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Global Warming Potential and Cost Minimization for the Centralized Carrier Collaboration and Multi-Hub Location Problem

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Abstract

In this work, a Particle Swarm Algorithm is developed in order to solve the Carrier Collaborative Multi-Hub Location Problem (CCCMLP) for the small to medium-sized Less-than-Truckload (LTL) industry with the objective of minimizing both the total cost and the total Global Warming Potential (GWP). The main costs considered are the transportation costs for direct and collaborative shipping, the holding, loading, and unloading costs, and the hub allocation costs. For the Global Warming Potential, the emissions considered are those produced the trucks during shipping. 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 Global Warming Potential. In the present work, a new Particle Swarm algorithm is developed to solve the CCCLMP.

Keywords
Particle Swarm, Global Warming Potential, Centralized Carrier Collaboration

1. Introduction
Global warming endangers our health, jeopardizes our national security, and threatens other basic human needs. Some impacts—such as record high temperatures, rising seas, and severe flooding and droughts—are already increasingly common (*Union of Concerned Scientists*).While transportation is crucial to our economy and our personal lives, as a sector it is also a significant source of greenhouse gas (GHG) emissions. Through the combustion of fuel we release carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) among other pollutants to the atmosphere. Also a small amount of hydrofluorocarbon (HFC) is produced by the use of mobile air conditioners and refrigerated transport. In 2013, the transportation sector contributed to 27% of total U.S. greenhouse gas emissions and over 5 percent of global GHG emissions, the second largest contributor after the Electricity sector. The largest sources were freight trucks (20%) (*U.S. Department of Transportation*).In 2006, emissions from on-road vehicles accounted for 79 percent of transportation GHG emissions. Greenhouse gas emissions in other sectors decreased 15% between 1990 and 2007 but emissions from transportation increased 36% during the same period. This increase happened despite improved vehicle efficiency because the amount of personal and freight transport has increased (European Commission. 2015). These increases have been created by the largest demand for travel and limited gains in fuel efficiency.

The U.S. Energy Information Administration estimates that U.S. gasoline and diesel fuel consumption for transportation in 2014 resulted in the emission of about 1,075 million metric tons and 444 million metric tons of CO_2, respectively, for a total of 1,519 million metric tons of CO_2. This total was equivalent to 83% of total CO_2 emissions by the U.S. transportation sector and equivalent to 28% of total U.S. energy-related CO_2 emissions in 2014 (*U.S. Energy Information Administration*). Additionally, between 1990 and 2012, GHG emissions in the transportation sector increased more in absolute terms than any other sector (i.e. electricity generation, industry, agriculture, residential, or commercial) (*EPA*, *EPA,2*). Consequently, it has been estimated that baseline global GHG emissions from human sources will increase between 25 percent and 90 percent between 2000 and 2030(*U.S. Department of Transportation, 2010*).The Intergovernmental Panel on Climate Change (IPCC) projects that global temperatures will raise between 2°F to 11.5°F by 2100, and global sea level will rise between 7 to 23 inches. The increase of emissions can be reduced by implementing approached to contribute to GHG emissions reduction, for example, the use of low-carbon fuels, new and improved vehicle technologies, improved transportation system efficiency, strategies to reduce the number of vehicle miles traveled and operating vehicles more efficiently. According to the U.S. Department of Transportation, different system efficiency strategies will help reduce the GHG emissions by optimizing the design, construction, operation, and use of transportation networks to reduce trip frequencies and it has been estimated that the collective impact of these strategies on total U.S. transportation GHG emissions could range from 5-to-17 percent reduction in 2030, or 6-to-21 percent reduction in 2050 (U.S. Department of Transportation, 2010). In the present paper we propose an optimization approach to minimize the Global Warming Potential and Cost for the Centralized Carrier Collaboration and Multi-Hub Location Problem.

