Centralized Carrier Collaboration and Multi-Hub Location Optimization Using a Genetic Algorithm

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Abstract

In the present work a new genetic algorithm is developed to solve the Centralized Carrier Collaborative Multi-Hub Location Problem (CCCMLP) for the small-to medium-sized less-than-truckload (LTL) industry with the main objective of minimizing the total collaborative costs and carbon dioxide emissionsconsidering a set of collaborative carriers. The main costs considered in the present study are the transportation costs for direct shipment, collaborative transportation costs, loading, unloading and operations costs, holding costs and maintenance costs. The main emissions considered in the present study are those produced by the trucks in terms of carbon dioxide emissions. The CCCMLP represents a strategy in which a central system looks for a set of hybrid collaborative consolidation transshipment hubs with the main objective of establishing a collaborative hybrid hub-and-spoke system considering the minimization of the system costs and the minimization of the CO_2 emissions. In the present work, a new Genetic Algorithm is developed to solve the CCCLMP.

Keywords
Genetic Algorithms, Supply chain, Centralized collaboration, Optimization

1.Introduction
As the internet became widespread during the 1990s, there has been an increased demand for the less-than-truckload (LTL) shipment industry(Hernandez et al, 2011). Large manufacturers and retailers have increased their demands and requirements due to the increase of online shopping and new inventory practices (Song and Regan, 2004). Not only this, but the Internet and Information Communication Technologies (ICTs) have changed the market by inserting a more spatially spread demand into it. (Anderson et al, 2003). These changes have brought up new challenges for the LTL carriers (Hernandez et al, 2011). Most of the implications of these changes have been endured by the small to medium-sized LTL industry, which have faced increased costs of shipping, jeopardizing their capabilities of sustaining profit. These low profit margins and spatially spread demand has resulted in their use of ICTs and the Internet in search for solutions (Mowery, 1999). As so, some small to medium-sized LTL carriers have begun collaboration by exploiting synergies such as excess capacity, overlapping lanes and facilities (Hernandez et al, 2011).LTL carrier collaboration can become a new model for reducing supply chain costs and increasing utilization of resources while improving the position of the carriers in the market (Hernandez et al, 2011).One of the main challenges for LTL collaboration lies in balancing the service requests and the capacity to service these requests. This balance relies on the affordability of the transportation as well as the size and value of the shipment (Hernandez et al, 2010, 2011, 2012). It is important to take this into consideration since small to medium-sized LTL carriers operate under a point-to-point network. These networks move shipments from origin to destination without middle points. As such, the objectives of this research are to identify and locate transfer hubs to ease and promote carrier collaboration and evaluate the environmental impacts in terms of CO_2 emissions.

One of the main challenges for carrier collaboration is to identify the potential locations to install collaboration hubs. Many factors influence the decision of locating a hub, ranging from contract agreements to holding, collaboration, and congestion costs (Hernandez et al, 2011). Additionally, costs may depend on the transfer point (e.g. a city or town) in which they occur, and also the incoming and outgoing of trucks (Boardman, 1997). In addition, hub location selection may depend on product handling and storage capabilities. Some goods may require refrigeration or humidity control, while other goods may not. If we were to consider a heterogeneous product market, the complexity

of the problem would increase greatly (Hernandez et al, 2012; Hernandez et al, 2011). In this study, we assume a homogeneous fleet handling a single type of non-perishable goods.

In the present research a new genetic algorithm will be developed to address the Centralized Carrier Collaboration Multi-Hub Location Problem (CCCMLP) considering a group of small to medium-sized Less-than-Truckload (LTL) carriers. Here, a central entity organizes the collaboration of the carriers so as to minimize the total (collaborative) system costs subject to the behavior of the individual carriers that need a set of hubs to service demand. The problem is studied under the condition that all the information about costs and demands are known beforehand. Costs associated with events in the hub locations like loading and unloading and delays are considered in the holding costs. Moreover, in the present research, we will solve the CCCMLP problem considering the minimization of carbon dioxide emissions, as an ecologically sustainable system towards the long term sustainability, in order to estimate the CO_2 emissions we used information from the Environmental Protection Agency (EPA).The following sections of this paper are as follows. Section 2 consists of a review of literature associated to carrier collaboration as well as hybrid hub-and-spoke systems. Section 3 explains the notation for the variables considered in the CCCMLP problem. In section 4 will further describe the CCCMLP problem as well as stating the assumptions made in the present research. Section 5 will show the development of the mathematical model to solve this problem. Section 6 will show an example in which this method was applied. Finally, in section 7 we present some concluding comments.

