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A supply-chain optimization model of the allocation of containerized imports from Asia to the United States

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ABSTRACT

This article proposes a mixed integer non-linear programming model for the optimizing supply chains of importers of waterborne containerized goods from Asia to the USA. This model determines the least-cost strategy for an importer, in terms of ports and landside transportation modes to be used, where costs considered include costs for transportation and handling, pipeline inventory, and safety-stock. We introduce a heuristic algorithm to quickly solve the mathematical model to near optimality. We assess the proposed heuristic compared to use of a commercial solver, and provide general recommendations for efficient supply-chain strategies as a function of the value of imported goods.

1. Introduction

This article proposes a mathematical-programming model for optimization of the supply chains of importers of waterborne containerized goods from Asia to USA. This optimization model determines the least-cost supply-chain strategy for an importer, in terms of ports and landside transportation modes (channels) to be used.

A typical large US importer/retailer operates Regional Distribution Centers (RDCs) that restock retail outlets. Differences in inventory costs resulting from use of alternative supply channels typically extend only as far as the RDCs, which are usually located within an overnight drive to the outlets they supply. In this article, we consider the origins for import shipments to be factories in China and elsewhere in Asia, and the destinations are RDCs spread across the Continental USA. While the portfolio of products for an importer may encompass multiple origins, typically, any particular product is to be distributed across the Continental USA and is sourced from a single Asian origin.

Marine containers from Asian origins are shipped on vessels to ports of entry (POE) to the USA, called “ports” in this article. The containers may be directly shipped inland to the RDCs, called “direct shipment,” or they may be unloaded at trans-load or import warehouse facilities and the contents sorted and re-shipped in domestic vehicles to multiple RDCs, under a strategy termed “consolidation–de-consolidation” shipment. In the consolidation–de-consolidation case, marine containers containing goods destined to multiple RDCs are channeled through a common port and routed to a de-consolidation center (trans-load warehouse) located in the hinterland of the port of entry. The goods are unloaded from the marine boxes, sorted and re-loaded into domestic containers or trailers for final landside movement to the RDCs, possibly after some valued-added processing. Both direct and consolidation–de-consolidation shipments may use different landside transportation modes (channels) to RDCs; i.e., train, truck, and local drayage (dray).

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Depending on the selected port of entry and the landside mode of transportation, the importer will face different transportation costs. Another source of cost is the opportunity cost of working capital tied up in the inventory throughout the supply chain. This cost is usually expressed as an interest rate times the amount of capital invested per unit of inventory times the average inventory level.

There are three types of inventories in a chain: cycle inventory, in-transit inventory, and safety stock. Cycle inventory is a function of the replenishment frequency (e.g., weekly) and is otherwise independent of the selection of the supply-chain strategy and channel, and therefore is not considered in this article. In-transit inventory is the amount of inventory in the pipeline, and it is a function of the transportation time. Safety stock is the extra inventory kept by retailers to satisfy the customer demand on time. Safety stock is maintained as a hedge against potential delays to shipments and potential errors in sales forecasts. It is a function of the customer service level, the uncertainties in the shipment lead time, and the demand forecast error. Requiring a higher customer satisfaction level, or making use of supply channels that entail longer or more unreliable lead times, may result in the need for larger safety stocks at RDCs.

The consolidation–de-consolidation strategy uses concepts of ‘‘postponement’’ and ‘‘risk pooling’’ to reduce the requirement for safety stocks at destination RDCs. By postponing the commitment to specific channels and RDCs, the importer can exploit an updated match-up of supply versus demands to reduce safety stocks. The risky exposure to demand surges or supply shortages over the long lead times from Asian factories to the RDCs can be reduced to a relatively low-risk exposure over the short lead times from the trans-load warehouse to the RDCs. Furthermore, by pooling the forecast errors of demands at different RDCs together, served by a single port, importers face less uncertainty, and can reduce the level of safety stocks. In typical practice, the contents of five 40-ft marine containers fit into three or three and one-quarter domestic containers or trailers that have much larger cubic capacities. The savings from fewer inland vehicle movements partially off-sets the extra costs for the transportation circuitry and for trans-load handling of goods associated with the consolidation–de-consolidation strategy.

Most importers make little or no investment in facilities upstream from the RDCs. They review their supply-chain strategies annually. Their transportation, trans-loading and import warehousing services are put out for bid, leading to annual contracts for such services provided by steamship lines, intermodal marketing companies, and third-party logistics providers. Thus import supply-chain strategies are static over a 12-month time frame but can be changed in minor ways or major ways from year to year in response to changing transportation or inventory economics.

In this article, we propose a mixed integer non-linear programming model for the optimization of the annual supply-chain strategy for importers of waterborne containerized goods from Asia to USA. This optimization model determines the least-cost supply-chain strategy for an importer, in terms of ports and landside transportation mode to be used. This model allows the importer to select efficient direct-shipment, trans-loading, or a mixed strategy. The costs considered include costs for transportation and handling, pipeline inventory, and safety-stock inventory at RDCs. Here, we integrate location/allocation problem with risk pooling, routing, and selection of transportation modes, while considering stochastic demand and random transportation time to achieve a desired customer satisfaction level.

Based on our observation of industry practices, the structure of the data, and the existing channels, we develop a heuristic algorithm to solve the mixed integer non-linear program to near optimality. The performance of the proposed heuristic is then compared with the solutions generated by a commercial solver for a large set of importers. This model and analysis can be beneficial to many stakeholders of the supply chain such as importers, public policy makers, port authorities, and landside transportation companies (trucks, railroad, drayage, etc.) These stakeholders need to consider the response of all importers to changes in services, rates, fees or infrastructure, and so an algorithm that can rapidly calculate and tally supply-chain channel volumes across all importers is of considerable interest. In this article we assume there is enough capacity available in all ports and transportation channels, and therefore we do not consider capacity constraints.

The rest of the paper is organized as follows: In Section 2, the data and the framework used by the model are introduced. In Section 3, the mixed integer non-linear programming model is proposed. In Section 4, our heuristic, and an application of a hybrid genetic/evolutionary algorithm to solve the mathematical-programming model are introduced. In Section 5, the performance of the above methods are studied in terms of the efficiency in producing fast results, and the effectiveness in producing quality results. We further provide sensitivity analysis, and make recommendations for best strategies over a wide range of selected parameters. Finally, conclusions, recommendations and directions for future research are presented in the last section.

2. Background

The problem under study lies in the intersection of facility location and supply chain management (SCM) research areas. A general facility location problem considers a set of spatially distributed customers and a set of facilities to serve customer demands. Research in this domain addresses problems such as: Which facilities should be used (opened), and which customers should be assigned to which facility (or facilities) so as to minimize total costs (location–allocation problem)? For recent reviews of facility location research we refer readers to ReVelle et al. (2008).

