

**A Less-Than-Truckload Single Freight Carrier Collaboration Planning Problem under
Dynamic Capacities**

by

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Abstract

This paper addresses the deterministic dynamic single carrier collaboration problem for the small- to medium-sized less-than-truckload (LTL) industry. It is formulated as a binary (0-1) multi-commodity minimum cost flow problem and solved using a branch-and-cut algorithm. Its inherent network structure is exploited to generate the lower bounds to the branch-and-cut algorithm using the network simplex method and by relaxing the integrality constraints. Results from numerical experiments indicate inherent trade-offs at the higher degrees of collaboration between waiting for more affordable collaborative capacity and incurring higher holding costs. They also suggest that collaborating LTL carriers experience increased capacity utilization.

Keywords: Collaborative logistics, Freight transportation, Less-than-truckload trucking, Minimum cost flow

1. Introduction

Less-than-truckload (LTL) carriers, which operate on thin margins, have significant negative impacts due to empty trips, idled capacity on lots, and rising energy costs. The impacts can cascade to other industries; for example, empty trips may affect global food prices. Recent advances in Internet and information communication technologies (ICT) foster the possibility of innovative new business and operational paradigms within the small- to medium-sized LTL industry to address these concerns. One promising innovation is the concept of LTL carrier-carrier collaboration, which provides opportunities for LTL carriers to exploit synergies in operations (such as excess capacity), reduce costs associated with fleet operation, decrease lead times, increase asset utilization (power units), and enhance overall service levels (Esper and Williams, 2003).

LTL carrier-carrier collaboration is a relatively unexplored concept within the freight domain. Past studies have focused on collaboration within the truckload (TL) carrier, liner shipping, and rail industries (Agarwal and Ergun, 2008a, 2008b; Song and Regan, 2004; Figliozzi, 2006; Kuo et al., 2008). Recently, Hernandez and Peeta (2010) introduced and examined the viability of LTL carrier-carrier collaboration from a static planning perspective for a single carrier, termed the carrier of interest. The study explored the potential benefits of the LTL carrier-carrier collaborative paradigm for the carrier of interest based on the degree of collaboration. It formulated single and multiple product collaboration problems as binary (0-1) multicommodity minimum cost flow problems. The study insights from numerical experiments suggest that collaboration can reduce dead-heading for the collaborating carriers, alleviate the consequences of fuel price increases, and reduce operating costs relative to a non-collaborative leasing option. However, the time dimension is not considered in the problem formulation due to

its static planning perspective.

The time dimension is a key operational factor in freight carrier operations, as a carrier is under the clock after it elects to serve a shipment. It raises additional sources of complexity in the enabling of a LTL collaborative network due to the need to route shipments over multiple origin-destination (O-D) pairs. First, the carrier of interest must be able to identify which collaborative carriers are available and determine their available time-dependent capacities for collaboration on the various network links. There are two challenges from a time dimension in this context. The required collaborative capacity may not be available at a transfer location at the time a load arrives to it, indicating the possibility of holding costs. Further, a potential collaborative capacity may itself be in transit to the transfer location or waiting to unload its cargo at the transfer point. Second, as a consequence of the aforementioned complexity, there is a need to factor the holding costs in addition to the capacity acquisition costs to determine the various permutations of collaborative routes to generate the operational plan. Hence, the dynamics associated with the time-dependent availability of the collaborative capacity in conjunction with the costs of holding loads at transfer points are essential to generating the optimal collaboration strategy for the carrier of interest.

Delays at transfer points can occur due to mechanical breakdowns of power units, and congestion on the physical network as well as at terminals, depots and/or warehouses. These delays manifest as holding costs in the LTL collaboration context due to increased driver pay, delivery delay costs (especially on the perishable items), potential revenue loss from idled capacity, and increased transfer site fees for utilized space. The LTL carrier-carrier collaboration paradigm provides an opportunity to explore the impacts of increased asset utilization (collaborative capacity) and crossdocking practices on alleviating the monetary impacts of

delays.

This study addresses a dynamic LTL carrier-carrier collaboration problem among a group of small- to medium-sized LTL carriers. Here, a carrier of interest seeks collaborative routes to service multiple shipments so as to minimize costs while factoring the availability and cost structure of the time-dependent collaborative capacity on the associated network links and holding costs at transfer points (nodes). The problem, addressed from a dynamic planning perspective, is labeled the deterministic dynamic single carrier collaboration problem (DDSCCP). In the DDSCCP, the demand between an O-D pair for the carrier of interest is fixed, but subject to thresholds on the latest entry into the carrier service network and the earliest exit from it to meet the load time windows associated with pickup and delivery, respectively. Further, the time-dependent availability of the collaborative capacities and the corresponding magnitudes on the network links are known *a priori* for the entire planning horizon. The problem is deterministic because the demand is fixed and the time-dependent collaborative capacities are known for the planning horizon. It is dynamic in the sense that the demand has time windows for load pickup/delivery, the collaborative capacities are time-dependent, and the actual holding costs encountered by a load depend on the number of intervals it is held at a transfer location (though the holding cost rate itself is fixed for a location). Due to the planning perspective of the DDSCCP, operational aspects related to link travel time variability are ignored here. Thereby, the link travel times are fixed. However, the costs associated with congestion effects due to both traffic and terminal delays are captured through holding costs that vary with transfer locations.

The remainder of this paper is organized as follows: Section 2 reviews related literature on dynamic carrier collaboration and holding costs in the context of the TL, liner shipping, and rail industries. Section 3 describes the formulation of the DDSCCP problem. It also discusses the

formulation characteristics and illustrates some of its properties. Section 4 summarizes the design of experiments for the DDS CCP. Section 5 summarizes the insights from the experimental results. It conducts sensitivity analyses and studies the effects of collaboration by comparing the DDS CCP strategies to the short-term leasing option, analyzing the effects of holding costs on the carrier of interest, and estimating the levels of collaborative capacity utilization. Section 6 presents some concluding comments.

2. Literature review

For the freight transportation and carrier industries, the carrier collaborative paradigm is an emerging trend that addresses system inefficiencies and lost profits. From the dynamic perspective, most studies center on liner shipping, rail, and TL industries. While the literature does not address the issue of time in relation to LTL collaboration, the time dimension is a vital aspect of LTL carrier-carrier collaboration in an operational context, both for operational planning and deployment. By introducing the time dimension to the LTL collaborative paradigm, we seek to capture the dynamic effects of the spatial availability of time-dependent collaborative capacity over an LTL point-to-point network and understand the impacts of congestion effects on the collaborative routes.

Past studies that employ a dynamic context in relation to the collaborative paradigm in the liner shipping and rail industries primarily consider the issue of efficient allocation of collaborative capacity. They rely on techniques from the operations research domain, such as vehicle routing problems and simulation, to model the problem. Agarwal and Ergun (2008b) studied the collaborative paradigm from the perspective of the liner shipping industry. They analyzed the collaboration of liner shipping companies over a large-scale dynamic network and

formulated a network design problem that considered both transshipment (transfer) and holding costs (costs related to overnight stays) at ports. Kuo et al. (2008) proposed a discrete-time carrier collaboration simulation-assignment framework to address an international rail-based intermodal freight transport problem. Figliozzi (2006) introduced dynamic auction-based mechanisms for TL carrier-carrier collaboration where loads are dynamic and collaboration is through the auctioning of loads to members in the collaborative. There are some key differences between the characteristics of the aforementioned studies and the LTL context.

First, the liner shipping, rail, and TL industries operate under planning periods which range from a few days to many weeks. By contrast, the small- to medium-sized LTL carriers operate on much shorter operational delivery planning periods that range from a few hours to a day or two. These shorter planning periods add complexity to LTL networks due to the shorter pickup and delivery time windows for shipments. Also, due to the shorter planning periods, congestion effects have a greater impact on LTL operations (Golob and Regan, 2001).

