Optimisation of NGL rail car distribution

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Abstract: In this paper we address the optimisation of a rail-car natural gas liquids distribution and sales revenue supply chain. A network-based goal programming model is used to allocate rail cars to deliver contracted supply quantities from supply plants to regional demand terminals with different product prices. The planning horizon is one year broken down into months and includes futures prices of NGL products. The model incorporates terminal storage capacities, potential demurrage and detention constraints, and inventory carrying costs. The model integrates the distribution and transportation aspects of the problem. Results are reported for a Fortune 500 NGL company.

Keywords: revenue management; optimisation; NGL rail car distribution; goal programming; futures prices.

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1 Introduction

Energy companies dealing in natural gas liquids (NGL) have to source the products and distribute them to various markets or sales locations. In this paper we focus on the distribution and inventory problem faced by a Fortune 500 master limited partnership (MLP) company. Each contract year (typically April 1–March 31 following year) the company enters into purchase contracts with NGL source plants and storage facilities in various locations across the USA and Canada. Purchased quantities are determined well in advance of delivery to terminals in various markets. The problem addressed is concerned with the optimal allocation and distribution of rail cars from supply points to terminals. Decisions need to be made over a planning horizon of one year. Terminals have limited inventory storage capacity and need to use the NGL product throughout the current period to meet demand. Future prices of NGL products are also a key factor in deciding how many rail cars loads are to be routed from plants to terminals and affect how long rail cars should be held in storage at terminals. The inventory costs are multi-tiered in that rail cars stored in excess of threshold capacities can incur significantly higher inventory storage costs (This is called detention costs from the railroad for holding cars beyond terminal storage capacity. In addition, there is the monthly cost of ownership/lease cost of railcars).

The contracted quantities of NGL products must be taken from the plants within specified time intervals (monthly is the standard with assumed ratability of shipment). The problem addressed in this paper deals with a monthly time frame pertaining to the distribution of rail cars. Some NGL products are highly seasonal and contracts can cause excess deliveries in months of low demand. In cold weather months it is sometimes a challenge to meet demand with existing inventories and current distribution of rail cars. Given the situation in which demand sometimes exceeds supply, it is not always feasible to require that total demand be met. Other challenges include the fact that future NGL prices affect the revenue generated from each of the time periods in the future. For example, when the NGL market is in contango, a contract to buy NGL products in the future costs more than the current price or when there is backwardation in the forward curve the future price may cost less than the current price and thus encouraging the marketplace to not carry inventory. In the NGL marketplace, contango and backwardation markets play a very significant role due to the heavy seasonality of the business, especially propane and butane. This is common in commodity markets. The objective of the proposed model is to maximise the profit of NGL operations considering distribution and inventory costs as well as future sales revenues.

2 A goal programming approach

Goal programming is a mathematical programming approach that is suitable for problems with multiple objectives and or soft constraints. The NGL rail car distribution problem has both. The soft constraints arise from the situation in which not all NGL demand can be met, but management wants to satisfy as much of the most profitable demand as possible.

Goal programming was developed by Charnes and Cooper (1961, 1977) in the 1960s and has been utilised in many applications. This solution approach has been extended by Ijiri (1965), Lee (1972), Ignizio (1976) and others. The basic idea is to express goals as constraints and measure the deviation from these goals. The deviation variables are utilised in the objective function and allow some underachievement of goals such as the satisfaction of demand. Thus, goal programming is a type of penalty function approach. In linear goal programming some of the constraints can be goal or soft constraints and some can be traditional hard constraints. The objective function consists of a weighted average of deviation variables associated with various goals. This is the non-preemptive case in which goals are prioritised by a real number. In the preemptive case, high priority goals are infinitely more important than lower priority goals. The preemptive case implies a lexicographic ordering and the models are solved successively for each priority level. The NGL distribution problem addressed in this paper is non-preemptive.

There is a wealth of literature on goal programming applications in a wide range of areas of application. The applications are too numerous to delineate. However, there are some useful surveys that cover many applications. Tamiz et al. (1998) present an overview of the state-of-the art of goal programming for decision making. Aouni and Kettani (2001) discussed the history and promising future of goal programming.

