1997

Dynamic routing and service network design for less-than-truckload (LTL) motor carriers

B. Muralidharan
Iowa State University

Dynamic routing and service network design for less-than-truckload(LTL) motor carriers

by

B. Muralidharan

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Industrial and Manufacturing Systems Engineering

Major Professor: Raymond Cheung

Iowa State University

Ames, Iowa

1997

UMI Number: 9826592

Graduate College
Iowa State University

This is to certify that the Doctoral dissertation of

B. Muralidharan

has met the dissertation requirements of Iowa State University

Signature was redacted for privacy.

Major Professor

Signature was redacted for privacy.

For the Major Program

Signature was redacted for privacy.

For the Graduate College

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGEMENTS

I gratefully acknowledge my major professor, Dr. Raymond Cheung, for his invaluable insight and guidance in my doctoral research.

Dr. Raymond Cheung is responsible for providing the stepping stones on which I began my work toward a doctoral degree. His unique and convincing perceptions of the field of Operations Research proved to be a great source of motivation; his patience and understanding proved to be a great source of strength. I am truly indebted to him for this.

I also thank Dr. H.T. David, Dr. John Even, Dr. Les Miller and Dr. Soma Chaudhuri for serving as my committee members.

I am deeply grateful to my brother and sister for their affection and lasting support throughout my doctoral degree. I also wish to thank all my friends who have made my tenure at ISU enjoyable.

Finally and most importantly, words cannot express the amount of affection, encouragement, and support given by my parents during my doctoral endeavor. I owe them my heartfelt gratitude.

LIST OF SYMBOLS

t^e_{ij}	- Enroute time from terminal i to terminal j
t^{wu}_i	- Time waiting to unload at terminal i
t^u_i	- Time to unload at terminal i
t^{wd}_{ij}	- Time waiting to dispatch at terminal i to terminal j
x	- Threshold capacity at which a trailer is closed
x^p	- Threshold capacity at which a trailer is closed for primary service
x^d	- Threshold capacity at which a trailer is closed for direct service
x^o	- Threshold capacity at which a trailer is closed for opportunistic direct service
x^{pt}	- Threshold capacity at which a trailer is closed for primary service when TTMS has expired
x^{dt}	- Threshold capacity at which a trailer is closed for direct service when TTMS has expired
x^{ot}	- Threshold capacity at which a trailer is closed for opportunistic direct service when TTMS has expired
t^{md}	- Maximum loading time at a dock for direct trailers
t^{mo}	- Maximum loading time at a dock for opportunistic direct trailers
t^{mp}	- Maximum loading time at a dock for primary trailers
T^r	- Time spent on road
T^t	- Time spent at terminals
$t^P_{i,j}$	- Transit time at terminal i if $i \rightarrow j$ is a primary route
$t^D_{i,j}$	- Transit time at terminal i if $i \rightarrow k$ is a direct route

t_{i,k_j}	- Time needed to transfer shipments from the direct trailer $(i \rightarrow k)$ to the primary trailer $(i \rightarrow j)$ plus the waiting time until the primary trailer is dispatched
p_{i,k_j}	- Probability that the shipments on the direct trailer $(i \rightarrow k)$ need to be transferred onto the primary trailer $(i \rightarrow j)$
$r_{i,j}$	- Travel time on the road from terminal i to terminal j
ξ_{i,k_j}	- Bi-valued random variable with the following probability mass function: $\Pr(\xi_{i,k_j} = 0) = p_{i,k_j}$ and $\Pr(\xi_{i,k_j} = \infty) = 1 - p_{i,k_j}$
$\tilde{c}_{ij}$	- Random cost of arc (i,j) where $(i,j) \in A$
c_{ij}^k	- k^{th} realization of the cost of arc (i,j)
V_i	- Cost of the dynamic shortest path from node i to node n
$\bar{V}_i$	- Expected cost of the dynamic shortest path from node i to node n
$S(i)$	- Set of successor nodes of node i (that is, the set of $\{j \mid (i,j) \in A\}$)
N	- Set of nodes
A	- Set of arcs
R	- Number of arcs starting from a node
K	- Number of possible arc costs of an arc
$\tilde{x}_{ij}^k$	- Bi-valued random variable that takes values of $\tilde{c}_{ij}$ and ∞ only
q_{ij}^k	$= \Pr(\tilde{x}_{ij}^k = c_{ij}^k)$
$\tilde{U}_m$	- Bi-valued random variable that takes values of $\tilde{x}_{ij}^k$ and ∞ only
F	- Fixed cost to dispatch a truck over the link
h	- Holding cost per time period for holding a unit of freight
K	- Vehicle capacity
T	- Planning horizon for the model
α	- Discount factor

I_t	- Amount of freight at the origin of the link waiting to be dispatched over the link at time t
a_t	- Amount of freight arriving at the origin at time t to be moved over the link
y_t	- Binary variable that takes on a value 1 if a truck is dispatched at time t
$r_t(y_t, I_t)$	- Cost incurred in period t, given state I_t and dispatch decision y_t
$R_t(I_t)$	- Optimum total cost from time t to T
$R_T(I_T)$	- Terminal cost function at time T
x	- Static threshold value at which to dispatch a trailer
$h(w_t)$	- Stationary dispatch function
$h_t(I_t)$	- Dynamic threshold function
w_t	- Time since the last dispatch of the truck at time t

1 INTRODUCTION

With recent advancements in high-speed communication networks. global vehicle tracking and positioning systems. satellites and high speed computers. shipment routing and vehicle dispatching decisions can be made in real-time based on information currently available. Shipment routing and vehicle dispatching problems for less-than-truckload (LTL) carriers have been addressed using classical mathematical models in the literature. However. these models ignore the stochasticity and dynamism embedded in these problems. The major goal of this research is to develop models and solution approaches to address the dynamic load planning problem. The dynamic load planning problem decides where and when to dispatch the truck based on the current state of the system and current time. In particular. this research addresses two problems. namely dynamic priority shipment routing problem. and dynamic service network design problem on a single link. The dynamic priority shipment routing problem decides where the consolidation needs to be done in real-time to minimize delays to priority shipments and thus reduce penalty costs. based on current information available. The dynamic service network design problem decides when to dispatch a truck in real-time to minimize the total cost. trading off the costs of holding freight vs. sending a truck that might not be full. based on current time and information available at current time.

Several classes of research problems exist in LTL networks. In the literature. several of these problems are addressed. The hierarchy of the problems addressed in the literature is shown in the Figure 1.1. The following section briefly describes where dynamic load planning fits in the hierarchy of research problems that exist in LTL literature.

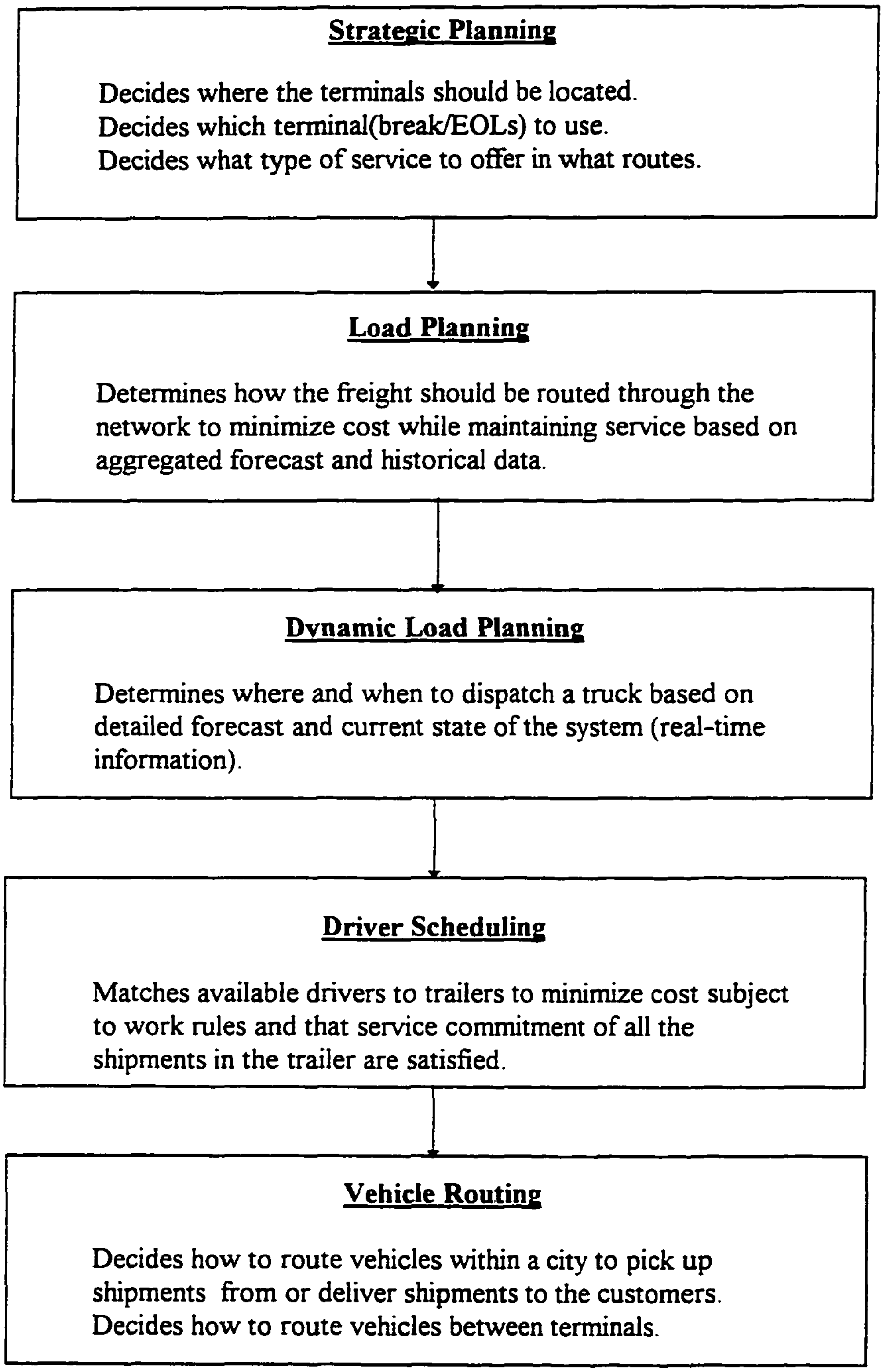


Figure 1.1 Hierarchy of LTL network research problems

- Strategic planning: For LTL carriers. strategic planning generally means deciding where the terminals should be located and which of the terminals selected should be breaks and which should be end-of-lines (EOL). Furthermore. it selects the type of (regular/priority) service to offer between terminals based on the number of shipments between the given terminals. the revenue potential. and other factors.

- Load planning: Load planning determines how the freight should be routed through the network. That is. load planning determines which consolidation terminal(s) should be used for freight between any two given terminals. The consolidation terminals for origin-destination pairs are determined based on aggregated forecast and historical data such that the total cost is minimized while maintaining the service. While load planning decides which consolidation terminals the freight should be routed through. it takes into consideration the work rules for the drivers. capacity of the terminals to handle a certain number of trailers at any given time. and the balance of equipment (trailer/tractor) flow.

- Dynamic load planning: Dynamic load planning (DLP) determines where and when to dispatch a truck based on the current state of the system. and detailed forecast of the system. DLP decides where the consolidation needs to be done to minimize cost while maintaining service based on the real-time information available. and when the truck needs to be dispatched so as to minimize cost over time based on the current time and information available at the current time.

- Driver scheduling: Driver scheduling creates routes the drivers. based on the number of trailers that needs to be dispatched and the number of drivers available subject to driver work rules. such that the service commitment of all the shipments in the trailer are satisfied. As a result of this module. a driver is assigned to each of the trailers that needs to be dispatched.

- Vehicle routing: For LTL carriers, vehicle routing decides how to route the vehicles within a city to pick up shipments from or deliver shipments to the customers. Vehicle routing also decides how the vehicle will be routed between a given origin-destination pair to minimize the distance traveled.

In this chapter, LTL carrier operations are described briefly and various terms used in the dissertation are explained. There are two major terminal types in an LTL service network: end-of-line (satellite) and break (hub). An end-of-line maintains a fleet of small trucks that pick up and deliver shipments in the local area. Typically, a shipment goes from an end-of-line terminal, passes through one or two breaks where consolidation takes place (unloading, sorting, and loading), and then reaches the destination. This research considers the LTL line-haul network comprised of the end-of-lines, the breaks, and the shipment routes between them.

The majority of shipments that LTL motor carriers deal with are less than 1,000 pounds. Thus, a tractor-trailer combination can carry an average of 20 to 30 shipments that can have different origins and destinations. As a result, shipments need to be consolidated at some breaks in order to build more economical loads. A typical shipment route between a pair of origin and destination terminals may consist of one or two breaks. To maintain a service level standard and to comply with work rules, however, companies limit the number of allowable shipment routes from one terminal to another terminal and generally use fixed routes. This fixed set of routes is referred to as the load pattern or load plan that is updated periodically (such as monthly).

The shipment routes are given by two fixed load patterns: (1) the primary load pattern, and (2) the direct load pattern. Given an origin-destination (OD) pair of terminals, the primary load pattern gives the primary break of the origin whereas the direct load pattern indicates which terminal to go to if the primary break is bypassed. For example, consider the shipment moving from *Boston* to *Los Angeles*, which are both end-of-lines in Figure 1.2. The primary break of *Boston* (going to *Los Angeles*) is *New York*. and the primary break of *New York* (going to *Los Angeles*) is *San Francisco*. Thus. the primary shipment route is *Boston* → *New York* → *San Francisco* → *Los Angeles*. If the load pattern indicates that *San Francisco* is a direct for the *Boston-Los Angeles* pair. then shipments can bypass *New York* and go to *San Francisco* directly provided that there is enough of such shipments. In most cases. there is one primary route and there is at most one direct route for any OD pair of terminals. Notice that in practice. shipments may not follow routes that are in load patterns: such routes are referred to as *opportunistic directs*. However. opportunistic directs are exceptions rather than rules in LTL operations. Hereafter. a trailer that is moving on a primary route is referred to as a *primary trailer* whereas a trailer that is moving on a direct route a *direct trailer*.

Generally speaking. the shipments using direct routes pass through the least number of breaks. but spend more time at each terminal since it usually takes longer to fill a direct trailer. Furthermore. if a direct trailer cannot be filled to certain level (of capacity) within a given period of time. the shipments on this trailer may be unloaded and then reloaded in the corresponding primary trailer.

1.1 Terms

Some of the terms specific to LTL carriers used extensively in this dissertation are described as follows.

- Breakbulk terminal: A breakbulk terminal is a primary sorting facility in an LTL network. At breakbulk terminals. the shipments are sorted by destination and sent by linehaul truck either to the destination or to another breakbulk terminal. Each breakbulk terminal serves a set of satellite EOLs. giving rise to hub and spoke networks.

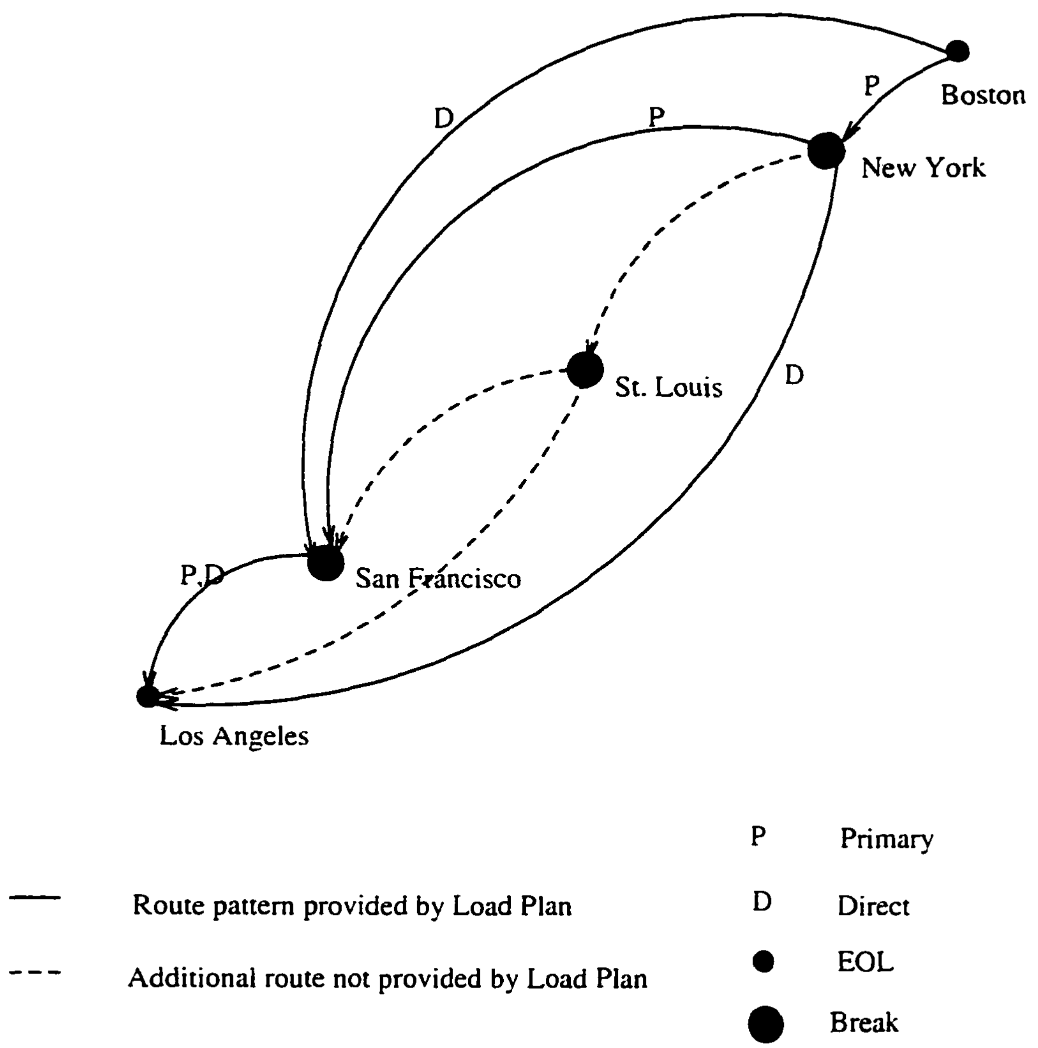


Figure 1.2 Primary and direct load patterns for shipments from Boston to Los Angeles

- Current inventory level/shipment level: The amount of shipments between a OD pair at current time is referred to as the current inventory level/shipment level.

- Daily dispatch service: Between certain OD pairs. a trailer is dispatched daily at the same time. if the minimum trailer capacity is reached. This type of dispatch is called the daily dispatch service.

- Direct service: Starting from an origin (EOL or breakbulk) when there are enough shipments either to the destination or to the consolidation facility closest to the destination. the linehaul trailer is sent to the destination or to the breakbulk closest to the destination in order to minimize the handling cost at the nearby breakbulk facility. Such a service between a given origin terminal and the destination or consolidation facility closest to the destination is called direct service.

- End of line terminal (EOL): An LTL network typically consists of a large number of EOL terminals located in various cities in a region for a regional carrier or located across the country for a large national carrier. Freight is picked up in a city or from nearby locations by a fleet of pickup and delivery trucks and then carried to the EOL terminal where the freight is usually unloaded. sorted. and loaded into the linehaul trailers.

- Far break: Starting from an origin when a direct service is used to reach a destination (which is a breakbulk). this breakbulk is called a far break (FBreak).

- Far EOL: Starting from an origin when a direct service is used to reach a destination (which is an EOL). this EOL is called a far EOL (FEOL).

- Holding time: The time between the opening of a trailer and the closing of a trailer is called holding time. A trailer is opened when first shipment between a particular OD pair is loaded into it. A trailer is closed for dispatch for several different reasons. A trailer can be closed because it is filled to capacity or if one or more of the shipments in the trailer cannot meet its service commitment if the trailer is delayed any further. Also, it may be closed if it has been occupying one of the terminal longer than planned causing congestion.

