Capacitated Centralized Carrier Collaboration Multihub Location Problem

Tabu Search Approach

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This study proposes a capacitated centralized carrier collaboration multihub location problem (CAP-CCCMLP) for the small- to medium-sized less-than-truckload industry, with a central entity (e.g., a third-party logistics firm) seeking a set of hybrid collaborative consolidation transshipment hubs to help establish a collaborative hybrid hub-and-spoke network that minimizes the total collaborative costs for the set of collaborating carriers in the system. A mathematical programming formulation is provided for the CAP-CCCMLP and shown to be NP-hard. The model was solved with two-phase tabu search heuristics. Computational runs were conducted to study the efficiency of the tabu search heuristic versus the CPLEX-based solution and the savings obtained through collaboration for different network sizes and maximum number of consolidation hubs. The tabu search heuristic was found to deliver significant computational savings over CPLEX and the optimality gap between the true optimal solution and the tabu search solution was found to be low for most cases. As the expected cost reduction at the shipment level needed to incentivize collaboration decreases, the likelihood that carriers will enter into collaboration increases. If the carriers expect significant cost reductions to enter into a collaborative strategy, the potential savings from the collaboration will decrease.

Developments in information technology, online marketplaces, globalization, and new practices such as just-in-time inventory have led to more geographically and temporally dispersed freight loads (*1*). Meeting the demands of the spatially spread loads combined with increased fuel costs has led to reduced profits for the small- to medium-sized less-than-truckload (LTL) operators. Moreover, a significant number of LTL trips do not utilize the full truck capacity. According to the American Trucking Associations, in February 2008 nearly 28.6% of the total miles traveled by trucks operated by small trucking companies were classified as zero loads. A large fraction of these zero loads were attributed to the LTL industry, which moves loads through a network of warehouses, depots, and distribution centers with shipment sizes that vary from a few hundred pounds to roughly 50,000 lb. Collaboration has the potential to improve operational efficiency (e.g., through increased capacity utilization) and reduce supply chain costs, especially for the small- to medium-sized LTL trucking industry. Several studies have been conducted on collaboration from the perspective of this industry (*2–6*). However, these earlier studies concentrated on identifying collaborative opportunities through routing and increased truck capacity utilization.

More recently, Hernández et al. introduced a centralized carrier collaboration multihub location problem (CCCMLP) for the small- to medium-sized LTL industry in which the CCCMLP represented a strategy in which a central entity (e.g., a third-party logistics firm) sought a set of hybrid collaborative consolidation transshipment hubs to help establish a collaborative hybrid hub-and-spoke network that minimized the total collaborative costs for the set of collaborating carriers in the system (*7*). As with previous work on carrier collaboration, Hernández et al. also focused on the LTL industry, but the work differed from earlier work in that the authors also focused on transfer locations rather than simply identifying potential collaborative routes. These transfer locations (or hybrid hubs) were assumed to be uncapacitated.

In this study, the recent work of Hernández et al. is extended in two directions (*7*). In this study, the transshipment facilities are assumed to be capacitated. Also, every collaborative carrier will incur a fixed cost for a hub only if the hubs are used to transport the carrier's goods in the collaborative freight network. Similar to the study by Hernández et al., the current study assumes a homogenous fleet that handles a single product type (*7*). The capacitated CCCMLP (CAP-CCCMLP) is addressed from the perspective of long-term strategic planning. Thus the demand, transshipment facility capacities, and carrier collaborative rates are known a priori. A unit holding cost is used to capture the hub-associated delays. The rate setting behavior of the carriers is assumed to follow that presented by Hernández and Peeta (*3*). The recent study by Hernández et al. solved the CCCMLP by using a Lagrangian relaxation–based approach (*7*). In addition to the complexity of the problem, a tabu search approach is introduced that exploits the characteristics of the CAP-CCCMLP by allowing for larger problem instances to be considered.

LITERATURE REVIEW

In recognition of the potential of collaboration in reducing system-wide transportation costs, a number of optimization and game-theoretical-based frameworks were developed in the past 10 years to model collaborative decision making among various freight

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transportation agents. Fischer et al. developed a distributed artificial intelligence–based framework to enable dynamic replanning and collaboration among various freight agents (*8*). Figliozzi and Figliozzi et al. developed and evaluated several dynamic auction-based mechanisms for truckload acquisitions in an electronic marketplace (*9, 10*). Song and Regan demonstrated through simulations of a transportation marketplace that a combinatorial auction strategy can benefit both shippers and carriers in the truckload industry (*11*). Krajewska and Kopfer applied principles of combinatorial auctions and cooperative game theory to aid cooperation among freight forwarders (*12*). Ergun et al. developed an optimization model and heuristic solution algorithms that can be used by shippers to identify load sequences that lead to continuous truckload tours resulting in reduced deadheading or zero load trips (*13, 14*). Agarwal and Ergun developed mathematical models based on principles of cooperative game theory to incentivize alliance formation among carriers in the liner shipping industry (*15–17*). Houghtalen et al. extended the foregoing work to determine capacity exchange prices by using inverse optimization and cooperative game theory to promote collaboration among air cargo carriers (*18*). Lei et al. studied the benefit of collaborative vessel scheduling from a shipping company perspective and showed that collaboration can lead to reduced costs if all participating carriers are fully committed to sharing demand and resources (*19*). Audy et al. investigated several cost allocation mechanisms to promote collaboration and reduce transportation costs in the wood industry (*20*). Kuo et al. evaluated three collaborative decision-making strategies for effective utilization of capacity in rail-based intermodal freight corridors and showed that collaboration can lead to significant benefits (*21*).