SCM deals with planning, implementing and controlling the operations of the supply chain. SCM spans all movements and storage of raw materials, work-in-process inventory, and finished goods from the point-of-origin to the point-of-consumption. Historically, researchers have focused on elements of the chain rather than treating the supply chain as a whole. Here, we integrate the location–allocation problem with risk pooling, routing, and selection of transportation modes, while considering stochastic demand and random transportation time to achieve a desired customer satisfaction level.

Melo et al. (2009) provide a review of recent literature of facility location models in the context of supply chain management and report that the majority of the literature deals with deterministic environments, ignoring the uncertainties involved in location decisions. Their survey further shows that the facility location decision is frequently combined with inventory decisions. In contrast, routing and the choice of transportation modes (alone or integrated with other types of decisions) have not received much attention. Shen and Qi (2007), Ambrosino and Scutellà (2005), Ma and Davidrajuh (2005) and Liu and Lin (2005), have considered routing decision-making simultaneous with inventory management. Wilhelm et al. (2005) have considered choice of transportation mode along with inventory management. Manzini and Bindi (2009) consider transportation mode selection along with routing and inventory management.

Managing inventory involves two key tasks: the first is to determine the number of stocking points; the second is to define the level of inventory to maintain at each of these points. Inventory control policies may be included in a facility location problem to recognize risk pooling benefits due to stochastic demands or randomness in supply. This combination of tactical and strategic decisions has been addressed by some authors – see Snyder et al. (2007), Shu et al. (2005), Miranda and Garrido (2004), Shen et al. (2003), Daskin et al. (2002), and Erlebacher and Meller (2000). However, within the context of the location/allocation problem, there is a lack of publications which consider risk pooling simultaneously with choice of transportation mode and routing. To the best of our knowledge, simultaneous optimization of risk pooling, choice of transportation mode, and routing hasn't been addressed heretofore.

As discussed by Melo et al. (2009) the existing literature in location/allocation problem is still far from combining many aspects relevant to SCM. In fact, this integration leads to much more complex models due to the large size of the problems, in particular when tactical/operational decisions are integrated with strategic ones. The literature integrating uncertainty in SCM with location decisions is still scarce. Furthermore, many relevant tactical/operational decisions in SCM, as it is the case with routing and the choice of transportation modes, are far from being integrated with location decisions. In this article, we target these gaps by addressing problems involving stochastic demand and random transportation time, while considering risk pooling, routing, and choice of transportation modes.

In terms of solution methodology, optimization models, especially non-linear optimization models, have been widely used to solve the minimization of the total cost that includes location costs and inventory costs at the facilities, and distribution costs in the supply chain. Shen (2007) provides a survey of recent developments in this research area. The author indicates that most of these problems are NP-hard, and therefore difficult to solve. Thus, researchers have used techniques such as Lagrangian-relaxation and genetic algorithms to provide solutions. Due to the difficult nature of these problems, the solutions may take a long time to generate and may not be optimal. For industrial applications, researchers mostly have focused on exploiting the properties of the problems and developing special solution techniques to reduce the computational effort. For example, You and Grossman (2008) provide such an approach in chemical industries.

As discussed in the introduction, the model developed in this article can influence the practices of many stakeholders of the supply chain. In the domain of intermodal freight transport systems, Caris et al. (2008) provide an overview of the planning decisions and solution methods proposed in the scientific literature. The authors identify four types of decision-makers based on four main activities in intermodal freight transport: (1) drayage operators, who organize the planning and scheduling of trucks between terminals and shippers and receivers; (2) terminal operators, who manage transshipment operations from road to rail or barge, or from rail to rail or barge to barge; (3) network operators, who are responsible for the infrastructure planning and organization of rail or barge transport; (4) intermodal operators, who are the users of the intermodal infrastructure and services and select the most appropriate route for shipments through the whole intermodal network. In each category decisions can be made at three levels: long-term strategic, medium-term tactical, and short-term operational. The authors find a lack of research on the strategic- and tactical-level issues of intermodal operators. All four types of decision-makers can benefit from our research. Intermodal decision-makers, in particular, can benefit from the proposed methodology in this article to make better decisions at strategic and tactical levels.

Except for Leachman (2008), the problem, as outlined in previous section of this article, has not been addressed by researchers. In particular, note that most research has dealt with the challenges posed by potential investments in intermediate warehouses in the supply chain, which, because of the outsourcing in annual service contracts, is not a concern here. Leachman (2008) assumes a single homogenous supply-chain strategy for each importer. Using the results of a heuristic, the author investigates the effect of increasing container fees at a San Pedro Bay port in terms of diversion of cargoes to other ports.

In this article, we adopt the framework of the data and the structure of the supply chain suggested by Leachman (2008). However, here we introduce a mathematical-programming model for the problem and develop solutions for the case of non-identical RDCs. The proposed optimization model considers mixed-strategies for each importer. Furthermore, we provide details of a heuristic approach to solve the problem over a wide range of parameters, and analyze the results. Using our heuristic, we provide sensitivity analysis and general recommendations for importers to choose supply-chain strategies most suitable for their businesses.

For this research, we secured US customs data for year 2006 as summarized in the PIERS (http://www.piers.com/) commercial data subscription. These data specify for each US port, each importer, and each of 99 commodity codes the total volumes of imports from Asian origins (measured in 20-ft equivalent units, or TEUs). We also secured the customs data for year 2006 as summarized in the World Trade Atlas commercial data subscription, which summarizes total volumes of imports to the Continental USA from Asian origins by total declared value for each of the 99 commodity codes. These data enabled the authors to make estimates for volumes and declared values per cubic foot by commodity type. Here we assume a particular distribution of imports among 83 large, nation-wide importers and 19 sets of generic importers acting as proxies for small and regional importers. The major North American ports of entry are as follows:

(1) Vancouver, BC (VAN), no trans-loading, only direct shipment of marine boxes (to USA destinations) is assumed through this port.
(2) Seattle–Tacoma, WA (SEA), assumed trans-load warehouse site is Fife, WA.
(3) Oakland, CA (OAK), assumed trans-load warehouse site is Tracy, CA.
(4) Los Angeles–Long Beach, CA (LA), assumed trans-load warehouse site is Ontario, CA.
(5) Lazaro Cardenas, Mexico (LAZ), no trans-loading, only direct shipment of marine boxes (to USA destinations) is assumed through this port.
(6) Houston, TX, (HOU), assumed trans-load warehouse site is Baytown, TX.
(7) Savannah, GA (SAV), assumed trans-load warehouse site is Garden City, GA.
(8) Charleston, SC (CHA), assumed trans-load warehouse site is Summerville, SC.
(9) Norfolk, VA (NOR), assumed trans-load warehouse site is Suffolk, VA.
(10) Port of New York–New Jersey (NY), assumed trans-load warehouse site is 50% East Brunswick, NJ and 50% Allentown, PA.
(11) Prince Rupert, BC (PRU), no trans-loading, only direct shipment of marine boxes (to USA destinations) is assumed through this port.