- Intermodal: If the freight uses more than one mode of transportation, such as truck, rail and/or ship to reach its destination, then it is called intermodal.
- Load plan: For all possible OD pairs, specifying the consolidation terminals for primary, direct, and opportunistic direct service is called load plan.
- Loading time: The time difference between the trailer closing time and the actual loading time of a shipment in the trailer is called the loading time for the shipment.
- Maximum holding time: The maximum time that a trailer can be held at a terminal after it has been opened is called maximum holding time. This time is dependent on the type of terminal.
- Opportunistic Direct: Starting from an origin (EOL or breakbulk) when there are enough shipments between a given O-D pair, the trailer is dispatched directly to the destination without going through a consolidation facility. Such a service is called opportunistic direct service.
- Primary service: Starting from an origin (EOL or breakbulk) when there are not enough shipments to the destination, the linehaul trailer is sent to the nearest consolidation (breakbulk) facility in order to minimize the number of empty miles traveled. Such a service between a given origin terminal and the nearest consolidation terminal is called primary service.
- Time to make service (TTMS): For any shipment, the time to make service (TTMS) is the time difference between the service commitment and the average time it takes

to transport the shipment from the current location to its destination. In other words. TTMS is the maximum amount of time a shipment can be delayed without affecting the service commitment at any time.

- Transfer ratio: The average number of consolidation terminals at which a shipment is handled other than the origin and destination terminal is called transfer ratio.
- Unloading time: The amount of time needed to unload a trailer is called the unloading time.
- Waiting to dispatch time: The time difference between the actual dispatch time and trailer closing time is called the waiting to dispatch time.
- Waiting to unload time: The time difference between the actual time of unloading and arrival time of the trailer is called the waiting to unload time.

1.2 Costs

The following costs are associated with transporting a shipment from an origin to its destination:

- Pick up cost: The cost to pick up shipments from customers using pickup trucks and bringing them back to an EOL is called the pick up cost.
- Delivery cost: The cost to deliver shipments to customers using delivery trucks. usually from an EOL is called the delivery cost.
- Transfer handling cost: The cost incurred in handling a shipment at an intermediate consolidation terminal is called the transfer handling cost.
- Travel cost: The cost incurred in the actual transportation of shipments is the travel cost. Examples are the costs of fuel. equipment. and driver.

- Origin handling cost: The cost incurred in handling shipments at the origin terminal is called the origin handling cost.
- Destination handling cost: The cost incurred in handling shipments at the destination terminal is called the destination handling cost.

1.3 Parameters

The following parameters affect the cost of transporting a shipment from an origin to its destination:

- Holding time
- Type of terminal
- Day of the week
- Time of the day
- Current inventory level
- TTMS of shipment
- Minimum capacity of the trailer that needs to be filled for dispatch
- Load plan
- Daily dispatch
- Interaction between the factors (holding time. TTMS. minimum capacity of the trailer that needs to be filled)

Next. a brief overview of other chapters in this dissertation is provided. Chapter 2 describes the literature on the dynamic priority shipment routing problem. the dynamic stochastic shortest path problem. the dynamic service network design. vehicle dispatching problems over a single link. and literature on simulation models developed for logistics support. In addition. the models and solution approaches developed in this research are compared to the ones available in the literature.

Chapter 3 describes a decision support system developed to assist LTL managers in day-to-day operations. as well as for strategic and tactical analysis (for scenario evaluation) of new decisions and policies of the management. The model simulates the load (bill) movements on a trailer based on the load plan (routes). speed restrictions. trailer capacity. currently available load at the terminal. rail schedules. and certain minimum utilization of the trailers. Because the simulation model was created using an object oriented programming approach. the user is presented with a model in which input can be easily changed to implement the different load plans. service level or the logic can be changed to incorporate new service policies such as daily dispatches and opportunistic directs. The model developed is also used by LTL carriers to estimate the number of trailers that will be closed in the next 24 or 48 hours so that LTL carriers can move the necessary empty trailers and drivers to those locations based on the number estimated. The model is also used to perform some numerical experiments to find the effects of direct service. opportunistic direct service. TTMS. holding time. and minimum capacity at which the trailer is closed on the total cost of the system and number of bills delayed.

Chapter 4 focuses on routing priority shipments in LTL service networks. Currently. LTL carriers route both regular and priority shipments through their service networks by using some fixed route patterns known as load plans. In this research. an alternative routing strategy for priority shipments in LTL networks is considered. This strategy exploits the stochasticity and dynamism embedded in the routing process and uses the real-time information at terminals (such as loading status of trailers and driver availability) to determine the shipment routes dynamically. This strategy is formulated as the problem of finding the dynamic shortest path over a network with random arc costs. An efficient algorithm that can solve this optimization problem in real-time is developed. The numerical testing using real data sets suggests that the proposed strategy can improve the level of service for priority shipments.

Chapter 5 describes how to optimize the dispatch of a trailer over a single link. Existing solutions to the vehicle dispatching problem are limited to simple problems with assumptions such as stationary demand pattern. An approximate dynamic control policy for dispatching a trailer in which the demand is assumed to be dynamic is proposed in this research. Since the solution to the single link problem can be further extended to solve large LTL networks. the developed approximate solution procedure should be fast. A recourse function is developed which gives the total future cost from current time. given the current state of the system. The dynamic control policy exploits the linearity of the recourse function in solving the trailer dispatching problem efficiently. The algorithm is easy to implement and computationally fast. The dynamic control policy developed in this research is not proved to be optimal. but the numerical results show that it is effective.

Chapter 6 briefly summarizes the results of this research and points out future possible extensions to this research.

2 LITERATURE REVIEW

Modeling of freight transportation systems results in mathematically complex problems and that the design of exact optimal algorithms for problems of this complexity tends to be cumbersome and slow. Moreover, no formulation can capture all interaction possibilities, all the written and unwritten policies and rules, or all the complexities of the real life transportation system. So the first part of the research develops a decision support system for LTL managers to investigate the possibilites of scenario evaluation by using a simulation model. Kelton [34] discusses recent developments in simulation research and current directions as well as how research interacts with practice and software development and makes projections for future research. Some of the simulation research that attempts to do this is described in this chapter.

Lai, Lam, and Chan [38] developed a simulation model of the shipping company's operational activities and used the model to identify the policies that yield the lowest operating costs in terms of leasing, storage, pickup, and drop-off charges. According to the authors, this study provides insights that result in substantial savings to the shipping company while increasing customer satisfaction. Sheikh, Paul, Harding, and Balmer [64] developed a microcomputer-based simulation model for planning future berth requirments at a third world port and described how this simulation model was helpful to the consultants. Park and Noh [46] developed a port simulation model to simulate the future economic port capacity to meet the projected cargo demand. The first part of the model determines the effects caused by the port capacity expansion and the second part evaluates the port economics due to changes in the port capacity. Park and Noh also tested the simulation model by applying it to the actual port expansion followed at the Port of Mobile in Alabama.

Petersen and Taylor [47] developed a discrete event simulation model for rail and used it to evaluate train performance and line capabilities. different track facilities and dispatching procedures and rules. Since. the simulation models are usually detailed representations of the actual network and the operations of the rail company they are considered highly credible by the industry. according to Dejax and Crainic [19]. Rail companies have traditionally used simulation models to assess the impact of operating policies and strategies. a review of such simulation models for the rail industry are given by Assad [2]. Sharma. Asthana. and Goel [63] described a decision support system to assist railroad managers in day-to-day as well as long term planning of train operation and studied advantages of augmentation of infrastructure by simulating the train movements on a rail road. Randhawa. Brunner. Funck. and Zhang [60] developed a discrete event object-oriented modeling environment for sawmill simulation. The model is flexible in modeling different sawmill configurations and production scenarios. and the system represents a library of objects developed in an object-oriented framework. Semenzato. Lozano. and Valero [62] described a discrete event simulation model for sugar cane harvesting operations to minimize the quantity of discarded cane and to optimize the utilization of resources.

Although available literature suggest decision support tools and simulation models for the rail/shipping industry. little is known about the availability of such decision support tools for the LTL industry. Therefore. this research develops a decision support tool for LTL managers to study. analyze. and plan LTL operations so that scarce resources are used more effectively and efficiently. The decision support tool also illustrates the complicated interactions among the shipment route. closing rules. cost. and service level. The decision support tool can also be used by LTL managers in day-to-day operations as well as for long-term planning of LTL operations. For example. the decision support tool can be used to estimate the number of trailers that will be closed in the next 24 or 48 hours. This data can then be used by LTL managers to determine empty vehicle repositioning and driver scheduling.

In the existing literature. simulation models are also used with an optimization model to optimize certain criteria. One such paper by Ratcliffe. Vinod. and Sparrow who uses a hybrid approach of simulation and optimization to optimally preposition the empty freight cars by increasing the number of revenue trips accomplished in a given period of time. A linear transportation program is used to find the optimal car movements based on supply and demand. The excess supply is moved to nodes that minimize the total expected transit time given the demand distribution. which is solved using a stochastic linear programming model. The two optimization programs are linked and driven by a simulation model. that simulates the actual operation of a rail carrier.

Literature related to the second part of the research falls into two categories: (1) research on LTL networks. and (2) research on solving dynamic and stochastic shortest path problem (DSSP). Majority of the literature available on LTL networks determine the best driver routes and shipment routes (that is. the load plan) on the basis of average flow pattern which is briefly described below. Powell and Sheffi [54] and Powell [57] formulated the design problem as a large-scale mixed integer programming problem and developed some heuristics to determine how to consolidate flows of shipments over the network. Powell and Sheffi [55] further extended this work by developing an interactive optimization system so that the users can more effectively plan for hard to quantify constraints. Keaton. M. H. [33] determines number of terminals. and the routing of trucks between terminals. to minimize costs subject to service level constraints. Heuristic techniques are used to solve this problem and using the model he determines the minimum operating costs for hypothetical firms at various density levels. Crainic and Rosseau [11] used a decomposition and column generation principle to determine what type and level of service to offer on what routes. in what modes. and how often.

Akyilmaz [1] proposed a method to determine shipment routes with the objective of minimizing the total empty ton-km. Hall [28] and Daganzo [14] developed a routing scheme where shipments are consolidated at the terminals that are nearest to the origin or destination. Recently, Farvolden and Powell [22] used a subgradient optimization approach for determining where to introduce and cancel service in the network. In contrast, rather than determining the shipment route pattern, Crainic and Roy [12] focused on determining the routes for intercity drivers in an LTL network. Finally, Barnhart and Sheffi [3] developed a primal-dual heuristic approach for solving large-scale multicommodity networks and applied this technique to the problem of determining optimal vehicle routes.

The majority of research on the stochastic shortest path problem has focused on a static version where it is assumed that the arc costs are realized at once and the path is fixed once the path is chosen. Such static versions of the stochastic shortest path problem are discussed by Frieze and Grimmet [24] and Mirchandani [42]. Frieze and Grimmet [24] considered the problem of finding the shortest distance between all pairs of vertices in a complete digraph of n vertices, whose arc lengths are non-negative random variables. On the other hand, Mirchandani [42] developed an algorithm to compute the expected shortest time between nodes when the travel time on each link has a given independent discrete probability distribution.

Research on solving DSSP has been found to be limited: it is noticeably absent from the surveys by Dreyfus [21], Pierce [48], Deo and Pang [20]. Croucher [13] proposed an algorithm to determine a dynamic shortest route when there is a positive probability associated with each node that a particular outbound arc does not exist. Furthermore, it assumed that if an outbound arc does not exist, each of the remaining arcs has an equal probability of being traversed, regardless of their costs. Hall [27] developed a dynamic programming approach to find the expected fastest path between two nodes in a network with travel times that are both random and dependent on arrival time at a node. Psaraftis and Tsitsiklis [59] and Bertsekas and Tsitsiklis [4] considered the shortest path problem in acyclic networks where the arc costs depend on certain environmental variables that evolve according to a Markov process. Mirchandani and Veatch [41] considered the routing of a hot job through a job shop network to minimize its expected completion time when workstation processing time changes in a Markov fashion. Finally. Orda *et. al.* [44] considered the problem of traveling with the least expected delay in dynamic computer communication networks where link delays change probabilistically according to Markov chains. In addition. Orda *et. al.* provided a simple polynomial optimal solution for networks with nodal stochastic delays. Polychronopoulos [49] summarized the results of static version of the shortest path problem and also described the DSSP and also proposed was a simple solution approach to find the expected cost of the dynamic shortest path in a network where arc costs are discrete. independent. and finite random variables.

Differing from most research on LTL networks that focus on static planning for shipment routes. this research addresses a dynamic aspect of shipment route planning. This research considers an alternative strategy for routing priority shipments and this alternative routing strategy is formulated as a DSSP model. This model is different from those studied in the literature in the following ways (1) the arc costs are independent. discrete. and finite random variables. and (2) the arc costs are realized dynamically. and re-routing can be made whenever a node is reached. For solving the DSSP model. a low-order. polynomial-time algorithm is developed. Through some numerical experiments using a real data set. the impact of the explicit considerations of stochasticity and dynamism for shipment routing in LTL networks is also highlighted.

Literature related to dynamic service network design falls into two categories: (1) research on LTL networks and (2) research on the single-link vehicle dispatching problem. Several criteria may be used to classify the vast amount of literature on LTL networks. The three different levels of planning problems are usually classified as strategic level.

tactical level and operational level. At the strategic level. the following types of decisions are made: the physical network design (size and location of breakbulks and end-of-lines and the alignment of end-of-lines with breakbulks). allocation of investments. pricing and costing policies. At the tactical level. the following types of decisions are made: demand forecasting. fleet sizing. routing of loaded trailers based on the forecast data and flow restrictions (Maximum number of trailers that can be handled at a breakbulk facility). where to offer direct service. and when to move the empty trailers to appropriate locations based on the forecast data. At the operational level. the following types of decisions are made: day-to-day operational decisions such as scheduling(which load must be assigned to which driver). when to release the loads. when to use rail. and how to route/schedule the drivers and what should be the optimum dispatching rules.

The models which address the operational level problems can be real-time approaches or can address problems over a short planning horizon. The problems can also be classified based on the fundamental nature of the problem. such as transportation mode (rail. truck navigation. or multimode). type of company (freight carrier or an industrial firm for interplant transportation or for distribution of products or for transportation of supplies). and type of flow (flow of empty vehicles only or flow of both loaded vehicles and empty vehicles sequentially or concurrently). The problems can also be differentiated based on solution methodology such as modeling assumptions (time domain may be static or dynamic. and quantities such as demand. and travel time may be stochastic or deterministic). modeling approach (algebraic formulation for subsequent optimization using mathematical programming techniques. analytic stochastic models such as queueing models or simulation models). and solution techniques (such as mathematical programming. network algorithms. stochastic optimization. or simulation). Several of these problems are addressed by the researchers in the literature. The related literature is summarized in Table 2.1.

Literature related to dynamic service network design and service network design for

Table 2.1 Related literature

Topic	**References**
Tactical planning	T. G. Crainic. and J. M. Rousseau [11]
Strategic planning for rail/intermodal	T. G. Crainic. M. Florian. and J. Leal [9] J. Guelat. M. Florian. and T. G. Crainic [25]
Intermodal policies for rail road	M. S. Bronzini. and D. Sherman [5] K. Morlok. Edward. and Linda Nozick [43]
Train routing and empty car distribution makeup	A. E. Haghani [26]
Truck backhaul optimization	W. C. Jordan [31]
Freight consolidation	J. F. Campbell [6] C. F. Daganzo [15]
Routes for LTL carriers	C. Barnhart. and Y. Sheffi [3] J. F. Campbell [6] R. W. Hall [28] R. W. Hall [29] Jacques Roy. and T. G. Crainic [61]
Comparative evaluation of route choice models	M. A. McGinnis [40]
Common carrier/private fleets shipment frequency optimization	R. W. Hall. and M. Racer [30]
Hub location problems	J. F. Campbell [7]
Routing priority shipments	Raymond K. Cheung. and B. Muralidharan [8]
Survey(predictive models and service design models)	T. G. Crainic [10] [10]
Survey (Empty flows and fleet management models)	P. J. Dejax. and T. G. Crainic [19]
Design of driver routes	T. G. Crainic. and J. Roy [12]
Dynamic fleet management	W. B. Powell. T.A. Carvalho. G.A. Godfrey. and H. P. Simao [51]

Table 2.1 (Continued)

Topic	**References**
Service network design	C. F. Daganzo [14] J. M. Farvolden. and W. B. Powell [22] M. H. Keaton [33] W. B. Powell [50] W. B. Powell. and Y. Sheffi [54] W. B. Powell. and Y. Sheffi [55]
Stochastic/Dynamic vehicle allocation	L. F. Frantzeskakis. and W. B. Powell [23] W. B. Powell. [57] W. B. Powell. [58]
Origin-Destination specific operating costs	A. F. Daughety. M. A. Turnquist. and S. L. Griesbach [16]
Dynamic arc routing	J. Lysgaard [39]
Simulation and optimization	K. K. Lai. K. Lam. and W. K. Chan [38] E. R. Petersen. and A. J. Taylor [47]

LTL carriers are briefly described below. Powell. Carvalho. Godfrey and Simao [51] introduced a new framework called the Logistics Queueing Network for modeling and solving dynamic fleet management problems. The large problem was broken down into smaller subproblems. and the subproblems were solved to obtain the solution for the large problem. Frantzeskakis and Powell [23] used a convex approximation method to solve the dynamic fleet management problem on stochastic networks. Jacques Roy and Crainic [61] evaluated the changes in routing due to changes in demand variations. transportation services (rail). and changes in network configuration by modeling the freight routing problem as a non-linear mixed integer programming problem. McGinnis [40] compared the four models of freight transportation the classical economic model. the inventory theoretic model. the trade off model and the constrained optimization model.

Powell [58] proposed a simple methodology that calculates the marginal value of an additional vehicle in each region in the future and uses this information to generate a standard pure network that can be efficiently optimized to give dispatching decisions for current operations. Lysgaard [39] used heuristics to solve the vehicle routing and scheduling problem in dynamic transportation networks. He assumes in his dynamic network that some of the arcs are present only during discrete times (arcs due to trucks traveling in ferries). Daughety. Turnquist and Griesbach [16] developed a model for rail that allows estimation of marginal operating costs on an OD basis and used this estimation to compute service cost and also to decide between which O-D pairs service needs to be provided to maximize profit. Powell [56] addressed the vehicle dispatching problem with general holding and cancellation strategies. His study assumes that a vehicle dispatch could be cancelled if the dispatch rule was not satisfied within a certain period of time. For example a driver should not be kept waiting at a terminal for an extended period of time.

The vehicle dispatching problem over a single link have been addressed by many in the literature. In particular, Kosten [35] (Medhi [37], and Kosten [36]) addressed the problem of dispatching a truck over a single link in which a truck was dispatched whenever the number of waiting passengers exceeded a certain threshold. Deb and Serfozo [18] assumed that the waiting cost per customer was an increasing function of the number of customers in the queue and showed that the optimal decision to this problem had a control limit structure, proving that Kosten's [35] solution to the single link problem was optimal. Weiss and Pliska [65] assumed that the waiting cost per customer was a function of the waiting time of the customer. They showed that the optimal decision is to send a vehicle if the marginal waiting cost is equal to the optimal long run average cost.

Differing from most research on the single link vehicle dispatching problem, this research addresses a dynamic aspect of when to dispatch a trailer over a single link. Most of the literature assumes a steady state and finds a single threshold value by optimizing a particular function. As, most practical applications are dynamic, a dynamic control policy is needed. But, calculating a dynamic dispatch policy cannot be done effectively using the techniques proposed in the literature because most of the literature assumes steady state. Therefore, a dynamic control policy for dispatching a trailer has been the major focus of this research. This research has been considered to be different from those in the literature in that a new algorithm has been developed to calculate an approximate dynamic dispatch policy. A recourse function is developed which gives the total cost of the system starting from current time, given the state of the system at current time. This policy exploits the linearity of the recourse function thus developed in solving the trailer dispatching problem. Numerical experiments show that the dynamic dispatch policy outperforms the stationary dispatch strategy and that the solution obtained is close to the optimal. The algorithm developed has been found to be computationally fast and hence can be used for optimizing large LTL networks efficiently and effectively.

3 SIMULATION MODEL AND ANALYSIS

3.1 Introduction

The objective of the first part of this research is to develop a decision support tool to assist LTL managers in studying, analyzing, and planning LTL operations so that scarce resources (tractors, trailers, drivers, doors) are used more effectively and efficiently. The decision support tool is based on simulation model because there are multiple goals that often contradict each other and a simulation model assists in understanding the complicated interactions between the shipment route, closing rules, cost, and service level. The advantages of coordinated decision making as compared to local decision making are also better understood when using a simulation model. Its use also helps in reducing the risk involved in implementing new or modified policies since these new or modified policies can be tested through the simulation model before being implemented. In addition, this model provides a tool for forecasting day-to-day operations of an LTL carrier under various policies, control strategies, and network structure. This forecasting tool can help the LTL carrier in determining how many drivers and empty trailers are needed in the next 24 to 48 hours.