2. Literature Review

LTL carrier collaboration is a relatively unexplored concept within the ground freight domain. In the past, different researchers (Hernandez et al., 2011, Agarwal and Ergun, 2010, Kuo et al,2008 and Voruganti et al, 2011) have studied collaboration within the truckload (TL) carriers, liner shipping, and rail industries. Recently, Hernandez *et al.*, (2012), and Hernandez and Peeta, (2010, 2011) introduced and studied the viability of LTL carrier collaboration with a static and dynamic context for a single carrier, and centralized planning perspective for multiple carriers. They explored the potential benefits of LTL carrier collaboration models. For instance, Vorugant*iet al*., (2011) studied partial and full carrier collaboration and applied the Shapley value principle to distribute the profits. The topology of the network was found to have a significant impact on the collaboration success. Moreover, Bayley *et al*., (2011a) developed integer programming models and heuristic algorithms usable by medium-sized freight companies to evaluate collaborative savings by minimizing deadheading. Additionally, Bayley (2011b), developed a cardinality and capacity constrained lane covering formulation for shipper collaboration and used Tabu search to solve the problem, in his work, the location of hubs to facilitate collaboration was not addressed as separate objective component.

The concept of hybrid hub-and-spoke is a relatively new one. Although not explicitly as collaboration, Zang*et al*., (2007) introduced the concept of hybrid hub-and-spoke for a single LTL carrier trying to minimize transportation costs. In their work, hybrid refers to the addition of direct routes to a pure hub-and-spoke system. The authors formulate the problem as a combinatorial one and solve it using a genetic algorithm methodology. Similarly, Zapfel and Wasner (2002) developed a hub-and-spoke system for cooperative third party logistics firms. From an LTL and pure hub-and-spoke perspective, Cunha and Silva, (2007) focused on configuring a hub-and-spoke network for a LTL trucking company in Brazil. They sought to determine the number of consolidation terminals (hubs), their locations, and the assignment of the spokes to the hubs, while aiming to minimize the total cost. The authors used a genetic algorithm and a local improvement procedure to solve the problem.

In the majority of the literature, collaboration is addressed without consideration of multi-hub location or addresses the multi-hub location from the context of a single LTL carrier; moreover, the problem has not been solved considering the minimization of CO_2 emissions. Additionally in, the hybrid hub-and-spoke system we will consider a set of collaborative consolidation transshipment hubs from a current point-to-point network structure, as in Hernandez *et al.*, (2011). Simply speaking, a hub-and-spoke system is formed without costly investments in new facilities. With this structure, the centralized carrier collaboration network can benefit from the hub-and-spoke system by consolidating shipments at specific locations to increase the efficiency of the operations and it can also be evaluated considering the CO_2 emissions.

3. Problem Description and Assumptions

The CCCMLP seeks to determine a set of hybrid collaborative consolidation transshipment hubs for a central entity (e.g., third party logistics firm) to help establish a collaborative hybrid hub-and-spoke system that minimizes the total collaborative costs or the total CO_2 emissions for the set of collaborating carriers. Hence, a carrier in this system is

classified as either a collaborative carrier (shares the costs to set up hybrid hubs), or non-collaborative (decides to ship directly). The operational networks of the collaborating carriers can be completely identical geographically or overlap in some segments relative to other carriers in the collaborative network. The collaborative rate structure of the collaborative carriers is represented by a revenue oriented behavior. If a collaborative opportunity cannot be identified with regards to hybrid collaborative consolidation transshipment hubs, a non-collaborative option is considered. It is assumed that the costs of shipping directly fall upon the carrier itself. The following assumptions are made in the CCCMLP: (*i*) candidate hybrid collaborative consolidation transshipment hubs are uncapacitated, and (*ii*) homogenous products are shipped. In addition, the problem is deterministic in the sense that the demand is known and the available holding times at facilities are time invariant. By contrast, a stochastic version of the problem would entail stochasticity of demand of the collaborating carriers.