There are other ports handling Asian imports to USA, but in much smaller volumes than handled by the above ports. Other important data concern mean and standard deviation statistics on container dwell times in port terminals, and on container flow times in landside channels, as reported in private communications from major importers, terminal operators and railroads.

In our study, the continental United States is divided into 21 regions, with the entire import demand for each region concentrated at a single location. The geographical distribution of import destinations is assumed to be the same for all importers. In this study, this distribution was set to be proportional to purchasing power in the regions, but other distributions could be input to the model. Data on per-capita personal incomes by state and state populations were obtained from US Department of Commerce web sites, then aggregated into the regions.

Year 2007 rate quotations to various importers from steamship lines, non-vessel-operating common carriers, intermodal marketing companies, trans-loading warehouse operators, railroad carriers and trucking companies were obtained. Considerable variation in rates from carrier to carrier and customer to customer was encountered. Average rates were developed from a basket of rates for each channel.

Costs to ship imports from the ports of Shenzen, Yantian and Chiwan in mainland China to selected single destinations within each region were researched. While many other Asian origins are used in actual practice, we believe the results are generally insensitive to consideration of them. This is because (1) any particular product typically has a single origin, and (2) steamship rate differentials to the various Continental North American ports from any Asian origin from Singapore up to Yokohoma are essentially the same.

Transportation costs to importers for routing imports from the Chinese origins via eleven alternative North American ports of entry to the 21 RDC destinations were developed. For each port of entry and each destination, rates were developed for two alternative supply-chain channels: (1) shipping marine containers direct from Asia to RDC destinations, and (2) shipping marine containers to trans-loading warehouses in the hinterlands of the ports of entry, thence re-loading the imports in domestic rail containers or truck trailers for re-shipping from trans-loading warehouses to regional destinations. We have observed in practice that typically each RDC is supplied using only one channel. Volume is concentrated on a channel in order to negotiate a favorable rate as well as to simplify information management. We have therefore assumed in the model below that each RDC must be replenished using a single port and a single landside channel. We assume independent and identically distributed normal variables for demands and lead-times, with no correlation among these variables.

3. Mixed integer non-linear programming (MINLP) model

Here we propose a mixed integer non-linear programming model which optimizes the distribution of import volumes by port and landside channel for a given port and transportation infrastructure network. This model helps the importers to select ports of entry and landside channels so as to minimize their total cost of transportation and handling, pipeline inventory, and safety-stock inventory at RDCs. This model admits direct-shipment, trans-loading, and mixed strategies. Here we assume each RDC is served only by one port using one mode of transportation. In this model we do not consider capacity constraints or minimum contracted volumes. While there are certainly capacity limitations on ports, terminals and rail lines, no single importer imports enough volume to reach such limits. (The largest importer of Asian goods to the USA, Wal-Mart, accounts for only about 10% of such imports.) Contracts negotiated with transportation carriers may require certain minimum volumes, but we assume here that our model is to be applied at the pre-negotiation stage to identify the best supply-chain

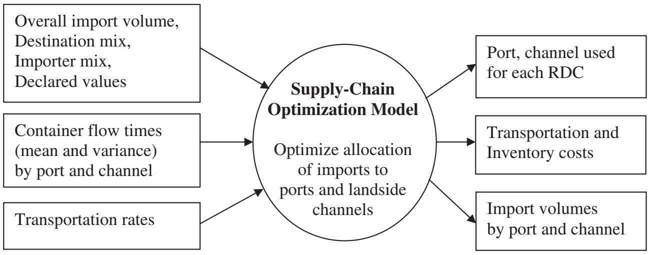

Fig. 1. Inputs and outputs of the supply chain model.

strategy to be pursued by the importer in negotiations with carriers. Fig. 1 displays a schematic of the optimization model and the required inputs and generated outputs.

3.1. Notation for parameters

- n – index of set of RDCs ($n = 1, 2, 3, \ldots, N$);
- m – index of set of ports of entry (POEs);
- i – index of set of land transportation modes (channels);
- D – nation-wide average sales volume for the importer per week (expressed in physical units);
- $MAPE$ – mean absolute percentage error (expressed as a fraction of one) in 1-week-ahead forecasts of nation-wide sales for the importer;
- σ^D – standard deviation of errors in 1-week-ahead forecasts of nation-wide sales. A standard assumption is $\sigma^D = (1.25)(MAPE)(D)$ (see, e.g., Silver and Peterson, 1985);
- D_n, σ_n – mean (D), and the standard deviation (σ) of sales distributed from RDC n. It is assumed that $\sum_n D_n = D$ and the proportion of nation-wide sales handled by each RDC is fixed;
- R– time between replenishment orders (from Asian suppliers). R is assumed to be 1 week for all importers;
- L^A– mean value of the lead time (expressed in weeks) from when a nation-wide replenishment order is placed until an allocation of the order among USA ports of entry is fixed and vessel passages are booked;
- L^M_m, σ^M_m – mean value (L), and the standard deviation (σ) of the lead time (expressed in weeks) for shipments from point of origin to port of entry POE m, measured from when vessel passage is booked until land transport to RDC from POE m begins (direct shipping case), or until land transportation to destination RDC from POE m is booked (consolidation–de-consolidation case);
- L^S_m, C^S_m – mean value (L) of the lead time (expressed in weeks), and transportation cost (C) per unit of load, from departure from point of origin until land transport from POE m to RDC begins (direct shipping), or until land transport from POE m (consolidation–de-consolidation) to destination RDC is booked;
- $L^N_{m,n,i}$, $\sigma^N_{m,n,i}$, $C^N_{m,n,i}$ – mean value (L) and standard deviation (σ) of transportation lead times (expressed in weeks), and transportation cost (C) per unit of load, shipped using land transportation mode i, from departure from POE m until processed through RDC n (direct shipping); or from when land transport from POE m to RDC n is booked until processed through the RDC n (consolidation–de-consolidation);
- z – safety factor determining the level of safety stocks at RDCs. (Choosing $z = 2.05$ implies approximately a 98% probability of no stock-out.) It is assumed all RDCs have the same customer satisfaction level;
- V^S – the amount of capital tied up in a unit of pipeline stock from origin to POE;
- V^N – the amount of capital tied up in a unit of pipeline stock from POE to RDC;
- V^R – the amount of capital tied up in a unit of RDC safety stock (assumed to be the same for all RDCs in this article);
- r – inventory carrying rate (inventory holding cost rate).

