OPTIMAL WASTE REDUCTION AND INVESTMENT PLANNING UNDER UNCERTAINTY

Aninda Chakraborty and Andreas A. Linninger
Laboratory for Product and Process Design
Department of Chemical Engineering, University of Illinois at Chicago.
email: {achakr1, linninge}@uic.edu

Richard D. Colberg
Eastman Chemical Company
Kingsport, TN 37662; email: rcolberg@eastman.com

Abstract

Ever-changing production campaigns complicate the management of recovery and treatment options for unavoidable effluents at pharmaceutical plants. Each campaign produces large amounts of by-products differing in their number, amount as well as composition. Future business strategies designed to address changing market demands add uncertainty to this already challenging design problem. In such a dynamic and uncertain environment, the selection of operating policies as well as decisions to support future business operations by plant investments such as new reactors and separators is a formidable task. This paper will propose a systematic methodology for long-range, site-wide management strategies for batch manufacturing sites. Rigorous modeling of future regulatory changes will allow decision-makers to anticipate the monetary, infrastructural and ecological impact such new legislation may have on their businesses at a specific sites or an entire regions. The methodology will be illustrated by means of industrial case studies.

Keywords

Combinatorial Process Synthesis, Forecast, Plant Model, Multi-Period Optimization.

Introduction

A novel *combinatorial process synthesis* methodology was introduced by Linninger and coworkers (Chakraborty and Linninger, 2002a & b). This methodology aimed at constructing optimal recovery and treatment policies for entire manufacturing sites using a two-step procedure. The first step, *superstructure synthesis*, synthesized a superstructure of all feasible recovery and treatment options for effluents on a plant-wide level. Step two of the methodology, *superstructure optimization*, searched for the best operating policy embedded within the superstructure.

This paper will propose the application of the combinatorial process synthesis methodology for finding optimal long-range waste management and plant investment strategies for entire manufacturing sites for a planning horizon of 5 years. This methodology will not only propose the best treatment and recovery options for the entire planning horizon but will also guide decision-makers in making optimal investment decisions. In our novel framework, optimal infrastructure and waste management is regarded as an uncertain multi-period optimization problem.

Optimal long term waste management strategies must satisfy *site-specific regulations* during each time period. Future regulations are anticipated by a *regulatory forecast*. Moreover, investment decisions made in any time period (e.g. a fiscal year) to augment a plant infrastructure should sustain future business and market demands for the entire manufacturing site, as obtained from *business and market* *forecasts*. Hence a dynamic vision of the changing market demands and regulations are necessary. Figure 1 outlines the schematic of our long term planning methodology for a multi-purpose batch manufacturing site. In our model, business and regulatory forecasts are used as input to the combinatorial process synthesis methodology. Our solutions synthesize a network of process operations to recover useful raw materials and solvents, treat unavoidable effluent streams to compliance, and suggest optimal capacity and timing of investment decisions for new facilities or process technology. In addition, the expected environmental discharges are measured annually and the plant wide technological capacities of available treatment capacities are updated dynamically in accordance with every plant investment. Our strategy is very similar to closed looped model predictive control scheme depicted in Fig. 1.

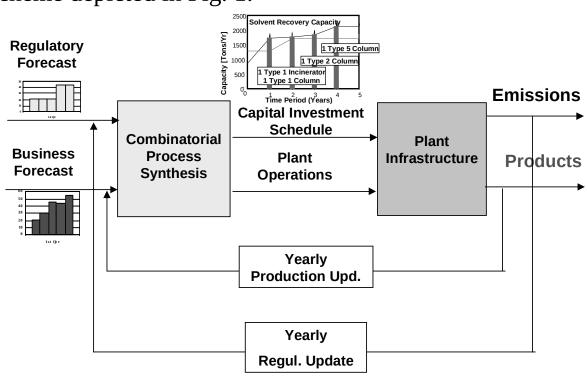

Figure 1. Overview of the Multi-Period Planning Methodology,

Outline. Sections 2 and 3 will briefly outline the proposed plant models and investments, and introduce the mathematical programming framework. Section 4 will discuss industrially relevant case studies. The article will close with conclusions.

2. Plant Model and Investment

The plant model represents the available plant-infrastructure for different treatment or recovery options within a batch manufacturing facility. The purpose of the plant model is to represent mathematically significant inventory and track its evolution due to investment decisions. The plant has to handle all waste loads from all batch production campaigns by either recovery or destructive waste treatment. Materials or excess loads that cannot be treated onsite may also be sent to specialized offsite facilities.