Second, the aforementioned carrier collaboration studies from liner shipping, rail, and TL industries do not explicitly account for congestion. However, for the small- to medium-sized LTL carrier industry, congestion effects can represent up to 50% of the time spent in moving a shipment (Cheung and Muralidharan, 2000; Kawamura, 1999; Boardman, 1997). Consequently, congestion effects can have significant monetary impacts on LTL operations. Hence, in the LTL collaboration context, there is a need to model these effects and develop efficient strategies that can alleviate the associated costs. As discussed in Section 1, in the DDS CCP context, we account for these congestion effects through the holding costs.

Third, the physical characteristics of the liner shipping, rail, and TL industries cannot be generalized to the small- to medium-sized LTL carrier collaboration problem in scale, and

possibly other aspects. For example, the liner shipping industry operates on large-scale sea-based networks that span the globe, and routes can change due to demand fluctuations which dictate the service area. Rail industry networks are typically large point-to-point networks with fixed routes, and hence, the shipments are restricted to the fixed network. By contrast, the small- to medium-sized LTL carriers operate under much smaller point-to-point network systems; that is, with fewer number of interconnected transfer facilities (Belman and White III, 2005). Point-to-point networks move LTL shipments directly between facilities, such as end-of-line terminals, without intermediate stops to consolidate loads.

Large LTL carriers use hub-and-spoke networks. The point-to-point network configuration has two significant advantages over the hub-and-spoke models: (i) the carriers do not have to digress to potentially distant intermediate terminal locations, thus making the trips faster, and (ii) they save carriers additional transfer and transit costs because they bypass consolidation terminals (Belman and White III, 2005; Taylor et al., 1995). Another key advantage of the LTL point-to-point network structure over others is the spatial flexibility in terms of routing shipments between points. For example, in the case of a single shipment, the minimum amount a carrier of interest incurs is the total cost associated with the least cost collaborative route over the point-to-point network. That is, a minimum cost flow problem (Ahuja et al., 1993) can be solved for each shipment.

To this point, the current dynamic carrier collaborative literature and the dynamic LTL carrier collaboration problem have been compared in terms of the planning horizon, congestion effects, and characteristics of the operating networks. There are two additional key conceptual differences between them. The first relates to the handling of shipments and the second to the deterministic time-dependent collaborative capacities. In the first context, shipments are fixed

but are subject to entry and exit time thresholds. This allows us to capture the decision processes of load dispatchers with regard to meeting the shipment time windows over a collaborative network. The second aspect enables us to capture the combinatorial aspect of the DDS CCP routes over a time expanded graph.

To the best of our knowledge, no previous study has explicitly modeled a time-dependent carrier-carrier collaborative problem for the small- to medium-sized LTL industry. As discussed in Section 1, Hernandez and Peeta (2010) address carrier-carrier collaboration for small- to medium-sized LTL firms from a static perspective. It focuses on analyzing the influence of relevant factors on the potential for collaboration. The current study differentiates itself from Hernandez and Peeta (2010) and the previous studies discussed heretofore in terms of how shipments enter and exit the collaborative system and how combinatorial routes are captured in a dynamic context. While the planning-focused DDS CCP addressed in this study represents congestion effects through holding costs and assumes prior knowledge of the time-dependent collaborative capacities, it also provides a starting point to address the small- to medium-sized LTL collaborative paradigm in an operational context. For example, a rolling horizon method (Peeta and Mahmassani, 1995; Mitrović-Minić et al., 2004) can be used to operationally deploy the dynamic LTL carrier collaborative problem, as better estimates of the available collaborative capacities can be obtained closer to real-time.

3. Mathematical formulation of DDS CCP

3.1 Problem description and assumptions

The DDS CCP seeks to determine a time-dependent collaborative strategy for the carrier of interest by identifying a set of collaborative routes that minimize the total cost to service its

demand needs. Thereby, the carrier of interest may acquire some capacity from the collaborative partners for some legs of an origin-destination route based on the available time-dependent collaborative capacities. The operational networks of the various collaborating carriers can be completely identical geographically or overlap in some segments relative to the carrier of interest. The associated network characteristics include the available collaborative capacities and collaborative rates.

The following assumptions are made in the DDS CCP: (i) all carriers first utilize their available capacity before committing excess capacity for collaboration, (ii) the costs associated with loading/unloading a shipment (transfers) and the costs associated with the holding of a shipment at a transfer location (collaborative holding costs) are divided equally between the collaborative carriers and the carrier of interest, and (iii) transfer locations are capable of crossdocking operations. Further, the DDS CCP assumes that shipments are not split under the collaborative strategy: (i) a shipment is not split to multiple carriers during a transfer in a time period, and (ii) a shipment is not split to multiple truck routes (arcs) of the same carrier during a transfer in a time period.

3.2 Problem formulation

This section describes the mathematical programming formulation of the DDS CCP. The notation, constraints, and objective function are discussed, followed by the characterization of the formulation properties.

3.2.1 Sets

Let a shipment $k \in K$ be served in time interval $t \in T$ of the planning horizon (24-hour period) by a set of fixed transshipment facilities $i \in N$ (labeled facilities or nodes) which are interconnected by transit corridors $a \in A$ (labeled arcs). The transit corridors $a \in A$ that originate

from facility $i \in N$ are depicted as $a \in \Gamma(i)$ and those heading to facility $i \in N$ are $a \in \Gamma^{-1}(i)$. A shipment $k \in K$ may be served by a transit corridor $a \in A$ only through a collaborative carrier $q \in Q$ operating in this corridor in time interval $t \in T$. Fixed transshipment facilities $i \in N$ and collaborative carriers $q \in Q$ form our collaborative network. A shipment $k \in K$ enters the collaborative network through an origin facility $O(k)$ and exits through a destination facility $D(k)$. For a shipment $k \in K$, its origin facility $O(k)$ and its destination facility $D(k)$ constitutes its origin-destination pair.

3.2.2 Parameters

Each shipment $k \in K$ has an associated volume d_k , a latest entry time threshold β_k at its origin facility $O(k)$, and an earliest exit time threshold λ_k at its destination facility $D(k)$. The travel time of any shipment through transit corridor $a \in A$ is τ_a for all collaborative carriers $q \in Q$. The cost of acquiring a unit of capacity (volume) from a collaborative carrier $q \in Q$ on transit corridor $a \in A$ is the collaborative rate ς_{aq} . The functional form of the collaborative rate ς_{aq} is as follows:

$$\varsigma_{aq} = C_{TC} + C_{AC} \quad (1)$$

where C_{TC} represents the transfer cost per shipment d_k . In equation (1), C_{AC} denotes the per unit collaborative capacity acquisition cost as defined in Hernandez and Peeta (2010):

$$C_{AC} = (1 - \delta)L_a + S_a \quad (2)$$

where L_a represents the per unit linehaul cost for arc a , S_a represents the fuel surcharge cost for arc a , and δ represents the collaborative discount rate. The discount rate δ is associated only with the linehaul costs as in practice carriers do not discount the fuel surcharge costs which are usually a percentage of the non-discounted linehaul costs. We view δ as representing the degree of collaboration among the carriers. Hence, a larger δ value would imply a greater degree of

collaboration among the various carriers in terms of enabling the collaboration.

For each time interval a shipment in a facility $i \in N$ is not transshipped immediately (as in cross-docking operations) and held in the same facility for the next time interval, we assign a holding cost ϑ_i per time interval. As discussed in Section 1, the holding costs ϑ_i are assumed to vary for each facility $i \in N$. They are obtained using the ranges specified in Kawamura (1999) on the value of time per unit of shipment for LTLs. As stated in Section 3.1, they are divided equally between the carrier of interest and the collaborating carriers related to that transfer.