From the perspective of LTL carrier collaboration, Bailey et al. recently developed two models for minimizing backhauls through freight collaboration for small- to medium-sized LTL carriers (*2*). In this work, freight agents attempt to minimize deadheading by making extra pickups and deliveries and sharing the revenue with their collaborators during their backhaul. Hernández and Peeta and Hernández et al. explored the benefits of different levels of collaboration and rate-setting strategies for a single carrier and a centralized planning perspective for multiple carriers (*3, 4, 6*). Liu et al. (*5*), Dai and Chen (*22*), Voruganti et al. (*23*), and Xu et al. (*24*) developed various cost allocation mechanisms for LTL carriers in a collaborative setting. To the best of the authors' knowledge, the work by Hernández et al. (*7*) was the first that focused on locating collaborative hubs to aid consolidation of loads for small- to medium-sized LTL carriers. The current work differs from the work by Hernández et al. in the following manner: (*a*) transshipment hubs are capacitated and (*b*) the carrier will bear the fixed cost of using the hub only if the hubs are used to transport the carrier's shipment (*7*).

Since the mathematical model of the current work is a hub location problem, a brief review of hub location models is provided next. O'Kelly (*25, 26*) provided the first integer quadratic formulation for the hub-and-spoke network design problem, which was subsequently linearized by Campbell (*27, 28*). Ernst and Krishnamoorthy developed an efficient reformulation that minimized the number of variables used (*29, 30*). Different variants of those models have been studied, such as those that account for hub capacities (*31, 32*), hub as well as edge capacities (*33*), uncapacitated hubs (*34, 35*), and hub congestion (*36–38*). The techniques used to solve the hub-and-spoke location problems include Lagrangian relaxation (*39, 40*), branch and bound (*31*), Benders decomposition (*38*), and metaheuristics like genetic algorithms and tabu search (*35, 41*). Alumur and Kara (*42*), Campbell and O'Kelly (*43*), and Farahani et al. (*44*) provide a comprehensive review of the hub location problem and its variants. The current work is unique for hub location literature since it studies a capacitated hub location problem from a collaborative perspective in which carriers have the option of not using the hubs to transport their goods. An efficient tabu-search-based solution procedure is used to determine the location of the hubs.

MATHEMATICAL MODEL OF CAP-CCCMLP

Problem Description

The goal of the CAP-CCCMLP is to determine a set of consolidation transshipment hubs in a collaborative freight network comprising geographically dispersed carriers and managed by a central entity like a third-party logistics firm. The objective of the CAP-CCCMLP is to minimize the total collaborative system costs. The freight transport networks of the carriers may or may not overlap. The transshipment hubs will help in reducing the overall transportation costs through consolidation. Every carrier whose shipments use a specific transshipment hub will have to bear a fixed cost. The carrier will have the option of transporting the goods directly to the destination if the collaborative routing strategy does not deliver significant benefits.

The CAP-CCCMLP differs from the CCCMLP in the following manner: (*a*) transshipment hubs are capacitated and (*b*) the carrier will bear the fixed cost of using the hub only if the hub is used to transport the carrier's shipment (*7*). Similar to the CCCMLP, the CAP-CCCMLP assumes that homogenous products are shipped and all parameters such as demand and holding times are deterministic.

Notation

The mathematical formulation of CAP-CCCMLP is described in this section. Q, I, J, and N denote, respectively, the set of carriers, the set of origin nodes where the shipment enters the collaborative network, the set of destination nodes where the shipment leaves the collaborative network, and the set of nodes. The origin and destination nodes can represent a supplier, distribution center or warehouse, or retailer. A shipment from collaborative carrier $q \in Q$ either enters the collaborative network through an origin node $i \in I \subseteq N$ and travels via collaborative transshipment hubs $l, m \in N$ and exits through a destination facility $j \in J \subseteq N$ or is routed directly from origin facility $i \in I \subseteq N$ to destination node $j \in J \subseteq N$ without consolidation.

The demand to be transported from origin node $i \in I \subseteq N$ to destination node $j \in J \subseteq N$ by carrier $q \in Q$ is denoted d_{ijq}; ς_{ijlm} is the collaborative transportation costs associated with a unit of demand for carrier $q \in Q$ to travel between origin node $i \in I$ to destination node $j \in J$ via hybrid collaborative transshipment facilities at node $l \in N$ and $m \in N$. A revenue-oriented cost structure is followed (*3*):

$$\varsigma_{ijlm} = \varsigma_{il} + \delta\varsigma_{lm} + \varsigma_{mj} \tag{1}$$

In Equation 1, ς_{il}, ς_{lm}, and ς_{mj} represent the cost of transporting a unit of demand from origin node $i \in I$ to collaborative transshipment facility $l \in N$, from collaborative transshipment facility $l \in N$ to collaborative transshipment facility $m \in N$, and from collaborative transshipment facility $m \in N$ to destination node $j \in J$, respectively. In Equation 1, δ represents the collaborative discount parameter (between 0 and 1) between consolidation collaborative transshipment facilities $l, m \in N$ and is composed of transfer rates per shipment and line-haul costs (*3*).

