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EFFICIENCY AND RELIABILITY IN FREIGHT TRANSPORTATION SYSTEMS

Final Report

by

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DISCLAIMER

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EXCUTIVE SUMMARY

The efficiency and reliability of its freight transportation system greatly affect the economic competitiveness of the U.S. and the standard of living of its citizens. For instance, production systems have become increasingly dependent on "just-in-time" deliveries, which can reduce inventory and handling costs but depend critically on reliable deliveries. Efficient coordination of vehicle movements and freight transfers in transportation networks and at intermodal terminals, such as ports, airports and rail yards, can reduce the dwell time of vehicles and freight at the transfer terminals where various routes interconnect, such as ports, airports and rail yards, thereby also increasing the vehicles utilization rates, reducing the need for direct routes to connect many origins and destinations, and reducing storage requirements at terminals. Efficient coordination of vehicle arrivals can also improve the overall system efficiency through reduced handling costs (e.g., fewer handling stages, direct vehicle-to-vehicle transfers, and reduced transfer distances). The reliability of vehicle operations and goods deliveries can also be significantly improved by properly planning and controlling transfer operations at terminals.

This report specifies a mixed integer nonlinear programming problem (MINLP) for assisting intermodal logistics operators with coordination decisions in freight transfer scheduling. A hybrid technique combining sequential quadratic programming and genetic algorithms (GA-SQP) is developed to solve the proposed MINLP. We first formulate an optimization model for coordinating vehicle schedules and cargo transfers at intermodal freight terminals, which is done primarily by optimizing coordinated service frequencies and slack times, while also considering loading and unloading, storage and cargo processing operations. This study also provides flexibility in managing general and perishable cargos with different cargo value functions that depend on dwell times. Numerical results indicate that the developed algorithm is capable of producing optimal solutions efficiently for both small and large intermodal freight networks.

1.0 INTRODUCTION AND BACKGROUND RESEARCH

Increasing integration of intermodal transport resources is a valuable approach toward achieving green logistics, and most operations at intermodal freight terminals require transfer movements among modes to serve cargos with diverse destinations, especially for break-bulk, cross-docking, or transshipment systems. According to the 2002 and 2007 Commodity Flow Survey (CFS) results, shown in Table 1, shipments (in terms of million ton-miles) using a single transportation mode increased by only 0.9% over these six years, while multi-modal shipments almost doubled. CFS is a survey of shippers sponsored by the Bureau of Transportation (BTS), which provides detailed information on U.S. freight flows. CFS data are collected every five years as a component of the national Economic Census and provide a benchmark on the value, tonnage, ton-miles, distances, and mode use of commodity shipments.

Several previous studies consider the schedule coordination problem in transit transfer systems, but only a few deal with intermodal freight transfer operations. Voss *(1992)* formulates the schedule synchronization problem as a multi-commodity network design problem, exploiting the quadratic semi-assignment problem (QSAP), and proposes a tabu search algorithm to solve the problem. The QSAP is related to the quadratic assignment problem by the requirement of assigning a set of objects to the candidate locations (i.e. time slots). The QSAP can assign to each location zero, one, or multiple objects, unlike the QAP which requires a one-to-one mapping function. The work presented in Voss *(1992)* mainly seeks to jointly optimize the slack times and service schedules, but this model does not fully fit our requirements.

Table 1 CFS DATA Comparisons Based on Mode Types

Mode of Transportation	Shipment Characteristics by Mode in Ton-miles		
	2002(million)	2007(million)	Percentage Change
Single Modes	2,867,938	2,894,251	0.9
Truck	1,255,908	1,342,104	6.9
Rail	1,261,612	1,344,040	6.5
Water	282,659	157,314	-44.3
Air	5,835	4,510	-22.7
Multiple Modes	225,715	416,642	84.6

(Source: BTS Special Report, 2009)

Gue *(1999)* develops a trailer scheduling model based on the layout of the terminal to minimize the worker travel distances, which can provide a basis of scheduling coordination between delivery and cargo processing vehicles within the terminal. In this study we focus on transfer movements through the studied networks. Detailed transfers inside terminals, such as scheduling and operation problems of crane and other loading / unloading facilities, and cargo processing procedures subject to security concerns, are worth considering in possible extensions.

Anderson *et al. (2009)* also propose a capacitated multi-commodity network design model with schedule coordination of multiple fleets. They design a scheduled service network for a transportation system where several entities provide transportation services and coordination with neighboring systems. Their model determines departure times of the service fleets by minimizing throughput time of the shipments in the system. They analyze how collaborating transportation services should be synchronized and evaluate how border-crossing operations impact the throughput time for the shipments. Their study has two main weaknesses. First, service collaborations among different organizations may be difficult in a freight transportation system unless under a consortium or alliance. Second, the proposed border-crossing operations mainly coordinate services with neighboring systems, so the compromise solutions among these neighboring systems may be not efficient through entire networks.

In order to develop an effective freight shipment transfer scheduling process, Chen and Schonfeld *(2010)* contribute a method for quantifying and simultaneously optimizing the service frequencies and slack times among all routes within the studied network based on different coordinated policies. The studied problem is first tested in small networks and solved by GA and SQP. In this study, a hybrid technique combining sequential quadratic programming and genetic algorithms (GA-SQP) is further developed for solving the large-scale intermodal logistics timed transfer problems.

Our previous logistic timed-transfer models develop coordinated and optimized schedules for given freight networks, which minimize transfer delays, among other factors. Three different coordinated methods are analyzed, namely: uncoordinated operations, coordinated operations with a common service headway, and coordinated operations with integer-ratio service headways. Uncoordinated operation means that all modes and routes are optimized independently; other coordination methods are developed for different characteristics and combinations of modes. It should be noted that several related models (Lee and Schonfeld, *1994*; Ting and Schonfeld, *2007*) have been developed for urban passenger transportation and air transportation systems; however, some important differences pertaining to freight logistics (e.g. factors affecting demand, lack of self-guidance, storage requirements, perishability, heterogeneous characteristics of cargos, information availability about shipments) require special attention in this study.

The models for uncoordinated service and coordination with a common headway are formulated as nonlinear programming problems (NLP). Since constraints in the proposed models are not convex functions, standard heuristic algorithms for solving these NLPs can guarantee convergence only to a local minimum. The model of integer-ratio coordination including both integer and linear variables (i.e. integer ratio multipliers) with nonlinear cargo time values is known as a mixed-integer nonlinear program (MINLP). The optimization of such models is typically difficult due to their combinatorial nature and potential existence of multiple local minima.