Simulation models have been developed and used in the literature for several different reasons. Real system exist, such as transportation or material handling systems, but experimentation is expensive or can seriously disrupt the system. Mathematical modeling of a system provides no practical, analytical or numeric solutions, which occurs in stochastic problems. The optimum parameters computed in the analytical/mathematical model can be embedded in the simulation model, and the accuracy of the mathematical model can be verified. Simulation models have also been used in the literature to analyze long periods of time in a compressed format. In addition, simulation model in the literature were developed for use as a design tool and later were transported into the actual system and reused. Since routing shipments in LTL networks satisfy most of the above reasons, a simulation model has been developed.

The primary motivation for this research sprung from the interest to develop a simulation model that could be used in day-to-day operations of an LTL carrier for accurately forecasting the number of empty trailers and the number of drivers needed in the next 48 hours at each terminal based on the present state of the system. Since, modeling a real world transportation system using an analytical/mathematical model that incorporates real world conditions, such as the union rules and other written and unwritten policies of a company is difficult, a simulation model was developed to describe the system to desired level of complexity and to easily verify that the developed model represents the actual system. Also, experimentation of new techniques can be initially tested with this model because experimentation of techniques such as dynamic routing of priority shipments, dynamic service network design in the real world is expensive or can seriously disrupt the transportation system. The simulation model developed can do a 15 day simulation in a few minutes, and several different scenarios with different parameters can be analyzed for their effect on cost/service in a relatively short period of time.

The main contribution that this decision tool makes is to provide an understanding of the complicated interactions between the shipment route, closing rules, cost, and service level. The simulation model is also used to obtain loading time distribution for the dynamic priority shipment routing problem. An object oriented style was used for the simulation model, therefore it can be easily extended for the rail/container industry. The following performance measures are examined using the simulation model:

- Utilization of the terminal
- Utilization of the trailers
- Total cost
- Service level

Numerical experiments in this chapter are done by varying the following parameters to improve the above performance measures have been summarized in this chapter and the results are tabulated:

- Closing capacity for trailers
- Number of primary. direct. and opportunistic directs in the load pattern
- TTMS parameters
- Maximum amount of time an open trailer can be held (holding time)

The remainder of this chapter has been organized as follows: First. it lists out the assumptions made in this model. Second. it lists out the policies currently followed by LTL carriers to close/unload a trailer. Third. it explains the general framework of the simulation model with an example. Fourth. it describes the input. output. and implementation details of the simulation model. Finally. the calibration and validation done on the simulation model and the numerical results obtained are explained in detail.

3.2 Model

3.2.1 Assumptions

The following simplifying assumptions are made in the simulation model:

- LTL carrier operations are restricted to domestic operations.

- Travel time between terminals is assumed to be deterministic.
- Time to load and unload the vehicle is assumed to be constant.
- Once closed, the trailer will be dispatched in a fixed amount of time, but the time is dependent on terminal type.
- Holding times for the trailers depend on terminal type.

3.2.2 Input to the model

The simulation model takes the following as input:

- Parameters/policies (rules for closing the trailer)
- Network
- Shipments
- Travel time information
- Load plan
- Service requirements
- Terminal/trailer characteristics
- Rail schedules

3.2.3 Rules for closing/unloading a trailer

The following policies are usually followed by LTL carriers in deciding when to close the trailers and when to unload the trailers. The same policies are used in this simulation model to close/unload a trailer:

- If the trailer is filled to a certain minimum capacity, the trailer is closed.

- If the TTMS of a certain number of shipments is violated for a direct service trailer and if the trailer is filled to a certain minimum capacity, the trailer is closed. The reason for closing is not to delay the shipments and thus violate service commitment.

- If the TTMS of a certain number of shipments is violated for a direct service trailer and if the trailer is not filled to a certain minimum capacity, the trailer is unloaded and the shipments are loaded to its primary consolidation facility. The reason for unloading is not to ship the trailers almost empty for a long distance (direct service) and thus increase the operating cost.

- If the TTMS of a certain number of shipments is violated for a primary service trailer, the trailer is closed. The reason for closing the trailer is not to delay the shipments and thus violate the service commitment. Since the trailer is going to travel empty for a short distance(primary service), it will not have a big impact on the operating cost.

- If the maximum holding time is reached for an open direct service trailer then the trailer is unloaded. The reason for unloading is not to have a trailer open in one of the terminal doors for a very long time causing congestion at the terminal. Also, if closed the trailer will be traveling empty for a long distance (direct service), so the trailer is unloaded.

- If the maximum holding time is reached for an open primary service trailer, the trailer is closed. The reason for closing is, not to have a trailer open in one of the terminal doors for a long time, thus causing congestion at the terminal and also, the trailer, if closed is going to travel empty for only a short distance (primary service).

In order to describe the closing of a trailer mathematically the following variables are defined where:

T: the time domain

s^{ttms}: the time to make service(TTMS) for the trailer $s^{ttms} \in T$

t_o: the trailer opening time. $t_o \in T$

t: the current time. $t \in T$

N: the set of terminals

i: the current terminal $i \in N$

j: the next terminal $j \in N$

S: the current inventory level ($S \in R$)

g: a function of several factors that affect unloading of a trailer

h: a function of several factors that affect the closing of a trailer

$z_t(S_t)$ a binary variable. which takes on a value of 1 if the trailer is closed at time t. 0 otherwise

$y_t(S_t)$ a binary variable. which takes on a value of 1 if the trailer is unloaded at time t from a opportunistic or direct service otherwise it takes a value of 0

The closing of a trailer is shown mathematically as follows:

$$y_t(S_t) = \begin{cases} 1 & \text{if } S_t \leq g(S, s^{ttms}, t_o, t, i, j) \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

The unload of a trailer can be mathematically shown as follows:

$$z_t(S_t) = \begin{cases} 1 & \text{if } S_t \geq h(S, s^{ttms}, t_o, t, i, j) \\ 0 & \text{otherwise} \end{cases} \tag{3.2}$$

In order to minimize cost by determining when to close/unload a trailer it is necessary to optimize the functions g and h. Numerical experiments are done using the simulation model in order to understand how the different variables in the functions g and h interact with each other.

3.2.4 General framework of simulation

The basic steps in the simulation are described as follows:

Step 1. READ network information/loadplans/service level/parameters

Step 2. FOR time_step = 1 TO N DO

Step 3. FOR each of the options = opportunistic direct. direct. primary DO

Step 4. READ bills and store in Q_t (where Q_t is defined as an ordered queue at terminal t)

Step 5. IF (capacity of the terminal is not violated) THEN

Move the bills to Q_{od} (where Q_{od} is defined as an ordered queue for bills going between origin o and destination d) based on the load pattern

Step 6. FOR each of the bills in Q_{od} available in the current time step

Step 7. IF ((certain predefined minimum capacity(x^p, x^d, x^o) of the trailer is filled between the origin and destination of the trailer) OR (((any or some of the bills in the trailer have been held for too long (t^{mp})) OR (waiting for any longer will result in TTMS constraints being violated)) AND (the trailer is a primary trailer)))

Close the trailer and dispatch:

Compute the time the trailer will reach its destination:

IF (bills have reached their original destination)

Remove the bills from the system :

IF (bills have not reached their original destination)

Add the bills to the queue Q_d at the destination:

Step 8. IF (((any or some of the bills in the trailer has been held for too long (t^{md}, t^{mo})) OR (waiting for any longer will result in TTMS constraints being violated)) AND (the trailer is a direct trailer) AND (capacity of the trailer is less than certain minimum (x^{dt}, x^{ot})))

Remove the bills and move to the primary OD:

Step 9. IF (time_step < N) GOTO Step 2.

3.2.5 Example of the simulation model

The general framework of the simulation model can be described by using a small example shown in Figure 3.1 (A. B. C. D. E. F. G). If a shipment originates at *Boston* and its final destination is *Los Angeles* and if there is an opportunistic direct service between *Boston* and *Los Angeles*. the shipment will be loaded on a trailer going to *Los Angeles* (A). If the capacity of the trailer exceeds a certain minimum capacity. the trailer is dispatched from *Boston* to *Los Angeles*: Otherwise. if the TTMS or holding time expires. then the shipment is unloaded (E) and loaded into the primary service trailer going to *New York* (D). The amount of time that the shipment spends at the *New York* terminal before being loaded into a trailer depends on the current inventory level and the congestion level at *New York* terminal. If there is no opportunistic direct service between *Boston* and *Los Angeles*. then the shipment going from *Boston* to *Los Angeles* will be loaded into a direct service trailer going from *Boston* to *San Francisco* along with shipments going to other nearby cities such as *Sacramento* and *San Diego* (B). At *San Francisco*. the trailer is unloaded. sorted based on destination and loaded into the appropriate trailer. The amount of time the shipment spends at the *San Francisco* terminal before being loaded into a trailer depends on the current inventory level and the congestion level at *San Francisco* terminal. However. if the capacity of the direct service trailer does not exceed certain minimum capacity and if the TTMS or holding time expires. then the shipment is unloaded from the direct service trailer (C) and moved into a primary service trailer going to *New York* along with the shipments going to other breaks such as *Seattle* and *Portland* (D). If the primary service trailer has a certain minimum capacity filled. the trailer is dispatched(F). but if it does not meet a certain

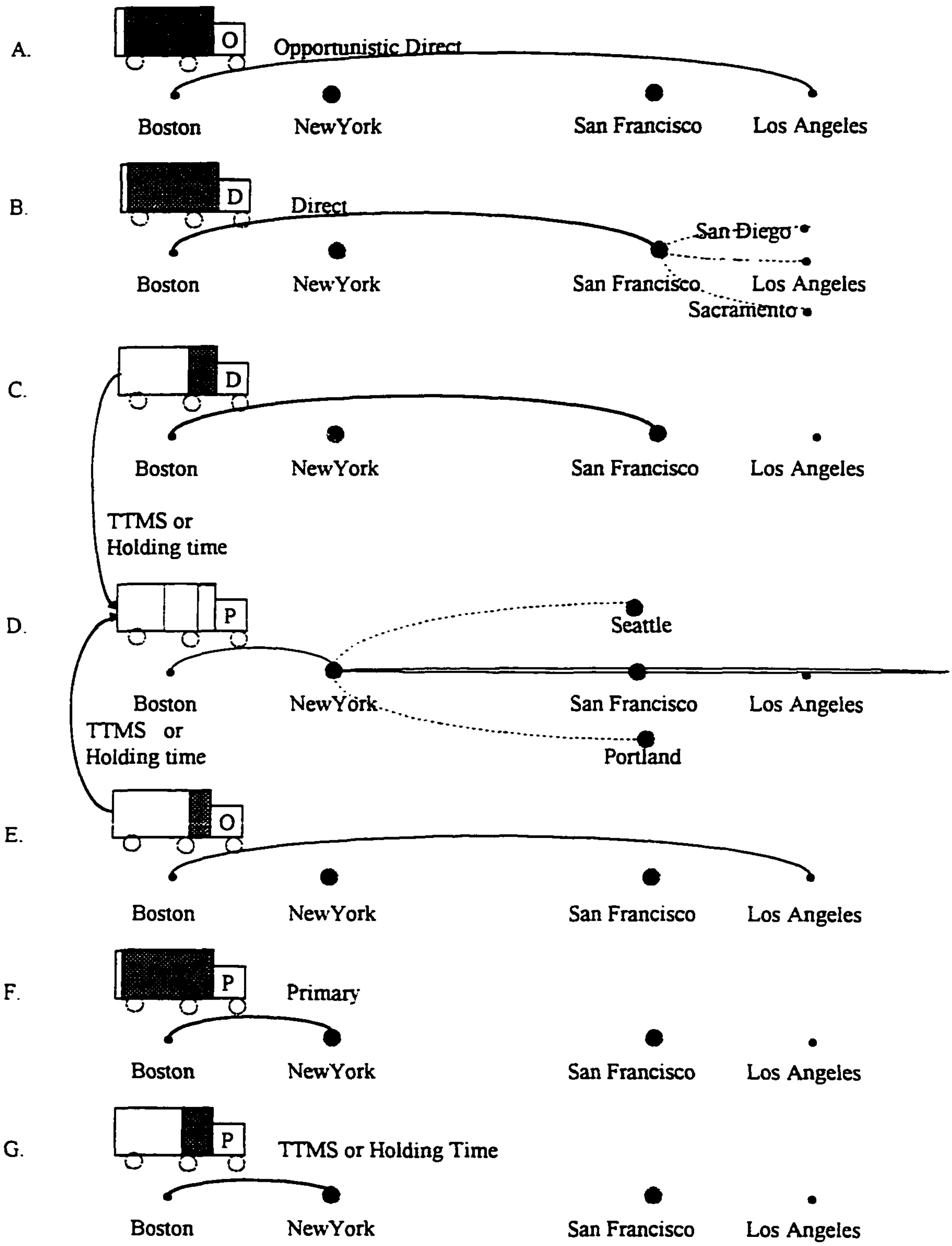


Figure 3.1 Example to describe the simulation model

minimum capacity and either the holding time or the TTMS expires. then the primary trailer is dispatched (G).

3.2.6 Output of the model

The simulation model produces the following output.

- List of trailers dispatched and related information
- OD statistics. such as the number of trailers closed. number of bills. weight of bills. and loading time.
- Bill statistics. such as number of bills delayed. transfer ratio. and average delay.
- Trailer statistics. such as capacity filled. number of bills. breakdown of closed/unloaded trailers. and trailer miles traveled.

3.3 Implementation and Object Design

In this section. object design and implementation are described briefly. The simulation model was developed using an object-oriented approach. There are several objects such as trailer. bill. OD and terminal. Functions associated with each of these objects manipulate these objects. For example. the trailer object contains all the information about the trailer such as the trailer origin. trailer destination. number of bills in the trailer. total weight in the trailer. the time the trailer was closed. the total volume in the trailer. opening time of the trailer. the time the trailer needs to depart from the current terminal in order to meet service requirements. the bucket to store the bills loaded in the trailer and the current terminal. The bill object contains information about the bill. its size. its volume. current terminal. its origin. its destination. and service date. The OD object contains information about the distance between the current origin and destination. the service commitment. whether there is a rail schedule available between the given origin and destination. and a bucket to store the bills between the given origin and destination. The terminal object contains information about terminal such as its latitude. longitude. terminal closing time. the bucket to store the bills at the terminal. the time zone. and the type of terminal. The buckets in the trailer. OD and terminal objects are implemented by using a heap data structure because it is more efficient. In the terminal bucket and the OD bucket the bills are stored according to arrival time. but the bills are stored based on the time to make service. in the trailer bucket. The bills are stored in the terminal object according to arrival time because the bill that comes first will be sorted first at the terminal and then moved to the door where it is being loaded for the corresponding OD. The bills in the trailer object are stored in a heap based on the TTMS. because it is easier to compute the time the trailer can wait at the current terminal without affecting the service commitment made to the customer. The terminal and OD objects are stored in a hash table for the following reason. A national LTL carrier can have several hundred terminals and thousands of OD pairs. In the simulation model developed. there is a need to access the terminal/OD objects from the name of the terminal/OD several times for each of the bills in the system. The name of the terminal/OD is obtained from the origin and destination of the bill. In order to access the terminal/OD object of interest from the name of the terminal/OD quickly. hash tables were used. Also. in order to check whether the above implemented model represents the actual operation of the LTL carrier. calibration and validation of the model are done as described in the next section.

3.4 Calibration and Validation

Calibration and validation are needed to show that the model developed is credible and accurately represents the system and to prove that the model is trustworthy. Calibration and validation of the model were done to ensure that the model behavior is the same as the actual system behavior.

Calibration was done by comparing the output results of the model to the actual data. Policies/control strategies used in real life were used to calibrate the model. The following statistics and measurements were used to evaluate the accuracy of the simulation. The number of trailers closed from each break in the model was compared to the actual numbers. The number of trailers closed from each end-of-line is compared with the actual numbers. The incremental/cumulative number/total weight of bills processed at each terminal and for each OD pair was compared to the actual numbers every hour. The incremental/cumulative number of trailers closed at each terminal and for each OD pair was compared to the actual numbers every hour. The number/total weight of bills processed on each day of the week was compared against the actual values for each terminal and OD pair. The number/average weight of trailers closed on each day of the week was compared against the actual values for each terminal and OD pair. Between EOL-EOL. EOL-Break. EOL-FBreak. Break-Break and Break-FEOL the number of trailers closed. number/weight of bills processed. and the average weight in each trailer were compared against the actual values. Figure 3.2 shows the plot of actual trailers dispatched against the number of trailers dispatched in the simulation model for some of the major terminals in an LTL network. Figure 3.3 shows the plot of actual trailers dispatched against the number of trailers dispatched in the simulation model for some of the major links in an LTL network.

An example of how calibration was done in the simulation model after comparing to the actual data is explained. Some specific rules were ignored in the forecasting/simulation model because these rules did not seem to have a significant impact on LTL carrier operation. However. certain other rules were incorporated in the simulation model. Since the simulation model identified the existence of some inconsistencies in the simulation data and actual data at some specific terminals and services. where these rules are applied. such as the daily dispatch. reduction in threshold capacity for closing

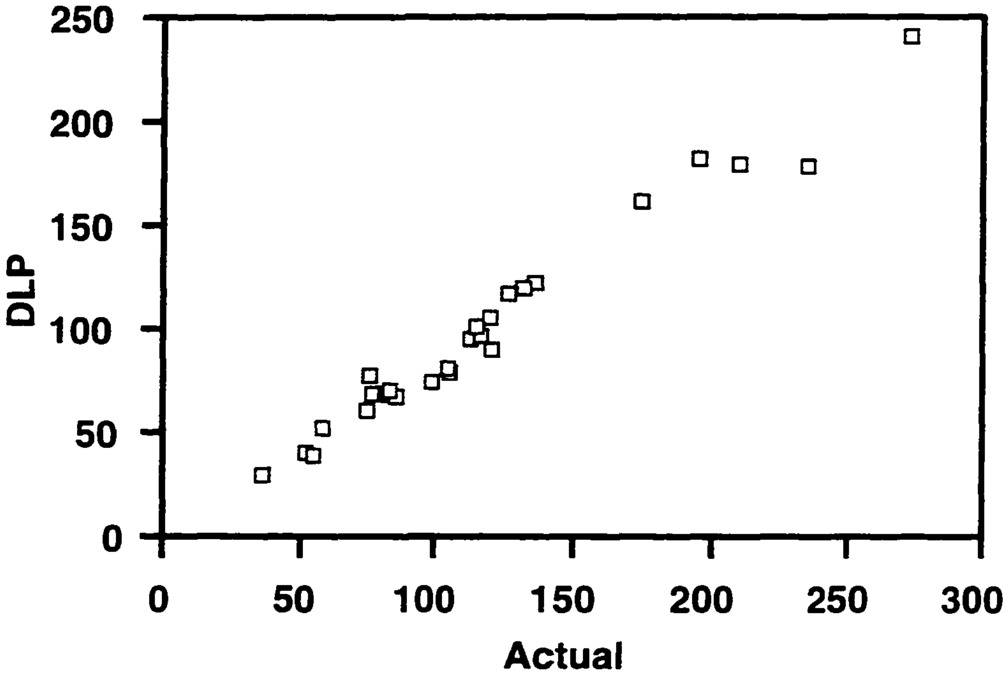


Figure 3.2 Actual vs DLP number of trailers dispatched for major terminals (Graph scaled for confidentiality)

trailers, holding time, and TTMS parameters. Therefore, these rules were incorporated in the simulation model.

After the calibration, the simulation model was found accurate. The output statistics of the simulation model was compared against the actual values. The error of the simulation model when compared to the actual model was found to be less than four percent.

