ABSTRACT

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Increasing awareness that globalization and information technology affect the patterns of transport and logistic activities has increased interest in the integration of intermodal transport resources. There are many significant advantages provided by integration of multiple transport schedules, such as: (1) Eliminating direct routes connecting all origin-destinations pairs and concentrating cargos on major routes; (2) improving the utilization of existing transportation infrastructure; (3) reducing the requirements for warehouses and storage areas due to poor connections, and (4) reducing other impacts including traffic congestion, fuel consumption and emissions.

This dissertation examines a series of optimization problems for transfer coordination in intermodal and intra-modal logistic networks. The first optimization model is developed for coordinating vehicle schedules and cargo transfers at freight terminals, in order to improve system operational efficiency. A mixed integer nonlinear programming problem (MINLP) within the studied multi-mode, multi-hub, and multi-commodity network is formulated and solved by using sequential quadratic programming (SQP), genetic algorithms (GA) and a hybrid

GA-SQP heuristic algorithm. This is done primarily by optimizing service frequencies and slack times for system coordination, while also considering loading and unloading, storage and cargo processing operations at the transfer terminals. Through a series of case studies, the model has shown its ability to optimize service frequencies (or headways) and slack times based on given input information.

The second model is developed for countering schedule disruptions within intermodal freight systems operating in time-dependent, stochastic and dynamic environments. When routine disruptions occur (e.g. traffic congestion, vehicle failures or demand fluctuations) in pre-planned intermodal timed-transfer systems, the proposed dispatching control method determines through an optimization process whether each ready outbound vehicle should be dispatched immediately or held waiting for some late incoming vehicles with connecting freight. An additional sub-model is developed to deal with the freight left over due to missed transfers.

During the phases of disruption responses, alleviations and management, the proposed real-time control model may also consider the propagation of delays at further downstream terminals. For attenuating delay propagations, an integrated dispatching control model and an analysis of sensitivity to slack times are presented.

INTERMODAL TRANSFER COORDINATION IN LOGISTIC NETWORKS

By

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Dedication

To My Dear Parents, Sisters, and Brothers

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Chapter 1

Introduction

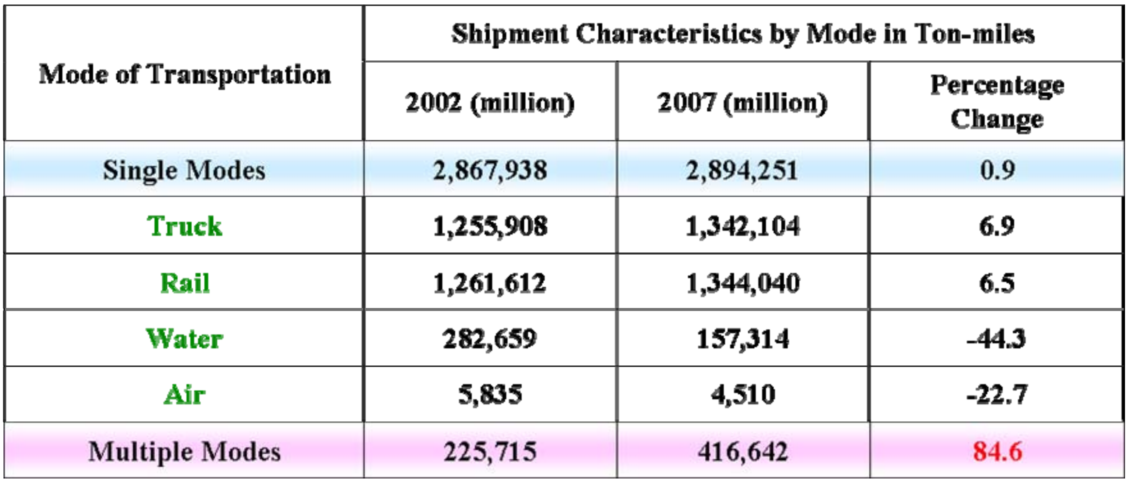
1.1 Background and Motivation

Increasing awareness that globalization and information technology affect the patterns of transport and logistic activities has increased interest in the integration of intermodal transport resources. A global reduction in the cost of transportation was a key to the rapid growth of global trade in the past two decades (World Bank report, 2009.) The term “intermodal” has been used in many applications that include passenger and freight transportation. For the purposes of this study, intermodal freight transport is defined as the use of two or more modes to move a shipment from origin to destination, which involves the physical infrastructure, goods movement and transfer, and other relevant activities under a single freight bill (TRB Special Report 252, 1998).

Most operations at intermodal freight terminals require transfer movements from one mode to others to serve cargos with diverse destinations, especially for break-bulk, cross-docking, or transshipment systems. This study focuses on one interesting operational issue in logistics: how should we develop and operate timed transfer systems for shipments through intermodal or intra-modal networks. A timed transfer system requires a well-defined strategy of schedule coordination, which can benefit transportation firms, terminal operators, infrastructure providers, shippers, and forwarders.

According to the 2002 and 2007 Commodity Flow Survey (CFS) results, as shown in Table 1.1, shipments (in terms of million ton-mile) shipped by means of a single transportation mode increases only 0.9%. Within these five years, multi-modes shipments increase rapidly, almost double the demand. CFS is a survey of shippers sponsored by the Bureau of Transportation (BTS), which provides detailed freight flow information in the U.S. 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 to shipped commodity.

Table 1.1 CFS DATA Comparisons Based on Mode Types (Data Source: U.S. DOT, RITA, BTS special report, 2009)



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**

There are many significant advantages provided by integration of multiple transport schedules, such as:

(1) Eliminating direct routes connecting all origin-destinations pairs and concentrate cargos on major routes with faster (e.g. airplanes) or lower cost (e.g. container ships) modes, which also imply the economic of scale in transportation.
(2) Improving the utilization of existing transportation infrastructure.
(3) Reducing the requirements for warehouses and storage areas due to poor connections.
(4) Reducing other impacts including traffic congestion, fuel consumption and emissions.

In the conventional freight shipment scheduling design process, operating schedules are selected from several candidate alternatives based on practical experience; however, the selected results may become somewhat arbitrary due to lack of an objective evaluation process. Thus, this dissertation first contributes 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.

As shown in Figure 1.1, a studied logistic network contains general road networks and freight rail routes connecting the Washington and Baltimore metropolitan areas. The proposed approach can be adapted to realistic network configurations, origin destination (OD) demand information, probabilistic distributions (including irregular empirical ones) for link travel time, and commodities with different cargo time values.

It is expected that transportation firms, terminal operators, infrastructure providers, dispatchers, shippers, and forwarders may greatly benefit from the proposed schedule coordination model, which offers optimized service frequencies (or headways) and slack times and comprehensive evaluation procedures. The problem definition, research objective and scope are discussed in the following sections.

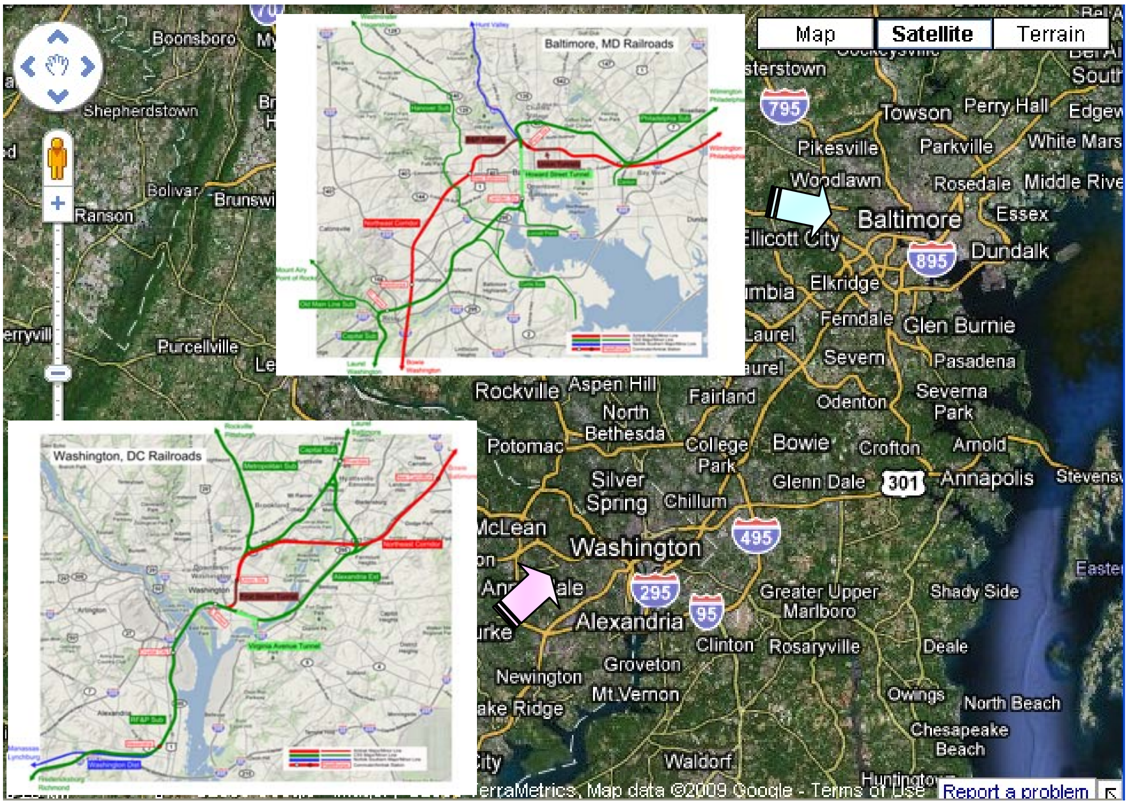


Figure 1.1 Illustration of the Logistic Networks (Source: Road Networks - Google Map & Railroad Freight Networks - www. greatergreaterwashington.org)

1.2 Problem Statement

Efficient transfer coordination in transportation networks can reduce the dwell time of freight at the terminals where various routes interconnect, thereby also increasing the vehicle utilization rates, reducing the need for direct routes to connect many origins and destinations, reducing storage requirements at terminals and improving total system efficiency.

In this dissertation, a comprehensive model for intermodal and intra-modal timed transfers is developed for coordinating vehicle movements and cargo transfers whenever such coordination is beneficial, subject to probabilistic variations in demand, traffic and other conditions, at ports, rail yards, airports and other cargo terminals. The model seeks to minimize total system costs while improving system performance (e.g., reliability, capacity, delays, security, and inventories). To achieve the above, several specific but significant characteristics of the intermodal freight logistics are also considered and discussed, such as:

(1) Multi-hub, Multi-mode, and Multi-commodity Network Flows

Unlike for passenger transportation, a multi-commodity network approach is widely used for freight transportation due to the very different characteristics of various cargos. In addition, different modes may have different vehicle sizes, turnover rates, travel speeds and time which may affect the dispatching frequencies. Three different network configurations are considered: (a) single hub (b) multiple hubs and (c) multiple hubs forming loops with multiple routes. Uniform cargo, multiple commodities with the same time value, and multiple commodities with different time values will be analyzed here.

(2) Cargo Processing and Storage Issues within the Terminal

Different shipping patterns may yield different dwell times for cargos and various spatial requirements for warehouses and storage areas. Even for cross-docking shipments, the cargos still need some temporary storage areas for loading and unloading. Starting from a given demand, lower service frequencies may increase vehicle loads, but also increase required cargo storage space. If missed connections occur, the extra dwell time and storage requirements are also considered.

(3) Nonlinear Time Value Functions for Perishable Cargos

Most previous studies assume that passengers’ time value varies linearly with time; however, some cargos (e.g. perishable goods, high technology products, spare parts, shortage of inventories, holiday gifts) may have quite nonlinear time value functions. The proposed model assumes that the value of time of cargos may decrease over time, for example, according to a continuous non-convex piecewise linear function or a nonlinear probabilistic time value function.

We initially assume a constant unit time value of cargo (Figure 1.2a). For perishable cargos, the applicable time value functions may be nonlinear, as suggested in Figures 1.2b, 1.2c and 1.2d. Figures 1.2c and 1.2d represent a continuous non-convex piecewise linear function and a nonlinear probabilistic time value function, respectively. A multi-commodity network problem can be formulated with multiple values of time (Figure 1.2e) for heterogeneous goods. $\mu 1$ and $\mu 2$ represent different values of time for different cargos.

(4) **Cargo Loading and Unloading Operations**

Service frequencies affect vehicle loading and unloading quantities and times. Such issues are usually neglected in transit-related studies; however, these operations may significantly affect the system performance and should be considered in our models.

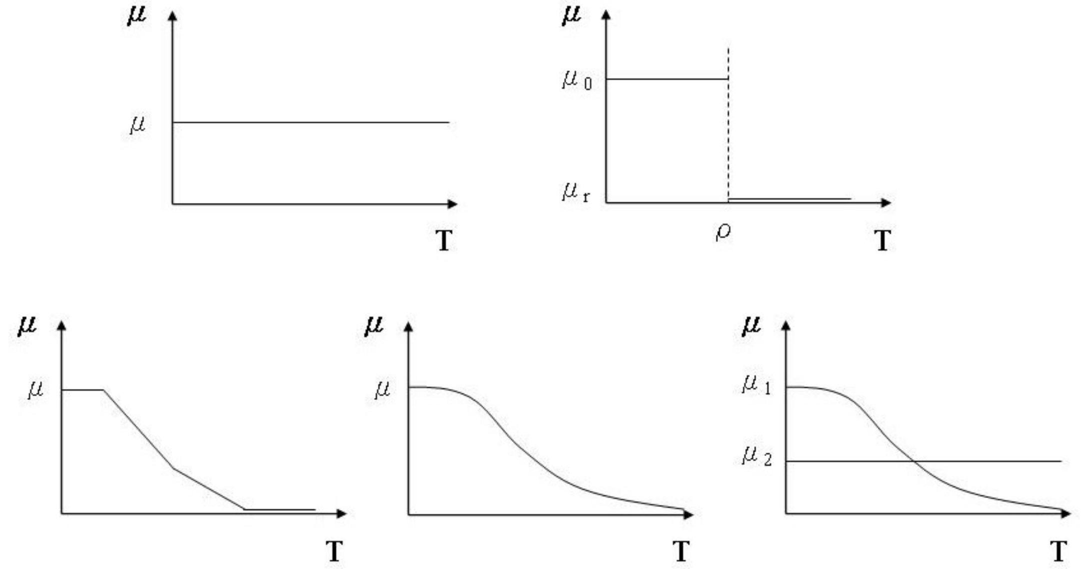


Figure 1.2 Different Settings of Cargo Time Value Functions

(5) **Collaboration and Competition**

For transit system operations, the system operators, infrastructure providers, and planners are usually not competitors and mostly belong to the public sector. Thus, these various decision makers can easily collaborate with others to pursue the maximum net system benefits or other objectives. They share information without worrying much about competitive advantage. In addition, public transit systems may be required to satisfy some basic service quality and level of service, so the minimal transfer waiting time or minimal number of transfers may also be considered while planning the operational timetables. Freight systems also have service quality constraints analogous to those of passenger transport systems; however, the "basic" level of service in passenger system is usually better than that in freight system since it affects humans.

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 describe their details.

In this dissertation, most of our case studies are developed for multi-mode transfer operations. General models are developed for most combinations of modes, which can be described in terms of their vehicle capacities, unit operating costs, average speeds and travel time variances. These models might also be used 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, and 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.

1.3 Research Objective

The major objective of this study is to develop an effective optimization model that deals with the timed transfer problem for the multi-hub, multi-mode and multi-commodity network configurations defined in Section 1.2. To achieve this objective, this dissertation pursues several research goals listed as follows. Figure 1.3 shows the required input data and expected outputs among the research goals. More details are described below.

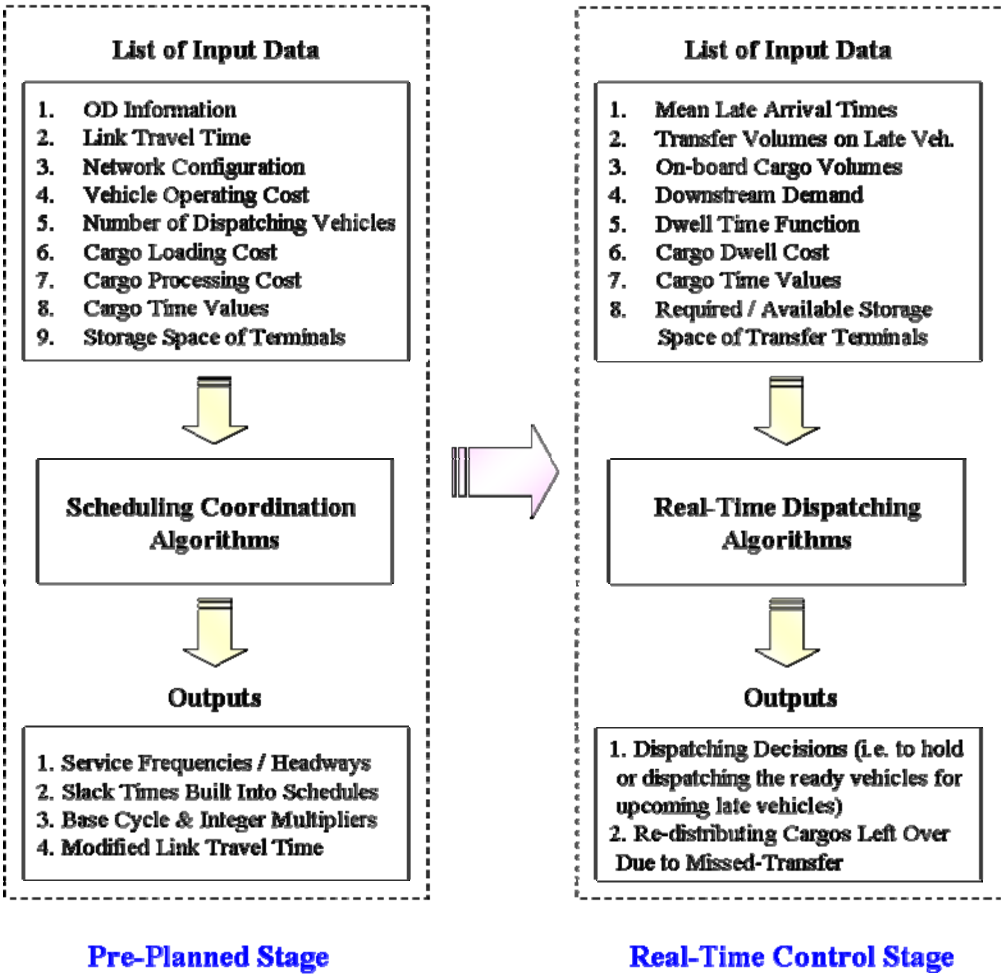


Figure 1.3 Different Settings of Cargo Time Value Functions

1.3.1 A Pre-Planned Scheduling Optimization and Coordination Model

The objective in this section is to develop an off-line model for analyzing and optimizing freight transportation systems dependent on reliable transfers at transportation nodes such as truck terminals, airport hubs, ports and rail yards. This will be done primarily by:

(1) Providing a model framework for simultaneously optimizing network and vehicle characteristics, service frequencies and slack times;
(2) Formulating cost functions for evaluating system improvements obtained from timed transfers additions to the existing logistics network with multiple transfer terminals (or hubs) as well as estimating detailed transfer and non-transfer costs.
(3) Developing effective solution search methods for enhancing computational efficiency and solution quality of the scheduling coordination optimization process.
(4) Applying these models to determine which type of coordination strategy is preferable under given conditions.
(5) Conducting case studies with simplified network configurations that test the developed model.
(6) Realistically representing large network configuration of case studies.
(7) Analyzing the effects of different input data (i.e. the sensitivity analysis) to observe the optimizing results varied with the demand uncertainties.

1.3.2 Real-Time Dispatching Control to Alleviate Schedule Disruptions at Intermodal Freight Transfer Terminals

The real-time control model focuses on decisions regarding vehicle dispatching from transfer terminals before all expected loads are on board. Thus, when some connecting vehicles are delayed, the control model will determine through an optimization process which vehicles should wait for which other ones. Detailed formulations and optimized results will be provided in Chapter 6. This will be done primarily by:

(1) Providing information on downstream demand, mean late vehicle arrival time, mean cargo dwell time, additional required and available storage spaces within the transfer terminals, total volumes of upcoming transfer and already on-board cargos, etc.

(2) Formulating cost functions for evaluating system improvements obtained from recovery of routine disruptions.

(3) Developing a model structure for optimizing the holding and dispatching timing based on given information.

(4) Conducting case studies with simple network configurations that test the developed model.

(5) Analyzing the effects of different input data to determine how the optimized results vary with the uncertainties.

1.3.3 An Analysis of Propagation of Delays through Networks and Schedules

When routine service disruption (e.g. incidents or traffic congestions) occur within a logistic network in which schedules are coordinated, the above real- time control model may adjust the pre-planned schedules to response the deviations between two consecutive transfer terminals. However, some propagation of delays may affect further downstream so that coordination might be disrupted later downstream. An analysis of the delay propagations and possible attenuation strategies will be addressed in Chapter 7.

It should be noted that several related models have been developed by Lee (1993), Chang (1994), Chien (1995), and Ting (1997) for urban public transportation and air transportation systems. Although some of these earlier models have been very useful and successful, we still face considerable challenges (e.g., factors affecting demand, service quality and choices, lack of self-guidance, storage requirements, cargo perishability, information availability about shipments) in developing a comprehensive and integrated model for freight transportation management.

1.4 Scope

Figures 1.4 (a) – (c) illustrate some example logistic networks considered in this dissertation, which may be encountered in real world situations. Complicated network configurations may increase the difficulty of timed transfers. Figure 1.4 (a) shows a single cargo terminal connected to one air route and 9 truck routes, which is a relatively simple network because all arrival times of the routes may be synchronized. In Figure 1.4 (b), two transfer terminals connected with one rail route and many truck routes. The interaction between these two interacting terminals should be considered in our scheduling coordination model.

A conceptual loop network, as shown in Figure 1.4 (c), has a more complex configuration. Coordination at one transfer terminal will affect the other transfer hubs within the loop. Unlike the above Figure 1.4 (b), considering the coordination of a pair of transfer nodes may lead to conflicts at another pair of terminals. Thus, the interaction among these transfer hubs must be taken into account. The logistic networks analyzed in this study are similar to the above three types. Cargos shipped from multiple origins toward multiple destinations and transferred at certain transfer terminals are considered. Additional complex and large scale network configurations are also discussed in Chapter 4.

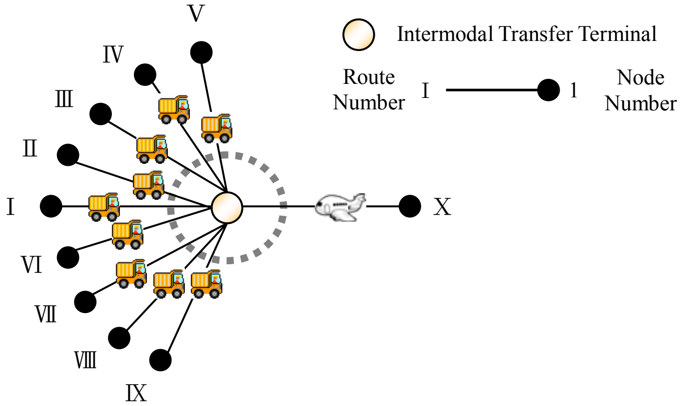


Figure 1.4 (a) A Conceptual Network for Multiple Modes and Single Hub Operation

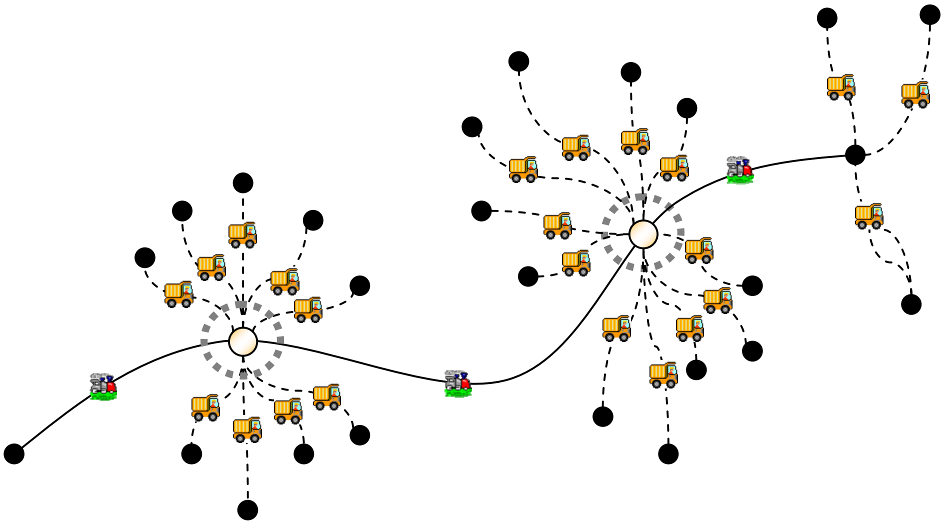


Figure 1.4 (b) A Network Configuration with Multiple Modes and Multiple Hubs

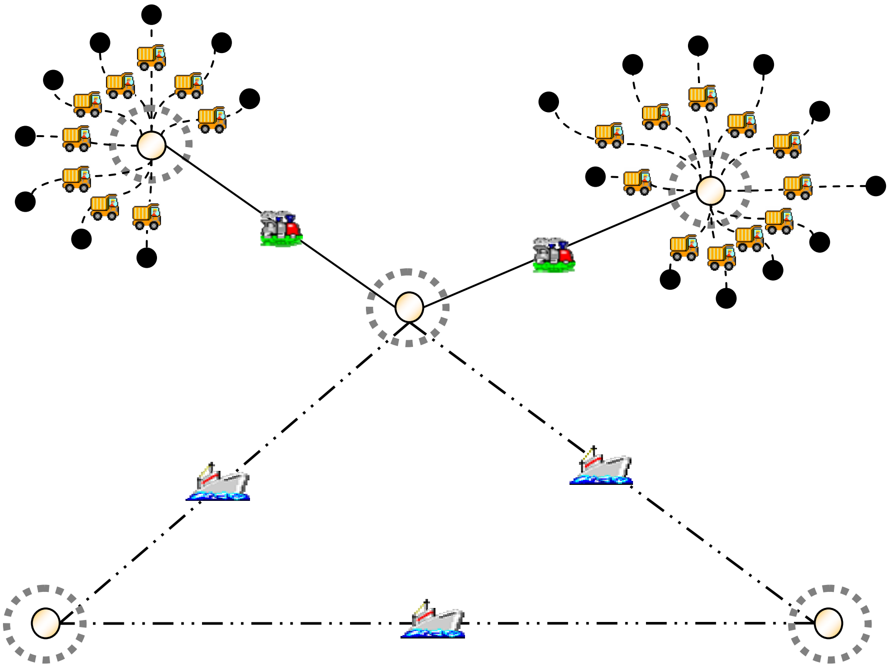


Figure 1.4 (c) A Loop Network for Multiple Modes and Multiple Hubs Operation

1.5 Dissertation Overview

The developed methods are combining (1) a system planning model for optimizing in advance various characteristics of intermodal freight transportation systems such as terminal locations and capacities, vehicle sizes, routes, schedules and probabilistic reserve factors built into operating schedules and into the capacities of networks, vehicles and terminals; (2) a real-time dispatching control model for dealing with deviations from schedules and routine service disruptions; and (3) an analysis of the effects of the above control methods on the propagation of delays through networks and schedules.

Some vehicle and terminal characteristics such as vehicle size and terminal storage capacity are also being optimized. In order to improve transfer opportunities and minimize expected transfer delays, both service frequencies (or headways) and scheduled travel times to transfer hubs will often, but not necessarily, be integer multiples of T*. In a system without probabilistic variations of vehicle arrival times this underlying cycle time concept would allow many vehicle arrivals to be synchronized. Some degree of synchronization is still achievable in a probabilistic system, if we distribute the right amounts of slack in schedules and then control the system in real time to exploit that slack.

The real-time dispatching control model focuses on decisions regarding vehicle dispatching from transfer terminals before all expected loads are on board. Thus, when some connecting vehicles are delayed, the control model will determine through an optimization process which vehicles should wait for which other ones. Comprehensive probabilistic evaluation functions will be used to combine and minimize the various costs of leaving sooner (and thus missing some freight, especially from connecting vehicles that have not yet arrived) or leaving later (and thus delaying freight already on board or waiting downstream, or missing downstream connections and thereby propagating delays and missed connections through the system). Vehicle travel times may also be partially controllable in real time although, unlike for public transportation vehicles, traffic signal adjustments are usually not allowable.

Once we determine to hold a ready vehicle and dispatch it later, this may propagate some delays at further downstream terminals. Thus, making integrated decisions instead of dealing with problems on an ad hoc basis is our third goal in this dissertation. Some strategies are being analyzed for attenuating the delay propagations.

It should be noted that attempts to coordinate vehicle arrivals at transfer stations have some costs and are not always desirable. In general, coordination becomes undesirable when (1) service headways decrease (thus reducing the delays due to missed connections) and /or when (2) the variance of vehicle arrival times exceeds certain levels. Our pre-planning model will determine which of the system's vehicles should be coordinated with which other vehicles at any particular transfer terminal. Slack times, which may be considered safety factors or reserve margins, are included in schedules to improve possibilities of recovery from delays, but they do increase the scheduled travel times.

In our preplanning model the slack times are optimized either explicitly (for route sections whose travel times are not integer multiples of T*) or implicitly (as the resulting difference between optimized travel times that are integer multiples of T* and the expected travel times). After the optimized slack times are distributed throughout the preplanned schedule the control model uses them as well as possible in making its real-time dispatching decisions.

In this dissertation, Chapter 1 introduces the research background and motivation, the problem definition, the research objectives, and the research approach. Chapter 2 presents a literature review of descriptive studies of timed transfer system, existing methodologies for schedule coordination in transit systems, and relevant works in freight transportation and further intermodal logistic systems. Several previous studies of real-time control methods to deal with deviations from schedules in transit system and analysis of propagation of delays through networks and schedules (mainly in the airline researches) are also discussed in this chapter.

The remainder of this dissertation is organized as follows. Chapter 3 discusses the methods for analyzing and pre-optimizing freight transportation systems dependent on reliable transfers at transportation nodes such as truck terminals, airport hubs, ports and rail yards. Three different coordination policies are described in detail. Some mathematical formulations describing the optimized scheduling coordination problems are introduced and illustrated.

The proposed mixed integer nonlinear programming (MINLP) problems are solved by using sequential quadratic programming (SQP), genetic algorithms (GA), and a hybrid GA-SQP heuristic algorithm, as described in Chapter 4. Multiple commodities with different time value functions are discussed. Applications of the above models with numerical examples are analyzed in Chapter 5.

In Chapter 6 tasks required for modeling a real-time dispatching control problem are addressed. According to the pre-optimized results of a system's routes, schedules, vehicles and terminals, the methodologies for real-time control operations to deal with deviations from schedules and other disruptions are developed. The basic model structure of the proposed network problem and its optimization procedure are also discussed in this chapter.

In Chapters 7, an analysis of the delay propagations, an integrated dispatching control model, and a sensitivity analysis with different slack time settings for attenuating propagation of delays are presented. Finally, Chapter 8 presents a summary of major findings, contributions and suggested future research directions.

Chapter 2

Literature Review

The literature review for this study includes five sections. Some existing studies of timed transfer systems and methodologies for schedule coordination in transit systems and freight transportation fields are described in the first section. Models for dealing with schedule disruption management are reviewed in the next section. Although routine disruptions are the primary concerns in this dissertation, some previous studies related to the major disruptions are also reviewed. In the third section, analyses of delay propagations resulting from the schedule disruptions are also discussed. Various constraint handling techniques used in heuristic algorithms (particularly for genetic algorithms and sequential quadratic programming methods) are investigated in the fourth section. A summary of findings from the literature review is provided at the end.

2.1 Timed Transfer System

Timed transfer concepts are widely implemented in public transit systems, and are emerging in intermodal freight systems. Several uncertainties (e.g. randomness of vehicle travel time) may cause missed connections in timed transfer systems; however, most studies neglect these issues. Some previous studies do not consider slack times, which are important safety margins built into schedules to response the deviations or disruptions of coordinated timetables.

Salzborn (1980) develops a method to generate timetables by considering transfers between one inter-town and many feeder bus routes. Ceder and Wilson (1986) present a hierarchical model for the whole planning process, network design, headway or frequency setting, and timetable development of bus transit systems. Abkowitz et al. (1987) simulate a variety of dispatching strategies at single timed transfer hub. Their simulation results on two bus lines show that a no holding strategy is preferable when the bus lines have unequal headways and a holding strategy is preferable when the bus lines have equal headways.

Some studies focus on transfer costs in attempting to synchronize schedules. Domschke (1989) coordinates transit schedules by minimizing the total users' transfer waiting time with given operation hours. Ross (2003) investigates the optimal repeating base headway for the pulsed-hub network, hub spacing, locations, and hub station design to minimize passengers' transfer walk times. Fabian and Fang (2006) also present a GA approach to synchronize bus schedules by minimizing riders' transfer times. Their algorithm considers randomness in bus arrivals and attempts to find an optimum solution for the bus schedule synchronization problem by shifting existing timetables. These studies ignore the trade-off between non-transfer and transfer costs with different coordinated strategies.

Since slack times can provide an operating buffer to reduce the impacts of schedule deviations and disruptions, some studies consider this factor in their models. Sullivan (1975, 1980) presents a timed transfer system in a light rail transit network, which can benefit for both users and operators. He further analyzes how adding slack time in the schedule can enhance the system reliability. Lee and Schonfeld (1991, 1994) formulate a model for determining optimal vehicle slack times for single transfer terminal serving multiple bus routes. Stochastic vehicle arrivals are considered while formulating the objective coordinated transfer cost function. Analytic results show that the standard deviation of vehicle arrival times is an important factor affecting the durations of slack times. Chowdhury and Chien (2002) develop a schedule coordination method for a rail transit line and multiple feeder routes connecting at different transfer stations. The slack times of coordinated routes are optimized by balancing the savings from transfer delays and additional cost from slack delays and operating costs. Dessouky et al. (2003) also develop a simulation-based model to demonstrate that technology for communication, tracking and passenger counting is most advantageous when the schedule slack is close to zero, when the headway is large, and when there are many connecting bus lines.

Zhao et al. (2006) present an analytical model for a schedule-based transit system to determine the optimal slack times that minimize the passengers' expected waiting times. Ting and Schonfeld (2005, 2007) optimize the headways and slack times jointly to minimize the total costs of operating a multiple-hub transit timed transfer network. Their results show that for routes with significantly different demand or route length, coordination with integer-ratio headways is preferable to a single common headway. (Common, or at least integer–ratio, headways on connecting routes greatly reduce the potential for transfer delays.) Similarly to the above models, Bruno et al. (2009) propose a schedule optimization model by balancing the operation costs of the service and the passenger waiting time at the transit terminal.

Several studies also address the freight schedule optimization problem and coordination issues. 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 allow each location assigned none, one, or multiple objects, unlike the QAP which requires a one by one mapping function. The work presented here mainly seeks to jointly optimize the slacks and service schedules, so Voss's model does not fully fit our requirements.

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. Since the proposed models in this dissertation are focused 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 would be considered 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 demand in the system. They analyze collaborating transportation services should be synchronized and evaluate how border-crossing operations impact the throughput time for the shipments. There are two main weaknesses in this study. First, as mentioned before, service collaborations from different agencies may be not easily fulfilled in a freight transportation system, unless under a consortium or an 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.

Most of the approaches in transit applications are interpreted in a macroscopic view through the network (e.g. many bus stops along a service route are aggregated into a single resource.) Some recent logistic studies are also formulated based on a microscopic view so as the models can take the cargo movements into account and easily be implemented in practice. In addition, these schedule coordination methods are mainly designed for public transit systems and neglect freight transportation aspects such as loading and unloading, cargo processing and storage, and shipments with different freight types. Moreover, an assumption about constant value of time of passenger in these papers may not be suitable for some perishable goods. Although some specific characteristics in freight transportation are quite different from those in public transit systems, the conceptual basis for optimizing transfers is fairly similar.

Table 2.1 lists several previous timed transfer studies with different formulations of objective functions. Most of these works are focused on transfer costs and the results may be biased. An overall consideration between transfer and non-transfer costs is developed in this dissertation.