Many previous studies apply genetic algorithms (GAs) to solve scheduling and schedule coordination problems. Shrivastava *et al. (2002)* formulate scheduling and schedule coordination problems as conflicting objectives with user's costs and operator's costs. Sarker and Newton *(2002)* develop a method for determining an optimal batch size for a product and purchasing policy for associated raw materials, given limited storage space and capacities of transportation fleets. Torabi *et al. (2006)* investigate the delivery schedule that would minimize the average of holding, setup, and transportation costs per unit time for the supply chain. Cao and Lai *(2007)* present a vehicle routing problem with time windows constraints and simultaneous delivery and pick-up operations. A hybrid optimization algorithm is proposed based on the combination of differential evolution techniques and GAs.

In other MINLP applications, Cheung *et al. (1997)* integrate GAs and a modified grid search method to minimize the cost development problem within oil fields and optimize the design of the multiproduct batch plant. Ponsich *et al. (2007)* also test similar batch plant problems by using GAs. In general, the objective of the batch plant problem is to minimize the plant investment cost. The formulation usually accounts for the synthesis of m products treated in n batch stages and k semi-continuous units (pumps, heat exchangers, etc.). Ozçelik and Ozçelik *(2004)* mention that the traditional gradient methods for solving the MINLP must separate the problem into Mixed Integer Linear Programming (MILP) and NLP, with some special formulations where continuity or convexity has to be imposed. They develop a heuristic algorithm based on a simulated annealing algorithm to solve this problem.

SQP methods are appropriate for solving smooth nonlinear optimization problems when the problem is not too large (although this limitation has been alleviated in some of the studies discussed below for large scale problems), the functions and gradients can be evaluated with sufficient precision, and the problem is smooth and well-scaled (Hock and Schittkowski, *1983*). In this approach, an approximation is made of the Hessian of the Lagrangian function using a quasi-Newton updating method. Boggs and Tolle *(2000)* apply the general SQP methods to solve nonlinear constrained optimization problems. They point out that large scale problems (i.e., with a large number of variables and / or constraints) may lead to inefficient solution procedures when using SQP. Thus, they propose reduced Hessian SQP methods for solving large scale problems. Cervantes *et al. (2000)* describe a modified SQP method for solving the nonlinear optimal control formulation, which has been applied in some general nonlinear programming problems. This method employs a line search, a merit function, and reduced-space quasi-Newton Hessian approximations. Tenny *et al. (2004)* develop a feasibility perturbation – sequential quadratic programming method (FP-SQP). One main advantage is that the latest iterate can be used as a (suboptimal) feasible solution, if it is necessary to terminate the solution process early, thus avoiding unpredictable algorithmic behavior associated with allowing infeasible points. Based on this approach, Wright and Tenny *(2004)* seek an approximate minimizer of the model function over the intersection of the trust region with the original feasible set at every iteration.

Although deterministic methods (e.g. SQP) are relatively fast, they might get trapped in local optima since such problems may have many local solutions *(Fatemi et al., 2005)*. Still, a good initial point or initial range could lead to the global solution. On the other hand, stochastic methods (e.g. GAs) are more suitable for solving such type of problems because a wide range of values for parameters would be searched and probability of getting trapped into local optima would decrease. Nevertheless, their convergence in the final problem solving steps is relatively slow. Therefore, several researchers have developed some hybrid / combination optimization methods for solving nonlinear programming problems.

Victoire *et al. (2006)* present a hybrid tabu search (TS), particle swarm optimization (PSO) and SQP technique for scheduling generating units based on the fuzzy logic decisions. Youssef et al. (2007) describe a hybrid TS – GA – SQP method for optimizing the fitting of non-uniform rational B-Spline surfaces to laser-scanned point clouds. Pedamallu and Ozdamar *(2008)* develop a hybrid simulated annealing (SA) and SQP method for solving nonlinear and non-convex constraint problems. They develop two versions of hybrid SA - SQP methods. The first version incorporates penalties for constraint handling and the second one eliminates the need for imposing penalties in the objective function by tracing feasible and infeasible solution sequences independently. Numerical experiments show that the second version is more reliable in the worst case performance. Mansoornejad *et al. (2008)* use a hybrid GA - SQP method to determine the kinetic parameters of the set of highly nonlinear hydrogenation reactions. Gasbarri *et al. (2009)* also use a hybrid GA – SQP method to solve an integrated dynamic and structural optimization procedure for a composite wing-box design problem. Since hybrid methods can adopt advantages of both deterministic and stochastic methods and avoid certain existing disadvantages, some of the above hybrid techniques are considered in this study. Based on the proposed nonlinear programming models (e.g. some components of objective function, constraints, and nonlinear time value settings), GAs and SQP are well suited for such problems with complex and nonlinear formulations. One hybrid GA – SQP method is developed for solving our problem. The basic concept for the hybrid method is to do the global search with GAs and use SQP for the deeply local search.

2.0 MODELING FRAMEWORK

In this section, three analytical models for different schedule coordination policies are developed based on the predetermined logistic networks, given origin-destination information for a specific time period, and some suggested values for certain parameters, in order to minimize the total system costs. Based on problem's characteristics, it is modeled as nonlinear programming problem (NLP) and mixed-integer nonlinear programming problem (MINLP) within the studied networks. To deal with the stochastic vehicle arrivals and uncertain route travel times, optimized slack times are built into the operating schedules.

2.1 MODEL FOR SCHEDULING UNCOORDINATED OPERATIONS

The mathematical model for uncoordinated operation is based on independently optimized schedules for different routes. The objective is to minimize the total system costs (Equation 1), which include delivery vehicle operating cost (C_o), cargo dwell time cost (C_w), loading/unloading cost (C_l), cargo processing cost (C_p), and cargo transfer cost (C_f). Cargo in-vehicle cost is not affected by service frequencies; hence it is not included in the total system cost function. B_i = unit vehicle operating cost (\$/vehicle-min); T_i = round trip time of Route i (min), including the lay-over time; f_i = service frequencies of Route i (veh/min); a_i = fixed vehicle operating cost of Route i (\$/min); b_i = variable vehicle operating cost of Route i (\$/lb-min); and S_i = vehicle size on Route i. Equation 3.3 specifies that the total demand of Route i includes m types of cargos. D_i = demand along the Route i (lb / min); μ^m = unit time-dependent cargo value function of type m cargo (\$/lb-min); w_i = dwell time on Route i; θ = unit cargo loading / unloading time (min); σ^2_i = variance of service headways of the Route i (min^2).