The available collaborative capacity of a carrier $q \in Q$ for transit corridor $a \in A$ at time interval $t \in T$ is w_{aqt} . If a collaborative carrier $q \in Q$ does not provide service for transit corridor $a \in A$, it is assumed that its available collaborative capacity w_{aqt} for that corridor is 0.

3.2.3 Variables

There are two set of decision variables. The first variable set models the shipments' entrance and exit in the collaborative network. If a shipment $k \in K$ enters the collaborative network from facility $i \in N$ in time interval $t \in T$ we define variable Φ_{kit} to take the value of 1, and 0 otherwise. If a shipment $k \in K$ exits the collaborative network from facility $i \in N$ in time interval $t \in T$ we define variable Θ_{kit} to take the value of 1, and 0 otherwise.

The second variable set represents the collaborative decision variables. If a shipment $k \in K$ is served through transit corridor $a \in A$ by collaborative carrier $q \in Q$ in time interval $t \in T$ we define Y_{kaqt} to take the value of 1, and 0 otherwise. If a shipment $k \in K$ is held in facility $i \in N$ in time interval $t \in T$ we define X_{kit} to take the value of 1, and 0 otherwise. It should be noted here that while holding of shipments at facilities entails costs, it may be required in the dynamic collaborative network to either establish the feasibility of transshipment or allow optimal routing of shipments in later time intervals when congestion effects are lower.

3.2.4 Modeling latest entry and earliest exit time widows

A key conceptual difference between the more conventional dynamic network problems and the problem addressed here is how shipments enter and exit the collaborative system for the carrier of interest. Conventional dynamic network problems treat shipments dynamically while holding arc capacities constant (Aronson, 1989; Hall et al., 2007). By contrast, in the DDS CCP the shipments d_k are fixed, but capacities are dynamic and known *a priori*. To ensure consistency with real-world freight operations, the shipments d_k are subject to thresholds on the latest entry into the carrier service network and the earliest exit from it to meet the shipment time windows associated with pickup and delivery, respectively. By introducing shipments into a time-expanded network in this manner, we are able to reduce the number of variables and constraints, entailing greater computational savings. This is because the number of time periods for a shipment to enter or exit a system is constrained by the time window thresholds $t: 1 \leq t \leq \beta_k$ and $t: \lambda_k \leq t \leq |T|$, respectively. From an operational perspective, this representation is important because we are now able to more closely model load dispatchers decisions when faced with the task of ensuring the timely routing of their shipments over a dynamic collaborative network. To illustrate this further, Fig. 1, 2, and 3 represent graphical depictions for the latest entry, intermediate, and earliest exit “flow” decisions through a time expanded network, respectively. They are discussed hereafter.

[Insert Fig. 1, 2 and 3]

3.2.4.1 Latest entry

Fig. 1 illustrates the dynamic graph representation of a shipment entrance decision under a latest entry time threshold $t: 1 \leq t \leq \beta_k$. A unit decision of “flow” Φ_{kit} enters the system in a time interval t subject to the latest time entry threshold $t: 1 \leq t \leq \beta_k$ via an origin facility

instantaneously. Further, this unit decision is either held X_{kit} at that facility or it is transshipped to the next facility through a collaborative carrier acquisition decision Y_{kaqt} . This represents the decision of the load dispatcher having received the shipment, and it either being held for some time period (that is, waiting to be loaded) until collaborative capacity is available or it being immediately assigned to an available collaborative carrier for further shipment. From a model formulation standpoint, using this explicit time-expanded approach reduces the problem computational complexity by circumventing the need for several more time-dependent entry time variables and the associated feasible search space.

3.2.4.2 Intermediate

Fig. 2 illustrates the dynamic graph representation of a shipment propagating through intermediate facilities. Here, shipment flow decisions propagate through the time-expanded graph and are either held (X_{kit}) at a facility or propagated through by collaborative carrier acquisition decisions (Y_{kaqt}).

3.2.4.3 Earliest exit

Fig. 3 illustrates the dynamic graph representation of a shipment exit decision under earliest exit time threshold $t: \lambda_k \leq t \leq |T|$. A unit decision of “flow” Θ_{kit} exits the system instantaneously in a time interval t subject to the earliest time exit threshold $t: \lambda_k \leq t \leq |T|$ in one of the following two ways. First, it may be an upstream-acquired collaborative capacity acquisition decision $Y_{kaq(t-\tau_a)}$ related shipment exit. Here, as stated in Section 3.2.2, τ_a represents the amount of time for the shipment to travel the length of the transit corridor a . Second, the exit may be from a holding decision X_{kit} , where the holding represents the waiting of a shipment to be unloaded due to congestion at the facility.

3.2.5 Constraints

Next, we formulate the constraint set of the DDS CCP. It consists of two sets of constraints. The first set of constraints (3, 4a, 4b, 4c, and 5) models the independent transshipment of shipments through the collaborative networks. The second set of constraints (6) establishes an upper bound on the available collaborative carrier capacity (in terms of volume).

The constraints are as follows:

$$\sum_{t:1 \leq t \leq \beta_k} \Phi_{kit} = 1 \quad \forall k \in K, i \in O(k) \quad (3)$$

$$-\sum_{q \in Q} \sum_{a \in \Gamma(i)} Y_{kaqt} - X_{kit} + \Phi_{kit} = 0 \quad \forall k \in K, i \in O(k), t \in T \quad (4a)$$

$$\sum_{q \in Q} \sum_{a \in \Gamma^{-1}(i)} Y_{kaq(t-\tau_a)} + X_{ki(t-1)} - \sum_{q \in Q} \sum_{a \in \Gamma(i)} Y_{kaqt} - X_{kit} = 0 \quad \forall k \in K, i \in N \setminus \{O(k), D(k)\}, t \in T, t \geq \tau_a \quad (4b)$$

$$\sum_{q \in Q} \sum_{a \in \Gamma^{-1}(i)} Y_{kaq(t-\tau_a)} + X_{ki(t-1)} - \Theta_{kit} = 0 \quad \forall k \in K, i \in D(k), t \in T, t \geq \tau_a \quad (4c)$$

$$\sum_{t:\lambda_k \leq t \leq |T|} \Theta_{kit} = 1 \quad \forall k \in K, i \in D(k) \quad (5)$$

$$\sum_{k \in K} d_k Y_{kaqt} \leq w_{aqt} \quad \forall a \in A, q \in Q, t \in T \quad (6)$$

$$\Phi_{kit}, \Theta_{kit}, X_{kit} \in \{0,1\} \quad \forall k \in K, i \in N, t \in T \quad (7)$$

$$Y_{kaqt} \in \{0,1\} \quad \forall a \in A, k \in K, q \in Q, t \in T \quad (8)$$

Constraints (3) to (5) are the mass balance constraints. Constraint (3) ensures that a shipment k enters the collaborative network at exactly one time instance while satisfying the latest entry time threshold β_k (as discussed in Section 3.2.4 and illustrated in Fig. 1).

Constraint (4) consists of three node flow propagation conservation constraints corresponding to the origin, intermediate, and destination nodes in the network, respectively. Constraint set (4a) corresponds to the origin nodes (facilities). It states that at most one unit of flow may enter an origin facility, and that it will either be serviced to the next facility or remain in the same facility for that time interval (as shown in Fig. 1). Constraint set (4b) is the mass

balance equation at intermediate nodes (at non-origin and non-destination facilities). The shipments at an intermediate facility may arrive from upstream facilities or may be held at that facility in the previous time interval. They can either be shipped out of the facility to a downstream facility or remain in the same facility for that time interval (as shown in Fig. 2). Constraint set (4c) corresponds to the destination nodes. A shipment may originate from an upstream facility that reaches the destination facility in this time interval or be held at the destination facility in the previous time interval. This shipment either exits from the network at this destination facility or is held in it for this time interval (as shown in Fig. 3). Constraint (5) ensures that a shipment k exits the collaborative network at exactly one time instance while satisfying the earliest exit time threshold λ_k (as discussed in Section 3.2.4 and illustrated in Fig. 3).