Table 2.1 Different Objectives in Timed Transfer Systems

Author(s)	Objective Functions
Domschke (1989), Wirasinghe and Liu (1995), Maxwell (1999), Ceder et al. (2001), Zhao et al. (2006)	Minimizing (total or expected) waiting time caused by transfers
Gue (1999), Ross (2003)	Minimizing passengers' transfer travel distance or time
Fabian and Fang (2006)	Minimizing riders' transfer time
Anderson et al. (2009)	Minimizing cargos throughput time
Lee and Schonfeld (1991 & 1994), Chowdhury and Chien (2002), Ting and Schonfeld (2005 & 2007), Chen & Schonfeld (2010 & 2011)	Minimizing total system costs (including transfer and non-transfer costs)

2.2 Solution Techniques

A major problem faced by this study is how to develop a logistic timed transfer system for shipments through the entire intermodal network. This problem is formulated as a multi-mode, multi-hub, and multi-commodity network problem with nonlinear time value functions of cargos. The objectives of this dissertation are to develop mathematical models which can fully represent this problem, and to propose an algorithm which can effectively solve the model. The models of uncoordinated and coordinated with the common service headway are attributed to nonlinear programming problems (NLP). Since constraints in the proposed models are not convex functions, then standard heuristic algorithms for solving these NLP are able to 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 value settings 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 in the search space.

Many previous studies apply GAs to solve the scheduling and schedule coordination problems (e.g. Shrivastava et al., 2002; Sarker and Newton, 2002; Torabi et al., 2006; Cao, 2008). Shrivastava et al. (2002) formulate scheduling and schedule coordination problems as conflicting objectives with user's costs and operator's costs. They select GAs to solve this multi-objective problem. Sarker and Newton (2002) develop a method to determine an optimal batch size for a product and purchasing policy of associated raw materials with 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 (2008) presents 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 the oil fields and optimize the design of the multiproduct batch plant. Ponsich et al. (2007) also test the batch plant problem by using GAs. In general, the objective function of the batch plant problem consists in the minimization of 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 need separated the problem to Mixed Integer Linear Programming (MILP) and NLP, when some special formulations where the continuity or convexity has to be imposed. They develop a heuristic algorithm based on the 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), functions and gradients can be evaluated with sufficiently high 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 develop the ideas of 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 makes use of 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, and avoid unpredictable algorithmic behavior that comes with allowing infeasible points. Based on this approach, Wright and Tenny (2004) revise the iterative feasible method proposed by Conn et al. (2000). The approach of Conn et al. seeks 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 steps of problem solving is relatively slow (Mansoorjaned et al., 2008). Therefore, several researchers have developed some hybrid / combination optimization methods to solve the nonlinear programming problems.

Victoire and Jeyakumar (2006) present a hybrid tabu search (TS), particle swarm optimization (PSO) and SQP technique to schedule the generating units based on the fuzzy logic decisions. This hybrid approach can guarantee quality solutions with sufficient level of spinning reserve throughout the scheduling horizon for secure operation of the system. Youssef et al. (2007) describe a hybrid TS – GA – SQP method to optimize 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 to solve the 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 address a hybrid GA – SQP method to solve an integrated dynamic and structural optimization procedure for a composite wing-box design problem.

Since the hybrid methods can adopt advantages of both deterministic and stochastic methods and avoid certain existing disadvantages, some of the above hybrid techniques are being considered in this dissertation. 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. In this dissertation, a deterministic method (i.e. SQP), a stochastic approach (i.e. GAs), and one hybrid GA – SQP method are developed. The basic concept for the hybrid method is to do the global search with GAs and use SQP to run the deeply local search. More detailed settings are illustrated in Chapter 4.

2.3 Disruption Management

Disruption management is an important issue in scheduling and overall system management. Assume we have an operational schedule plan for the timed transfer system based on the expected environments and OD information. Any significant change in the given environment can be considered a disruption. Disruptions may occasionally affect the system operations, and the previous optimal plan may become non-optimal or even infeasible. When disruptions occur, the means to adjust or re-optimize the original plan to adapt the changing environment and to get back on track in a timely manner while effectively using our available resources are primary issues discussed in this section and Chapter 6.

Disruptions can be classified as routine or major disruptions; these classes require different response strategies. Routine disruptions represent the schedule perturbations caused by the stochastic uncertainties (e.g. traffic congestion, vehicle failures or demand fluctuations), which tend to have moderate effects and short-term impacts. Major disruptions (e.g. storms, earthquakes or terrorist attacks) are defined as situations during the operation's execution in which the deviation from plan is sufficiently large that the plan has to be changed substantially (Clausen et al., 2001).

Disruption management has been widely applied in the airline field in recent years. Clarke (1998) provides an overview of operation control during the post-disruption phases. He analyzes how airlines can re-assign aircraft to scheduled flights after a disruptive situation. Thengvall et al. (2000) develop an airline schedule recovery approach with minimal deviations from the original aircraft routings when disruptions occur. Delays and cancellations are used to deal with aircraft shortages in a way that ensures a significant portion of the original aircraft routings remain intact. Clausen et al. (2001) summarize the developments of disruption management from an operations research viewpoint in airline operations, shipbuilding, and telecommunications.

Yu and Qi (2004) consider disruption management based on flight and crew scheduling problems simultaneously. Kohl et al. (2007) provide a description of the planning processes in the airline industry. They report on experiences gained in managing major disruptions for airlines. Ball et al. (2007) describe the infrastructure and constraints of airline operations, and develop optimization and simulation models for aircraft, crew and passenger recovery. Liu et al. (2008) present a method of inequality-based multi-objective GA to generate an aircraft routing algorithm in response to the schedule disruption of short-haul flights. It attempts to optimize objective functions involving ground turn-around times, flight connections, flight swaps, total flight delay time and a 30-minute maximum delay time of original schedules. In general, passengers are given a relatively low priority or even ignored in the airline disruption management references, which usually focus on crew and flight scheduling.

Several studies also consider disruption management in logistics. Rice and Caniato (2003) note that disruptions occurring at any point in the supply chain may cause failures of the entire system. Qi et al. (2004) investigate a supply chain coordination problem with a disruption caused by demand uncertainties. They find that such disruptions may impose considerable penalty costs on suppliers. Another problem of updating a machine schedule when either a random or an anticipated disruption occurs is also solved with similar methodologies (Qi et al., 2006). Wu et al. (2007) present a model for analyzing how disruptions propagate and affect the supply chain system. Wang et al. (2009) propose a vehicle monitoring and dispatching system to monitor and schedule the vehicles in logistics, and a decision support system to manage the disruption events.

In Chapter 6, a routine service disruption analysis focuses on decisions about whether to dispatch vehicles from transfer terminals when some connecting vehicles are delayed. Through an optimization process we can determine which vehicles (if any) should wait for which others. Although routine disruptions are less severe than major disruptions, they occur more frequently and require an efficient tool for managing them.

2.4 Propagation of Delays

When routine service disruptions occur in the pre-coordinated schedules, some propagation of delays may affect further downstream. Delays may not only occur at terminals experiencing the disruptions, but at terminals with service routes connecting from the initial terminals affected by service disruptions. Before analyzing the delay propagations, some terminologies are defined as follows: the *expected total delays* can be measured as the difference between the estimated late arrival time and the original schedules at a relevant point within the network. These delays are classified into two categories. Delays caused by the disruptions are called the *initial delays* or *primary delays*, which may propagate and increase perturbations later downstream. Those delays occurring downstream are defined as the *resulting delays* or *consecutive delays*.

Delay propagation is an important issue in the railroad and airline fields. One of the first papers addressed stochastic delay propagation is Weigand (1981). In his model a train delay distribution is on the basis of a delay probability function plus an exponential arrival delay distribution, so as to compute the delays and the expected delay propagations. Mühlhans (1990) extends Weigand's method, and provides an analytical algorithm but without any case studies.

Carey and Kwieciński (1995) address general recursive relations for delay propagation. Higgins and Kozan (1998) describe an analytical model to investigate the arrival delay of trains at stations and delay propagation to subsequent trains. They provide expressions to determine expected secondary delays from specified primary delays. Wang et al. (2003) also present a simple analytic model to identify factors affected delays and delay propagations of flight schedules. The above models are mainly assumed independence of delays on different service lines or routes.

Meester and Muns (2007) propose an approximation method suited to stochastic railway networks and an example of an implementation that can yield accurate approximations to delay distributions. They use a multidimensional distribution of relevant variables to reflect the delay dependence. Hsu et al. (2007) construct models to analyze flight-delay propagation, allowing for behavioral response. It investigates three scenarios: the same aircraft operating consecutive flights, consecutive flights with different aircraft using the same gate, and different flights using different aircraft involving the transfers.

Some existing microscopic simulation tools such as RailSys (Radtke & Hauptmann, 2004) and OpenTrack (Nash & Huerlimann, 2004) can be used to analyze the propagation of train delays in large complex railway networks by incorporating the stochastic dependence of train delays. However, working with these models may require enormous amounts of preparation and computing times, and simulation offers generally less insight into structural relations between input and output than analytical models (Yuan and Hansen, 2007).

Most of the previous studies analyze delay propagations in passenger transportation systems, but seldom deal with the logistics of freight movements. These studies tend to re-optimize the operational time tables so as to respond and recover systems from disruptions. Since re-optimization of entire schedules normally requires far more computation, it may be more suitable for major disruption cases rather than routine ones.

In Chapter 7, an analytical model of delay attenuations resulting from routine service disruptions is developed. Its purpose is to analyze delay propagations with given networks, schedules and arbitrary primary delay information. Some numerical examples and sensitivity analysis of the total resulting delays absorbed by different settings of slack time and affected by ready vehicles' holding time will also be addressed.

2.5 Summary

This dissertation focuses on a series of optimization problems within the studied intermodal logistic networks. In Table 2.1, most previous studies related to the scheduling coordination focus on minimizing the total system transfer costs; however, some non-transfer costs are affected by service schedules and should be also considered in the objective function.

Some previous studies applied in transit systems are interpreted with a macroscopic view (e.g. route to route transfers) through the entire network; however, some recent logistic studies have been formulated from a microscopic viewpoint (e.g. the movement of the cargo or one container) in order to describe cargo movements in detail.

In addition, these schedule coordination methods are mainly designed for public transit systems and neglect freight transportation aspects such as loading and unloading, cargo processing and storage, and shipments with different freight types. Moreover, an assumption about the constant value of time of passenger in these papers may be unsuitable for some perishable goods. Thus, a mixed integer nonlinear programming problem (MINLP) with the studied multi-mode, multi-hub, and multi-commodity network is formulated and solved with GA, SQP, and a hybrid GA-SQP (combining genetic algorithms and sequential quadratic programming) heuristic algorithm. Some previous studies applying these techniques are introduced in Section 2.2.

Section 2.3 reviews relevant works in disruption management, because the second problem considers ways of countering schedule disruptions within intermodal freight systems operating in time-dependent, stochastic and dynamic environments. When routine disruptions occur in pre-planned intermodal timed-transfer systems, real-time dispatching control methods are then applied to deal with deviations from schedules due to disruptions.

Sometimes delays may occur not only at terminals experiencing the disruptions, but also at terminals with service routes connecting from the primary terminals affected by initial disruptions. Several previous studies which discuss delay propagations are summarized in Section 2.4.

Chapter 3

Modeling Timed Transfers at Freight Terminals

3.1 Problem Statement

This section first provides an overview of the schedule coordination and uncoordinated operations at intermodal freight terminals. The detailed mathematic models are then formulated. At a transfer terminal (i.e. a hub), three different operating methods are presented, and the resulting effect of each operation on the logistic network and cargo movements are described. Later in Chapter 5, some numerical examples within the studied multi-mode, multi-hub, and multi-commodity network problem will be addressed.

The first model is developed to optimize service frequencies and slack times jointly for routes from one or more modes connecting at intermodal freight terminals, in order to minimize the total system cost of operating an intermodal logistic network. The routes and terminal locations within the network are pre-determined. All demand information is given and assumed to be deterministic and uniformly distributed during the specified time periods. The problem is formulated as a multi-hub, multi-mode, and multi-commodity network. Procedures for optimizing the schedule coordination plan are specified in Figure 3.1.

In uncoordinated operations, the service frequencies of all routes are optimized independently based on given OD information and relevant constraints. For the common service headway / frequency coordinated operations, both service frequencies and slack times are jointly optimized. These two sub-models are formulated as general nonlinear programming problems. In the integer-ratio based coordination, the slack times, the base cycle, and the corresponding integer multipliers for all routes are simultaneously optimized. This sub-problem is considered a mixed-integer nonlinear programming problem and some heuristic algorithms are being discussed in Chapter 4.

Headway is a measurement of the distance between vehicles in a transit / freight system. The precise definition varies depending on the application, but it is most commonly measured as the distance from the trip of one vehicle to the trip of the next one behind it, expressed as the time it will take for the trailing vehicle to cover that distance. Slack time is a probabilistic reserve margin built in the operating schedule, which can effectively help system operators in response of deviation or disruption of existing schedules due to traffic delay or congestions.

Additional assumptions are addressed in the following sub-sections that analyze uncoordinated operations, coordinated operations with a common service frequency (or its reciprocal - 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.

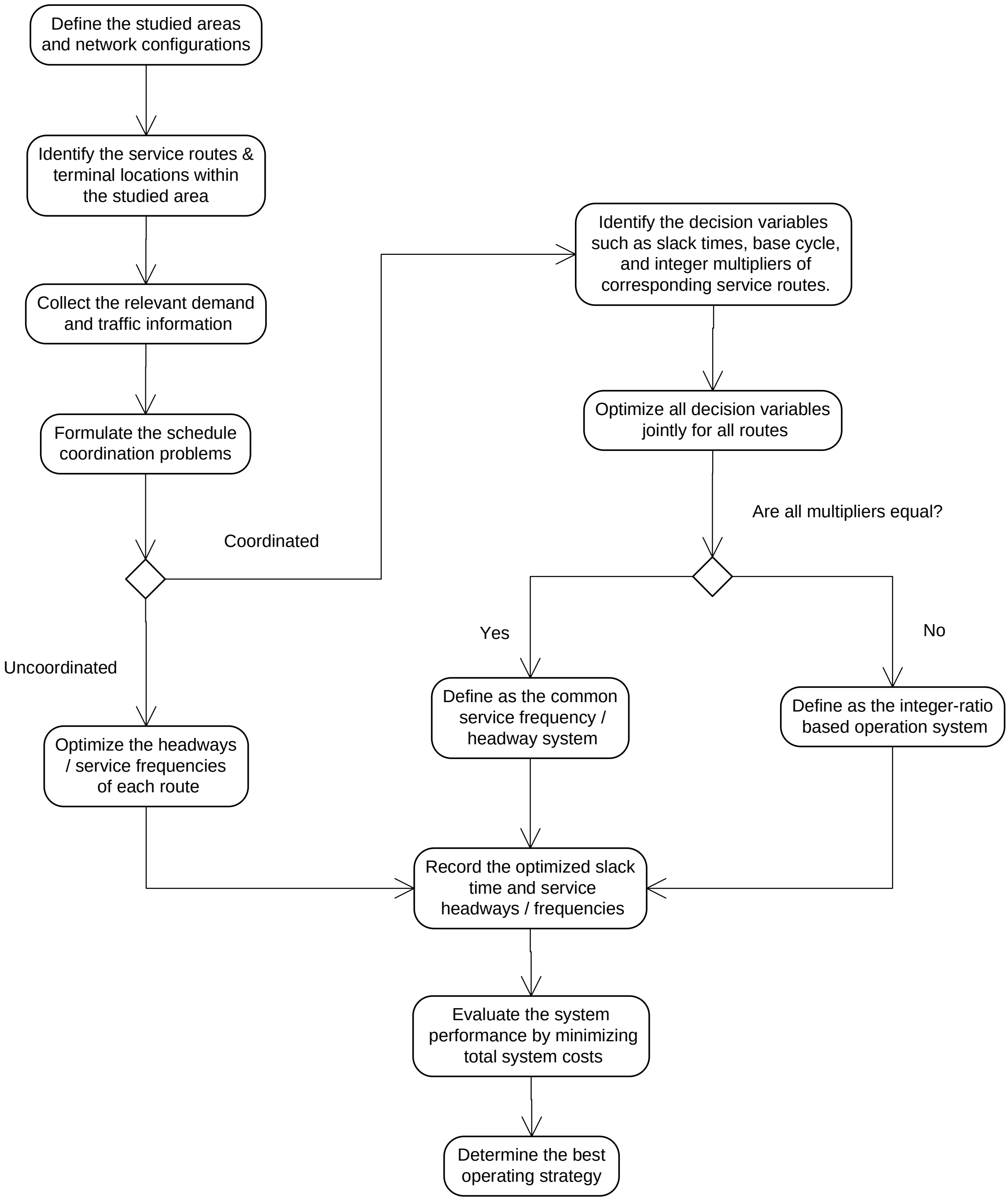


Figure 3.1 Flow Chart for Optimizing Schedule Coordination

3.2 Model Formulation

Three different analytical models (uncoordinated, common headway coordination, and integer-ratio coordination) are described as follows. For pre-planned purposes, the analytical models are formulated as a total system cost minimization problem based on stochastic vehicle arrivals and nonlinear cargo time value functions.

3.2.1 Proposed Sub-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 which include delivery vehicle operating cost (Co), cargo dwell time cost (Cw), loading/unloading cost (Cl), cargo processing cost (Cp), and cargo transfer cost (Cf). Cargo in-vehicle cost is not affected by service frequencies; hence it is not included in the total system cost function.

Initially, to simplify this problem, we assume the constant values of dwell / loading / unloading / processing time, and move to nonlinear cases later. Let G (N, E) denote a directed transportation network where N is a set of nodes and E is a set of links. To simplify the notation, we define i and j as the arrival and departure routes, respectively; each route contains several nodes (e.g. Fedex offices) and links, as shown in Figure 3.2.

Figure 3.2 Conceptual Illustration of a Service Route (Pictures Source: Fedex Website)

The model is expressed as follows:

Minimize $C_T = C_o + C_w + 2C_l + C_p + C_f$ (3.1)

Subject to

$$C_o = \sum_{i \in E} B_i T_i f_i = \sum_{i \in E} (a_i + b_i S_i) T_i f_i \qquad (3.2)$$

The minimized objective function (Equation 3.1) is formulated as the sum of operating cost of delivery vehicles, dwell / loading / unloading / processing time costs of cargos, and transfer cost from a particular transfer terminal to feeder routes. In Equation 3.2, the operating cost of route i is the product of the required fleet size and the unit operating cost. C_o = the operating cost of Route i; 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).

$$D_i = \sum_{m \in M} D_i^m \qquad (3.3)$$

Equation 3.4 expresses the sum of total dwell time cost of cargos, and corresponding loading time cost along the route i. Let μ^m = unit time cost of the m_{th} category of cargo ($/lb-min); w_i = dwell time on Route i; θ = unit cargo loading / unloading time (min); $\sigma^2{}_i$ = variance of service headways of the Route i (min^2).

Assuming that shipped cargos arrive at the local freight collection station randomly and uniformly over time, the stochastic dwell time (w_i) can be estimated with Equation 3.5 (Osuna and Newell, 1972). Equation 3.6 expresses the sum of total unloading cost of cargos, and corresponding cargo processing cost from the route i, where ϕ = unit cargo processing time (min). This assumes the total cargo unloading time is equal to the total cargo loading time.

$$C_w + C_l = \sum_{m\in M}\sum_{i\in E}\mu^m (D_i w_i + \theta S_i l_i) = \sum_{m\in M}\sum_{i\in E}\mu^m D_i (w_i + \frac{\theta}{f_i}) \tag{3.4}$$

$$w_i = \frac{1}{2E(f_i)} + \frac{\sigma_i^2 E(f_i)}{2} \tag{3.5}$$

$$C_l + C_p = \sum_{m\in M}\sum_{i\in E}\mu^m S_i l_i (\theta + \phi) = \sum_{m\in M}\sum_{i\in E}\frac{\mu^m (\theta+\phi) D_i}{f_i} \tag{3.6}$$

Equation 3.7 indicates the transfer costs incurred by the transfer demand from routes j to i at the transfer terminal k. Where C_f = the transfer cost along the route i; q^{mk}_{ji} = amount of freight of type m transferred at the intermodal terminal k to route i; R_i = total transfer demand to route i.

$$\begin{aligned} C_f &= \sum_{k\in N}\sum_{m\in M}\sum_{j\in E}\sum_{i\in E, i\neq j}\mu^m (q^{mk}_{ji} w_i) \\ &= \sum_{k\in N}\sum_{m\in M}\sum_{j\in E}\sum_{i\in E, i\neq j}\mu^m q^{mk}_{ji}\left(\frac{1}{2E(f_i)} + \frac{\sigma_i^2 E(f_i)}{2}\right) \\ &= \sum_{i\in E}\mu^m R_i \left(\frac{1}{2E(f_i)} + \frac{\sigma_i^2 E(f_i)}{2}\right) \end{aligned} \tag{3.7}$$

Equation 3.8 assumes that the round-trip time of route i is the summation of travel times of all the links α along the route i. $E(t_\alpha)$ = expected travel time on link i.

$$T_i = \sum_{\alpha\in E} E(t_\alpha) \tag{3.8}$$

Equation 3.9 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.

$$\left(\sum_{i \in E} \frac{R_j}{f_i} + \sum_{j \in E} \frac{R_i}{f_j} \right) \varepsilon \leq A^k \tag{3.9}$$

Equation 3.10 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.

$$f_i \leq f_{\max} = \frac{N_i}{T_i} \tag{3.10}$$

Equation 3.11 states that the service frequency on any feeder route i should exceed the minimum acceptable service frequency (f_{min}) that provides sufficient capacity on that route.

$$f_i \geq f_{\min} = \frac{D_i}{S_i l_i} \tag{3.11}$$

3.2.2 Sub-model for Scheduling a Coordinated Operation with a Common Service Frequency

The main differences between the uncoordinated and coordinated systems are the slack times for coordinated ones. These 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 (see above Equations. 3.2 - 3.7).

Since the exact vehicle travel and arrival times are uncertain, adding some reserve or "slack" time into the schedule can provide better 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. 3.12 to 3.15.

Equation 3.12 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).

$$C_f = C_s + C_x + C_d \tag{3.12}$$

The slack time cost includes the extra dwell cost for loaded cargos and additional operation cost during the slack time. In Equation 3.13 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 the m_{th} category of cargo already loaded at terminal k on route i (cargo / min); $F^{mk}{}_i$ = amount of the m_{th} category of cargo 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 the route i and 0 otherwise.

$$C_s = \sum_{m \in M} \sum_{i \in E} \sum_{k \in N} [\mu^m (H_i^{mk} + F_i^{mk}) + B_i f_i] s_i^k \delta_i^k \tag{3.13}$$

Assuming that vehicles do not wait for other vehicles that arrive behind schedule, the missed-connection cost (C_x) is:

$$C_x = \sum_{m \in M} \sum_{k \in N} \sum_{j \in E} \sum_{\substack{i \in E \\ i \neq j}} \mu^m q_{ji}^{mk} \delta_i^k \delta_j^k \times f_x(t_i, t_j) \qquad (3.14)$$

Different probability distributions can be used for the travel time and arrival time random variables. For model simplification, we select the normal distribution to express them and assume that vehicle arrivals are independent among routes. The missed-connection cost can be expressed by using the joint probability distributions for vehicle arrivals on any coordinated pair of routes (i, j).

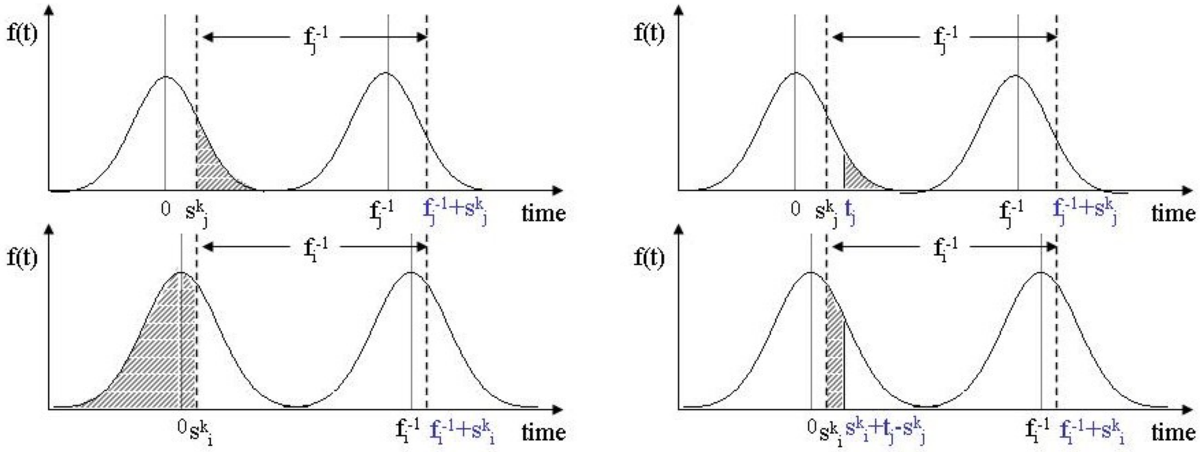


Figure 3.3 Joint Probability of Missed Connection from Route j to Route i

Two cases are considered: (1) the inbound vehicle on the route j arrives late, and the outbound one on the route i is not late; and (2) both vehicles are late, but the inbound vehicle arrives after the outbound one leaves. Figure 3.3 shows the joint probability of missed connections (i.e. $f_x(t_i, t_j)$) for transfer cargos on some particular pair of routes where f(t) = probability density function of arrival time.

The connection delay cost can be also expressed by using the joint probability distributions for vehicle arrival on any coordinated pair of routes (i, j). Two cases are considered for this cost component: (1) the inbound vehicle on the route j arrives early, but the outbound one on the route i is late; and (2) both vehicles are late, but the inbound vehicle arrives before the outbound one leaves.

Equation 3.15 represents the corresponding cost, and Figure 3.4 shows the joint probability of connection delay (i.e. $f_d(t_i, t_j)$) for transfer cargos on some particular pair of routes.

$$C_d = \sum_{m \in M} \sum_{k \in N} \sum_{j \in E} \sum_{\substack{i \in E \\ i \neq j}} \mu^m q_{ji}^{mk} \delta_i^k \delta_j^k \times f_d(t_i, t_j) \tag{3.15}$$

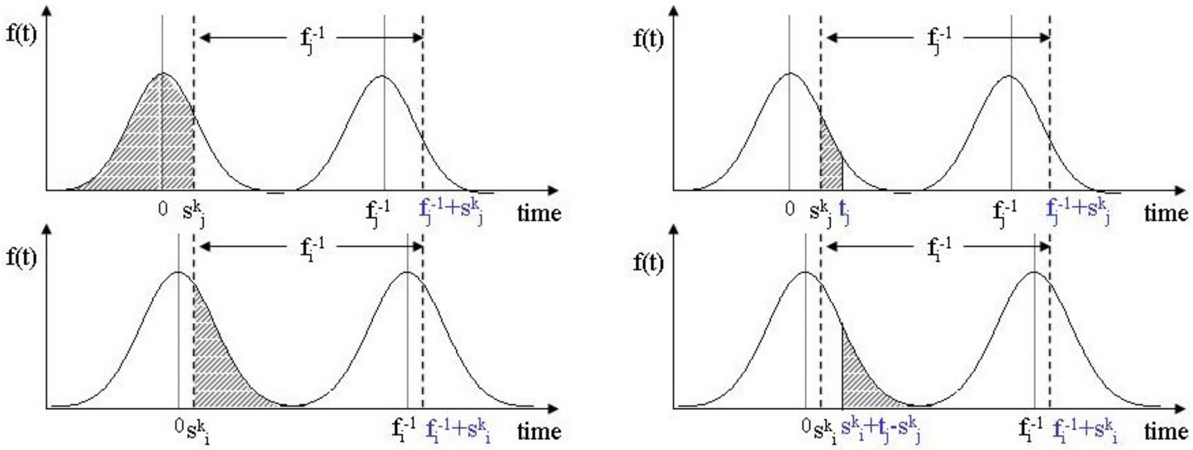


Figure 3.4 Joint Probability of Dispatching Delay from Route j to Route i

3.2.3 Sub-model for a Coordinated Operation with Integer-Ratio Service Headways

As mentioned in Ting and Schonfeld (2005), the common service frequency is not efficient when the demands or lengths of different routes vary much. Especially for the international intermodal freight transportation network, the characteristics of route and modes are significantly different. Thus, the concepts proposed by Ting and Schonfeld (2005) for coordinating operations with integer ratios for headways and segment travel times are adapted here and revised as follows.

Under this control policy, the model can simultaneously optimize slack times, the "base cycle", and corresponding integer multipliers. Assumed the base cycle (y) is an hour. If the service headway of the Route A is 2 hour and the headway in Route B is 3 hour, then every 6 hours these two routes have the great chance to meet together.

The transfer movements related cost terms are sensitive to the slack time and service frequency. These cost components are expressed in Equations. 3.16 to 3.23.

Equation 3.16 states that the transfer cost of the coordinated operation with an integer-ratio service headways includes four cost components, namely: the slack time cost (C_s), the inter-cycle transfer delay cost (C_i), the missed connection cost (C_x), and the connection delay cost (C_d).

$$C_f = C_s + C_i + C_x + C_d \tag{3.16}$$

The formulation of C_s is the same as for the common frequency method; all other cost terms are as shown in Equations 3.17 to 3.20. The inter-cycle cost includes all routes connecting to the transfer center, as shown in Equation 3.17.

$$C_i = \sum_{m \in M} \sum_{k \in N} \sum_{j \in E} \sum_{\substack{i \in E \\ i \neq j}} \mu^m q_{ji}^{mk} z_{ji}^{mk} \tag{3.17}$$

$$z_{ji}^{mk} = g_{ji} y \left(\frac{1}{2 g_{ji} y f_i} - \frac{1}{2} \right) + s_i^k = g_{ji} y \left(\frac{h_i}{2 g_{ji} y} - \frac{1}{2} \right) + s_i^k \tag{3.18}$$

The frequencies and headways 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 dwell time from route j to route i; g_{jk} = the greatest common divisor of β_i and β_j. Figure 3.5 shows an example to calculate the average transfer dwell time.

Assuming that two service routes operated based on different service headway (2y and 5y), the expected transfer dwell time (z_{12} and z_{21}) are expressed as follows:

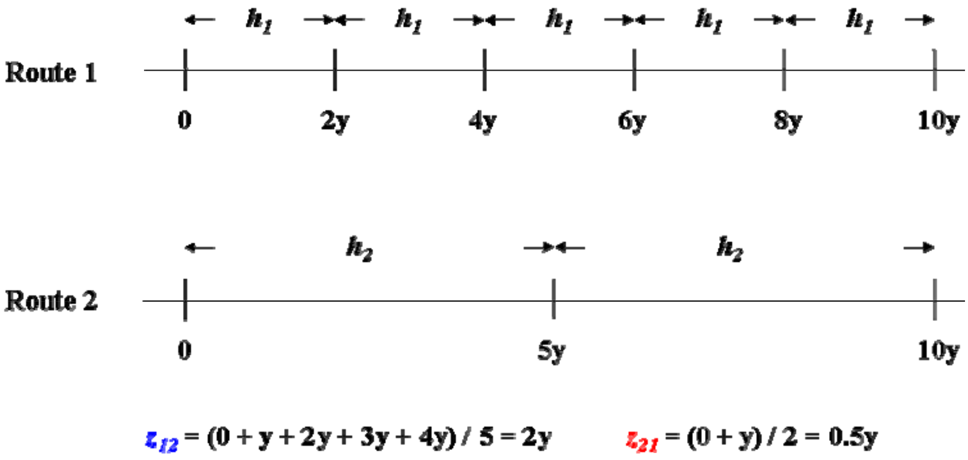


Figure 3.5 An Illustration for Computing Average Transfer Dwell Time

In Equations 3.19 and 3.20, the missed connection cost (C_x) and the connection delay cost (C_d) are slightly adjusted from those of the common service frequency model. The average transfer demand is derived from the integer ratio of two headways.

$$C_x = \sum_{m \in M} \sum_{k \in N} \sum_{j \in E} \sum_{\substack{i \in E \\ i \neq j}} \mu^m q^{mk}_{ji} \frac{g_{ji} y}{h_i} \delta^k_i \delta^k_j \times f_x(t_i, t_j) \tag{3.19}$$

$$C_d = \sum_{m \in M} \sum_{k \in N} \sum_{j \in E} \sum_{\substack{i \in E \\ i \neq j}} \mu^m q^{mk}_{ji} \frac{g_{ji} y}{h_i} \delta^k_i \delta^k_j \times f_d(t_i, t_j) \tag{3.20}$$

Here we assume that each shipment may miss the delivery vehicle only once. Delivery vehicles from different service routes meet at the transfer terminal once every h_j*h_i / (g_{ji}*y) min. In Ting's (1997) model, link travel time and headways are expected to be rounded to the "nearest" integer ratio of the selected base cycle y. Ting uses the geometric average, shown in Equation 3.21, to justify the "nearest" ratio.

$$\sqrt{(n-1)\times n}\,y < h_i^* \leq \sqrt{n\times(n+1)}\,y \quad h_i^* = ny \tag{3.21}$$

3.3 Summary

In this chapter, 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 (NLP) and mixed-integer nonlinear programming (MINLP) problems within the studied networks. To deal with the stochastic vehicle arrivals and uncertain route travel times, slacks are built into the operating schedules.

In our models, we specify two types of costs – non-transfer and transfer costs. There are four types of sub-costs attributed in the non-transfer cost and up to other four types of sub-costs attributed in the transfer cost. Both cargo dwell time cost and loading/unloading costs are classified into non-transfer cost category because these costs are mainly affected by the vehicle service frequency (i.e. with or without transfer movements, these costs are still generated). Costs caused by the transfer movements are counted in our "transfer cost." Transfer costs include another cargo dwell costs within the transfer terminals for uncoordinated operations and slack time cost, missed-connection cost, dispatching delay cost, and inter-cycle cost for coordinated operations.

Other studies may focus on different objective functions and cost terms, and each cost term may have different definition. Here we still incline to maintain our original settings.

In addition, for long term planning stage, the slack times and service frequencies are jointly optimized based on the given fleet sizes. For short term operational stage, the slack times could be considered as a function of fleet size.

In this study, a pre-planned schedule coordination problem is formulated and optimized to determine slacks based on the given fleet sizes. Although the slack times are not directly formulated as a function of the fleet size, the joint optimization processes of slack times and service schedules do take the fleet size into consideration. As shown in equation 3.13, additional vehicle operation cost during the slack time is counted in the objective function.

For short term operations, slack times may be really influenced by fleet sizes. Due to vehicle failures, drivers' absences, or other unexpected accidents with short notices, the above models may need some modifications to ensure the service quality and reliability. Minimal required slack times may be also formulated as constraints on the number of available operational vehicles.

Chapter 4

NLP & MINLP Solution Approach

In this chapter, some heuristic approaches for both NLP and MINLP will be described. Sections 4.1 and 4.2 briefly introduce the solution procedures of genetic algorithms (GAs) and sequential quadratic programming (SQP) starting from initializing and verifying input data until obtaining the optimal solutions. GAs and SQP are also being developed in the system planning model for optimizing routes and schedules based on an optimized cycle time T*. Some basic concepts for both GAs and SQP are introduced as follows. A hybrid GA-SQP method is then described specifically for the proposed models in Section 4.3. The hybrid method is related to but somewhat different from the one proposed by Mansoornejad et al. (2008).

4.1 Fundamentals of Genetic Algorithms

An efficient optimization algorithm must satisfy two requirements for finding the global optimum: exploring the search space and exploiting the knowledge gained at the previously visited points. In the recent decades, GAs have attracted research interest from different disciplines. Because GAs (Goldberg 1989; Michalewicz 1996) perform global search probabilistically and consider the evolution process after generations, the algorithms can handle any kind of objective functions and constraints with a quite promising performance in approaching a global optimum. In addition, GAs have been widely used for solving scheduling and schedule coordination problems (e.g. Shrivastava et al., 2002; Sarker and Newton, 2002; Torabi et al., 2006; Cao, 2008).

This algorithm could be applied to solve a variety of optimization problems that are not well suited for standard optimization algorithms, including problems with the discontinuous, non-differentiable, stochastic, or nonlinear objective functions and constraints. Before applying GAs to our proposed models, some aspects of the GA components should be first considered, for example: solution encoding, genetic operators, stopping criteria, and infeasible solutions repairing processes. All of them are designed to feature the characteristics of NLP and MINLP.

4.1.1 Background

In GAs, the problem is treated as the environment, and a set of possible solutions to the problem is treated as the population. Each individual in the population is represented by a set of encoded genes called a chromosome. A procedure that mimics natural evolution is established to select individuals for reproducing offspring according to their "fitness" to the environment (the problem). After several generations, the most adapted individual will survive and has a higher chance to reproduce offspring.