Detailed formulations are shown in Chen and Schonfeld (2010). The model is expressed as follows:

Minimize $C_T = C_o + C_w + 2C_l + C_p + C_f$ (1)

$$C_o = \sum_{i \in E} B_i T_i f_i = \sum_{i \in E} (a_i + b_i S_i) T_i f_i \quad (2)$$

$$C_w + C_l = \sum_{m \in M} \sum_{i \in E} \mu^m (D_i w_i + \theta S_i l_i) = \sum_{m \in M} \sum_{i \in E} \mu^m D_i (w_i + \frac{\theta}{f_i}) \quad (3)$$

$$C_l + C_p = \sum_{m \in M} \sum_{i \in E} \mu^m S_i l_i (\theta + \phi) = \sum_{m \in M} \sum_{i \in E} \frac{\mu^m (\theta + \phi) D_i}{f_i} \quad (4)$$

$$C_f = \sum_{k \in N} \sum_{m \in M} \sum_{j \in E} \sum_{i \in E, i \neq j} \mu^m (q_{ji}^{mk} w_i) = \sum_{k \in N} \sum_{m \in M} \sum_{j \in E} \sum_{i \in E, i \neq j} \mu^m q_{ji}^{mk} \left(\frac{1}{2E(f_i)} + \frac{\sigma_i^2 E(f_i)}{2} \right) \quad (5)$$

Subject to

$$0 \le \left(\sum_{i \in E} \frac{R_j}{f_i} + \sum_{j \in E} \frac{R_i}{f_j} \right) \varepsilon \le A^k \quad (6)$$

$$f_i \le f_{\max} = \frac{N_i}{T_i} \quad (7)$$

$$f_i \ge f_{\min} = \frac{D_i}{S_i l_i} \quad (8)$$

Equation (6) assumes that the required storage areas for the total transfer demand cannot exceed the available storage areas at the transfer terminal k. ε = unit cargo storage areas; A^k = available storage areas at the transfer terminal k. Equation (7) states that the service frequency on any feeder route i should not exceed the maximum allowable service frequency (f_{max}), where N_i = total available vehicles for dispatching on route i (vehicles); l_i = load factor on route i. Equation (8) states that the service frequency on any feeder route i should exceed the minimum acceptable service frequency (f_{min}).

2.2 MODEL FOR SCHEDULING A COORDINATED OPERATION WITH A COMMON SERVICE FREQUENCY

A major difference between the uncoordinated and coordinated systems is the provision of slack times for coordinated systems. Slack times are additional decision variables within the proposed sub-models. For the uncoordinated system, we address the cost terms related to the service frequency (or headway). Since the exact vehicle travel and arrival times are uncertain, adding some reserve or "slack" time into a schedule can improve adherence to scheduled departures at the transfer terminal and allow a better response to demand fluctuations, congestion and other contingencies. For a coordinated operation, the costs of vehicle operation and cargo dwell, loading, unloading and processing are the same as those for an uncoordinated system. However, some costs related to the transfer movements are sensitive to the slack times and service frequencies. These cost components are formulated in Equations (9)-(12).

$$C_f = C_s + C_x + C_d \quad (9)$$

$$C_s = \sum_{m \in M} \sum_{i \in E} \sum_{k \in N} [\mu(H_i^{mk} + F_i^{mk}) + B_i f_i] s_i^k \delta_i^k \tag{10}$$

Equation (9) states that the transfer cost of the coordinated operation with a common service frequency includes three cost components: the slack time cost (C_s), the missed connection cost (C_x), and the connection delay cost (C_d). The slack time cost includes the costs of additional in-vehicle time for loaded cargos and processing operations during the slack time. In Equation (10) the first term is the slack time delay cost for the cargos already loaded in vehicles serving route i; the second term is the dwell time cost for cargos transferred to route i; the third term is the additional vehicle operating cost due to the slack time. Let $H^{mk}{}_i$ = amount of m types of cargos already loaded at terminal k on route i (cargo / min); $F^{mk}{}_i$ = amount of m types of cargos transferred at terminal k from other routes to route i (cargo / min); $s^k i$ = slack time at transfer terminal k on route i (min); $\delta^k i$ (a binary variable) = 1 if transfer terminal k is located on route i and 0 otherwise. Equations (11)-(12) represent the missed-connection and connection-delay costs based on the corresponding probabilities.

$$C_x = \sum_{m \in M} \sum_{k \in N} \sum_{j \in E} \sum_{\substack{i \in E \\ i \neq j}} \mu q_{ji}^{mk} \delta_i^k \delta_j^k \times f_x(t_i, t_j) \tag{11}$$

$$C_d = \sum_{m \in M} \sum_{k \in N} \sum_{j \in E} \sum_{\substack{i \in E \\ i \neq j}} \mu q_{ji}^{mk} \delta_i^k \delta_j^k \times f_d(t_i, t_j) \tag{12}$$

2.3 MODEL FOR SCHEDULING A COORDINATED OPERATION WITH INTEGER-RATIO SERVICE HEADWAYS

The common service frequency is not efficient when the demands or vehicle round-trip times of different routes vary much. Especially for international intermodal freight transportation networks, the characteristics of routes and modes differ significantly. Thus, the concepts proposed by Ting and Schonfeld *(2007)* for coordinating operations with integer ratios for headways and segment travel times (in passenger transportation systems) are adapted here and revised as follows. The cost terms related to transfer movements are sensitive to the slack time and service frequency. These cost components are expressed in Equations (13)-(17).

$$C_f = C_s + C_i + C_x + C_d \tag{13}$$

$$C_i = \sum_{m \in M} \sum_{k \in N} \sum_{j \in E} \sum_{\substack{i \in E \\ i \neq j}} \mu q_{ji}^{mk} z_{ji}^{mk} \tag{14}$$

$$z_{ji}^{mk} = g_{ji} y \left(\frac{1}{2 g_{ji} y f_i} - \frac{1}{2}\right) + s^k{}_i = g_{ji} y \left(\frac{h_i}{2 g_{ji} y} - \frac{1}{2}\right) + s^k{}_i \tag{15}$$

$$C_x = \sum_{m \in M} \sum_{k \in N} \sum_{j \in E} \sum_{\substack{i \in E \\ i \neq j}} \mu q_{ji}^{mk} \frac{g_{ji} y}{h_i} \delta_i^k \delta_j^k \times f_x(t_i, t_j) \tag{16}$$

$$C_d = \sum_{m \in M} \sum_{k \in N} \sum_{j \in E} \sum_{\substack{i \in E \\ i \neq j}} \mu q_{ji}^{mk} \frac{g_{ji} y}{h_i} \delta_i^k \delta_j^k \times f_d(t_i, t_j) \tag{17}$$