Constraint (6) represents the collaborative capacity constraints. It ensures that the capacity acquired from a collaborative carrier (left-hand side of (6)) is less than its time-dependent available capacity (right-hand side of (6)) on that transit corridor. Constraint sets (7) and (8) represent the 0-1 integrality conditions for the decision variables.

3.2.6 Objective function

The objective function of the DDSCCP problem seeks to minimize the total costs incurred by the carrier of interest and is represented as follows:

$$Min \sum_{k \in K} \sum_{a \in A} \sum_{q \in Q} \sum_{t \in T} \zeta_{aq} d_k Y_{kaqt} + \sum_{k \in K} \sum_{i \in N} \sum_{t \in T} \vartheta_i d_k X_{kit} \quad (9)$$

It consists of two terms. The first term represents the collaborative capacity acquisition costs, and the second term denotes the holding costs at the facilities. The overall acquisition costs are obtained as the summation of the product of the collaborative capacity acquisition rate ζ_{aq} , the demand d_k , and Y_{kaqt} (the decision on whether time-dependent capacity is acquired on a transit

corridor). The overall holding costs are obtained as the summation of the product of the holding costs ϑ_i for that facility, the demand d_k , and X_{kit} (the decision on whether this demand is held by this facility in this time interval). Hence, equation (9) subject to constraints (3) through (8) represents the formulation of the DDSCCP.

3.2.7 Properties

This section discusses some properties of the proposed DDSCCP formulation.

3.2.7.1 Classification

The proposed formulation of the DDSCCP belongs to the class of binary (0-1) multi-commodity minimum cost flow problems. This is because, as depicted in Fig. 1, 2, and 3, constraints (3) to (5) are node flow conservation constraints. They illustrate how a shipment will “flow” through a time-expanded network. The (static) nodes of this time-expanded network are the fixed transshipment facilities and the (static) arcs are collaborative carriers at each of the transit corridors. It can be noted that constraints (3) to (5) can be written independently for each shipment. Constraint set (6) is the equivalent shared capacity constraint, which binds the rest of the formulation together.

Due to the above mathematical structure, branch-and-cut algorithms can be applied to modest-sized problem instances (Mitchell, 2002), as is the case here since small- to medium-sized LTL carriers operate under modest collaborative network sizes. Another common approach to solve multi-commodity minimum cost flow problems is the Lagrangian relaxation method, especially for large problem instances (such as large operating networks) involving the shared capacity constraint (6). By dualizing this constraint, independent multiple minimum cost flow problems can be solved. However, due to the (0-1) binary nature of the formulation, this implies solving multiple independent shortest path problems. Other mathematical decomposition

methods have also been proposed for this class of problems (Ahuja et al., 1993; Martin, 1999).

3.2.7.2 The DDSCCP corresponding graphs are acyclic

The acyclic property is characteristic of time-expanded graphs. It is proved for the DDSCCP by contradiction. Assume that there is a directed cycle in the graph structure. The directed cycle will allow a flow to pass either from an X_{kit} or Y_{kaqt} arc twice in time interval $t \in T$. But the flow entering the X_{kit} or Y_{kaqt} arc arrives from previous time intervals and exits at later time intervals, which are exclusively connected by adjacent X_{kit} or Y_{kaqt} arcs following the single direction that time flows. Hence, a flow can never go back in time in order to re-enter the same X_{kit} or Y_{kaqt} arcs in time interval $t \in T$. This contradicts the initial assumption and completes the proof.

The physical interpretation is that there is no path in the corresponding graphs of the DDSCCP allowing a decision unit of capacity acquisition to return back in time. This property allows the implementation of the reaching shortest path algorithm for acyclic networks (Ahuja et al, 1993), which has a running time complexity of $O(|A|)$.

3.2.7.3 Total unimodularity

The DDSCCP formulation is characterized by total unimodularity, which guarantees optimum integer decision variable values. The proof for this guarantee is provided in Ahuja et al. (1993) as the DDSCCP is classified as a binary (0-1) multi-commodity minimum cost flow problem. This property enables the circumvention of much slower integer programming solution algorithms through the use of computationally less expensive linear programming techniques.

The total unimodularity property aids our problem in the following ways. First, in this study, we use the GAMS/CPLEX package to solve the DDSCCP. In the context, the branch-and-cut algorithm in GAMS/CPLEX is utilized which solves the linear program without the integer

constraints to obtain the optimal solution. The unimodularity property precludes the need for triggering the cutting plane algorithm here. Second, for larger problems instances' involving large networks, where decomposition methods may be appropriate (as discussed in Section 3.2.7.1), unimodularity helps in the context of the decomposition to multiple independent shortest path problems. Therefore, for each independent shortest path problem, the integrality constraints can be dropped and the problem can be solved using linear shortest path algorithms (like the reaching shortest past algorithm) to obtain integer 0-1 solution sets which satisfy the original integrality constraints.

Third, the total unimodularity property implicitly addresses the two key assumptions related to precluding the splitting of shipments as stated in Section 3.1. Constraints (3) to (5), along with integrality constraints (7) and (8), intrinsically ensure that a shipment is not split to multiple carriers during a transfer in a time period, and that a shipment is not split to multiple truck routes (arcs) of the same carrier during a transfer in a time period. Therefore, the following constraints, which would otherwise be required, are redundant:

$$\sum_{q \in Q} Y_{kaqt} \leq 1 \quad \forall a \in A, k \in K, t \in T \quad (10)$$

$$\sum_{a \in \Gamma(i)} Y_{kaqt} \leq 1 \quad \forall k \in K, i \in N, q \in Q, t \in T \quad (11)$$

4. Experiments

The study experiments analyze the performance of the DDSCCP model for various scenarios in terms of the numbers of shipments and network sizes. The performance is assessed in terms of the computational time required to solve the problems to optimality. In addition, experiments are conducted to explore the benefits of collaboration in a dynamic setting: (i) as a viable option to the non-collaborative strategy of short-term leasing, through varying degrees of

collaboration, and (ii) as a means to reduce the effects of holding costs.

4.1 Data generation

The data generated for this study closely follows the industry ranges introduced in Hernandez and Peeta (2010) for: (i) the collaborative rates from equation (1), (ii) the short-term leasing costs, (iii) the O-D demand for multiple O-D pairs, (iv) the collaborative capacities, and (v) the holding costs ϑ_i using the value of time ranges from Kawamura (1999) for commercial vehicle operations. A diesel fuel price of \$2.79 per gallon is assumed.

4.2 Solution and implementation details

The computing environment consists of a DELL XPS machine with an Intel Core™ 2 Duo processor T8300, under the Windows Vista™ operating system with 2.40GHz and 4GB of RAM. The GAMS/CPLEX optimization software version 22.9 with ILOG CPLEX 11.0 is used.

The binary (0-1) multi-commodity minimum cost flow problem representation of the DDSCCP is solved using the branch-and-cut algorithm (Caprara and Fischetti, 1997; Martin, 1999) in GAMS/CPLEX. This algorithm is used because the scope of the operations in this study represents that of the small- to medium-sized LTL carrier industry. That is, these carriers can be classified as local (carriers that typically operate within the confines of a state) or regional (carriers that typically operate between two or more states in a region), and may at most be associated with about a dozen or so transfer facilities (Belman and White III, 2005). Hence, their network sizes are modest. A network simplex (NS) method is used to exploit the inherent network structure of the DDSCCP and to provide the branch-and-cut algorithm with an initial solution (Ahuja et al., 1993; Hindim and Basta, 1994). This initial solution represents an optimal solution when the integrality constraints are relaxed for the DDSCCP problem, and is obtained before the branch-and-bound portion of the branch-and-cut algorithm is utilized. The optimal

initial solution is then used to initiate the branch-and-bound portion of the branch-and-cut algorithm. Also, the NS method is imbedded in the branch-and-cut algorithm and is used to determine the solutions for the subproblems in the fathoming and pruning portions after the algorithm has been initiated (Mitchell, 2002).