The fixed cost to carrier $q \in Q$ for using the collaborative consolidation hub at location $l \in N$ is denoted φ_{lq}, and U_l denotes the available capacity at the consolidation hub at location $l \in N$. The maximum number of collaborative consolidation facilities to be established is p. The cost of moving a unit demand from origin node $i \in I$ to destination node $j \in J$ directly for carrier $q \in Q$ is denoted w_{ijq}. In the problem variant studied here, a shipment enters a collaborative network only if there is a significant savings obtained through consolidation. The parameter r captures the cost reduction expected at a shipment level for the carrier to consider consolidation worthwhile.

There are four decision variables. The decision variable Y_{ijlmq} takes the value 1 if a shipment originating from origin $i \in I$ headed to destination $j \in J$ by collaborative carrier $q \in Q$ travels via consolidation hubs at nodes $l \in N$ and $m \in N$, and 0 otherwise. This binary variable captures whether a shipment is routed through a consolidation hub. The problem formulation uses one more binary decision variable, which captures whether a shipment is routed directly to the destination. The decision variable V_{ijq} takes the value 1 if a shipment from origin $i \in I$ headed to destination $j \in J$ by carrier $q \in Q$ is shipped directly, and 0 otherwise. The next decision variable captures whether a facility is used by a carrier for consolidation. The decision variable Z_{lq} takes the value 1 if a carrier $q \in Q$ uses the facility at node $l \in N$ to consolidate and route the shipment, and 0 otherwise. The decision variable X_l takes the value 1 if the facility at node $l \in N$ is used by any carrier to consolidate, and 0 otherwise.

Problem Formulation

The integer formulation of the CAP-CCCMLP seeks to minimize the total collaborative system costs. The decision variables are Y_{ijlmq}, V_{ijq}, Z_{lq}, and X_l. The formulation is as follows:

$$\min \sum_{i\in I}\sum_{j\in J}\sum_{l\in N}\sum_{m\in N}\sum_{q\in Q} \varsigma_{ijlm} d_{ijq} Y_{ijlmq} + \sum_{i\in I}\sum_{j\in J}\sum_{q\in Q} w_{ijq} d_{ijq} V_{ijq} + \sum_{l\in N}\sum_{q\in Q} \varphi_{lq} Z_{lq} \tag{2}$$

$$\sum_{l\in N} X_l \le p \tag{3}$$

$$\sum_{l\in N}\sum_{m\in N} Y_{ijlmq} + V_{ijq} = 1 \qquad \forall i \in I;\ j \in J;\ q \in Q \tag{4}$$

$$\sum_{m\in N} Y_{ijlmq} \le X_l \qquad \forall i \in I;\ j \in J;\ l \in N;\ q \in Q \tag{5}$$

$$\sum_{l\in N} Y_{ijlmq} \le X_m \qquad \forall i \in I;\ j \in J;\ m \in N;\ q \in Q \tag{6}$$

$$\varsigma_{ijlm} Y_{ijlmq} \le w_{ijq}\left(1 - V_{ijq}\right)(1-r) \qquad \forall i \in I;\ j \in J;\ l \in N;\ m \in N;\ q \in Q \tag{7}$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{q\in Q} d_{ijq} Y_{ijllq} + \sum_{i\in I}\sum_{j\in J}\sum_{m\in N}\sum_{q\in Q}\left(d_{ijq} Y_{ijlmq} + d_{ijq} Y_{ijmlq}\right) \le U_l X_l \qquad \forall l \in N \tag{8}$$

$$\sum_{i\in I}\sum_{j\in J} d_{ijq} Y_{ijllq} + \sum_{i\in I}\sum_{j\in J}\sum_{m\in N}\left(d_{ijq} Y_{ijlmq} + d_{ijq} Y_{ijmlq}\right) \le \left(\sum_{i\in I}\sum_{j\in J} d_{ijq}\right) Z_{lq} \qquad \forall q \in Q;\ l \in N \tag{9}$$

$$Z_{lq} \le X_l \qquad \forall q \in Q;\ l \in N \tag{10}$$

$$X_l \in \{0,1\} \qquad \forall l \in N \tag{11}$$

$$Z_{lq} \in \{0,1\} \qquad \forall q \in Q;\ l \in N \tag{12}$$

$$Y_{ijlmq} \in \{0,1\} \qquad \forall i \in I;\ j \in J;\ l \in N;\ m \in N;\ q \in Q \tag{13}$$

$$V_{ijq} \in \{0,1\} \qquad \forall i \in I;\ j \in J;\ q \in Q \tag{14}$$

The objective function, Equation 2, comprising three terms, seeks to minimize the total collaborative transportation costs in the system. The first term represents the total collaborative carrier transportation costs, the second represents the total costs associated with carriers shipping directly, and the third represents the total collaborative consolidation facility location costs.