Equation (13) states that the transfer cost of the coordinated operation with integer-ratio service headways includes four cost components. In order to describe the inter-cycle transfer delay cost (C_i), the frequencies and headways (which are reciprocal terms) of routes i and j can be expressed with integer multipliers (β_i and β_j) of the base cycle y (headway): $h_i = \beta_i$ y and $h_j = \beta_j$ y (or $f_i = \beta_i^{-1} y^{-1}$ and $f_j = \beta_j^{-1} y^{-1}$). Let $z^{mk}{}_{ji}$ = the average transfer waiting time from route j to route i; g_{ji} = the greatest common divisor β_i of and β_j. The inter-cycle cost includes all routes connecting at the transfer center, as shown in Equations (14)-(15). All other formulations are similar as those for the common frequency method.

3.0 SOLUTION METHODS

In this section, three heuristic approaches for both NLP and MINLP are described. Here we first briefly introduce the solution procedures of genetic algorithms (GAs) and sequential quadratic programming (SQP), starting from initializing and verifying input data until obtaining the optimized solutions. A hybrid GA-SQP method is then described specifically for the proposed models, which is related to but somewhat different from the one proposed by Mansoornejad *et al. (2008)*, as explained later in this section .

The application of GAs to a specific problem includes several steps. A proper encoding method should be devised first. A fitness function is required for selecting individuals and evaluating produced offspring, which is derived through some problem-specific genetic operators. Thus the main components of GAs should contain (1) solution encoding, (2) initial population, (3) fitness function, (4) selection, (5) genetic operators, and (6) population replacement. The proposed GAs comprise three kinds of chromosomes with linear and integer genes to represent the strategic planning variables of different control policies, as shown in Figure 1.

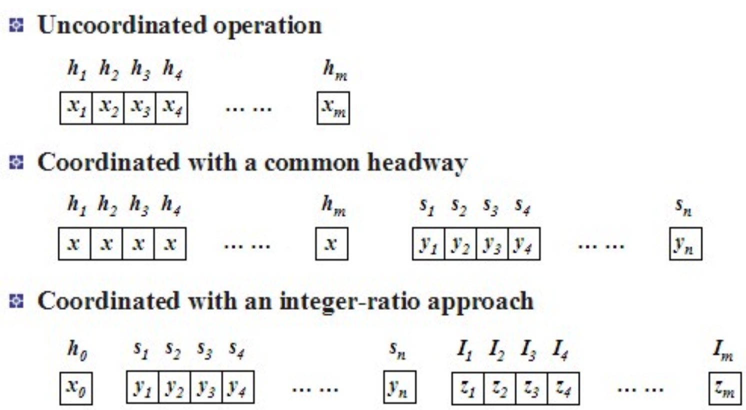

Figure 1 Settings of Chromosomes for (a) Uncoordinated, (b) Common Headway Coordination, and (c) Integer-ratio Coordination approaches

SQP is another widely used approach for solving nonlinear constrained optimization problems. Since its popularization in the late 1970s, SQP has arguably become the most successful method for solving nonlinearly constrained optimization problems. This method attempts to solve a nonlinear program directly rather than convert it to a sequence of unconstrained minimization problems. With a solid theoretical and computational foundation, SQP algorithms have been developed and used to solve a remarkably large set of important practical problems (e.g. Cervantes *et al., 2000*; Tenny *et al. 2004*).

Although both GA and SQP have been widely applied in solving the nonlinear optimization problems, both approaches still have some drawbacks. Hybrid heuristic algorithms have been favored recently due to the potential combinatorial advantages. We first introduce the hybrid GA – SQP approach of Mansoornejad et al. 2008, and explain some differences between their approach and our proposed algorithm.

In Mansoornejad's approach, a GA is applied first to produce a proper starting solution and then calculations shift to SQP. Furthermore, the GA and SQP are used sequentially. The algorithm starts with the GA since the SQP is sensitive to the starting point. The calculation continues with the GA for a specific number of generations or a user-specified number for the stall generation, during which the approximate solution approaches to the final solution. The stall generation is one possible stopping criterion. In other words, the GA keeps running until the number of generations meets a specified value or the objective function value stays unchanged for a specified number of generations, both specified by the user based on the nature of the problem. Their algorithm then shifts to the SQP, which is a faster solution method. If the improvement with the SQP is insufficiently large, the algorithm returns to the GA. The criterion for "enough improvement" depends on the nature of the problem and can be specified by users. Otherwise, the algorithm continues until no further improvement in the objective function is observed. This sequence of shifting between GA and SQP in series could be applied more than once until the final solution is reached.

The hybrid GA – SQP method proposed by Mansoornejad et al. is sound; however, there are still some drawbacks which can be improved by our approach. Details of the hybrid GA - SQP approach proposed here are illustrated in the flowchart of Figure 2.