While there appears to be little literature pertaining to solving the NGL rail car distribution problem, there are some related applications of goal programming. Ahem et al. (1998) used goal programming to prioritise railway projects for investment. El-Wahed and Lee (2006) used an interative fuzzy goal programming approach to determine the preferred compromise solution for a multi-objective transportation problem. Calvete et al. (2007) applied goal programming to the vehicle routing problem with soft time windows. Perhaps the most relevant previous work is not an application of goal programming but the utilisation of heuristics or metaheuristics for rail car fleet sizing. Sherali and Tuncbilek (1997) developed a dynamic approach to solving the rail car fleet sizing problem. Their approach is based on a time space network and uses a decomposition heuristic to solve sub-problems for overlapping time segments. Their dynamic approach yielded near optimal solutions to the total fleet size requirement. Sayarshad and Ghoseiri (2009) solve a mathematical model of the rail-car fleet size and car utilisation problem by simulated annealing. However, neither of these applications consider the revenue aspect of the products being transported.

The focus of this paper is the use of goal programming to maximise the profit generated by rail car operations in the allocation and distribution of NGL products over a one year planning horizon. There is a vast literature on the topic revenue management. The interested reader can find a comprehensive survey of revenue management applications in the paper by Chiang et al. (2007).

2.1 Problem formulation

The planning horizon for the rail car allocation is p periods. It is assumed that a single product is produced at the plant and delivered by the set of contracted identical rail cars to the terminals to satisfy demand. The parameters are defined as:

m	Number of production plants.
n	Number of supply terminals.
p	Number of time periods.
d_{jt}	Forecasted demand of terminal j during month t.
a_{it}	Contracted supply amount at plant i in month t.
b_j	Beginning inventory of terminal j.
c_{isjt}	Net cost of rail car sent from plant i in period s to terminal j in period t. Based on plant purchase price, freight cost, and terminal price differential.
C_j	Tier 1 storage capacity of terminal j.
$\alpha, \beta, \gamma, \lambda$	Objective function weights for transportation, unmet demand, tier 1, and tier 2 inventory.

The decision variables are:

x_{isjt}	number of rail cars sent from plant i in period s to terminal j for sale in period t
$U1_{jt}$	total shipments less than demand at terminal j in period t
$V1_{jt}$	total shipments more than demand at terminal j in period t
$U2_{jt}$	total shipments less than tier 1 capacity at terminal j in period t
$V2_{jt}$	total shipments in excess of tier 1 capacity at terminal j in period t.

The rail car allocation problem can be formulated as:

$$\text{minimise } \alpha c_{isjt} \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{s=1}^{t} \sum_{t=1}^{p} x_{isjt} + \beta \sum_{j=1}^{n} \sum_{t=1}^{p} U1_{jt} + \gamma \sum_{j=1}^{n} \sum_{t=1}^{p} V1_{jt} + \lambda \sum_{j=1}^{n} \sum_{t=1}^{p} V2_{jt} \tag{1}$$

s.t.

$$\sum_{j=1}^{n} \sum_{t=s}^{p} x_{isjt} = a_{is} \qquad \forall i = 1, \ldots, m,\ s = 1, \ldots, p \tag{2}$$

$$\sum_{i=1}^{m} x_{i1j1} + U1_{j1} - V1_{j1} + b_j = d_{j1} \qquad \forall j = 1, \ldots, n \tag{3}$$

$$\sum_{i=1}^{m} \sum_{t=s}^{p} x_{isjt} + U1_{js} - V1_{js} + V1_{js-1} = d_{js} \qquad \forall j = 1, \ldots, n,\ s = 2, \ldots, p \tag{4}$$

$$V1_{jt} + U2_{jt} - V2_{jt} = C_j \qquad \forall j = 1, \ldots, n,\ t = 1, \ldots, p \tag{5}$$

$$x_{isjt} \text{ integer}, U1_{jt}, V1_{jt}, U2_{jt}, V2_{jt} \geq 0 \qquad \begin{array}{l} \forall j = 1, ..., n, t = 1, ..., p \\ \forall i = 1, ..., m, s = 1, ..., p \end{array} \tag{6}$$

The objective function (1) consists of four weighted costs. The first term represents the rail car transportation 'cost' or net profit of shipping a car from plant i to terminal j in period t. The c_{isjt} include not only the transportation cost but also the difference between the contracted purchase price at plant i and the selling price (current or future) at terminal j in period t. Thus, a negative value reflects a net profit. The next term calculates the sum of unmet demand for all terminals through the planning horizon and assigns a cost of β per rail car unit. The third term in the objective function assigns a cost of γ to the sum of ending inventory at all terminals over all p time periods. The fourth term uses the weight, λ, to calculate the total incremental cost of inventories, $V2$, that are in excess of the terminals' tier 1 capacity. The cost factor, λ, is generally much larger than γ.