There are several characteristics distinguishing GAs from other conventional optimization techniques:

(1) GAs start with an initial set of feasible solutions rather than a single point, thus taking advantage of population-to-population search. This feature gives GAs the chance to escape from local optima in multi-directional global search.

(2) GAs do not require any specific function for the mathematical expression of a given problem. Thus GAs can handle any kind of objective function and constraints, especially when the objective function is quite noisy.

(3) GAs discard deterministic rules but apply stochastic operators, thus being a stochastic search approach.

4.1.2 Basic Terminology

Because genetic algorithms are rooted in both natural genetics and computer science, the terminology used in literature is mixed. Generally, GA can be mapped as a natural evolution process. The corresponding explanations for GAs and optimization are summarized in Table 4.1.

Table 4.1 Genetic Algorithms Terminology

Terms	Explanations
Chromosome (individual, string)	Encoded solution
Phenotype	Decoded solution
Gene	A portion of chromosome
Locus	Position of gene in a chromosome
Alleles	Value of gene
Gene pool	The set of possible alleles
Population	A set of solutions

4.1.3 Genetic Algorithms Components

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. All components are described below:

(1) Solution encoding (chromosome)

Originally, a potential solution to the problem is encoded into a binary string, called a chromosome, of a given length which depends on the required precision. In terms of problem needs, some other ways of representing solutions are necessary. Figure 4.1 (a) – (c) shows the chromosomes designed for three different control policies.

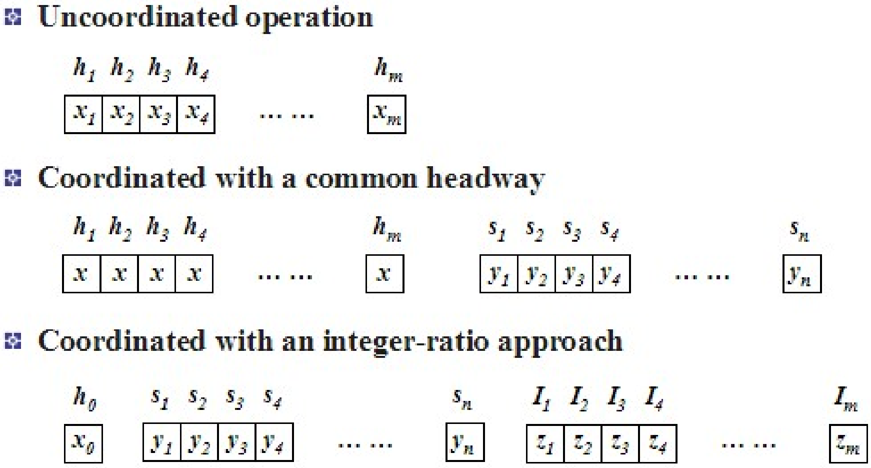


Figure 4.1 Settings of Chromosomes for (a) Uncoordinated, (b) Common Headway Coordinated, and (c) Integer-ratio Coordinated approaches

For uncoordinated operations, there is only one type of decision variable (x_1, x_2, … …, x_m) representing the service headway of each route. For the common headway coordinated method, additional type of decision variable (y_1, y_2, … …, y_m) representing the service slack time is included. In the integer-ratio coordinated approach, three categories of decision variables are defined: a base cycle, the corresponding integer multipliers, and the slack times built into the schedules.

(2) Initial population

Generally, the initial population is randomly generated. Including the information about the distribution of the optimum solution in initial population would be helpful to speed up the final convergence.

(3) Fitness function

In most cases where GAs are applied, the fitness function is the objective function to be optimized (i.e. total system cost value in this study). The fitness value of each individual solution from a population must be evaluated.

(4) Selection

The individuals in the population are selected to reproduce offspring according to their fitness value. Typically, proportional selection chooses individuals by calculating their relative fitness values. If necessary, scaling and ranking schemes provide alternatives for measuring fitness other than using raw values directly.

(5) Genetic operators

Classic GAs provide two types of genetic operators – crossover and mutation. Crossover function combines two individuals, or parents, to form a new individual, or child, for the next generation. A crossover operator generates the offspring by swapping parents' genes at some randomly chosen locus of the chromosomes. In this dissertation, a scattered crossover function creates a random binary vector. It then selects the genes where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child.

As shown in Figure 4.2, we first generate two parents, and generate two binary strings (one is randomly generated and another is switched all 0 and 1 numbers from the previous one binary string.) According to the two strings, two child solutions can be produced.

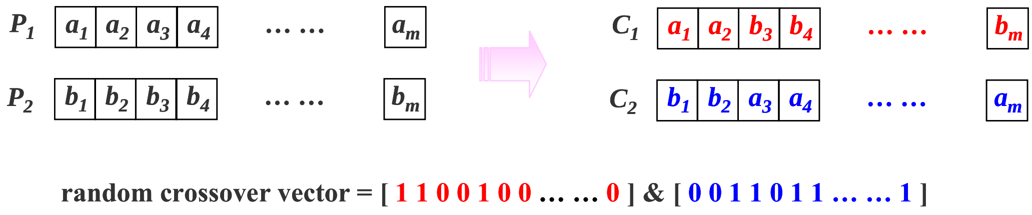


Figure 4.2 Examples of Genetic Operators

Mutation functions make small random changes in the individuals in the population, which provide genetic diversity and enable the GA to search a broader space. A mutation operator arbitrarily alters one of more genes of a selected chromosome to increase the population variability. In this study, a probabilistic distribution adds a random number to each vector entry of an individual. This random number is taken from a Gaussian distribution centered on zero.

(6) Population replacement

Replacement creates a new population for the next generation and is strongly related to the selection process. Two issues arise in this phase – sampling space and sampling mechanism. Along with selection, both of them have a significant influence on selective pressure and thereby on genetic algorithm behavior.

4.1.4 Solution Procedure

Figure 4.3 shows the general structure of GAs. The termination conditions here are mainly based on some stopping criteria including: number of generations, the tolerance function, and the stall generation. The number of generation specifies the maximum number of iterations the genetic algorithm performs. The tolerance function defines whether the change in the fitness function value is worth to let program keep search or not. For example, if the cumulative change (or the weighted average change) in the fitness function value over stall generations is less than tolerance settings, the algorithm also stops.

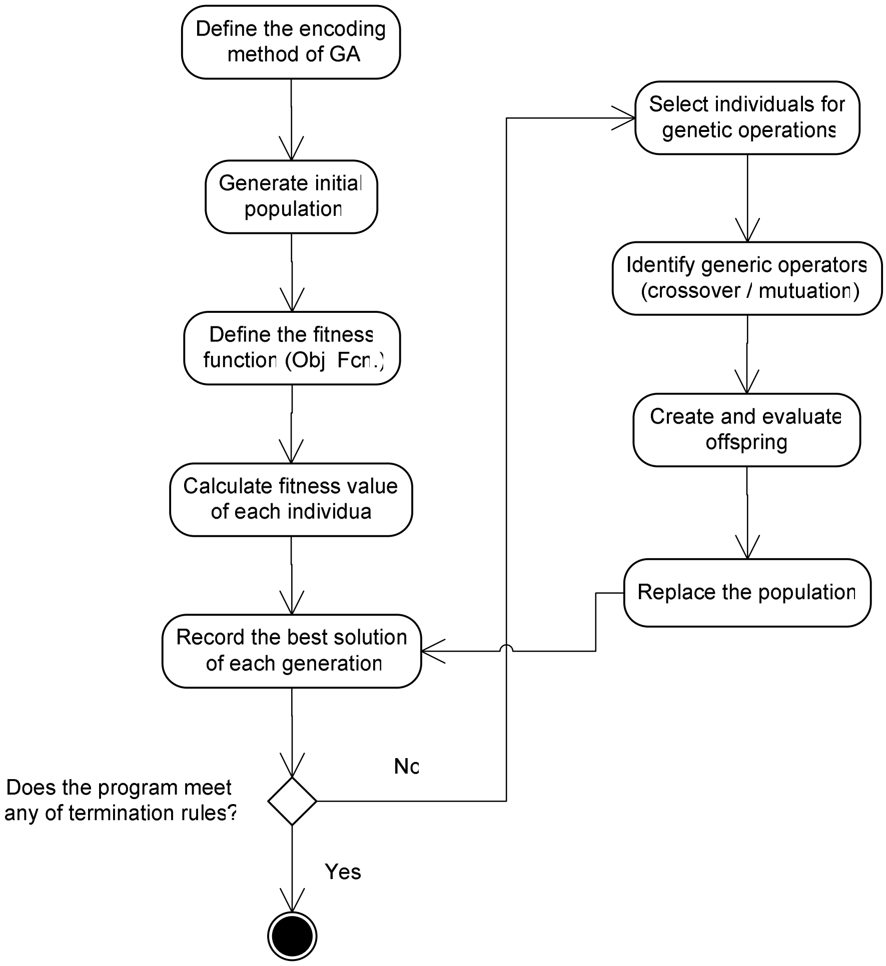


Figure 4.3 General Structure of Genetic Algorithms

Generally, more generations allow the GAs to do a more thorough search and find a better solution. However, there are diminishing returns in searching through additional generations. Different random seeds may lead to various populations and result in different final solutions (i.e. different local optima.)

4.2 Fundamentals of Sequential Quadratic Programming

SQP is another widely used approach to solve 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. According to a solid theoretical and computational foundation, the SQP algorithms have been developed and used to solve a remarkably large set of important practical problems (Boggs and Tolle, 1989, 1995, and 2000; Dohrmann and Robinett, 1997; Tenny et al., 2004; Wright and Tenny, 2004; Behrang et al., 2008). More details about these works have been discussed in Chapter 2. Some introductions of SQP are addressed below.

4.2.1 Basic SQP Algorithms

Given Z(x) is an objective function of n real variables, subject to the m_1 nonlinear equality constraints and m_2 nonlinear inequality constraints on the variables, as shown in Equation 4.1.

$$\begin{aligned} &\min_{x\in\Omega} Z(x) \\ &\Omega = \{x \in R^n \mid c_i(x) = 0, i \in m_1; c_i(x) \geq 0, i \in m_2\} \qquad (4.1) \\ &x = (x_1, x_2, ..., x_n)^T \end{aligned}$$

An SQP method uses a quadratic model for the objective function and a linear model of the constraint. A nonlinear program in which the objective function is quadratic and the constraints are linear is called a quadratic program (QP). SQP is an iterative method which solves at each iteration a QP. For the above Equation 4.1 at the k_{th} iteration, constraints can be approximated and replaced based on a given estimate $x^{(k)}$ of a solution x^*. Taking the equality constraint $c_i(x) = 0$ for an example, it can be replaced by Equation 4.2.

$$c_i(x^{(k)} + p) \cong \nabla c_i(x^{(k)})^T p + c_i(x^{(k)}) \tag{4.2}$$

Similarly, the nonlinear objective function can also be approximated by using Taylor's expansion method, as shown in Equation 4.3.

$$z(x^{(k)} + p) \cong z(x^{(k)}) + \nabla z(x^{(k)})^T p + \frac{1}{2}\nabla^2 p^T z(x^{(k)}) p \tag{4.3}$$

Thus, we can solve the QP below to find the next search direction, as shown in Equation 4.4. Where $w_k = \nabla^2 z(x^{(k)})$, usually represents a positive semi-definite approximation of Hessian matrix of Lagrange multipliers and estimated $x^{(k)}$.

$$\begin{aligned} &\min_p \frac{1}{2} p^T w_k p + \nabla z(x^{(k)})^T p \\ &s.t.\ \ \nabla c_i(x^{(k)})^T p + c_i(x^{(k)}) = 0, i \in m_1 \\ &\qquad \nabla c_i(x^{(k)})^T p + c_i(x^{(k)}) \ge 0, i \in m_2 \end{aligned} \tag{4.4}$$

4.2.2 Relations between Newton's Method and SQP

The SQP method is based on solving a series of sub-problems designed to minimize a quadratic model of the objective subject to a linearization of the constraints. If the problem is unconstrained, then the method reduces to Newton's method. In other words, the SQP method is equivalent to Newton's method applied to the first-order necessary conditions.

The advantage of the SQP framework over simply applying Newton's method is to modify the step when the initial estimate ($x^{(k)}; \lambda^{(k)}$) is not sufficiently close to ($x^{*}; \lambda^{*}$) that pure Newton's method defines a good step. Similarly, in unconstrained minimization problems, Newton's method can be viewed as repeatedly minimizing a quadratic model rather than as trying to find a zero gradient. Thus, sequential quadratic programming can be defined as a convergent algorithm, and Figure 4.4 shows the general relation between Newton's method and SQP algorithms.

A quadratic approximation to this minimization function is now constructed that along with linear constraints forms a quadratic programming problem. The solution of the original optimization problem, say x^*, is now obtained from an initial estimate and solving a sequence of updated quadratic programs. It is found that SQP is very sensitive to initial feasible solutions (i.e. initial estimates). Thus, the method used for selecting a quality estimate is an important issue in resolving this variability of solutions.

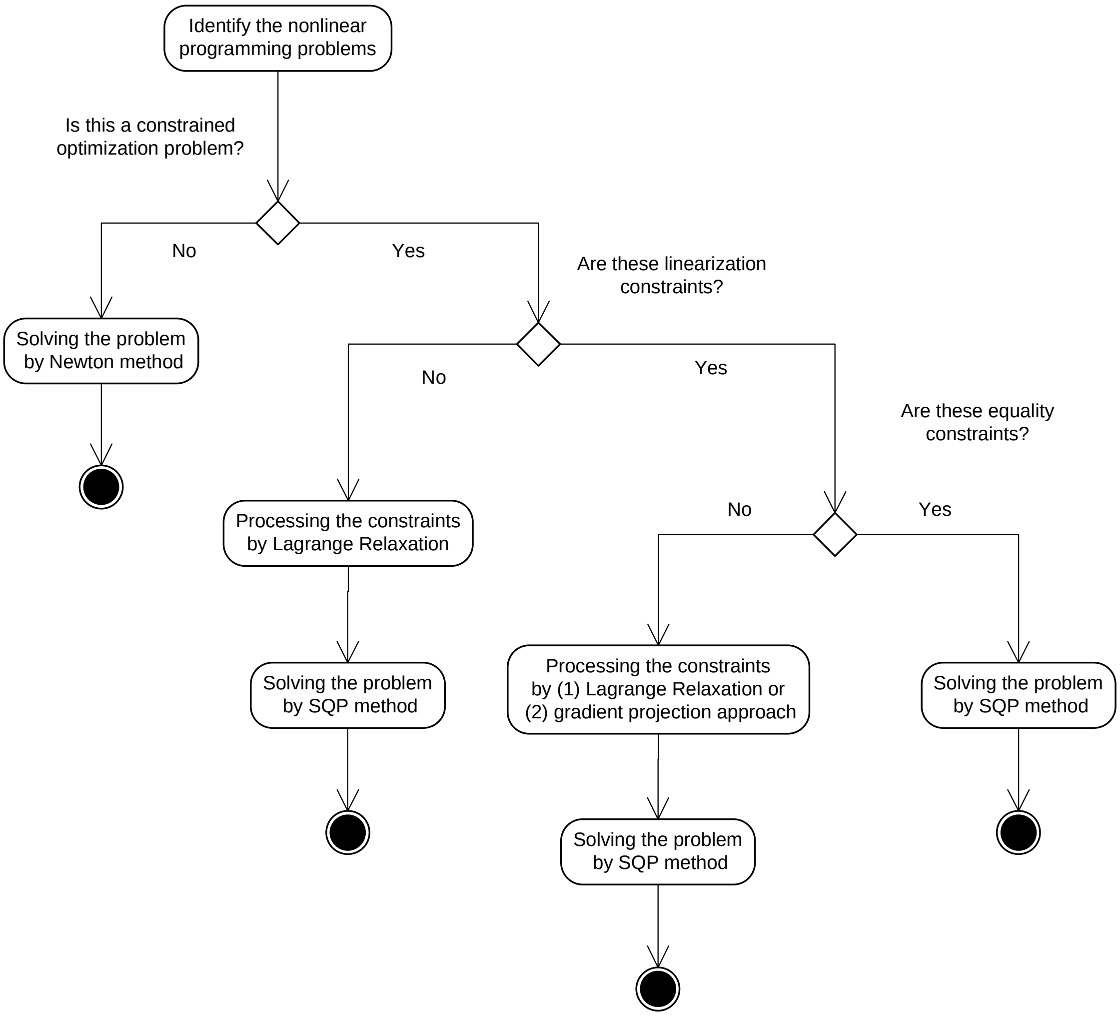


Figure 4.4 General Relation between Newton's Method and SQP Algorithms

4.3 The Proposed Hybrid GA – SQP Approach

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., and explain some differences between their approach and my proposed algorithm.

In Mansoornejad's approach, a GA is applied first to produce the 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 stall generation during which the approximate solution becomes closer to the final solution. In other words, the GA will continue until the number of generations meets a specified value or the objective function value would not change 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 method. If the improvement of the SQP is not large enough, it will shift to the GA again. The criterion for "enough improvement" depends on the nature of the problem and can be specified by users. Otherwise, it continues until no 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. Details of this procedure are illustrated in the flowchart shown in Figure 4.5.

In order to create more diversity for GA, Mansoornejad et al apply the final population in existing GA to be an initial population in another new GA, and our approach tries to apply different random seeds for GA. The hybrid GA – SQP method proposed by Mansoornejad is sound; however, there are still some drawbacks which can be improved by our approach. First, it seems somewhat arguable to determine the user-specified number for the stall generation in advance. The stall generation is one kind of stopping criterion for determining the appropriate timing for terminating the algorithm. The "better" is only in comparison to other solutions. As a result, the stop criterion is not clear. Additionally, users without experience may have difficulties in setting a suitable threshold value. In our approach, we use SQP to produce the starting solution to provide a reasonable threshold for the following GAs.

Second, the sequence of alternating between GA and SQP may be inefficient because the GA may not exploit its main advantage, the “diversity”. Different random seeds lead to different parents and populations, and generate different results in GA. Thus, an important problem with a hybrid method is determining the suitable switching timing.

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. 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 switch timing from SQP to GA. If the step size of the SQP is too small, the algorithm shifts to the GA. This switching strategy may raise two additional questions: (1) How should we determine the “large enough” step size to proceed 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. Details of the hybrid GA - SQP approach proposed here are illustrated in the flowchart shown in Figure 4.6.

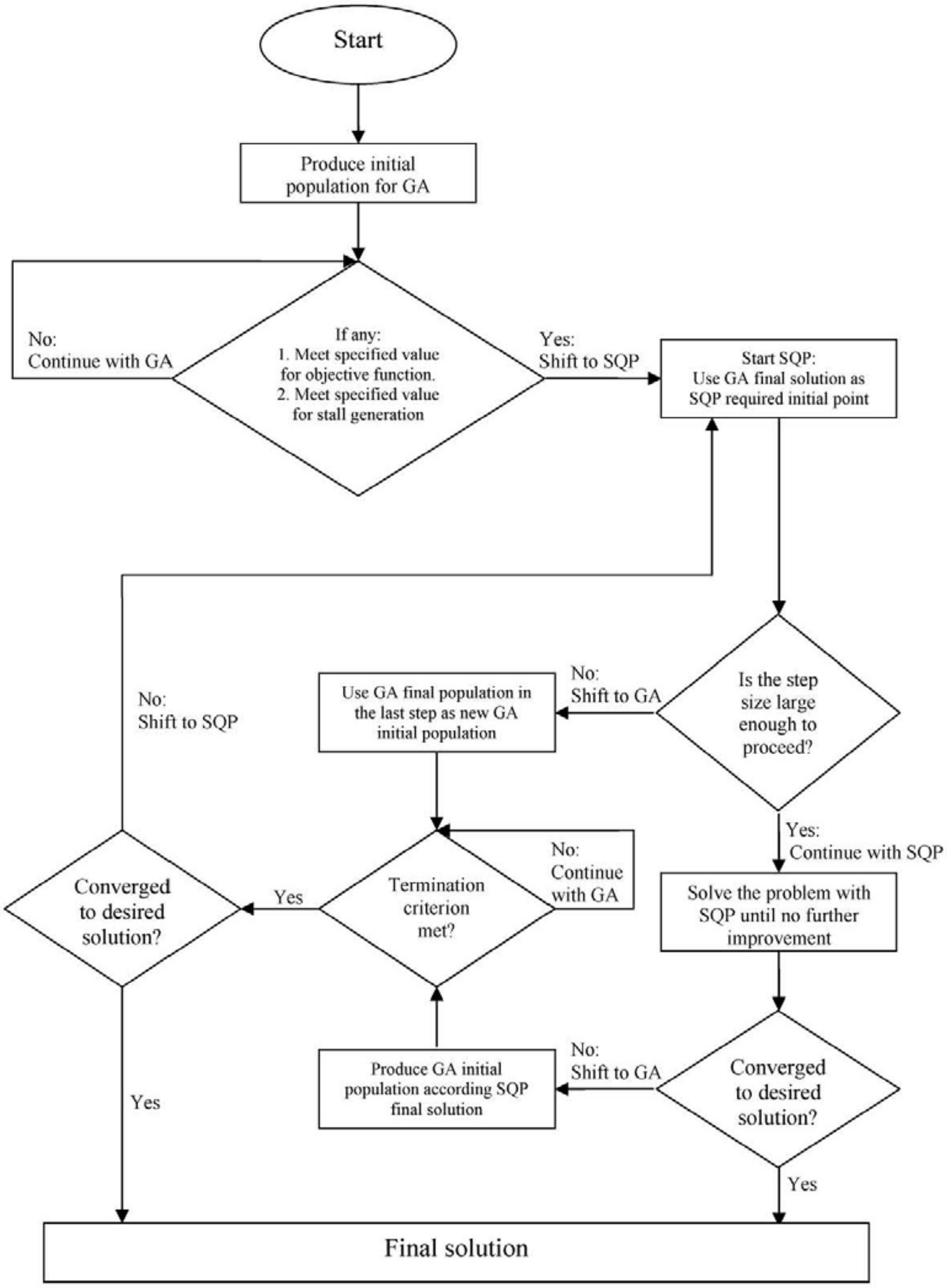


Figure 4.5 Flow Chart of Mansoornejad's Hybrid GA - SQP Method

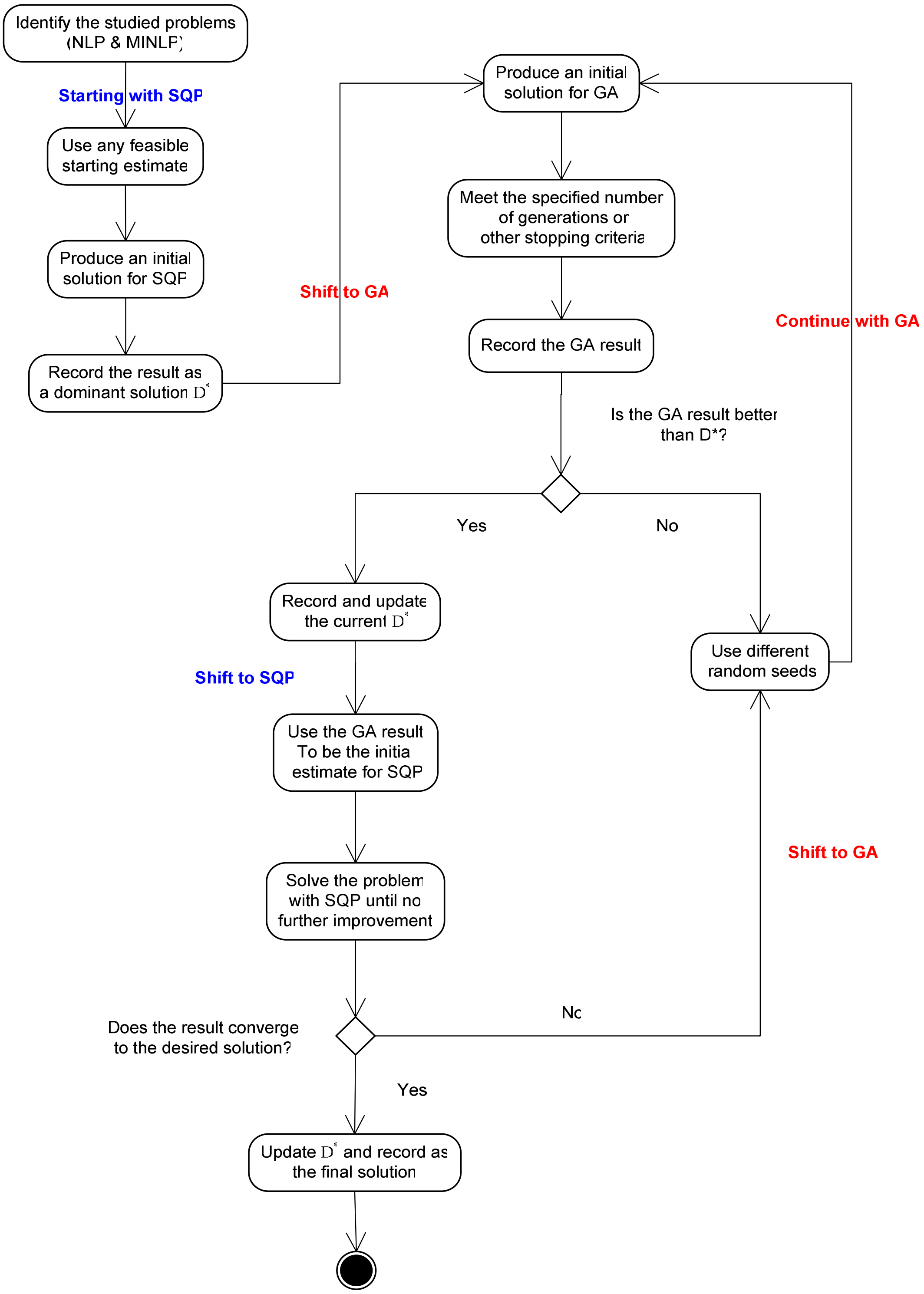
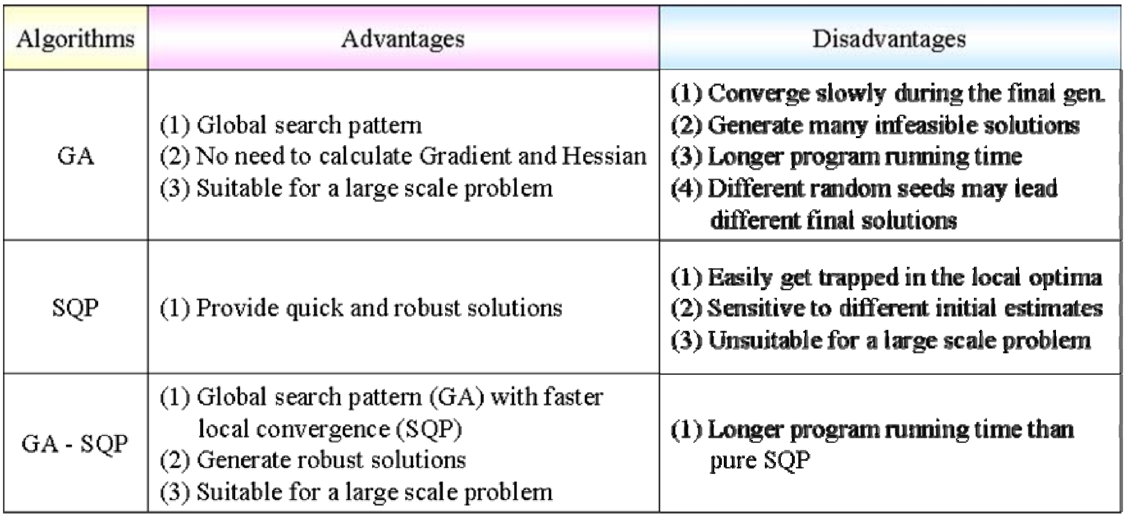


Figure 4.6 Flow Chart of Proposed Hybrid GA - SQP Method

4.4 Summary

For these nonlinear optimization models, three heuristic algorithms (GA, SQP, and a hybrid GA - SQP) are developed. Both GA's and SQP are widely applied in the general nonlinear programming problems; however, these two popular algorithms still have some drawbacks, as shown in Table 4.2.

Table 4.2 Analysis of GA, SQP, and a Hybrid GA-SQP



Algorithms	Advantages	Disadvantages
GA	(1) Global search pattern (2) No need to calculate Gradient and Hessian (3) Suitable for a large scale problem	**(1) Converge slowly during the final gen.** **(2) Generate many infeasible solutions** **(3) Longer program running time** **(4) Different random seeds may lead different final solutions**
SQP	(1) Provide quick and robust solutions	**(1) Easily get trapped in the local optima** **(2) Sensitive to different initial estimates** **(3) Unsuitable for a large scale problem**
GA - SQP	(1) Global search pattern (GA) with faster local convergence (SQP) (2) Generate robust solutions (3) Suitable for a large scale problem	**(1) Longer program running time than** pure SQP

In order to exploit the major advantages of both GA and SQP and improve the defects of the algorithms, a hybrid GA – SQP method is developed and applied in case studies. In general, the proposed hybrid approach implements global search by GA first and runs SQP to reach the final solutions. Through this algorithm, the GA can converge very quickly at beginning and provide a fairly good initial solution for SQP until no further improvements are found. More details of parameter settings are addressed in Chapter 5.

Chapter 5

Performance Assessment of a Pre-Planned Schedule Coordination System

5.1 Introduction

Based on the proposed NP and MINLP models (e.g. some components of objective function, constraints, and nonlinear time value settings), SQP and GA are well suited for such problems with complex and nonlinear formulations.

The SQP method is based on solving a series of sub-problems designed to minimize a quadratic model of the objective subject to a linearization of the constraints. If the problem is unconstrained, then the method reduces to Newton's method for finding a point where the gradient of the objective vanishes. If there were some nonlinear constraints within the model, Lagrangian relaxation techniques (Chang, 2007; Mes and

Heijden 2007; Florian et al., 2007) could help maintain the linearization of the constraints. Moreover, GA's are widely used for many optimization problems.

With a GA a population of candidate solutions to an optimization problem evolves toward better solutions. The evolution usually starts from a population of randomly generated individuals and occurs over generations. In each generation, the fitness of every individual in the population is evaluated. Multiple promising individuals (also called parents) are stochastically selected from the current population and mutated to form a new population. The new population is then used in the next iteration of the algorithm. In general, the algorithm terminates when reaching the maximum number of generations or a predetermined threshold.

A traditional GA can rapidly locate good solutions, even for difficult search spaces. However, it may generate many infeasible solutions and have a tendency to converge towards local optima or even arbitrary points rather than the global optimum of the problem. Diversity is important in GA's because crossing over a homogeneous population does not easily yield new solutions.

The traditional deterministic methods (e.g. SQP) for solving the general nonlinear optimization problems may obtain the results faster than other approaches, but might get trapped in the local optima solutions. It is found that the deterministic methods are very sensitive to initial feasible estimates (Mansoornejad et al., 2008). Wide variation in results is seen based on different initial solutions. On the other hand, stochastic methods are more suitable for solving these problems because a wide range of values for parameters would be searched and the probability of getting trapped into local optima would be decreased. However, the convergence in the final steps of problem solving may be very slow and additional stopping criteria or thresholds may be needed.

Thus, to resolve this variability in optimal results in deterministic methods and reduce the running time of stochastic approaches, a hybrid algorithm is developed in this dissertation. Since GAs and SQP are successfully employed alone to solve many NLP problems, these two methods will be slightly modified and tested in our study. Additionally, a hybrid method is developed to overcome the difficulties appearing when only one of the above two algorithms is used.

5.2 Model Applications and Analytical Results

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 demand or travel time. Additionally, this study provides flexibility for general and perishable cargos with different inventory / dwell time value functions. Intuitively, there may be a significant interaction between different demand levels and schedule coordination operations. If demand decreases, service frequencies should also decrease, thereby increasing the potential value of arrival coordination that reduces miss-connection costs.

5.2.1 Case Study 1: Single Commodity, Multiple Modes, & Single Hub Operations

In Case 1, as shown in Figure 5.1, 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 carrying capacities of light and container trucks are 7,300 and 22,000 pounds, respectively. Vehicle operating cost function is expressed as the "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. It should be noted that value of parameter b is suggested by Coyle, Bardi, and Novack (1994); however, this value may be affected by different modes and commodities. The following case studies are adopted this value but still allowed to change based on users' requirements. The unit cargo dwell cost (μ) is $0.2/lb-hr (Hall, 1987). Unit cargo loading and processing time are set as 0.03 and 0.05 (min/lb), respectively. Other given inputs are listed in Table 5.1.

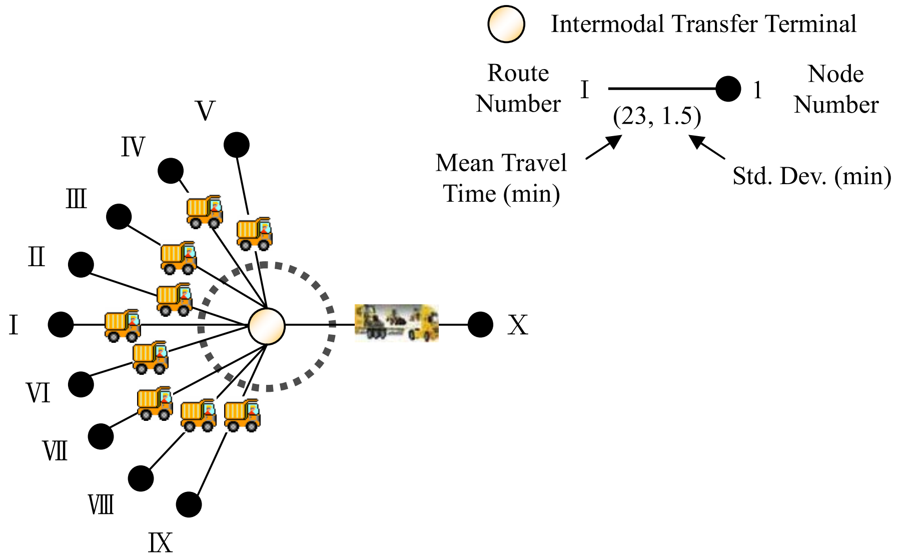


Figure 5.1 Network Configuration for Multi-Modes and Single Hub Operation

Table 5.1 Demand and Route Information for Case 1

Inbound Route	Outbound Route (Unit: 100 lb / hr)	Route Travel Time (min)	
		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 coordinated method has the same result as the integer-ratio approach. As shown in Table 5.2, 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 terms.

When comparing the values for coordinated and uncoordinated objective functions, we observe that the coordinated approaches are better than the uncoordinated system, especially for transfer costs. It is clear that higher service frequencies lead to higher operating cost, lower cargo dwell, loading, unloading, and processing time and costs due to lower load factors. A similar trend is also observed in Case 2. There is no inter-cycle cost when running the common coordinated operations.

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 is developed for overcoming this weakness of SQP. However, if the initial estimate were 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 %). The GA-optimized integer-ratio results are illustrated in Figure 5.2. 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 to stop the GA, as mentioned in Chapter 4.