3.2. Variables

- $\delta_{m,n,i}$ – binary variable (0 or 1) indicating if land transportation mode i is used for transportation from departure from POE m to RDC n. This variable is set to zero if land transportation mode i cannot be used for transportation from m to n;
- $\delta_{m,n}$ – binary variable (0 or 1) indicating if RDC n is served by port m;
- δ_m – binary variable (0 or 1) indicating if port m is used by the importer;
- $L^N_{m,n}, \sigma^N_{m,n}$ – mean value and standard deviation of the lead times (expressed in weeks) using selected land transportation from departure from POE m until processed through RDC n (direct shipping); or from when land transport from POE m to RDC n is booked until processed through the RDC n (consolidation–de-consolidation);
- $\Re$ – set of RDCs served by direct shipment; $\Re = \{n|\delta_{m,n,i} > 0, i \in Direct\}$;
- $\Re^C$ – set of RDCs served using trans-loading; $\Re^C = \{n|\delta_{m,n,i} > 0, i \in Transloading\}$;
- Ω_m – set of RDCs served using port m; $\Omega_m = \{n|\delta_{m,n} > 0\}$;

- Φ – set of ports used by the importer $\Phi = \{m|\delta_m > 0\}$;
- ss – positive continuous variable showing the total safety stock in the chain.

3.3. Constraints

$$\sum_{m,i} \delta_{m,n,i} = 1 \quad \forall n \tag{1}$$

This constraint guarantees that each RDC is served; and it is served only by one port and one mode of transportation.

$$L^N_{m,n} = \sum_i \delta_{m,n,i} L^N_{m,n,i} \quad \forall m, n \tag{2}$$

$$\sigma^N_{m,n} = \sum_i \delta_{m,n,i} \sigma^N_{m,n,i} \quad \forall m, n \tag{3}$$

$$\delta_{m,n} = \sum_i \delta_{m,n,i} \quad \forall m, n \tag{4}$$

$$\sum_{n,i} \delta_{m,n,i} \le N\delta_m \quad \forall m \tag{5}$$

The mean and standard deviation of the lead times from ports to RDCs are calculated in (2) and (3). Constraint (4) sets the port – RDC combinations used by the importer. Constraint (5) identifies the ports that are used by the importer.

3.4. Objective function

Our objective is to minimize the total cost (total cost = transportation cost + inventory holding cost). The cost of the cycle stock has been omitted because that cost is independent of the supply-chain channel alternative. Eq. (6) shows the total transportation cost.

$$\sum_m \sum_n \sum_i \left(\left(C^S_m + C^N_{m,n,i} \right) \delta_{m,n,i} D_n \right) \tag{6}$$

The inventory holding cost is due to the in-transit inventory cost and the required safety-stocks, and is expressed in Eq. (7).

$$(r) \sum_m \sum_n \left(V^S L^S_m \delta_{m,n} D_n \right) + (r) \sum_m \sum_n \left(V^N L^N_{m,n} \delta_{m,n} D_n \right) + (r)(V^R)(ss) \tag{7}$$

The first two terms of Eq. (7) show the in-transit inventory cost from Asia to POEs, and from POEs to RDCs, respectively. The last term shows the cost due to the safety stock.

3.4.1. Calculating the safety stocks

Eppen (1979) showed that significant inventory cost savings can be achieved by grouping demands of customers together, and thus capitalizing on "risk-pooling effects". Using Eppen's risk-pooling result, the amount of safety stock required to ensure that stock-outs occur with a probability of α or less is $z_\alpha \sqrt{N \sum \sigma_n^2}$, where N is the number of demand locations (nodes) pooled together and σ_n is the standard deviation of the demand at node n. The safety stock is proportional to the square-root of the number of pooled demands ($\sqrt{N}$) in the consolidation case, while the safety stock required for separate inventories in the direct shipment case is proportional to the number of demand nodes (N). Eppen and Schrage (1981) consider a depot-warehouse echelon system, where the depot serves several warehouses and does not hold any inventory itself. The authors derive a closed form expression for the order-up-to level assuming an equal fractile allocation for identical warehouses with constant (zero variance) shipment lead-times. Such a system takes advantage of reduced inventory because of a portfolio effect over the lead-time from the supplier (joint ordering effect). The port-RDCs structure in our study has similar characteristics; ports do not hold inventories, and all inventories are at RDCs. Using Eppen and Schrage (1981) results, and in the simple case in which all RDCs are replenished by trans-loading through one port with common lead times, (i.e., $L^M_m = L^M_0,\ L^N_{m,n} = L^N_0,\ \forall m,\ n$), the total safety stock can be calculated as:

$$(z)\sqrt{\left(L^A + L^M_0\right)(\sigma^D)^2 + (N)^2\left(L^N_0 + R\right)\left(\frac{(\sigma^D)^2}{N}\right)} \tag{8}$$

which shows the root-square effect on the pooled demand over the supply chain route from the supplier to the port.

Considering variability in the lead-time significantly increases the required safety stock. In the simplest form of one supply node and one demand node considering lead-time (with mean L, and standard deviation of σ^L) and no risk pooling, safety stock can be expressed as (Silver and Peterson, 1985):

$$(z)\sqrt{(L+R)(\sigma^D)^2+D^2(\sigma^L)^2} \tag{9}$$

In the case of N identical RDCs with common mean and variance for lead-times ($\sigma_m^M=\sigma_0^M,\ \sigma_{m,n}^N=\sigma_0^N,\ \forall m,\ n$), using Eqs. (8) and (9), Leachman (2008) derives the total safety stock for direct-shipment and trans-loading as Eqs. (10) and (11), respectively.

$$(z)\sqrt{(L^A)(\sigma^D)^2+N^2\left(L_0^M+L_0^N+R\right)\left(\frac{(\sigma^D)^2}{N}\right)+D^2\left((\sigma_0^M)^2+(\sigma_0^N)^2\right)} \tag{10}$$

$$(z)\sqrt{\left(L^A+L_0^M\right)(\sigma^D)^2+N^2\left(L_0^N+R\right)\left(\frac{(\sigma^D)^2}{N}\right)+D^2\left(\frac{(\sigma_0^M)^2}{N}+(\sigma_0^N)^2\right)} \tag{11}$$

Eq. (11) is meaningful for the case where multiple containers are shipped in each review interval to the trans-loading center, and lead-time uncertainties across the individual container shipments are independent. Like Eppen and Schrage, Leachman assumes the equal fractile allocation policy which aims to equalize the stock-out probabilities at the end stock points (i.e., the RDCs). Equal fractile is a form of fair-share policy which is the optimal rationing policy for base stock control under the cost structure presented in Eppen and Schrage (1981). Bollapragada et al. (1999) showed that the results of Eppen and Schrage (1981) still apply even in situations where there are non-identical warehouses. The authors show the fair share for node n, out of the required safety-stock for the pooled nodes set of J, will be proportional to the ratio of $(\sigma_n/\sum_{v\in J}\sigma_v)$, assuming the same customer satisfaction level is to be maintained at all nodes.