Tables 1 and 2 exemplify relevant properties of standard industrial equipment types available for distillative solvent recovery and thermal incineration. The purchase cost for the different equipment types are approximated using Gutherie's correlation (Gutherie, 1969). The installed cost are typically five times that of purchase cost (Lang factor = 5). The economy of scale for choosing optimal equipment sizes is typically following a *6/10th rule* (Peters and Timmerhaus, 1980).

Table 1. Investment Portfolio for Solvent Recovery - Installed Cost of Distillation Columns.

Diameter (in)	Height 22ft	Height 35ft	Height 82ft	Height 200ft
12	$ 329,840	$ 368,510	$ 493740	
18	–	$ 440,280	$ 642,080	–
24	–	$ 516,800	$ 801,120	$ 1,432,230
36	–	–	–	$ 2,182,878

Table 2. Investment Portfolio for Incinerators.

Thermal Rating (MBtu/hr)	Approx Hourly Capacity (lbs/hr)	Installed Cost ($)
30	7,500	3,195,780
50	12,500	4,933,420
80	20,000	7,356,140
120	30,000	10,383,110

Figure 2 depict simple plant inventory model for two hypothetical industrial sites A and B located at different geographical locations. Site A has superior plant infrastructure as compared to site B and is therefore termed the *flexible site*. Site B, on the other hand, is termed the *bottleneck site*.

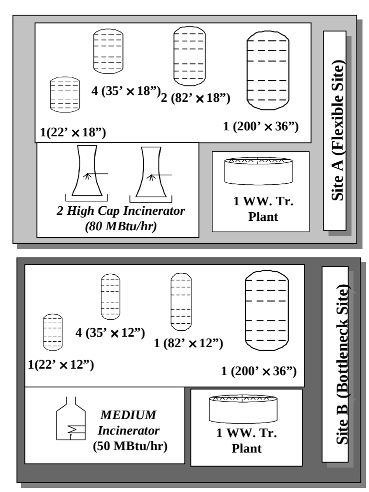

Fig. 2. Plant Models for two Hypothetical Sites

Phase two of the combinatorial process synthesis methodology is applied for long term planning. Optimal long term operating and investment decisions will be derived by solving a rigorous multi-period mixed integer linear program (MILP). Similar mathematical models for obtaining long-term investment decision have been extensively discussed in the literature (e.g. Sahinidis et al, 1989; Liu and Sahinidis, 1996).

3. Multi-period Decision Making: Mathematical Formulation

In the multi-period mixed integer linear program of (1) – (8), the objective is to minimize the net present cost, NPC, representing annualized capital (investment) and operating cost, for the entire planning horizon. Typically, a planning horizon of n = 5 - 10 years is considered (e.g. Henn and Fava, 1994). Investments made in the planning horizon, n, must optimize the plant operation cost for entire economic horizon, N (20 – 30 years). The objective function also considers penalties for capacity constraint violations. δ^{max} and μ make up penalties for exceeding available capacities at the site, see (2) and (7). These penalties may account for additional cost of transportation and/or off-site handling. Investment decisions counting the number of new modules, $y(t)$, may be taken at each period [c.f. Equ. (3)]. Emission constraints of inequality (4) may be subject to a change over time as anticipated by the regulatory forecast. The original infrastructure of the plant is expressed by $d_{max}(0)$. Investments increment the available capacity, d_{max}, of the respective technologies at the site by $dC(\mathrm{t}) = S \cdot \mathrm{y(t)}$, equation (6). Note that new equipment comes in discrete size increments as expressed by constant S. Emission constraints are hard, i.e. no violations allowed, The matrix D(t) stores the waste load sent to each plant. Similarly, E(t), captures the amount of final emissions caused by terminal waste residuals. Both matrices are computed in the *superstructure generation* step and may change in different time interval (t = 1 … n) due to uncertainties in the waste streams. The design variables in this optimization include choices for recovery and treatment operations expressed by the binary variables, x(t), in the superstructure generated in phase one of the methodology. The logical path constraints of equation (8) enforce correct connectivity of the flowsheets as it was found in phase one of the methodology.