Table 5.2 Overall Results of Different Policies in Case 1

	Optimized Headways (hr/veh) / Frequencies (veh)					
	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 ($ / hr)						
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	

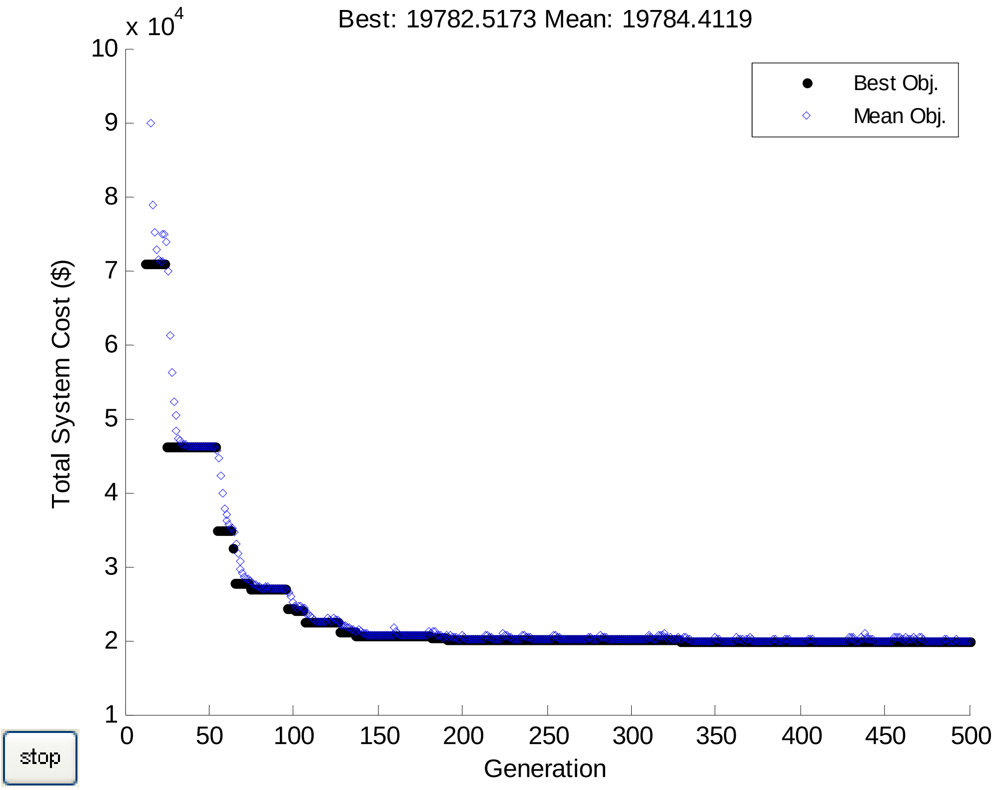


Figure 5.2 Results of Genetic Algorithm (500 Generations) in Case 1

5.2.2 Variability in Optimal Results

As mentioned in Chapter 4, 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. In order to pursue a robust solution, a hybrid GA-SQP heuristic algorithm has been proposed. Some numerical examples generated based on 30 different initial solutions (for SQP) and 30 different random seeds (for GAs) are testing in this section. Results will also be compared with the proposed hybrid GA-SQP method by using the same set of random seeds for GAs.

All other settings are as in the above Case 1. One of the stopping criteria in GAs is the number of generations; here we set a threshold at 500 generations. For the hybrid GA – SQP approach, we let GAs run 100 generations first and switch to SQP by using the results obtained by the initial GA. It should be noted that both GAs and the hybrid GA – SQP may be terminated and switched by other criteria, as noted in sections 4.1 and 4.3. The purpose of using the pre-determined thresholds is only 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 5.3, 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 value to those of our hybrid GA- SQP approach due to the good initial estimates (2 times within the 30 examples), it may be difficult to obtain good initial solutions without any experience or knowledge of the final solutions.

Some examples indicate that results solved by GA in 100 generations may still not be qualified to be switched to SQP. Although the GA can provide fairly good solutions in 500 generations, it cannot guarantee to reach the same optima. 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.

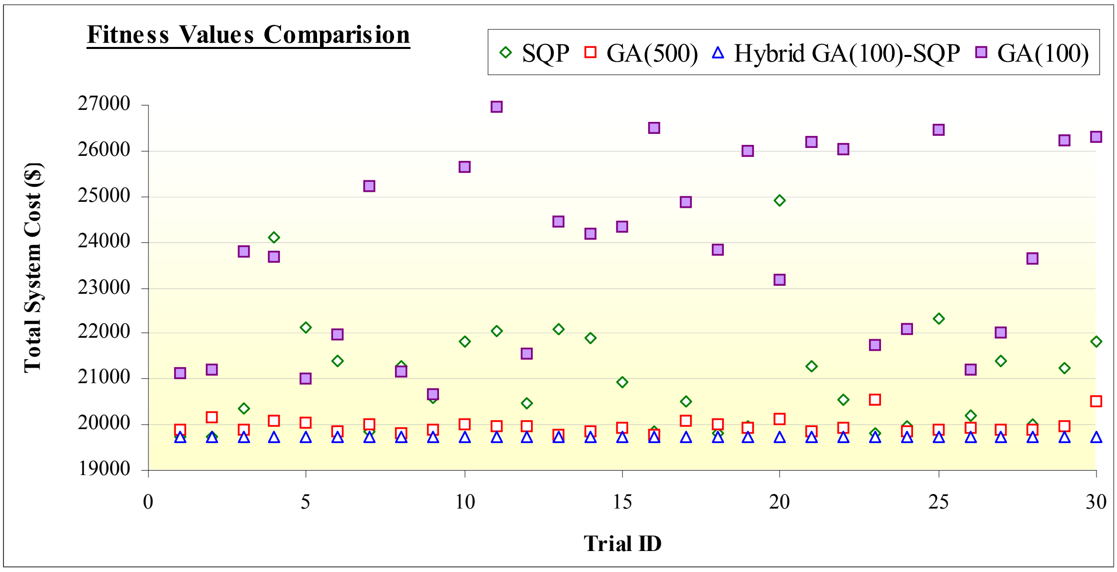


Figure 5.3 Optimized Results Solved by GA, SQP, and a Hybrid GA-SQP in Case 1

5.2.3 Program Running Time

The computation time is important for future real-time applications. On average, Figure 5.4 shows that 500 generations of GAs, the hybrid GA (in 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 the PC with 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 results within one minute, which provide a competitive ability for further 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.

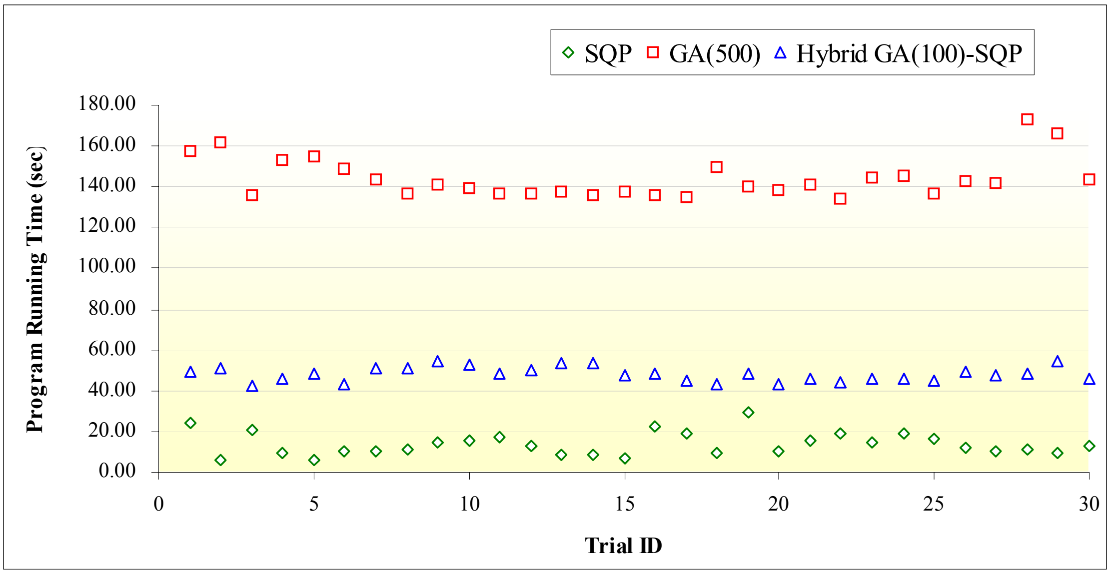


Figure 5.4 Program Running Time with Different Solution Approaches in Case 1

5.2.4 Time Path Analysis of Storage Requirement in Case 1

One advantage expected from such an intermodal timed transfer system is a reduced requirement for storage areas inside the terminals due to poor connections. In order to observe the storage requirement based on different control policies, a simplified time path analysis is provided below.

According to the previous optimized service schedules in Case 1, cargos carried by inbound vehicles are assumed first unloaded in a temporarily storage facility. Once the outbound pick-up trucks arrive, those cargos will be moved from the storage space to those vehicles.

Figures 5.5 and 5.6 show the storage requirement under uncoordinated and coordinated operations, respectively. The utilization rate of the storage facility under uncoordinated operations is much higher than that in coordinated operations, because vehicles' arrival schedules may vary due to non-synchronized timetables.

In addition, well-coordinated schedules force inbound vehicles carrying the cargos fit the capacities of outbound vehicles, so the storage facility can be utilized by other service routes. Within the time path analysis period, maximum storage requirement for uncoordinated operations (i.e. 37,546 pounds) is also higher than that in coordinated operations (i.e. 21,999 pounds.)

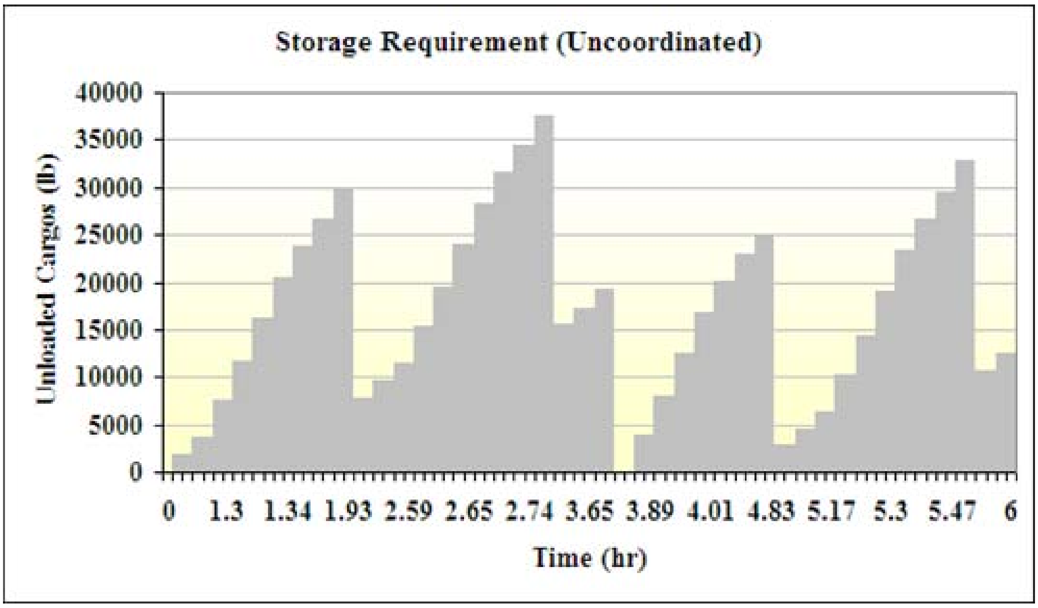


Figure 5.5 Time Path of Uncoordinated Intermodal Freight System

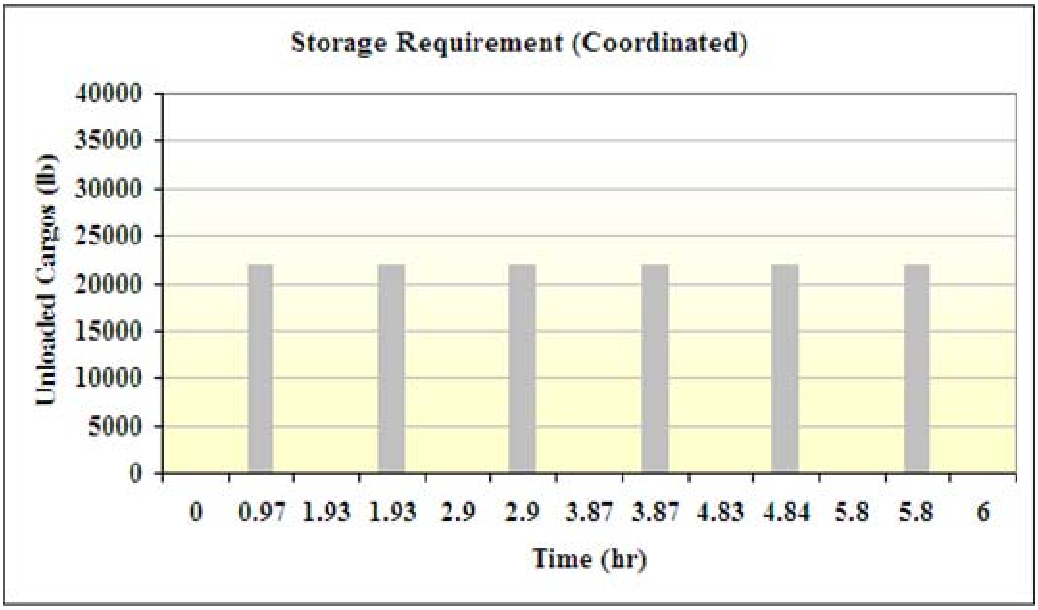


Figure 5.6 Time Path of Coordinated Intermodal Freight System

5.2.5 Case Study 2: Multiple Commodities, Multiple Modes, & Multiple Hubs Operations

Two truck routes and one rail route are analyzed in Case 2 (Figure 5.7). The vehicle capacities for truck and rail are 22,000 and 100,000 pounds, respectively. In this case, a = 200 (truck) and 300 (rail), and b = 0.03. Two types of shipments with different unit time values are assumed in this case, as suggested in Figure 1.1 (e). μ_1 and μ_2 are equal to \$0.5*exp(-t) /lb-hr and \$0.2/lb-hr. The notation “t” expresses the total transportation time including dwell time, loading/unloading, cargo processing, and mean travel time from origin to destination. Demand information is shown in Table 5.3.

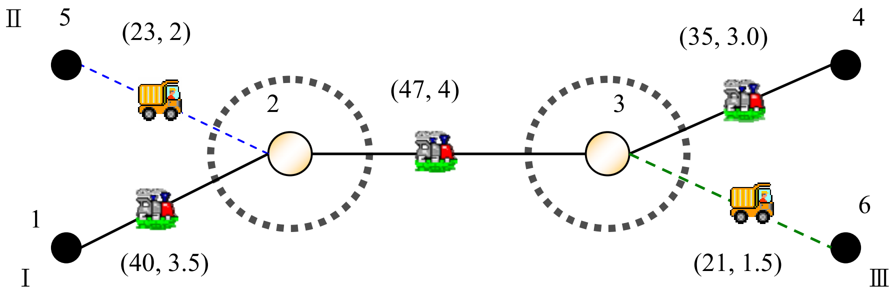


Figure 5.7 Network Configuration for Multi-Modes and Multi-Hubs Operation

Table 5.3 OD Demand Information for Case 2 (Units: 100 lbs/hr)

O \ D (type 1 & 2)	1	2	3	4	5	6
1	0	16.50	14.50	17.00	14.50	4.65
	0	16.50	14.50	17.00	14.50	4.65
2	16.50	0	31.85	14.50	10.60	16.50
	16.50	0	31.85	14.50	10.60	16.50
3	14.50	31.85	0	21.25	17.00	19.10
	14.50	31.85	0	21.25	17.00	19.10
4	17.00	14.50	21.25	0	6.35	17.60
	17.00	14.50	21.25	0	6.35	17.60
5	14.50	10.60	17.00	6.35	0	0
	14.50	10.60	17.00	6.35	0	0

6	4.65	16.50	19.10	17.60	0	0
	4.65	16.50	19.10	17.60	0	0

As shown in Table 5.4, the integer-ratio schedule coordination outperforms the uncoordinated and the common-headway coordinated operations for the given input information. Similarly to Case 1, schedule coordination can reduce transfer costs more than the uncoordinated system. Transfer costs can still be reduced by up to 40.76% in common-headway coordinated operations; however, the common service-headway method is inefficient due to higher non-transfer costs when the demands or lengths of different routes vary much. S_1^{2a} and S_1^{2b} express slack times of Route 1 at the transfer terminal 2 with two service directions. The optimized base cycle of the integer-ratio schedule coordination is equal to 0.8506 (hr/veh). The inter-cycle costs are due to the cargo transfers from Routes 2 and 3 to Route 1.

Table 5.4 Overall Results for Different Policies in Case 2

	Optimized Headways (hr/veh)			
	Uncoordinated (GA-SQP)	**Common Headway Coordination (GA-SQP)**	**Integer-ratio Coordination (GA)**	**Integer-ratio Coordination (GA-SQP)**
Base Cycle (y)	--	--	0.933	0.931
Route 1	1.91	1.29	2y	2y
Route 2	0.70	1.29	y	y
Route 3	0.62	1.29	y	y
Slack Time				
S_1^{2a}, S_1^{2b}	--	0.02, 0.02	0.02, 0.02	0.02, 0.02
S_1^{3a} ,S_1^{3b}	--	0.02, 0.02	0.03, 0.02	0.02, 0.02
S_2^2	--	0.02	0.02	0.02
S_3^3	--	0.02	0.02	0.02
Costs ($ / hr)				
C_o	8915.3	11391	8546.4	8549.1
C_w	6868	6427	7301.9	7299.6
C_l	13.6	13	14.5	14.5
C_p	29.4	23	29.7	29.7

Non-transfer	15826.3	17854	15892.5	15892.9
C_i	--	--	721.8	721.4
C_s	--	346	338.2	321.9
C_m	--	740	727.8	733.7
C_d	--	231	210	215.3
Transfer	2132.1	1317	1997.8	1992.3
Total System	17958.4	19171	17890.3	17885.2

The GA-optimized integer-ratio results are illustrated in Figure 5.8. Both the hybrid GA - SQP and GA reach similar results; the difference in total system costs is only 0.0285%.

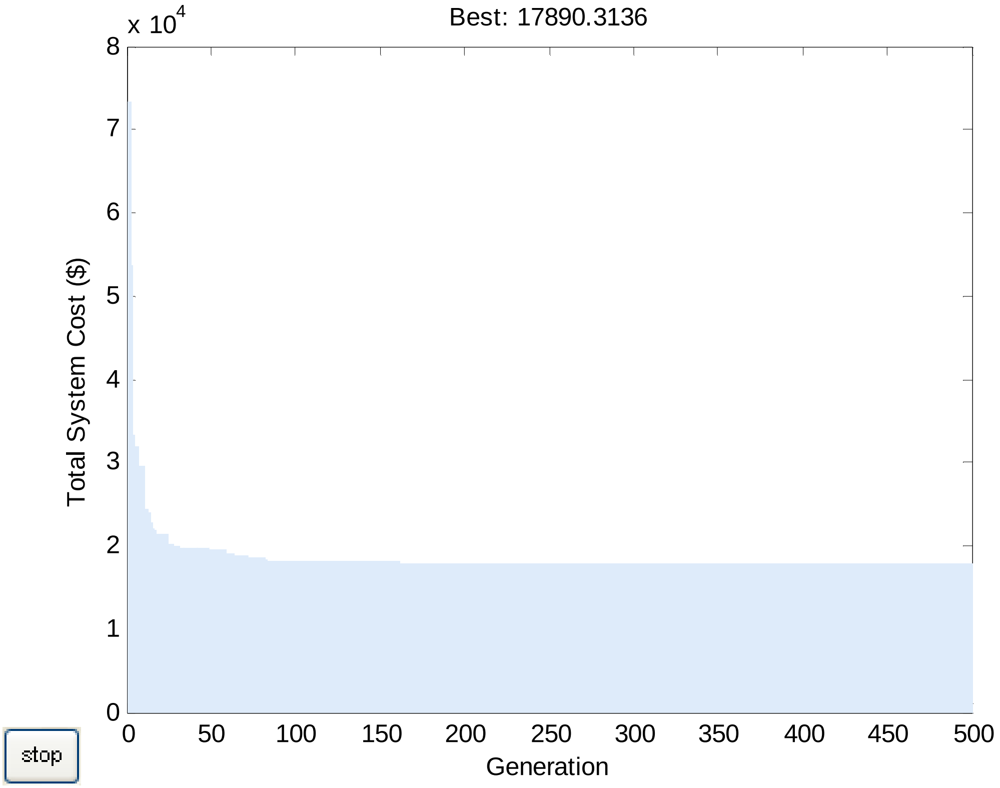


Figure 5.8 Results with Genetic Algorithm over 500 Generations for Case 2

5.2.6 Sensitivity to Different Demand Levels

Figure 5.9 shows the results of sensitivity analysis for different demand levels in case 2. A demand multiplier of 2 means the original demand is doubled.

The results in Table 5.4 show that the integer-ratio coordinated approach outperforms than uncoordinated operation or coordinated method with common service headway. Coordination seems more desirable under lower demand conditions, and it may be not worthwhile to attempt coordination in higher demand situations.

In Figure 5.9, the illustrated results are very reasonable because the service frequencies during the lower demand are relatively low, the costs of missed-connection (C_x) or connection delays (C_d) may become more significant. On the other hand, if the demand is very high, then the impacts of missed-connection may not affect the shipments so much. Higher service frequencies or shorter headways can diminish the extra cargo dwell time due to missed-connection or connection delays.

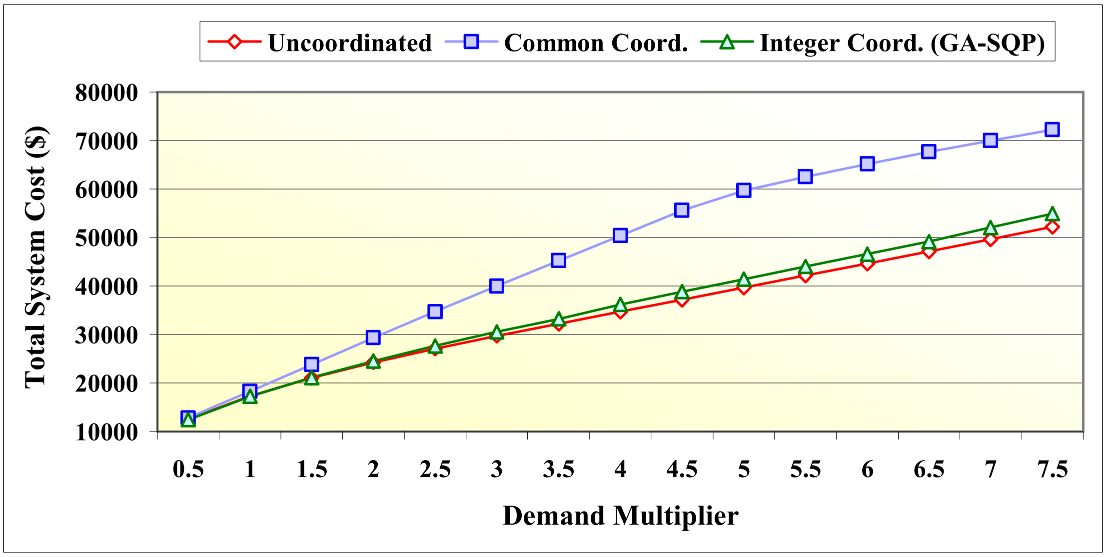


Figure 5.9 Results of Sensitivity Analysis with Different Demands

5.2.7 Case Study 3: 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 3. As shown in Figure 5.10, the three hubs form a loop. 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 the same as case 2. All other settings are the same as Case 1. Demand information is given in Table 5.5.

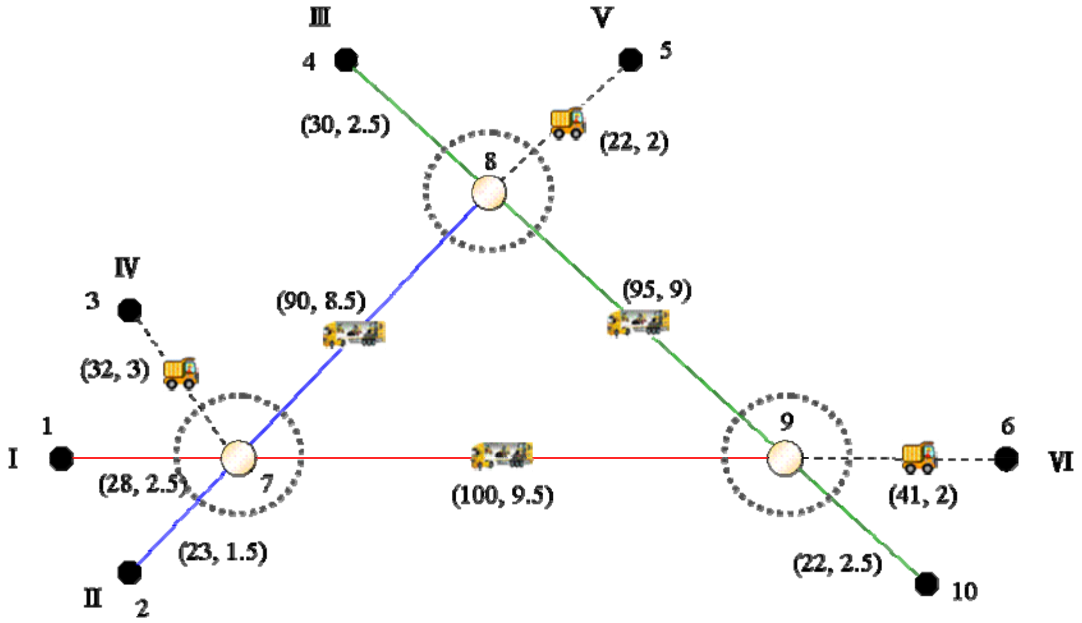


Figure 5.10 Loop Network Configuration for Multi-Modes and Multi-Hubs Operation

Table 5.5 OD Demand Information for Case 3 (Units: 100 lbs/hr)

Type 1 Cargo										
O \ D	1	2	3	4	5	6	7	8	9	10
1	0	1	6.55	6.85	6.30	5.02	1.23	3.50	1.28	3.01
2	1.65	0	6.50	5.36	5.88	6.28	1.16	1.00	4.75	5.40
3	3.25	1.30	0	5.87	5.93	6.45	1.55	3.15	3.38	5.03
4	5.35	3.96	4.50	0	6.40	4.12	2.58	1.50	4.81	1.68
5	5.21	3.68	5.53	5.50	0	6.62	2.85	1.96	5.60	3.50

6	5.12	6.78	5.85	4.22	5.60	0	4.55	2.90	4.85	4.75
7	5.23	5.36	5.05	5.70	6.85	6.55	0	1.21	5.66	4.56
8	1.00	4.45	1.35	4.30	4.96	6.50	4.81	0	4.30	4.36
9	4.18	2.75	5.58	2.28	5.90	6.81	5.66	1.50	0	4.85
10	5.48	7.63	6.83	2.08	6.54	6.75	4.96	1.16	3.85	0
Type 2 Cargo										
O \ D	1	2	3	4	5	6	7	8	9	10
1	0	3.50	9.30	9.70	8.20	7.95	3.10	4.00	3.45	6.80
2	2.05	0	9.50	8.93	9.80	9.83	3.45	2.20	6.35	9.85
3	4.50	2.70	0	9.60	8.20	8.70	3.80	6.00	6.10	9.90
4	8.70	4.30	9.70	0	9.60	6.80	4.40	2.70	9.30	3.60
5	7.97	6.28	7.80	8.30	0	9.00	4.30	2.40	9.25	6.25
6	8.40	8.65	8.20	6.95	8.85	0	6.95	4.50	7.45	6.75
7	8.80	8.95	6.85	9.20	9.90	9.95	0	2.05	8.85	7.20
8	2.50	9.80	3.10	7.60	7.80	8.20	7.70	0	8.20	8.40
9	9.70	4.30	8.50	2.30	9.60	8.25	8.95	2.20	0	8.00
10	7.50	9.45	9.10	2.60	9.70	9.15	9.45	3.30	5.20	0

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 with another pair of terminals. The conflicts may increase the difficulties of solving this problem and even cause infeasibility of 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.

Table 5.6 indicates the optimized results based on the given OD information and the loop network configuration. Basically, under uncoordinated operations, 3 light truck routes tend to be served by smaller headways than those in 3 container truck routes. The value of optimized common headway is between the minimal and maximal headways in uncoordinated operations. For integer-ratio coordination operations, both GA and the hybrid GA-SQP obtain the same integer multipliers but with different base cycle values. Similar to case 2, common headway coordination is still undesirable in this case due to inefficient non-transfer costs. The optimized result of integer-ratio coordination solved with the hybrid approach is the dominant solution in case 3.

Table 5.6 Overall Results for Different Policies in Case 3

	Optimized Headways (hr/veh)			
	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 ($ / hr)				
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

5.2.8 Case Study 4: Large Scale Network Applications in Intermodal Logistic Timed Transfer Systems

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 large scale network with 30 light truck routes (Routes 1-30), two container truck routes (Routes 31-32), and one rail route (Route 33) are analyzed in Case 4. As shown in Figure 5.11, the three transfer terminals are arrayed in a loop.

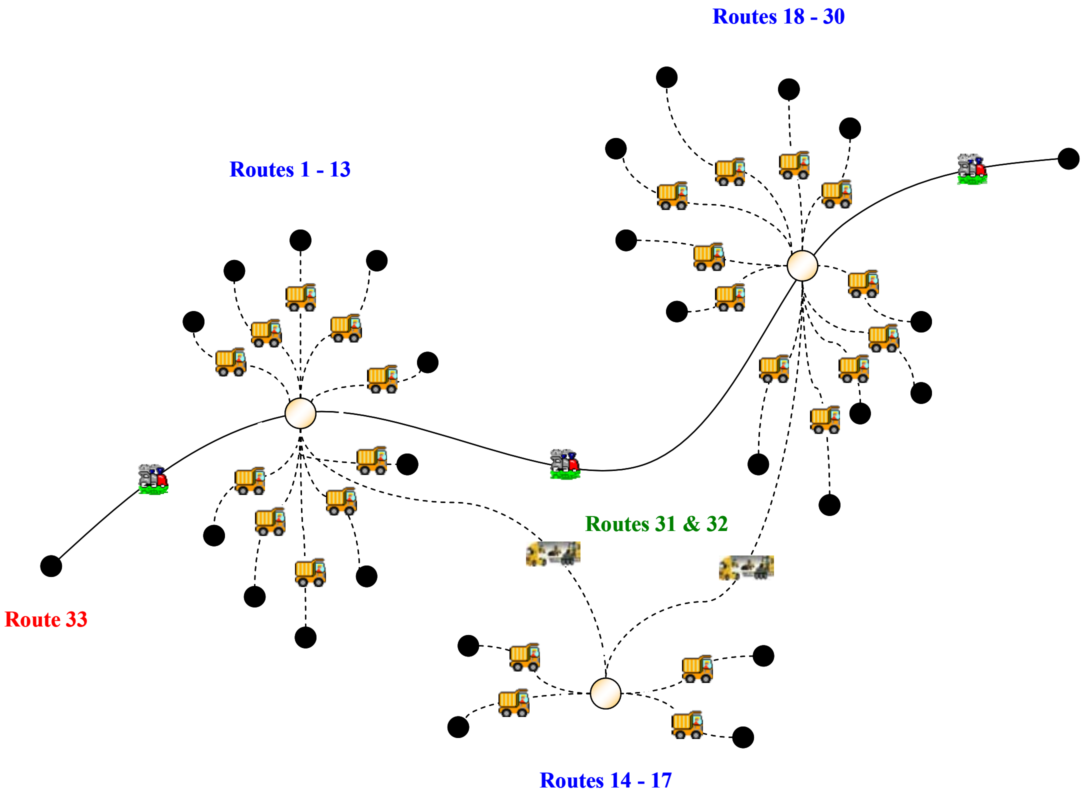


Figure 5.11 Large Scale Loop Network Configuration

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. Demand information is as shown in Tables 5.7 (a) – (f). There are totally 35 nodes illustrated in Figure 5.12. Nodes 1-30 represent the starting terminal of each light truck service route (i.e. black dots). Nodes 31-33 represent three intermodal transfer terminals within the network (i.e. big open circles.) Nodes 34 and 35 represent the starting and ending stations of the route.