Constraint 3 restricts the number of candidate collaborative consolidation hubs to be less than or equal to a prespecified number. Constraint 4 ensures that a shipment corresponding to every origin–destination pair and every carrier is either assigned to one consolidation hub pair or transported directly without participating in the collaboration. Since l may equal m under this constraint, the possibility that the shipment between origin–destination pair (i, j) may only go through a single hub is not precluded. Constraint Sets 5 and 6 ensure that shipments are not assigned to a hub that is not located or opened. Constraint 7 states that a specific carrier will participate in the collaboration only if the collaborative routing costs through the hubs are lower than the direct shipment costs by a reasonably significant margin. Constraint 8 ensures that the volume of goods routed through a collaborative consolidation hub is less than the total capacity of the hub. Constraint 9 ensures that a carrier is associated with a consolidation hub only if a carrier uses that hub to transport shipments. Constraint 10 ensures that a hub is opened if any carrier in the system seeks to open the hub. Constraint Sets 11 through 14 represent the 0-1 integrality conditions for the decision variables.

Properties

From a hub location perspective the CAP-CCCMLP is a single-allocation formulation since every load d_{ijq} is either assigned to a single hub or routed directly. Single-allocation problems are tougher to solve than multiple-allocation problems (*42*). The mathematical programming structure of the CAP-CCCMLP is closest to a P-hub median location problem (*45*). Constraints 3, 4, 5, 6, 8, 11, and 13 without the variable V_{ijq} (the decision on whether to ship directly) are reduced to a capacitated P-hub median problem. P-hub median problems are NP-hard because the network and number of hubs increase (i.e., for $p > 2$) (*45, 46*). Hence, a solution methodology based on tabu search is proposed to solve this problem (*47, 48*).

SOLUTION METHOD

In this study a two-phase solution heuristic using the principles of the tabu search framework is adopted to solve the CAP-CCCMLP. An initial feasible solution is constructed in Phase 1 and improved in Phase 2. The two-phase approach has been found to be efficient in solving complex combinatorial freight optimization problems (*49*).

First an overview of the tabu search procedure is provided followed by the description of the two-phase heuristic.

Tabu Search

Tabu search (*47, 48*) is a metaheuristic that is intended to overlay a core search heuristic and seeks to help heuristics break out of local optima and explore other regions of the solution space. The basic tabu search employs tabu restrictions that inhibit certain moves and aspiration criteria that allow very good solutions to overcome any tabu status. The tabu restrictions are generally implemented with a short-term memory function to make them time dependent. Designing tabu search heuristics involves defining what types of moves to restrict and the nature of the aspiration criteria and short-term memory to utilize. In addition to these features, most tabu search designs include other strategies such as a long-term memory function to diversify the search into other areas of the solution space. A generic overview of the tabu search is as follows:

Step 1. Initialize the parameters associated with the tabu search. The common parameters are tabu list size, memory size, incumbent solution, and the maximum number of iterations.

Step 2. Generate a candidate list of moves or potential new solution from the current solution. The details of the moves are provided in the next subsection.

Step 3. Check whether each potential new solution is tabu. If the potential new solution is tabu, go to Step 4, else go to Step 5.

Step 4. Check whether the tabu solution satisfies the aspiration criteria. If yes, proceed to Step 5 or else go back to Step 2 and generate a new candidate list. The aspiration criteria in a tabu search are used as insurance against restricting moves that would have led to finding high-quality solutions. In other words, the aspiration criteria determine when a solution neighbor can be moved, even if tabu. In this study, the typical criteria are used, which state that if a move produces a solution better than the best-known solution (and the resulting solution is feasible), the tabu status is disregarded and the move is executed.

Step 5. Evaluate the candidate solution and check whether it is better than the incumbent solution. If yes, set the incumbent solution to be equal to the current solution and insert the candidate solution into the tabu list. If not, proceed to the next step.

Step 6. Move to the candidate solution and check whether stopping criterion is met. If the stopping criterion is met go to Step 7. If not, go to Step 2.

Step 7. Terminate the report; the incumbent solution is the optimal solution.

Moves and Tabu Restrictions

In the search heuristics used with tabu search, each iteration of the search focuses on a neighborhood of the current solution (set S of open facilities with all the shipment routing plans). The neighborhood is defined as that set of solutions that can be reached by a single move. Moves can be of several different types. In the heuristic developed in this research, two types of moves are permitted: ADD/DROP hubs and swap shipment insertion order. In the ADD procedure, a non-tabu node from $\{N-S\}$ is selected that when added to S results in the best possible value of the objective function. In the DROP procedure, a node is selected from S that when dropped from S results in the best possible value of the objective function. This node is moved into $\{N-S\}$ (dropping it from $\{S\}$). The second type of move is to exchange the order in which shipments are inserted while the capacity constraints are respected. Thus, there are three types of neighborhoods: constructive neighborhoods resulting from adding a node to the set of open facilities, destructive neighborhoods resulting from dropping a node from the set of facilities, and swap neighborhoods resulting from exchanging the insertion order for different shipment demands.

