KKU ENGINEERING JOURNAL 2016;43(S1):130-132 Research Article

KKU Engineering Journal

https://www.tci-thaijo.org/index.php/kkuenj/index

Robust goal programming approach to an intermodal routing decision problem

Wichitsawat Suksawat Na Ayudhya*

International College King Mongkut's Institute of Technology, Ladkrabang, Bangkok 10520, Thailand.

Received April 2016
Accepted June 2016

Abstract

Under fierce competition for today business, it is very important for companies to reduce their logistic cost. Intermodal transport can exploit transportation cost structure and gain service response. Selecting transportation routes under various factors such as minimum transportation cost, just-in-time commitment, and transit time variability is a crucial decision. Unlike traditional model assumption, uncertainty for data collection in each parameter is presented. In this paper, the intermodal transportation problem is formulated as a robust goal programming to address data uncertainty in transit time variability. The numerical result was tested against tapioca transportation network in Thailand.

Keywords: Transportation, Intermodal transportation, Goal programming, Robust optimization

1. Introduction

The economic integration is one of important driven forces of the growth of world's trading. Multinational companies exploit the benefit of reducing trade barrier so that raw material, parts, sub-assemblies and assemblies can freely be moved between borders or boundaries. The developing countries started to upgrade their physical infrastructure such as highway or railway to lure foreign investors. The containerization is a driver of intermodal transportation due to the ease of handling between 2 modes of transports. "Intermodal" or "multimodal" is the way that shipment is transported by at least 2 different modes of transport and under a single freight bill.

In recent year with the increasing demand of freight transport, intermodal route transport gains a lot of attention from practitioners and scholars. However, there are some difficulties of collecting accurate data for each mode of transport. Data uncertainty is not uncommon in practice. The decision maker needs mathematical model to deal with this uncertainty to find the appropriate route to ship commodity. The objective of this paper is to address data uncertainty of transit time variability into mathematical programming model, since traditional mathematical model assume parameters to be known. This paper formulated a robust goal programming model for the intermodal transport, dealing with uncertain of data. The remainder of the paper is organized as follows. Section 2 reviews the literature review. Section 3 presents the model description and formulation, and Section 4 discusses the computational results and Section 5 conclusions.

2. Literature review

For a recent review of intermodal freight transportation, the reader is referred to Bontekoning and Priemus [1] and Macharis and Bontekonings [2].

Grasman [3] presented a dynamic programming approach to strategic and operational multimodal routing decisions. Cho et al [4] presented a dynamic programming to show the optimal intermodal freight routing and presented a weighted constrained shortest path problem (WCSPP). Yang et al. [5] proposed a goal programming as a mixed integer linear programming for solving an intermodal network optimization model that evaluated 36 alternative routes for freight moving from china to beyond Indian Ocean. Kuchta [6] proposed a robust approach to goal programming based on Bertimas and Sim [7]'s approach. Chang [8] formulated a multiple multi-commodity flow problem (MMMFP) model to select best routes for shipments through the international intermodal network. Min [9] developed a chance constrained goal programming model which minimizes cost and risk, and at the same time satisfies various on-time service requirements.

While the literatures presented above provide solutions to a number of applications, they are mainly limited to known parameter values for planning application and not taking account to uncertain elements in the network. A robust integer programming to address data uncertainty for discrete optimization and control the degree of conservation of the solution in term of probability of constraint violation was proposed in Bertimas and Sim [7]. This paper formulated a problem as a robust goal programming and assumed that freight rates are linear and used tapioca distribution network in Thailand as the case study.

*Corresponding author. Tel.: +66 2329 8261
Email address: wichitsawat@gmail.com
doi: 10.14456/kkuenj.2016.39

3. Model Description

We consider a acyclic directed transportation network where a tapioca product was shipped from its origin (Udon Thani) to its destination port e.g. Laem Chabang port, Bangkok port, Sri Chang Island area, etc. There are modal shifts between origin and destination ports. We consider the cost of transportation, including packing, up-loading, un-loading, and documentations only from origin, northeastern of Thailand to Thailand's exporting port, since selling price is quoted as FOB (Free on Board). Time and other expenses at exporting port are not taking account to this model. We assume this related logistic time and costs are equal among exporting ports.