We assume the nation-wide normal demand is a linear combination of normal random demands at each of the RDCs. Using Eqs. (8) and (9) and considering the proportional fractile allocation policy, we calculate the safety stock required by each RDC. The safety stock in the system can then be presented as the tally of safety stocks required by each RDC. Thus, in the simple case of pure direct strategy in which all RDCs are replenished by direct shipping with common lead times, the total safety stock can be expressed as:

$$z\sum_n\sqrt{L^A\sigma_n^2\frac{\sum_v\sigma_v^2}{\left(\sum_v\sigma_v\right)^2}+\sigma_n^2(L_0^M+L_0^N+R)+D_n^2((\sigma_0^M)^2+(\sigma_0^N)^2)} \tag{12}$$

In a pure trans-loading strategy in which all RDCs are replenished by trans-loading through a single port with common lead times, safety stock can be calculated as:

$$z\sum_n\left[L^A\sigma_n^2\frac{\sum_v\sigma_v^2}{\left(\sum_v\sigma_v\right)^2}+L_0^M\sigma_n^2\frac{\sum_v\sigma_v^2}{\left(\sum_v\sigma_v\right)^2}+\sigma_n^2(L_0^N+R)+D_n^2\left(\frac{\sum_v D_v^2}{\left(\sum_v D_v\right)^2}(\sigma_0^M)^2+(\sigma_0^N)^2\right)\right]^{1/2} \tag{13}$$

Eq. (14) provides the formula for the mixed strategies of direct shipment to some RDCs and consolidation–de-consolidation shipments to others. This equation also accommodates unequal channel lead times and unequal RDC demands.

$$\begin{aligned}
ss={}&z\sum_{n\in\Re}\sum_m\delta_{m,n}\left[L^A\sigma_n^2\frac{\sum_v\sigma_v^2}{\left(\sum_v\sigma_v\right)^2}+\sigma_n^2(L_m^M+L_{m,n}^N+R)+D_n^2((\sigma_m^M)^2+(\sigma_{m,n}^N)^2)\right]^{1/2}\\
&+z\sum_{n\in\Re^C}\sum_m\delta_{m,n}\left[\begin{array}{c}L^A\sigma_n^2\frac{\sum_v\sigma_v^2}{\left(\sum_v\sigma_v\right)^2}+\sigma_n^2L_m^M\frac{\sum_{v\in\Re^C}\delta_{m,v}\sigma_v^2}{\left(\sum_{v\in\Re^C}\delta_{m,v}\sigma_v\right)^2}\\ +\sigma_n^2(L_{m,n}^N+R)+D_n^2\left(\frac{\sum_{v\in\Re^C}\delta_{m,v}D_v^2}{\left(\sum_{v\in\Re^C}\delta_{m,v}D_v\right)^2}(\sigma_m^M)^2+(\sigma_{m,n}^N)^2\right)\end{array}\right]^{1/2}
\end{aligned} \tag{14}$$

The first term of Eq. (14) shows the safety stock in RDCs served by direct shipment. The second term shows the safety stock in RDCs served by trans-loading.

4. Proposed solutions

The simplest setting of the problem under study can be translated to a p-median problem, in which p facilities are to be selected to minimize the total (weighted) distances or costs for supplying customer demands. In addition, we consider more complexities such as the inventory costs, which are non-linear in the assignment variables, and the selection of transportation modes in a multi-echelon setting. Thus the problem we are studying is more difficult than the standard p-median problem, which is already a notorious NP-hard problem (e.g. see Revelle et al., 2008).

In this article, we propose two approaches to solve the MINLP model presented in Section 3. First, we develop a heuristic which decomposes the problem into choosing among alternative location-level strategies (i.e., direct shipping vs. use of trans-load warehouses), then optimizes the choice of modes and allocation of volumes to routes for each location-level strategy, and finally identifies the best of the alternatives considered. This heuristic considers only "pure" import strategies, i.e., it does not allow an importer to practice a mixed strategy featuring some RDCs served by trans-loading and others served by direct-shipment. Second, we apply a commercial solver and try to directly solve the optimization model.

4.1. Heuristic approach to solve MINLP

The mathematical-programming model addresses mixed strategies of trans-loading and direct shipments. But in the heuristic we only allow one homogeneous strategy selected from among six strategies actually practiced by importers. Here is the list of strategies:

(1) TL_LA: Consolidate–de-consolidate and trans-load using a warehouse at LA-LB only. Importers of expensive goods, difficult-to-forecast goods and goods experiencing rapid obsolescence have been observed to practice TL_LA supply chains. Such supply chains permit inventory to be managed as tightly as possible, albeit with transportation costs higher than for other alternatives. LA-LB is chosen as the single port of entry because Southern California is the largest local market, and so transportation costs are minimized compared to using a different single port of entry.
(2) TL_2: Consolidate–de-consolidate and trans-load using warehouses at two specific ports. Compared to TL_LA, this strategy can reduce transportation costs by making use of all-water transit to a de-consolidation center located on the East Coast. However, safety stocks and pipeline inventories are increased.
(3) TL_4: Consolidate–de-consolidate and trans-load using warehouses at four specific ports. Compared to TL_2, transportation costs are reduced further, but safety stock requirements are increased. Such "Four Corners" strategies have been practiced by several large retailers of moderate-value goods.
(4) TL_5: Consolidate–de-consolidate and trans-load using warehouses at 5 specific ports. Compared to TL_4, this strategy economizes on transportation costs a little bit more, but in exchange for slightly higher safety stocks and pipeline inventories. Wal-Mart has practiced such a "Five Corners" import strategy.
(5) Direct_WC: Direct-ship marine boxes to RDCs considering use of only West Coast ports. Small and regional importers of relatively expensive goods have been observed to practice such an import supply-chain strategy.
(6) Direct_All: Direct-ship marine boxes to RDCs considering use of all ports. This strategy is commonly adopted by importers of low-value goods and by small importers with insufficient volume to effectively practice consolidation–de-consolidation. It offers the potential for lowest transportation and handling costs, in exchange for inventory requirements greater than that of the alternatives.

