MULTI-SCENARIO POLICIES FOR MARITIME REPOSITIONING PROBLEMS UNDER DATA SHORTAGE

Teodor Gabriel Crainic[a], Massimo Di Francesco[b], Paola Zuddas[c]

[a]Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT)
[a]Department of Management and Technology, Université du Québec à Montréal, C.P. 8888, succursale Centre-ville, Montréal, Canada, H3C 3P8
[b][c]Network Optimization Research and Educational Centre, University of Cagliari, Cagliari, Italy (CRIFOR)
[b][c]Department of Land Engineering, University of Cagliari, Cagliari, Italy

[a]theo@crt.umontreal.cal, [b]mdifrance@unica.it, [c] zuddas@unica.it

ABSTRACT
Due to the global trade imbalance, some ports tend to accumulate unnecessary empty containers, while others face container shortages. As a consequence, shipping companies must properly reposition their empty containers between ports. A major difficulty in this activity consists in the many sources of uncertainty. Sometimes historical data are useless for estimating uncertain parameters, because they are inadequate, insufficient or they do not consider future changes in the operational environment. In these cases, point forecasts and uncertain parameter distributions can be generated by shipping companies' opinions. They can be incorporated in standard deterministic optimization models and multi-scenario formulations linked by non-anticipativity conditions. In this study, we explain the importance of multi-scenario policies.

Keywords: empty container repositioning, optimization under uncertainty.

1. INTRODUCTION

The need to perform the maritime repositioning of empty containers occurs because directional imbalances in freight flows lead to the accumulation of empty containers in import-dominant ports and to shortages in export-dominant ones. Since empty containers only generate costs for shipping companies, they must be repositioned so as to minimize inventory, transportation and handling costs, while at the same time meeting demand and supply requirements in every port. The maritime repositioning of empty containers represents a crucial activity for shipping companies. According to their strategies, the demand for empty containers at ports must be met, in order to take advantage of future transportation opportunities and to reduce the risk of competitors providing containers as requested (Di Francesco 2007).

Many parameters are typically uncertain at the time repositioning decisions must be made. For example, information on the number of empty containers required in each port is usually imprecise, because unexpected transportation demands may arise. Moreover the number of empty containers available in ports is uncertain, because shipping companies do not know precisely when they will be returned by import customers.

Sometimes shipping companies do not have adequate statistics based on historical data, to estimate uncertain parameters. Statistical information may be insufficient or it could be necessary to take into account information not derived from historical data. As a consequence, the future evolution may exhibit no probabilistic dependence on the past and historical data may be useless for decision-making processes.

In order to solve empty container repositioning problems, both deterministic and stochastic optimization models have been proposed (Crainic 2003). Deterministic formulations assume that all data are precisely known. They might yield low-quality repositioning plans for the needs of shipping companies, in fact, since they allocate empty containers according to expected values, they can provide an insufficient number of empty containers, when larger demands or lower supply values will be eventually observed. Stochastic programming approaches take into account the influence of data uncertainty on the solution of optimization models. However, they require a good knowledge of the distributions of uncertain data. Moreover in many cases it is difficult to specify reliably these distributions.

The contribution of this paper is to introduce a new methodology of modelling to deal with uncertainty and data shortage. Since historical data may be unavailable or unreliable, expert-based opinions are used to build subjective distributions of uncertain parameters and to generate several possible futures or scenarios. They are collected in a multi-scenario optimization model and are linked by non-anticipativity constraints, so that current decisions cannot take advantage of information not yet available.

We compare the multi-scenario formulation to a single-scenario deterministic model, where uncertain parameters are replaced by the expected values derived from the subjective distributions. Our results emphasize the opportunity of adopting multi-scenario policies instead of standard deterministic ones. Multi-scenario policies exhibit higher demand fulfilment percentages, because they can over-allocate the flows of empty containers with respect to point forecasts and meet a larger number of potential requests.

2. PROBLEM DESCRIPTION

In this section we describe a general maritime network over which empty container repositioning is performed. The backbone of maritime repositioning systems is represented by ports, which serve as transit facilities for empty containers in order to meet potential transportation requests arising in the landside. Shipping companies must make decisions on the number of empty containers to be stored in ports.

To introduce transportation decisions, we need to define the demand and the supply of empty containers at ports. In import-dominant ports we refer to the empty container supply, which represents the number of empty containers available in a given port at any given time, due to past inventory, trucks and trains arriving from the landside. In export dominant ports, we consider empty container demand, that represents the number of empty containers requested in a given port at any given time. The demand for empty containers must be met using the supply available in other ports, that is, empty containers must be repositioned. This activity is performed by vessels sailing well-established routes according to tight schedules. Shipping companies must decide how many containers must be repositioned by vessels.