4. Model Formulation

Let the carrier company be denoted by $q \in Q$, the origin of a shipment by $i \in I \subseteq N$, its destination by $j \in J \subseteq N$, and the hubs by which it may travel by $k, l \in N$, where N is the total number of nodes in the network.Each carrier q has an associated demand denoted by d_{ijq}, the number of shipments that must be made from the origin point *i* to the destination point *j* by the carrier q. The collaborative carrier revenue oriented cost associated to demand d_{ijq} is given by

$$C_{ijkl} = C_{ik} + \delta C_{kl} + C_{lj} \tag{1}$$

where δ is the collaboration discount associated with transporting from hub k to hub l, and $0 \leq \delta \leq 1$, the collaborative discount of a shipment from hub to hub. The cost associated with a carrier q establishing a hub in node k is denoted as

$$P_{kq} = \vartheta_{kq} + \phi_k \tag{2}$$

whereϑ_{kq} is the holding cost associated with carrier q storing merchandise at the hub in node k, and ϕ_k is the connection cost of the hub, that is, the cost associated with the loading and unloading of merchandise from one truck to another. The costs of shipping directly from node to node by each carrier will be denoted by W_{ijq}.

Let:

$Y_{ijklq} = 1$, if a shipment is sent from node *i* to node *j* via the hubs *k* and *l* by the carrier *q*. That is, if the shipment is sent through a collaborative network. Otherwise, it will be equal to 0.

$V_{ijq} = 1$, if a shipment is sent directly from node *i* to node *j* by carrier *q*, and 0 otherwise.

$X_k = 1$, if the node at point k will become a hub, and 0 otherwise.

For the solution to this problem, we have determined the following constraints to be relevant to this problem. Constraint (3) makes it so that there is an exact number of hubs that can be implemented. In order to limit the number of routes from one point to the next, constraint (4) impedes the programming of more than one different route between two points in the system. Constraints (5,6) state that shipments from origin$i \in I$ to destination$j \in J$ cannot be assigned to a hub at location $k \in K$ or $l \in L$ unless a hybrid collaborative consolidation hub is located in these candidate sites. Constraint (7), ensures that the shipment will only go through the collaborative network if the cost of going through it is smaller than the cost of direct shipping. γ denotes the profit margin expected by a company in order to participate in the collaboration. Constraints set (8-10) constraints variables *X*, *Y*, and *V* into the binary space.

$$\sum_k X_k = p \tag{3}$$

$$\sum_k \sum_l Y_{ijklq} + V_{ijq} = 1 \quad \forall i, j, q \tag{4}$$

$$\sum_l Y_{ijklq} \leq X_k \tag{5}$$

$$\sum_k Y_{ijklq} \leq X_l \tag{6}$$

$$C_{ijkl} Y_{ijklq} \leq V_{ijq}\left(1 - V_{ijq}\right)(1 - \gamma) \quad \forall i, j, k, l, q \tag{7}$$

$$X_k \in \{0,1\} \tag{8}$$

$$Y_{ijklq} \in \{0,1\} \tag{9}$$

$$V_{ijq} \in \{0,1\} \tag{10}$$

4.1 Objectives considered

The objective function seeks a set of candidate hybrid collaborative consolidation hubs as to minimize the total transportation collaborative costs in a supply chain. It consist of three terms, the first term represents the total transportation costs associated to the carrier collaborative, the second part represents the total costs associated with carriers not collaborating and shipping directly, and third represents the total carrier collaborative costs associated with locating a collaborative candidate hybrid consolidation facilities. The second objective function considered in the present study (Equation 12) considers the minimization of the CO_2 emissions, similarly as in the previous cost function, the objective consists of two main terms, the first term represents the total emissions associated to the carriers collaborating, the second part represents the total CO_2 emissions associated with carriers not collaborating and shipping directly. The collaborative transportation costs are obtained as the summation of the product of the cost of travel for a shipment C_{ijkl}, the collaborative carrier demandd_{ijq} and Y_{ijklq}(the decision on whether a shipment travels via the collaborative hubs). The non-collaborative costs are obtained as the summation of the cost of shipping directlyW_{ijq}, the collaborative carrier demand d_{ijq}, and the V_{ijq} (the decision on whether to ship directly). The collaborative candidate hybrid consolidation hub location costs are obtained as the summation of the product of the costs of locating a collaborative hub P_{kq}, and the X_k(the decision on whether a collaborative facility is located). Equation (11 and 12) subject to constraints (3) through (10) represents the mathematical formulation of the centralized carrier 31 collaborative multi-hub location problem (CCCMLP).