Freight rates for truck, rail, and barge are nonlinear. This paper modeled these costs as ceiling function. No split deliveries are allowed. We treat time variability as data uncertainty. Cardinal weight on each criterion is depended on decision maker to arbitrarily choose the number. We formulate robust goal programming by following model of [7] and [9]. Because of small size of Thailand transportation network, we exploit the structure of network so that we use separate links to present for each route and mode of transport. Figure 1 shows the Tapioca transportation network in Thailand.

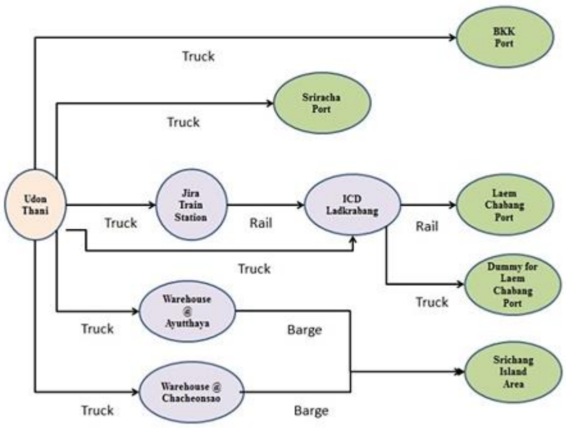

Figure 1 Tapioca transportation network in Thailand

Subscripts

i, j set of all nodes {Udon Thani, Warehouse@Ayutthaya, Warehouse@Chacheonsao, BKK port, Sriracha port, BKK port, Jira Train Station, ICD, Srichang Island Area, Laem Chabang port}

J_i set of coefficients $V_{ij}, j \in J_i$ that are subject to parameter uncertainty, i.e., $\tilde{V}_{ij}$ (independent, symmetric and bounded random variable but unknown distribution)

Parameters

s shipment size (ton) R total shipping time

T_{ij} transit time from node i to node j

$F_{ij}(s)$ unit freight rate from node i to node j according to shipment size s

V_{ij} transit time variability node i to node j

W_1^+ cardinal weight (lower transportation cost)

W_2^+ cardinal weight (late shipment)

Γ_4 the protection level for 4th constraints

W_2^- cardinal weight (just in time shipment)

W_3^+ cardinal weight (transit time variability)

$\hat{V}_{ij}$ range of V_{ij} that are subject to parameter uncertainty

Decision variables

X_{ij} 1, if we send shipment from node I to node j, 0, otherwise

s_2^- negative deviational variable that represent just in time requirement

s_3^+ positive deviational variable that represent transit time variability

p_{4j} robustness decision variables of 4th constraint

s_1+ positive deviational variable that represent distribution cost

s_2^+ positive deviational variable that represent late shipment

z_4 robustness decision variables of 4th constraint

y_j robustness decision variables

The robust goal programming can now be formulated as follows in which the formulation and notion is similar to Min's [19].

$$\text{Minimize } W_1^+ s_1^+ + W_2^- s_2^- + W_2^+ s_2^+ + W_3^+ s_3^+, \text{ subject to}$$

$$\sum_{i \in I} \sum_{j \in J} X_{ij} F_{ij}(s) - s_1^+ = 0 \tag{1}$$

$$\sum_{i \in I} \sum_{j \in J} T_{ij} X_{ij} + s_2^- - s_2^+ = R \tag{2}$$

$$\sum_{j \in J} X_{ij} - \sum_{j \in J} X_{ji} = \begin{cases} 0 & \text{for all i} \neq \text{source and sink} \\ 1 & \text{for source and -1 for sink} \end{cases} \tag{3}$$

$$\sum_{i \in I} \sum_{j \in J} V_{ij} X_{ij} + z_4 \Gamma_4 + \sum_{j \in J_i} p_{4j} - s_3^+ = 0 \tag{4}$$

$$z_4 + p_{4j} \geq \hat{V}_{4j} y_j, \quad j \in J_i \tag{5}$$

$$p_{4j} \geq 0, \ \forall i, j \in J_i, y_j \geq 0 \ \forall j, X_{ij} = \{0,1\}, z_4, s_1^+, s_2^+, s_2^-, s_3^+ \geq 0,$$

The objective function minimize the weighted sum of deviations from the lowest total distribution cost, just in time (JIT), and the lowest transit time variability. Constraints (1) minimize total transportation cost. Constraints (2) minimize total shipment time. Constraints (3) are conservative network flow. Constraints (4) adjust the robustness of time variability against the level of conservatism of the solution. Constraints (5) enforce robustness decision variables.