Constraints (2) require that the contracted amount of NGL products is shipped out of plant i for each time period t. Constraints (3) and (4) are soft constraints that attempt to meet demand at terminal j in period t. The deviation variables $U1$ and $V1$ capture the amount that the shipment in rail cars is less than or more than demand, respectively. Constraints (5) define the inventory held at terminal j for use in a future time period. Constraints (6) capture the amount of rail car inventory $V2$ that is in excess of the tier 1 terminal capacity.

Table 1 Monthly contracted supply amounts per plant

	Apr	*May*	*June*	*July*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*	*Jan*	*Feb*	*Mar*
Plant 1	35	35	33	33	33	40	70	80	83	83	90	75
Plant 2	20	20	20	20	20	20	40	40	40	40	40	40
Plant 3	15	15	15	15	15	15	45	45	50	50	50	15
Plant 4	0	0	0	0	0	0	43	43	43	43	43	15
Plant 5	40	40	40	40	40	40	100	100	100	100	100	100
Plant 6	0	10	10	10	10	10	32	32	32	32	32	32
Plant 7	30	28	29	17	27	56	84	134	134	134	83	41
Plant 8	50	50	50	50	50	50	50	100	100	100	100	100
Plant 9	0	0	0	0	0	0	0	10	10	10	10	10
Plant 10	7	7	7	7	7	7	25	50	50	50	50	50
Plant 11	0	0	0	0	0	0	0	0	25	26	17	2
Plant 12	0	0	0	0	0	0	0	17	18	18	18	2
Plant 13	0	0	0	0	0	0	0	10	70	70	70	10
Plant 14	0	0	0	0	0	0	0	0	0	10	0	0
Plant 15	0	0	0	0	0	0	0	0	0	10	0	0
Plant 16	0	6	6	6	6	6	18	18	18	18	18	18

3 Computational results

The problem data is comprised of a 12 month planning horizon and monthly rail car demand data. In a typical rail planning problem there are approximately 16 source plants and 19 or 20 terminal demand locations. Table 1 shows the contracted monthly supply amounts at each plant during the one-year planning horizon. The contracted amounts are clearly higher in the winter months in anticipation of increased demand.

Table 2 shows the monthly forecasted demand amounts for the next year. The far right column shows the tier 1 rail car storage capacity. Some terminals have no storage capacity for the upcoming year.

Table 2 Monthly forecasted rail car demand at terminals

	Apr	*May*	*June*	*July*	*Aug*	*Sept*	*Oct*	*Nov*	*Dec*	*Jan*	*Feb*	*March*	*Cap*
Terminal 1	22	16	10	8	20	29	25	42	61	63	45	32	29
Terminal 2	0	0	1	1	1	1	2	2	2	2	2	1	0
Terminal 3	8	13	14	13	11	14	11	14	18	19	21	17	0
Terminal 4	18	15	25	27	27	27	55	60	70	70	60	40	53
Terminal 5	0	0	0	0	0	0	15	15	15	15	15	15	6
Terminal 6	0	0	0	4	5	6	5	14	22	25	23	16	6
Terminal 7	2	3	3	3	3	3	5	7	8	8	5	2	0
Terminal 8	15	15	10	9	10	13	22	15	36	21	21	15	3
Terminal 9	45	36	26	23	26	29	38	62	90	96	72	61	56
Terminal 10	20	15	20	30	25	25	58	67	65	65	50	40	23
Terminal 11	9	9	5	7	6	12	18	24	35	26	21	12	7
Terminal 12	0	2	2	2	8	1	1	2	2	2	2	2	10
Terminal 13	14	18	16	18	30	30	27	34	47	33	18	14	0
Terminal 14	10	1	0	1	1	1	2	2	2	2	3	1	0
Terminal 15	25	30	25	28	30	42	50	66	88	64	56	42	26
Terminal 16	14	0	0	0	0	0	0	0	0	0	0	0	15
Terminal 17	0	0	0	0	0	0	0	0	0	4	0	0	0
Terminal 18	0	0	0	0	0	0	0	0	0	2	0	0	39
Terminal 19	84	71	74	59	73	74	95	121	170	225	196	156	37