2. Literature Review

The highest percentage of greenhouse gas emissions is attributed to road transportation; consequently, thorough research is being made to achieve an optimized transportation system. Collaborative Carrier Collaboration in the transportation industry can help reduce environmental emissions in the transportation sector, as it can also reduce the number of necessary trips, consequently increasing the efficiency of the system. Extensive literature can be found addressing the problem of collaboration in road transportation. For instance, Sadegheigh et al, 2011developed a mixed integer programming and a genetic algorithm model to study the behavior of global supply management and collaborative network design, they showed advantageous results that can lower carbon emissions and still provide the different parties competitive advantages. The implementation of a genetic algorithm proved to be successful for complex transportation problems. Jemai J. et al, 2012, applied evolutionary algorithms as an approach to solve a bi-objective green vehicle routing problem. The objectives were to minimize the total traveled distance and the CO_2 emissions. In contrast to past research, collaboration in transportation was not considered in this analysis. Some more literature found on supply chain collaboration to reduce carbon emissions was done by Jaegler, A., & Burlat, P, 2012 and Pradenas, L. et al, 2013.

There are several ways to cooperate: carriers can collaborate with each other (horizontal cooperation), shippers can collaborate among themselves (horizontal cooperation), and carriers and shippers can also collaborate (vertical cooperation). Ballot E. & Fontane, 2010 proposed a concept of logistical network pooling achieving savings of at least 25% of CO_2 emissions from pooled networks versus current setup. They demonstrated that vertical supply chain optimizations can still be improved by horizontal collaboration. The needs of finding strategies for collaboration lead Xu, (Xu, 2013)to identify two organizational forms of horizontal logistics collaboration; centralized and decentralized. Later, Bernabeu et al, 2015 contributed to the subject by analyzing the importance of horizontal transportation for small and medium companies. The analysis consisted on contrasting three possible scenarios; cooperative, non-cooperative in a cluster topology and non-cooperative in a scattered topology. Numerical examples were based on well-known Multi-depot vehicle routing problem with the assumption that carriers and shippers were directly controlled by the same companies, giving an ideal scenario of collaboration where disagreements and own interests are eliminated. Experimental results provided a noticeable reduction in expected costs as well as in terms of greenhouse gas emissions for the horizontal cooperation strategy. Going further into the study of carrier collaboration in the transportation industry, recent studies in freight transportation have also focused on carbon dioxide emissions. For example, Li, H. et al 2013, solved a vehicle routing problem with full truckloads between any two depots of the network, and an integer programming model with the objective to minimize CO_2 emissions per ton-kilometer is proposed. A two stage approach with the same core steps of the simulated annealing algorithm in both stages was designed.

Lin, D. Y. & Ng, K. H, 2012 investigated to see if collaboration between carriers can reduce the environmental issues of freight movement in a carbon constrained business context. Their proposed model corresponded to a stochastic mixed integer programming problem that was modeled and transformed to an equivalent large scale integer programming model with numerous constraints. The problem was solved using tabu search algorithm with Monte Carlo bounding techniques. Numerical results provided evidence that the collaborative method can effectively reduce emissions in a freight network by 3-20%. Later, the concept of network pooling of Ballot E. & Fontane was implemented by Pan, S. et al, 2013 on freight industry exploring the effect of reducing CO_2 emissions considering two different transportation modes, i.e. road and rail. The mode of road transportation refers to transportation by Heavy Duty Vehicles, and in the rail mode it considers only the electrically powered locomotive. De Mello, P. F. B., & Frayret, J. M., 2014 extended the research from an economical and environmental view into a complete sustainability analysis proposing a freight transportation model based on the resource sharing methodology. Sustainability is assessed in terms of logistic performance, drivers working condition, and environmental impact. An agent based simulation model was developed by making use of the software Netlogo. Results indicated that resource sharing can significantly improve all performance, social and environmental.