These strategies are summarized in Table 1 in terms of candidate ports and in terms of whether or not trans-loading is utilized. The procedure of the heuristic is explained in detail in Appendix A. Here is the short summary of the procedure:

(First) For every strategy in Table 1, identify the least-cost assignment of RDCs to ports and landside channels. This is done by choosing for each RDC a single port and a single landside channel that minimizes total transportation cost and pipeline inventory costs, for the given transportation fees/rates and the given transit times.

(Second) Apply analytical safety-stock inventory formulas developed in the previous section (for given transit times and fees/rates) to calculate the total cost (in terms of total transportation, pipeline inventory and safety stock costs).

(Third) Compare total costs developed as above for all alternative supply-chain strategies and identify the least-cost strategy.

The foregoing heuristic is designed such that all the constraints of the MINLP problem are satisfied. The solution is generated very efficiently in terms of speed, and is feasible for the MINLP problem. However, there is no guarantee of optimality of the solution. To investigate the quality of the results, we compare the heuristic solutions with the solutions of a genetic/evolutionary based approach to the formal optimization problem.

Table 1
Alternative strategies considered by the heuristic.

Strategy	TL_LA	TL_2	TL_4	TL_5	Direct_WC	Direct_All
Consolidation	Yes	Yes	Yes	Yes	No	No
Possible ports	LA–LB	LA–LB NY–NJ	LA–LB NY–NJ Seattle–Tacoma Savannah	LA–LB NY–NJ Seattle–Tacoma Savannah Houston	LA–LB Oakland Seattle–Tacoma Vancouver Prince Rupert	LA–LB Oakland Seattle–Tacoma Vancouver Prince Rupert NY–NJ Houston Savannah Charleston Norfolk Lazaro-Cardenas

Table 2
Sample parameter values for the solver.

Parameter	Value
Max Time (s)	3000
Max Iterations	100,000
Precision	1e−008
Convergence	0.0001
Population	200
Mutation rate	0.075

4.2. Genetic algorithm/hybrid method approach to solve MINLP

Due to the hard nature of MINLP problems, we use the Premium Solver Platform® application from Frontline Systems Inc., which applies a hybrid of techniques to solve the MINLP problem. This genetic/evolutionary solver applies a hybrid of genetic algorithm methods and classical methods (including gradient-free "direct search" methods, quasi-Newton, Simplex, and non-linear Generalized Reduced Gradient – GRG) to solve the problem. In a genetic algorithm the problem is encoded in a series of bit strings that are manipulated by some algorithms. In an "evolutionary algorithm," the decision variables and problem functions are used directly.

In the best case, the solver will find the globally optimal solution. However, finding the optimal solution is not always possible. The solver may become trapped in a locally optimal solution, or it may stop after a certain amount of time with the best solution it has found so far. Furthermore, since evolutionary algorithms rely on random sampling, they may yield different solutions in different runs made with different starting points. Therefore, we run each experiment with several different starting points, and select the best of the solutions. In particular, we use the following multi-start procedure in each of our experiments:

- Start from a cold start, in which all variables are initially set to zero.
- Start from a random set of initial values for the variables.
- Start from the solution found based on the heuristic proposed above.

To reduce the number of variables in order to improve the performance of the solver, we removed the variables associated with very expensive routes. We have examined a range of parameters for the solver for each experiment to see if we can generate meaningful results, and to investigate if we can improve the results of the heuristic. The results of each experiment were carefully studied. Table 2 provides an example of settings for parameters of the solver.

Max Time determines the maximum amount of time the Solver will run before it stops. Max Iterations determines the maximum number of iterations that the Solver may perform on one problem. This number was set to be sufficiently large, so it did not provide any constraint on our experiments. The Precision option governs how close a constraint value must be to its bound to be considered satisfied, and how close to an exact integer value a variable must be to satisfy an integer constraint. The Convergence option controls the stopping conditions used by the solver to generate results. The Population option sets the number of candidate solutions in the population. Throughout the solution process, the Solver maintains a population of candidate solutions, rather than a "single best solution". The initial population consists of candidate solutions that always include at least one instance of the starting values of the variables. The Mutation Rate is the probability that some member of the population will be mutated to create a new trial solution during each generation considered by the evolutionary algorithm. In the Solver, a sub-problem consists of a possible mutation step, a crossover step, an optional local search in the vicinity of a newly discovered best solution, and a selection step where a relatively unfit member of the population is eliminated. For further information on these parameters, and the algorithms, interested readers are encouraged to refer to the software application documents at http://www.solver.com.

5. Simulation experiments

To assess the quality of results generated by the proposed heuristic, we compare its results with the results generated by the hybrid solver. We used a laptop computer with a 2-GHz CPU and Visual Basic programming language to run these simulation experiments. We have focused on two different performance measures of the model which we term efficiency and effectiveness. In the efficiency test, the emphasis is on the study of the performance of proposed methods in terms of the CPU run-time. The effectiveness test measures the quality of the result (in terms of the MINLP objective function value) from the heuristics method, and whether it can be improved using the hybrid method discussed above.

We found that the MINLP hybrid method may take a long time (from 10 min to several hours) to generate any meaningful results for the MINLP problem for each starting point in each experiment. Meanwhile, for the same experiments, the heuristic takes less than 1 s to generate results. Therefore, the proposed heuristic shows its superior performance in terms of the CPU-time over the hybrid method by a wide margin.

We observed that specifying an appropriate starting point plays an important role in generating good results using the solver. In particular, starting from the solution found from the heuristic significantly helps the solver in its search process. Staring from a cold or a random starting point often makes the solver take a longer time, and generate inferior-quality results, if any. Therefore, in these experiments, the solver benefits from the results generated by the proposed heuristic.

5.1. Effectiveness tests

To study the quality of the heuristic solutions, we developed a sample of actual importers which represent the wide range of importers, and investigate whether the hybrid method can improve the results generated by the heuristic in this sample.

First we have examined 71 major importers which import low-valued products (e.g., Ikea, Wal-Mart), medium-range products (e.g., Target, Payless Shoe Source), and high-end products (e.g., Samsung). With the total annual volume of 5.4 million TEUs in 2006, these companies' imports represent more than 90% of volume of goods imported by importers that are large enough to consider adopting a consolidation–de-consolidation supply-chain strategy (out of total of 83 large companies, as discussed in Section 2). For these importers, both direct shipments and consolidation–de-consolidation can be used.

We have classified these importers based on their US customs declared value for imported goods, which is the value per cubic foot of container capacity and not the value per cubic foot of the actual cargo within the container. These values reflect the manufactured or purchased cost of the goods in Asia plus waterborne transportation rather than their full retail values in the US. As imports move through the supply chain, they accumulate more cost. One index to the amount of capital tied up can be the value declared to US customs. Based on our analysis of data and for the purposes of this study, the assumption was made that the landside pipeline inventories are valued by importers at 125% of the value declared to customs. It was further assumed that RDC inventories are valued at 150% of the value declared to customs.