The time-dependency of transportation decisions also characterizes the relationship between shipping companies and ports. Shipping companies must decide how many empty containers will be loaded and unloaded in ports one day before the arrival of vessels, so that the ports can organize their internal activity on time and all terminal operations can be performed as requested.

Several parameters are uncertain, when these decisions must be made. The uncertain parameters we consider are future supplies and demands at ports, transportation capacities for empty containers and maximum number of empty containers that can be loaded and unloaded. Uncertainty as to supply depends on returning times of empty containers in ports. Customers can hold containers for several days. It is not simple to estimate when they will be returned and how much time is needed to move them to ports. Uncertainty on empty container demand at ports is associated with unexpected transportation opportunities arising in the landside. Moreover, unexpected transportation requests result in loaded containers modifying both the transportation capacity for empty containers and the maximum number of empties that can be loaded and unloaded. While a part of these parameters is known, others offer less precise information, especially towards the end of the planning horizon.

3. RELATED LITERATURE

In recent years some shipping companies have adopted decision support systems based on deterministic optimization models, to reposition empty containers. This is a consequence of the intensive research developed over past years in this issue.

Dejax and Crainic (1987) reviewed past papers in the management of empty flows. They mentioned few authors addressing the problem of allocating empty containers in a dynamic environment by deterministic optimization models.

Lai *et al.* (1995) evaluated several allocation policies in the maritime reposition issue to prevent the shortage of empty containers when the demand for them is uncertain. They exploited probability distributions derived from historical data to estimate uncertain parameters, whereas in many cases reliable statistics are not available.

Shen and Khoong (1995), focusing on the business perspective of the shipping industry, developed a deterministic optimization model for repositioning empty containers to minimize repositioning costs.

Cheung and Chen (1998) applied a two-stage stochastic network model to the dynamic allocation of empty containers. They relied on available probability distributions to estimate uncertain parameters.

Choong *et al.* (2002) addressed the end-of-horizon issue to manage a fleet of empty containers in the context of an inland distribution system. They proposed a time-extended deterministic optimization model. To deal with uncertain parameters, decisions were implemented in a rolling horizon fashion.

Leung and Wu (2004) developed a dynamic optimization model for repositioning empty containers, to generate solutions insensitive to the realization of uncertain parameters. They assumed customer demands as a single source of uncertainty and exploited the reliability of available data to estimate uncertain parameters.

Erera *et al.* (2005) proposed a time-extended optimization model to manage loaded and empty tank containers simultaneously. However, their formulation is deterministic and recourse actions are performed implementing decisions in a rolling horizon fashion.

Olivo *et al.* (2005) proposed a time-extended optimization model for the centralized control of empty container repositioning in the context of multimodal networks. However, their formulation is still deterministic and uncertain parameters are taken into account by implementing decisions in a rolling horizon fashion.

To our knowledge, there is currently no optimization model aimed at the repositioning of empty containers, when historical data are inappropriate for estimating uncertain data. To address this problem, in this paper we propose a multi-scenario optimization model, where scenarios are generated by expert-based opinions.

4. DETERMINISTIC AND MULTI-SCENARIO OPTIMIZATION MODELS

In this section we present a deterministic single-scenario model and a multi-scenario formulation to solve the previous problem. To facilitate the understanding of the modeling process, first we introduce to the deterministic model, then the multi-scenario formulation is presented.

As for the deterministic model, let $G = (N, A)$ be a time-expanded network, where nodes represent ports replicated in every period of the planning horizon and vessels in the periods when they arrive at ports. We consider several types of arcs, representing different types of decisions. Arcs from a given port in a period to the same port in the next period represent the number of empty containers to be kept in stock. Arcs from a given vessel in a period to the same vessel berthing in another port in another period represent the number of empty containers to be repositioned. Arcs from ports to vessels represent the number of empty containers to be loaded, whereas arcs from vessels to ports represent the number of empty containers to be unloaded.

We minimize the cost of loading, unloading, repositioning and storing empty containers over maritime networks. Mass balance constraints must be satisfied for every node in every period. Constraints ensure an upper capacity on the number of empty containers that can be loaded and unloaded from vessels arriving in every port. Moreover the stock level of empty containers in ports must not exceed storage capacities. Finally, the volume of empty containers repositioned between ports cannot be larger than the space available on vessels.