As these moves are performed, tabu restrictions are employed to prevent moving back to previously investigated solutions. In general, these restrictions can be associated with any or all permissible moves; however, in the heuristic developed here, they are linked to the solution structure. That is, once the solution is selected, this solution is classified as tabu. By utilizing short-term memory, the tabu status is still not permanent. Rather, there is a tabu time (or tabu tenure), which is the time, measured in terms of iterations, that must elapse for a solution to be removed from the tabu list. If *Add_Time(v)* is the memory function holding the iteration at which solution v was last selected, and *Current_Time* denotes the current iteration, the selected solution is tabu if *Add_Time(v)* ≥ *Current_Time-Tabu_Time.* The parameter *Tabu_Time* represents the number of iterations for which a solution structure retains its tabu status.

Two-Phase Solution Heuristic

The two-phase heuristic comprises a construction phase to obtain a feasible solution and an improvement phase to improve the current feasible solution. The improvement phase uses the tabu search framework explained earlier.

Phase 1. Construction Phase

Step 1. Get one feasible solution of two hubs by enumerating all different two-node combinations and inserting all shipment demand in a certain order while capacity constraints are satisfied. Set number of hubs = 2.

Step 2. Fix the located hub nodes and select one hub node from the rest of the nodes with the lowest induced cost.

Step 3. If the number of hubs < P, go to Step 2, else go to Phase 2.

Phase 2. Improvement Phase

In the improvement phase, the tabu search algorithm is used to improve the current feasible solution. As explained earlier, two types of move operations are considered here. The first type is the exchange hubs operation (i.e., ADD and DROP). An exchange operation swaps nodes between the located hub node set and the rest node set. A move is considered feasible if the operation does not violate any constraint. In this study, the steepest descent search was applied, and at every iteration the feasible move that gives the best improvement of the objective is selected. The other type of move operation is the exchange of insertion order for each pair of shipment demand while the constraint of capacities is respected.

To avoid the search from revisiting the same solution, the tabu list mechanism was introduced. A tabu list (tabu time) records the n previous moves performed. A potential move is considered tabu if it is on the tabu list. The tabu status is disregarded and the move is executed when an exchange move produces a solution better than the best-known solution (and the resulting solution is feasible).

STUDY EXPERIMENTS

The experimental setup has two main goals: (*a*) to compare the performance of tabu search heuristics versus the CPLEX-based solution method in terms of computational times and (*b*) to compare the benefit of collaborative strategies for various simulated scenarios. In the computational runs conducted, it was assumed that there are three collaborating carriers. Two network sizes are considered: 10 nodes and 20 nodes. The maximum number of hubs generated was restricted to two, three, four, and five. The networks were randomly generated by using MATLAB, as done by Hernández and Peeta (*6*). A single data set was created by averaging 10 randomly generated data sets consistent with the ranges observed for the small- to medium-sized LTL industry (*6*). In addition to the network size and the number of hubs, the collaborative rates, noncollaborative costs, fixed cost to the carrier for using the hubs, and the demand are randomly generated. Facility capacities were also randomly generated following industry ranges for each of the network sizes. The diesel fuel price is assumed to be US$3.79 per gallon.

As for the tabu search parameters, the tabu list length was set to 2,000; the number of iterations for each stage step was set to 500 and 10 min for each constraint controlling the tabu search. The two-phase tabu search–based heuristic is coded in C++ and run on a Dell computer with an Intel Core i5-2430M at 2.40-GHz processor and 6 GB of RAM.

ANALYSIS OF RESULTS

The goal of the first set of experiments is to obtain insights on the impact of expected cost reductions at the shipment level on selection of collaborative consolidation hub locations, number of collaborative routes, number of direct shipments, and the total overall savings. The collaboration potential is investigated by studying the impact of expected cost profit margins at the shipment level reflected by the parameter *r,* which is assumed to take values of 18%, 36%, 48%, 60%, 72%, 84%, and 96%. As the cost reduction parameter increases the collaborative potential is expected to decrease. The cost reduction parameters were chosen arbitrarily in increments of 12% to 18% to try to capture changes in the total savings.

Tables 1 and 2 illustrate the comparison of the number of hubs and total savings with respect to changes in *r* for a 10-node and a 20-node network, respectively. The total percent savings reflects the cost savings from the collaborative routes compared with the noncollaborative direct routes. As the expected cost reduction from collaboration increased, the number of direct route shipments increased.