Table 5.7(a) OD Demand Information for Case 4 (Units: 100 lbs/hr)

Type 1 Cargo												
O \ D	1	2	3	4	5	6	7	8	9	10	11	12
1	0	.62	.77	.28	.55	.88	.33	.68	.49	.41	.51	.35
2	.82	0	.16	.18	.44	.44	.32	.72	0	.10	.28	.16
3	.58	.84	0	.54	.45	.67	.55	.44	.73	.60	.54	.65
4	.26	.97	.61	0	.28	.51	.45	.46	.59	.98	.21	0
5	.25	.94	.32	0	0	.88	.18	.81	.43	.83	.96	.73
6	.81	.41	.37	.75	.11	0	.34	.33	.79	.12	.62	.51
7	.61	.97	0	.44	.36	.43	0	.45	.73	.22	.16	.11
8	.86	.47	.14	.99	0	.87	.38	0	.88	.51	.13	.40
9	0	.10	.78	.58	.67	.67	0	.84	0	.26	.30	.67
10	.45	.38	.14	.43	.77	.15	.21	.84	.24	0	.93	0
11	.45	.74	.87	.88	.86	0	.22	.49	.56	.12	0	.50
12	.26	.32	.72	.71	.10	.31	.41	.55	.61	.71	0	0
13	.75	0	0	.91	.81	.50	0	.72	.42	.54	.89	.13
14	.26	.49	.70	.52	0	.10	.36	.21	.24	.70	.74	.93
15	.42	.63	.13	.36	.44	.47	.17	.60	.61	.87	.73	.39
16	0	1.91	1.21	1.55	1.47	.22	1.41	1.63	.20	.19	1.08	1.51
17	.45	1.67	1.82	.41	1.22	.83	1.94	1.19	1.00	.98	.15	1.98
18	.19	.46	.36	1.76	1.75	1.04	1.17	.52	.55	1.36	1.25	1.95
19	.96	.69	.77	1.90	1.73	1.51	.87	.23	0	.94	.96	1.78
20	.16	.27	1.58	.59	1.15	.27	.21	1.07	1.23	.72	1.02	.73
21	1.66	.85	.66	.69	0	.91	1.03	1.56	.77	.12	.67	.72
22	1.70	.71	.73	1.96	1.09	1.46	.40	.24	1.25	.26	1.11	.49
23	.77	.54	.27	.62	.84	1.00	1.41	1.63	.81	0	1.38	1.80
24	1.50	1.22	.53	.47	1.11	1.71	.68	.97	1.45	.67	.86	.67
25	1.69	.47	.73	.73	1.20	.45	1.93	.85	.55	.28	1.18	.59

26	.56	0	1.77	.83	1.05	107	40	115	189	141	95	57
27	1.84	.77	.49	1.64	1.81	.76	.84	.74	.58	1.35	1.62	1.75
28	1.42	1.34	.29	1.85	1.15	1.08	.50	1.78	1.02	1.22	1.15	.74
29	1.90	.38	.16	1.08	1.54	.77	.29	1.16	.98	1.02	.41	0
30	0	.52	.26	1.47	1.72	.39	1.53	.44	1.18	1.27	.96	1.54
31	1.27	1.49	.85	.66	.92	2.49	2.25	.79	1.41	0	.80	1.83
32	.53	1.47	.63	2.73	.31	2.86	.32	1.07	1.73	.59	1.80	.32
33	1.28	.53	0	.68	.88	.24	1.49	.88	1.44	1.32	.50	.23
34	1.17	.20	1.49	1.09	1.29	2.20	2.95	1.88	1.98	.27	1.94	2.71
35	1.76	4.00	.99	2.51	2.24	2.93	.40	2.16	3.34	1.51	2.53	.33

Table 5.7(b) OD Demand Information for Case 4 (Units: 100 lbs/hr)

Type 1 Cargo												
O \ D	13	14	15	16	17	18	19	20	21	22	23	24
1	.25	.80	.80	1.98	.43	1.98	1.09	1.57	1.56	.27	.80	.82
2	.30	.24	.72	1.80	1.66	1.45	1.14	1.42	1.58	1.30	1.92	.45
3	.68	.16	.38	.75	.37	1.75	.25	1.28	.55	1.12	1.44	1.22
4	.88	.96	.30	.42	.14	1.72	.16	.52	1.31	1.69	1.73	1.30
5	.80	0	.81	.37	.37	.23	1.21	.33	.37	1.65	1.78	1.25
6	.81	.77	.58	.55	.11	1.12	1.32	1.79	.66	.69	1.14	.22
7	.78	.47	.76	.51	.63	1.74	1.98	1.27	1.73	.69	1.87	1.31
8	.80	.54	.56	.87	1.98	.35	1.87	.26	1.12	1.91	1.86	1.60
9	.15	.69	.83	.55	1.60	.14	1.30	1.23	.57	1.81	.56	.28
10	.89	.74	.28	.82	.95	.59	.98	.27	1.92	.43	.75	.20
11	.34	.72	.48	1.25	1.67	1.87	1.23	1.97	1.63	0	1.52	.25
12	.97	.96	.86	.52	.17	1.20	1.67	1.54	1.64	1.24	1.42	1.18
13	0	.76	.50	1.29	.41	.10	1.87	.53	0	.39	1.07	.31
14	.31	0	.34	1.05	1.70	.42	.11	.19	1.33	.63	1.04	0
15	.13	.44	0	1.83	1.80	1.34	.67	.89	1.93	1.84	1.54	1.17
16	.85	.26	1.01	0	.76	.24	.51	.45	.97	0	.86	.22
17	1.17	.48	1.74	.72	0	.53	.98	.68	.28	.58	.95	.42
18	1.35	0	.46	.73	.70	0	.38	.69	.17	.45	.49	.70
19	.13	1.40	0	.98	.22	.75	0	0	.15	.54	.15	0
20	1.17	.83	.93	.95	.85	.93	0	0	.26	.10	.10	.12
21	1.31	1.53	.64	.37	.34	.49	.45	.92	0	.94	0	.95
22	.41	.98	.80	.52	.95	.58	.22	0	.14	0	.68	.97
23	1.60	1.94	0	.61	0	.86	0	.67	.24	0	0	.15
24	0	.20	1.61	.16	.37	.89	.14	.12	.86	.85	.79	0
25	.48	1.36	.94	.90	.42	.18	0	.14	.17	.46	.52	.12
26	.28	1.11	1.91	.74	.25	.49	.62	.51	.60	.91	.46	.19

27	.95	.32	.79	.26	0	.11	.40	.29	.15	1.00	.34	.97
28	.81	.17	1.60	.59	.51	.10	.92	.69	.89	.22	.64	.93
29	.22	1.10	1.24	.38	0	.41	.43	.42	.39	1.00	.58	.81
30	.50	1.86	.91	.19	.87	.41	.26	.38	.61	.19	0	.14
31	1.47	2.27	2.23	1.80	.14	1.06	1.69	1.03	1.73	1.97	1.93	2.17
32	1.78	1.69	1.99	1.15	1.52	2.79	.99	1.09	1.68	2.43	2.58	.57
33	1.14	.55	.31	.86	.43	2.52	2.41	.14	1.57	2.56	1.73	1.42
34	2.67	.38	2.00	.53	.55	.22	.59	.16	.36	.73	.64	.98
35	2.70	1.08	.49	.36	.55	2.68	2.23	1.95	.31	2.81	1.46	1.14

Table 5.7(c) OD Demand Information for Case 4 (Units: 100 lbs/hr)

Type 1 Cargo											
O \ D	25	26	27	28	29	30	31	32	33	34	35
1	.28	.96	.35	.26	1.11	.15	.34	.70	1.02	.69	1.22
2	1.80	.70	1.83	.74	1.25	1.52	.87	1.13	1.09	1.85	.42
3	1.96	0	.89	1.33	.76	1.31	1.55	0	1.36	1.27	1.60
4	1.55	.53	1.20	.71	1.48	.23	2.09	.51	0	.66	2.73
5	.78	1.70	.37	.73	.84	1.21	1.50	0	1.48	1.79	2.90
6	1.63	.12	.62	1.50	0	1.17	.22	2.99	.42	1.71	.22
7	1.15	.83	1.20	1.84	1.42	.24	1.82	.71	1.45	.85	3.33
8	1.18	1.45	.35	0	1.79	1.38	.86	.84	1.25	1.29	.45
9	.35	1.12	1.08	.58	.25	1.45	1.26	1.23	.11	2.21	.63
10	.59	1.73	.98	.72	.93	1.78	1.79	1.49	.87	2.33	2.76
11	.91	1.76	1.60	1.91	.30	1.21	.19	.61	1.12	2.76	3.20
12	1.20	1.85	.40	.96	.49	.37	1.63	.40	1.30	1.29	3.91
13	.35	1.55	.20	.98	.48	1.03	.36	.13	.84	2.24	1.71
14	.14	.15	.15	1.78	1.63	.47	2.20	2.68	.74	2.84	1.81
15	.54	.84	.73	1.77	.94	.13	1.45	.11	1.33	.20	2.35
16	.27	.90	.75	.98	.13	.83	.66	1.64	1.50	.65	2.05
17	.64	0	.61	.77	.93	.45	1.52	1.59	1.53	1.24	2.65
18	.30	.54	.70	.64	.62	.71	.37	3.02	.30	.52	1.62
19	.97	.57	.83	.94	.52	.15	2.19	3.83	.62	1.24	.19
20	.76	.35	.60	.51	.16	.96	.29	.61	2.81	1.32	2.65
21	.40	.75	.90	.45	.86	.92	1.79	3.12	1.92	1.47	.37
22	.81	.51	.23	.66	.87	.47	.19	.63	2.32	.20	.14
23	.31	.77	.37	.81	.44	.75	1.71	.12	2.29	.93	2.64
24	.31	.54	.45	.87	.16	.11	2.31	.81	.88	1.35	.72
25	0	.61	0	.16	.19	.67	2.37	.25	2.11	.18	2.58
26	.50	0	.43	.74	.73	.57	.69	1.34	1.16	1.35	.79
27	.60	.82	0	.88	.89	.75	.52	.69	2.53	.93	2.12

28	.63	.38	.44	0	.94	.11	1.42	1.65	.74	7	5
29	.15	.71	.23	.36	0	.19	.29	1.88	1.03	.74	1.80
30	.46	.73	.55	.36	0	0	1.63	0	1.68	.31	2.88
31	.71	2.23	1.26	1.45	.99	2.20	0	4.00	2.00	2.00	4.00
32	.97	1.34	2.61	2.68	2.44	1.01	4.00	0	2.00	3.00	4.00
33	.53	2.39	1.03	2.46	2.85	2.47	2.00	2.00	0	2.00	3.00
34	.17	1.49	1.47	1.32	.42	1.11	2.00	3.00	2.00	0	2.00
35	2.41	2.03	1.18	1.88	0	1.00	4.00	4.00	3.00	2.00	0

Table 5.7(d) OD Demand Information for Case 4 (Units: 100 lbs/hr)

Type 2 Cargo												
O \ D	1	2	3	4	5	6	7	8	9	10	11	12
1	0	1.33	1.66	.60	1.18	1.89	.71	1.46	1.05	.88	1.10	.75
2	1.76	0	.34	.39	.95	.95	.69	1.55	.15	.22	.60	.34
3	1.25	1.81	0	1.16	.97	1.44	1.18	.95	1.57	1.29	1.16	1.40
4	.56	2.09	1.31	0	.60	1.10	.97	.99	1.27	2.11	.45	0
5	.54	2.02	.69	.17	0	1.89	.39	1.74	.92	1.78	2.06	1.57
6	1.74	.88	.80	1.61	.24	0	.73	.71	1.70	.26	1.33	1.10
7	1.31	2.09	0	.95	.77	.92	0	.97	1.57	.47	.34	.24
8	1.85	1.01	.30	2.13	0	1.87	.82	0	1.89	1.10	.28	8.6
9	0	.22	1.68	1.25	1.44	1.44	.11	1.81	0	.56	.65	1.44
10	.97	.82	.30	.92	1.66	.32	.45	1.81	.52	0	2.00	0
11	.97	1.59	1.87	1.89	1.85	.15	.47	1.05	1.20	.26	0	1.08
12	.56	.69	1.55	1.53	.22	.67	.88	1.18	1.31	1.53	.13	0
13	1.61	0	0	1.96	1.74	1.08	.11	1.55	.90	1.16	1.91	.28
14	.56	1.05	1.51	1.12	0	.22	.77	.45	.52	1.51	1.59	2.00
15	.90	1.35	.28	.77	.95	1.01	.37	1.29	1.31	1.87	1.57	.84
16	0	4.11	2.60	3.33	3.16	.47	3.03	3.50	.43	.41	2.32	3.25
17	.97	3.59	3.91	.88	2.62	1.78	4.17	2.56	2.15	2.11	.32	4.26
18	.41	.99	.77	3.78	3.76	2.24	2.52	1.12	1.18	2.92	2.69	4.19
19	2.06	1.48	1.66	4.09	3.72	3.25	1.87	.49	0	2.02	2.06	3.83
20	.34	.58	3.40	1.27	2.47	.58	.45	2.30	2.64	1.55	2.19	1.57
21	3.57	1.83	1.42	1.48	.13	1.96	2.21	3.35	1.66	.26	1.44	1.55
22	3.66	1.53	1.57	4.21	2.34	3.14	.86	.52	2.69	.56	2.39	1.05
23	1.66	1.16	.58	1.33	1.81	2.15	3.03	3.50	1.74	0	2.97	3.87
24	3.23	2.62	1.14	1.01	2.39	3.68	1.46	2.09	3.12	1.44	1.85	1.44
25	3.63	1.01	1.57	1.57	2.58	.97	4.15	1.83	1.18	.60	2.54	1.27
26	1.20	0	3.81	1.78	2.26	2.30	.86	2.47	4.06	3.03	2.04	1.23
27	3.96	1.66	1.05	3.53	3.89	1.63	1.81	1.59	1.25	2.90	3.48	3.76
28	3.05	2.88	.62	3.98	2.47	2.32	1.08	3.83	2.19	2.62	2.47	1.59

29	4.09	.82	.34	2.32	3.31	1.66	.62	2.49	2.11	2.19	.88	11
30	.15	1.12	.56	3.16	3.70	.84	3.29	.95	2.54	2.73	2.06	3.31
31	2.73	3.20	1.83	1.42	1.98	5.35	4.84	1.70	3.03	0	1.72	3.93
32	1.14	3.16	1.35	5.87	.67	6.15	.69	2.30	3.72	1.27	3.87	.69
33	2.75	1.14	.17	1.46	1.89	.52	3.20	1.89	3.10	2.84	1.08	.49
34	2.52	.43	3.20	2.34	2.77	4.73	6.34	4.04	4.26	.58	4.17	5.83
35	3.78	8.60	2.13	5.40	4.82	6.30	.86	4.64	7.18	3.25	5.44	.71

Table 5.7(e) OD Demand Information for Case 4 (Units: 100 lbs/hr)

Type 2 Cargo												
O \ D	13	14	15	16	17	18	19	20	21	22	23	24
1	.54	1.72	1.72	4.26	.92	4.26	2.34	3.38	3.35	.58	1.72	1.76
2	.65	.52	1.55	3.87	3.57	3.12	2.45	3.05	3.40	2.80	4.13	.97
3	1.46	.34	.82	1.61	.80	3.76	.54	2.75	1.18	2.41	3.10	2.62
4	1.89	2.06	.65	.90	.30	3.70	.34	1.12	2.82	3.63	3.72	2.80
5	1.72	0	1.74	.80	.80	.49	2.60	.71	.80	3.55	3.83	2.69
6	1.74	1.66	1.25	1.18	.24	2.41	2.84	3.85	1.42	1.48	2.45	.47
7	1.68	1.01	1.63	1.10	1.35	3.74	4.26	2.73	3.72	1.48	4.02	2.82
8	1.72	1.16	1.20	1.87	4.26	.75	4.02	.56	2.41	4.11	4.00	3.44
9	.32	1.48	1.78	1.18	3.44	.30	2.80	2.64	1.23	3.89	1.20	.60
10	1.91	1.59	.60	1.76	2.04	1.27	2.11	.58	4.13	.92	1.61	.43
11	.73	1.55	1.03	2.69	3.59	4.02	2.64	4.24	3.50	.19	3.27	.54
12	2.09	2.06	1.85	1.12	.37	2.58	3.59	3.31	3.53	2.67	3.05	2.54
13	0	1.63	1.08	2.77	.88	.22	4.02	1.14	.17	.84	2.30	.67
14	.67	0	.73	2.26	3.66	.90	.24	.41	2.86	1.35	2.24	.11
15	.28	.95	0	3.93	3.87	2.88	1.44	1.91	4.15	3.96	3.31	2.52
16	1.83	56	2.17	0	1.63	.52	1.10	.97	2.09	.11	1.85	.47
17	2.52	1.03	3.74	1.55	0	1.14	2.11	1.46	.60	1.25	2.04	.90
18	2.90	.11	.99	1.57	1.51	0	.82	1.48	.37	.97	1.05	1.51
19	.28	3.01	0	2.11	.47	1.61	0	0	.32	1.16	.32	0
20	2.52	1.78	2.00	2.04	1.83	2.00	0	0	.56	.22	.22	.26
21	2.82	3.29	1.38	.80	.73	1.05	.97	1.98	0	2.02	.13	2.04
22	.88	2.11	1.72	1.12	2.04	1.25	.47	.17	.30	0	1.46	2.09
23	3.44	4.17	.17	1.31	0	1.85	0	1.44	.52	0	0	.32
24	.17	.43	3.46	.34	.80	1.91	.30	.26	1.85	1.83	1.70	0
25	1.03	2.92	2.02	1.94	.90	.39	0	.30	.37	.99	1.12	.26
26	.60	2.39	4.11	1.59	.54	1.05	1.33	1.10	1.29	1.96	.99	.41
27	2.04	.69	1.70	.56	.11	.24	.86	.62	.32	2.15	.73	2.09
28	1.74	.37	3.44	1.27	1.10	.22	1.98	1.48	1.91	.47	1.38	2.00
29	.47	2.37	2.67	.82	.15	.88	.92	.90	.84	2.15	1.25	1.74

30	1.08	4.00	1.96	.41	1.87	.88	.56	.82	1.31	.41	.17	.30
31	3.16	4.88	4.79	3.87	.30	2.28	3.63	2.21	3.72	4.24	4.15	4.67
32	3.83	3.63	4.28	2.47	3.27	6.00	2.13	2.34	3.61	5.22	5.55	1.23
33	2.45	1.18	.67	1.85	.92	5.42	5.18	.30	3.38	5.50	3.72	3.05
34	5.74	.82	4.30	1.14	1.18	.47	1.27	.34	.77	1.57	1.38	2.11
35	5.81	2.32	1.05	.77	1.18	5.76	4.79	4.19	.67	6.04	3.14	2.45

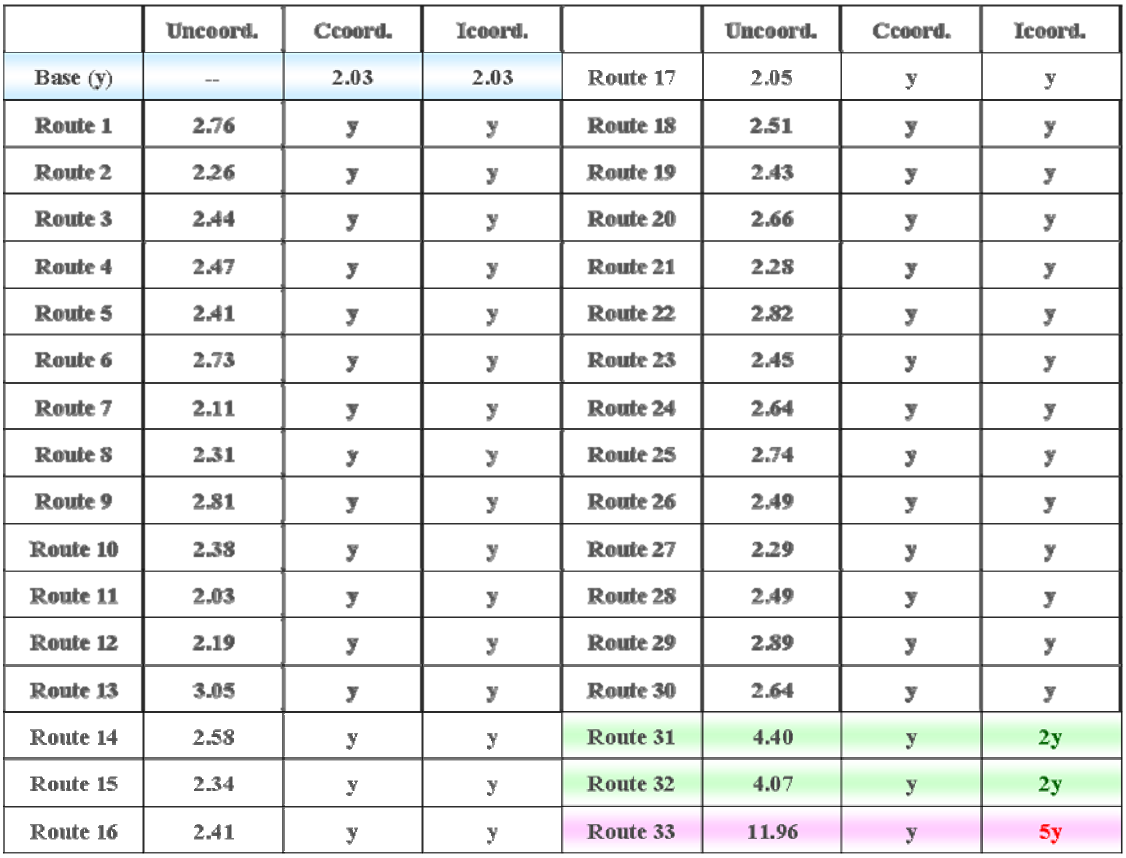
Table 5.7(f) OD Demand Information for Case 4 (Units: 100 lbs/hr)

Type 2 Cargo											
O \ D	25	26	27	28	29	30	31	32	33	34	35
1	.60	2.06	.75	.56	2.39	.32	.73	1.51	2.19	1.48	2.62
2	3.87	1.51	3.93	1.59	2.69	3.27	1.87	2.43	2.34	3.98	.90
3	4.21	0	1.91	2.86	1.63	2.82	3.33	0	2.92	2.73	3.44
4	3.33	1.14	2.58	1.53	3.18	.49	4.49	1.10	.15	1.42	5.87
5	1.68	3.66	.80	1.57	1.81	2.60	3.23	0	3.18	3.85	6.24
6	3.50	.26	1.33	3.23	0	2.52	.47	6.43	.90	3.68	.47
7	2.47	1.78	2.58	3.96	3.05	.52	3.91	1.53	3.12	1.83	7.16
8	2.54	3.12	.75	0	3.85	2.97	1.85	1.81	2.69	2.77	.97
9	.75	2.41	2.32	1.25	.54	3.12	2.71	2.64	.24	4.75	1.35
10	1.27	3.72	2.11	1.55	2.00	3.83	3.85	3.20	1.87	5.01	5.93
11	1.96	3.78	3.44	4.11	.65	2.60	.41	1.31	2.41	5.93	6.88
12	2.58	3.98	.86	2.06	1.05	.80	3.50	.86	2.80	2.77	8.41
13	.75	3.33	.43	2.11	1.03	2.21	.77	.28	1.81	4.82	3.68
14	.30	.32	.32	3.83	3.50	1.01	4.73	5.76	1.59	6.11	3.89
15	1.16	1.81	1.57	3.81	2.02	.28	3.12	.24	2.86	.43	5.05
16	.58	1.94	1.61	2.11	.28	1.78	1.42	3.53	3.23	1.40	4.41
17	1.38	0	1.31	1.66	2.00	.97	3.27	3.42	3.29	2.67	5.70
18	.65	1.16	1.51	1.38	1.33	1.53	.80	6.49	.65	1.12	3.48
19	2.09	1.23	1.78	2.02	1.12	.32	4.71	8.23	1.33	2.67	.41
20	1.63	.75	1.29	1.10	.34	2.06	.62	1.31	6.04	2.84	5.70
21	.86	1.61	1.94	.97	1.85	1.98	3.85	6.71	4.13	3.16	.80
22	1.74	1.10	.49	1.42	1.87	1.01	.41	1.35	4.99	.43	.30
23	.67	1.66	.80	1.74	.95	1.61	3.68	.26	4.92	2.00	5.68
24	.67	1.16	.97	1.87	.34	.24	4.97	1.74	1.89	2.90	1.55
25	0	1.31	0	.34	.41	1.44	5.10	.54	4.54	.39	5.55
26	1.08	0	.92	1.59	1.57	1.23	1.48	2.88	2.49	2.90	1.70
27	1.29	1.76	0	1.89	1.91	1.61	1.12	1.48	5.44	2.00	4.56
28	1.35	.82	.95	0	2.02	.24	3.05	3.55	1.59	.15	.11
29	.32	1.53	.49	.77	0	.41	.62	4.04	2.21	1.59	3.87
30	.99	1.57	1.18	.77	0	0	3.50	.15	3.61	.67	6.19

31	1.53	4.79	2.71	3.12	2.13	4.73	0	8.60	4.30	4.30	8.60
32	2.09	2.88	5.61	5.76	5.25	2.17	8.60	0	4.30	6.45	8.60
33	1.14	5.14	2.21	5.29	6.13	5.31	4.30	4.30	0	4.30	6.45
34	.37	3.20	3.16	2.84	.90	2.39	4.30	6.45	4.30	0	4.30
35	5.18	4.36	2.54	4.04	.15	2.15	8.60	8.60	6.45	4.30	0

Table 5.8 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 4.

Table 5.8 Optimized Service Headways for Different Policies in Case 4



	Uncoord.	Ccoord.	Icoord.		Uncoord.	Ccoord.	Icoord.
Base (y)	--	2.03	2.03	Route 17	2.05	y	y
Route 1	2.76	y	y	Route 18	2.51	y	y
Route 2	2.26	y	y	Route 19	2.43	y	y
Route 3	2.44	y	y	Route 20	2.66	y	y
Route 4	2.47	y	y	Route 21	2.28	y	y
Route 5	2.41	y	y	Route 22	2.82	y	y
Route 6	2.73	y	y	Route 23	2.45	y	y
Route 7	2.11	y	y	Route 24	2.64	y	y
Route 8	2.31	y	y	Route 25	2.74	y	y
Route 9	2.81	y	y	Route 26	2.49	y	y
Route 10	2.38	y	y	Route 27	2.29	y	y
Route 11	2.03	y	y	Route 28	2.49	y	y
Route 12	2.19	y	y	Route 29	2.89	y	y
Route 13	3.05	y	y	Route 30	2.64	y	y
Route 14	2.58	y	y	Route 31	4.40	y	2y
Route 15	2.34	y	y	Route 32	4.07	y	2y
Route 16	2.41	y	y	Route 33	11.96	y	5y

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 by the base cycle (y). Two container truck routes and the rail train route are scheduled by 2y and 5y, respectively. Overall results (both schedules and total system costs) of uncoordinated operations and those of integer-ratio coordination operations are quite similar. As in cases 2 and 3, common headway coordination is still undesirable in this case due to extremely high non-transfer costs. More detailed results are shown in Table 5.9.

Table 5.9 Optimized Costs for Different Policies in Case 4

Costs ($ / hr)	**Uncoordinated Approach**	**Common Headway Coordination**	**Integer-ratio Coordination**
Operating Cost	**83072**	**205990**	**87569**
Dwell Cost	**3591**	**1750**	**3187**
Loading	**274**	**70**	**240**
Cargo Processing	**170**	**40**	**150**
Non-transfer Cost	**87107**	**207850**	**91146**
Inter-cycle	**--**	**--**	**3949**
Slack time	**--**	**1350**	**1319**
Miss-connection	**--**	**3580**	**3524**
Connection delay	**--**	**4910**	**4812**
Transfer Cost	**18440**	**9840**	**15604**
Total System Cost	**105547**	**217690**	**100750**

5.3 Conclusions

In Chapter 5, an analytical model is developed for coordinating vehicle schedules and cargo transfers at intermodal freight terminals, in order to improve system operational efficiency and to minimize total system costs. The proposed general models can be applied to different combinations of modes (e.g. trucks to rail trains, trucks to airplanes, rail trains to ships, etc.) 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. Through a series of case studies, the model has shown its ability to jointly optimize service frequencies and slack times. The usefulness of the numerical results can be increased by further developing a real-time control model for dealing with routine as well as major service disruptions.

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 approaches are better than the uncoordinated system, especially for transfer costs.

In Case 2, a multi-hub and multi-commodity problem with a nonlinear time value function is explored. The integer-ratio scheduling coordination has the best system performance because the common service frequency is inefficient when the route demands or lengths differ significantly. Given the uncertainties regarding demand and traffic congestion, it would be highly unlikely that all trucks scheduled to meet a rail train actually arrive before that train unless an excessive and wasteful amount of slack is built into the truck schedules. The right amount of slack, based on tradeoffs between wasting truck costs and terminal storage costs versus missing connections and delaying cargo until the next train departure, is just one of the variables optimized by the model.

In Case 3, a case with multiple commodities and multiple hubs forming a loop is investigated. This case is 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. Similarly to case 2, the integer-ratio schedule coordination approach outperforms the uncoordinated and common headway coordination methods. Results obtained with the hybrid GA-SQP outperforms than those solved by general GA and SQP, although results optimized with these three approaches differ very slightly.

A large-scale problem with multiple commodities and multiple hubs forming a loop is addressed in Case 4. 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.

The usefulness of the numerical results can be increased by further developing a real-time control model for dealing with routine as well as major 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. The benefits would also extend to the economy and the environment.

Chapter 6

Real-Time Dispatching Control to Alleviate Schedule Disruptions

6.1 Problem Statement

This chapter develops methods for countering schedule disruptions within intermodal freight systems operating in time-dependent, stochastic and dynamic environments. When routine disruptions occur (e.g. traffic congestion, vehicle failures or demand fluctuations) in pre-planned intermodal timed-transfer systems, our dispatching control model determines through an optimization process whether each ready outbound vehicles should be dispatched immediately or held waiting for some late incoming vehicles with connecting freight.

Though the above timed transfer models can optimize operational schedules based on the expected environments and Origin-Destination (OD) information, service disruptions may occasionally occur and affect the system operations. Disruptions can be classified as routine or major disruptions; these classes require different response strategies. Routine disruptions represent the schedule perturbations caused by the stochastic uncertainties (e.g. traffic congestion, vehicle failures or demand fluctuations), which tend to have moderate effects and short-term impacts. Major disruptions (e.g. storms, earthquakes or terrorist attacks) are defined as situations during the operation's execution in which the deviation from plan is sufficiently large that the plan has to be changed substantially (Clausen et al., 2001).

Managing disruptions is an important issue in scheduling operations. When disruptions occur, the previously optimized schedules may become far from optimal or even infeasible, and means are needed for adjusting or re-optimizing the original plan to adapt the changing environment and to get back on track in a timely manner while effectively using the available resources.

Our previous logistic timed-transfer models develop coordinated and optimized schedules for given freight networks, which minimize transfer delays, among other factors. However, in systems subject to variability in traffic conditions and demand fluctuations, some routine disruptions are inevitable. In this chapter, a real-time dispatching control model focuses on decisions made in response to disruptions regarding vehicle dispatching from transfer terminals before all expected loads are on board.

The proposed model determines through an optimization process which ready outbound vehicles, if any, should wait for which others. It should be noted that holding decisions at transfer terminals should be based on tradeoffs. We develop probabilistic evaluation functions to combine and minimize the various costs of leaving sooner (and thus missing some freight, especially from connecting vehicles that have not yet arrived), or leaving later (and thus delaying freight already on board or waiting downstream, and possibly missing downstream connections.)

After making the dispatching decisions, another newly developed optimization model is used for distributing those cargos which missed their transfers (i.e. for some vehicles that arrived after the intended receiving vehicles had left). The freight left over is then re-assigned to the next vehicles departing on the appropriate routes, based on their remaining spaces and priorities of cargos.

The remainder of this chapter is organized as follows: the relevant optimization problems are described in detail. Based on the given service routes, schedules, vehicles and terminals, the methods for real-time control of schedule deviations are developed. Multiple commodities with different time value functions are also considered. Some numerical examples are presented for evaluating the best dispatching decisions.

6.2 Model Assumptions and Formulations

The model components developed to deal with service disruptions are classified into three stages, as shown in Figure 6.1. Stage 1 pre-plans an intermodal logistic timed transfer system in ways that minimize transfer delays and unreliability, largely by coordinating schedules and optimizing the slack times (i.e. reserve or safety factors) within those schedules. In stage 2, the real-time information and relevant data are provided when disruptions occur and affect the timed-transfer operations. In stage 3, we seek to optimize the dispatching decisions made in response to disruptions in time-dependent, stochastic and dynamic environments. Another sub-model is developed to reschedule the distribution of cargos left over due to missed connections.

The mathematical model for disruption response is based on independent dispatching decisions for different ready outbound routes. The vehicles are “ready” to depart but may be deliberately held waiting for some of the late vehicles in order to reduce the missed-connection delays. Since the missed-connection costs are incurred among the late arrival routes and each ready outbound route (i.e. one ready outbound route does not impose any delay costs on other ready outbound routes in this model), the optimized dispatching time of each service route is independent of and separable from dispatching decisions for other routes.

The routes and terminal locations within the network are pre-determined. Three different operating methods are defined in our previous study, 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.

When disruptions occur, the real-time dispatching decisions consider all routes which are mutually coordinated at the transfer terminals. Uncoordinated routes are dispatched based on originally scheduled departure times. It should be noted that several related models have been developed for urban passenger transportation and air transportation systems (Lee, 1992; Lee and Schonfeld, 1994; Ting, 1997; Ting and Schonfeld, 2007); 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 chapter. Additional assumptions and details are provided below.

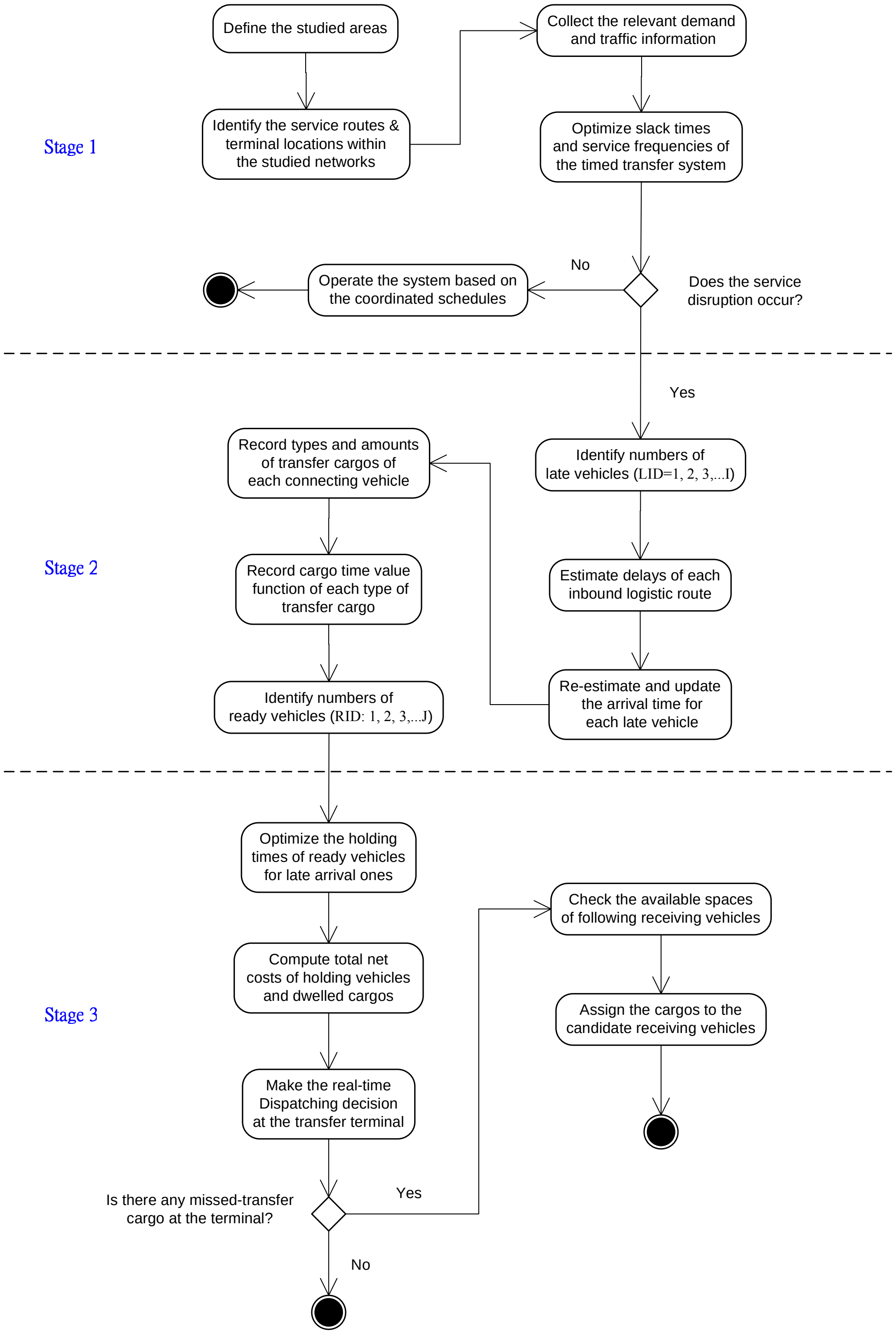


Figure 6.1 Flow Chart for Real-Time Dispatching Control

6.2.1 Optimized Problem for Real-Time Dispatching Control in Response to Schedule Disruptions

Let G (N, E) denote a directed transportation network where N is a set of nodes and E is a set of links. We define $i \in I$ as the ready vehicles on outbound routes and $j \in J$ as the late vehicles on inbound routes; each route contains several nodes and links.

Here we assume that there is no further interrelation among the ready routes during the decision time; thus holding or dispatching decisions are independent for each ready vehicle. The model is expressed as follows:

$$\text{Minimize} \qquad Z_i^k = y_i C_{n,i}^k + (1 - y_i) C_{h,i}^k \tag{6.1}$$

The minimized objective function (Equation 6.1) is formulated as the sum of costs resulting from holding or not holding. For each ready vehicle i at the terminal k, y_i is a binary decision variable representing whether to hold ($y_i = 0$) for any late inbound vehicle or to dispatch immediately ($y_i = 1$). $C_{n,i}$ and $C_{h,i}$ represent the system net costs caused by dispatching without holding and holding decisions, respectively.

$$C_{n,i}^k = \sum_{m \in M} \sum_{j \in J} \mu^m q_{ji}^{mk} h_j \delta_i^k \delta_j^k \times \left[h_i - \int_{s_j^k}^{h_j} t \ f_j^d(t) dt \right] \tag{6.2}$$

If the ready outbound vehicles are dispatched immediately, without holding for any late vehicle, the sum of total missed-connection cost ($C^k_{n,i}$) for transfer cargos from late inbound routes is expressed in Equation 6.2. The additional dwell time of waiting for next vehicle is formulated as the service headway minus the probabilistic late arrival time.

We assume that delay probability density function ($f^d_j(t)$) can be estimated with real-time monitor systems. μ^m = unit time cost of type m cargo (\$/lb-hr); q^{mk}_{ji} = amount of type m cargo transferred at the terminal k from Route j to Route i (lb/hr); h_i = pre-optimized service headway of Route i (hr); δ^k_i (a binary variable) = 1 if terminal k is connected to the Route i and 0 otherwise; s^k_j = slack time at terminal k on Route j (min).

The probability of lateness for any inbound vehicle is illustrated in Figure 6.2a, in which f(t) = probability density function of arrival time, $f^o(t)$ = the probability density function for pre-planned vehicle arrival time, and $f^d(t)$ = the probability density function for vehicle late arrival time. In Figure 6.2b, the shadowed area illustrates the probability that a late vehicle arrives after the holding time T_i.