LTL carrier collaboration is a relatively unexplored concept within the ground freight domain. In the past, researchers have studied collaboration within the truckload (TL) carriers, liner shipping, and rail industries. Okan " Ozener et al, 2007 investigated the potential of collaborative opportunities in truckload transportation by developing optimization models to determine the maximum benefit that can be derived from collaborating. They present a Multi- Carrier Lane Covering problem and use heuristic approaches to solve the integer programming problem, the first heuristic approach relaxes the precision by specifying a relative optimality criterion, whereas the second exploits the structure of the solution by fixing integral flows along cycles before starting branch-and-bound process. Liu R. et al 2010addressed a special optimization problem in the carrier collaboration system called the multi-depot capacitated arc routing problem with full truckloads (MDCARPFL) by proposing heuristic algorithms for real-world larger scale instances. Recently, Hernandez and Peeta, (2010, 2011) addresses a time-dependent, centralized multiple-carrier collaboration problem (TD-MCCP) with a static and dynamic context for the small to medium-sized less-than-truckload (LTL) industry. The TD-MCCP is modeled as a binary (0–1) multicommodity minimum cost-flow problem formulation for two rate-setting behavioral cases and solved with a branch-and-cut algorithm.

The concept of hybrid hub-and-spoke is a relatively new one on logistics collaboration, and although not explicitly, Zang*et al*., 2007 introduced the concept for a single LTL carrier trying to minimize transportation costs. Referring to hybrid as the addition of direct routes to a pure hub-and-spoke system. A genetic algorithm approach was used to solve the combinatorial problem. Other researchers have approached pure hub-and-spoke LTL problems through the use of genetic algorithms for instance, Cunha and Silva, 2007focused on configuring a hub-and-spoke network for an LTL trucking company in Brazil aiming to determine the number of consolidation terminals (hubs), their locations, and the assignment of the spokes to the hubs, while having the objective to minimize the total cost. As previously mentioned, there is a very active research area in transportation but there is limited literature addressing environmental emissions, especially when analyzing deeper hub-and-spoke applications. In relation to Centralized Carrier Collaboration Multi-hub Location Problem (CCCMLP) the majority of the literature addresses collaboration without consideration of multi-hub location or addresses the multi-hub location from the context of a single LTL carrier. In addition, the hybrid hub-and-spoke system being considered on this paper will consist of a set of collaborative consolidation transshipment hubs from a current point-to-point network structure, as stated by Hernandez et al, 2011. Considering 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. Until today, no research has been done on LTL carrier collaboration neither on CCCMLP that considers not only minimizing costs and at the same time the minimization of the Global Warming Potential (GWP). Therefore, in the present research we propose the development a Particle Swarm algorithm to solve the Centralized Carrier Collaboration Multi-hub Location Problem with the main objective of minimizing cost and the Global Warming Potential. Moreover, this paper can be found as a pioneer in introducing emissions into the LTL carrier collaboration by introducing life cycle assessment concepts.

3. 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

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

where ϑ_{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.

$$\sum_k X_k = p \tag{3}$$
$$\sum_k \sum_l Y_{ijklq} + V_{ijq} = 1 \quad \forall i, j, q \tag{4}$$
$$\sum_l Y_{ijklq} \leq X_k \tag{5}$$
$$\sum_k Y_{ijklq} \leq X_l \tag{6}$$
$$C_{ijkl} Y_{ijklq} \leq V_{ijq}\left(1 - V_{ijq}\right)(1 - \gamma) \quad \forall i, j, k, l, q \tag{7}$$
$$X_k \in \{0,1\} \tag{8}$$
$$Y_{ijklq} \in \{0,1\} \tag{9}$$
$$V_{ijq} \in \{0,1\} \tag{10}$$

3.1. Objective Function

$$\min \sum_i \sum_j \sum_k \sum_l \sum_q C_{ijkl} d_{ijq} Y_{ijklq} + \sum_i \sum_j \sum_q W_{ijq} d_{ijq} V_{ijq} + \sum_k \sum_q P_{kq} X_k \tag{11}$$
$$\min \sum_i \sum_j \sum_k \sum_l \sum_q GWPCC_{ijkl} d_{ijq} Y_{ijklq} + \sum_i \sum_j \sum_q GWPNCC_{ijq} d_{ijq} V_{ijq} \tag{12}$$