TABLE 1 Comparison of Number of Hubs and Total Savings with Changes in Cost Reduction Parameter: 10-Node Network with Three Collaborative Carriers

r-Value (profit margin)	Selected Hubs		Number of Direct Routes		Number of Collaborative Routes		Route Collaborated (%)		Total Savings (%)		Difference (%)[a]
	CPLEX	Tabu	CPLEX	Tabu	CPLEX	Tabu	CPLEX	Tabu	CPLEX	Tabu	
Two Hubs											
0.18	3, 7	3, 7	80	105	190	165	70.4	61.1	33.62	25.39	24.5
0.36	7, 8	3, 7	104	114	166	156	61.5	57.8	32.66	28.99	11.2
0.48	8, 10	8, 10	153	156	117	114	43.3	42.2	27.28	26.04	4.5
0.6	8, 10	8, 10	192	192	78	78	28.9	28.9	18.24	18.24	0.0
0.72	6, 10	6, 10	240	240	30	30	11.1	11.1	5.4	5.4	0.0
0.84	No hubs	No hubs	270	270	0	0	0	0	0	0	0.0
0.96	No hubs	No hubs	270	270	0	0	0	0	0	0	0.0
Three Hubs											
0.18	3, 8, 10	3, 4, 7	57	49	213	221	78.9	81.9	43.79	37.49	14.4
0.36	3, 8, 10	3, 7, 8	61	73	209	197	77.4	73	43.67	37.95	13.1
0.48	3, 8, 10	3, 8, 10	111	119	159	151	58.9	55.9	36.18	33.99	6.1
0.6	3, 8, 10	3, 8, 10	158	158	112	112	41.5	41.5	26.18	26.18	0.0
0.72	3, 5, 8	3, 5, 8	217	217	53	53	19.6	19.6	9.93	9.93	0.0
0.84	3, 8, 10	3, 8, 10	252	252	18	18	6.7	6.7	0.91	0.91	0.0
0.96	No hubs	No hubs	270	270	0	0	0	0	0	0	0.0
Four Hubs											
0.18	3, 4, 8, 10	4, 7, 8, 10	16	25	254	245	94.1	90.7	50.14	43.64	13.0
0.36	3, 4, 8, 10	4, 7, 8, 10	37	46	233	224	86.3	83	49.11	43.59	11.2
0.48	3, 4, 8, 10	3, 4, 8, 10	75	80	195	190	72.2	70.4	42.54	40.73	4.3
0.6	3, 5, 8, 10	3, 5, 8, 10	127	127	143	143	53	53	33.13	33.13	0.0
0.72	3, 5, 8, 10	3, 5, 8, 10	196	196	74	74	27.4	27.4	15.33	15.33	0.0
0.84	3, 6, 8, 10	3, 6, 8, 10	234	234	36	36	13.3	13.3	4.16	4.16	0.0
0.96	No hubs	No hubs	270	270	0	0	0	0	0	0	0.0

(continued)

TABLE 1 *(continued)* **Comparison of Number of Hubs and Total Savings with Changes in Cost Reduction Parameter: 10-Node Network with Three Collaborative Carriers**

r-Value (profit margin)	Selected Hubs		Number of Direct Routes		Number of Collaborative Routes		Route Collaborated (%)		Total Savings (%)		Difference (%)[a]
	CPLEX	Tabu	CPLEX	Tabu	CPLEX	Tabu	CPLEX	Tabu	CPLEX	Tabu	
Five Hubs											
0.18	3, 4, 7, 8, 10	2, 3, 4, 8, 10	8	15	262	255	97	94.4	52.57	48.94	6.9
0.36	3, 4, 7, 8, 10	2, 3, 4, 8, 10	23	33	247	237	91.5	87.8	51.68	48.14	6.8
0.48	3, 4, 7, 8, 10	3, 5, 8, 9, 10	51	46	219	224	81.1	83	46.85	45.49	2.9
0.6	3, 4, 5, 8, 10	3, 4, 5, 8, 10	92	92	178	178	65.9	65.9	39.97	39.97	0.0
0.72	3, 4, 5, 8, 10	3, 4, 5, 8, 10	165	165	105	105	38.9	38.9	20.89	20.89	0.0
0.84	3, 6, 7, 8, 10	3, 6, 7, 8, 10	210	210	60	60	22.2	22.2	8.47	8.47	0.0
0.96	No hubs	No hubs	270	270	0	0	0	0	0	0	0.0

[a]Average for two, three, four, and five hubs are 5.8, 4.8, 4.1, and 2.4, respectively.

TABLE 2 Comparison of Number of Hubs and Total Savings with Changes in Cost Reduction Parameter: 20-Node Network with Three Collaborative Carriers