$$\min \sum_i \sum_j \sum_k \sum_l \sum_q C_{ijkl} d_{ijq} Y_{ijklq} + \sum_i \sum_j \sum_q W_{ijq} d_{ijq} V_{ijq} + \sum_k \sum_q P_{kq} X_k \tag{11}$$

$$\min \sum_i \sum_j \sum_k \sum_l \sum_q GWPCC_{ijkl} d_{ijq} Y_{ijklq} + \sum_i \sum_j \sum_q GWPNCC_{ijq} d_{ijq} V_{ijq} \tag{12}$$

5. Algorithm Development

In the present research, a new Genetic Algorithm (GA) is developed to solve the CCCMLP problem. A Genetic Algorithm is a metaheuristic search method that imitates the process of natural selection. It was first introduced by Holland in 1975 through his book “Adaptation in Natural and Artificial Systems.” It follows the “survival of the fittest” theory as the “weakest” (less optimal) individuals are eliminated and the “strongest” or “fittest” individuals remain and serve to create a new population.The genetic algorithm has been used to solve problems in many different fields such as flowshop problems (Reeves, 1995), flexible docking, and project scheduling (Hartmann, 1998) among others.In the present research, the GA developed is flexible enough to solve problems considering any number of destinations and consolidation hubs. The GA first generates an initial random population, and then the objective function is evaluated for each chromosome and they are ranked according to the result. Elitism is used to keep the best solutions.Then the current population is considered to select two parents that will go through the crossover operator to form the new population. Additionally, a random mutation is introduced to the population to add variation in the search process. The process of evaluating, ranking, crossover and mutating will be repeated a number of iterations until stopping criteria is satisfied.Each of the steps taken by the algorithm are shown in Fig.1.

5.1 Initial generation

The first step the algorithm takes is the creation of a random population of individual chromosomes. For this, it will create a zero matrix of size *m x n+1*, where *m* is the size of the population. Following this, the matrix will randomly select points in the individual chromosomes, until each of them has *p* elements equaling one, thus meeting the constraint for number of hubs allowed.

5.2 The Fitness Function

The Fitness Function is determined via the use of an optimized cost matrix S. This matrix starts being the same as the cost matrix W given as a superposition of tables 4 and 5, and changes the values in the matrix to those in the Collaborative cost matrix C if $\gamma S_{ijq} > C_{ijkl}$ for all values of l, k. The fitness value, which is equal to the objective function, is determined as a point product of the Optimized Cost Matrix S and the Demand Matrix D, added to the Hubs cost, given as a scalar multiplication of the hub creation costs for each carrier times the first n values of the chromosome.