The first objective function shown in Equation 11, 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 collaborative transportation costs are obtained as the summation of the product of the cost of travel for a shipment C_{ijkl}, the collaborative carrier demand d_{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 directly W_{ijq}, the collaborative carrier demand d_{ijq}, and the V_{ijq} (the decision on whether to ship directly). The second objective function considered in the present study (Equation 12) considers the minimization of the Global Warming Potential, similarly as in the previous cost function, the objective consists of two main terms, the first term represents the Global Warming Potential associated to the carriers collaborating, the second part represents the total Global Warming Potential associated with carriers not collaborating and shipping directly. The collaborative candidate hybrid consolidation hub location costs are obtained as the summation of the product of the costs of locating a collaborative hubP_{kq}, and the X_k(the decision on whether a collaborative facility is located). Equations (11 and 12) subject to constraints (3) through (10) represents the mathematical formulation of the centralized carrier 31 collaborative multi-hub location problem (CCCMLP).

4. Particle Swarm Algorithm

Kennedy and Eberhart (1995) introduced the concept of Particle Swarm Optimization (PSO) which is a metaheuristic method widely used in different operations research problems. The PSO algorithm works by scattering various points "solutions" across a multidimensional field, and evaluating each of these points. At each iteration, the points move towards the best, "current optimal" point, which may change as the algorithm evolves to find the best solution. After specified number of iterations or by satisfying a specific stopping criterion, the points will be converging around the optimal position, which will be is the solution to the problem. This kind of optimization algorithm can be used to solve problems such as optimization of reactive power and voltage control, biological system models, transportation, amongst other areas (Eberhart and Shi, 2001).

4.1Algorithm Development

The PSO algorithm for the Centralized Carrier Collaboration and Multi-Hub Location Problem (PSO-CCCMLP) starts by generating a number n of random p-dimensional points across space. These points are continuous in order to best calculate the necessary velocity function. After generating the initial population, their objective value is calculated as described in equation 11. The selected hubs will be the up-rounded values of the coordinates in which each particle is located. The particles are then organized according to their objective value, from best to worse. Following this, the velocity function is calculated for each dimension, and the particles change their positions according to the velocity. At this point, the algorithm returns to calculating the objective value, looping itself for a set number of iterations before returning the optimal point and its objective function.

4.2 The Velocity Function

At each iteration, the Velocity function for each dimension of each particle is calculated as follows:

$$V(\,) = 2 * rand(\,) * [p(best) - p(current)] \tag{13}$$

Where rand( ) is a random number from 0 to 1, p( ) refers to the position in one dimension of the corresponding particle, and V( ) is the resulting one-dimensional velocity of the particle in the dimension for which velocity is being calculated. Then, the new position of the particle, for each of the p dimensions will be

$$present(\,) = present(\quad) + V(\,) \tag{14}$$

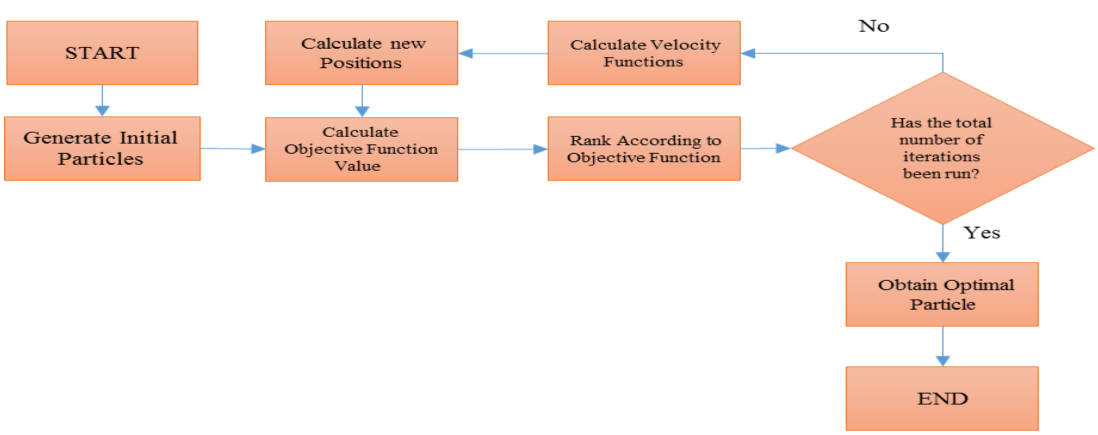

Figure 1: PSO-CCCMLP Algorithm

5. Examples

5.1 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

Demand 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

Demand 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

	Non-collaborative cost 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

Non-collaborative cost 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.