3.5 Numerical Results

The numerical experiments were done to assess the most effective closing rules/strategies, and to understand the complicated interactions between the shipment route, closing rules, cost, and service level and their effects on the final cost of the system and the

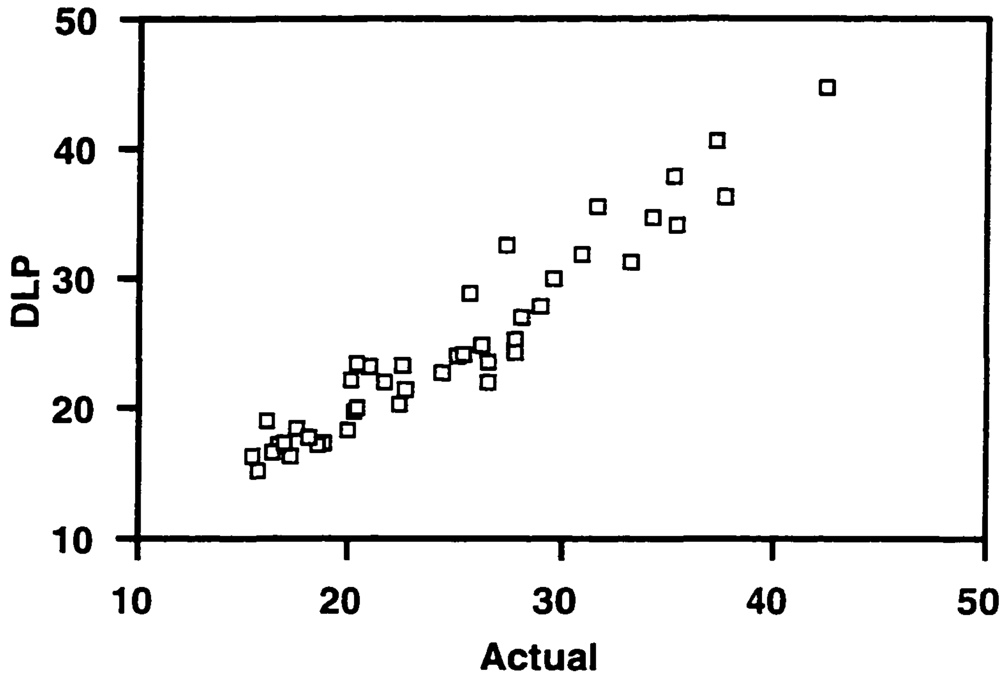


Figure 3.3 Actual vs DLP number of trailers dispatched for major links (Graph scaled for confidentiality)

service level provided.

Numerical experiments were done to compare the primary service, with primary + direct service and primary + direct + opportunistic direct service. Numerical experiments were also done to assess the effects of holding time, TTMS, closing capacity on the total cost of the system, and service level provided. The numerical experiments have been described in detail in the following sections.

3.5.1 Primary vs Primary + Direct

Hypothesis: Using primary + direct service is better than using primary service.

Expected Outcome: Primary + direct service will reduce delay, reduce operating cost, reduce transfer ratio, increase percentage of early bills, reduce percentage of late bills, and reduce trailer utilization.

As can be seen from Table 3.1. the number of bills delayed and the average time the bills were delayed was drastically reduced in the model in which both the primary and direct service are used. This was due to the fact that the bills go through a smaller number of breakbulk terminals when using direct service. It was found that the direct service also reduced the operating cost and transfer ratio. The reduced transfer ratio indicated that bills were handled in fewer breakbulk terminals and hence handling cost was reduced. Using direct service reduced consolidation. and hence the trailers travel with lesser capacity filled on average.

Table 3.1 Comparison of different service policies

Characteristic	Primary	Primary + Direct	Primary + Direct + Opportunistic
	(Values scaled for confidentiality)		
Operating cost	1.05	1.03	1.00
Number of trailers	0.94	0.93	1.00
Average trailer Capacity	1.15	1.08	1.00
Transfer ratio	1.33	1.17	1.00
Percent of bills late	1.84	1.19	1.00
Average time early	0.75	0.81	1.00
Average time late	1.30	1.19	1.00

3.5.2 Primary + Direct vs Primary + Direct + Opportunistic direct

Hypothesis: Using primary + direct + opportunistic direct service is better than using primary service.

Expected Outcome: Primary + direct + opportunistic direct service will reduce delay. reduce operating cost. reduce transfer ratio. increase percentage of early bills. reduce percentage of late bills, and reduce trailer utilization.

As can be seen from Table 3.1, the number of bills delayed and the average time the bills were delayed was drastically reduced in the model in which primary, direct and opportunistic direct services were used. This was due to the fact that the bills go through a smaller number of breakbulk terminals when using opportunistic direct service. The opportunistic direct service also reduced the operating cost and transfer ratio. Reduced transfer ratio indicated that bills were handled in fewer breakbulk terminals and hence handling cost was reduced. Using opportunistic direct service reduced consolidation and hence the average weight a trailer is filled is reduced.

3.5.3 Holding time

In the numerical experiments, the holding time was fixed at three different levels (two days, one day, half a day) to determine the effects of holding time on the total cost of operations.

As can be seen from Table 3.2, increasing the holding time reduced the transfer ratio, operating cost, the number of trailers used and the average time the bills were early. Due to increased holding time, the trailers waited for a longer period of time at a terminal to get filled. Due to this reason there was a high possibility of the trailers being closed to a direct service and hence the number of trailers utilized reduced as holding time increased. Since direct service is used more often due to increased holding time, the handling cost that was present in primary service was eliminated, which in turn reduced the total operating cost. The bills waited for a long period of time at a terminal due to increased holding time, and hence the average time the bills were early at the destination decreased. Interestingly, although the bills were held for a longer time at a terminal due to increased holding times, the average time a bill was late and the number of bills that were delayed reduced when the holding time was increased.

Table 3.2 Comparison of different holding time policies (scaled)

TTMS	Capacity	Characteristic	Holding time		
			2 day	1 day	1/2 day
75 %	High	Operating cost	1.00	1.05	1.13
		Number of trailers	1.00	1.03	1.11
		Average trailer capacity	1.00	1.03	1.06
		Transfer ratio	1.00	1.10	1.15
		Percent of bills late	1.00	0.86	0.98
		Average time late	1.00	0.80	1.02
		Average time early	1.00	0.93	0.90
	Medium	Operating cost	1.00	1.03	1.10
		Number of trailers	1.00	1.01	1.08
		Average trailer capacity	1.00	1.02	1.04
		Transfer ratio	1.00	1.06	1.09
		Percent of bills late	1.00	1.00	1.18
		Average time late	1.00	0.97	1.22
		Average time early	1.00	0.96	0.94
	Low	Operating cost	1.00	1.02	1.09
		Number of trailers	1.00	1.00	1.06
		Average trailer capacity	1.00	1.02	1.05
		Transfer ratio	1.00	1.06	1.09
		Percent of bills late	1.00	1.05	1.33
		Average time late	1.00	0.98	1.27
		Average time early	1.00	0.97	0.95

3.5.4 TTMS

In the numerical experiments. the TTMS was fixed at three different levels (55 percent. 65 percent and 75 percent of capacity filled before sending the trailer) to determine the effect of TTMS on the total cost of operations.

As can be seen from Table 3.3 decreasing the TTMS closing capacity increased operating cost and the number of trailers closed and on the other hand. reduced the percentage of late bills and average amount of time the bills were late. Since the trailers were closed with less capacity when the TTMS of the trailer expires. more trailers are closed. As many trailers were closed. the fuel. equipment. and labor costs increased and hence. increased the total operating cost. Since the trailers were closed early when the TTMS of the trailer expired. the number of late bills is reduced and the average time that the bills were late was less.

3.5.5 Capacity

In the numerical experiments. the minimum fill capacity for closing a trailer was fixed at three different levels (high. medium and low to determine its effect on the total cost of operation and on the amount of early/late bills.

As can be seen from Table 3.4. decreasing the closing capacity increased the operating cost. the number of trailers closed. the number of late bills. amount of time the bills were late and the average amount of time the bills were early and on the other hand reduced the utilization of the trailer and the transfer ratio. Since the closing capacity was reduced. more trailers were closed at less capacity and hence operating cost increased due to increase in labor. equipment. and fuel costs. Since the trailers are closed at low capacity. the bills were early and. hence the average amount of time the bills were early increased. Interestingly. decreasing the closing capacity did not decrease either the number of late bills or the average amount of time the bills were late.

Table 3.3 Comparison of different TTMS policies (scaled)

Capacity	Holding Time	Characteristic	TTMS Closing 55%	65%	75%
High	2 day	Operating cost	1.07	1.04	1.00
		Number of trailers	1.08	1.04	1.00
		Average trailer capacity	1.01	1.01	1.00
		Transfer ratio	1.02	1.01	1.00
		Percent of bills late	0.51	0.65	1.00
		Average time late	0.63	0.76	1.00
		Average time early	0.98	0.99	1.00
	1 day	Operating cost	1.07	1.04	1.00
		Number of trailers	1.06	1.03	1.00
		Average trailer capacity	1.01	1.00	1.00
		Transfer ratio	1.02	1.01	1.00
		Percent of bills late	0.57	0.68	1.00
		Average time late	0.68	0.78	1.00
		Average time early	0.99	0.99	1.00
	1/2 day	Operating cost	1.05	1.02	1.00
		Number of trailers	1.04	1.02	1.00
		Average trailer capacity	1.00	1.00	1.00
		Transfer ratio	1.01	1.01	1.00
		Percent of bills late	0.62	0.73	1.00
		Average time late	0.68	0.79	1.00
		Average time early	1.00	1.00	1.00

Table 3.4 Comparison of different policies (Capacity)(scaled)

TTMS	Holding Time	Characteristic	Capacity		
			High	Medium	Low
75%	2 day	Operating cost	1.00	1.02	1.04
		Number of trailers	1.00	1.03	1.07
		Average trailer capacity	1.00	0.95	0.89
		Transfer ratio	1.00	0.98	0.97
		Percent of bills late	1.00	1.05	1.11
		Average time late	1.00	1.03	1.14
		Average time early	1.00	1.01	1.02
	1 day	Operating cost	1.00	1.01	1.03
		Number of trailers	1.00	1.04	1.07
		Average trailer capacity	1.00	0.94	0.88
		Transfer ratio	1.00	0.98	0.97
		Percent of bills late	1.00	1.05	1.05
		Average time late	1.00	1.03	1.07
		Average time early	1.00	1.02	1.03
	1/2 day	Operating cost	1.00	1.02	1.03
		Number of trailers	1.00	1.03	1.07
		Average trailer capacity	1.00	0.95	0.90
		Transfer ratio	1.00	0.99	0.98
		Percent of bills late	1.00	1.00	1.00
		Average time late	1.00	1.03	1.05
		Average time early	1.00	1.02	1.04

3.5.6 Congestion

The simulation model can also be used to identify the most congested breaks/under-utilized breaks so that the EOL's can be reassigned to reduce congestion/increase utilization. Figure 3.4 shows congested breaks and breaks which are underutilized if specific load plan and policy were used and for specific configuration of the terminal. The policies and load plans can be changed to ensure that the congestion is avoided and that underutilized terminals are properly utilized. These experiments in changing the policies. and the load plans to reduce the congestion or to increase utilization are costly and impossible to be done on the actual operations of an LTL carrier. Thus. the simulation model is very helpful in doing such experiments and for analyzing the results in a short period of time.

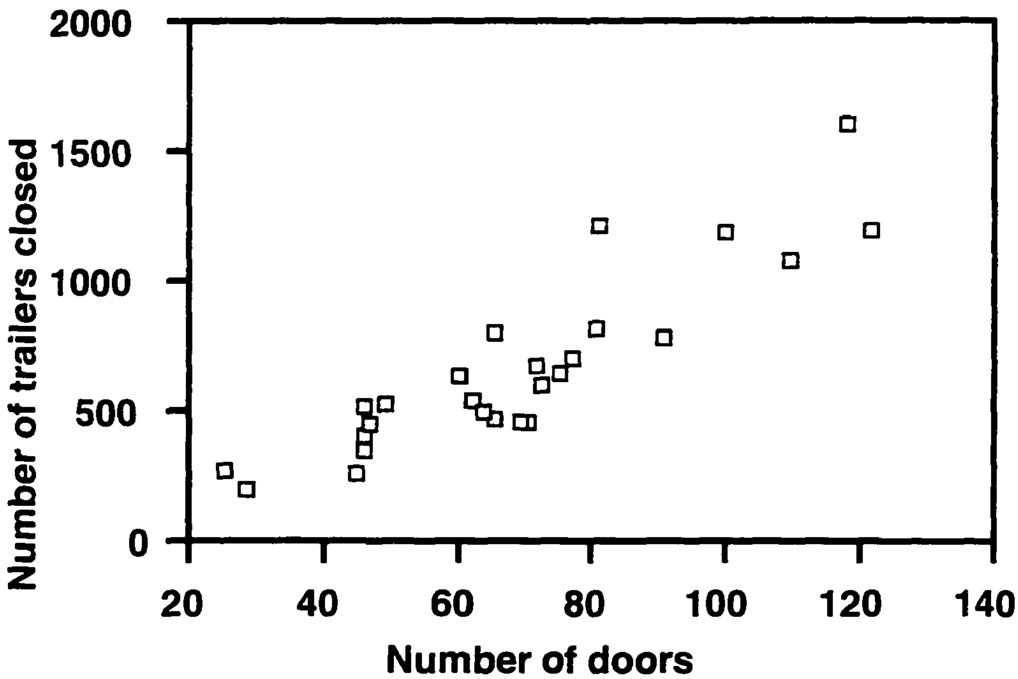


Figure 3.4 Number of doors at the terminal vs number of trailers departing from the terminal (Graph scaled for confidentiality)

The simulation model is also helpful in finding out the effects of TTMS, holding time and capacity on the total operating cost of the system and the number of bills delayed. The simulation model also indicates that decreasing the minimum capacity to be filled does not necessarily decrease the number of delayed shipments. The numerical experiments also show that decreasing the holding time does not decrease the number of delayed shipments. The number of delayed shipments is only affected by TTMS. The numerical experiments also show that using opportunistic direct service with direct and primary service is better than using primary service alone. The simulation model suggests different strategies to improve LTL carrier operations by identifying certain parameters that need to be optimized. For example, the simulation model points out that in dynamic service network design the threshold value for closing a trailer is not a single number, but a continuous function dependent on t, S_t. Also, the simulation model is useful in obtaining loading time distributions for the dynamic priority shipment routing problem. The simulation model after calibration is accurate and can be used in day-to-day operations of an LTL carrier in forecasting the number of empty trailers and the number of drivers needed in the next 24 to 48 hours.

4 DYNAMIC ROUTING OF PRIORITY SHIPMENTS

4.1 Problem Description

Currently, both regular shipments and priority shipments are routed through the LTL network using the same fixed load patterns. At a break, priority shipments receive special attention and thus require less transit time. In this research, an alternative strategy for routing priority shipments is assessed, a strategy where the route of priority shipments can be changed dynamically (that is, the choice of route is not bound by the load patterns) and is determined on the basis of real-time information, such as the congestion level and the availability of drivers at the current break.

The contributions of this research are the following. First, the proposed dynamic routing strategy is formulated as the problem of finding the expected length of the dynamic stochastic shortest path (DSSP) in networks with discrete, independent random arc costs. Second, a new efficient algorithm to solve DSSP in real-time is developed. It is also shown that the dynamism of DSSP can actually help break down the combinatorial nature that appears in the static verison of stochastic shortest path problems which are NP-hard (Kamburowski, [32]). The results of this research allows to measure the time that can be saved if the real-time information at terminals is fully used. This strategy is evaluated for conditions under which it works well, using real data.

The research was primarily motivated by the fact that a typical shipment spends more than 50 percent of the time in transit at terminals. Time spent by a typical shipment going from Boston to Los Angeles through the breaks at New York and San

Francisco is shown in Figure 4.1. While the travel time on the road over the long-haul is relatively stable, the transit time at terminals, such as the time for loading the trailer, and the waiting time for the trailer to be dispatched, can vary substantially. For example, the loading time can range from one hour to 48 hours. Thus, a natural strategy to reduce the delivery time of a shipment is to reduce the time it spends at terminals. One way is to allow shipments to use routes that are not available in the load pattern. Consider the shipments currently at the New York break that are scheduled for dispatch to Los Angeles. The load pattern indicates that the shipment should go through the San Francisco break with an estimated travel time (on road and in transit) of 80 hours. However, if the trailer that goes from New York for San Francisco had departed recently, the next trailer will not depart for at least another 20 hours. In contrast, the trailer that goes from New York for St. Louis is ready to depart and the estimated travel time using this route is 90 hours. In this example, it will be faster to send the shipments through St. Louis. In the network context, this strategy can be represented by DSSP or rather finding the shortest path between a pair of nodes in a network with random arc costs (details are discussed later). Furthermore, the path can be re-routed whenever a node is reached and the costs of the arc emanating from this node are realized.

In general, there is a trade-off between the delivery time and the total cost involved. Any routing deviating from the load patterns may result in a higher cost over time. This study focuses on routing priority shipments since such shipments constitute only a small portion (typically 5 % - 10 %) of total shipments, the deviation of these shipments from the load patterns may not cause a major increase in total cost. The capability to route these shipments dynamically, however, can reduce the delivery time, which is the most critical objective for priority shipments. The assumption that the possible small increase in total cost is well compensated by the improvement of the level of service, motivates this research.

The objectives of this research are:

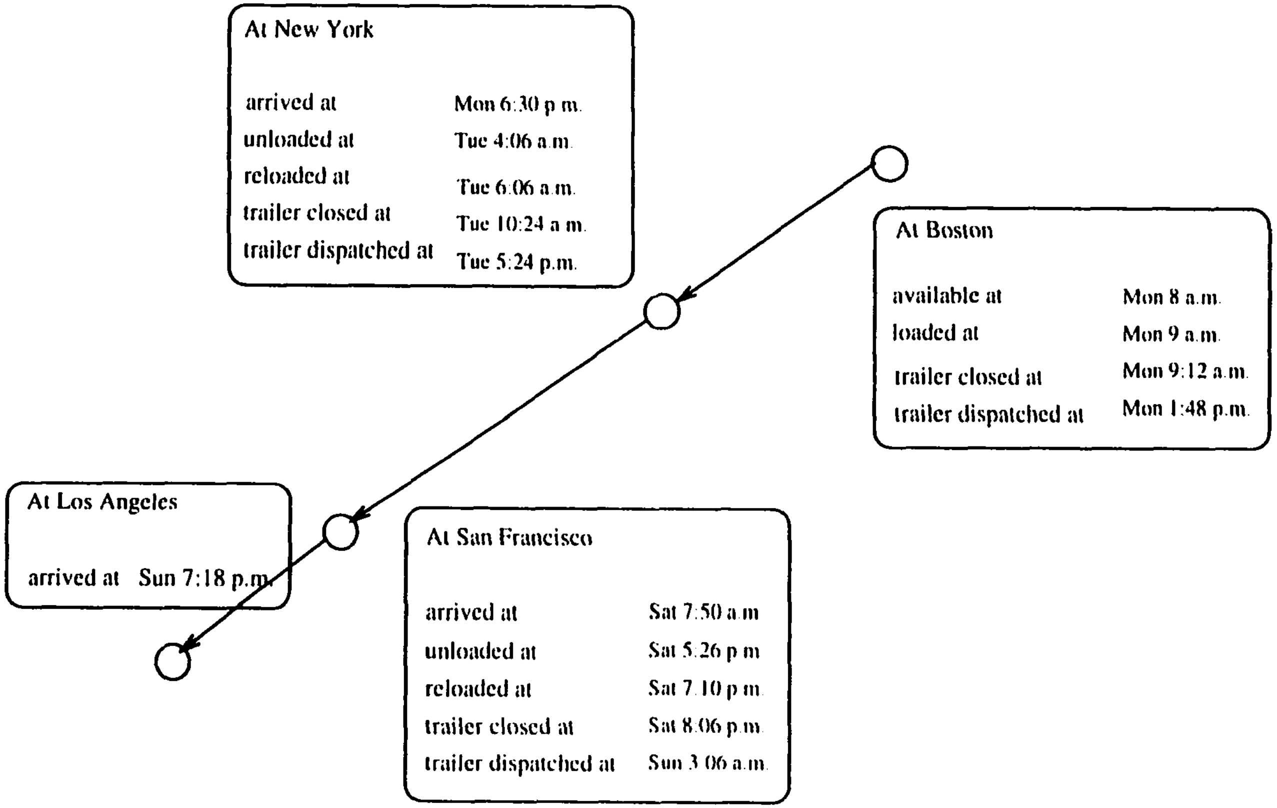


Figure 4.1 Itinerary of a shipment moving from Boston to Los Angeles.