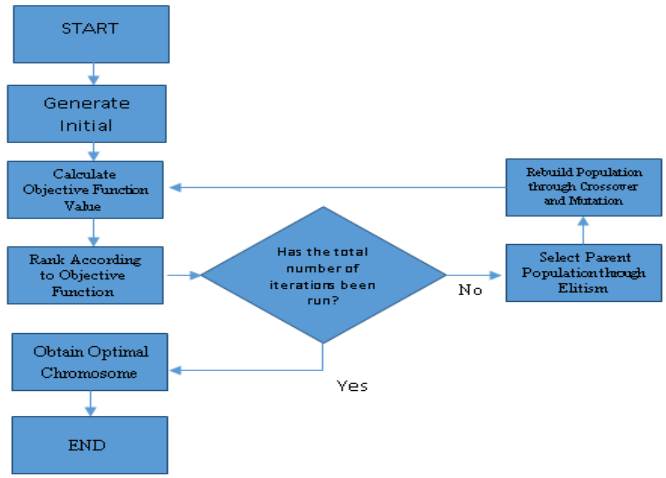

Figure 1: Genetic Algorithm Flowchart

5.3 Crossover

Crossover is the process by which a new generation is built. This process can be performed via single point or multi point crossover. For this algorithm, a single point crossover is considered. The single point crossover function consists on mixing two parents at a random point to create a new individual, as shown in Fig 2. For the crossover function, it was decided that a random process would be more likely to produce results that vary more between each other. A set of parents is selected from the population by elitism, as the top *x* percentage of the population. As so, the algorithm selects a random point in two random chromosomes amongst the parent population, taking the first part of the new chromosome from the first parent and the second from the second parent.

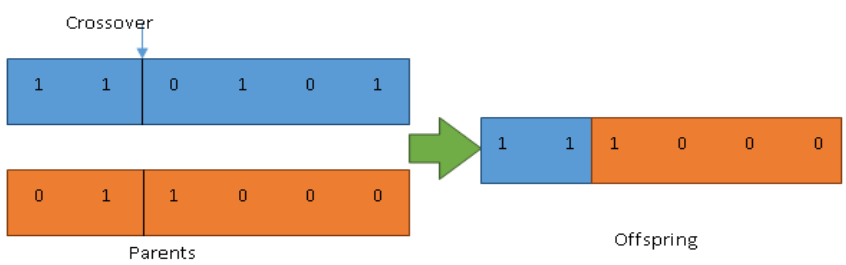

Figure 2. Single Point Crossover

5.4 The Mutation Function

In order to adequately mimic the natural evolutionary process, a random mutation element must be included. As so, if a random number between zero and one is smaller than the specified mutation factor, a random point in the chromosome is changed from zero to one or from one to zero. This is shown in Figure 3 as follows. An adjuster for the number of chromosomes then randomly selects points in the chromosome to change to one or zero if the number of hubs is different to *p*, the selected number of hubs specified in Equation 3.

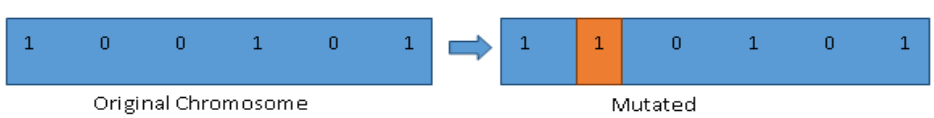

Figure 3. Mutation Function

6. Examples

6.1 Case Study 1: Cost minimization

Using data from tables 1-6, we will determine the savings obtained by implementing a 10 node hub-and-spoke network and establishing collaboration between 2 carriers with varying degrees of expected profit margins γ.

Table 1: Assumed demand for Carrier 1

Nodes	1	2	3	4	5	6	7	8	9	10
1	0	495	291	855	608	172	272	490	701	651
2	415	0	282	554	249	296	505	607	396	369
3	262	249	0	599	447	304	310	339	407	584
4	916	596	577	0	734	939	931	774	274	774
5	572	226	495	685	0	330	798	760	543	119
6	162	303	297	816	375	0	371	551	594	460
7	257	529	285	851	653	389	0	270	700	848
8	463	563	357	758	832	628	255	0	463	947
9	762	400	425	235	537	615	566	436	0	750
10	679	348	617	765	140	405	793	999	726	0

Table 2. Assumed demand for Carrier 2

Nodes	1	2	3	4	5	6	7	8	9	10
1	0	495	291	978	499	198	240	463	716	623
2	450	0	285	560	249	292	535	512	338	382
3	313	288	0	671	533	262	300	357	367	557
4	844	499	627	0	653	873	921	766	277	867
5	566	277	539	653	0	379	742	769	590	124
6	162	306	288	778	375	0	407	525	580	495
7	283	505	278	960	734	429	0	264	686	904
8	452	544	303	709	823	557	285	0	469	865
9	624	355	416	229	590	594	566	528	0	685
10	609	395	563	765	127	410	765	927	718	0

Table 3: Hub establishing cost for carriers 1,2.