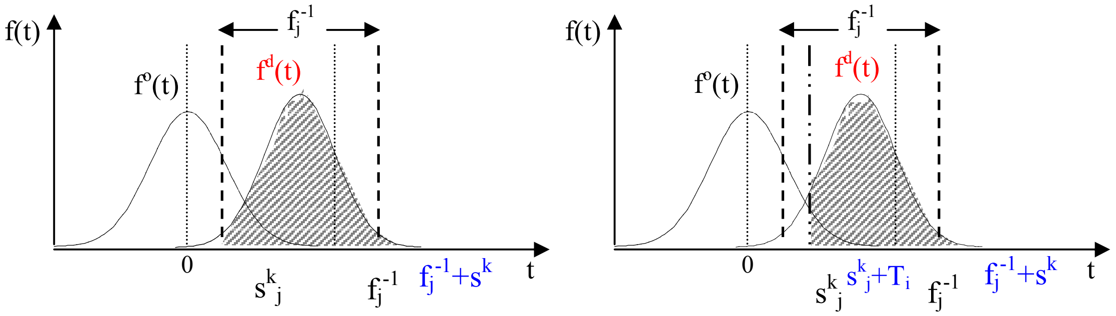


Figure 6.2 Probability of Inbound Vehicle on Route j (a) Arrives Late (b) Arrives Late After Holding Time T_i

Equation 6.3 expresses the sum of costs generated by holding vehicle i until late vehicle j^* arrives ($j^* \le j$). To simplify this problem, we assume that holding decisions would mainly affect the current and next consecutive transfer terminals (i.e. delay propagation is not considered in this study.) Thus, the relevant costs can be classified into two groups: costs incurred at the current transfer terminal k ($C^k_o + C^k_w + C^k_x$) and the downstream terminal k' ($C^{k'}_w + C^{k'}_d + C^{k'}_x$). These cost components are formulated in Equations 6.4 – 6.10.

$$C^k_{h,i} = \sum_{m\in M}\sum_{j\in J}\delta^k_i\delta^k_j \times (C^k_o + C^k_w + C^k_x + C^{k'}_w + C^{k'}_d + C^{k'}_x) \qquad (6.3)$$

Assume the decision is to hold ready vehicle i for time T_i. Thus, the additional vehicle operating cost at the terminal k during the holding period can be formulated as Equation 6.4. B_i = unit vehicle operating cost ($/vehicle-hr).

$$C_o^k = B_i T_i \tag{6.4}$$

Equation 6.5 expresses the additional dwell cost of existing loaded cargos on the outbound Route i. The loaded cargos have three sources: originally loaded shipments (Q_i^{mk}) from inbound routes to terminal K, cargos transferred from other ready vehicles ($q_{i'i}^{mk}$), and cargos collected from the local center (q_i^{mk}) during the original scheduled headway (h_i) plus holding time (T_i). Thus, the first three terms in Equation 6.5 express the corresponding dwell costs of each source. The last term shows the expected dwell cost for those cargos transferred from the late arrival vehicles during the holding time.

$$\begin{aligned} C_w^k = {} & \sum_{m\in M} \mu^m T_i \left[Q_i^{mk} h_i + \sum_{i'\in I, i'\neq i} q_{i'i}^{mk} h_{i'} + q_i^{mk}(h_i + T_i) \right] \\ & + \sum_{m\in M} \sum_{j=1}^{j'-1} \mu^m q_{ji}^{mk} h_j \times \left[T_i - \int_{s_j^k}^{s_j^k+T_i} t \; f_j^d(t)dt \right] \end{aligned} \tag{6.5}$$

Equation 6.6 states the missed connection costs of those vehicles arriving after the holding time T_i. The incremental dwell time for these cargos is the service headway of Route i minus the expected late arrival time.

$$C_x^k = \sum_{m\in M} \sum_{j=j^*+1}^{j=J} \mu^m q_{ji}^{mk} h_j \times \left[h_i - \int_{s_j^k+T_i}^{h_j} t \; f_j^d(t)dt \right] \tag{6.6}$$

Assume the holding time would not affect the estimated link travel time. Thus, the dwell time of cargos collected during the regular service headway will also increase T_i. Conversely, cargos collected during the holding period would save some dwell time.

Equation 6.7 specifies the overall cargo dwell cost incurred at the downstream terminal k' due to the holding decision.

$$
\begin{aligned}
C_w^{k'} &= \sum_{m\in M} \mu^m \left[T_i (q_i^{mk'} h_i) - (\frac{h_i - T_i}{2})(q_i^{mk'} T_i) \right] \\
&= \sum_{m\in M} \mu^m q_i^{mk'} T_i (\frac{h_i + T_i}{2})
\end{aligned}
\tag{6.7}
$$

The holding decision may also create some possible dispatching delay costs from Route i to other routes ($C^{k'}_{d1}$) and from other routes to Route i ($C^{k'}_{d2}$). These costs are formulated in Equations 6.8 – 6.10.

$$C_d^{k'} = C_{d1}^{k'} + C_{d2}^{k'} \tag{6.8}$$

The dispatching delay cost (see Equation 6.8) can be expressed by the joint probability distributions for vehicle arrival on any coordinated pair of routes (i, r). Two cases are considered in this cost component: 1. the feeder vehicle on the Route r arrives early, but the receiving one on the Route i is late; and 2. both vehicles are late, but the feeder vehicle arrives before the receiving one. $f_d(t_i, t_r)$ denotes the joint probability of dispatching delay for transfer cargos on some particular pair of routes. Thus, the dispatching delay costs from Route i to other routes and those from other routes to Route i at the downstream terminal k' are expressed in Equations 6.9 and 6.10, respectively.

$$C_{d1}^{k'} = \sum_{m\in M} \sum_{\substack{r\in E \\ r\neq i}} \mu^m Q_{ir}^{mk'} \delta_i^{k'} \delta_r^{k'} f_d(t_i, t_r) \tag{6.9}$$

$$C_{d2}^{k'} = \sum_{m\in M} \sum_{\substack{r\in E \\ r\neq i}} \mu^m q_{ri}^{mk'} \delta_i^{k'} \delta_r^{k'} f_d(t_i, t_r) \tag{6.10}$$

Equations 6.11 – 6.13 state that the missed-connection cost ($C^{k'}_{x}$) occurs at the downstream terminal k' due to the holding decisions for both directions ($C^{k'}_{x1}$: from Route i to other routes and $C^{k'}_{x2}$: from other routes to Route i). The missed-connection cost can be expressed by the joint probability distributions for vehicle arrival on any coordinated pair of routes (i, r). Two cases are considered: (1) The feeder vehicle on the Route r arrives late, and the receiving one on the Route i is not late. (2) Both vehicles are late, but the feeder vehicle arrives after the receiving one leaves. $f_x(t_i, t_r)$ denotes the joint probability of missed connections.

$$C_x^{k'} = C_{x1}^{k'} + C_{x2}^{k'} \tag{6.11}$$

$$C_{x1}^{k'} = \sum_{m \in M} \sum_{\substack{r \in E \\ r \neq i}} \mu^m Q_{ir}^{mk'} \delta_i^{k'} \delta_r^{k'} f_x(t_i, t_r) \tag{6.12}$$

$$C_{x2}^{k'} = \sum_{m \in M} \sum_{\substack{r \in E \\ r \neq i}} \mu^m q_{ri}^{mk'} \delta_i^{k'} \delta_r^{k'} f_x(t_i, t_r) \tag{6.13}$$

Equation 6.14 assumes that the required storage areas for the total missed-connection cargos cannot exceed the available storage areas at the transfer terminal k. ε = unit cargo storage areas; A^k = available storage areas at transfer terminal k. For the no-holding policy, j^* should be zero.

$$\varepsilon \left(\sum_{m \in M} \sum_{j=j^*+1}^{j=J} \mu^m q_{ji}^{mk} h_j \delta_i^k \delta_j^k \right) \leq A^k \tag{6.14}$$

6.2.2 Optimized Distribution Plans for Missed-Connection Cargos at Transfer Terminals

For those cargos left over due to missed connections caused either by the no-holding decision or arrival after the ready vehicles have been dispatched, another problem arising here is how to re-distribute them. The mathematical model describing the distributing plan is revised based on the well known location choice problem (Revelle and Laporte, 1996). To simplify the problem, the formulated model first considers the cargo movements among the transfer terminals. After cargos are shipped toward the latest transfer terminal, the same optimization model can be re-applied to distribute them toward the final destinations.

As shown in Figure 6.3a, given the missed-transfer cargos left over at terminal 0 and shipped toward terminal 1, there are a network configuration with multi-hubs formed a loop (i.e. terminals 0, 1, and 2), two possible shipping routes (i.e. terminals 0-1 and 0-2-1), and four candidate delivery vehicles (p = 1-4) with certain remaining spaces.

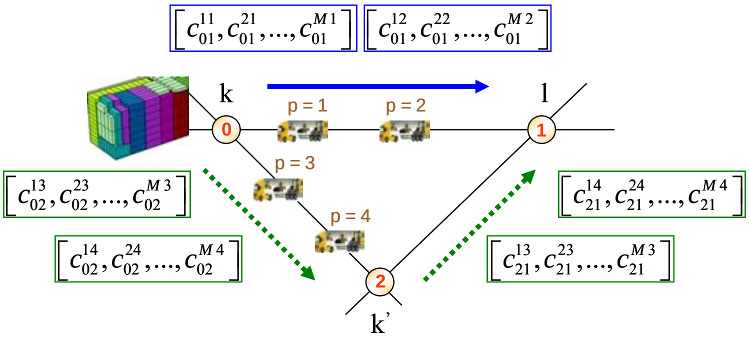


Figure 6.3(a) Re-distribution Plan and Costs from Terminal 0 to Terminal 1

In Figure 6.3b, for those missed-transfer cargos from terminal 0 to terminal 2, there are also two possible shipping routes (i.e. terminals 0-2 and 0-1-2) within the same logistic network. Because all missed-transfer cargos with different destinations may share the limited available resources simultaneously, the proposed optimization model should be able to determine which missed-connected cargos would be assigned to which available vehicle through what route.

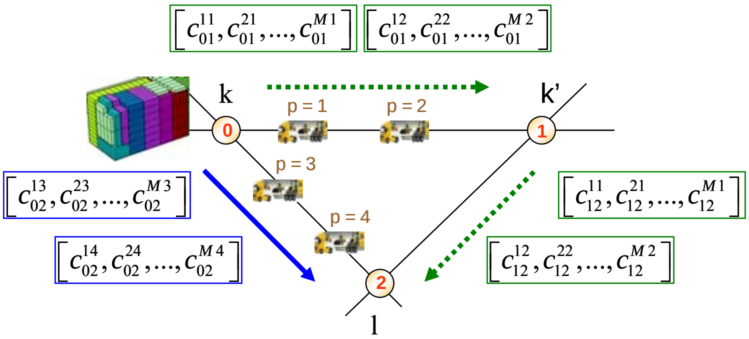


Figure 6.3(b) Re-distribution Plan and Costs from Terminal 0 to Terminal 2

We assume the remaining space of each upcoming vehicle is known and given. Hence, the model is expressed as:

$$\text{Minimize} \quad \omega = \sum_{m \in M} \sum_{\substack{k,l \in N \\ k \neq l}} \sum_{p \in n_p} c_{kl}^{mp} \pi^p \alpha_{kl}^{mp} \beta^p + \sum_{p \in n_p} \lambda^p \beta^p \tag{6.15}$$

$$\sum_{\substack{k,l \in N \\ k \neq l}} \sum_{p \in n_p} \pi^p \alpha_{kl}^{mp} \beta^p \geq d_{kl}^m \tag{6.16}$$

$$\sum_{m \in M} \sum_{\substack{k,l \in N \\ k \neq l}} \alpha_{kl}^{mp} d_{kl}^m \leq \pi^p \tag{6.17}$$

$$\sum_{m \in M} \sum_{\substack{k,l \in N \\ k \neq l}} \sum_{p \in n_p} \alpha_{kl}^{mp} \leq 1 \tag{6.18}$$

$$c_{kl}^{mp} = g(\mu_{kl(t=t_0)}^{mp}, \mu_{kl(t=t_e)}^{mp}) = \int_{t=t_e}^{t=t_0} \mu_{kl}^{mp} d_t \tag{6.19}$$

$$0 \le \alpha_{kl}^{mp} \le 1 \qquad (6.20)$$

$$\beta^{p} \in \{0,1\} \qquad (6.21)$$

where ω = objective value of this optimization problem; π^{p} = available space of the p_{th} pick-up vehicle; α_{kl}^{mp} = fraction of the type m cargos shipped from terminal k to terminal l by vehicle p; d_{kl}^{m} = the amount of type m cargos shipped between transfer terminals k and l; β^{p} = binary variable: if the vehicle p is assigned to pick-up missed-connection cargos, then β^{p} = 1 (otherwise, β^{p} = 0); λ^{p} = additional cost to use the vehicle p; n_p = set of pick-up vehicle candidates; $c^{mp}{}_{kl}$ = the expected travel time cost for the type m cargos shipped from the terminal k to terminal l through the p_{th} vehicle. The cost is defined as the changes of cargo time values during the current time ($t = t_0$) until the estimated shipping time ($t = t_e$).

The objective function (Equation 6.15) consists of the sum of the total costs, including the vehicle activation cost. Equations 6.16 – 6.18 ensure that total amount of missed-connection cargos will be re-assigned toward the candidate pick-up vehicles and satisfy their remaining capacity limits. Equation 6.19 states the expected travel cost for the type m cargos shipped from the terminal k to terminal l. Equations 6.20 – 6.21 limit the range of the decision variables.

6.3 Model Applications and Analytical Results

Through this work we seek to optimize the dispatching decisions of ready outbound vehicles waiting for late inbound vehicles at an intermodal freight terminal. This study also provides flexibility in managing general and perishable cargos with different dwell time value functions. The network configurations for two case studies are illustrated in Figures 6.4a and 6.4b.

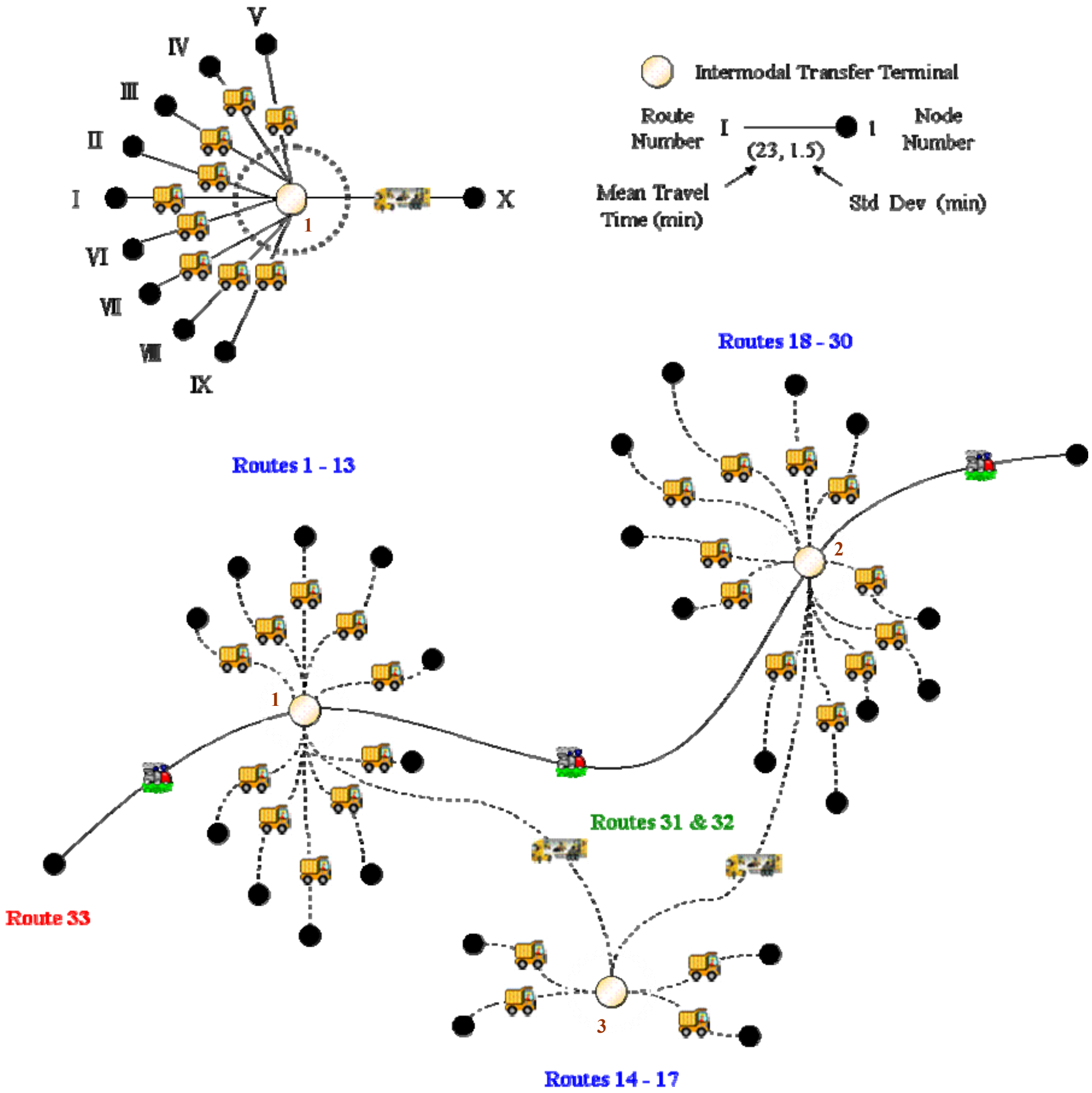


Figure 6.4 Network Configurations for (a) Case 1 and (b) Case 2

6.3.1 Case Study 5: Real-Time Dispatching Applications in Single Commodity, Multi-Modes, and Single Hub Networks

As in Case 1, there are 9 light truck routes (Routes 1-9) and 1 container 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 carrying capacities of light and container trucks are 7,300 and 48,500 pounds, respectively. The average vehicle operating costs are \$350/light-truck hr and \$2,000/container-truck hr. The unit cargo dwell cost is \$0.2/lb-hr (Hall, 1987). Unit cargo loading and processing time are set as 0.03 and 0.05 (min/lb).

Similarly to the results optimized in Case 1, the common headway coordination method has the same results as the integer-ratio approach. When comparing the values for coordinated and uncoordinated objective functions, we observe that the coordinated approaches are better than the uncoordinated system, especially for transfer costs. A small ten-route network with a single transfer terminal and homogenous cargos is considered in the following dispatching analysis. Based on the above coordinated results, these ten routes are synchronized at transfer terminal 1. It is assumed here that inbound vehicles on Routes 1, 3, 5, 6, 8, and 9 have some estimated delays while the vehicle on Route 10 is ready to be dispatched. The delay information is shown in Table 6.1.

As shown in Figure 6.5, vehicle operation cost (C_o) and cargo dwell cost (C_w) increase while increasing the holding time of the ready vehicle. Conversely, the missed-connection cost (C_x) decreases because more late inbound vehicles arrive during the longer holding period. At the end, the missed-connection cost would approach to zero which means all delayed cargos are being picked up.

As mentioned above, Genetic algorithms (GAs) and sequential quadratic programming (SQP) are well suited for solving such nonlinear programming problems with complex and nonlinear formulations. GAs can perform global search probabilistically and consider the evolution process after generations, and the algorithms can handle any kind of objective functions and constraints with a quite promising performance in approaching the global optimum.

The SQP method is based on solving a series of sub-problems designed to minimize a quadratic model of the objective subject to a linearization of the constraints. If the problem is unconstrained, then the method is reduced to Newton's method for finding a point where the gradient of the objective vanishes. If there were some nonlinear constraints within the model, Lagrangian relaxation techniques could help maintain the linearization of those constraints.

Although both GAs and SQP have been widely applied in solving the nonlinear optimization problems, there are some drawbacks to these two approaches. Hybrid-based heuristic algorithms have become increasingly preferred because of their combinatorial advantages. In order to exploit the major advantages and improve the defects of the algorithms, an improved hybrid GA-SQP algorithm has been developed. Detailed procedures for our proposed hybrid algorithm are specified in Chapter 4.

In this multi-variable nonlinear optimization 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. This problem can also be solved by GA. Although the 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. Thus, a hybrid GA-SQP algorithm is developed which can save some GA running time and provide better solutions.

In our hybrid approach, we use SQP (with any initial solution) to produce the starting solution to provide a reasonable threshold (i.e. the stopping criteria) for the following GA. The proposed algorithm then implements global search by GA because the GA can initially converge very fast. The GA results can then provide a fairly good initial solution for SQP, until no further improvements.

Since there is only one transfer terminal in Case 5, costs incurred at the downstream terminal are not considered. The optimized holding time and cost solved with the hybrid GA-SQP algorithm are 15.3 (min) / 0.255 (hr) and 1272 ($), respectively. The results indicate that the ready vehicle should wait until the 5_{th} late vehicle (from Route 6) arrives.

Table 6.1 Inbound Routes Delay Information for Case 5

Inbound Route	Outbound Route 10 (Unit: lb / hr)	Route Travel Time (min)		Delay Information (min)	
		Mean	Std. Dev.	Mean	Std. Dev.
1	2450	82	8.0	14.5	0.25
2	3150	99	9.5	--	--
3	1550	43	3.5	6.5	0.25
4	3250	107	10.0	--	--
5	1500	39	3.5	12.0	0.20
6	2250	79	7.5	16.0	0.35
7	3500	115	10.5	--	--
8	3000	94	9.0	7.5	0.35
9	2100	73	6.5	22.5	0.20

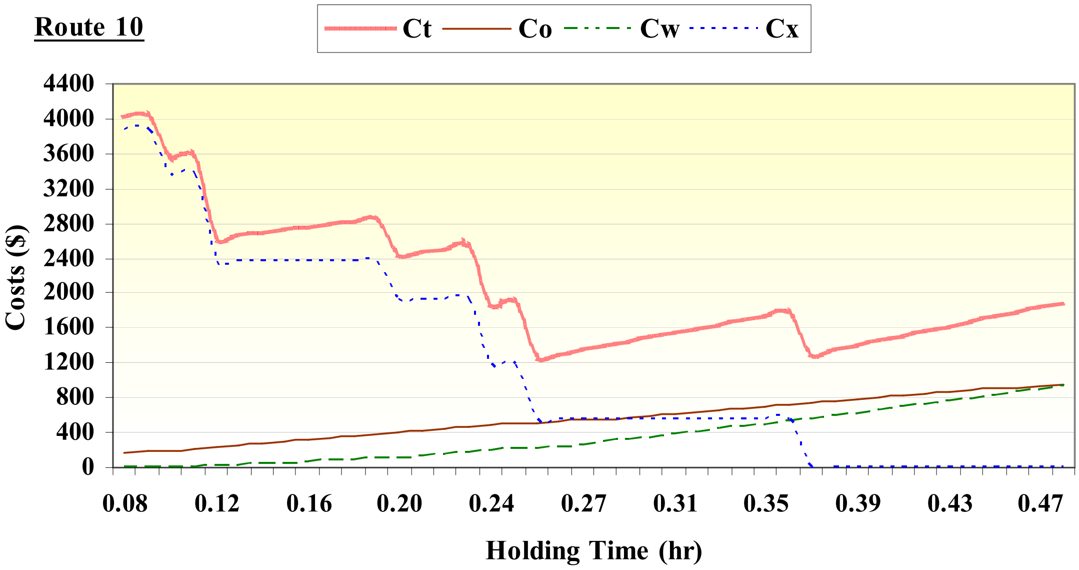


Figure 6.5 Costs for Different Holding Times on Route 10 in Case 5

6.3.2 Case Study 6: Real-Time Dispatching Applications with Multiple Commodities, Multiple Modes, and Multiple Hubs in a Loop

As in Case 4, 30 light truck routes (Routes 1-30), two container truck routes (Routes 31-32), and one rail route (Route 33) are analyzed in Case 6. As shown in Figure 6.4b, the three transfer terminals are arrayed in a loop. Coordination at one transfer terminal will affect the other transfer hubs in the loop. Considering only the coordination of a pair of transfer terminals may lead to coordination conflicts for another pair of terminals. More transfer terminals within the loop and more loops within the entire networks would increase the complexity of the studied problem. Similar conflicts will also appear in the re-distributing tasks.

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. The corresponding vehicle operating costs are \$970/truck-hr, \$1,850/truck-hr, and \$30,500/rail-hr. 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.

Under uncoordinated operations, 30 light truck routes tend to be served with smaller headways than those of the two container truck routes and the rail route. The integer-ratio schedule coordination outperforms the uncoordinated and the common-headway coordinated operations for the given input information. The common service method is inefficient and undesirable in this case due to the excessive variation in route lengths or demands. ε represents the base cycle value for coordination approaches. The optimized headways are ε (light truck), 2ε (container truck), and 5ε (rail) where ε is about rounded in two hours. Detailed results are provided in Table 5.8.

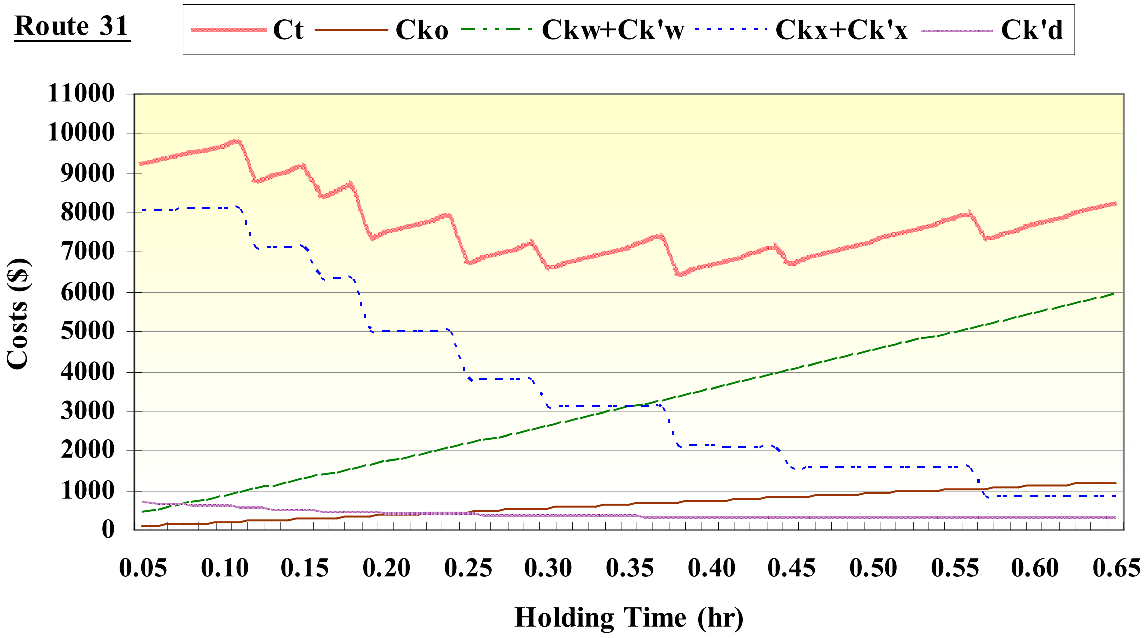
In this multi-hub operation problem, costs at the downstream terminal k' are considered. For the transfer terminal 1, we assume that inbound vehicles on Routes 1, 2, 3, 5, 6, 8, 10, and 13 have estimated delays while the vehicles on Routes 31 and 33 are ready to be dispatched. Table 6.2 provides some OD data and delay information. In Figure 6.6a, vehicle operation cost (C^k_o) and cargo dwell costs (C^k_w and $C^{k'}_w$) increase as the holding time increases. Similarly to the Case 5, the missed-connection cost (C^k_x) decreases because fewer cargos miss their connections during the longer holding period.

However, missed-connection ($C^{k'}_{x}$) and dispatching delay ($C^{k'}_{d}$) costs are also incurred at the downstream terminal. Steps and local optima in Figure 6.6a are due to the arrival of additional inbound vehicles and the resulting successful connections. The overall trade-off results are illustrated by the total cost (C_t) curve.

Table 6.2 Inbound Routes Delay Information for Case 2

Inbound Route (From)	Route Travel Time (min)		(To) Outbound Truck Route 31 (Unit: lb / hr)		(To) Outbound Rail Route 33 (Unit: lb / hr)		Delay Information (min)	
	Mean	Std. Dev.	m = 1	m = 2	m = 1	m = 2	Mean	Std. Dev.
1	97	8.6	503	1081	1311	2817	23	0.4
2	60	5.3	551	1185	1937	4166	12	0.3
3	68	7.4	302	649	1674	3598	18	0.35
4	104	10.5	189	406	1752	3767	--	--
5	53	5.5	303	652	1714	3688	10	0.25
6	93	8.8	243	523	1395	3000	27.5	0.45
7	85	9.1	382	821	2145	4612	--	--
8	64	7.2	520	1118	1688	3630	15.5	0.3
9	83	7.7	378	812	1356	2915	--	--
10	41	4.5	366	786	1696	3647	7.5	0.25
11	32	3.6	524	1127	2221	4775	--	--
12	56	4.8	381	820	2036	4378	--	--
13	99	10.1	380	817	1289	2772	35	0.5

The optimized holding time (T_{31}) solved with the hybrid GA-SQP algorithm is 22.21 (min), which indicates that the ready outbound container-truck on Route 31 should wait until the 6_{th} late light-truck (from Route 1) arrives. In Figure 6.6b, the trends of all cost terms are similar to those in previous cases. The optimized holding time (T_{33}) is 26.874 (min), which means that the ready outbound rail train on Route 33 should wait until the 7_{th} late light-truck (from Route 6) arrives.



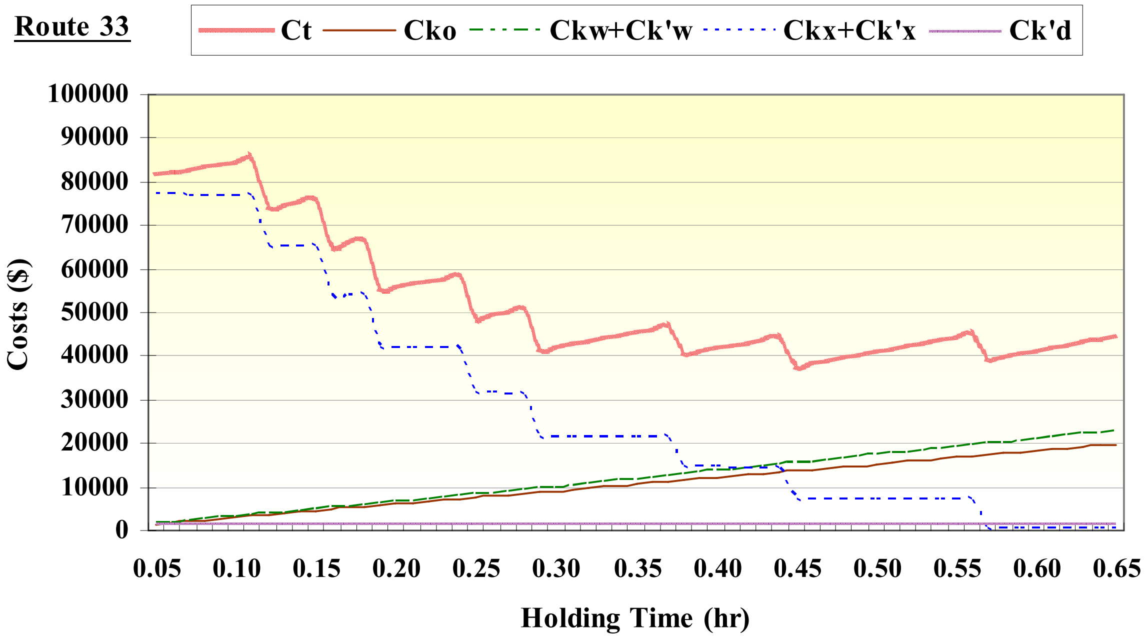


Figure 6.6 Costs with Different Holding Time of (a) Route 31 and (b) Route 33 in Case 2

6.3.3 Testing for Distribution Plans of Missed-Connection Cargos at Transfer Terminals

According to the real-time dispatching decisions, some missed-transfer cargos are left over at terminal 1, as shown in Table 6.4. The amount of missed-connection cargos are derived from the OD information and the service headway of the light truck routes. Assume some candidate pick-up vehicles including one rail train (p = 1) and three container trucks (p = 2~4) can pick-up those cargos from the terminal 1 toward terminals 2 and 3. The train and three trucks will arrive based on the original optimized and coordinated schedules. The remaining spaces are also listed in Table 4.

Table 6.4 Re-Distribution Results in Case 6

Missed-Transfer Cargos Left Over at the Terminal 1				
(From) Terminal 1	(To) Terminal 2 (Unit: lb)		(To) Terminal 3 (Unit: lb)	
	m = 1	m = 2	m = 1	m = 2
6	--	--	494	1,063
13	2,621	5,636	773	1,661
Candidate Delivery Vehicles for Re-Distribution				
Vehicle ID	p = 1	p = 2	p = 3	p = 4
Space (lb)	50,000	2,250	2,400	2,000
Optimized Re-Distribution Results				
(From) Terminal 1	(To) Terminal 2 (Unit: lb)		(To) Terminal 3 (Unit: lb)	
	m = 1	m = 2	m = 1	m = 2
p = 1	--	5,636	--	--
p = 2	983	--	1,267	--
p = 3	1,638	--	--	762
p = 4	--	--	--	1,982

In general, most of cargos are re-assigned to candidate vehicles based on their shortest path (e.g. terminal 1 – 3 or terminal 1 – 2). However, certain cargos with higher time value (m = 1) are re-assigned to farther path (i.e. terminal 1 – 3 – 2) so as to minimize total shipping time (i.e. longer travel time but much shorter dwell time.) The results may vary based on different cargo time value settings.

6.3.4 Testing with Different Cargo Time Value Settings in Case Study 6

Unit cargo time value functions describe the characteristics of the shipments, which also imply the priorities of cargos. To observe how decisions may be affected by cargo time values, a sensitivity analysis is described below. The parameter settings in Figure 6.6b (type 1: \$0.25*exp(-t)/lb-hr and type 2: \$0.1/lb-hr) duplicate the base case. Two different time value settings are tested (high settings: \$0.4*exp(-t)/lb-hr and \$0.2/lb-hr; low settings: \$0.08*exp(-t) /lb-hr and \$0.03/lb-hr).

As mentioned above, the optimized holding time (T_{33}) of the base case is 26.874 (min), which indicates the ready vehicle should wait until the 7_{th} late vehicle arrives. If the unit cargo time values are relatively low, then the optimized holding time becomes 17.502 (min), which means the ready vehicle leaves once the 5_{th} late vehicle arrives. At the higher time value settings, the holding time becomes 34.008 (min), which means the ready vehicle should wait for all delayed vehicles to avoid high missed-connection costs. Detailed results are illustrated in Figure 6.7.

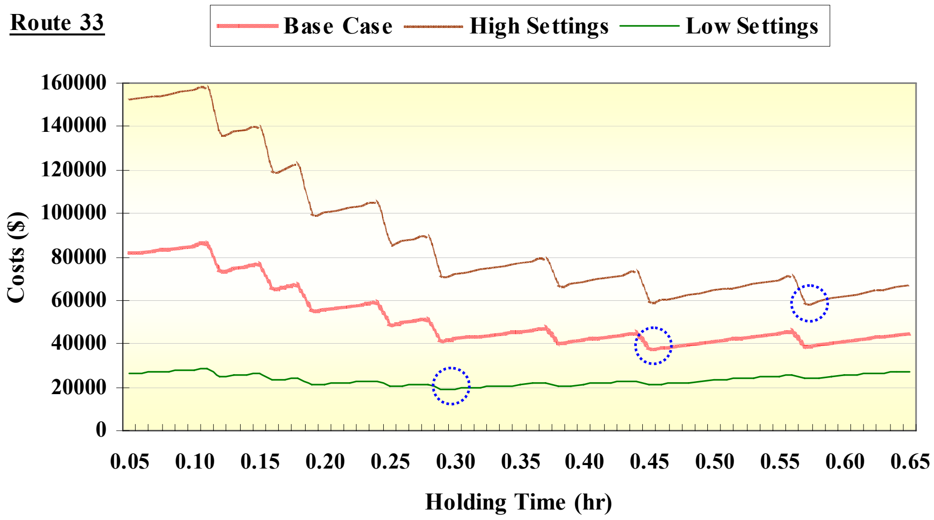


Figure 6.7 Sensitivity Analyses with Different Time Value Settings in Case 6

6.4 Summary

According to the pre-optimized results of a system's routes, schedules, vehicles and terminals, the methodologies for real-time control operations to deal with deviations from schedules and other disruptions are developed. A real-time dispatching control model is being developed for decisions regarding vehicle dispatching from transfer terminals when some connecting vehicles are delayed. The control model will determine through an optimization process which vehicles should wait for which others or should be dispatched immediately. In general, the extra waiting time for holding the ready vehicles may be absorbed from the probabilistic reserve factors built into operating schedules, the so-called slack times. Another possible source to compensate the extra waiting time is to increase the subsequent operating speeds of vehicles.

It should be noted that a trade-off occurs when using the holding strategies at downstream transfer terminals. They increase the total shipping time for those non-transfer cargos dwelling at the transfer terminals and other shipments waiting for the holding vehicles downstream. When disruptions occur, we must determine how to adjust or re-optimize the original plan to adapt the changing environment and how to get back on track in a timely manner while effectively using our available resources. In short, whether to dispatch the ready vehicles or to hold them till the late inbound connecting vehicles arrival is the main decision analyzed in this chapter.

The decisions could be made based on many steps ahead once the delay information is received, or only one step ahead before the original departure schedules of the ready vehicles. However, the program computation feasibility and the size of studied networks would also affect the computational performances.

In this study, we consider several logistic problems arising when the routine service disruptions occur. The adjustments the original schedules needed to adapt the changing environment and to get back on track fast enough are the main decisions optimized in this work. A real time dispatching control model can help operators to determine through an optimization process whether the ready outbound vehicles should be dispatched immediately or held for which others. Another sub-model is developed to deal with the freight left over due to missed connections. Some numerical examples solved with a hybrid GA – SQP algorithm illustrate the potential advantages of the proposed models.

In this multi-variable nonlinear optimization 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. This problem can also be solved by a GA. The GA objective value can be improved by running additional generations, although with diminishing improvements. The proper number of generations that should be run depends on tradeoffs between solution quality and the program running time. Thus, a hybrid GA-SQP algorithm is developed which can save some GA running time and provide better solutions.