- To find an alternative routing strategy for routing priority shipments that can improve the level of service for priority shipments
- To determine whether this alternative routing strategy can be used in real-time for a large LTL carrier
- To determine if the consideration of the stochastic and dynamic aspects of LTL routing is worthwhile

The remainder of this chapter is organized as follows. Next section. models the routing of priority shipments in a LTL network as a dynamic and stochastic shortest path problem and describes the solution approach in detail. Finally. the numerical experiments indicate the time can be saved if real-time information at the terminals is fully used. using real data sets.

4.2 Solution Methodology

As mentioned earlier. the travel time for a shipment from its origin terminal to its destination terminal consists of the time spent on the road (T_r) and the time spent at terminals (T_t) where the latter may include the following:

- Waiting to be unloaded from a trailer to an empty dock.
- Unloading shipments from the trailer.
- Loading shipments onto a trailer until the trailer door is closed.
- Waiting for the closed trailer to be dispatched.

Furthermore. if a direct trailer cannot be closed (due to excessive loading time and low capacity). additional time is needed for transferring the shipments on this trailer to a primary trailer. Although T_r and T_t are both random variables. the variance of T_r is considerably smaller than that of T_t. which depends on a wide range of factors. such as day of the week. closing times at terminals. service deadlines of the shipments. sizes of the shipments. and driver availability. Since the physical mileage between the terminals is fixed. a substantial decrease on T_r is unlikely. Hence. the primary focus should be to decrease T_t.

Consider that terminal i is an end-of-line. terminal j is its primary break. and terminal k is a far break where $i \rightarrow k$ is a direct route if the destination is terminal n.

Let.

$t^P_{i,j}$ = Transit time at terminal i if $i \rightarrow j$ is a primary route

$t^D_{i,k}$ = Transit time at terminal i if $i \rightarrow k$ is a direct route

$t_{i,kj}$ = Time needed to transfer shipments from the direct trailer ($i \rightarrow k$) to the primary trailer ($i \rightarrow j$) plus the waiting time until the primary trailer is dispatched.

$p_{i,kj}$ = Probability that the shipments on the direct trailer ($i \rightarrow k$) need to be transferred onto the primary trailer ($i \rightarrow j$)

$r_{i,j}$ = Travel time on the road from terminal i to terminal j

Routing of shipments from terminal i to the next terminal (heading to terminal n) is modeled as a network. Arc costs are used to represent the travel times. Since there are different components of travel time. some artificial nodes need to be generated in addition to creating nodes for the physical terminals. First. a node for each terminal is created as denoted by i. j and k in Figure 4.2. Second. two nodes are created. as denoted by i_j and i_k to represent the primary route and the direct route. respectively. Also. an additional node is generated as denoted by i'_k (described later). Third. arcs between nodes i and i_j and nodes i and i'_k are created with arc costs of $t^P_{i,j}$ and $t^D_{i,k}$. respectively. These arcs capture the transit time at terminals if the shipments use the primary trailer and the direct trailer. Moreover, arcs from node i_j to node j with the cost of $r_{i,j}$ and from node i'_k to k with the cost of $r_{i,k}$ are created. Such arcs reflect the travel times between terminals. Fourth, an arc is added from node i_k to node i'_k to reflect the case where the shipments on the direct trailer may need to be unloaded and put on the primary trailer. Thus, the arc cost, denoted by $\xi_{i,kj}$, is a bi-valued random variable with the following probability mass function: $\Pr(\xi_{i,kj} = 0) = p_{i,kj}$ and $\Pr(\xi_{i,kj} = \infty) = 1 - p_{i,kj}$. Finally, an arc is added from node i_k to node i_j with the arc cost of $t_{i,kj}$ to capture the transfer time.

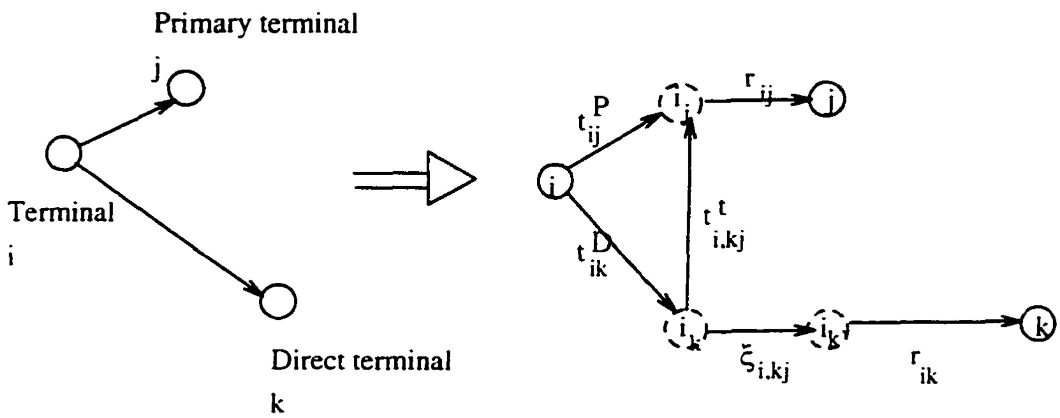
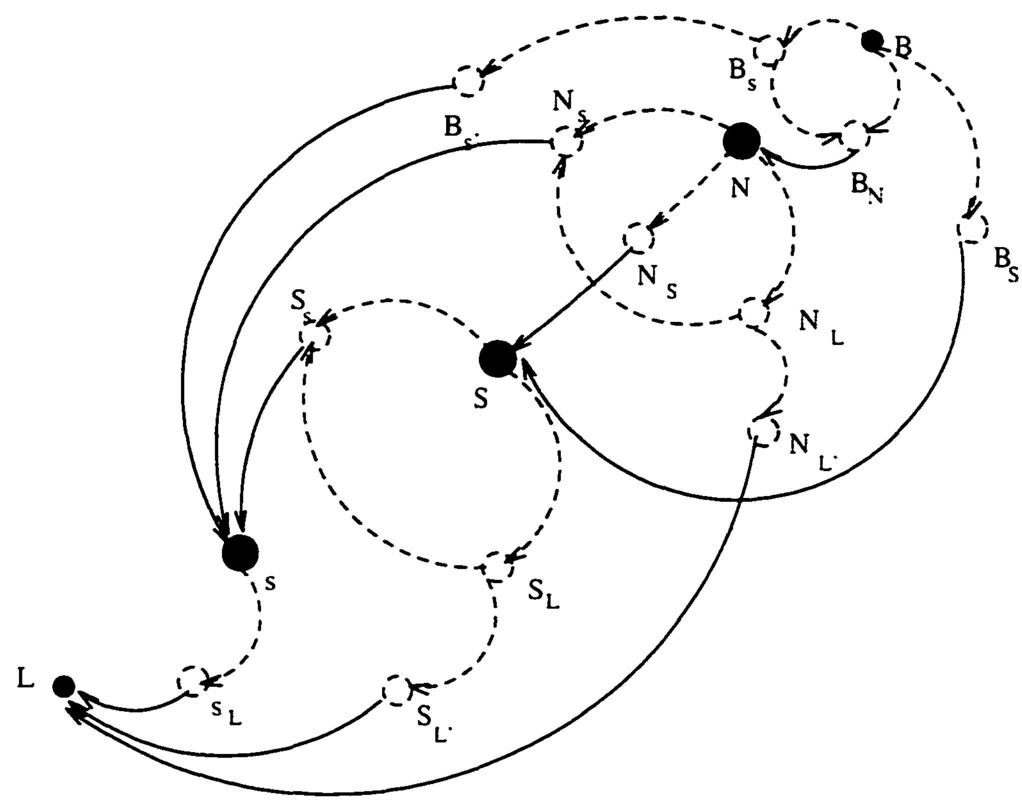


Figure 4.2 Network representation of the load patterns

The small network described above represents only the direct and primary patterns for the given OD pair. If use of other shipment routes is allowed, the number of nodes and arcs needs to be increased in the network. For example, Figure 4.3 depicts the network when *St. Louis* is being considered as an alternative break for the shipments going out of *San Francisco* and heading to *Los Angeles*.



● EOL

——— Time Spent on Travel

● Break

- - - - - - Time Spent on Loading at a Terminal

◌ Dummy Nodes

B : Boston
N : New York
S : St. Louis
s : San Francisco
L : Los Angeles

Figure 4.3 Network for the Boston - Los Angeles shipments with St. Louis as an alternative break

The following assumptions are made in such a network: (1) arc costs are independent discrete random variables, and (2) the network is acyclic. The independence assumption is used to simplify the network model. Since an LTL network can have several hundred terminals and serves hundreds of thousands of shipments daily, the possible states of the entire LTL network is practically infinite, making the problem extremely large and complex. Furthermore, the arc costs depend on many independent factors (such as a large number of independent shipments and availability of drivers); thus the independent assumption seems reasonable. The second assumption reflects the situation where once a shipment leaves a terminal, the shipment will not return to the same terminal again.

Next, a model is presented in a more generic stochastic network framework where the node types and arc types are not differentiated. Let $G = (N, A)$ be a network where N is the set of nodes and A is the set of arcs. Without loss of generality, consider that the shipment is going from node 1 to node n. Let the indexes of the nodes be topologically ordered such that for every arc (i, j), $i < j$. Note that by the acyclic property, there is no directed path from j to i.

Let,

$\tilde{c}_{ij}$ = Random cost of arc (i, j) where $(i, j) \in A$

c_{ij}^{k} = k^{th} realization of the cost of arc (i, j)

V_i = Cost of the dynamic shortest path from node i to node n

$\bar{V}_i$ = Expected cost of the dynamic shortest path from node i to node n

$S(i)$ = Set of successor nodes of node i (that is, the set of $\{j \mid (i, j) \in A\}$)

If the shipment is going from node 1 to node n, then the DSSP can be mathematically written as:

$$\bar{V}_1 = E[V_1] = E\left[\min_{j \in S(1)} \{\tilde{c}_{1j} + \bar{V}_j\}\right] \tag{4.1}$$

where,

$$\bar{V}_j = E[V_j] = E\left[\min_{k \in S(j)} \{\tilde{c}_{jk} + \bar{V}_k\}\right] \qquad \forall j = 2, \ldots, n-1 \tag{4.2}$$

with the boundary condition $\bar{V}_n = 0$. If the arc costs $\tilde{c}_{1j}$ are known as c^k_{1j}, then Equation (4.1) can be replaced by

$$V_1 = \min_{j \in S(1)} \{c^k_{1j} + \bar{V}_j\}$$

Except for the expectation operator, Equations (4.1) and (4.2) are similar to the classical Bellman's equation that defines the optimal conditions for the shortest path in a deterministic network. For acyclic, deterministic networks, the label-setting method is the most efficient algorithm. Therefore, for DSSP, a label-setting method is expected to be the most efficient solution approach as well. By assuming that the values of $\bar{V}_j$, $j \in S(i)$ have been determined, $\bar{V}_i$ is computed as follows.

For simplicity, the number of possible realizations of arc costs is assumed to be the same for all arcs. Let

R = Number of arcs emanating from node i (that is, $|S(i)|$)

K = Number of possible arc costs of an arc

A naive approach to computing $\bar{V}_i$ is by total enumeration: for each possible combination of the cost realizations, corresponding probability is found, the minimization problem is solved that is embedded in expectation of Equation (4.2), then the expected value is obtained. Clearly, this approach needs $O(K^R)$ steps and therefore not practical for large problems.

Notice that the minimization in Equation (4.2) is simply a problem of finding the minimum of R independent random variables. Thus, to compute $\bar{V}_i$, the fact that the event of $V_i \geq c$ is equivalent to the event of $\tilde{c}_{ij} + \bar{V}_j \geq c$ for all $j \in S(i)$ is utilized, where c is some real number. Due to the independence assumption, $\Pr(V_i \geq c)$ can be written as,

$$\Pr(V_i \geq c) = \prod_{j \in S(i)} \Pr(\tilde{c}_{ij} + \bar{V}_j \geq c) \tag{4.3}$$

Since the number of possible values of c is $R \cdot K$ and for each c. Equation (4.3) needs $O(R)$ steps. the computation of the probability mass function of V_i requires the $O(R^2 \cdot K)$ steps.

In the following discussion. the random variables on the right side of Equation (4.3) are decomposed into some special. bi-valued random variables that are ranked in increasing order which will be described later. By using these random variables. the required computation steps can be further reduced. Without altering the model and results. $\tilde{V}_j = 0$. $\forall j \in S(i)$ is assumed. There two major steps in computing $\tilde{V}_i$ are: (1) for each arc cost $\tilde{c}_{ij}$. K bi-valued random variables are created. and (2) for all bi-valued random variables generated from all $\tilde{c}_{ij}$. $j \in S$ are used to obtain $\tilde{V}_i$.

Let $\tilde{x}_{ij}^k$ be a bi-valued. random variable that takes the values of c_{ij}^k and ∞ only and denote.

$$q_{ij}^k = \Pr(\tilde{x}_{ij}^k = c_{ij}^k)$$

That is. $\Pr(\tilde{x}_{ij}^k = \infty) = 1 - q_{ij}^k = \Pr(\tilde{x}_{ij}^k \geq c_{ij}^k) = 1$. First. the goal is to compute the values of q_{ij}^k such that

$$\tilde{c}_{ij} = \min\{\tilde{x}_{ij}^1 . \tilde{x}_{ij}^2 . \ldots . \tilde{x}_{ij}^K\} \tag{4.4}$$

Let c be some real value. The random variable $\tilde{c}_{ij} \geq c$ if and only if all $\tilde{x}_{ij}^k \geq c . k = 1.2 . \ldots . K$. and thus

$$\Pr(\tilde{c}_{ij} \geq c) = \prod_{k=1}^{K} \Pr(\tilde{x}_{ij}^k \geq c) \tag{4.5}$$

Assume further that the possible arc costs are ordered:

$$c_{ij}^1 < c_{ij}^2 < \cdots < c_{ij}^K \tag{4.6}$$

Then. for any index l. $l < k$ (that is. $c_{ij}^l < c_{ij}^k$). the result is

$$\Pr(\tilde{x}_{ij}^l \geq c_{ij}^k) = \Pr(\tilde{x}_{ij}^l = \infty) = 1 - q_{ij}^k \tag{4.7}$$

On the other hand. for $l \geq k$. the result is

$$\Pr(\tilde{x}_{ij}^l \geq c_{ij}^k) = \Pr(\tilde{x}_{ij}^l \geq c_{ij}^l) = 1 \tag{4.8}$$

Therefore, for $c = c_{ij}^k$ and for $c = c_{ij}^{k+1}$ and by using Equations (4.5), (4.7), and (4.8), the result is

$$\Pr(\tilde{c}_{ij} \geq c_{ij}^k) = \prod_{l=1}^{K} \Pr(\tilde{x}_{ij}^l \geq c_{ij}^k) = \prod_{l=1}^{k-1} \Pr(\tilde{x}_{ij}^l \geq c_{ij}^k) = \prod_{l=1}^{k-1} (1 - q_{ij}^l) \quad (4.9)$$

$$\Pr(\tilde{c}_{ij} \geq c_{ij}^{k+1}) = \prod_{l=1}^{K} \Pr(\tilde{x}_{ij}^l \geq c_{ij}^{k+1}) = \prod_{l=1}^{k} \Pr(\tilde{x}_{ij}^l \geq c_{ij}^{k+1}) = \prod_{l=1}^{k} (1 - q_{ij}^l) \quad (4.10)$$

By subtracting Equation (4.10) from Equation (4.9), the result is

$$\Pr(\tilde{c}_{ij} = c_{ij}^k) = (1 - q_{ij}^1)(1 - q_{ij}^2) \cdots (1 - q_{ij}^{k-1}) q_{ij}^k \quad (4.11)$$

Hence, the value of q_{ij}^k can be determined by the recursion

$$q_{ij}^k = \frac{\Pr(\tilde{c}_{ij} = c_{ij}^k)}{\prod_{l=1}^{k-1} (1 - q_{ij}^l)} \quad (4.12)$$

For each arc (i, j), computing q_{ij}^k can be achieved in $O(K)$ steps. Such a method is also discussed in Mirchandani (1976) [42] where an arc with random arc costs is transformed to a set of parallel arcs, resulting in an "emergency equivalent" network. Each arc in the resulting network has a positive probability of failure such that the expected cost for the resulting network and the expected cost of the original arc are the same.

If the set of variables $\tilde{x}_{ij}^k$ is defined for each arc $(i, j) \in S(i)$, then the random variable V_i can be written as

$$V_i = \min_{j \in S(i)} \left\{ \tilde{c}_{ij} \right\} \quad (4.13)$$

$$= \min_{j \in S(i)} \left\{ \min\{\tilde{x}_{ij}^1, \tilde{x}_{ij}^2, \ldots, \tilde{x}_{ij}^K\} \right\} \quad (4.14)$$

To compute the probability mass function for V_i, all arc costs c_{ij}^k, $k = 1, 2, \ldots, K$, $j \in S(i)$ are sorted and renamed as c^m where $m = 1, 2, \ldots, RK$ such that

$$c^1 < c^2 < \cdots < c^{RK}$$

Next, $\tilde{U}^m$ is defined as a bi-valued variable such that

$$\tilde{U}^m = \begin{cases} \tilde{x}_{ij}^k & \text{if } c_{ij}^k = c^m \\ \infty & \text{otherwise} \end{cases} \quad (4.15)$$

and denoted as $\Pr(\tilde{U}^m = c^m)$ by q^m where the q^m is obtained by Equation (4.12). Therefore, Equation (4.14) becomes

$$\tilde{V}_i = \min\left\{\tilde{U}^1, \tilde{U}^2, \ldots, \tilde{U}^{RK}\right\} \quad (4.16)$$

By using the arguments of deriving Equation (4.11), the result is

$$\Pr(\tilde{V}_i = c^m) = (1 - q^1)(1 - q^2)\cdots(1 - q^{m-1})q^m \quad (4.17)$$

Once q^m's are determined and c^m's are sorted, finding $\Pr(\tilde{V}_i = c^m)$ for each c^m can be obtained in linear time. Thus, finding $\Pr(\tilde{V}_i = c^m)$ for all possible c^m required $O(RK)$ steps. The bottleneck of this method is the sorting of all possible arc costs for the arcs going from node i. An efficient sorting algorithm, such as the heap sort algorithm, requires only $O(RK\log(RK))$ steps. Thus, this method can compute $\tilde{V}_i$ in $O(RK\log(RK))$ steps.

Methods to compute $\tilde{V}_i$ for a particular i in Equation (4.2) is described. Since the network is acyclic and topologically ordered, $\tilde{V}_i$ can be computed starting from $i = n$ to $i = 1$. Furthermore, once $\tilde{V}_i$ is determined, its value will not change. Therefore, the recursion for computing $\tilde{V}_i$ is a label-setting method.

The procedure for DSSP algorithm is as follows:

Procedure: DSSP-ALG

1. Initialize

$\tilde{V}_i = \infty, \quad i = 1, \ldots, n-1$

$\tilde{V}_n = 0$

2. Let $i = n$

Repeat

$i = i - 1$

For arc $(i, j) \in A$, define $\tilde{x}_{ij}^k$ and compute $\Pr(\tilde{x}_{ij}^k = c_{ij}^k)$ (i.e. q_{ij}^k)

by Equation (4.12)

Sort all c_{ij}^k for $j \in S(i)$ and define $\tilde{U}^m$ by Equation (4.15)

Compute $\Pr(V_i = c^m)$ for all m using Equation (4.17)

Compute $\bar{V}_i$.

until $i = 1$

End Procedure

Since there are n nodes in the network, algorithm DSSP-ALG needs $O(nRK \log(RK))$ steps to compute $\bar{V}_1$. The speed of DSSP-ALG depends on the values of R and K. The next section discusses the performance of this algorithm using real data.

4.3 Numerical Results

In this section, numerical experiments that were performed to assess the effectiveness of applying the dynamic routing strategy to a real LTL network is explained. Because of the availability of data, only the loading times (the time between a shipment being loaded onto a trailer until the trailer is closed) were considered to be random variables. The ranges of loading times were typically between one to 48 hours or between one to 24 hours, depending on the type of terminal. The loading time was assumed to increase in two-hour intervals. For all other times, such as travel time on the road and waiting time for a closed trailer to be dispatched, the average times provided by the data set was used. The main objective was to compare the travel times for the priority shipments using the given load plan (LP) with the times using DSSP. When the routes provided by LP were used, a shipment heading from the current terminal to a destination terminal can have at most two choices of the next stop (either primary or direct). On the other hand DSSP offers, some additional choices of next stops, that are selected on the basis of the smallest average travel times of the paths from the current terminal to the destination via these stops. The number of additional choices are O-D pair dependent. Nevertheless, this number was less than three in most cases.