Nodes	1	2	3	4	5	6	7	8	9	10
Carrier 1 Hub cost	24685	20644.9	19934.5	35574.2	25805.3	22662	26899	28702.9	26668.6	30581
Carrier 2 Hub cost	24931.9	21883.6	16745	29526.5	22966.7	20849.1	27437	24971.5	23201.7	34250.7

Table 4. Non-collaborative shipping costs for Carrier 1

Nodes	1	2	3	4	5	6	7	8	9	10
1	0	134	83	284	182	60	74	134	212	197
2	137	0	80	166	85	88	182	171	106	103
3	84	79	0	188	139	91	85	88	119	197
4	284	166	212	0	220	276	270	218	81	238
5	161	69	149	213	0	109	210	241	187	39
6	52	88	82	265	122	0	107	186	187	144
7	76	153	83	244	223	131	0	75	189	230
8	150	154	103	235	220	156	76	0	134	256
9	196	103	130	79	169	182	208	147	0	210
10	185	116	177	241	37	129	230	287	198	0

Table 5. Non-collaborative shipping costs for Carrier 2

Nodes	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	0	134	92	300	150	58	76	157	190	202
2	126	0	78	151	81	93	181	182	101	104
3	78	90	0	193	131	85	90	107	119	167
4	253	153	216	0	210	273	279	193	81	263
5	172	79	134	227	0	113	230	217	193	35
6	56	107	89	256	109	0	126	190	176	126
7	71	159	86	267	218	123	0	90	187	254
8	157	159	89	223	217	177	86	0	139	269
9	206	119	118	74	179	172	195	134	0	213
10	174	112	169	230	34	140	274	253	196	0

Table 6. Collaborative shipping costs for Carriers 1, 2.

Nodes	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	0	46	31	101	60	20	26	50	70	66
2	48	0	28	55	27	35	60	61	38	40
3	31	27	0	66	50	29	31	33	43	60
4	101	57	69	0	78	88	92	75	27	89
5	58	28	48	76	0	38	79	87	67	14
6	19	36	31	86	39	0	42	60	65	47
7	28	60	29	90	78	43	0	28	64	86
8	54	61	35	74	86	61	27	0	48	98
9	72	40	42	27	63	69	69	50	0	75
10	67	39	63	86	14	46	83	102	77	0

In the genetic algorithm,an initial population of 100 will be considered, running the algorithm for 200 iterations with a 10% elitism, a mutation factor of 10%, and considering a δ of 10% and values for γ of 9%, 48%, and 96%. The results of these tests in terms of γ, # of hubs, Total Cost, number of collaborative and non-collaborative routes, percentage of routes picked as collaborative, and relative saving percentages are presented in table 7.

Table 7: Results summary for Case Study 1.1

γ Value	**# of hubs**	**Hubs Selected**	**Cost**	**Collaborative Routes**	**Non-Col. routes**	**% of col. routes**	**Percent Savings**
9%	1	3	$ 7,365,653.50	88	92	48.9%	56.5%
48%	1	3	$ 8,503,193.50	79	101	43.9%	49.8%
96%	1	3	$ 16,936,922.50	9	171	1.6%	0%
9%	2	3,5	$ 5,698,410.10	88	92	48.9%	66.4%
48%	2	3,5	$ 6,102,394.10	79	101	43.9%	64.0%
96%	2	1,4	$ 16,041,353.90	9	171	5.0%	5.3%
9%	3	4,5,7	$ 4,046,494.30	88	92	48.9%	76.1%
48%	3	3,4,5	$ 4,202,134.00	79	101	43.9%	75.2%
96%	3	4,7,10	$ 14,612,113.30	9	171	5.0%	13.7%

7.2 Case Study 2: Emissions minimization

Considering the data from tables 1 & 2, and the estimated emissions data from tables 8 through 10, we estimated the total tons of CO_2emitted by the trucks traveling through the network.This was done by estimating the cost of gas for each route, and calculating the tons of carbon dioxide emitted according to the EPA standard of $8.887*10^3$ metric tons of carbon dioxide for each gallon of gas consumed.