The appropriate inventory carrying rate to apply depends on a number of factors. In the case of replenishment of goods with long-term demand, we use 20% for the inventory carrying rate. A higher rate is more appropriate if retail prices are declining with time, or if the products experience rapid obsolescence, such as is the case for technology goods, style goods and goods for special sales events. For such cases, a rate of 50% is considered. The sales of most retailers are a mixture of event items and standard items. For simplicity a simple average of the two cases was assumed, i.e., an inventory carrying rate of 35% is assumed for the purposes of costing pipeline and safety stocks.

Table 3 shows the summary of the results of the effectiveness test for selected major importers. As shown, in several experiments, the hybrid method was not able to improve on the heuristic solution. In the experiments where it was able to improve, the improvements are all less than 1.5% of the objective value.

We further investigated smaller importers (so-called "Generic proxy" importers) in different value categories. In 2006, small importers accounted for more than 60% of the total volume of imports from Asia to the US. In general, small importers simply do not have sufficient volume required for trans-loading; there would be too many partially-filled vehicles. Therefore, for the smaller importers only direct shipment methods can be used. The generic part of the importer category in Table 4

Table 3
Summary of effectiveness tests of heuristic for selected major importers.

Importer category	Examples of importers	Avg. customs declared value ($/cubic foot)	Assumed inventory carrying rate (%)	Total annual volume (1000 TEUs)	Percentage of major importers total volume (%)	Best strategy from heuristic	Cost improvement from solver (%)
Low-value goods	Ikea, Lowe's, Ashley Furniture, Pier 1 Imports, Dorel	$9	35	701	12.0	TL_5	1.04
	Big Lots, Michaels Stores, Walgreen, Dollar Tree, Family Dollar	$10	35	235	4.0	TL_5	0.81
	Home Depot, OfficeMax, Staples	$12	35	557	9.6	TL_4	0.52
	Wal-Mart	$14	35	979	16.8	TL_4	0.38
	Michelin, Bridgestone, Dollar General, Hankook, Goodyear	$15	35	347	5.9	TL_4	0.63
Medium-value goods	Target, Sears, Costco, Toyota, J C Penney, Ford	$20	35	1296	22.2	TL_LA	0.65
	Payless ShoeSource, GE, Williams-Sonoma, Nike, Whirlpool, Federated, Reebok	$25	35	637	10.9	TL_LA	0.43
High-value goods	Matsushita, LG, Philips, Thomson, Emerson, Sharp	$40	50	431	7.4	TL_LA	0.00
	Samsung, Sony, Canon	$44	50	214	3.7	TL_LA	0.00

Table 4
Effectiveness test results for the generic and hypothetical importers.

Importer category	Importer	Avg. customs declared value ($/cubic foot)	Assumed inventory carrying rate (%)	Best strategy from heuristic	Cost improvement from solver (%)
Generic	Generic_10	10	35	Direct_ALL	0.00
	Generic_14	14	35	Direct_ALL	0.00
	Generic_42	42	50	Direct_WC	0.00
	Generic_50	50	50	Direct_WC	0.00
Hypothetical	Hypothetical_1	100	60	TL_LA	0.03
	Hypothetical_2	100	10	TL_LA	0.00
	Hypothetical_3	5	60	TL_5	1.15
	Hypothetical_4	5	10	Direct_ALL	0.16

Table 5
Best importers strategies based on custom values ($/cubic foot) and inventory carrying rates.

Inventory carrying rate	10%	20%	30%	40%	50%	60%
Declared customs value						
$5.00	Direct	Direct	Direct	Direct	TL_5	TL_5
$10.00	Direct	Direct	TL_5	TL_4	TL_4	TL_LA
$15.00	Direct	TL_5	TL_4	TL_LA	TL_LA	TL_LA
$20.00	Direct	TL_4	TL_LA	TL_LA	TL_LA	TL_LA
$25.00	TL_5	TL_4	TL_LA	TL_LA	TL_LA	TL_LA
$30.00	TL_5	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA
$35.00	TL_5	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA
$40.00	TL_4	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA
$45.00	TL_4	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA
$50.00	TL_4	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA
$60.00	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA
$70.00	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA
$80.00	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA
$90.00	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA
$100.00	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA	TL_LA

shows the summary of the results for samples of generic importers. Based on our reported observations and on other unreported experiments, the hybrid method was not able to improve on the heuristic solution for generic importers.

We have also tested hypothetical scenarios in which two levels (extreme high and lows) of declared values are combined with two levels (extreme high and lows) of inventory carrying rates. The hypothetical part of the importer category in Table 4 shows the summary of the results of this test. As shown, in the experiments where the hybrid method was able to improve the solutions, the improvements are all less than 1.5% of the objective value.

Based on our experiments, we concluded that the proposed heuristic is a very efficient approach in terms of the CPU-time while generating effective results in terms of acceptable-quality solutions. As noted by Cordeau et al. (2006), expending considerable effort to solve a real-life problem to full optimality in logistics networks is usually not meaningful, considering the accuracy of the data estimates.

5.2. Sensitivity analysis

Here we use the proposed method to study the best supply chain practices for Asia – USA imports considering ranges of declared values for goods, and ranges of inventory carrying rates. The ranges encompass the majority of importers of Asian goods to North America. Table 5 shows the summary of proposed best strategies for importers based on goods values and inventory carrying rates.

Although we have provided our analysis over a range of goods values and inventory carrying rates, we have noticed there is a correlation between the value of goods and the inventory carrying cost for an importer. More expensive goods usually have a higher carrying rate. Therefore, the strategies presented on the diagonal line (from the top-left corner to the bottom-right corner) of Table 5 may be the most relevant to industrial practice.

