.20, 0.07).

4. RESULTS

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 performace 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 2 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. Table 3 also shows solutions with less EGRM but lower risk.

5. 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.

REFERENCES

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Table 1. Blended Specifications.

	Property	URG	UPR	LRG	GSO	JET	DSL	LSF	HSF	CKE
XRVI	RVP 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	Benzenes, 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. Alternative Stochastic Solutions

EGRM	VaR (5%)	OV (95%)	Drisk(x,Ω_{max})	EGRM Reduction (from Stochastic solution) (%)	VaR Reduction (from Stochastic solution) (%)	OV Reduction (from Stochastic solution) (%)	ıR Reduction ɔm Stochastic ɔlution) (%)	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	172.293	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