r-Value (profit margin)	Selected Hubs		Number of Direct Routes		Number of Collaborative Routes		Route Collaborated (%)		Total Savings (%)		Difference (%)[a]
	CPLEX	Tabu	CPLEX	Tabu	CPLEX	Tabu	CPLEX	Tabu	CPLEX	Tabu	
Two Hubs											
0.18	7, 17	17, 19	247	285	893	855	78.3	75	37.01	35.85	10.4
0.36	7, 18	7, 18	490	508	650	632	57	55.4	33.04	32.54	3.1
0.48	7, 11	7, 11	791	791	349	349	30.6	30.6	20.5	20.5	1.5
0.6	3, 19	3, 19	979	981	161	159	14.1	13.9	11.26	11.16	0.0
0.72	3, 10	3, 10	1,080	1,080	60	60	5.3	5.3	4.78	4.78	0.9
0.84	12, 17	12, 17	1,134	1,134	6	6	0.5	0.5	0.55	0.55	0.0
0.96	No hubs	No hubs	1,140	1,140	0	0	0	0	0	0	0.0
Three Hubs											
0.18	3, 7, 18	7, 9, 15	145	175	995	965	87.3	84.6	44.36	42.62	3.9
0.36	3, 7, 18	3, 7, 18	400	403	740	737	64.9	64.6	39.05	38.95	0.3
0.48	7, 11, 13	7, 11, 13	666	666	474	474	41.6	41.6	28.17	28.17	0.0
0.6	3, 18, 19	3, 18, 19	893	895	247	245	21.7	21.5	17.11	17.02	0.5
0.72	3, 7, 10	3, 7, 10	1,049	1,049	91	91	8	8	7.47	7.47	0.0
0.84	12, 17, 19	12, 17, 19	1,122	1,122	18	18	1.6	1.6	1.72	1.72	0.0
0.96	No hubs	No hubs	1,140	1,140	0	0	0	0	0	0	0.0
Four Hubs											
0.18	3, 7, 16, 18	3, 11, 17, 18	117	114	1,023	1,026	89.7	90	48.34	48.04	0.6
0.36	3, 7, 16, 18	7, 11, 13, 20	318	322	822	818	72.1	71.8	44.12	43.61	1.2
0.48	3, 7, 16, 18	3, 7, 16, 18	564	564	576	576	50.5	50.5	34.54	34.54	0.0
0.6	12, 17, 18, 19	12, 17, 18, 19	813	815	327	325	28.7	28.5	22.96	22.88	0.3
0.72	3, 11, 15, 17	3, 11, 15, 17	1,010	1,010	130	130	11.4	11.4	10.63	10.63	0.0
0.84	5, 12, 16, 19	5, 12, 16, 19	1,104	1,104	36	36	3.2	3.2	3.41	3.41	0.0
0.96	No hubs	No hubs	1,140	1,140	0	0	0	0	0	0	0.0
Five Hubs											
0.18	3, 5, 7, 16, 18	3, 5, 7, 17, 18	88	89	1,052	1,051	92.3	92.2	51.7	51.55	0.3
0.36	3, 5, 7, 16, 18	3, 5, 7, 16, 18	267	268	873	872	76.6	76.5	47.96	47.87	0.2
0.48	7, 12, 15, 16, 20	7, 12, 15, 16, 20	472	472	668	668	58.6	58.6	40.12	40.12	0.0
0.6	10, 12, 17, 18, 19	10, 12, 17, 18, 19	736	738	404	402	35.4	35.3	28.52	28.44	0.3
0.72	3, 11, 15, 17, 19	3, 11, 15, 17, 19	973	973	167	167	14.6	14.6	13.99	13.99	0.0
0.84	5, 9, 12, 16, 19	5, 9, 12, 16, 19	1,080	1,080	60	60	5.3	5.3	5.64	5.64	0.0
0.96	No hubs	No hubs	1,140	1,140	0	0	0	0	0	0	0.0

[a]Average for two, three, four, and five hubs are 2.0, 0.7, 0.3, and 0.1, respectively.

For high values of expected cost reductions, no collaborative hubs were established and all the loads used direct routes.

Tables 1 and 2 do not include computational times; the reason is that on average the proposed tabu search heuristics presented here solved the majority of scenarios within 15 min. The CAP-CCCMLP model was also solved by using CPLEX. However, the exact method (the branch-and-cut algorithm) was not able to solve to optimality in a reasonable amount of time. For example, for scenarios with a cost reduction parameter of 0.18, the optimal solution time by CPLEX exceeded 3 days. This solution time could also be a direct result of the random generation of the available facility capacities for the problem instance.

The heuristics perform well on average with gaps of 5.8%, 4.8%, 4.1%, and 2.4% and 2.0%, 0.7%, 0.3%, and 0.1% from the optimal solution for 10-node and 20-node networks, respectively, as indicated in Tables 1 and 2. The performance of the heuristics was better for the 20-node network (Table 2). In many instances, the heuristics were able to find the optimal solution. However, in the worst case, the solution was nearly 24.5% from optimal. A closer investigation of the solutions with higher optimality gaps showed that the cost difference was primarily due to the way shipments were assigned to the hubs. Thus, including steps in the improvement procedures that can diversify the way or order to insert shipment pairs in the hubs may produce more significant improvements.