Our study shows that for high-value goods, consolidation–de-consolidation supply-chain strategies are attractive; for low-value goods, much less so. Moreover, to achieve the least total cost, the trans-loading strategy must be tailored according to the value of the goods. For very-high-value goods, consolidating replenishment of all Continental USA RDCs via Los Angeles – Long Beach is optimal (this strategy is designated at “TL_LA” in Table 5). For medium-value goods, the optimal strategy is a “four corners” or “five corners” policy (designated as “TL_4” and “TL_5” in Table 5). For low-value goods, the

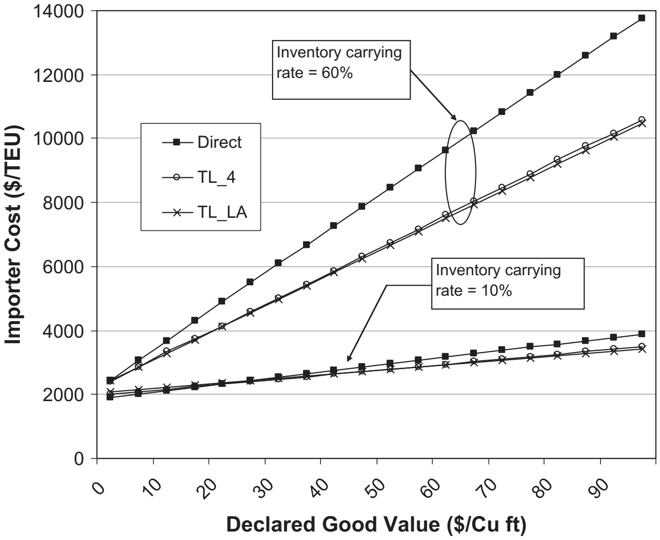

Fig. 2. Importer cost versus declared customs values and inventory carrying rates.

optimal strategy is direct shipment. This observation is also supported by Fig. 2, which shows the total cost to an importer based on the changes in the value of goods and inventory carrying rates.

As shown in Fig. 2, the importer's cost increases with an increase in the declared value of the goods, regardless of selected strategy. The cost difference between direct-shipment and trans-loading is more obvious for high-valued goods and/or for goods with higher carrying cost. It is therefore increasingly more expensive to use direct-shipment for high-value goods.

6. Summary and conclusions

In this article, we proposed a mixed integer non-linear programming model for the optimization of the supply chains of importers of waterborne containerized goods from Asia to USA. This optimization model determines the least-cost supply-chain strategy for an importer, in terms of ports and landside channels to be used. The costs considered include costs for transportation and handling, pipeline inventory, and safety-stock inventory at RDCs. Based on our observation of industry practices and the structure of the data and the existing landside channels, we designed a heuristic algorithm to solve the mathematical program. The performance of the proposed heuristic is then compared with the solutions generated from a commercial solver for a selected set of importers. Our analysis showed the superior performance of the proposed heuristic in terms of the CPU-time, and acceptable performance in terms of the quality of the results.

In general, use of the trans-loading channels entails a premium in terms of transportation and handling charges over the costs for direct shipping. These extra transportation costs must be traded off against potential inventory savings afforded by pooling shipments to multiple regional destinations over the segment of the supply chain between Asia and the trans-loading warehouse. Therefore, the best strategy for low-value goods can be quite different from the best strategy for high-value goods. Our study shows that for high-value goods, such consolidation–de-consolidation supply-chain strategies are attractive; for low-value goods, much less so. Moreover, to achieve the least total cost, the trans-loading strategy must be tailored according to the value of the goods. For very-high-value goods, consolidating replenishment of all Continental USA RDCs via Los Angeles – Long Beach is most efficient. (This strategy is designated at "TL_LA" in Table 5.) For medium-value goods, it is more efficient to practice a "four corners" or "five corners" policy (designated as "TL_4" and "TL_5" in Table 5), whereby Continental USA is divided into quarters or fifths served by consolidation of replenishments of the RDCs located in hinterlands of the ports of New York–New Jersey, Savannah, Los Angeles – Long Beach, and Seattle – Tacoma (TL_4) or those ports plus Houston (TL_5).

The contributions of this paper to the literature are in several domains: (a) it targets a gap in existing literature in location/allocation problems by considering risk pooling along with the choice of transportation mode, and routing, (b) it integrates uncertainties in SCM with location decisions by considering stochastic demand and random transportation time in a multi-echelon setting, (c) it enriches the literature on intermodal freight transport systems by providing models for decision-makers to make better decisions at strategic and tactical levels, (d) it introduces a mathematical-programming based model and a heuristic algorithm for optimization of the supply chain of importers of waterborne containerized goods from Asia to USA, (e) it provides recommendations for importers to choose best strategies according to their value of goods and the inventory holding rate.

Several directions for future research are apparent from this study. Firstly, this research could be expanded to include the shipments from other parts of the world to North America. Secondly, calculations of the shipments of all importers can be tallied in policy-level analyses to help decision-makers make wiser decisions on infrastructure investments and user fees for ports and landside channels, as well as to help transportation carriers and warehousing service providers to make more informed pricing decisions. Thirdly, this analysis could be enhanced to incorporate capacity constraints of existing channels and ports, and minimum contractual requirements for volumes by port or channel. Fourthly, in addition to transportation and inventory costs, the proposed model could be further expanded to include other parameters such as environmental impact factors. The efficiency and effectiveness of these approaches could be further studied under different scenarios.

Finally, in this article we assumed that infrastructure at ports and channels would be expanded as necessary to maintain current container flow times in the face of increased shares of imports routed through ports and channels. A particular desired enhancement to this analysis concerns the capability to perform a short-run analysis, in which port and landside infrastructure and operating schedules are fixed, rather than fixing statistics on container flow times. In a short-run analysis, container flow times by port and channel should be calculated as a function of traffic levels.

Appendix A. Details of the proposed heuristic for supply-chain strategy selection.

```
• Step 1. for every strategy $s$ selected from the set of strategies $S$ listed in Table 1, do
    • Step 2. for every $n$ in the set of RDCs, do
        • Step 3. for every port $m$ in $P_s$ (set of ports in strategy $s$), do
            • Step 4. for every land transportation mode $i$ used in strategy $S$, do
                • Step 5. Calculate transportation cost using $(C^S_m D_n + C^N_{m,n,i} D_n)$
                • Step 6. Calculate in-transit inventory cost using $(rV^S L^S_m D_n + rV^N L^N_{m,n,i} D_n)$
            • Step 7. end for
        • Step 8. end for
        • Step 9. Select port $m_0$ and land transport mode $i_0$ such that the transportation cost + in-transit inventory cost is minimized for selected $n$,
        • Step 10. Set $\delta_{m,n,i} = 1$ for $m = m_0$, $i = i_0$; and Set $\delta_{m,n,i} = 0$ for all other $m$, and $i$;
    • Step 11. end for
    • Step 12. Set $\Re = \{\}$ for trans-loading strategies (i.e. TL_LA, TL_2, TL_4, TL_5), and set $\Re^C = \{\}$ for direct shipment strategies (i.e. Direct_All, Direct_WC),
    • Step 13. Calculate Eqs. (2)–(4), $\Omega_m$, and $\Phi$,
    • Step 14. Calculate the total safety-stock using Eq. (14),
    • Step 15. Calculate the total cost = total transportation cost + in-transit inventory cost + safety stock cost using Eqs. (6) and (7).
• Step 16. end for
• Step 17. Select the best strategy which minimizes the total cost,
• Step 18. For the best strategy, report the total cost, and the ports and channels used for each RDC.
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