In this experiment, two groups of domestic O-D pairs were considered (International shipments are excluded since they are handled differently). The first group consisted of 150 O-D pairs that had the longest travel distance between the origin and the destination. In general, the shipments between these O-D pairs pass through a lot of breaks. The second group consisted of another 150 O-D pairs that had a high percentage of total travel time spent on loading. Though the shipments pass through few breaks, the distance between the origin and the destination of each of these O-D pairs was relatively small.

The experiments were conducted using an SGI Indigo2 R4000 machine. Of the 300 problems solved using DSSP, none required CPU time of more than one second; hence, the algorithm is quite efficient. Table 4.1 shows the results for the average travel times(in hours) of priority shipments for 10 typical O-D pairs (five from each group). Column 1 gives the O-D pair numbers. Columns 2 and 3 show the times for using LP and for using DSSP, respectively. Column 4 shows the time spent on the road by using LP. Column 5 shows the time saved by using the dynamic routing strategy. Since the dynamic routing strategy can save time on loading but may increase the time spent on the road, the net time-savings has been expressed as a percentage of the average loading time for each O-D pair in column 6; these percentages are called effectiveness indexes since in general a higher percentage indicates that the proposed strategy is more effective.

The average time spent on loading in group 1 is 50.5 hours whereas the average total travel time is 170 hours. The mean time savings is 7.5 hours with the standard deviation

Table 4.1 Comparison of solutions obtained by DSSP and by LP

OD Pair	LP	DSSP	Time on road	Savings	Effective Index
1	173	162	116	11	19.3
2	179	172	115	7	10.9
3	158	148	109	10	20.4
4	175	166	110	9	13.8
5	172	163	109	9	14.3
6	89	79	21	10	14.7
7	99	90	35	9	14.1
8	81	69	14	12	17.9
9	112	102	46	10	15.2
10	110	99	39	11	15.5

of mean of 1.5 hours. The mean effectiveness index is 14 percent. Furthermore, one-third of the O-D pairs in group 1 have a time-saving over 10 hours. For the second group, the average times spent on loading and the total travel times are 66.7 hours and 102 hours, respectively. The average time savings is 6.7 hours so that the mean effectiveness index is just over 10 percent. For group 2, although the loading time can be decreased, the travel distance can increase as well. Thus, the mean effectiveness index in group 2 is lower. Notice that only the loading times are treated as random variables. If the probability distributions for other travel time components (such as the waiting time for a trailer to be dispatched) are also available, then time-savings can be expected to increase.

In practice, using the dynamic routing strategy for shipments in every O-D pair is unlikely, partly because of the terminal layout at breaks. Therefore, the dynamic routing strategy should be used as an exception rather than as a rule. The numerical experiment suggests that this strategy is more effective for O-D pairs that are far apart than for those that are close to each other.

5 DYNAMIC SERVICE NETWORK DESIGN(DSND)

5.1 Introduction

The main objective of this research is to minimize cost over time by deciding when to dispatch a trailer for LTL motor carriers. As a first step in deciding when to dispatch a trailer this research concentrates on dispatch of trailers over a single link. The dispatch of a trailer over a single link can be solved optimally. The purpose of this research is not to find an optimal solution to dispatch a trailer over a single link, but to estimate a recourse function that can then be used to solve vehicle dispatching problems on large networks. This research attempts to address the problem of when to dispatch a truck dynamically (based on the current time and the shipment level at the current time), trading off the costs of holding shipments vs. the cost of sending a trailer.

The primary motivation for this research is the fact that LTL carriers use ad hoc stationary dispatch rules based on experience to decide when to dispatch a trailer. However, LTL carrier experience hour of day, day of the week and seasonal variations in the arrival rate of the shipments, so the solution should take into account this dynamism of the shipment arrival rate in deciding when to dispatch a trailer. A dynamic dispatch strategy to the DSND problem is important because it can reduce fixed and penalty costs incurred by LTL carriers and can increase service level provided by LTL carriers to customers.

The following simplifying assumptions are made in this research:

- Trailers are dispatched over a single link

- Shipments arrival rate at a terminal is either static or dynamic
- Fixed costs are associated with dispatching a trailer
- Shipment holding costs are associated with each unit of time that a shipment is held
- When a trailer is dispatched at time t. the following is assumed: $I_t + a_t \leq K$
- Trailers can be dispatched at any time of the day

The main contribution of this research is that for a single link problem. a recourse function which gives the future cost of having I_t shipments at current time t is developed and provides an approach to estimate the shape of this recourse function. The dynamic control policy described in this research exploits the linearity of the recourse function estimated. in solving the trailer dispatching problem efficiently. The dynamic control policy also takes into consideration real-time information(current time of the day and current shipment level) in deciding whether to close a trailer or not. Instead of ad hoc rules for closing a trailer. this research provides an analytical way for LTL carriers decide when to close a trailer. Numerical experiments with the dynamic control policy show that the solution obtained is close to the optimal solution. Since the recourse function can be estimated easily and is computationally fast. the method can be used to solve subproblems in large LTL networks.

The remainder of this chapter is organized as follows. First. a stationary infinite horizon problem is described. The infinite horizon problem supports that a linear approximation to the recourse function is a good approximation. Second. a finite horizon problem is described and shows how to optimally solve a deterministic dynamic problem. Finite horizon problem is primarily used to test different truncation strategies. Finally. this chapter describes a dynamic control policy for solving vehicle dispatching problems over a single link. The dynamic control policy described is approximate, and the demonstration of its value is experimental.

5.2 Terms

Some of terms used in this chapter are described below:

- Fixed costs: Fixed costs are those costs incurred in closing a trailer such as driver cost, fuel cost, equipment cost.
- Variable/holding costs: Variable costs include holding costs incurred in each delayed shipment and cost of lost revenue due to loss of customer goodwill.
- Stationary dispatch rule: A trailer is dispatched when a minimum capacity of the trailer is filled(such as 90 percent). The dispatch strategy does not depend on the time of day, or the day of the week and hence is called the static dispatch strategy.
- Dynamic dispatch rule: The decision to dispatch a trailer depends not only on the current shipment level, but also varies with the time of day, and day of the week and hence is called the dynamic dispatch strategy.

5.3 Problem Definition

The dynamic service network design problem addresses the problem of when to close a trailer based on information available at the current time. Currently, LTL carriers use the following strategies to decide whether to close a trailer or not. LTL carriers close the trailers if a certain minimum such as 90 percent of the trailer is filled, TTMS of several shipments such as 15 percent has expired, or the trailer is held open for a long period of time such as 24 hours at a dock door.

The dynamic dispatch strategy is to dispatch a truck based on a function h_t that varies with time. The time dependent function should consider what is likely to happen in the future. such as time of day. day of the week. holidays. and seasonal effects. In this research. an approximate algorithm is proposed which can be used to calculate h_t. which determines when to close a trailer.

5.4 Mathematical Model (Single Link Problem)

The dynamic dispatch strategy can be mathematically defined as follows.

Let.

$$y_t = \begin{cases} 1 & \text{if closing a trailer} \\ 0 & \text{otherwise} \end{cases} \tag{5.1}$$

and let the closing strategy be.

$$y_t = \begin{cases} 1 & \text{if} \quad I_t + a_t > \text{threshold} \\ 0 & \text{otherwise} \end{cases} \tag{5.2}$$

where.

$$threshold = \begin{cases} x & \text{static} \\ h_t(I_t) & \text{dynamic} \end{cases} \tag{5.3}$$

The aim of the dynamic service network design problem is to find y that minimizes the total cost of operations which can be mathematically written as.

$$\min_{\mathbf{y}} \sum_{t=0}^{T-1} r_t(I_t, y_t)\alpha^t + \alpha^T R_T(I_T) \tag{5.4}$$

The optimality equations for this problem are given by.

$$R_t(I_t) = \min_{y_t \in (0.1)} Fy_t + h(I_t + a_t - Ky_t)^+ + \alpha R_{t+1}((I_t + a_t - Ky_t)^+) \tag{5.5}$$

where $0 \leq \alpha < 1$

5.5 Solution Approach

The section presents dynamic control policy as a solution approach to the DSND problem. The solution procedure is based on a successive linear approximation of the value function $R_t(I_t)$. Such a solution procedure for the finite horizon problem is quite sensitive to truncation effects, and so a reasonable approximation to the terminal reward function $R_T(I_T)$ is needed. Next, an approach to develop an approximation for the terminal reward function using a stationary infinite horizon model is proposed. Also, the infinite horizon model supports the theory that the linear approximation to the recourse function is a valid approximation.

5.5.1 Infinite horizon problem

The infinite horizon problem is used as an approximation to the terminal reward in a finite horizon model. To develop a tractable model, the arrival rate a_t is assumed to be a constant a.

In the limit, the optimaility equations given in Equation 5.5 can be rewritten as follows for a stationary, infinite horizon, discounted problem.

$$R(I) = \min_{y \in (0,1)} Fy + h(I + a - Ky)^{+} + \alpha R((I + a - Ky)^{+}) \tag{5.6}$$

Let $y^*(I)$ be the optimal solution to above equation. Under certain conditions, Papastavrou et. al. [45] show that the optimal decision rule is the threshold rule to the above problem:

$$y^*(I, x) = \begin{cases} 1 & \text{if } I \geq x \\ 0 & \text{otherwise} \end{cases} \tag{5.7}$$

Therefore a closed form of Equation 5.6 can be obtained by substituting the above function.

$$R(I,x) = Fy^*(I,x) + h(I + a - Ky^*(I,x))^+ + \alpha R((I + a - Ky^*(I,x))^+) \tag{5.8}$$

Let the threshold value x be $< K$. Let the time be scaled so that $a = 1$. Since the time is scaled, the discount factor α is replaced by $\alpha_a = \alpha^{1/a}$, and the holding cost h is replaced by $h_a = h/a$.

5.5.1.1 Solution Approach

The steady state value function $R(I,x)$ given in Equation 5.6 can be estimated by solving a system of linear equations that relate $R(I,x)$ at time t to $R(I,x)$ at time $t+1$. This yields the following set of equations:

$$R(0,x) = 1h_a + \alpha_a R(1,x) \tag{5.9}$$

$$R(1,x) = 2h_a + \alpha_a R(2,x) \tag{5.10}$$

$$\cdot \quad \cdot \tag{5.11}$$

$$\cdot \quad \cdot \tag{5.12}$$

$$\cdot \quad \cdot \tag{5.13}$$

$$R(x-1,x) = xh_a + \alpha_a R(x,x) \tag{5.14}$$

$$R(x,x) = F + \alpha_a R(0,x) \tag{5.15}$$

Substituting Equation 5.9 into Equation 5.15 gives:

$$R(x,x) = F + \alpha_a h_a + {\alpha_a}^2 R(1,x) \tag{5.16}$$

Repeating the process gives:

$$R(x,x) = F + h_a \sum_{i=1}^{x} i{\alpha_a}^i + {\alpha_a}^{x+1} R(x,x) \tag{5.17}$$

Solving for $G(x.x)$ then gives:

$$R(x.x) = (1/1 - \alpha_a{}^{x+1})[F + h_a \sum_{i=1}^{x} i\alpha_a{}^{i}] \qquad (5.18)$$

Then $R(x-1.x). R(x-2.x)..... R(1.x). R(0.x)$ can be computed using Equations 5.9 to 5.15 recursively. This gives the function $R(I.x)$ for $I = 0.1.....x-1.x$ as a function of x.

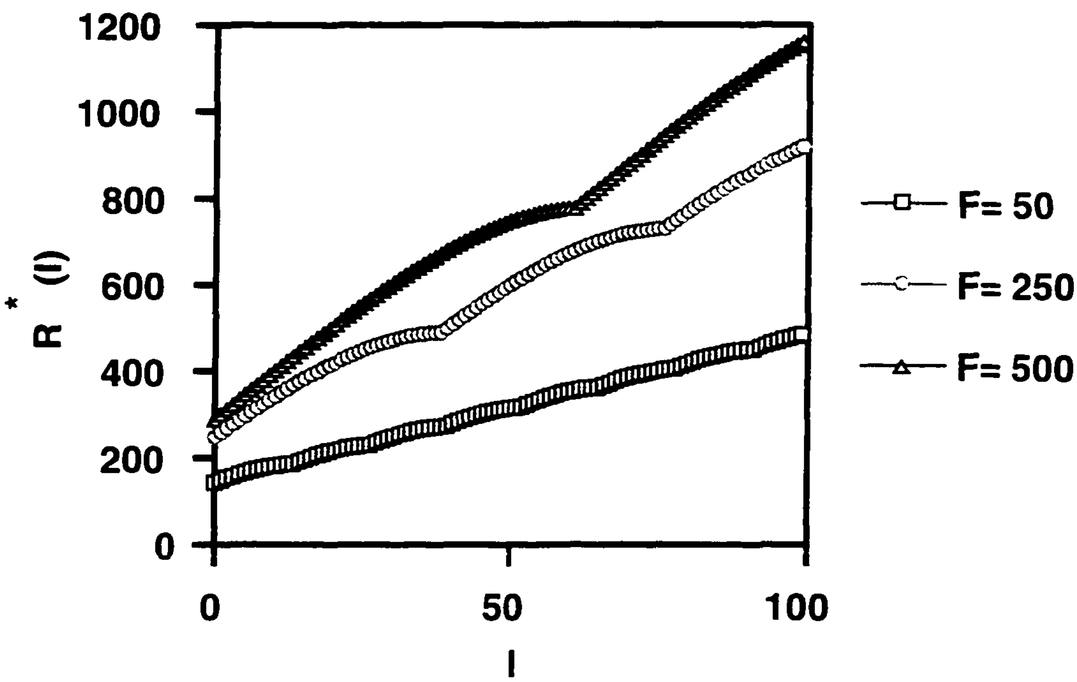


Figure 5.1 $R^*(I)$ vs. I for $h = 0.5. \alpha = 0.96$ and different values of F

The shape of $R^*(I)$ is illustrated for different values of F in Figure 5.1. Three different values of F namely 50. 250. 500 are used with $h = 0.5$ and $\alpha = 0.96$ and the resulting function $R^*(I)$ is plotted. The shape is roughly linear. suggesting a linear approximation is a good approximation for the recourse function. The shape of $R^*(I)$ is illustrated for different values of h in Figure 5.2. Three different values of h namely

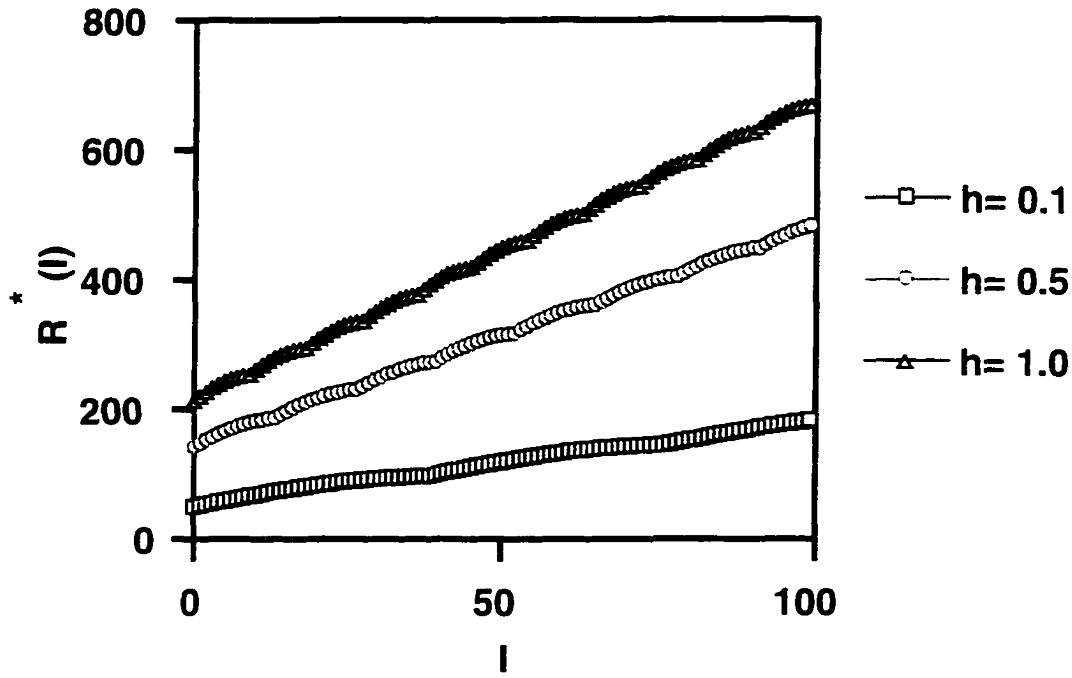


Figure 5.2 $R^*(I)$ vs. I for $F = 50, \alpha = 0.96$ and different values of h

0.1, 0.5, and 1.0 are used with $F = 50$ and $\alpha = 0.96$ and the resulting function $R^*(I)$ is plotted. The shape is roughly linear, suggesting a linear approximation is a good approximation for the recourse function. The shape of $R^*(I)$ is illustrated for different values of α in Figure 5.3. Three different values of α namely 0.5, 0.75, and 0.96 are used with $F = 50$ and $h = 0.5$ and the resulting function $R^*(I)$ is plotted. The shape is roughly linear suggesting a linear approximation is a good approximation for the recourse function.

The infinite horizon problem described here assumes a stationary demand pattern, infinite horizon, and steady state. The infinite horizon problem can be solved easily if a stationary demand pattern is assumed. The infinite horizon problem gives good results for a stationary demand pattern. But, LTL carriers are characterized by strong

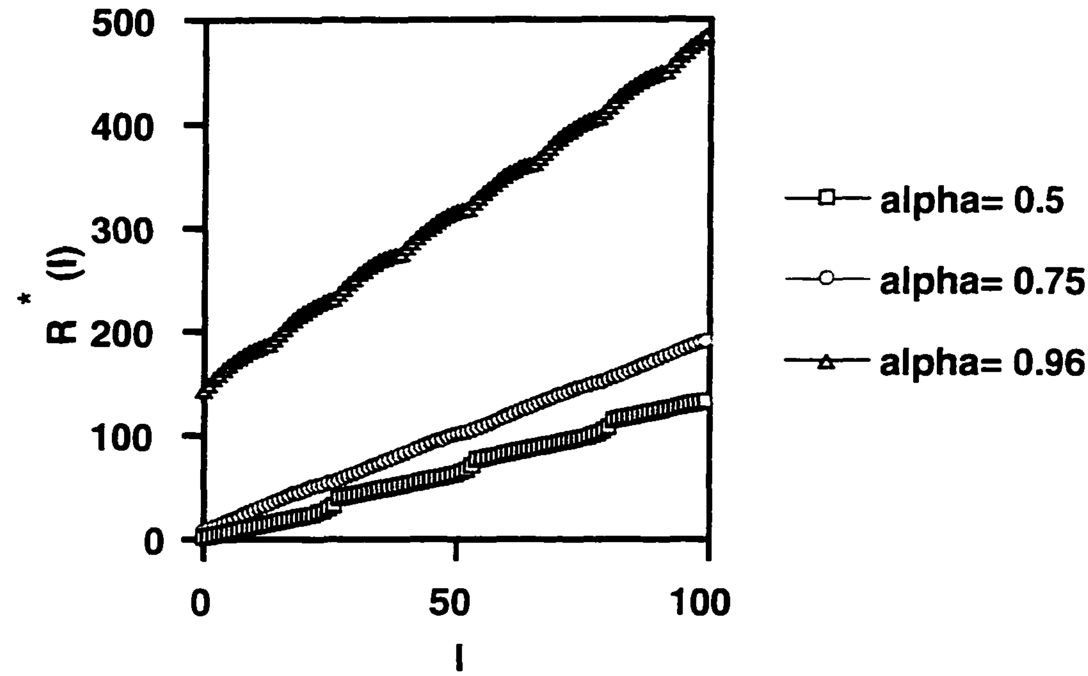


Figure 5.3 $R^*(I)$ vs. I for $F = 50, h = 0.5$ and different values of α

hour of day, day of week, and seasonal patterns that can significantly affect the optimal dispatch policy. Therefore, any solution strategy for LTL carriers should be able to handle dynamic demand patterns.