Similarly, initial solutions are also generated for the branch-and-cut algorithm through the use of the dual simplex (DS) method. As with the NS method, an optimal initial solution is obtained by relaxing the integrality constraints and using a DS method for the resulting linear program, which is then used to initiate the branch-and-cut algorithm. This DS method is also imbedded in the branch-and-cut algorithm and is used to solve the subproblems in the fathoming and pruning portions of the algorithm. The NS and DS based branch-and-cut algorithms are then compared. As discussed in Section 3.2.7, for larger and more complex LTL carrier operations, decomposition methods are expected to be more appropriate due to the added computational burden from larger operating networks and number of shipments.

4.3 Experiment setup

The experimental set up consists of the carrier of interest and four collaborating carriers, for a total of five collaborating carriers for the DDSCCP problem. The additional problem parameters take values according to the following ranges: network size in terms of the number of nodes (12 and 20), and the corresponding number of shipments (1, 5, 10, and 15), and (1, 5, 10, 15, and 20), respectively. The 12-node network represents the U.S. Midwest region, and the 20-node network was randomly generated using MATLAB as shown in Fig. 4. We use four degrees of collaboration, 0%, 30%, 50%, and 80%, to assess the viability of the collaboration. As the data is simulated, ten randomly generated data sets consistent with the small- to medium-sized LTL industry observed ranges are created for each test scenario (in terms of network size and number

of shipments). For each network size and number of shipment configuration, the collaborative rates and holding costs are identical in the randomly generated data. However, the demand and collaborative capacities are different for all cases.

[Insert Fig. 4]

5. Analysis of results

5.1 Collaboration versus short-term leasing option

The potential for collaboration among carriers is investigated by focusing on the level of monetary savings due to collaboration. As stated earlier, the level of collaboration is reflected through the degree of collaboration, which takes values 0%, 30%, 50% and 80%. Here, the 0% case represents a collaborative strategy in which the collaborative capacity is made available to the carrier of interest without any discount on the rate (Hernandez and Peeta, 2010). As seen in Table 1, even the 0% collaborative discount rate case for all scenarios led to savings over the short-term leasing option (which is the “no collaboration” case), indicating improved potential profits due to collaboration. Accordingly, the increased benefit under the higher discounted rates illustrates that higher discounted rates leads to greater operational efficiencies in terms of collaboration for the carrier of interest. Further, Table 1 illustrates that the cost to the carrier of interest increases with the number of shipments for both the collaborative and short-term leasing alternatives.

[Insert Table 1]

5.2 Effects of holding costs

Holding costs reduce the profits of the carrier of interest and can be attributed to waiting for a transfer to occur (queue at terminal) or to mechanical breakdowns. Table 2 illustrates the effect of holding costs on the carrier of interest as the degree of collaboration increases. This is

done by illustrating the holding costs as a percentage of the total collaborative costs. The results indicate that the holding costs incurred by the carrier of interest increase as the degree of collaboration increases. This is because the capacity acquisition costs decrease with the degree of collaborative due to the lower acquisition rates. Further, shipments may experience longer wait times in order to access more cost-attractive capacity. For the scenarios involving the 12-node network with 5 shipments, and 20-node network and 1 shipment, the percentage holding costs for each level of collaboration are relatively higher. This is attributed to the higher randomly generated values of the holding costs for these scenarios. Additionally, lower holding costs imply greater efficiency for the collaborative system. As seen in Table 2, even if the carrier of interest takes advantage of an 80% discount in collaboration, inefficiencies may occur due to the increased holding times. However, in most instances, the holding times for the collaborative discount scenarios represent a significant improvement over the values observed by Bartholdi and Gue (2000) of about 21.8%, who focus on improving terminal design to decrease holding time for LTLs.

[Insert Table 2]

Table 3 shows the average number of holding time periods for each arc that comprises the optimal collaborative route for each test scenario. The average number of holding time periods ranges from 1.01 to 1.24. The results illustrate that carrier collaboration can conceivably reduce the effects of delays by decreasing the amount of time spent idled at terminals, which can potentially be achieved by the adoption of crossdocking practices by these terminals (Bartholdi and Gue, 2000) .

[Insert Table 3]

5.3 Capacity utilization

Table 4 illustrates the capacity utilization by the carrier of interest as a percentage of the available capacity from the collaborating carriers. The values represent the average over ten runs conducted for each scenario consisting of the network size and number of shipments. The utilization percentages range from 48% to 61%. The results indicate the potential for carriers to reduce deadheading and produce returns on excess capacity, which is vital for the survivability of small- to medium-sized LTL carriers in a highly competitive industry.

[Insert Table 4]

5.4 Computational experience

Table 5 summarizes the CPU computational times for the optimal solutions obtained through the DS and NS based branch-and-cut algorithms. The computational times increase with the number of shipments and the network size. Optimality for each scenario was achieved through the DS and NS based branch-and-cut algorithms, and the solutions are identical irrespective of the method. However, as seen in Table 5, the DS and NS based branch-and-cut algorithms differ in the amount of time taken to reach an optimal solution for all scenarios.

[Insert Table 5]

This is further reinforced by Fig. 5 and 6, which illustrate the CPU computational times for the optimal solutions obtained through the DS and NS based branch-and-cut algorithms under the 12- and 20-node network configurations. They indicate that the NS initial solutions and solutions obtained for the fathoming and pruning segments provided to the branch-and-cut algorithm require lesser time to solve the DDS CCP as the number of shipments increases, as reflected by the substantial decrease in computational times over the DS based branch-and-cut algorithm. The significantly lower computational times under the NS based branch-and-cut algorithm are a direct result of the NS method exploiting the underlying network structure of the

problem by taking advantage of the unimodularity property (as discussed in Section 3.2.7.3) when the integrality constraints are relaxed (Ahuja et al., 1993).

[Insert Fig. 5 and 6]

6. Concluding comments

The contributions of the paper to the literature are twofold. First, this paper proposes a deterministic dynamic single carrier collaboration problem (DDSCCP) that provides a mechanism to analyze the potential benefits of carrier-carrier collaboration for the small-to-medium-sized LTL industry by analyzing the effects of dynamic collaborative capacity and system delays. Second, addressed from a planning perspective, the DDSCCP assumes that the time-dependent collaborative capacities are known *a priori*, and demand is fixed but subject to latest entry and earliest exit time thresholds consistent with LTL carrier operational networks. By viewing demand in this manner, we can model how load dispatchers make shipment decisions when faced with the task of ensuring the timely routing of their loads over a dynamic collaborative network. To the authors' knowledge, this represents the first time that both these aspects have been addressed in the literature. In addition, the DDSCCP problem seeks to leverage advances in ICT technologies to manage excess capacity made available by partner carriers so as to address the issue of deadheading. Practices such as crossdocking in turn synergistically aid the collaboration paradigm by reducing system delays through improved delivery times.

A binary (0-1) multi-commodity minimum cost flow problem is presented for the DDSCCP, and solved using a branch-and-cut algorithm. A network simplex (NS) method is used to exploit the inherent network structure of the binary (0-1) multi-commodity minimum cost flow problems and to provide initial solutions to initiate the branch-and-cut algorithm and to also

solve the subproblems for the fathoming and pruning segments of the branch-and-cut algorithm. The performance of the NS-based and DS-based branch-and-cut algorithms is compared. Significant computational gains are obtained using the NS-based branch-and-cut algorithm relative to the DS-based branch-and-cut algorithm in that the NS method leverages the underlying network structure of the problem. This approach is sufficient to address carrier collaboration in the small- to medium-sized LTL carrier networks due to their modest geographical extent of operation.