Table8: CO_2 emissions for Carrier 1

	CO_2 metric tons for Carrier 1									
\	1	2	3	4	5	6	7	8	9	10
1	0	0.3802	0.1990	0.9135	0.5509	0.1172	0.1670	0.3802	0.6575	0.6042
2	0.3909	0	0.1883	0.4940	0.2061	0.2167	0.5509	0.5118	0.2807	0.2700
3	0.2025	0.1847	0	0.5722	0.3980	0.2274	0.2061	0.2167	0.3269	0.6042
4	0.9135	0.4940	0.6575	0	0.6860	0.8850	0.8637	0.6789	0.1918	0.7499
5	0.4762	0.1492	0.4336	0.6611	0	0.2914	0.6504	0.7606	0.5687	0.0425
6	0.0888	0.2167	0.1954	0.8459	0.3376	0	0.2843	0.5651	0.5687	0.4158
7	0.1741	0.4478	0.1990	0.7713	0.6966	0.3696	0	0.1705	0.5758	0.7215
8	0.4371	0.4513	0.2700	0.7393	0.6860	0.4585	0.1741	0	0.3802	0.8139
9	0.6006	0.2700	0.3660	0.1847	0.5047	0.5509	0.6433	0.4265	0	0.6504
10	0.5615	0.3163	0.5331	0.7606	0.0354	0.3625	0.7215	0.9241	0.6078	0

Table 9: CO_2 emissionsfor Carrier 2

CO_2 metric tons for Carrier 2										
\	1	2	3	4	5	6	7	8	9	10
1	0	0.3802	0.2309	0.9703	0.4371	0.1101	0.1741	0.4620	0.5793	0.6220
2	0.3518	0	0.1812	0.4407	0.1918	0.2345	0.5473	0.5509	0.2629	0.2736
3	0.1812	0.2238	0	0.5900	0.3696	0.2061	0.2238	0.2843	0.3269	0.4976
4	0.8033	0.4478	0.6717	0	0.6504	0.8744	0.8957	0.5900	0.1918	0.8388
5	0.5153	0.1847	0.3802	0.7108	0	0.3056	0.7215	0.6753	0.5900	0.0283
6	0.1030	0.2843	0.2203	0.8139	0.2914	0	0.3518	0.5793	0.5296	0.3518
7	0.1563	0.4691	0.2096	0.8530	0.6789	0.3411	0	0.2238	0.5687	0.8068
8	0.4620	0.4691	0.2203	0.6966	0.6753	0.5331	0.2096	0	0.3980	0.8601
9	0.6362	0.3269	0.3234	0.1670	0.5402	0.5153	0.5971	0.3802	0	0.6611
10	0.5224	0.3020	0.5047	0.7215	0.0248	0.4016	0.8779	0.8033	0.6006	0

Table 10: Collaborative CO_2 emissions

CO_2 metric tons for collaboration between Carriers 1 & 2										
\	1	2	3	4	5	6	7	8	9	10
1	0	0.1155	0.0622	0.3110	0.1652	0.0230	0.0444	0.1297	0.2008	0.1866
2	0.1226	0	0.0515	0.1475	0.0479	0.0764	0.1652	0.1688	0.0870	0.0941
3	0.0622	0.0479	0	0.1866	0.1297	0.0550	0.0622	0.0693	0.1048	0.1652
4	0.3110	0.1546	0.1972	0	0.2292	0.2648	0.2790	0.2186	0.0479	0.2683
5	0.1581	0.0515	0.1226	0.2221	0	0.0870	0.2328	0.2612	0.1901	0.0017
6	0.0195	0.0799	0.0622	0.2577	0.0906	0	0.1013	0.1652	0.1830	0.1190
7	0.0515	0.1652	0.0550	0.2719	0.2292	0.1048	0	0.0515	0.1795	0.2577
8	0.1439	0.1688	0.0764	0.2150	0.2577	0.1688	0.0479	0	0.1226	0.3003
9	0.2079	0.0941	0.1013	0.0479	0.1759	0.1972	0.1972	0.1297	0	0.2186
10	0.1901	0.0906	0.1759	0.2577	0.0017	0.1155	0.2470	0.3145	0.2257	0

In the genetic algorithm, an initial population of 100 will be considered, running a Genetic Algorithm for 200 iterations with a 10% elitism, a mutation factor of 10%, and considering a δ of 10% and values for γ of 9%, 48%, and 96%. The results of these tests in terms of γ, # of hubs, Total metric tons of carbon dioxide, number of collaborative and non-collaborative routes, percentage of routes picked as collaborative and relative CO_2 reduction percentages are presented in table 11 and summarized in Figure 4. As we are considering the emissions by the trucks, the hubs will have no values on this problem.