Regarding notation, a compact form is provided for the deterministic single-scenario formulation, which assumes perfect knowledge of what information is going to arrive in the future. Let us denote by s the scenario representing the expected system future. The deterministic model can be expressed as follows:

$$\min \; cx_s \tag{1}$$

s.t.

$$Ax_s = b_s \tag{2}$$

where the decision variable x_s must be non-negative and integer.

The cost vector c in the objective function (1) includes loading, unloading, storage and transportation costs. The matrix A in constraint set (2) represents the coefficient matrix. We indicate the equality in constraint set (2), because capacity constraints can be expressed in terms of equality constraints by adding slack variables.

To take specifically into account the uncertain nature of supplies, demands, transportation and loading-unloading capacities, we consider a set S of scenarios. They are assumed to be identical up to a given period θ, because more precise information is available in the first part of the planning horizon. We collect all scenarios in an overall mathematical model, linked by non-anticipativity constraints. They guarantee that decisions are identical up to period θ for every scenario, so that we do not take advantage of information not yet available. We denote by w_s the weight associated with every scenario $s \in S$, to characterize its relative importance. We also denote by x_{ts} the set of decision variables to be implemented at time $t \in T$ in scenario $s \in S$. The multi-scenario formulation can be expressed in a compact form as follows:

$$\min \sum_{s \in S} w_s c x_s \tag{3}$$

s.t.

$$Ax_s = b_s \qquad \forall s \in S \tag{4}$$

$$x_{ts} = x_{tg} \qquad \forall t \in \{1 \ldots \vartheta\}, \forall s, g \in S \tag{5}$$

where (5) represents non-anticipativity constraints. According to (4), constraint systems (2) are replicated for every scenario. Since the uncertain parameters we consider are future supplies, demands, transportation and loading/unloading capacities, the index *s* denotes the RHS vector, as well as decision variables.

5. EXPERIMENTATION

In this section we apply the previous formulations to a time-extended network made up with five ports and five periods. We simulate the behavior of this system over a number of periods and compare multi-scenario policies with deterministic ones. In this simulation empty container supplies and demands are supposed to be the only sources of uncertainty.

First, we solve the multi-scenario model and the deterministic one in the first period. Next, we assume which values are taken by uncertain parameters, when they are observed. Since many joint realizations of uncertain parameters may become true in the next period, we limit our analysis to two significant cases:

- The expected values of these uncertain parameters will become true.
- The worst-case realization of these uncertain parameters will be observed (i.e. the largest values of demand and the lowest values of supply).

Then we add a new period at the end of the planning horizon, we run both models once again, we implement decisions, we evaluate policies and so on. We perform this simulation for five periods.

Expert-based opinions are used to estimate uncertain demands and supplies. Shipping company suggestions indicate the minimum, the most plausible and the maximum values for each uncertain parameter. Such information is collected in triangular distributions. Then, we consider three values of demand and supply for each port in each period: the mode, the minimum and the maximum, we build one scenario for each joint realization and we link all scenarios by non-anticipativity conditions. We also assume that every joint realization of uncertain parameters is independent one from the other, so the weight of scenarios can be calculated by multiplying probabilities derived from triangular distributions.

Taking into account shipping companies' needs, we compute demand fulfilment percentages and total repositioning costs (storage, transportation, loading and unloading costs) to evaluate deterministic and multi-scenario policies.

According to this simulation, if expected values are observed, the multi-scenario solution results in a larger number of empty containers loaded on vessels. As a result, shipping companies are put in position of satisfying unexpected demands in future periods, whereas this is not possible when the deterministic formulation is adopted.

When the worst combination of uncertain parameters occurs, the deterministic solution is particularly inappropriate, because usually there is no container to meet extra demands. As a result, at the end of the simulation we are not able to meet a number of requests for empty containers. When we adopt the multi-scenario one, the number of unfulfilled requests is significantly lower. In Figure 1, we show demand fulfillment percentages over the simulation periods, when the worst-case values are observed.

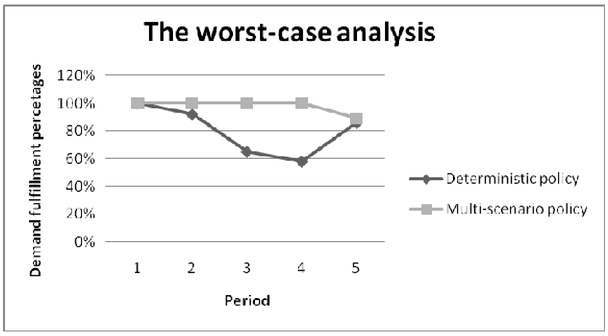

Figure 1: Demand fulfillment comparison between deterministic and multi-scenario solution in the worst-case

Due to the expensive loading and unloading costs, multi-scenario policies yield larger operating costs than the deterministic ones. The difference between these costs represents what shipping companies should pay to ensure high-quality decisions, whose effectiveness is immune to the influence of uncertain parameters.