5.5.2 Finite horizon problem

This section describes a finite horizon problem. The finite horizon problem was used to test different truncation strategies for use in the dynamic control policy described in the next section. Numerical experiments were done to compare the optimal solution with the finite horizon approximation in order to determine the best truncation strategy for the dynamic control policy. Infinite horizon approximation discussed in the previous section was used as one of the truncation strategies for the finite horizon approximation.

The finite horizon problem can be formulated as follows:

$$R_t(I_t) = \min_{y_t \in \{0,1\}} r_t(y_t, I_t) + \alpha R_{t+1}(I_{t+1}) \quad (5.19)$$

$$= \min_{y_t \in \{0,1\}} \{F y_t + h(I_t + a_t - K y_t)^+ + \alpha R_{t+1}((I_t + a_t - K y_t)^+)\} \quad (5.20)$$

for t= 0,1,....,T-1. Given $R_T(I_T)$ as a terminal reward function, the finite horizon problem formulated above can be solved by dynamic programming using a backward recursion algorithm.

There are several choices for the terminal reward function $R_T(I_T)$. The four alternative terminal reward functions given below are compared for the best choice as a boundary function. The first truncation approximation function(5.21) assumes that at time T, the cost of all current and future shipments is 0. The second approximation function(5.22) assumes that at time T, the cost of all current and future shipments is equal to the optimal solution of a stationary problem. The third approximation function(5.23) replaces the exact infinte horizon function with the linear approximation of the function. The fourth approximation function(5.24) assumes the terminal reward function to be the cost of holding I_T shipments, assuming the trucks are always dispatched full.

$$R_T^0(I_T) = 0 \quad (5.21)$$

$$R_T^1(I_T) = R_T^*(I_T) \quad (5.22)$$

$$R_T^2(I_T) = r_{1T}^* I_T \quad (5.23)$$

$$R_T^3(I_T) = F/K I_T \quad (5.24)$$

$$(5.25)$$

5.5.2.1 Numerical Work

Numerical experiments that were done to choose the best truncation strategy and the horizon to use in the dynamic control policy are explained in this section. First, the length of the planning horizon was assumed to be 20. and the recourse function given in Equation 5.20 is plotted using the four truncation strategies given in Equations 5.21. 5.22. 5.23. 5.24 in Figures 5.4. 5.5. 5.6. 5.7. respectively. The recourse function was plotted as a 3-D graph against length of the planning horizon and the current inventory level(s). A long planning horizon (500 time periods) was chosen and the problem is solved using dynamic programming recursion and the resulting graph was plotted in Figure 5.8.

Second. relative error in slope for each of the truncation approximations. when compared to the recourse function computed using a long planning horizon (500 time periods). was plotted as a function of the planning horizon in Figure 5.9. As can be seen in Figure 5.9. the truncation approximations $R^*(I.x)$ and $r_0 + r_1 I_t$ both have relative errors close to 0 when the length of planning horizon used was greater than 60. For truncation approximations 0 and $F/K * I_t$. the relative error in slope did not reach close to 0 even if a planning horizon length of 100 was used. This suggested that using a stationary infinite horizon solution or a linear approximation of it as the truncation strategy for the finite horizon problem terminal costs was a good approximation when using planning horizon lengths of greater than 60. Absolute actual errors for each of the truncation approximations. when compared to the recourse function computed using a long planning horizon was plotted as a function of the planning horizon in Figure 5.10. As can be seen from Figure 5.10. the truncation approximations $R^*(I.x)$ and $r_0 + r_1 I_t$ both have actual absolute errors close to 0 when the length of the planning horizon was greater than 60. For truncation approximations 0 and $F/K * I_t$. the relative error in slope did not reach close to 0 even if a planning horizon length of 100 was used. This suggested that using a stationary infinite horizon solution or a linear approximation of it as the truncation strategy for the finite horizon problem terminal costs was a good approximation when using planning horizon lengths of greater than 60.

In Figure 5.11. $R(I.x)$ is illustrated using different demand rates. at time period

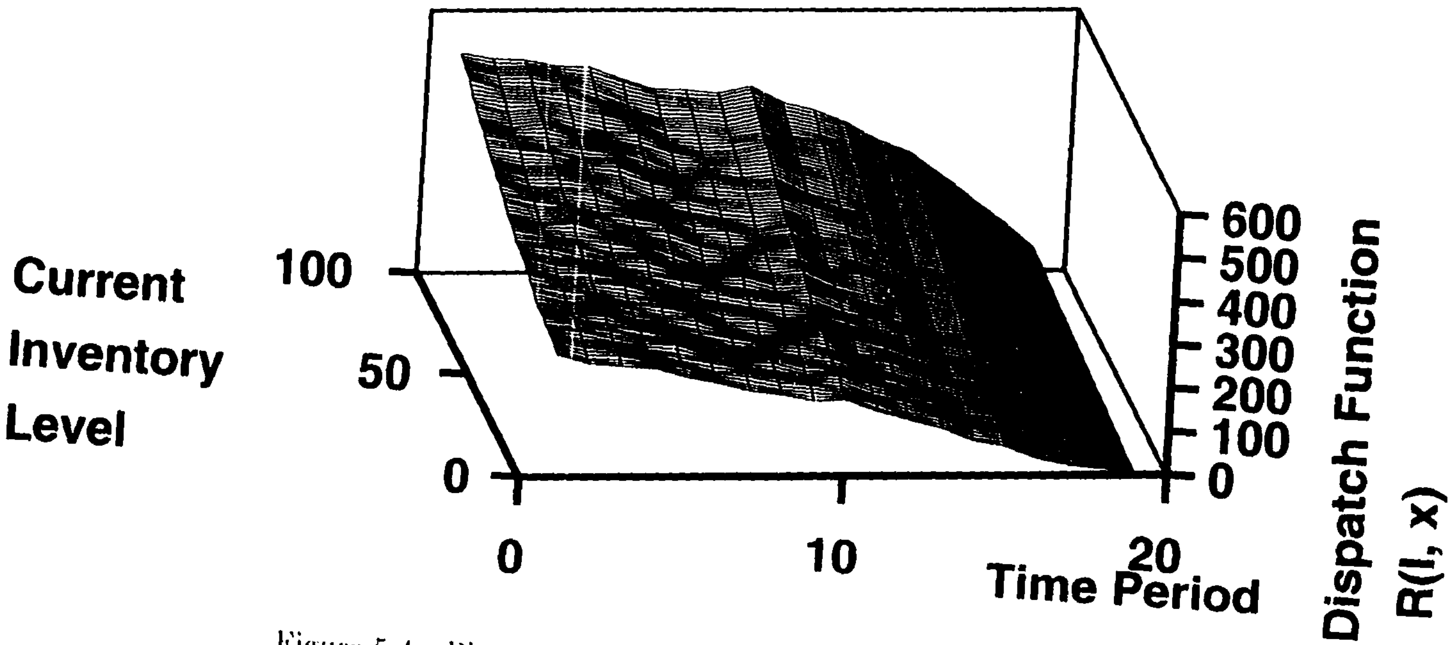


Figure 5.4 Plot of recourse function with truncation approximation 0

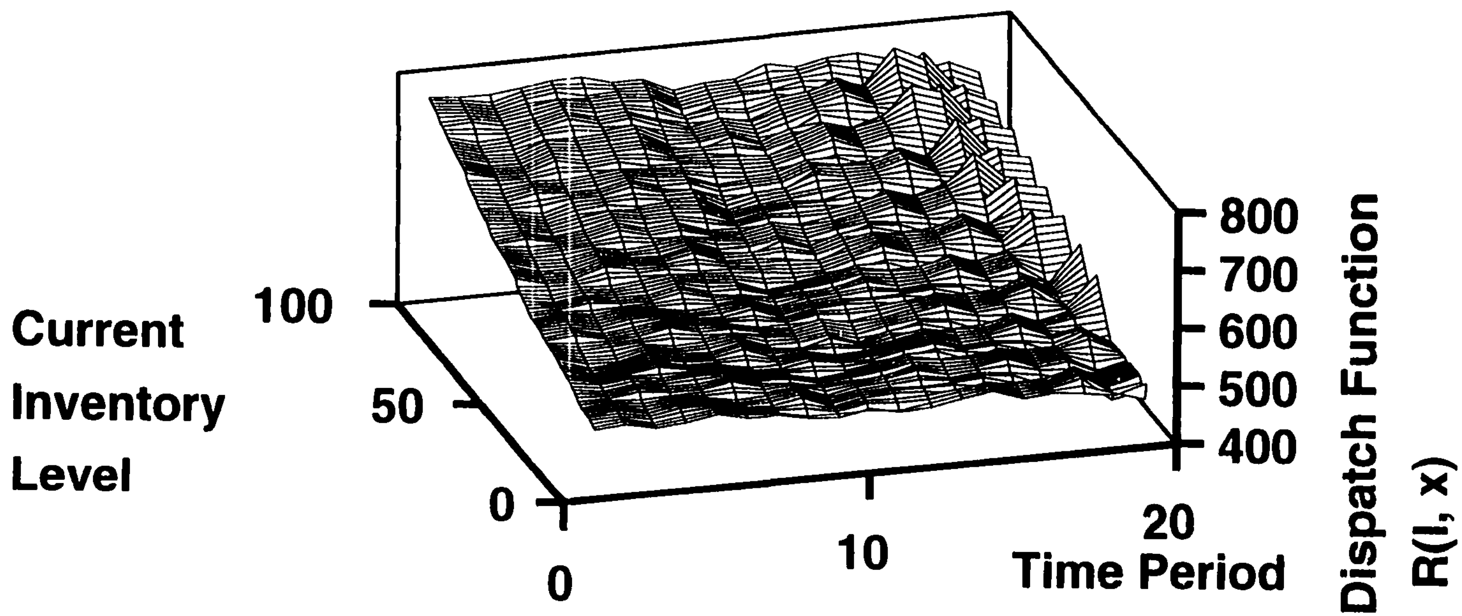


Figure 5.5 Plot of recourse function with truncation approximation $R^*(I)$

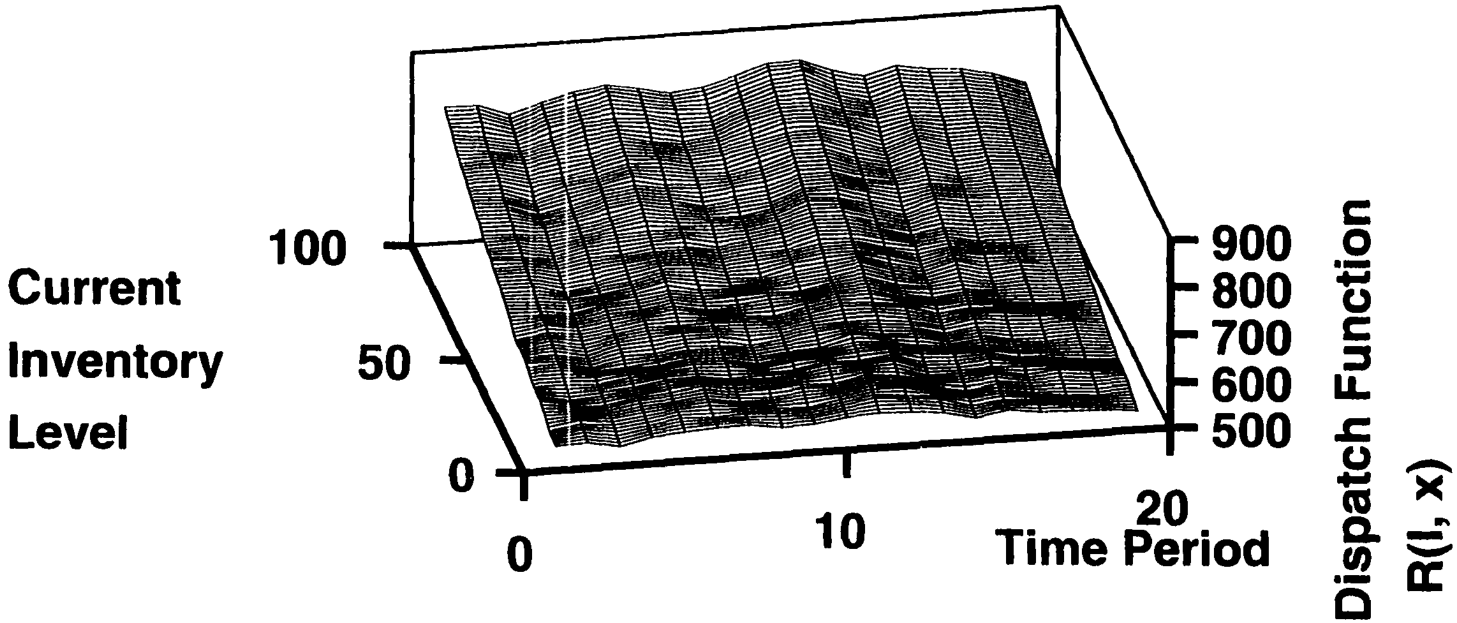


Figure 5.6 Plot of recourse function with truncation approximation $r_0 + r_1 * I_t$

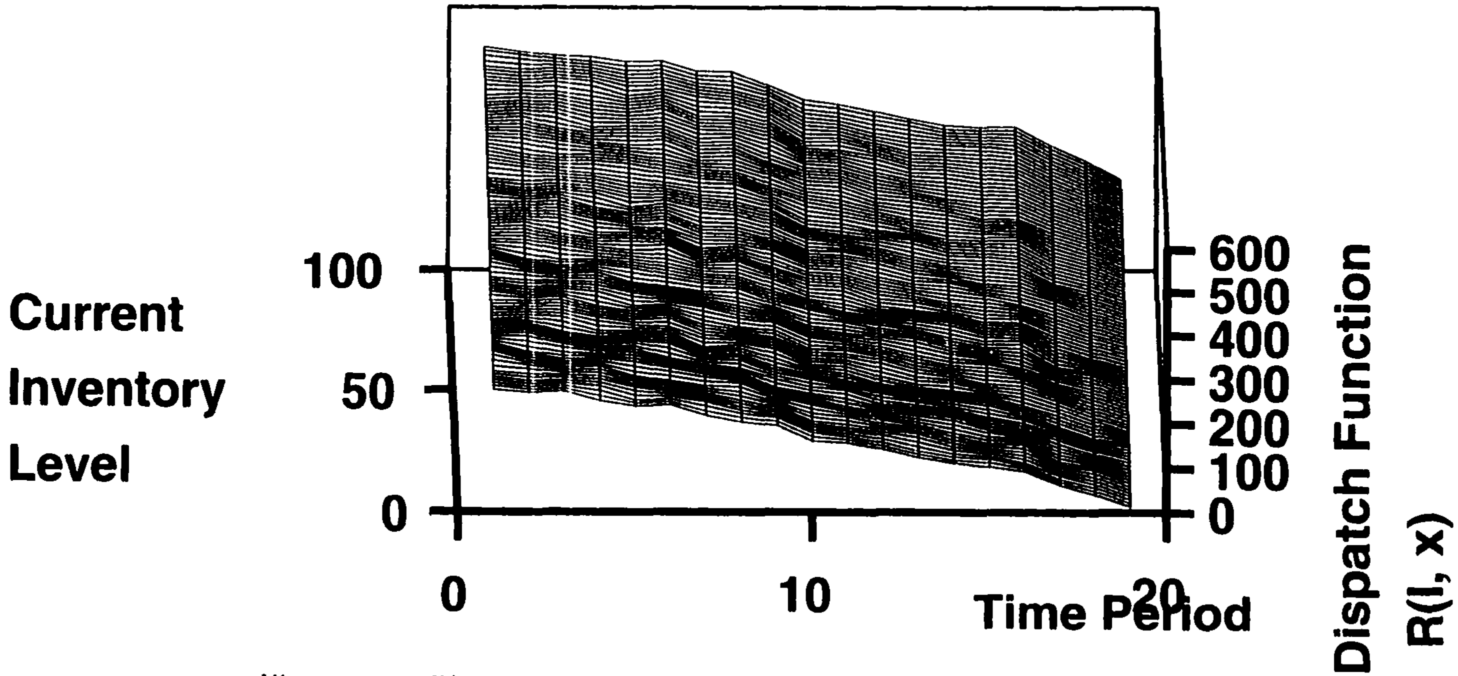


Figure 5.7 Plot of recourse function with truncation approximation $(F/K) * I_t$

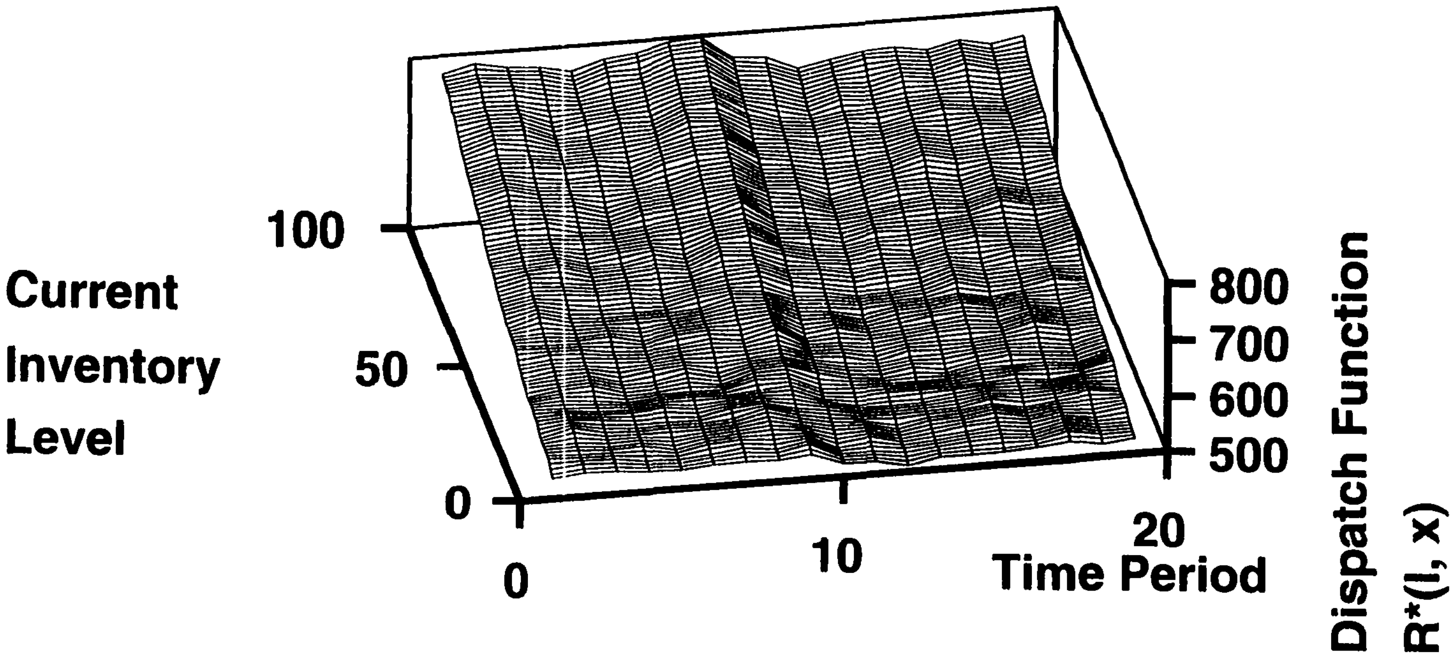


Figure 5.8 Plot of recourse function for a long planning horizon(T=500)

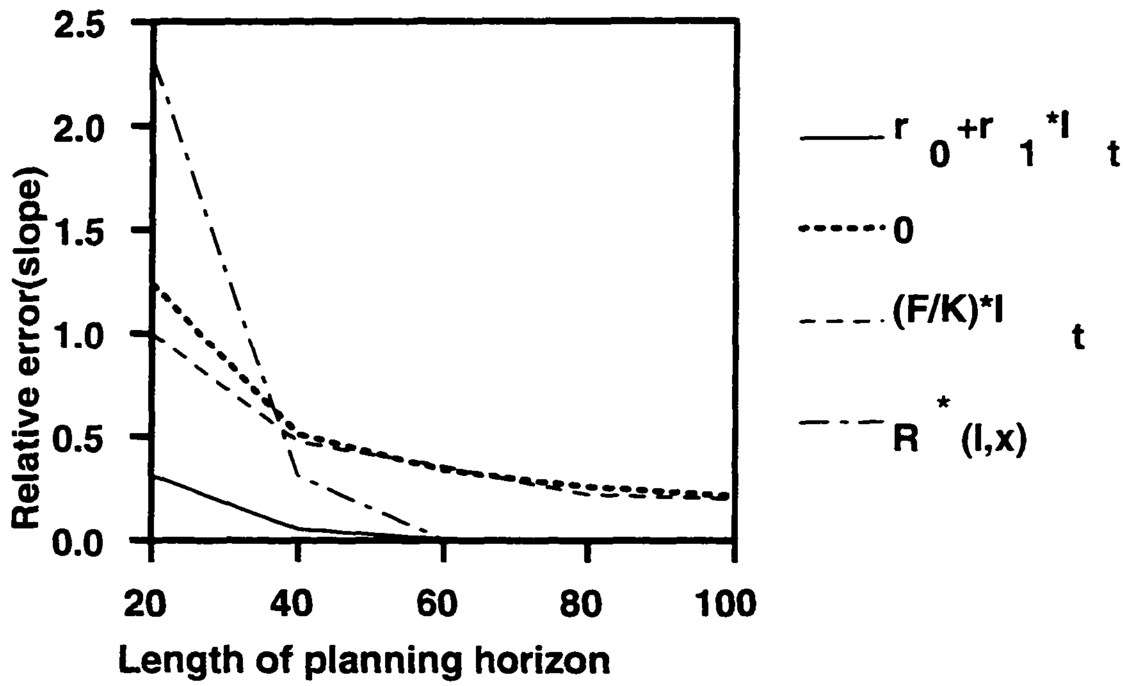


Figure 5.9 Plot of relative error (slope)

$t = 0$. and for different current inventory levels. As can be seen from Figure 5.11. the shape of the function is fairly independent of demand patterns for reasonable values of the parameters. The shape of the recourse functions is roughly linear suggesting that a linear approximation for dynamic control policy is a good approximation.