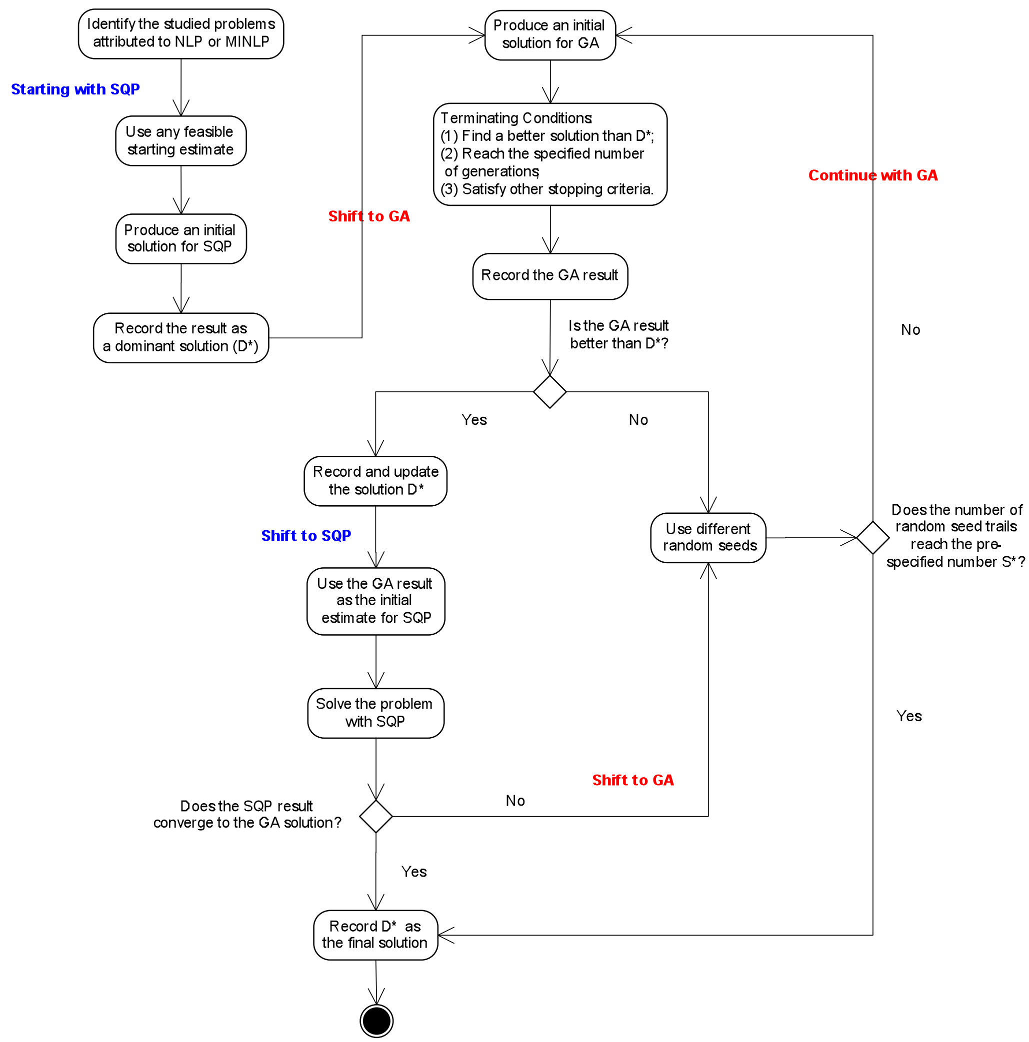

Figure 2 Procedures of proposed hybrid GA - SQP method

First, the GA stopping criterion in Mansoornejad's algorithm seems somewhat insufficient. In our approach, we use SQP to produce the starting solution which provides a reasonable threshold for the following GAs. As soon as the GA result overtakes the current dominant solution D*, the program switches back to SQP.

Second, the alternation between GA and SQP may be inefficient because the GA may not exploit its main advantage, the "diversity" of solutions. An important problem with a hybrid method is determining the appropriate switching time. In our approach, if the dominant solution is generated from SQP, then even if the current switch (i.e. GA) cannot find a better solution, the program does not terminate immediately. In order to increase diversity for the GA, different random seeds applied in the GA challenge the dominant solution again and are repeated several times until no further improvements are found. However, if the GA result can improve on the current dominant solution, this result is recorded as the new dominant solution and becomes the initial estimate for SQP. The proposed algorithm keeps running the SQP program to find a better solution or terminates when no further improvements are found.

Third, Mansoornejad's approach has another problem of timing the switch from SQP to GA. If the SQP step size is too small, the algorithm shifts to the GA. This switching strategy may raise two additional difficulties: (1) How should we determine the "large enough" step size for proceeding in SQP; and (2) The intermediate termination of SQP may not generate a useful base for the following GA. To solve these two problems, we switch to GA only if we reach a local optimun in SQP.

In order to exploit the major advantages of both GA and SQP and alleviate the weaknesses of these two approaches, a hybrid GA – SQP method is developed and applied in case studies. In general, the proposed hybrid approach first implements a global search with the GA and then runs SQP to reach the final solutions. Through this algorithm, the GA can converge very fast initially and provide a good initial solution for SQP, which then searches until no further improvements are found.

4.0 NUMERICAL EXAMPLES

Through this work we seek to coordinate the service frequency among inbound and outbound routes connecting to an intermodal freight terminal. Some applications arise when the service routes have significantly different demands or travel times. Additionally, this study provides flexibility for general and perishable cargos with different inventory / dwell time value functions.

4.1 CASE 1: SINGLE COMMODITY, MULTIPLE MODES, & SINGLE HUB OPERATIONS

In Case 1, we assume there are 9 light truck routes (Routes 1-9) and 1 heavy truck route (Route 10) connecting to the terminal. To simplify the problem, we start from the single-hub operation with symmetric demand between any pair of inbound and outbound routes.

The capacities of light and container trucks are 7,300 and 22,000 pounds, respectively. The vehicle operating cost function is expressed as a + b*c, where a represents the fixed cost ($/hr), b represents the variable cost ($/lb-hr), and c is the capacity for the vehicle. In this case, we assume a = 100 (light) and 200 (heavy), and b = 0.03. The value of parameter b is suggested by Coyle, Bardi, and Novack (1994); however, this value may differ for different modes and commodities. The following case studies adopt this value, but it is easily changeable based on user requirements. The unit cargo dwell cost (μ) is $0.2/lb-hr. Unit cargo loading and processing times are set as 0.03 and 0.05 (min/lb), respectively. Other given inputs are listed in Table 2.

Table 2 Demand and Route Information for Case 1

Inbound Route	Outbound Route (Unit: 100 lb /	Route Travel Time (min)

	hour)	Mean	**Standard Dev.**
1	24.50	82	**8**
2	31.50	99	**9.5**
3	15.50	43	**3.5**
4	32.50	107	**10**
5	15.00	39	**3.5**
6	22.50	79	**7.5**
7	35.00	115	**10.5**
8	30.00	94	**9**
9	**21.00**	**73**	**6.5**

In this case, the common headway approach has the same result as the integer-ratio approach. As shown in Table 3, both SQP (also same as the result via GA-SQP in this case) and GA can obtain better system performances in coordinated operations than in uncoordinated ones, especially for the transfer cost components.