As shown in Case 5, we mainly seek to determine the best dispatching decisions by minimizing net system costs and start by assuming a constant time value of cargos shipped through a single hub. When comparing the total costs with different holding time periods, we quantify how longer holding time would yield higher vehicle operation cost and cargo dwell cost but lower missed-connection cost.

In Case 6, we explore a problem with multiple hubs forming a loop and multiple commodities. Although increased holding time could reduce the missed-connection cargos at the current terminal, it may also increase the costs of extra cargo dwell time, dispatching delay, and missed connection at the downstream terminal. During the post-dispatching phase, the cargos left over due to missed connection can be re-distributed to other delivery vehicles based on their remaining spaces and priorities of cargos. Additionally, a sensitivity analysis shows that the ready outbound vehicle should wait longer to reduce the missed transfers and higher missed-connection costs as the cargo time value increases.

Chapter 7

Analyzing Propagations of Delays within Logistic Networks

7.1 Problem Statement

In Chapter 6, when routine service disruptions (e.g. incidents or traffic congestion) occur within a logistic network where schedule coordination is employed, a real-time dispatching control model can help terminal operators deal with delays of late arrival vehicles and provide appropriate response strategies. However, some propagation of delays may occur further downstream so that coordination may also be disrupted later downstream. Thus, an integrated dispatching decision should consider these potential missed-connection costs that occur not only at the next transfer terminals but also at some hubs located further downstream.

As mentioned above, several previous studies address delay propagation in passenger transportation systems, but seldom consider such propagation in the logistics of freight movements. Some studies tend to re-optimize the operational plan in order to recover systems from disruptions; however, re-optimization of entire schedules may require long program running times, which may be inappropriate for real-time dispatching applications.

In order to limit the propagation of delays, an improved dispatching model that minimizes the costs of deviations from the original off-line timetable is developed. The proposed model inherits part of design logic of the model described in Chapter 6 but considers more downstream terminals along the service routes.

We first analyze the sources of delays and then estimate the potential propagation of delays through schedules and networks. The optimal timing for dispatching ready outbound vehicles is then determined to help relieve the downstream delays. The purpose of this chapter is to analyze delay propagations with given networks, pre-optimized schedules and arbitrary primary delay information. Numerical examples and sensitivity analysis among the total delays, slack times, and dispatching decisions are also presented. The core concepts for integrating the treatments of delay propagation are illustrated in Figure 7.1.

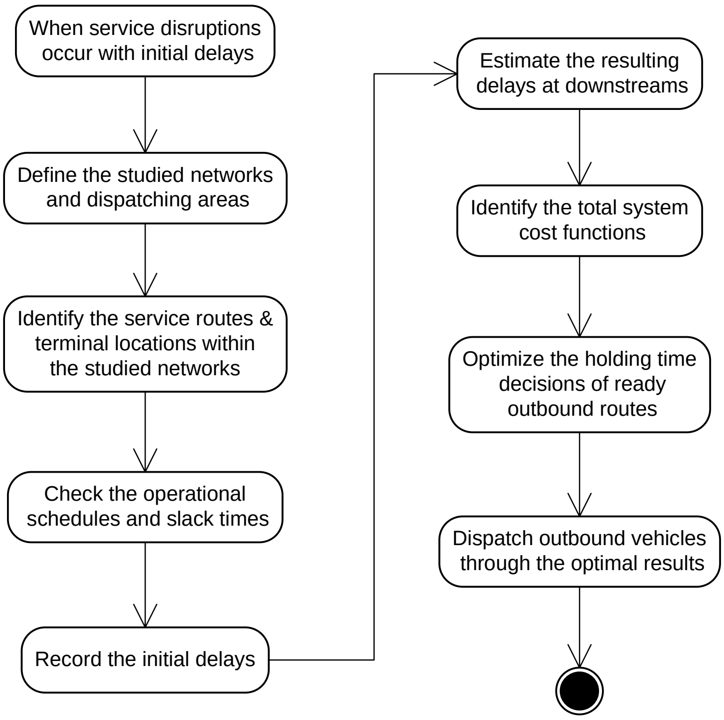


Figure 7.1 Flow Chart for Analyzing the Propagation of Delays

7.2 Mathematical Formulations

The real-time dispatching decisions should also consider delay propagations occurring at downstream transfer hubs and assume that all routes are mutually coordinated at the transfer terminals. As in the model of Chapter 6, uncoordinated routes are dispatched based on originally scheduled departure times. The mathematical model for delay propagations is still based on independent dispatching decisions for different ready outbound routes. Routes, terminal locations, and service schedules are pre-determined through the optimization processes illustrated in Chapter 3.

Let G (N, E) denote a directed transportation network where N is a set of nodes and E is a set of links. We define $i \in I$ as the ready vehicles on outbound routes and $j \in J$

as the late vehicles on inbound routes; each route contains several nodes and links. The objective function (Equation 7.1) is similar to Equation 6.1 but the system net cost caused by the holding decision ($\hat{C}_{h,i}^{k}$) is different.

Minimize $$Z_i^k = y_i C_{n,i}^k + (1 - y_i)\hat{C}_{h,i}^{k} \tag{7.1}$$

For each ready vehicle i at the terminal k, the sum of total missed-connection cost ($C^k_{n,i}$) for transfer cargos from late inbound routes is expressed in Equation 7.2.

$$C_{n,i}^k = \sum_{m \in M} \sum_{j \in J} \mu^m q_{ji}^{mk} h_j \delta_i^k \delta_j^k \times \left[h_i - \int_{s_j^k}^{h_j} t \ f_j^d(t) dt \right] \tag{7.2}$$

Equation 7.3 expresses the sum of costs incurred by holding vehicle i until late vehicle j^* arrives ($j^* \le j$). To consider the propagation of delays, the holding decisions would affect all transfer terminals along the outbound service routes. Thus, the relevant costs can be classified into two groups: costs incurred at the current transfer terminal k ($C_o^k + C_w^k + C_x^k$) and all downstream terminals affected by delay propagations ($C_w^p + C_d^p + C_x^p$). These cost components are formulated in the following equations.

$$\hat{C}_{h,i}^{k} = \sum_{m \in M} \sum_{j \in J} \delta_i^k \delta_j^k \times (C_o^k + C_w^k + C_x^k + C_w^p + C_d^p + C_x^p) \tag{7.3}$$

Assume the decision is to hold ready vehicle i for time T_i. All costs incurred at the current transfer terminal k are as those described in Chapter 6. Equation 7.4 states the additional vehicle operating cost at the terminal k during the holding period.

$$C_o^k = B_i T_i \tag{7.4}$$

Equation 7.5 expresses the additional dwell cost of existing loaded cargos on the outbound Route i. The first three terms express the corresponding dwell costs of originally loaded shipments from inbound routes to terminal k, cargos transferred from other ready vehicles, and cargos collected from the local center during the original scheduled headway and holding time. The last term shows the expected dwell cost for those cargos transferred from the late arrival vehicles during the holding time.

$$\begin{aligned} C_w^k &= \sum_{m\in M} \mu^m T_i \left[Q_i^{mk} h_i + \sum_{i'\in I, i'\neq i} q_{i'i}^{mk} h_{i'} + q_i^{mk}(h_i + T_i) \right] \\ &+ \sum_{m\in M} \sum_{j=1}^{j'-1} \mu^m q_{ji}^{mk} h_j \times \left[T_i - \int_{s_j^k}^{s_j^k + T_i} t \; f_j^d(t) dt \right] \end{aligned} \tag{7.5}$$

Equation 7.6 states the missed connection costs of those vehicles arriving after the holding time T$_i$. The incremental dwell time for these cargos is the service headway of Route i minus the expected late arrival time.

$$C_x^k = \sum_{m\in M} \sum_{j=j^*+1}^{j=J} \mu^m q_{ji}^{mk} h_j \times \left[h_i - \int_{s_j^k + T_i}^{h_j} t \; f_j^d(t) dt \right] \tag{7.6}$$

Along the ready outbound route i, all initial and resulting delays caused by the service disruptions can be expressed in terms of the holding time (T$_i$) and slack times built in the original schedules, as shown in Figure 7.2.

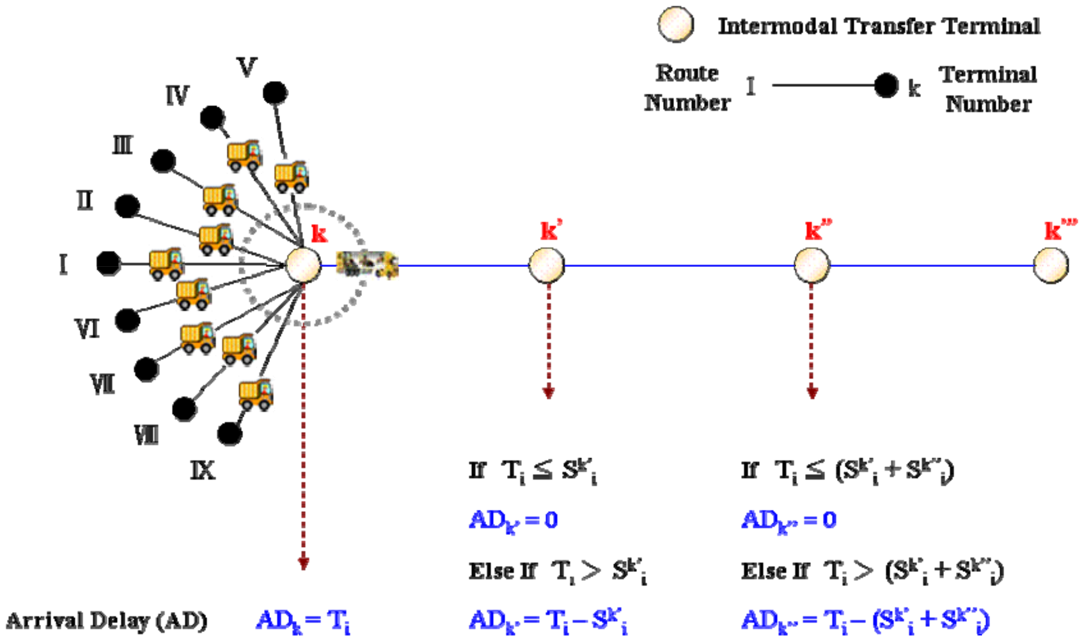


Figure 7.2 Conceptual Illustrations of Delay Propagations

In Figure 7.2, there are 9 light truck routes (inbound Routes 1-9) and 1 container truck route (outbound Route 10) connecting to the terminal k. There are three downstream terminals ($k^{'}$, $k^{''}$, and $k^{'''}$) located along the Route 10. At the current terminal k, all arrival delays eventually can be expressed as the holding time (T_i), denoted as the AD_k. There are many late arrival routes with different delay information, but the ready outbound vehicles eventually will be dispatched only right after the optimal holding time (T^*_i).

For the first downstream terminal $k^{'}$, the arrival delay ($AD_{k'}$) of the previous dispatched vehicle can be expressed in terms of the holding time (T_i) minus the slack time ($S^{k'}_i$) built in the off-line schedules. If the holding time is less than or equal to the slack time, this means that the primary delay has been absorbed by the safety margin of the original schedules, which means delays will not be propagated to downstream terminals.

Similarly, the arrival delay ($AD_{k''}$) of the next downstream terminal ($k^{''}$) can be expressed in terms of the holding time (T_i) minus the sum of following slack times ($S^{k'}_i$ and $S^{k''}_i$) built in the timetables, if the holding time exceeds those slack times. Based on the estimated arrival delay information, the missed-connection cost, the dispatching delay cost, and the dwell time cost incurred at the downstream terminals can be derived, as shown in Equations 7.7 – 7.22.

Assume the holding time would not affect the estimated link travel time, which means the departure delay at the upstream terminal will be equal to the arrival delay at the downstream terminal. Thus, the dwell time of cargos collected during the regular service headway will also increase T_i. Conversely, cargos collected during the holding period would save some dwell time. Equation 7.7 specifies the overall cargo dwell cost incurred at the first downstream terminal k' due to the holding decision.

$$\begin{aligned} C_w^{k'} &= \sum_{m\in M} \mu^m \left[T_i (q_i^{mk'} h_i) - (\frac{h_i - T_i}{2})(q_i^{mk'} T_i) \right] \\ &= \sum_{m\in M} \mu^m q_i^{mk'} T_i (\frac{h_i + T_i}{2}) \end{aligned} \tag{7.7}$$

For the next downstream terminal k'', the dwell time of cargos collected during the regular service headway increases to (T_i - $S^{k'}_i$). Cargos collected during the delay period would save some dwell time. Thus, the cargo dwell cost incurred at the second downstream terminal k'' due to the initial holding decision is expressed as:

$$C_w^{k''} = \sum_{m\in M} \mu^m q_i^{mk''} (T_i - S_i^{k'}) \left[\frac{h_i + (T_i - S_i^{k'})}{2} \right] \tag{7.8}$$

In order to derive the general form for n downstream terminals, we rewrite Equation 7.8 as Equation 7.9, where $k^{(1)}$ represents the first downstream terminal.

$$C_w^{k^{(2)}} = \sum_{m \in M} \mu^m q_i^{mk^{(2)}} (T_i - S_i^{k^{(1)}}) \left[\frac{h_i + (T_i - S_i^{k^{(1)}})}{2} \right] \qquad (7.9)$$

Equation 7.10 states the total cargo dwell cost incurred at the third downstream terminal $k^{(3)}$.

$$C_w^{k^{(3)}} = \sum_{m \in M} \mu^m q_i^{mk^{(3)}} (T_i - S_i^{k^{(1)}} - S_i^{k^{(2)}}) \left[\frac{h_i + (T_i - S_i^{k^{(1)}} - S_i^{k^{(2)}})}{2} \right] \qquad (7.10)$$

Similarly, the dwell cost incurred at the n_{th} downstream terminal $k^{(n)}$ is:

$$C_w^{k^{(n)}} = \sum_{m \in M} \mu^m q_i^{mk^{(n)}} (T_i - \sum_{\lambda=1}^{n-1} S_i^{k^{(\lambda)}}) \left[\frac{h_i + (T_i - \sum_{\lambda=1}^{n-1} S_i^{k^{(\lambda)}})}{2} \right] \qquad (7.11)$$

Thus, the overall cargo dwell costs affected by the propagation of delays can be summarized as:

$$C_w^p = C_w^{k^{(1)}} + C_w^{k^{(2)}} + C_w^{k^{(3)}} + ... + C_w^{k^{(n)}} \qquad (7.12)$$

At the first downstream terminal, the holding decision may also create some possible dispatching delay costs from Route i to other routes ($C^{k(1)}_{d1}$) and from other routes to Route i ($C^{k(1)}_{d2}$). These costs are formulated in Equations 7.13 – 7.15.

$$C_d^{k^{(1)}} = C_{d1}^{k^{(1)}} + C_{d2}^{k^{(1)}} \qquad (7.13)$$

The dispatching delay cost (see Equation 7.13) can be expressed by using the joint probability distributions for vehicle arrivals on any coordinated pair of routes (i, r). Two cases are considered in this cost component: (1) the feeder vehicle on the Route r arrives early, but the receiving one on the Route i is late; and (2) both vehicles are late, but the feeder vehicle arrives before the receiving one. $f_d(t_i, t_r)$ denotes the joint probability of dispatching delay for transfer cargos on some particular pair of routes. Thus, the dispatching delay costs from Route i to other routes and those from other routes to Route i at the downstream terminal k’ are expressed in Equations 7.14 and 7.15, respectively.

$$C_{d1}^{k^{(1)}} = \sum_{m\in M}\sum_{\substack{r\in E\\ r\neq i}} \mu^m Q_{ir}^{mk^{(1)}}\, \delta_i^{k^{(1)}}\, \delta_r^{k^{(1)}}\, f_d(t_i,t_r) \tag{7.14}$$

$$C_{d2}^{k^{(1)}} = \sum_{m\in M}\sum_{\substack{r\in E\\ r\neq i}} \mu^m q_{ri}^{mk^{(1)}}\, \delta_i^{k^{(1)}}\, \delta_r^{k^{(1)}}\, f_d(t_i,t_r) \tag{7.15}$$

Similarly, the dispatching delay cost incurred at the second downstream terminal $k^{(2)}$ is expressed as:

$$\begin{aligned} C_d^{k^{(2)}} &= C_{d1}^{k^{(2)}} + C_{d2}^{k^{(2)}} \\ &= \sum_{m\in M}\sum_{\substack{r\in E\\ r\neq i}} \mu^m (Q_{ir}^{mk^{(2)}} + q_{ri}^{mk^{(2)}})\delta_i^{k^{(2)}}\, \delta_r^{k^{(2)}}\, f_d(t_i,t_r) \end{aligned} \tag{7.16}$$

Thus, the overall dispatching delay costs affected by the propagation of delays can be summarized as:

$$C_d^p = C_d^{k^{(1)}} + C_d^{k^{(2)}} + C_d^{k^{(3)}} + \ldots\ldots + C_d^{k^{(n)}} \tag{7.17}$$

In Equations 7.18 – 7.20, the missed-connection cost ($C^{k(1)}_{x}$) the first downstream terminal $k^{(1)}$ due to the holding decisions occurs in two directions ($C^{k(1)}_{x1}$: from Route i to other routes and $C^{k(1)}_{x2}$: from other routes to Route i). The total missed-connection cost can be expressed by the joint probability distributions for vehicle arrival on any coordinated pair of routes (i, r). Two cases are considered: (1) the feeder vehicle on the Route r arrives late, and the receiving one on the Route i is not late; and (2) both vehicles are late, but the feeder vehicle arrives after the receiving one leaves. $f_x(t_i, t_r)$ denotes the joint probability of missed connections.

$$C_x^{k^{(1)}} = C_{x1}^{k^{(1)}} + C_{x2}^{k^{(1)}} \tag{7.18}$$

$$C_{x1}^{k^{(1)}} = \sum_{m \in M} \sum_{\substack{r \in E \\ r \neq i}} \mu^m Q_{ir}^{mk^{(1)}} \delta_i^{k^{(1)}} \delta_r^{k^{(1)}} f_x(t_i, t_r) \tag{7.19}$$

$$C_{x2}^{k^{(1)}} = \sum_{m \in M} \sum_{\substack{r \in E \\ r \neq i}} \mu^m q_{ri}^{mk^{(1)}} \delta_i^{k^{(1)}} \delta_r^{k^{(1)}} f_x(t_i, t_r) \tag{7.20}$$

Similarly, the missed-connection cost incurred at the second downstream terminal $k^{(2)}$ is expressed as follows:

$$\begin{aligned} C_x^{k^{(2)}} &= C_{x1}^{k^{(2)}} + C_{x2}^{k^{(2)}} \\ &= \sum_{m \in M} \sum_{\substack{r \in E \\ r \neq i}} \mu^m (Q_{ir}^{mk^{(2)}} + q_{ri}^{mk^{(2)}}) \delta_i^{k^{(2)}} \delta_r^{k^{(2)}} f_x(t_i, t_r) \end{aligned} \tag{7.21}$$

Thus, the overall missed-connection costs affected by the propagation of delays can be summarized as:

$$C_x^p = C_x^{k^{(1)}} + C_x^{k^{(2)}} + C_x^{k^{(3)}} + \ldots\ldots + C_x^{k^{(n)}} \tag{7.22}$$

All other constraints are the same as those in Chapter 6. Some illustrative numerical examples are presented in the section 7.3.

7.3 Model Applications and Analytical Results

Through this work we seek to optimize the dispatching decisions based on the considerations of delay propagated at further downstream terminals, which are connected by the same outbound service route. Although we derive the general form of models for n freight terminals, the studied area in practice may not include infinity downstream hubs. The initial delays caused by service disruptions may mainly influence first few downstream terminals; however, the decisions made in one dispatching area may affect the performance and feasibility of operational schedules in other areas. Thus, this section studies the problem of delay propagations through a pre-determined number of downstream terminals.

The study also provides flexibility in managing general and perishable cargos with different dwell time value functions. The studied network configurations are illustrated in Figures 7.3 and 7.5, which are extended from Route 33 and Route 31 in Figure 6.4b.

7.3.1 Case Study 7: Real-Time Dispatching Applications by Considering Propagation of Delays (Route 33)

As in Cases 4 and 6, 13 light truck inbound routes (Routes 1-13), one rail outbound route (Route 33), and 39 light truck transfer routes (Routes 18-30, 34-46, and 47-59) at downstream terminals are analyzed in Case 7. To simplify the problem, all downstream terminals are arrayed in a linearly sequential network configuration, as shown in Figure 7.3.

When service disruptions occur, the proposed dispatching method may affect further transfer hubs within the studied network due to the propagation of delays. Considering only the missed transfers of the consecutive terminals may lead to coordination conflicts at terminals further downstream. It should be noted that more downstream transfer terminals forming loops more loops within networks would significantly increase the problem's complexity. To compare the effects with and without considering the delay propagations, we consider here a series of terminals in a network without loops.

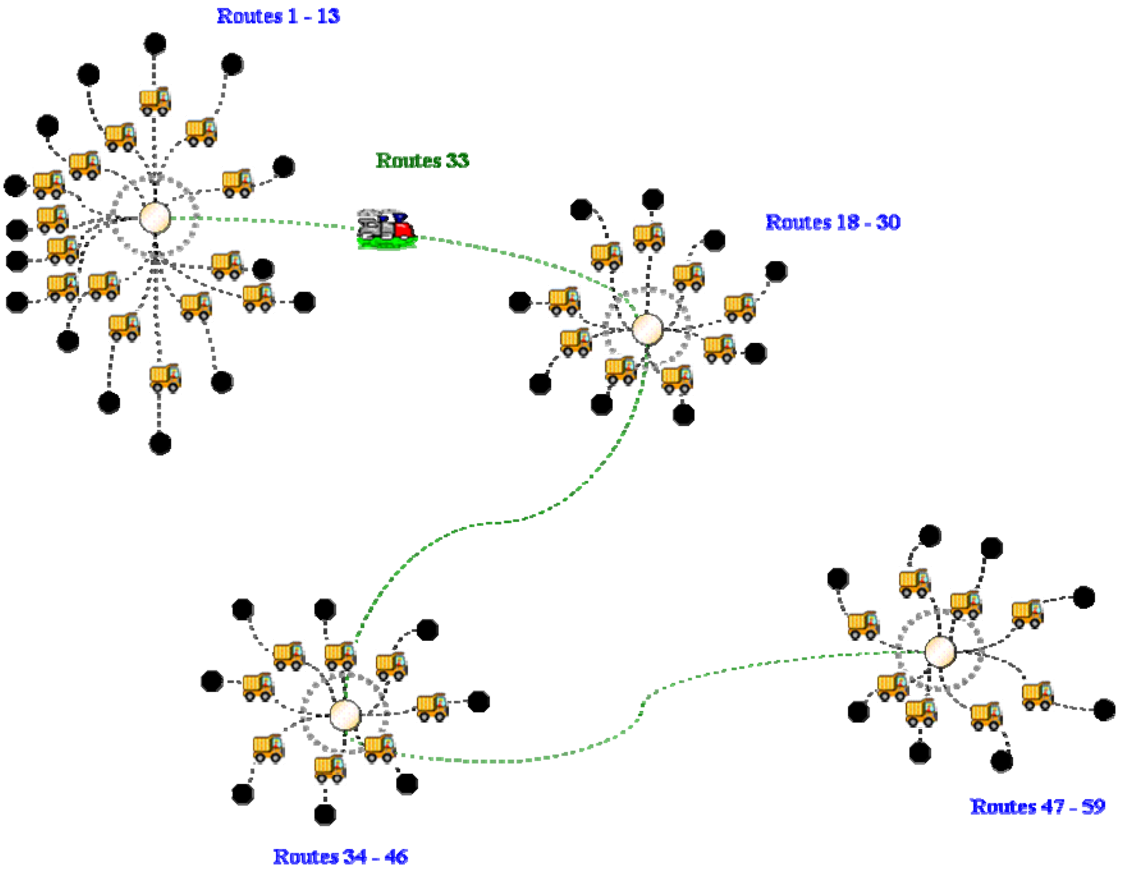


Figure 7.3 Illustration of Network Configuration for Case 7

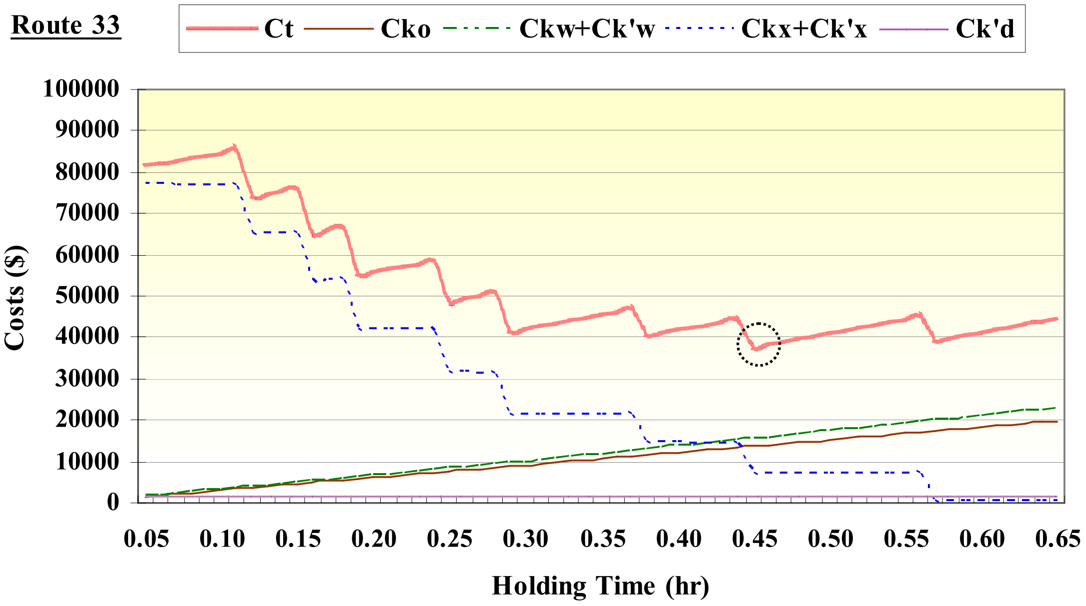
The vehicle capacities for light trucks and trains including 6 container stack railcars are 22,000 and 1,017,000 pounds, respectively. Different unit time values for two types of shipments are set as \$0.25*exp(-t) /lb-hr and \$0.1/lb-hr.

As mentioned above, all light truck routes tend to be served with smaller headways than those of the rail route. The integer-ratio schedule coordination outperforms the uncoordinated and the common-headway coordinated operations for the given input information. The common-headway service is inefficient and undesirable in this case because the route lengths and vary too much.

In this multi-hub problem, costs at all downstream terminals are considered. There are two types of control policies: WNDP (without considering delay propagations) and WDP (considering delay propagations). For the previous Case 6, we assume that inbound vehicles at the transfer terminal k on Routes 1, 2, 3, 5, 6, 8, 10, and 13 have estimated delays while the vehicles on Routes 31 are ready to be dispatched. Delay information is provided in Table 6.2. All service headways and slack times are pre-optimized and given.

In Figure 7.4a (WNDP), vehicle operation cost ($C^k{}_o$) and cargo dwell costs ($C^k{}_w$ and $C^{k'}{}_w$) increase as the holding time increases. The missed-connection cost ($C^k{}_x$) decreases because fewer cargos miss their connections during the longer holding period. However, missed-connection ($C^{k'}{}_x$) and dispatching delay ($C^{k'}{}_d$) costs are also incurred at the consecutive downstream terminal. Steps and local optima in Figure 7.4a are due to the arrival of additional inbound vehicles and the resulting successful connections. The overall trade-off results are illustrated by the total cost (C_t) curve. The optimized holding time (T_{33}) is 26.622 (min) / 0.4479 (hr), which means that the ready outbound rail train on Route 33 should wait until the 7_{th} late light-truck (from Route 6) arrives. The optimized total system cost is $37,547.

In Figure 7.4b (WDP), the trends of all cost terms are similar to those in Figure 7.4a. The optimized holding time (T_{33}) and total system cost solved by the proposed hybrid GA-SQP approach are 26.604 (min) and $39,867, respectively.



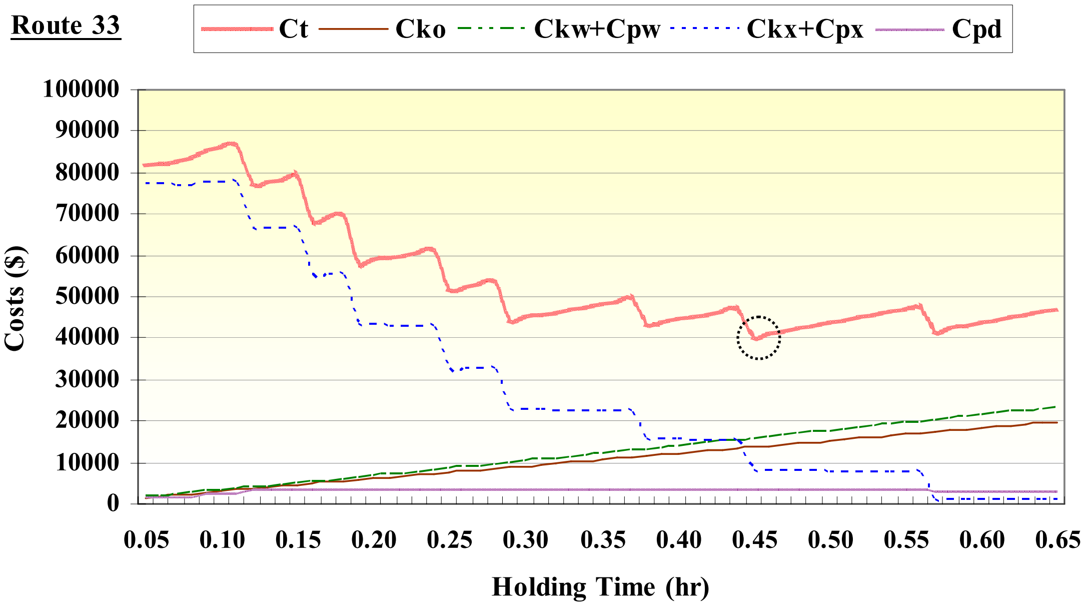
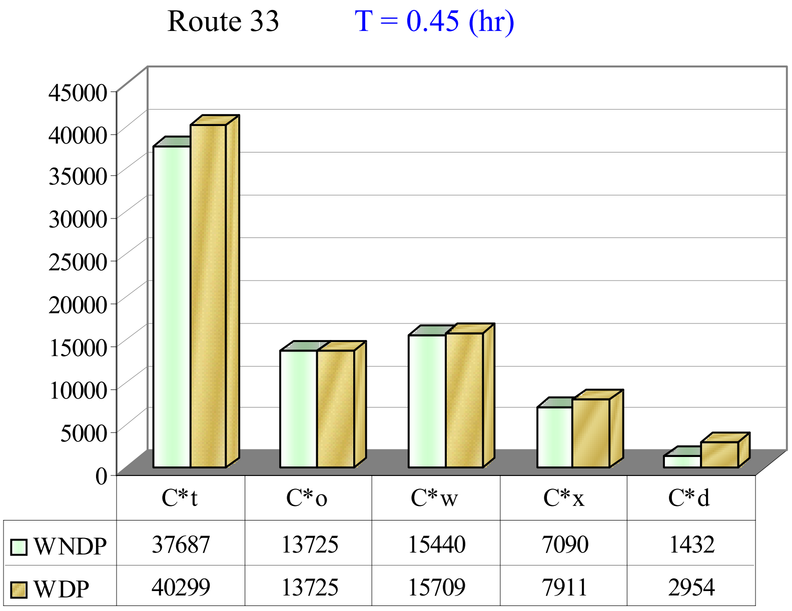


Figure 7.4 Costs with Different Holding Time of Route 33 (a) Without and (b) With Considering Delay Propagations

Although the resulting dispatching decision is the same with or without considering the propagation of delays, certain cost terms are somewhat different in this case.

Figure 7.5 illustrates the results of cost terms derived from the same holding time (T = 0.45 hr) under different control policies (WNDP and WDP). According to the WNDP policy, total cargo dwell costs (C^*_w) include dwell costs incurred at the current (C^k_w) and consecutive downstream ($C^{k'}_w$) transfer terminals during the holding time period. For the WDP consideration, the cargo dwell costs include those at all further downstream (C^p_w) terminals within the studied areas. All other cost terms (C^*_x and C^*_d) are calculated based on the same logic.

The total system cost of WDP is higher than that in WNDP, when considering the additional dwell time (C^*_w), missed-connection (C^*_x), and dispatching delay (C^*_d) costs occurred at further downstream terminals. The optimal dispatching decisions are determined based on the overall trade-off results among vehicle operating costs, cargo dwell time costs, and probabilistic missed transfer costs.



	C*t	C*o	C*w	C*x	C*d
☐ WNDP	37687	13725	15440	7090	1432
🟨 WDP	40299	13725	15709	7911	2954

Figure 7.5 Optimal Costs with Different Control Policies of Route 33

7.3.2 Case Study 8: Real-Time Dispatching Applications by Considering Propagation of Delays (Route 31)

As shown in Figure 7.6, 13 light truck inbound routes (Routes 1-13), one container truck outbound route (Route 31), and 12 light truck transfer routes (Routes 14-17, 60-63, and 64-67) at downstream terminals are analyzed in Case 8. All downstream terminals are still arrayed in a sequential network configuration.

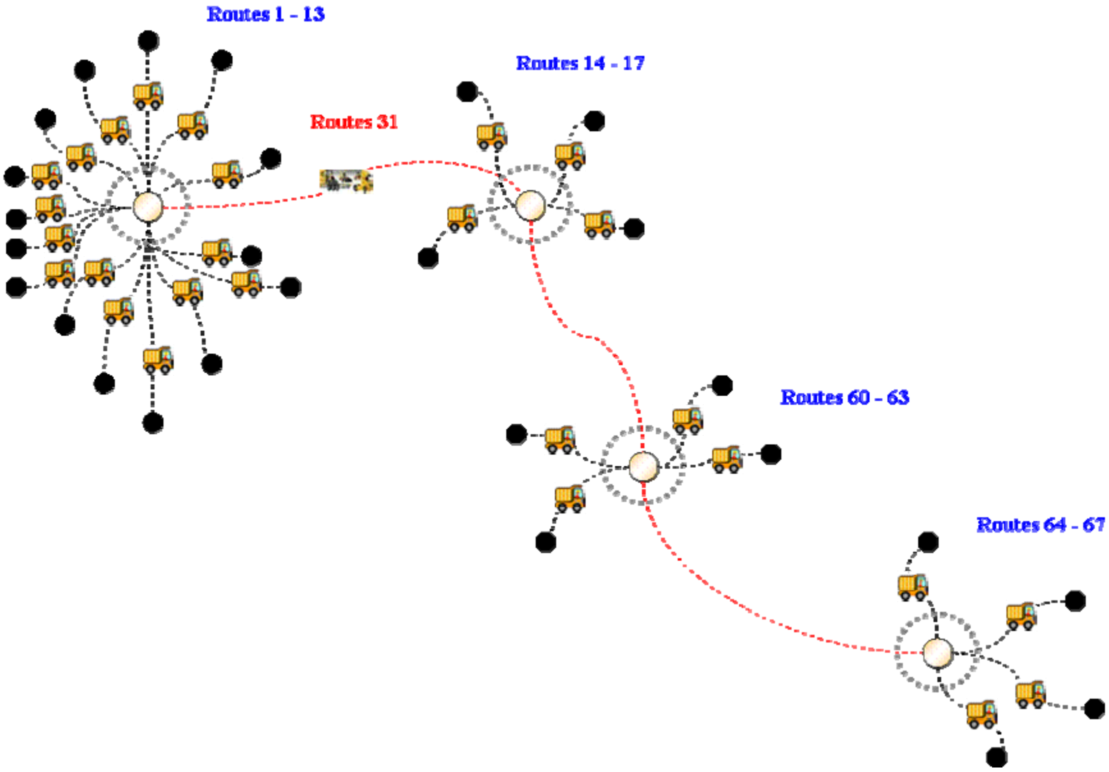


Figure 7.6 Illustration of Network Configuration for Case 8

The vehicle capacities of light trucks and container trucks are 22,000 and 44,000 pounds, respectively. Two types of shipments with different unit time values are as in Case 7. According to the demand information and travel lengths of service routes, light truck routes tend to be served with smaller headways than those of the container truck routes.