Figure 1 illustrates the percentage total savings through collaboration for varying numbers of collaborative hubs (P) for varying expected cost reduction parameters. As the expected cost reduction parameter increases, the total savings start to level off for different numbers of hubs. This finding implies that if the expected cost reduction needed to incentivize collaboration is high, there may not be a need to locate a higher number of collaborative hubs. The increases in savings in a larger, 20-node network appear to be marginal. When the expected

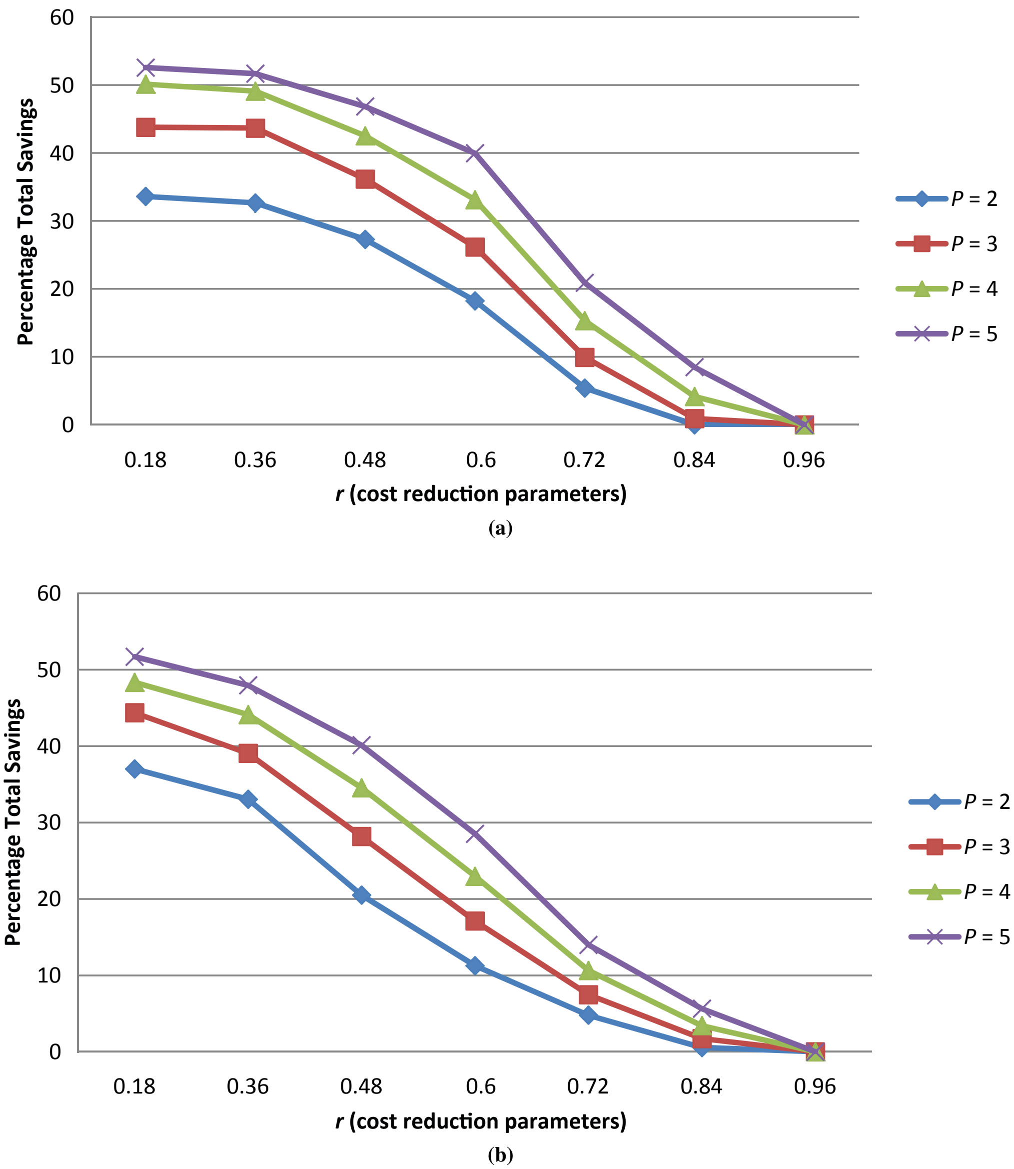

FIGURE 1 Comparison of percentage total savings for varying number of collaborative hubs (P): (*a*) 10-node network and (*b*) 20-node network.

cost reduction to incentivize collaboration is lower, locating a higher number of collaborative consolidation hubs will lead to significantly more savings.

CONCLUSION AND FUTURE WORK

This research proposed a mathematical programming formulation and a tabu search–based solution algorithm for the CAP-CCCMLP. A centralized entity (third-party logistics company) seeks to establish a set of hybrid consolidation transshipment hubs with capacities in a collaborative freight network. The LTL operators participating in the collaboration have the option of routing their goods directly or through the collaborative transshipment hubs depending on their expected cost reductions at the shipment level. The goal of the mathematical programming formulation was to minimize the total collaborative transportation and facility location costs. The model was shown to be NP-hard and solved with two-phase tabu search heuristics.

The tabu search heuristic was found to deliver significant computational savings. The gap between the true optimal solution and the tabu search solution was found to be low for most cases. As the expected cost reduction at the shipment level needed to incentivize collaboration decreases, the likelihood that carriers will enter into collaboration increases. If the carriers expect significant cost reductions to enter into a collaborative strategy, the potential savings from the collaboration will decrease.

This study will be extended in multiple directions. Future study will involve the impact of demand uncertainty and dynamic travel times and costs on the resiliency of the collaboration.

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