Table 3 Overall Results of Different Policies in Case 1

	Optimized Headways (hour/vehicle) / Frequencies (vehicle)					
	Uncoordinated (GA-SQP)		Coordinated (GA)		**Coordinated (GA-SQP)**	
Route 1	1.34	0.75	0.966	1.035	0.967	**1.034**
Route 2	1.30	0.77	0.966	1.035	0.967	**1.034**
Route 3	1.22	0.82	0.966	1.035	0.967	**1.034**
Route 4	1.33	0.75	0.966	1.035	0.967	**1.034**
Route 5	1.18	0.85	0.966	1.035	0.967	**1.034**
Route 6	1.37	0.73	0.966	1.035	0.967	**1.034**
Route 7	1.32	0.76	0.966	1.035	0.967	**1.034**
Route 8	1.29	0.77	0.966	1.035	0.967	**1.034**
Route 9	1.36	0.73	0.966	1.035	0.967	**1.034**
Route 10	0.97	1.03	0.966	1.035	0.967	**1.034**
Slack Time						
S_1^1	--		0.03		**0.02**	
S_2^1	--		0.08		**0.06**	
S_3^1	--		0.03		**0.03**	
S_4^1	--		0.11		**0.03**	
S_5^1	--		0.02		**0.02**	
S_6^1	--		0.02		**0.05**	
S_7^1	--		0.02		**0.02**	
S_8^1	--		0.08		**0.03**	
S_9^1	--		0.05		**0.06**	
S_{10}^1	--		0.05		**0.05**	
Costs ($/hour)						
Operating Cost	10382		12496		**12485**	
Dwell Cost	5216		4444		**4447**	
Loading / Unloading	10		9		**9**	
Cargo Processing	9		7		**7**	
Non-transfer Cost	15617		16956		**16948**	
Inter-cycle	--		0		**0**	
Slack time	--		661		**509**	
Miss-connection	--		1724		**1958**	
Connection delay	--		442		**328**	
Transfer Cost	5216		2827		**2795**	
Total System Cost	**20833**		**19783**		**19743**	

When comparing the values for coordinated and uncoordinated objective functions, we observe that the coordinated approaches are better than the uncoordinated one, especially for transfer costs. It is clear that, due to lower load factors, higher service frequencies lead to higher operating cost, lower cargo dwell, loading, unloading, and processing times and costs.
In this multi-variable problem, SQP can generate robust solutions based on given initial feasible solutions. However, the quality of the optimized solutions may be affected by different initial solutions. The proposed hybrid GA-SQP algorithm is developed for overcoming this weakness of SQP. However, if the initial estimate is fairly good, the SQP can still reach the same solution as the hybrid method.

In our GA applications, the optimized result is almost the same (i.e. the difference between total system costs is only 0.2 %). Although this GA objective value can be improved by running additional generations, those additional generations yield diminishing improvements. The proper number of generations that should be run depends on tradeoffs between solution quality and the program running time. In our hybrid approach, an initial solution solved by SQP with any random feasible estimate can be viewed as one threshold value for stopping the GA.

4.2 VARIABILITY IN OPTIMIZED RESULTS

As mentioned above, results solved by SQP may vary with different initial inputs and those optimized by GAs may reach various local optima due to different random seeds of initial populations. The GA-SQP performance in terms of objective function value is tested by comparing its results to those of GA and SQP. Some numerical examples generated based on 30 different initial solutions (for SQP) and 30 different random seeds (for GAs) are tested in this section. Results are also compared with the proposed hybrid GA-SQP method by using the same set of random seeds for GAs. All other settings are as in Case 1.

A hybrid GA-SQP heuristic algorithm proposed here shows the robust capability to find the same optimal solution based on different random seeds for its GA stage. One of the GA stopping criteria is the number of generations; here we set a threshold at 500 generations. For the hybrid GA – SQP approach, we first let a GA run 100 generations and then use those results when switching to SQP. It should be noted that both GAs and the hybrid GA – SQP may be terminated and switched by other criteria. The pre-determined thresholds are only used for comparison among different solution approaches. Results found by the GA after running 100 generations are also provided for comparison with those solved by other algorithms.

In Figure 3, when comparing the results solved by four different algorithms, both GA (with 500 generations) and the hybrid GA - SQP approaches are better than the GA (with 100 generations) and SQP. This figure also demonstrates that SQP is very sensitive to initial feasible solutions. Wide variation in results is seen based on different initial solutions. Although SQP can reach similar fitness values to those of our hybrid GA- SQP approach due to the good initial estimates (2 times within the 30 examples), it may be difficult for inexperienced users to obtain good initial solutions.

Some examples indicate that GA results after 100 generations may still be unable to surpass the current dominant solution solved by SQP. Moreover, results solved by GA may be affected by different random seeds of the initial populations. In further comparisons between the GA over 500 generations and the proposed hybrid method, the results obtained with the hybrid approach provide better and consistent optimized solutions, although the differences from those solved by GA are not significant.

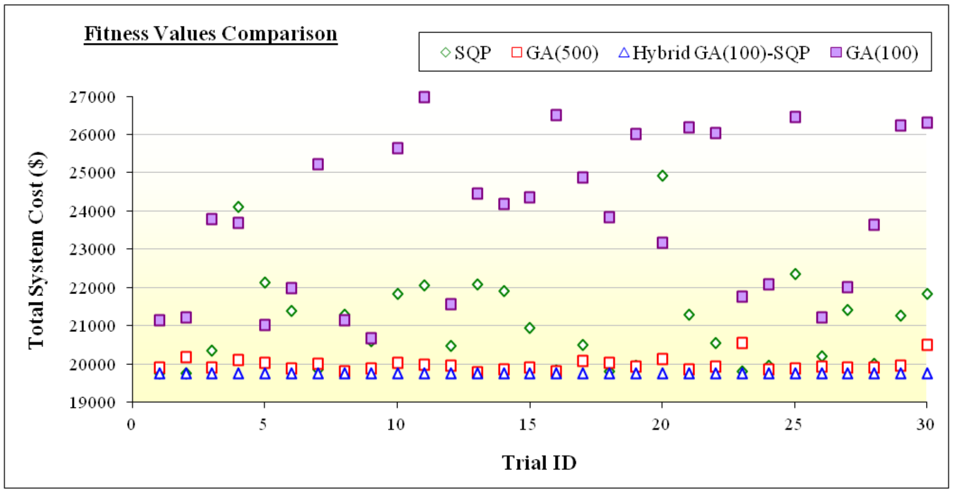

Figure 3 Optimized Results Solved by GA, SQP, and a Hybrid GA-SQP in Case 1

4.3 COMPUTATION TIME

The computation time is important for future real-time applications. On average, Figure 4 shows that the GA (with 500 generations), the hybrid GA (with 100 generations) –SQP, and SQP in Case 1 are completed in 144.22, 48.13, and 13.85 seconds, respectively. All programs are executed on a PC with a Pentium(R) 4 CPU 2.80 GHz and 512 MB of RAM.