All delay information of inbound vehicles on Routes 1, 2, 3, 5, 6, 8, 10, and 13 is still provided in Table 6.2. All service headways and slack times are operated with the original schedules. Figure 7.7a shows the dispatching decisions optimized based on the WNDP considerations. The optimized holding time (T_{31}) solved with the hybrid GA-SQP algorithm is 22.21 (min) / 0.3702 (hr), which indicates that the ready outbound container-truck on Route 31 should wait until the 6_{th} late light-truck (from Route 1) arrives.

Figure 7.7b illustrates the dispatching decisions while considering delay propagations within the studied networks. Although the holding decisions of ready outbound routes may save the possible missed-connection cargos from the late inbound routes, the coordination schedules at further downstream terminals may be disturbed in ways that increase total system costs due to missed transfers. Through the optimization process proposed in this chapter, the optimized holding time (T_{31}) becomes 0.2884 (hr), which represents that the ready outbound container trucks on Route 31 should wait until the 5_{th} late light-truck (from Route 3) arrives.

Detailed costs for above dispatching decisions are shown in Figure 7.8.
Based on the WNDP and WDP control policies, certain cost terms are somewhat different. Longer holding times would increase vehicle operating costs and cargo dwell time costs but also reduce the missed-connection costs from late arrival vehicles. When considering the delay propagation at hubs further downstream, the optimal holding time may become shorter so as to reduce potential cargo dwell, missed-connection and delay dispatching costs incurred at the downstream terminals. The optimal dispatching decisions are determined based on the overall trade-off results among vehicle operating costs, cargo dwell time costs, and probabilistic missed transfer costs.

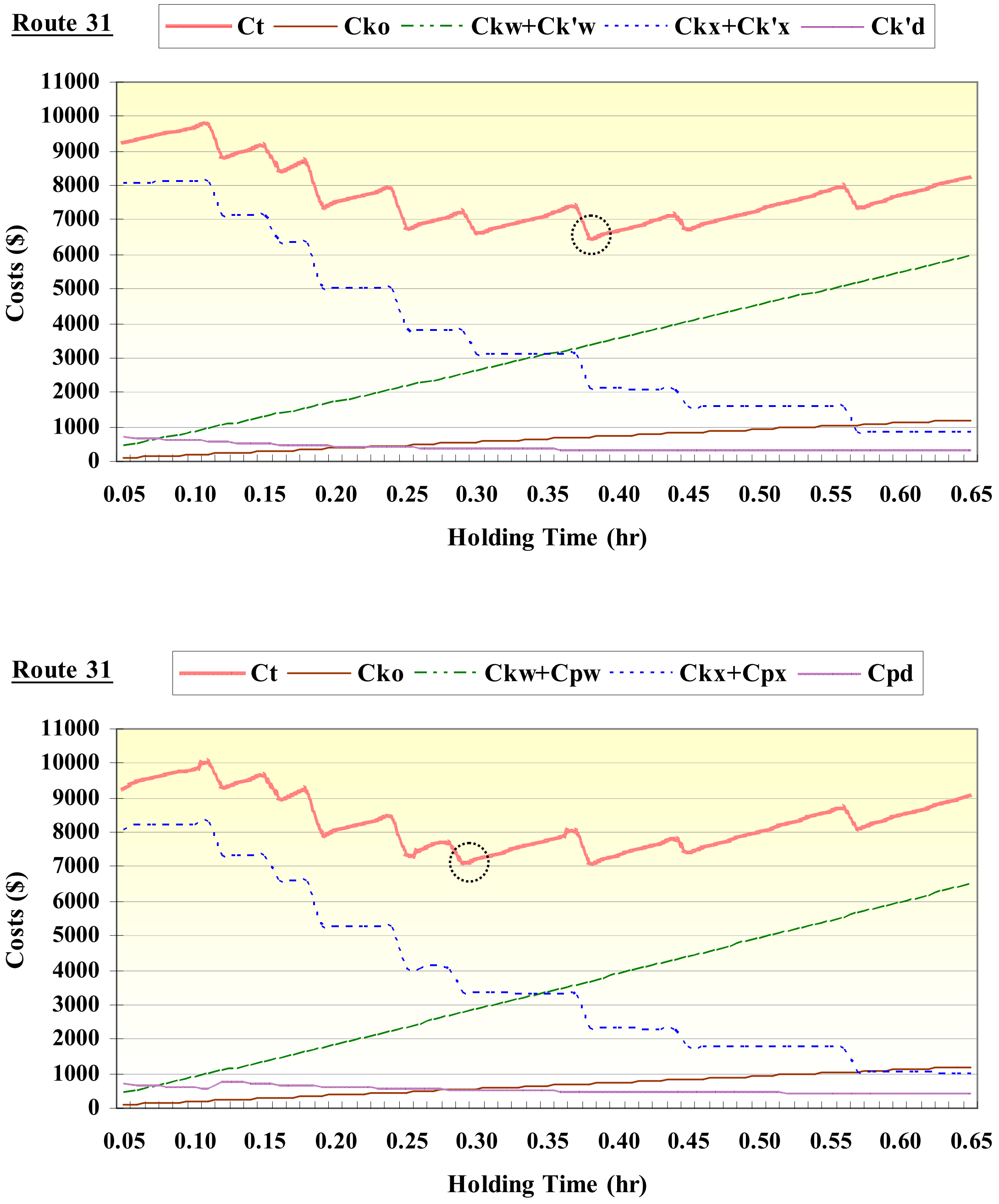
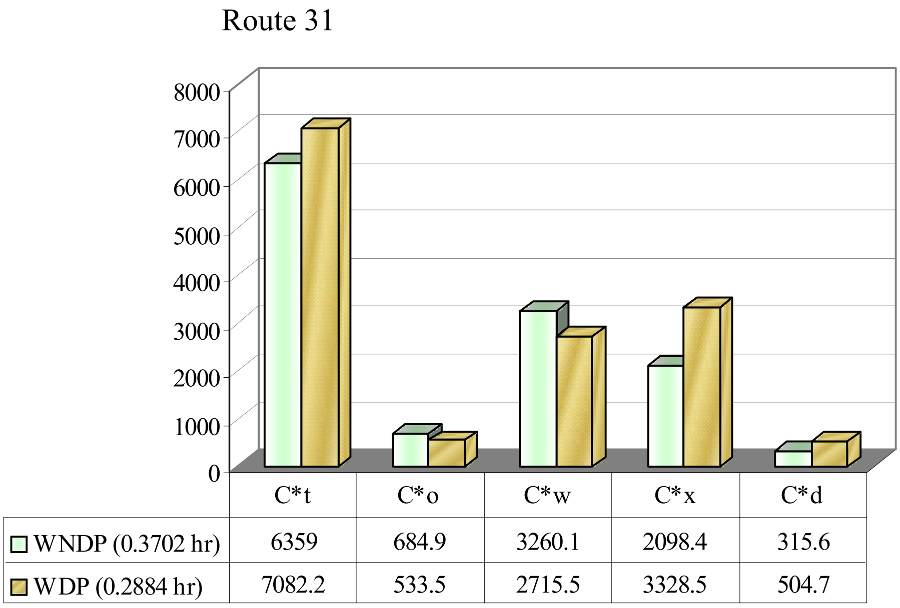


Figure 7.7 Costs with Different Holding Time of Route 31 (a) Without and (b) With Considering Delay Propagations



	C*t	C*o	C*w	C*x	C*d
🟩 WNDP (0.3702 hr)	6359	684.9	3260.1	2098.4	315.6
🟨 WDP (0.2884 hr)	7082.2	533.5	2715.5	3328.5	504.7

Figure 7.8 Optimized Costs with Different Control Policies for Route 31

7.3.3 Sensitivity Analysis of Slack Time Settings

Slack time is a safety margin of how much a schedule can be delayed without changing the original coordination plan. When service disruptions occur, the initial delays may cause delays downstream in the network. Additional slack times built into the schedule would increase the response and recovery abilities during the service disruptions; however, additional vehicle operation cost and the extra dwelled cost for loaded cargos may be incurred due to the higher slack time settings.

In this section, we perform a sensitivity analysis to observe the trade-off between the slack-based delay costs and the resulting delay-based costs. Where $C_{\omega,i}$ represents the sum of the resulting delay-based costs along the outbound Route i, $C_{s,i}$ describes the slack-based delay costs, and the minimization of the overall costs (C^*) is the main objective in this test, as shown in Equations 7.23.

$$\text{Minimize} \qquad C_i^* = C_{\omega,i} + C_{s,i} \tag{7.23}$$

As shown in Figure 7.9, the initial delays can be translated in terms of the holding time T of the ready outbound routes. Thus, the arrival delays of the outbound route at each downstream terminal can be expressed as the holding time (T_i) minus the sum of the slack times built in the schedule, except the delays absorbed by the slack times. The resulting delay-based costs can be formulated as Equations 7.24 – 7.26, where $H^{mk}{}_i$ = amount of the m_{th} category of cargo already loaded at upstream terminal k on Route i (cargo / hr).

$$C_{\omega}^{k^{(1)}} = \sum_{m \in M} \mu^m H_i^{mk^{(0)}} (T_i - S_i^{k^{(1)}}) \left(\frac{h_i + T_i}{2} \right) \tag{7.24}$$

Equation 7.24 specifies the arrival delay cost occurred at the first downstream terminal $k^{(1)}$ after making the holding decision. Cargos loaded at upstream terminal k are collected during the regular headway plus the additional holding time T. These cargos accompany the arrival delay (T_i - $S^{k(1)}{}_i$) when shipped to the first downstream terminal. Similar concepts are applied in the further downstream, as shown in Equations 7.25 and

7.26. Thus, the resulting overall delay-based costs are summarized in Equation 7.27.

$$C_{\omega}^{k^{(2)}} = \sum_{m \in M} \mu^{m} H_i^{mk^{(1)}} (T_i - S_i^{k^{(1)}} - S_i^{k^{(2)}}) \left(\frac{h_i + T_i - S_i^{k^{(1)}}}{2} \right) \tag{7.25}$$

$$C_{\omega}^{k^{(n)}} = \sum_{m \in M} \mu^{m} H_i^{mk^{(n-1)}} (T_i - \sum_{\lambda=1}^{n} S_i^{k^{(\lambda)}}) \left[\frac{h_i + (T_i - \sum_{\lambda=1}^{n-1} S_i^{k^{(\lambda)}})}{2} \right] \tag{7.26}$$

$$C_{\omega}^{p} = C_{\omega}^{k^{(1)}} + C_{\omega}^{k^{(2)}} + C_{\omega}^{k^{(3)}} + \ldots\ldots + C_{\omega}^{k^{(n)}} \tag{7.27}$$

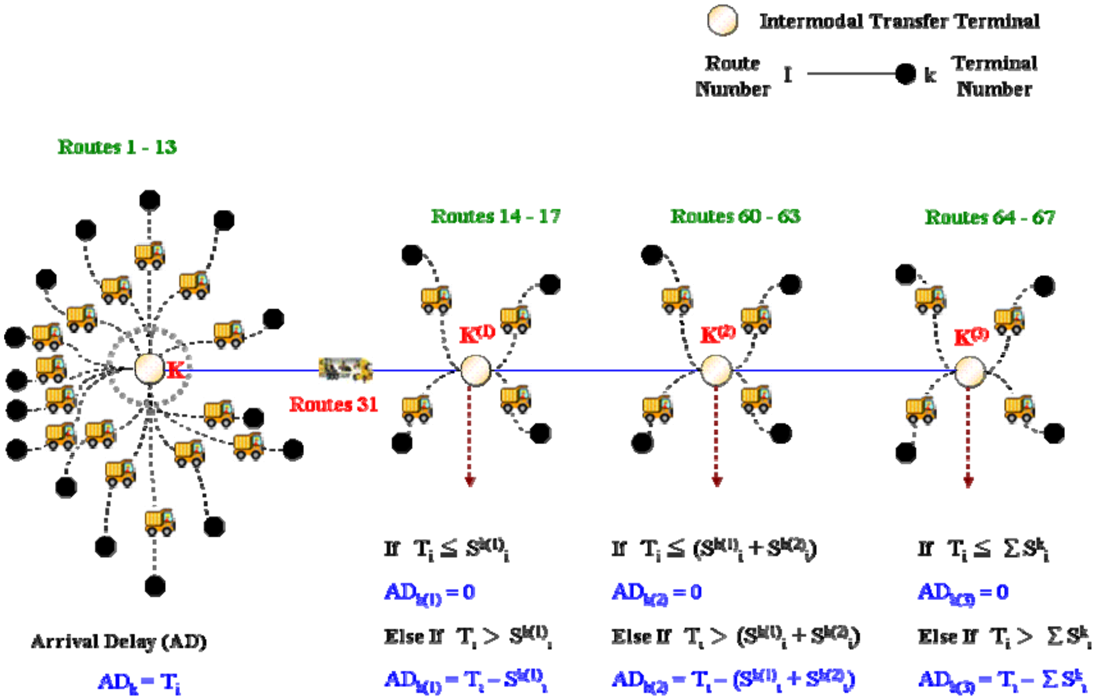


Figure 7.9 Pre-Analysis of Arrival Delays on Route 31

Equation 7.28 considers the extra dwelled cost for loaded cargos and additional operation cost during the slack time. Let H^{mk}_i = amount of the m_{th} category of cargo already loaded at downstream terminal k on Route i (cargo / hr); F^{mk}_i = amount of the m_{th} category of cargo transferred at downstream terminal k from other routes to Route i (cargo / hr); s^k_i = slack time at transfer terminal k on route i (hr).

$$C_s = \sum_{m \in M} \sum_{k \in N} [\mu^m (H_i^{mk} + F_i^{mk}) + B_i f_i] s_i^k \tag{7.28}$$

Figure 7.10 illustrates the trade-off between the resulting delay costs and slack-based delay costs with different slack time settings. We assume that the holding time (T) is 0.2884 (hr) in this sensitivity analysis; all other inputs are as in Case 8.

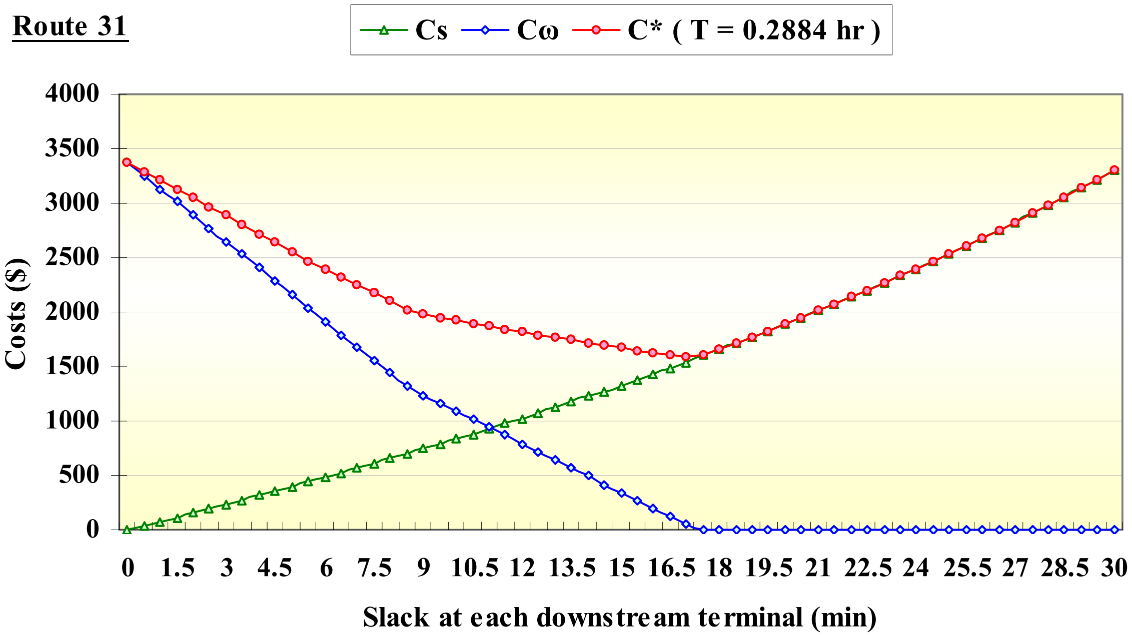


Figure 7.10 Delay-based Costs Analysis with Different Slack Time Settings on Route 31

To simplify the sensitivity analysis, we assume that all downstream terminals will have the same incremental amount of slack time S. Thus, the arrival delays at the first three downstream terminals will become T – S, T – 2S, and T – 3S. As shown in Figure 7.10, more slack times added into the schedule, the resulting delay costs would be gradually reduced; however, the slack-based delay costs are also increased. As mentioned in Figure 7.9, the propagated delay at each downstream terminal would be absorbed if the amount of slack time exceeds total delay time. In this case, no delay propagation would affect the original schedule if the scheduled slack time at each downstream terminal exceeds the holding time T.

Figures 7.11 and 7.12 illustrate the total resulting delay costs and total system delay costs with different slack time settings (unit: min) and different holding time durations (unit: hr). Longer holding time for ready outbound vehicles will cause more system delay costs. Similar to the trend in Figure 7.10, when more slack embedded into the system, the resulting delay costs are gradually diminished. In addition, the total system delay costs will be initially reduced but increased later due to the increasing slack-based delay costs.

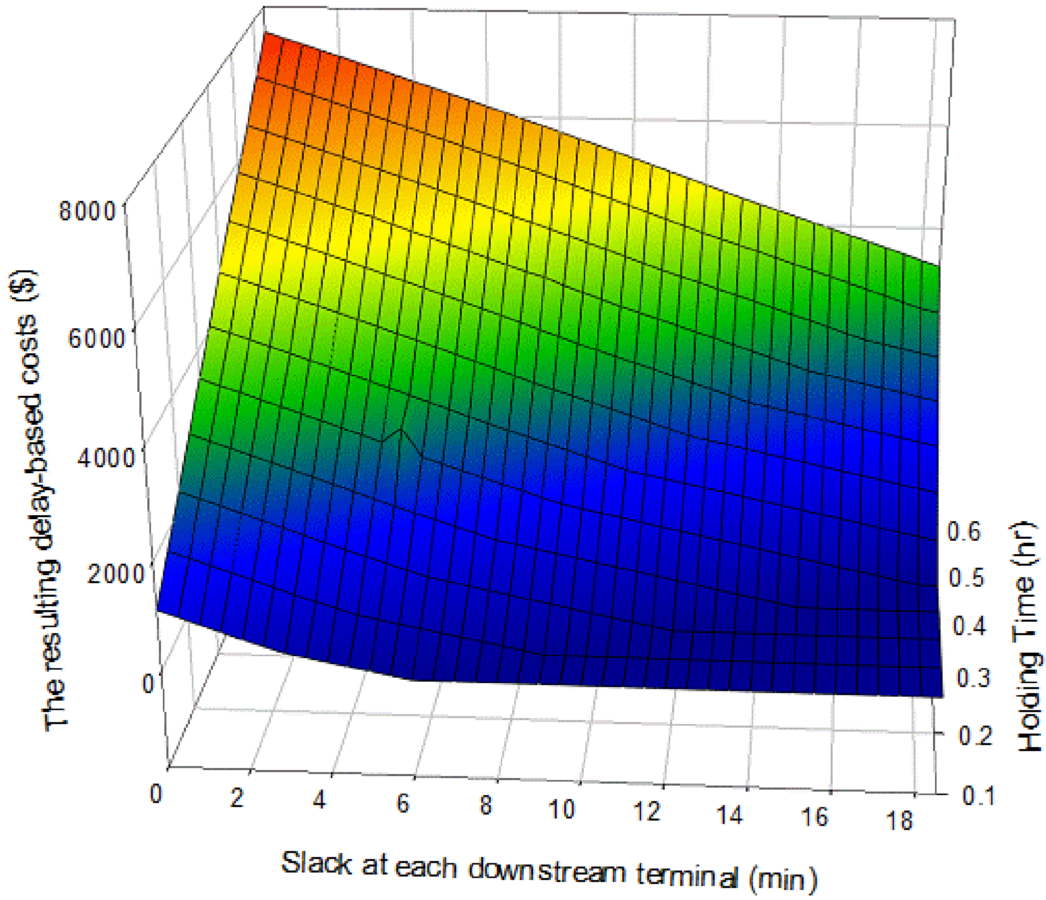


Figure 7.11 The Resulting Delay-based Costs with Different Slack Time Settings and Holding Time Periods

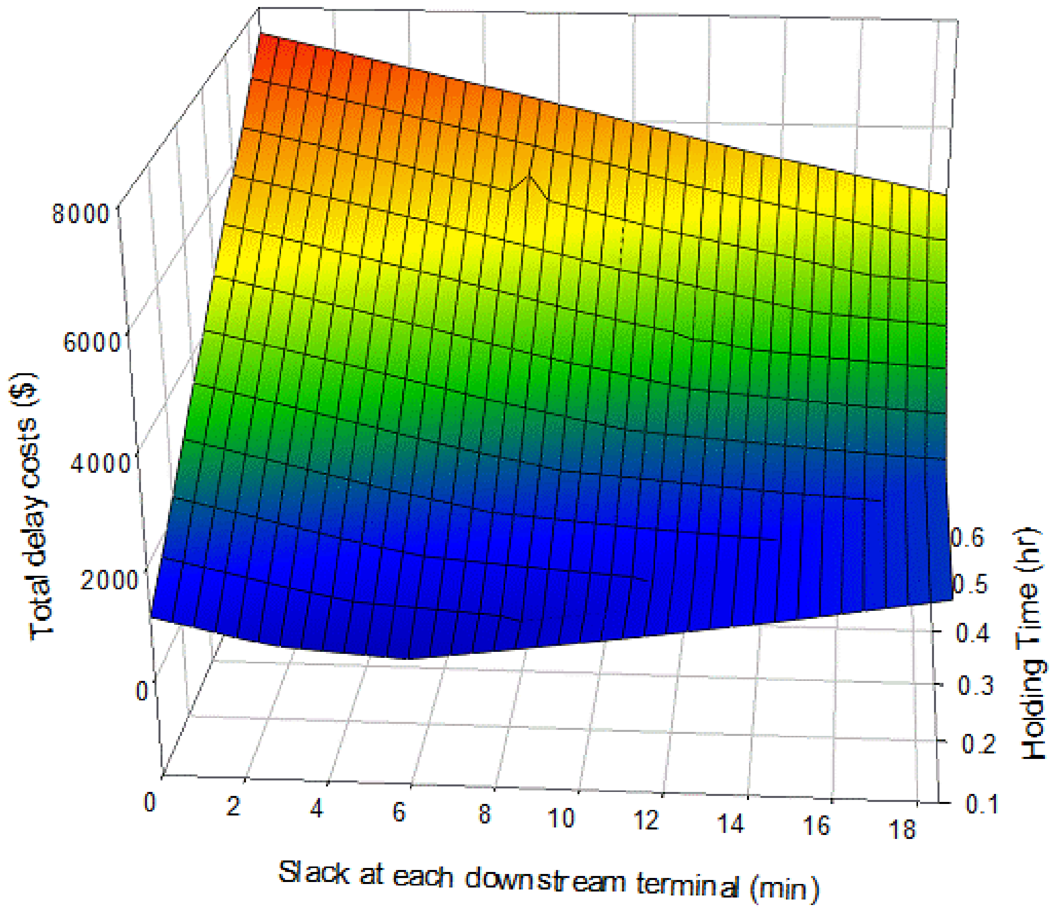


Figure 7.12 The Overall Delay-based Costs with Different Slack Time Settings and Holding Time Periods

7.4 Summary

In this chapter, we examine the previous dispatching model by considering the delay propagation through schedules and networks. Delay may be propagated through the entire networks and affect the operational schedules. In order to prevent the coordination destructed at later downstream, an analysis of the delay propagations within the studied network, an integrated dispatching control model, and a sensitivity analysis with different slack time settings for attenuating propagation of delays are presented.

It should be noted that off-line schedules and slack times are designed to satisfy all requirements and constraints during routine operations. Thus, the pre-optimized timetables may be unsuitable for unexpected events and needed to be adjusted. The results obtained with the proposed hybrid GA-SQP algorithm can help decision-makers response the delay propagations in a timely manner. Due to the complexity of directly analyzing complicated and large scale-network configurations, a relatively simple network with linearly sequential downstream terminals is considered to guide the analysis. In addition, the results can be fed back to the previous pre-planned models in order to develop the emergency plans for dealing with major disruptions.

Chapter 8

Conclusions and Future Research

The study mainly investigates the potential cost savings of coordinated operations compared to the uncoordinated ones for multi-mode, multi-hub, and multi-commodity networks. In Chapter 3, the general concepts of modeling the logistic timed transfer system are discussed in detail. To capture the operational characteristics, different network configurations are introduced and analyzed in Chapter 5. We start from a single hub – single commodity intermodal transfer problem and then move to a multi-hub and multi-commodities network. A more complex network problem with multi-hubs forming a loop is also studied.

In Chapter 6, the mathematical models for optimizing the real-time dispatching decisions are formulated and solved with the hybrid heuristic algorithm proposed in Chapter 4. Delay propagation is further considered in Chapter 7.

8.1 Contributions

This section summarizes the primary contributions of this study as follows:

1. The logistic timed transfer problem is defined as a mixed integer nonlinear programming problem within the studied multi-modes, multi-hubs, and multi-commodities networks and solved with the proposed hybrid GA-SQP heuristic approach. Two types of costs (i.e. transfer and non-transfer ones) based on three different operational plans (i.e. uncoordinated, coordinated with a common service headway, and coordinated with integer-ratio based approach) are formulated in this section. The safety margins (i.e. the slack times) built into the schedules are also optimized for the coordinated operations. Since, unlike passengers, cargos cannot transfer themselves, some microscopic activities are considered in the proposed models (e.g. loading, unloading, and processing time of cargos.)

2. Mathematical properties of real-time dispatching problems are exploited in the solution algorithms. Routine service disruptions, such as traffic congestion, demand fluctuations, or vehicle failures may cause delays of inbound vehicles that incur additional cargo dwell costs and ruin the coordination schedules at downstream terminals. Thus, for each ready outbound route, the dispatching timing is determined through an optimization process, which decides whether to dispatch vehicles according to the pre-planned schedules or hold them for certain late inbound vehicles.

3. The dispatching control process is extended to assess the delay propagations through the network and schedules. Initial delays occur at upstream due to the service disruptions may affect further downstream and cause more resulting delay costs through the studied networks. The initial delays can be translated in terms of the ready outbound vehicle’s holding time. Some delays may be absorbed by the slack times built into the schedules.

4. The algorithm is tested on a logistic network under various assumptions. As mentioned in Chapter 4, SQP may not be suitable for a large problem, and GA may face the slow convergence problem in the final steps. The proposed hybrid GA – SQP algorithm can provide efficient and reliable results for the large network problems.

8.2 Summary

After analyzing several test problems, including both small and large network problems, several findings are reached:

1. 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. In order to simplify the problem, a single terminal operation problem is first analyzed. Since interrelations among multiple terminals are common in real-world applications, the studied problems are further formulated as multi-hub, multi-mode, and multi-commodity network models and tested in the different cases. In the studied logistic network with several freight transfer terminals (or hubs,) each hub can operate the efficient service schedules optimized by considering the demand information and route lengths.

2. When comparing the total costs with different holding time periods, we quantify how longer holding time would yield higher vehicle operation cost and cargo dwell cost but lower missed-connection cost. The dispatching decisions are determined based on the overall trade-off results among vehicle operating, cargo dwell time, and probabilistic missed transfer costs.

3. When routine service disruptions occur in coordinated schedules, some propagation of delays may affect downstream operations so that coordination might be disrupted later. In order to prevent the loss of coordination at later

downstream, the dispatching decisions should consider the effects of delay propagations and be determined based on the overall trade-off costs incurred through the studied networks and schedules. Through the sensitivity analysis of slack times, we observe that greater slack times built into the schedule increase the response and recovery abilities during service disruptions. However, additional vehicle operation cost and the extra dwell cost for loaded cargos may be incurred due to the higher slack time settings.

8.3 Discussion

Several aspects of the analyses and mathematical models developed in this research are discussed below.

1. Data Availability

   Most of the values in the numerical section are based on the literature review and information gathered from websites. Although these values may be not typical enough, the model is quite general and can use whatever inputs its users consider most applicable. These values may be varied for different characteristics of modes and commodities; we apply them until more suitable references can be found.

   For detailed OD information of shipments, cooperation is desirable from shippers and carriers. Some data may also be obtained from the Census Bureau. For certain cost terms, one project sponsored by the National Cooperative Freight Research Program (NCFRP) may provide the required costs in this dissertation. The project (NCFRP - 26) is trying to identify specific types of transportation cost data and to assess different strategies for collecting the needed data.

2. Challenges of Model Applications

Since aircraft and ships usually have fixed and pre-determined schedules, this study can initially consider operations of different types of trucks and trains. Most of our case studies are developed for multi-mode transfer operations (e.g. light trucks transferring to heavy trucks or container trucks are still defined as multi-mode operations.)

In some cases, especially when the aircraft, ships or trains are not much larger than the connecting vehicles (for example in ferry crossings), the larger vehicles may well wait for cargo arriving late in smaller vehicles. Based on several previous studies of train scheduling problems (Adenso-Díaz et al., 1999; Sahin, 1999; Carey and Crawford, 2007; D'Ariano et al., 2008), certain holding times for out-going trains are still allowable to avoid having delays propagated through entire networks and schedules.

In this dissertation, general models are developed which should be suitable for most combinations of modes. Those modes can be described in terms of their vehicle capacities, unit operating costs, average speeds and travel time variances, etc.. Although the tested case studies seem relatively simple, the main purpose is to test and demonstrate the capabilities of our proposed models and optimize the dispatching decisions when routine disruptions occur.

The numerical examples presented in this study may not fully reflect the exact nature of the coordinated modes. (To generalize, the proposed models can be viewed as transfers between Mode A and Mode B.) However, we should note that even ships (e.g. small ferries) might in some cases wait for trucks if the ships are not very much larger and more expensive than the trucks.

3. Utilization of the Proposed Models

Intermodal freight operations are very complicated due to different combinations of modes, network structures, cargo compositions, and operating strategies. Although some specific characteristics in freight transportation are quite different from those in transit systems, the basic operating logic of dealing with transfer movements is similar. In the mentioned container – truck terminal, our model can at least reduce the vehicle operating cost of truck operators, assuming the schedules of ships are unchangeable. Coordination is still desirable in this market.

For planning purposes, the models can provide an overview for decision makers in developing a regional freight transportation system including the alignments of corridors, location choices of transfer terminals, and design of warehouses and storage facilities. From the operational viewpoint, the models can help shippers, carriers, forwarders, dispatchers, and terminal operators optimize the service routes and schedules so as to reduce the fleet operating costs, storage requirements, and potential external impacts. These models might also be used by consortiums or "alliances" of private freight transportation companies.

In order to facilitate the users' applications, the proposed models could be further developed into commercial software with user-friendly interfaces and detailed user guides.

4. Potential Improvements for Model Formulations

In this dissertation, models are formulated by minimizing total system costs and do not directly link to the user preferences. However, the settings of nonlinear cargo time value functions also reflect certain time sensitivities of cargos based on different user preferences.

The available fleet size has been expressed through constraints on service frequencies (or headways.) Although the slack times are not directly formulated as functions of the fleet size, the joint optimization processes of slack times and service schedules do take the fleet size into consideration.

The holding decision may indeed affect the drivers’ total working time during a day. Such a constraint should be incorporated in future model versions.

5. Differences between Passenger and Freight Transport Timed Transfer Systems

   Passenger transport systems may adopt several satisfaction criteria to maintain the level of service when designing and planning the operational schedules, such as: minimum acceptable service headway, minimal transfer waiting time, and minimal number of transfers. In order to improve the efficiency and reliability of the studied intermodal logistics system, several similar service-oriented constraints may also be considered in extensions, such as: maximum allowable holding time for the ready outbound vehicles, maximum acceptable delays, and minimum required slack times.

   For most U.S. public transit system operations, system operators, infrastructure providers, and planners are mostly in the public sectors and are not competitors. Thus, these various decision makers can easily collaborate with others to pursue the maximum total system benefits or social welfares. In addition, public transit systems may need to maintain the basic service quality and level of service, so the minimal transfer waiting time or minimal number of transfers may also be considered while planning the operational timetables. Similar applications are also implemented in air transportation.

   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 would still pursue the maximization of total profit. Competitive behaviors may become unavoidable and require other models to capture their details.

Service headways in public transit systems are usually small and typically determined in minutes; however, headways in freight transport systems may be determined in hours, days, or even weeks, which are more often rounded into normal calendar dates for periodic operations. These service schedules are largely determined by demand levels, route lengths, vehicle operating costs and the users' or shippers' time values.

6. Conventional versus Demand-Responsive Transportation Services

In the proposed models, all demand information is given and assumed to be deterministic and uniformly distributed during the specified time periods. This assumption is reasonable while providing the conventional transportation services with the fixed routes and periodic continuous operational timetables. The aggregated demand should be sufficient to maintain this kind of services, such as Baltimore – NYC freight operations through I-95 corridor.

The models developed here are designed for logistic systems with preset routes and schedules. Hence they are not yet suitable for areas with relatively low or highly variable demands. The models in this study can be modified to consider partial coordination, which means that some routes are coordinated and others (especially those with high demand and high service frequencies) are optimized independently of the other routes.

8.4 Conclusions

The optimization models developed in this study are used to generate analytic and numerical results. Some sensitivity analyses also verify the relationships established in the model formulations. The main conclusions are as follows:

1. Since system coordination can provide many advantages such as scale economies in transportation, lower storage requirements, and lower external costs, we can expect that transportation firms, terminal operators, infrastructure providers, shippers and forwarders may greatly benefit from adopting such an intermodal timed-transfer approach. The benefits would also extend to the economy and the environment.

2. At lower demand levels, the optimum service headways, and hence transfer delay times, are relatively high, so the costs of missed-transfer may be large. Conversely, if the demand level is very high, then the impacts of missed transfers may affect the shipment delays much less. Shorter headways can reduce the extra cargo dwell time due to missed-connection or connection delays.

3. The usefulness of such models can be increased by further developing a real-time control model for dealing with major as well as routine service disruptions. Different level of disruptions may require different operational plans in response to the deviations from the schedules and get the system back on the track in a timely manner.

4. The proposed models are mainly applied in realistic cases based on the given demand information and detailed network configurations. These models can be further improved and integrated by jointly optimizing the route choice decisions and schedules, which can also provide a guideline to design the service routes. This advantage can be applied in the development of the commercial software to provide decision makers prompt and reliable scheduling and dispatching

recommendations. Most of these works can be integrated into such software and would affect the routing decisions. For example, within a logistic timed transfer system, route decisions may consider the shortest path (i.e. less transfers), the quickest path (i.e. high speed modes with well coordinated transfers), or lowest cost path (i.e. economic modes with well coordinated transfers).

5. In this multi-variable nonlinear optimization problem, SQP can generate robust solutions based on given initial feasible solutions. However, the quality of the optimized solutions may be significantly affected by the initial solutions. This problem can also be solved by a genetic algorithm (GA). The GA objective value can be improved by running additional generations, although with diminishing improvements. The proper number of generations that should be run depends on tradeoffs between solution quality and the program running time. That is why a hybrid GA-SQP algorithm is developed which can save some GA running time and provide robust and efficient solutions.

8.5 Future Research

Although this study provides several contributions in the logistics planning and modeling fields, especially in the comparison of uncoordinated and coordinated operations, several additional elements could be considered in future studies.

1. Extending the above models from routine disruption cases to major disruptions. This dissertation is focused on the management of routine service disruptions. Major disruptions will cause more severe delays in short term and require different response and recovery strategies. Due to significant demand variations when major disruptions occur, slight adjustments to the original schedules may become insufficient. Some specific plans and even emergency operations should be developed to respond to major system disruptions and recover from them. In addition, analyzing transitions and developing a transition plan between regular

and emergency operational schedules is also an interesting research problem.

2. The developed models could be enhanced by considering detailed transfers inside terminals, such as scheduling and operation problems of crane and other loading/unloading facilities, storage facilities design based on the limited capacity constraints, and cargo processing procedures subject to security concerns.

3. Developing discrete event-based simulation models for such logistic systems. Simulation models can be statistically validated through comparisons with numerical optimization results.

4. Analyzing multi-source delay propagation within the large scale and complex networks. The interrelations among arrival, departure, and travel delays should be considered in developing an integrated real-time dispatching control model to alleviate delay propagation within the logistic timed-transfer system.

5. Incorporating various uncertainties into the scheduling coordination and dispatching problems. For example, various link travel time or demand uncertainties during the peak and off-peak hours would affect the pre-planned schedules and real-time response decisions.

6. Considering how the concepts and models presented here may be adapted to other transportation activities such as passenger airlines and urban public transit services.

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