The study results indicate that holding costs are a key factor for the carrier of interest to consider while forming the collaborative routes. That is, the carrier of interest has to consider the inherent trade-offs at the higher degrees of collaboration in terms of waiting for more affordable collaborative capacity and incurring higher holding costs. The study insights suggest that further improvement can be made through the common adoption of crossdocking practices. The results further indicate that as the degree of collaboration increases, the relative attractiveness of acquiring collaborative capacity also increases compared to the short-term leasing option, leading to increased capacity utilization. In summary, the study illustrates that carrier collaboration can be a viable strategy for reducing the effects of delays in a highly competitive industry where time has a direct impact on profits. To our knowledge, this is the first attempt to formulate a LTL carrier collaboration strategy which accounts for the effects of holding costs on LTL carrier collaboration from the perspective of small- to medium-sized LTL trucking firms.

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Table 1.

Comparison of short-term leasing (no collaboration) and carrier-carrier collaboration considering the effects of holding costs

Network size			Collaborative cost (\$)				Percentage savings over no collaboration				
Number of nodes	Number of arcs	Number of Shipments	No collaboration (\$)	Percentage degree of collaboration				Percentage degree of collaboration			
				0%	30%	50%	80%	0%	30%	50%	80%
12	29	1	1171	1156	909	679	559	1.34%	21.34%	41.27%	51.67%
		5	9050	8765	7507	5444	4618	3.25%	14.35%	37.89%	47.31%
		10	17584	16799	13540	10209	8510	4.67%	19.40%	39.23%	49.34%
		15	21816	21230	17366	13303	10581	2.76%	18.20%	37.34%	50.16%
20	55	1	1283	1267	1109	942	859	1.23%	12.45%	25.67%	32.21%
		5	5650	5569	4808	3823	3247	1.45%	13.67%	31.36%	41.70%
		10	10975	10832	8944	7642	6153	1.32%	17.43%	29.45%	43.20%
		15	17067	16721	14101	10850	8661	2.07%	15.67%	35.11%	48.20%
		20	24273	23414	18366	14439	12592	3.67%	21.56%	38.33%	46.22%

Table 2.
Effect of holding costs on collaborative costs for the carrier of interest

Network size			Holding costs as percentage of total collaborative costs			
Number of nodes	Number of arcs	Number of Shipments	Percentage degree of collaboration			
			0%	30%	50%	80%
12	29	1	9.08%	11.55%	15.47%	18.79%
		5	15.19%	17.73%	24.45%	28.82%
		10	12.32%	15.29%	20.28%	24.32%
		15	11.52%	14.08%	18.39%	23.12%
20	55	1	18.15%	20.73%	24.42%	26.78%
		5	7.27%	8.42%	10.59%	12.47%
		10	9.50%	11.50%	13.47%	16.72%
		15	9.18%	10.89%	14.15%	17.72%
		20	8.86%	11.30%	14.37%	16.48%

Table 3.

Average number of holding time periods for each arc that comprise the optimal collaborative route

Network size			
Number of nodes	Number of arcs	Number of Shipments	Average number of holding time periods for each arc
12	29	1	1.04
		5	1.14
		10	1.20
		15	1.24
20	55	1	1.19
		5	1.01
		10	1.07
		15	1.07
		20	1.04

Table 4.
Percentage collaborative capacity utilization

Number of nodes	Number of arcs	Number of Shipments	Average percentage collaborative capacity utilization
12	29	1	48%
		5	51%
		10	47%
		15	60%
20	55	1	51%
		5	48%
		10	50%
		15	54%
		20	61%

Table 5.

DS and NS based branch-and-cut algorithm optimal solution computational time results for the 12-node and 20-node networks

Network size			Optimal solution times	
Number of nodes	Number of arcs	Number of Shipments	DS (seconds)	NS (seconds)
12	29	1	1.34	0.36
		5	178.32	8.77
		10	789.63	201.93
		15	3175.30	678.21
20	55	1	1.49	0.56
		5	55.78	21.34
		10	334.77	67.89
		15	6269.72	468.34
		20	13564.52	1462.67

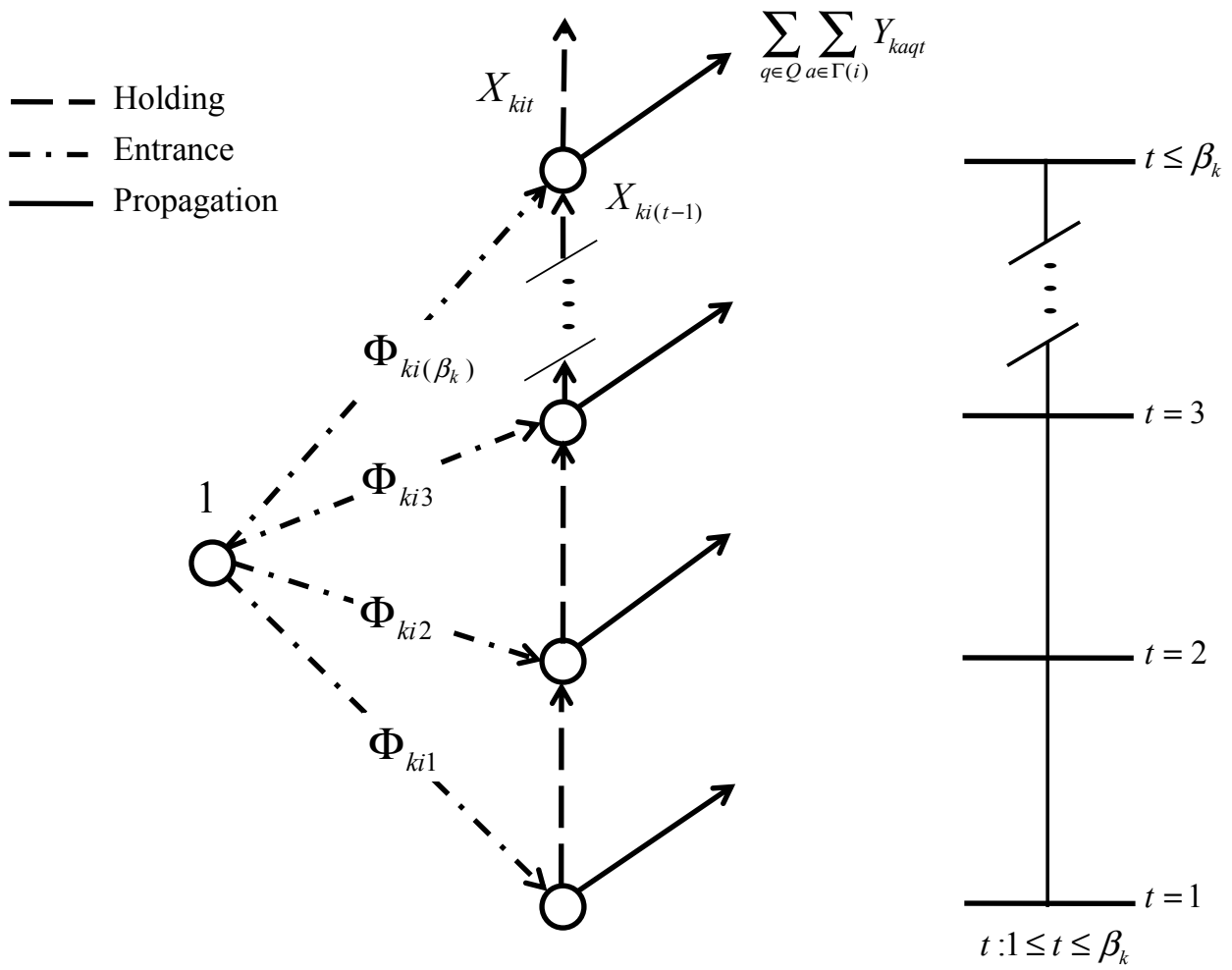


Fig. 1. Dynamic graph representation of shipment entrance decision with latest entry time threshold