Failing to satisfy empty container demand results in significant loss for shipping companies. Therefore, we add the expected possible loss associated with unfulfilled demands to repositioning costs. Our simulation shows that this sum is considerably lower when multi-scenarios policies are adopted. To conclude, they are by far better than the deterministic ones.

6. CONCLUSIONS

The contribution of this paper has been to introduce a new modelling process to address empty container repositioning under uncertainty and data shortage. This formulation has retained the advantage of a set of scenarios generated by expert-based opinions, to determine decisions which are not based on inadequate historical data.

We have illustrated that multi-scenario policies make for insight compared to deterministic ones, which provide high-quality repositioning plans only if expected values are observed. The multi-scenario formulation allows shipping companies to better satisfy empty container demands for the different values that may be taken by uncertain parameters, even though it yields slightly higher repositioning costs.

REFERENCES

Cheung, R.K., and Chen, C.Y., 1998. A Two-Stage Stochastic Network Model and Solutions Methods for the Dynamic Empty Container Allocation Problem. *Transportation Science*, 32(2), 142-162.

Choong, S.T.., Cole, M.H., and Kutanoglu, E., 2002. Empty container management for intermodal transportation networks. *Transportation Research Part E*, 38(6), 423-438.

Crainic, T.G., 2003. Long-haul Freight transportation. In: R.W. Hall, ed. *Handbook of Transportation Science*, Kluwer Academic Publishers, Norwell, MA, 451-516.

Dejax, P.J., and Crainic, T.G., 1987. A Review of Empty Flows and Fleet Management Models in Freight Transportation. *Transportation Science*, 21(4), 227-247.

Di Francesco, M., 2007. *New Optimization Models for Empty Container Management*. Thesis (PhD). Cagliari University.

Erera, A.L., Morales, J.C., and Savelsbergh, M.W.P., 2005. Global intermodal tank container management for the chemical industry. *Transportation Research Part E*, 41, 551–566.

Leung, S.C.H., and Wu, Y., 2004. A Robust Optimization Model for Dynamic Empty Container Allocation Problems in an Uncertain Environment. *International Journal of Operations and Quantitative Management*, 10(4), 1-20.

Lai, K.K., Lam, K., and Chan, W.K., 1995. Shipping Container Logistics and Allocation. *Journal of the Operational Research Society*, 46, 687-697.

Olivo, A., Zuddas, P., Di Francesco, M. and Manca, A. 2005. An Operational Model for Empty Container Management. *Maritime Economics & Logistics*, 7(3), 199-222.

Shen, W.S., and Khoong, C.M., 1995. A DSS for empty container distribution planning. *Decision Support Systems*, 15(1), 75-82.

AUTHORS BIOGRAPHY

Teodor Gabriel Crainic obtained his Ph.D. in Operations Research at the Université de Montréal in 1982. He is Professor of Operations Research, Transportation, and Logistics and NSERC Industrial Research Chair in Logistics Management at the School of Business Administration of the Université du Québec à Montréal. He is a member of CIRRELT and Director of its Intelligent Transportation Systems Laboratory. The research interests of Professor Crainic are in network and combinatorial optimization, meta-heuristics and parallel computation. The main application areas are transportation, logistics, telecommunications system planning, management and operations, Intelligent Transportation Systems, e-business and e-market design. He authored or coauthored over 130 scientific articles. He received the 2006 Merit Award of the Canadian Operational Research Society and has been a member of the Royal Society of Canada since the same year.

Massimo Di Francesco obtained his Ph.D. in Land Engineering at the University of Cagliari in February 2007. Next, he was a post-doctoral fellow at CIRRELT. At the moment, he is a post-doctoral researcher in Cagliari University. He is also a member of the Network Optimisation Research and Educational Centre (CRIFOR) of Cagliari University. His research interests are in fleet management problems in the domain of intermodal freight transportation and logistics. On the methodological side, his main areas of interest are approaches for solving time-extended optimization problems with data uncertainty.

Paola Zuddas is a Professor of Operational Research and Management Science in the University of Cagliari and develops her research activity at the Land Engineering Department. She is the Scientific Coordinator of the Network Optimisation Research and Educational Centre (CRIFOR) of Cagliari University. Her research interests are in the field of Operations Research with applications mainly to transportation, water resources management and telecommunications. On the methodological side, her main areas of interest are dynamic network optimization under uncertainty conditions, optimization of large dimension structured models, network optimization with complicating constraints.