As mentioned above, additional generations of GAs yield diminishing improvements in the value of the objective function. Thus, the suitable number of generations for each optimization process should be based on the available computation time and mission importance.
Apparently, both SQP and the hybrid algorithm can obtain satisfactory results within one minute, which provide a competitive ability for fairly complex real-time applications. It should be noted that the computation time may be affected by the scale of studied networks, number of decision variables and constraints, and equipment used.

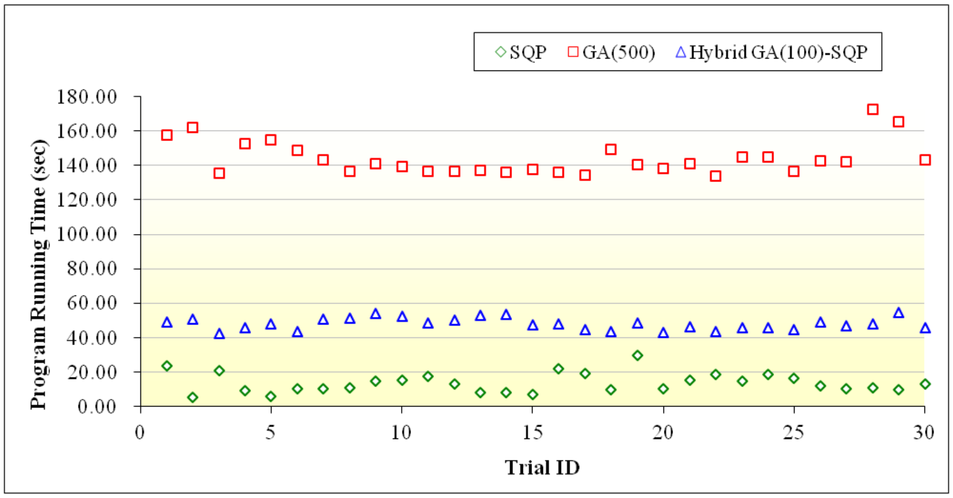

Figure 4 Program Running Time with Different Solution Approaches in Case 1

Case 2: multiple commodities, multiple modes, & multiple hubs with loop in network
Three container truck routes (Routes 1-3) and three heavy truck routes (Routes 4-6) are analyzed in Case 2. As shown in Figure 5, the three hubs form a loop, which generally complicates their coordination. The vehicle capacities are 44,000 and 22,000 pounds. In this case, a = 200 (heavy) and 250 (container), and b = 0.03. Two types of shipments with different unit time values are assumed in this case. μ_1 and μ_2 are \$0.5*exp(-t) /lb-hr and \$0.2/lb-h respectively. The notation "t" expresses the total transportation time, including dwell time, loading/unloading, cargo processing, and mean travel time from origin to destination. The average and the standard deviation of travel time are listed near each link. All other settings are as in Case 1.

Coordination at one transfer terminal affects the other transfer hubs in the loop. Considering only the coordination of a pair of transfer terminals may lead to coordination conflicts for other pairs of terminals. The conflicts may increase the difficulties of solving this problem and may even preclude feasible solutions. More transfer terminals within the loop and more loops within the entire networks would increase the complexity of the studied problem. The interaction among the hubs within the loop is quite important in this case.

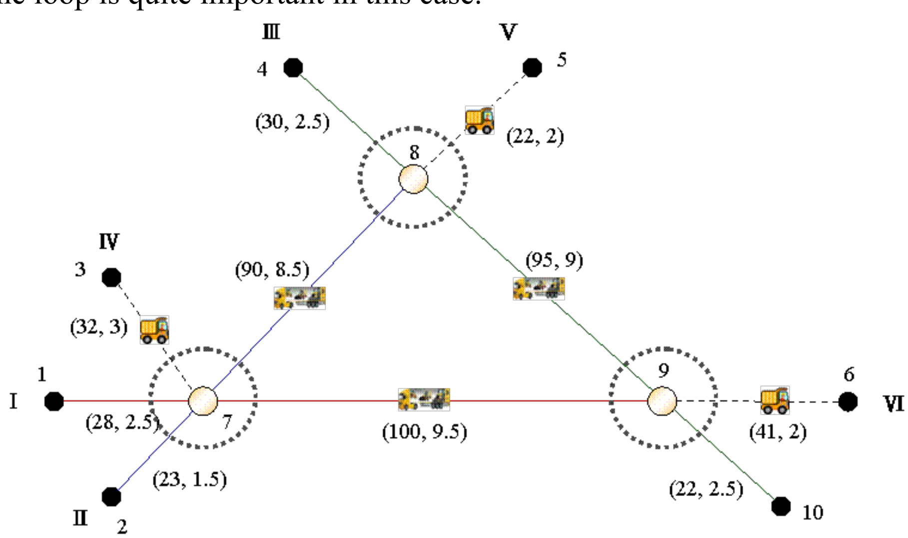

Figure 5 Network Configuration for Multi-Modes and Multi-Hubs Operation

Table 4 indicates the optimized results based on the given OD information and loop network configuration. Basically, under uncoordinated operations, 3 light truck routes tend to be served with smaller headways than those of 3 container truck routes. The value of the optimized common headway lies between the minimal and maximal headways in uncoordinated operations. For integer-ratio coordination, both GA and the hybrid GA-SQP obtain the same integer multipliers but with different base cycle values. In addition, common headway coordination is undesirable in this case due to high non-transfer costs. The optimized result of integer-ratio coordination solved with the hybrid approach is the dominant solution in Case 2.