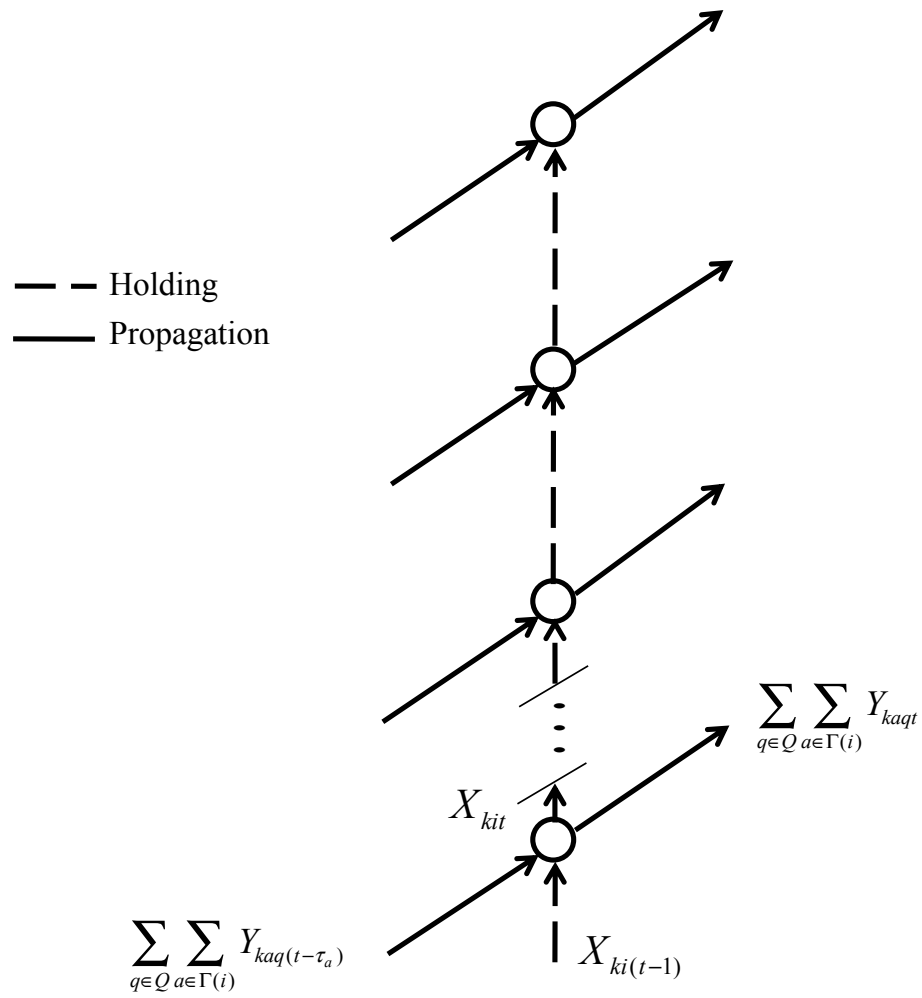


Fig. 2. Dynamic graph representation of shipment propagating through intermediate facilities

- — Holding
- . - Exit
- Propagation

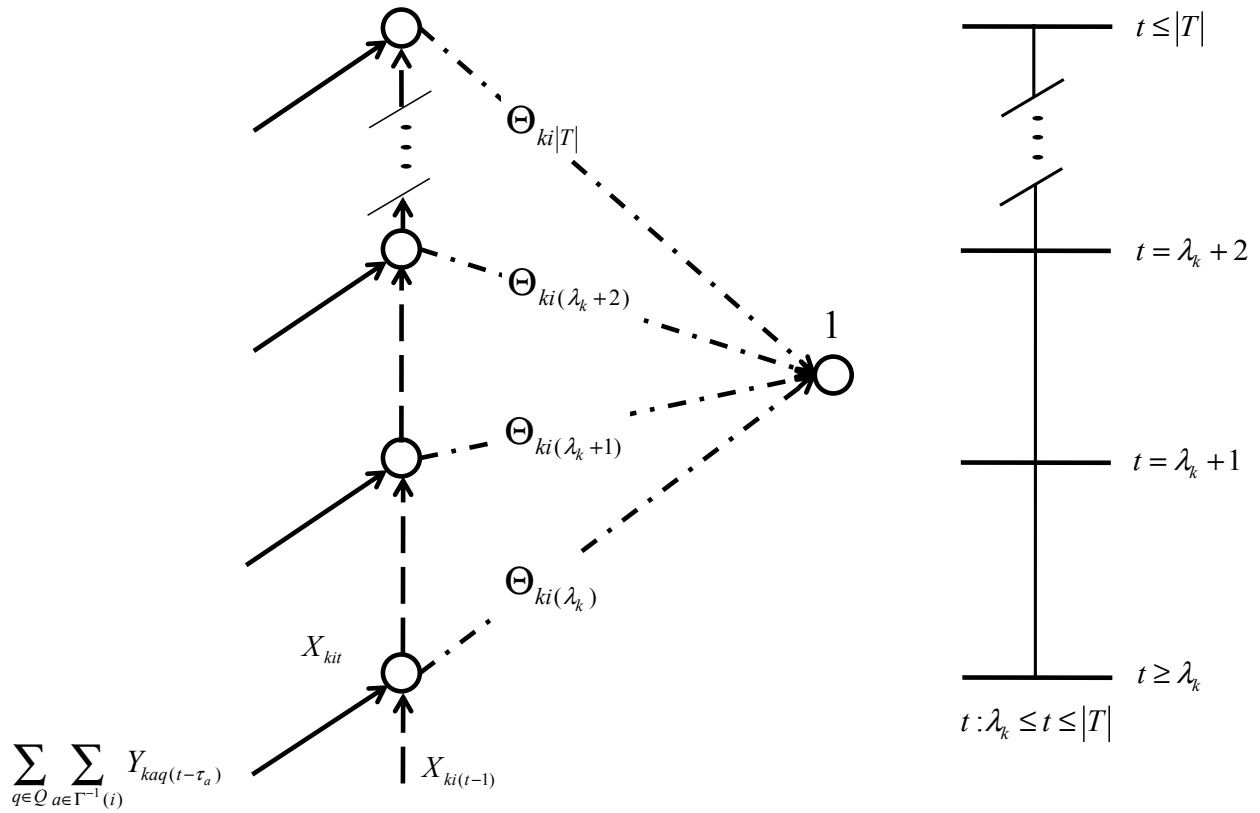
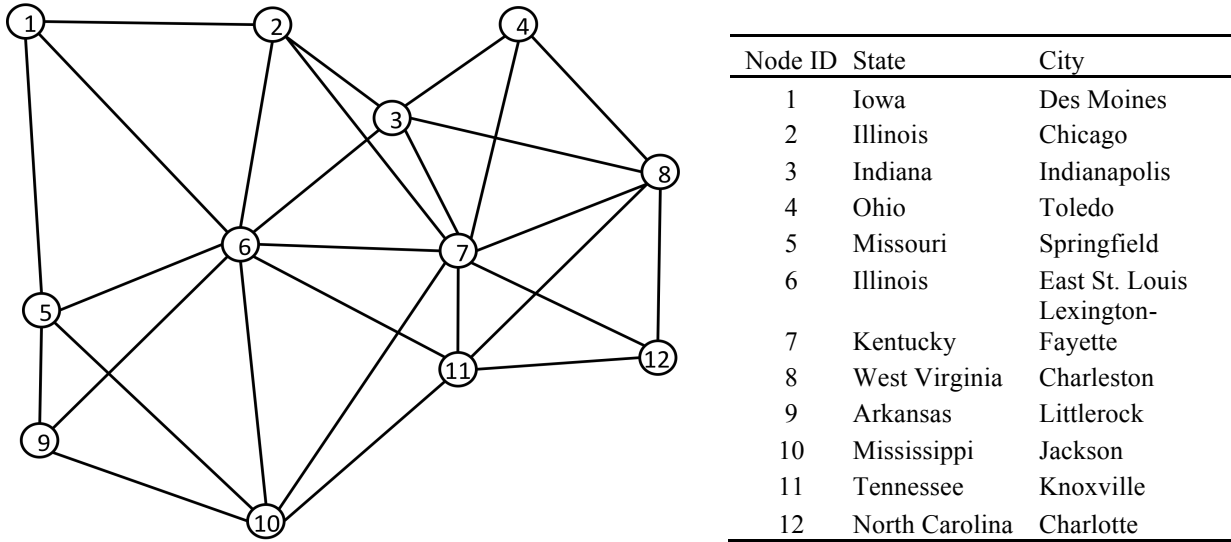
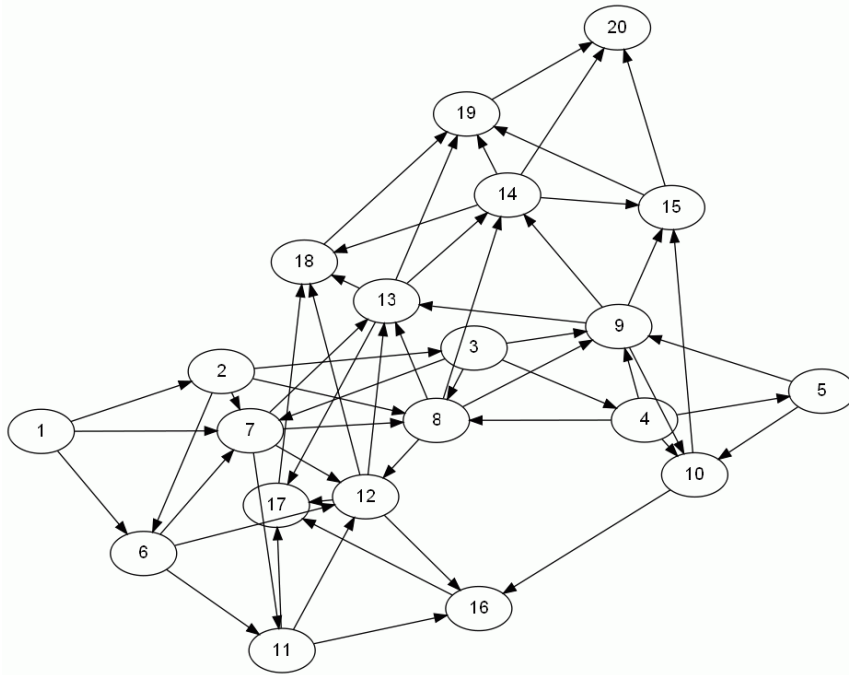