$$\min_{x(t),\ y(t),\ \delta(t),\ \delta^{max}(t)} \quad \mathrm{NPC} = \mathrm{NPC_{Operating}} + \mathrm{NPC_{Capital}} \tag{1}$$

$$\mathrm{NPC_{Operating}} = \sum_{t=1}^{N} (1+r)^{-t}\, c(t) \cdot x(t) + \sum_{t=1}^{N} (1+r)^{-t} \left(\mu \cdot \delta^{max}(t)\right) \tag{2}$$

$$\mathrm{NPC_{Capital}} = \sum_{t=1}^{n} (1+r)^{-t}\, C \cdot y(t) \tag{3}$$

$$E(t) \cdot x(t) \le e_{max}(t) \tag{4}$$

$$D(t) \cdot x(t) = d_{max}(t) + \delta(t) \tag{5}$$

$$d_{max}(t) = d_{max}(t-1) + dC(t)\,; \quad dC(t) = S \cdot y(t) \tag{6}$$

$$\delta^{max}(t) \ge \delta(t)\,; \ \delta^{max}(t) \ge 0 \tag{7}$$

$$\sum x_{k,j}(t) = x_{k,i}(t) \tag{8}$$

4. Case Study:

Four waste blends from a synthetic organic medicinal plant are considered to demonstrate our methodology. The components in these blends are extraction and wash solvents used in pharmaceutical manufacturing and therefore the effluents possess potential for solvent recovery. W_2 is waste water with trace organics. The superstructure of treatment and recovery options for these four waste blends implicitly embeds a total of 160 different waste treatment policies. More details are discussed elsewhere (Chakraborty and Linninger, 2002a).

Waste Forecast: The market and business forecasts lead to expected plant production data for the planning period. From production figures projected over typically 5 years or so, one can infer the expected waste loads and compositions, called the *waste forecast*. Figure 3 visualizes the forecast for 4 waste blends over 5 years. The waste blend, W_4, is associated with a manufacturing campaign whose product is expected to have a very high market demand in the near future. Therefore a high growth in business activities (and hence waste generation) is estimated for the same campaign.

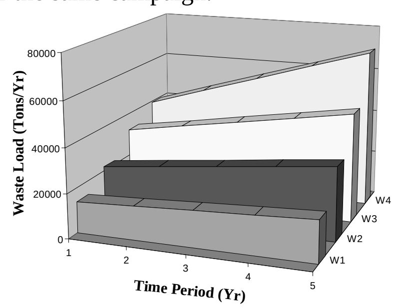

Fig. 3. Waste Load Forecast obtained from Business and Market Forecasts

Plant Model. The plant models of Figure 2 represent the available equipment inventory at two fictitious sites A and B. These sites are equipped with process units similar to the infrastructure available at real industrial plants.

Regulatory Forecast: In this case study it is assumed initially that there are no limits on CO_2 emissions. We want to study the possible impact of a future regulatory change that caps total CO_2 emission of the site to 70 KTons per year. This new regulation of this fictitious scenario is assumed to take effect after three years.

Results: The MILP of (1) – (8) was applied for both sites, A and B. Table 3 shows the different levels of CO_2 emissions of both these sites for the entire planning horizon. The regulatory change in the third year forces a swap in operating policy in both sites. For the flexible site A, the operating policy changes from π_1 to π_2 in year 3 and π_3 in year 5, involving more recycle instead of waste incineration. Hence, policies π_2 and π_3 burn less wastes (thus emitting less CO2) as compared to π_1. The capacity increment of the solvent recovery plant at site A is illustrated in Figure 4. Site A is flexible enough to change operating policies in order to meet the high growth in the waste loads and the future regulations without having to make any capital investments.

Table 3. Annual CO_2 emissions for Sites A and B.