Collaborative Cost										
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

5.2 Case Study 1: Solution

In the Particle Swarm algorithm, an initial population of 100 is considered, running the algorithm for 200 iterations and considering a δ of 10% and values for γ of 9%, 36%, 60% 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

γ value	# of hubs	Hubs Selected	Cost	Collaborative Routes	Non-Collaborative routes	% of collaborative routes	Percentage Savings
9%	1	3	$7,365,654	164	16	91.1%	56.5%
36%	1	3	$7,579,775	140	40	77.8%	55.2%
60%	1	3	10524898	83	97	46.1%	37.9%
96%	1	3	16936923	0	180	0.0%	0.0%
9%	2	3,5	5698410	172	8	95.6%	66.4%
36%	2	3,5	5781077	159	21	88.3%	65.9%
60%	2	3,5	7029645	126	54	70.0%	58.5%
96%	2	1,4	16041354	4	176	2.2%	5.3%
9%	3	4,5,7	4046494	176	4	97.8%	76.1%
36%	3	3,4,5	4112193	166	14	92.2%	75.7%
60%	3	3,5,9	4707666	148	32	82.2%	72.2%
96%	3	4,7,10	14612113	12	168	6.7%	13.7%

Table 8: GWP for Carrier 1

	GWP 100 kg-CO2 equivalent for Carrier 1									
\	1	2	3	4	5	6	7	8	9	10
1	0	0.0430	0.0266	0.0911	0.0584	0.0192	0.0237	0.0430	0.0680	0.0632
2	0.0439	0	0.0256	0.0532	0.0272	0.0282	0.0584	0.0548	0.0340	0.0330
3	0.0269	0.0253	0	0.0603	0.0446	0.0292	0.0272	0.0282	0.0381	0.0632
4	0.0911	0.0532	0.0680	0	0.0705	0.0885	0.0866	0.0699	0.0259	0.0763
5	0.0516	0.0221	0.0478	0.0683	0	0.0349	0.0673	0.0773	0.0600	0.0125
6	0.0166	0.0282	0.0263	0.0850	0.0391	0	0.0343	0.0596	0.0600	0.0462
7	0.0243	0.0490	0.0266	0.0782	0.0715	0.0420	0	0.0240	0.0606	0.0738
8	0.0481	0.0494	0.0330	0.0754	0.0705	0.0501	0.0243	0	0.0430	0.0821
9	0.0628	0.0330	0.0417	0.0253	0.0542	0.0584	0.0667	0.0471	0	0.0673
10	0.0593	0.0372	0.0567	0.0773	0.0118	0.0413	0.0738	0.0920	0.0635	0

Table 9: GWP for Carrier 2

GWP 100 kg-CO2 equivalent for Carrier 2										
\	1	2	3	4	5	6	7	8	9	10
1	0	0.0411	0.0282	0.0920	0.0460	0.0178	0.0233	0.0481	0.0583	0.0620
2	0.0386	0	0.0239	0.0463	0.0248	0.0285	0.0555	0.0558	0.0310	0.0319
3	0.0239	0.0276	0	0.0592	0.0402	0.0260	0.0276	0.0328	0.0365	0.0512
4	0.0776	0.0469	0.0663	0	0.0644	0.0838	0.0855	0.0592	0.0248	0.0807
5	0.0528	0.0242	0.0411	0.0696	0	0.0349	0.0706	0.0666	0.0592	0.0107
6	0.0171	0.0328	0.0273	0.0785	0.0334	0	0.0386	0.0583	0.054	0.0386
7	0.0217	0.0488	0.0264	0.0819	0.0669	0.037	0	0.0276	0.0574	0.0779
8	0.0481	0.0488	0.0273	0.0684	0.0666	0.0543	0.0264	0	0.0426	0.082
9	0.0632	0.0365	0.0362	0.0227	0.0549	0.0528	0.0598	0.0411	0	0.0653
10	0.0534	0.0343	0.0518	0.0706	0.0104	0.0429	0.0841	0.0776	0.0601	0