Fig. 3. Dynamic graph representation of shipment exit decision with earliest exit time threshold



(a)



(b)

Fig. 4. Physical representation of: (a) the 12-node network representing the U.S. Midwest, and (b) the randomly generated 20-node network using MATLAB

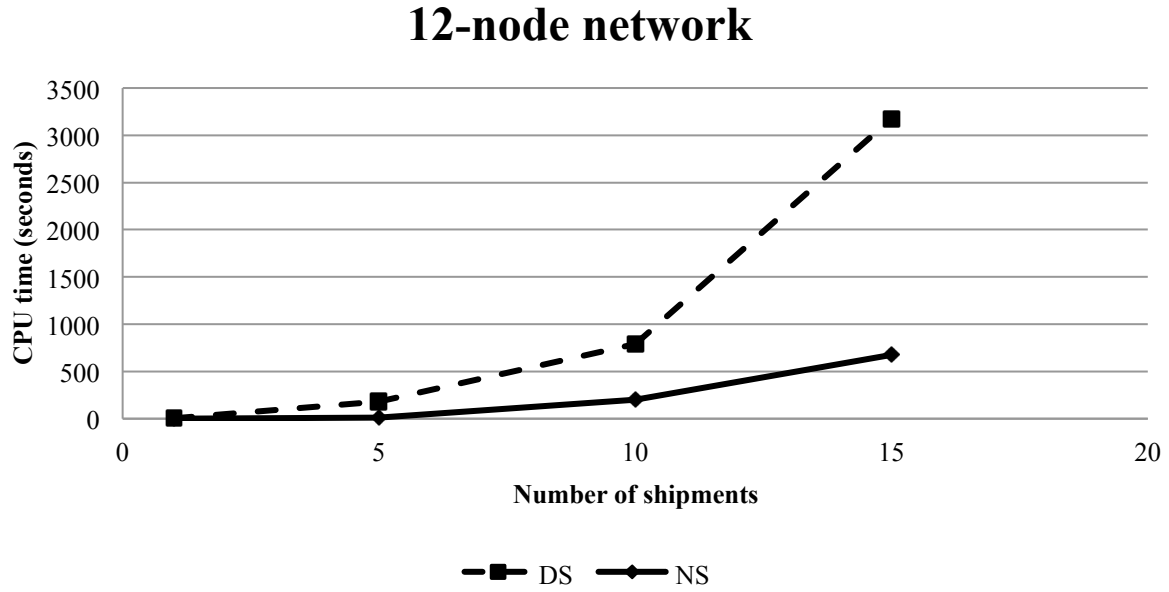


Fig. 5. Comparison of the computational performance for the 12-node network for the DS and NS based branch-and-cut algorithms

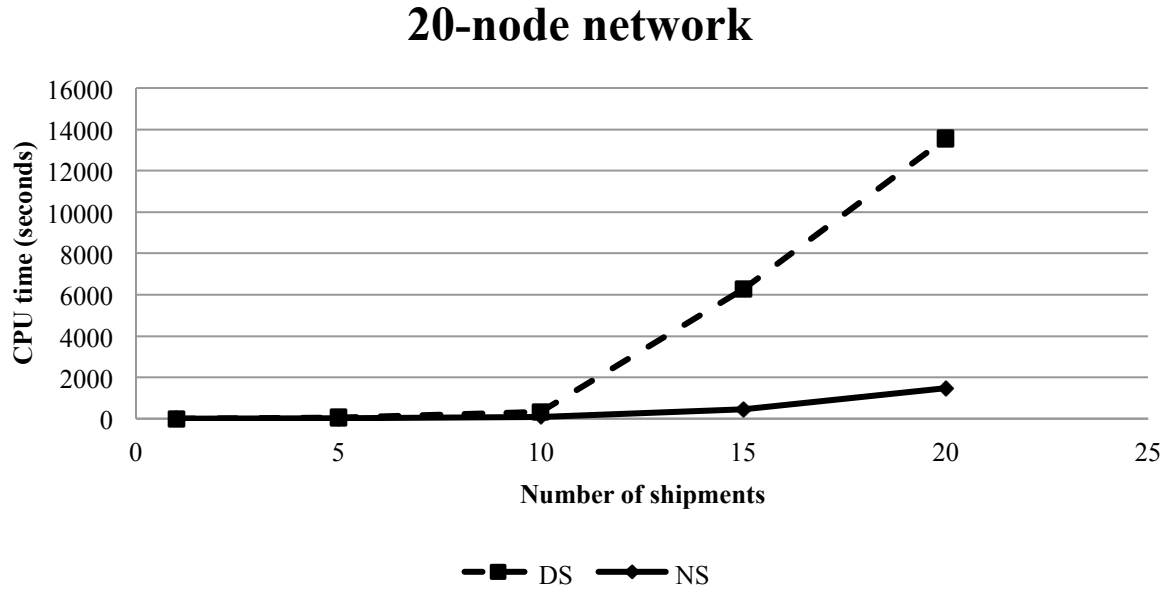


Fig. 6. Comparison of the computational performance for the 20-node network for the DS and NS based branch-and-cut algorithms