Table 4 Overall Results for Different Policies in Case 2

	Optimized Headways (hour/vehicle)			
	Uncoordinated (GA-SQP)	Common Headway Coordination (GA-SQP)	Integer-ratio Coordination (GA)	Integer-ratio Coordination (GA-SQP)
Base Cycle (y)	--	0.90	0.35	0.42
Route 1	1.43	y	4y	4y
Route 2	1.40	y	5y	5y
Route 3	1.06	y	3y	3y
Route 4	0.72	y	2y	2y
Route 5	0.57	y	2y	2y
Route 6	0.78	y	2y	2y
Slack Time				
S_1^{7a} ,S_1^{7b}	--	0.08, 0.05	0.08, 0.01	0.12, 0.01
S_1^{9}	--	0.05	0.18	0.18
S_2^{7a} ,S_2^{7b}	--	0.04, 0.05	0.06, 0.01	0.11, 0.01
S_2^{8}	--	0.15, 0.06	0.19	0.18
S_3^{8a}, S_3^{8b}	--	0.11, 0.05	0.07, 0.14	0.07, 0.18
S_3^{9a} ,S_3^{9b}	--	0.03, 0.03	0.06, 0.07	0.06, 0.14
S_4^{7}	--	0.06	0.09	0.08
S_5^{8}	--	0.05	0.07	0.08
S_6^{9}	--	0.06	0.07	0.06
Costs ($/hour)				
C_o	17078	21679	16431	13955
C_w	6700	5702	7083	8400
C_l	28	23	30	35
C_p	16	12	17	20
Non-transfer	23822	27416	23561	22410
C_i	--	--	48	428
C_s	--	1132	2681	2952
C_m	--	2459	1299	1208
C_d	--	2514	1186	1085
Transfer	6880	6105	5214	5673
Total System	30702	33521	28775	28083

4.4 CASE 3: A LARGE SCALE NETWORK APPLICATION WITH MULTIPLE HUBS WITH LOOP IN NETWORK

Based on the above cases, we attempt to synchronize service routes within the studied network. In the real world, one intermodal train may connect 240 - 300 trucks of the road. The tested examples may be relatively simple; however, the computation codes can be easily adapted to other network configurations with required information. A larger network with 30 light truck routes (Routes 1-30), two container truck routes (Routes 31-32), and one rail route (Route 33) is analyzed in Case 3. Similarly to Case 2, the three transfer terminals are arrayed in a loop. The vehicle capacities of light truck, container truck, and rail train including 6 container stack railcars are 22,000, 44,000, and 1,017,000 pounds, respectively. In this case, a = 200 (heavy), 250 (container), and 300 (rail); b = 0.03. Two types of shipments with different unit time values are $0.25*exp(-t) /lb-hr and $0.1/lb-hr. All other settings are as in Case 1.

Table 5 shows the optimized results based on the given OD information and the loop network configuration. Basically, the optimized result of integer-ratio coordination solved with the hybrid approach is the dominant solution in Case 3. The value of the optimized common headway is still between the minimal and maximal headways in uncoordinated operations. For integer-ratio coordination operations, all light truck routes are served with the base cycle y (y = 2.03 hours). Two container truck routes and the rail train route are scheduled with 2y and 5y headways, respectively. Overall results (both schedules and total system costs) of uncoordinated operations and those of integer-ratio coordination operations are quite similar. As in Case 2, common headway coordination is still less desirable in this case due to extremely high non-transfer costs.

Table 5 Overall Results ($/hour) for Different Policies in Case 3

	Uncoordinated	Common Headway Coordination	Integer-ratio Coordination
Non-transfer Costs	87,107	207,850	91,146
Transfer Costs	18,440	9,840	15,604
Total System Costs	105,547	217,690	100,750

5.0 CONCLUSIONS

In this paper, our case studies are developed for multi-mode transfer operations. General models are developed for most combinations of modes (e.g. trucks to rail trains, trucks to airplanes, rail trains to ships, etc.), which can be described in terms of their vehicle capacities, unit operating costs, average speeds and travel time variances. The pre-planning model is developed for optimizing in advance system characteristics such as terminal capacities, vehicle sizes, routes, schedules and probabilistic reserve factors built into operating schedules. The usefulness of the numerical results can be increased by further developing a real-time control model for dealing with service disruptions. Since system coordination can provide many advantages such as better scale economies in transportation, lower storage requirements, and lower external costs, transportation firms, terminal operators, infrastructure providers, shippers and forwarders, may greatly benefit from adopting such an intermodal timed transfer approach.

In Case 1, we mainly seek to analyze the coordinated service frequencies that minimize the total system cost and start by assuming the constant value of time of cargos shipped through a single hub. When comparing the values for coordinated and uncoordinated objective functions, we observe that the coordinated systems are better than the uncoordinated one, especially for transfer costs. In Cases 2 and 3, networks with multiple commodities and multiple hubs forming a loop are investigated. Both cases are more complex and difficult because coordination between any pair of transfer terminals may conflict with the coordination of those two hubs with other hubs in the network. Interrelation among all transfer terminals should be taken into account when considering the coordinated schedule plan. The integer-ratio schedule coordination approach outperforms the uncoordinated and common headway coordination methods.

The hybrid heuristic algorithm is developed for resolving the variability in optimal results in SQP and reducing the running time of the GA. It is found that SQP is very sensitive to different initial feasible solutions. Similarly, GA results may also be affected by different random seeds, resulting in different initial populations and local optimal solutions. Moreover, the convergence in final steps may be very slow in GA and additional stopping criteria or thresholds may be needed. Therefore, the hybrid GA-SQP algorithm is proposed which uses a GA to find a reasonable initial estimate for SQP, and then uses SQP to solve the problem until no further improvement can be found. In this approach, a random feasible initial starting point applied in SQP can be an appropriate threshold (i.e. one stopping criterion) for the GA.

In addition, for freight transportation operations, users (e.g. shippers) and operators (e.g. carriers) may have some conflicting interests regarding service quality. Shippers may prefer to send cargos at the lowest prices while minimizing total shipping time; however, carriers may choose a route with multiple transfers to create economies. Moreover, competition may exist among service providers because each of them eventually pursues the maximization of its own total profit. Competitive behaviors may become unavoidable and require other models to capture their details. Our models are mainly usable by consortiums or “alliances” of private freight transportation companies. Leader – follower decision making models of consortiums or alliances require different formulations. Different decision makers from various agencies may have different control abilities, market share rates, information flow knowledge, etc. Collaboration within alliances may sometimes switch to competition or partial competition. For large private logistics companies (e.g. Walmart, Sears), the models developed here should be quite applicable because routing and dispatching decisions may only be determined by single source decision makers.

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