4. Discussion

We solve above mixed integer programming problem with Excel Solver. We use data from appendix to test our model. Γ_4 take value in the interval [0, $|J_i|$], where $J_i = \{j \mid \hat{V}_{ij} > 0\}$ and Γ_4 are not necessarily integer. However, we use Γ_4, since the parameter uncertainty is a time variability of northeastern railway of Thailand (Jira Train Station to ICD). The average delay is 14.66 (V_{ij}) hours and the maximum delay is ($\tilde{V}_{ij}$) 22.34 hours.

4.1 Numerical examples

We run numerical examples for our model by selecting $W_1^+ = 1 W_2^+ = 1 W_2^- = 1 W_3^+ = 3$,and the result is shown in Table 1. The results indicate that the optimal route and mode of transport is to ship tapioca product from Udon Thani to the destination port via truck except for Sichang Island. The main reason behind this may results from long delivery time for other modes of transportation.

Table 1 Numerical example results

Γ_4	z_4	p_{41}	y_1	$X_{Udon,\ Laem\ chabang}$
0.2	0	22.34	1	1
0.4	0	22.34	1	1
0.6	0	22.34	1	1
0.8	0	22.34	1	1
1	22.34	0	1	1

5. Conclusions

This work is pilot study to address data uncertainty for Thailand's tapioca transportation problem. In the future, we investigate data uncertainty for both transit time and time variability of all links in the network. To take into account for those uncertainties, the size of the problem may too large, so that meta-heuristics such as Genetic algorithm (GA), or Tabu search, could be used to deal with large scale optimization problem.

6. References

[1] Bontekoning Y, Priemus H. Breakthrough innovations in intermodal freight transport. Transportation Planning and Technology 2004;27(5):335-345.

[2] Macharis C, Bontekoning,Y. Opportunities for OR in intermodal freight transport research: a review. European Journal of Operational Research 2004; 153(2):400-416.

[3] Grasman SE. Dynamic Approach to Strategic and Operational Multimodal Routing Decisions. Int J Logistics Systems and Management 2006;2(1):96-106.

[4] Cho JH, Kim HS, Choi HR. An Intermodal Transport Network Planning Algorithm Using Dynamic Programming–A Case Study: From Busan to Rotterdam in Intermodal Freight Routing. Applied Intelligence 2012;36(3):529-541.

[5] Yang X, Joyce Low MW, Tang LC. Analysis of intermodal freight from china to indian ocean: a goal programming approach. Journal of Transport Geography 2011;19(4):515-527.

[6] Kuchta D. Robust goal programming. Control and Cybernetics 2004;33(3):501-510.

[7] Bertimas D, Sim M. Robust discrete optimization and network flow. Mathematical Programming Series B 2003;98(1):49-71.

[8] Chang TS. Best routes selection in international intermodal networks. Computers & Operations Research 2008;35(9):2877-2891.

[9] Min H. International intermodal choices via chance-constrained goal programming. Transportation Research Part A 1991;25(6):351-362.

7. Appendix

Table 2 Data for freight cost, transit time, time variability

From	To	mode	T_{ij} (hours)	V_{ij} (hours)	F_{ij}/ (Baht/ton)
Udon Thani	BKK port	truck	14	5	18,000
Udon Thani	LCM port	truck	17	4	19,000
Udon Thani	Sriracha port	truck	17	4	19,000
Udon Thani	Jira Train Station	truck	5.5	1.5	13,000
Udon Thani	ICD	truck	16	4	18,000
Udon Thani	Warehouse@ Ayutthaya	truck	8.5	3	15,000
Udon Thani	Warehouse@ Chacheonsao	truck	10	3	20,000
Warehouse@ Ayutthaya	Srichang	barge	20	12	55,000
Warehouse@ Chacheonsao	Srichang	barge	8	12	55,000
Jira Train Station	ICD	rail	24	14.66	6,106
ICD	LCM	truck	5	1	6,000
ICD	LCM	rail	3	1.12	2,400