Period	CO2 Emissions (KTons/Yr)	
	Site A	Site B
0	106.66 (π_1)	50.89(π_4)
1	120.04(π_1)	58.53(π_4)
2	139.97(π_1)	66.16(π_4)
3	62.52(π_2)	20.32(π_5)
4	68.98(π_2)	22.42(π_5)
5	24.53(π_3)	24.53(π_5)

* π_1 - π_5 are different policies in the superstructure

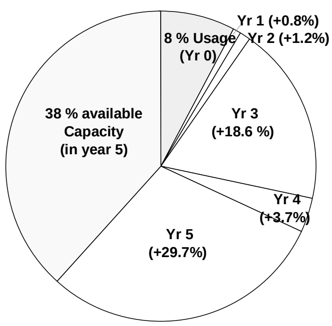

Fig. 4. Increment in Solvent Recovery Capacity for Site A (Tot Capacity = 16500 KTon/Yr)

Figure 5 plots the annual operating cost at different time period for site A. It also projects the operating costs if no change takes place in the environmental regulations. Without changes in regulation, policy π_1 can handle all wastes with a small cost increment due to higher waste outputs. Limits on CO2 emission for that site require different operating policies, π_2 and π_3 associated with higher operating cost due to more expensive physical separations.

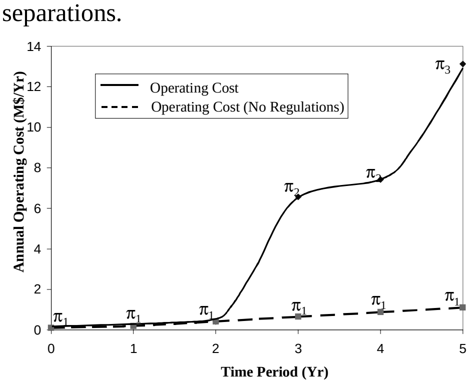

Fig. 5. Annual Operating Costs for Site A. Total Cost (20 yrs Economic Horizon): 81.04 M$

Site B (the bottleneck site) requires capital investment in order to sustain the future business demands and meet future regulatory constraints. Figure 6 plots the annual operating cost and the capital investments at different time period for site B. This site needs two additional separation columns (82 ft × 24 inches; 35 ft × 12 inches) in year 3 and 4. There is a change in operating policy in year 3 due to environmental regulations.

Figure 6 also displays the evolution of the annual cost for no limits on CO_2 emission. In this case, the operating policy is maintained at π_4 all throughout the planning horizon. This policy, π_4, burns more wastes and therefore needs an extra incinerator (~ 30 MBtu/hr) in year 2 and a distillation column (35 ft × 12 inches) in year 4.

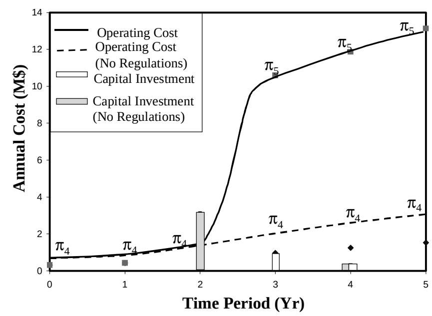

Fig. 6. Operating & Capital Cost for Site B. Total Cost (20 yrs Economic Horizon): 89.66 M$

Conclusions

In this paper, a novel multi-period decision making strategy is proposed by means of two industrial problems. Mixed integer optimization programs are deployed for finding long term plant wide operating policies and propose investment decisions for plant equipment. The effect of future regulatory changes on plant-operation has also been discussed. Using our computer-aided methodology, decision makers can examine a variety of different business and regulatory scenarios and arrive at plant-wide optimal strategies with little manual effort.

References

Chakraborty A and A. A. Linninger (2002a). Plant-Wide Waste Management. 1. Synthesis and Multi-Objective Design. *Ind. Engg. Chem. Res*, **41** (18), pp.4591 - 4604.

Chakraborty A and A. A. Linninger (2002b). Plant-Wide Waste Management. 2. Decision Making under Uncertainty *Ind. Engg. Chem. Res.* (in press).

Gutherie, K. M. Capital Cost Estimating (1969). *Chem. Eng.*, **76**(6): 114.

Henn, C. L. and J. A. Fava (1992). Life Cycle Analysis and Resource Management. *Environmental Strategies Handbook*, Kolluru, R. V., McGraw Hill, New York.

Liu, M. L. and N. V. Sahinidis (1996). Optimization in Process Planning with Uncertainty. *Ind. Engg. Chem. Res*, **35**, pp. 4154- 4165.

Peters, M. S. and K. D. Timmerhaus (1980). *Plant Design and Economics for Chemical Engineers*. McGraw Hill, New York.

Sahinidis N. V., Grossmann I. E., Fornari, R. E. and M. Chathrathi (1989). Optimization Model for Long Range Planning in Chemical Industry, *Comp. Chem. Eng.*, **13**, pp. 1049 – 1063.