Table 10: Collaborative GWP

GWP 100 kg-CO2 equivalent for collaboration between Carriers 1 & 2										
\	1	2	3	4	5	6	7	8	9	10
1	0	0.0207	0.0139	0.0455	0.0270	0.0090	0.0117	0.0225	0.0316	0.0297
2	0.0216	0	0.0126	0.0243	0.0121	0.0158	0.0270	0.0275	0.0171	0.0180
3	0.0139	0.0121	0	0.0297	0.0225	0.0130	0.0139	0.0148	0.0194	0.0270
4	0.0455	0.0257	0.0311	0	0.0352	0.0397	0.0415	0.0338	0.0121	0.0401
5	0.0261	0.0126	0.0216	0.0343	0	0.0171	0.0356	0.0392	0.0302	0.0063
6	0.0085	0.0162	0.0139	0.0388	0.0176	0	0.0189	0.0270	0.0293	0.0212
7	0.0126	0.0270	0.0130	0.0406	0.0352	0.0194	0	0.0126	0.0288	0.0388
8	0.0243	0.0275	0.0158	0.0334	0.0388	0.0275	0.0121	0	0.0216	0.0442
9	0.0325	0.0180	0.0189	0.0121	0.0284	0.0311	0.0315	0.0225	0	0.0338
10	0.0302	0.0176	0.0284	0.0388	0.0063	0.0207	0.0374	0.0460	0.0347	0

Case Study 2: Global Warming Potential minimization
Using the Demands from tables 1 & 2, and the estimated emissions data from Tables 8 through 10, we will estimate the total Global Warming Potential (100kg CO_2 equivalent) caused by the trucks traveling through the network. Global Warming Potential is a relative measure of how much heat is trapped in the atmosphere by a greenhouse gas, compared to the heat trapped by a similar mass of CO_2.

The emissions were calculated for a Diesel truck with a 12.4 ton capacity, by the use of GaBi® Life Cycle Assessment Software. The distances used for these calculations were taken as a proportion of each cost over the highest cost in the matrix by a distance of 1200 miles.

Emission minimization through the Particle Swarm Algorithm
In the Particle Swarm algorithm, an initial population of 100 was considered, running the algorithm for 200 iterations and considering a δ of 10% and values for γ of 9%, 36%, 60% 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 selected as collaborative, and the relative saving percentages are presented in table 11.

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 by new opportunities provided through advances in ICTs and e-commerce. The problem was solved via the use of a Particle Swarm 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 caused Global Warming Potential. A direct relation can be observed between the savings and the GWP 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. In future studies, we will incorporate other environmental impacts into the study as well as compare these results as obtained through other metaheuristic algorithms.

Table 11:Results for Case Study 2

γ value	**Number of hubs**	**Selected hubs**	**Global Warming Potential**	**Number of Collaborative Routes**	**Number of non-collaborative routes**	**Percentage of Collaborative routes**	**Relative Reduction percentage**
9%	1	3	3267.059	138	42	76.7%	38.4%
36%	1	2	3574.27	100	80	55.6%	32.6%
60%	1	4	5305.738	0	180	0.0%	0.0%
96%	1	8	5305.738	0	180	0.0%	0.0%
9%	2	3,5	2515.663	157	23	87.2%	52.6%
36%	2	3,5	2612.515	140	40	77.8%	50.8%
60%	2	4,6	3935.305	33	147	18.3%	25.8%
96%	2	5,8	5305.738	0	180	0.0%	0.0%
9%	3	4,5,7	1735.755	159	21	88.3%	67.3%
36%	3	4,5,7	1808.59	141	39	78.3%	65.9%
60%	3	4,5,7	2395.949	74	106	41.1%	54.8%
96%	3	3,8,9	5305.738	0	180	0.0%	0.0%

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