Given the 12 month planning horizon and the possibility of transporting from a plant in period t to any terminal in period t to 12, the problem size is greatly expanded from a 16 × 19 distribution problem. The decision variables are based on a time-based network representation of the problem. The resulting number of shipping quantity decision variables, x_{isjt}, for m = 16, and n = 19, and p = 12 is 24,852. These rail car shipping quantities are required to be integer and the resulting problem is a relatively large MIP model. There are 240 deviation variables in each of four types resulting in 960 deviation variables which are treated as continuous. The rail car distribution model for $m = 16$, $n = 19$, and $p = 12$ consists of 6,101 constraints. The relatively simple structure of the MIP model enables a relatively fast solution time to achieve optimality. The MIP model solves in 10 seconds using the CPLEX 12.6.2 solver executed on an Intel i7-3930K processor running at 4.4 Ghz. The fast solution time facilitates a practical real-world implementation.

4 Conclusions

The proposed mixed integer goal programming model facilitates the optimum allocation and distribution of NGL rail cars for a Fortune 500 company over a twelve month planning horizon. Key factors include plant purchase contract amounts, the NGL purchase price per time period, rail car transportation costs, current and future terminal selling prices, terminal storage capacities and inventory storage costs. The goal programming model is relatively easy to solve for a large-scale MIP model and achieves optimal solutions in approximately 10 CPU seconds.

The benefits include a more effective deployment of rail cars given contracted supply quantities, distribution costs, inventory capacities, and current and future NGL prices at terminals. The model addresses both the costs and revenues associated with rail car distribution. The company estimates that the use of the model enables an increase in profit for the rail car problem to be approximately \$250,000 to \$500,000 annually. Given the ease of solution and success of the monthly goal programming model, future plans include the expansion of the model to include weekly rather than monthly time periods. Another planned enhancement includes a multi-modal approach that incorporates pipelines and trucks as well as rail cars. These refinements should facilitate further revenue enhancement.

References

Ahem, A. et al. (1998) 'Railway projects prioritization for investment: application of goal programming', *Transport Policy*, Vol. 14, No. 1, pp.70–80.

Aouni, B. and Kettani, O. (2001) 'Goal programming model: a glorious history and a promising future', *European Journal of Operational Research*, Vol. 133, No. 2, pp.1–7.

Calvete, H. et al. (2007) 'A goal programming approach to vehicle routing with soft time windows', *European Journal of Operational Research*, Vol. 177, No. 3, pp.1720–1733.

Charnes, A. and Cooper, W.W. (1961) *Management Models and Industrial Applications of Linear Programming*, Wiley, New York.

Charnes, A. and Cooper, W.W. (1977) 'Goal programming and multiple objectives optimizations', *European Journal of Operational Research*, Vol. 1, No. 1, pp.39–54.

Chiang, W., Chen, J. and Xu, X. (2007) 'An overview of research on revenue management: current issues and future research', *Int. J. Revenue Management*, Vol. 1, No. 1, pp.97–128.

El-Wahed, W.F.A. and Lee, S.M. (2006) 'Interactive fuzzy goal programming for multi-objective transportation problems', *Omega*, Vol. 34, No. 2, pp.158–166.

Ignizio, J.P. (1976) *Goal Programming and Extensions*, Lexington Books, Lexington, MA.

Ijiri, Y. (1965) *Management Goals and Accounting for Control*, North Holland, Amsterdam.

Lee, S.M. (1972) *Goal Programming for Decision Analysis*, Auerbach, Philadelphia.

Sayarshad, H.R. and Ghoseiri, K. (2009) 'A simulated annealing approach for the multi-periodic rail car fleet sizing problem', *Computers and Operations Research*, Vol. 36, No. 6, pp.1789–1799.

Sherali, H.D. and Tuncbilek, C.H. (1997) 'Static and dynamic time-space strategic models and algorithms for multilevel rail-car fleet management', *Management Science*, Vol. 43, No. 2, pp.235–250.

Tamiz, M., Jones, D. and Romero, C. (1998) 'Goal programming for decision making: an overview of the current state-of-the art', *European Journal of Operational Research*, Vol. 111, No. 3, pp.569–581.