Table 11: Results summary for Case Study 2.1

γ value	Number of hubs	Selected hubs	CO_2 metric tons	# of Col. Routes	# of non-col. routes	% of Col. routes	Relative Reduction %
9%	1	3	17821.447570	85	95	47.2%	65.2%
48%	1	3	18847.153117	79	101	44%	63.2%
96%	1	9	51161.388498	6	174	5%	0%
9%	2	3,5	12432.336584	85	95	47.2%	75.7%
48%	2	3,5	12897.88741	79	101	44%	74.8%
96%	2	5,8	45940.88302	6	174	5%	10.2%
9%	3	3,5,9	7408.889212	85	95	47.2	85.5%
48%	3	3,5,9	7526.2011676	19	101	44%	85.3%
96%	3	4,5,7	39567.00573	6	174	5%	22.7%

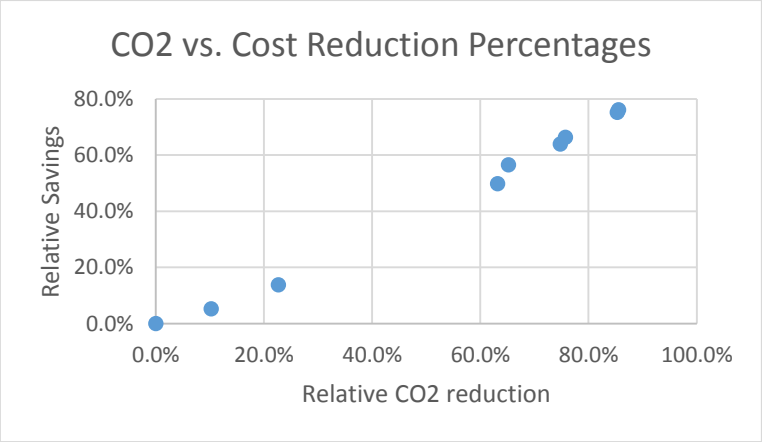

Figure 4: Relation between savings and CO_2 reduction percentages through GA

An important finding is that, in both studies, as the number of hubs in the network increases, so does the relative decrease in cost and emissions, respectively. Inversely, the increase in the minimum expected savings brought a decrease in the actual savings.

7. Conclusions and Future Work

A centralized collaborative carrier multi-hub location problem (CCCMLP) is introduced that provides a planning framework to analyze the benefits of a centralized multiple carrier collaborative network for the creation of hybrid hub-and-spoke system. It addresses the operational issues related to transfer locations and shipment consolidation by introducing the concept of hybrid consolidation hubs from existing locations without the need to construct or invest in new consolidation facility infrastructure. This is done by leveraging the current service locations of existing LTL collaborative carriers, synergized bynew opportunities provided through advances in ICTs and e-commerce. The problem was solved using a Genetic Algorithm. The study results indicated that larger expected profit margins and larger emission reductions from the collaborative carriers would decrease the likelihood of carriers collaborating. In addition, as the network size increases the effect of hybrid hub locational costs was reduced. Also, as the number of hubs increases, there is a reduction in the produced emissions. A direct relation can be observed between the savings and the emission reductions for the same parameters. A key inference of this study is that carrier collaboration in

terms of a collaborative hybrid hub-and-spoke system can become a critical strategy for small- to medium-sized LTL carriers to remain competitive. That is, by decreasing their operational costs when shipping across a point-to-point network.However, carbon dioxide is not the only emission produced by the burning of fuel. In order to better study these emissions and their effects on the environment, we plan on studying the Global Warming Potential of the trucks.

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