Using the given solution approach for the finite horizon problem. the quality of solution obtained is high as $T \to \infty$. The finite horizon problem can be easily solved for a general time dependent arrival vector a_t. However. the states are shipment level dependent with large state space and the solution approach can only handle deterministic data. It is difficult to embed the solution procedure for a single link into large LTL networks. A practical solution approach should be able to handle a general arrival vector a_t. which should be computationally fast and should be able to easily embed the solution approach for a single link problem into large LTL networks. Such an approximate

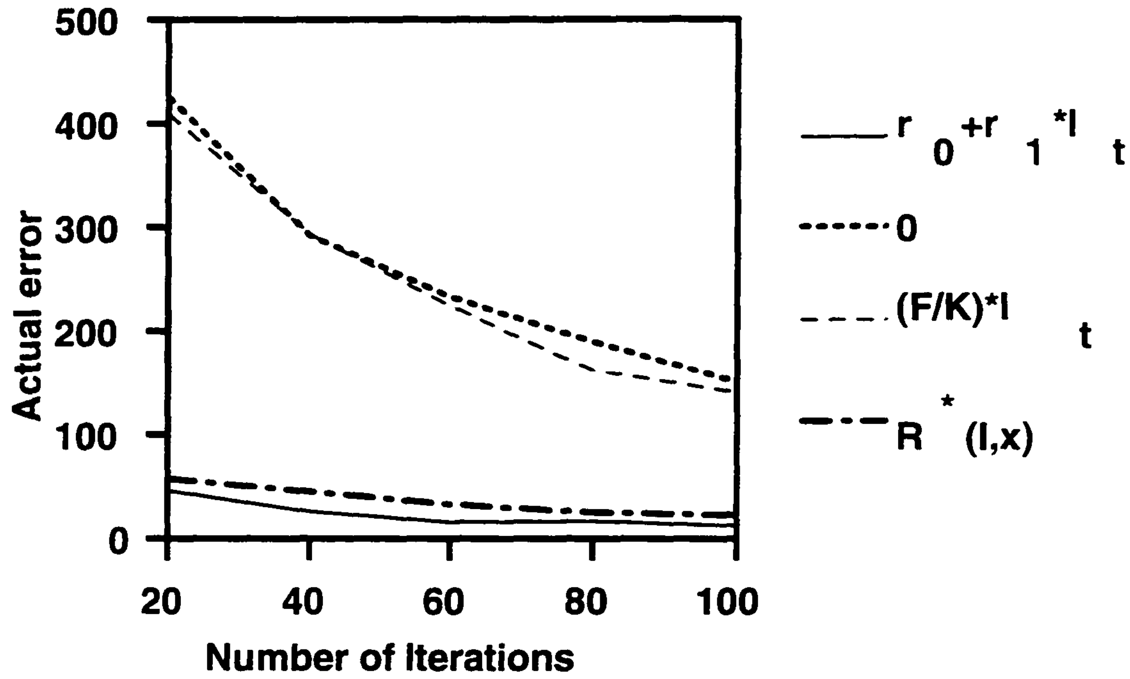


Figure 5.10 Plot of actual error (absolute value)

solution approach which can handle dynamic demand patterns and is computationally fast is described in the next section.

5.5.3 Dynamic Control Policy

LTL carriers are characterized by strong hour of day, day of week, and seasonal patterns hence, a dynamic control policy that varies over time will outperform simple static rules. A simple dynamic dispatch strategy can be derived by replacing $R_{t+1}(I_{t+1})$ in the equation given below:

$$R_t(I_t) = Fy(I_t) + h(I_t + a_t - Ky(I_t))^+ + R_{t+1}(I_{t+1}) \tag{5.26}$$

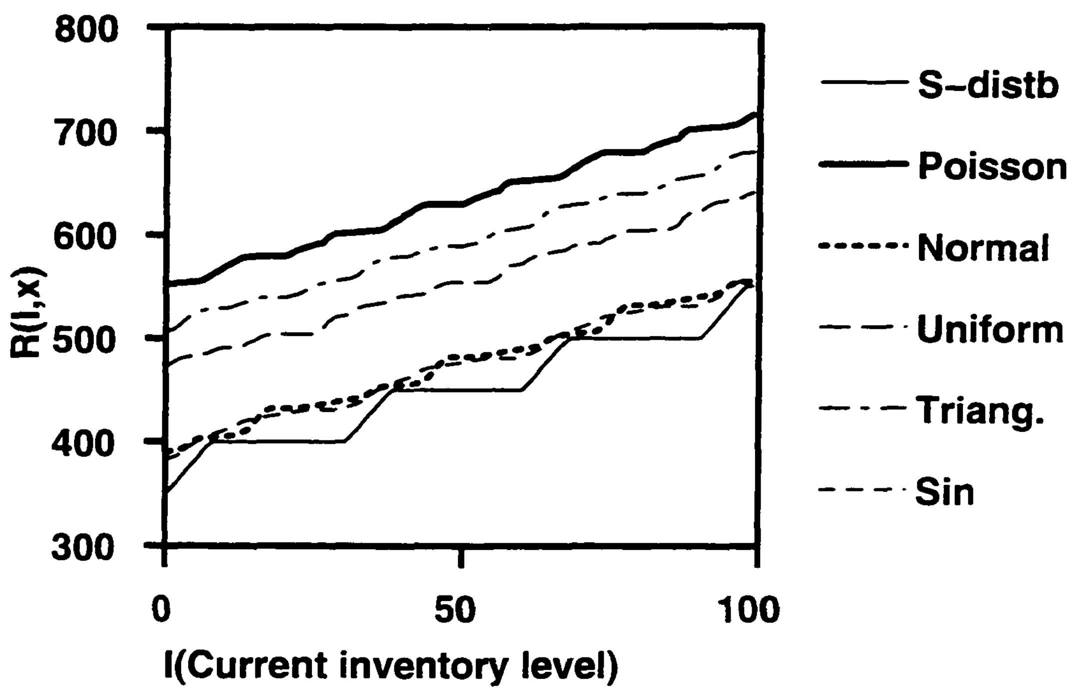


Figure 5.11 $R(I, x)$ vs. I for different demand rates

with a linear approximation (Equation 5.27)

$$\hat{R}_t(I_t) = \hat{r}_{0t} + \hat{r}_{1t} I_t \qquad (5.27)$$

and the resulting equation 5.28 is solved.

$$y_t = arg \min_{y_t \in (0,1)} Fy_t + h(I_t + a_t - Ky_t)^+ + \alpha(\hat{r}_{0t} + \hat{r}_{1t}(I_t + a_t - Ky_t)^+) \qquad (5.28)$$

If $y_t = 1$ then, from the above equation the following can be inferred.

$$F + h(I_t + a_t - K) + \alpha(\hat{r}_{0t} + \hat{r}_{1t}(I_t + a_t - K)^+ \quad < \qquad (5.29)$$

$$h(I_t + a_t) + \alpha(\hat{r}_{0t} + \hat{r}_{1t}(I_t + a_t) \qquad (5.30)$$

Since $I_t + a_t$ is assumed to be $\leq K$ when $y_t = 1$, the above equation can be rewritten as:

$$F \le (h + \alpha\hat{r}_{1t})(I_t + a_t) \tag{5.31}$$

Therefore, an approximate dispatch rule is that a truck should be dispatched whenever the above condition is satisfied, which can be written mathematically as follows:

$$y_t^*(I_t) = \begin{cases} 1 & \text{if } (I_t + a_t) \ge F/(h + \alpha\hat{r}_{1t}) \\ 0 & \text{otherwise} \end{cases} \tag{5.32}$$

In order to use the above dispatch strategy linear approximation $\hat{r}_{0t}$ and $\hat{r}_{1t}$ of the function $R_t(I_t)$ is needed. To estimate the linear approximation of the function $R_t(I_t)$, the function $R_t(I_t)$ is approximated by the function $\tilde{R}_t(I_t)$ given below:

$$\tilde{R}_t(I_t) = Fy(I_t) + h(I_t - x_t^* y(I_t))^+ + \alpha(r_{0,t+1} + r_{1,t+1} I_{t+1}) \tag{5.33}$$

Let ΔI_t be a small increment of I_t. Given change in the state variable ΔI_t, the change in the decision variable $\Delta y(I_t)$ can be written as follows:

$$\Delta y(I_t) = y(I_t + \Delta I_t) - y(I_t) \tag{5.34}$$

$$= \begin{cases} 1 & \text{if } I_t < \bar{x}_t \text{ and } I_t + \Delta I_t \ge \bar{x}_t \\ 0 & \text{otherwise} \end{cases} \tag{5.35}$$

If $\Delta I_t = 1$, then the slope of function $\tilde{R}_t(I_t)$ (given in Equation 5.33) at iteration k, for a given state I_t^k can be estimated as follows:

$$\hat{r}_{1,t}^k = \Delta\tilde{R}_t^k(\bar{I}_t^k) \tag{5.36}$$

$$= F\Delta y(I_t) + h(1 - \bar{x}_t \Delta y(I_t)) + \alpha\bar{r}_{1,t+1}^k \Delta I_{t+1} \tag{5.37}$$

$$= \begin{cases} h + \alpha\bar{r}_{1,t+1}^k & \text{if } (\bar{I}_t^k + \Delta I_t) < \bar{x}_t^k \\ F - h\bar{x}_t^k - \alpha\bar{r}_{1,t+1}^k \bar{x}_t^k & \text{otherwise} \end{cases} \tag{5.38}$$

Also, in Equation 5.32, a truck is dispatched if $I_t + a_t$ is $\ge F/(h + \alpha r_{1t})$. Therefore $F/(h + \alpha r_{1t})$ is the threshold value x_t at which to dispatch a truck at time t. The linear approximation $\hat{r}_{1t}$ is used in the approximate dispatch rule (given in Equation 5.32) to determine when to dispatch the trailer. Linear approximation $\hat{r}_{1t}$ of the function $R_t(I_t)$ can be iteratively estimated and updated as follows.

1. $I_0 = 0, \bar{r}^0_{1T} = F/K, \bar{r}^0_{1t} = \alpha\bar{r}^0_{1,t+1}, \bar{x}^0_t = F/(h + \alpha r^0_{1t})$.

2. For each iteration $k = 1, \ldots, K$

3. For time period $t = 0, 1, \ldots, T$ using linear approximation $\bar{r}_1$ and the dispatch rule in Equation 5.32, an initial state I_0 and arrival process a_t, the state variable I_t at time t can be simulated in a forward pass, using the following transfer function:

$$\hat{I}^k_{t+1} = (\hat{I}^k_t + a_t - Ky^*_t(\hat{I}^k_t))^+ \tag{5.39}$$

4. if (k=0) update $\bar{I}^k_t = \hat{I}^k_t$

5. Update $\bar{I}^{k+1}_t = (1-\gamma)\bar{I}^k_t + \gamma\hat{I}^k_t$

6. For time period $t = T, T-1, \ldots, 0$

7. Estimate the slope $\hat{r}^k_{1,t}$ at time t given threshold value x^k_t and state variable $\hat{I}^k_t$ as follows:

$$\hat{r}^k_{1,t} = \begin{cases} h + \alpha\bar{r}^k_{1,t+1} & \text{if } \bar{I}^k_t + \Delta I < \bar{x}^k_t \\ F - h\bar{x}^k_t - \alpha\bar{r}^k_{1,t+1}\bar{x}^k_t & \text{otherwise} \end{cases} \tag{5.40}$$

8. Update $\bar{r}^{k+1}_{1t} = (1-\gamma)\bar{r}^k_{1t} + \gamma\hat{r}^k_{1t}$

9. Update the threshold value $\hat{x}^k_t$ with new $\bar{r}^{k+1}_{1t}$ using Equation 5.32

10. Update $\bar{x}^{k+1}_t = (1-\gamma)\bar{x}^k_t + \gamma\hat{x}^k_t$

11. If $t > 0$ go to Step 6

12. If $k < K$ go to Step 2

The algorithm may not converge, so $\gamma_k = 1/k$ step size sequence is used, which satisfies the standard conditions $\sum_{k=1}^{\infty} \gamma_k = \infty$ and $\sum_{k=1}^{\infty} (\gamma_k)^2 < \infty$ as the smoothing factor for convergence. γ is initialized with a value 0.5, and then it is factored down every K iterations if no improvement in the objective function is found.

The advantage of this approach in estimating the linear approximation for dynamic control policy is its simplicity. This approach uses linear approximation at time $t+1$ to assist in making a decision at time t. Also, this approach is robust to variable data. Future research of this approach can be extended to handle the interaction between closing at different terminals. Numerical experiments were done using the dynamic control policy, and the total cost of operation in a planning horizon was compared against the static dispatch strategy and optimal solution. The results are described in the next section.

5.6 Numerical Experiments

Numerical experiments were done to evaluate the dynamic control policy when compared to static dispatch strategy and the optimal solution. Stationary, dynamic, and optimal solutions are compared in Figures 5.12, 5.13, 5.14, and 5.15. As can be seen from Figures 5.12, 5.13, 5.14, and 5.15, the dynamic control policy, which uses 100 iterations in estimating the linear approximation is better than the stationary dispatch strategy and is close to the optimal solution. Dynamic control policy has run times that are approximately linear as can be seen in Figure 5.16 and hence the solution procedure for the single link problem can be easily embedded in a large LTL networks.

Dynamic control policy develops a linear approximation for the recourse function and the developed linear approximation is then used to decide when to dispatch the trucks dynamically. The advantage of this approach is that numerical experiments show that

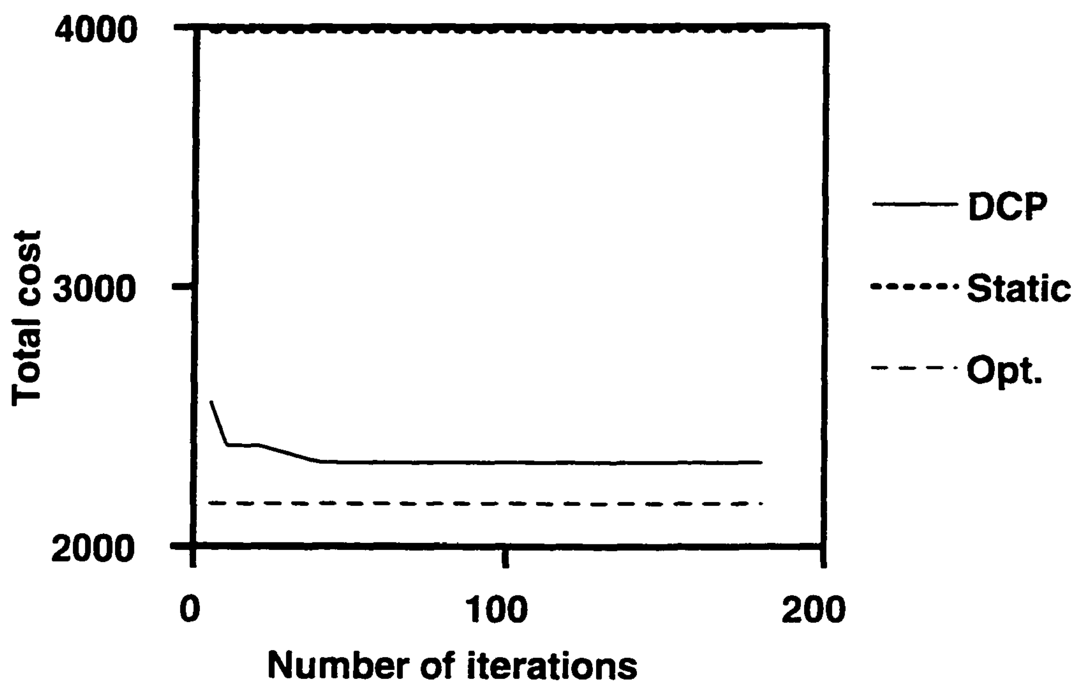


Figure 5.12 Comparison of dynamic, stationary, and optimal solutions for $F = 50$, $h = 1.5$, $\alpha = 0.96$

the solution obtained is close to the optimal solution and quality of the solution is much better when compared to a static dispatch strategy. The linear approximation developed is shown to be fast when compared to dynamic programming, so the technique can be used to solve subproblems in a large LTL network.

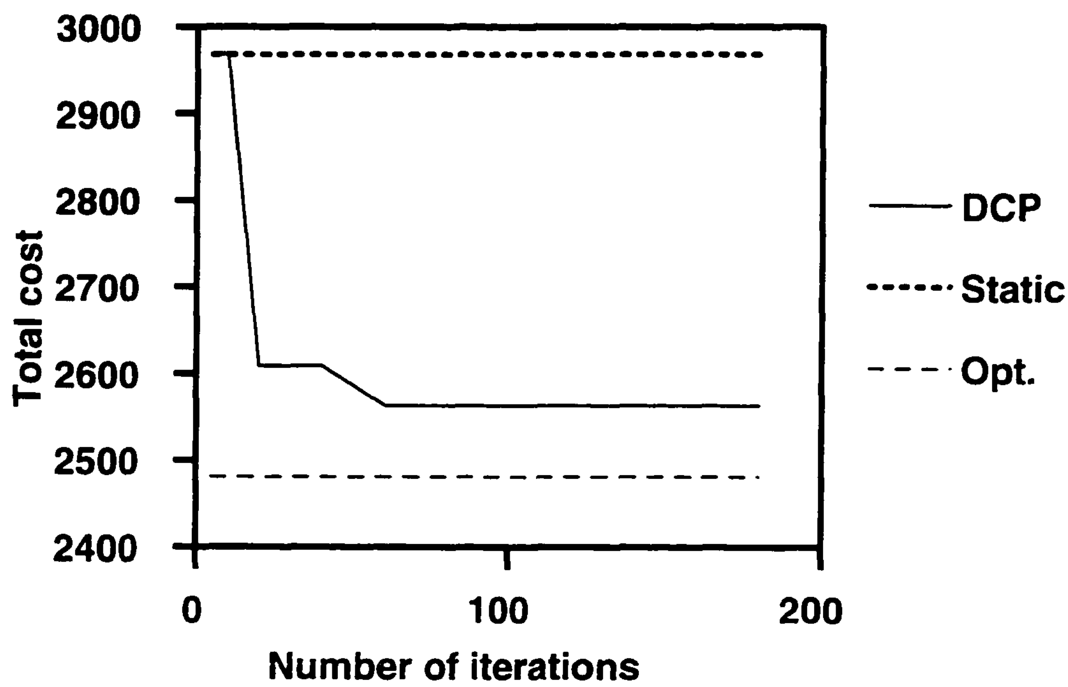


Figure 5.13 Comparison of dynamic, stationary, and optimal solutions for $F = 75$, $h = 1$, $\alpha = 0.96$

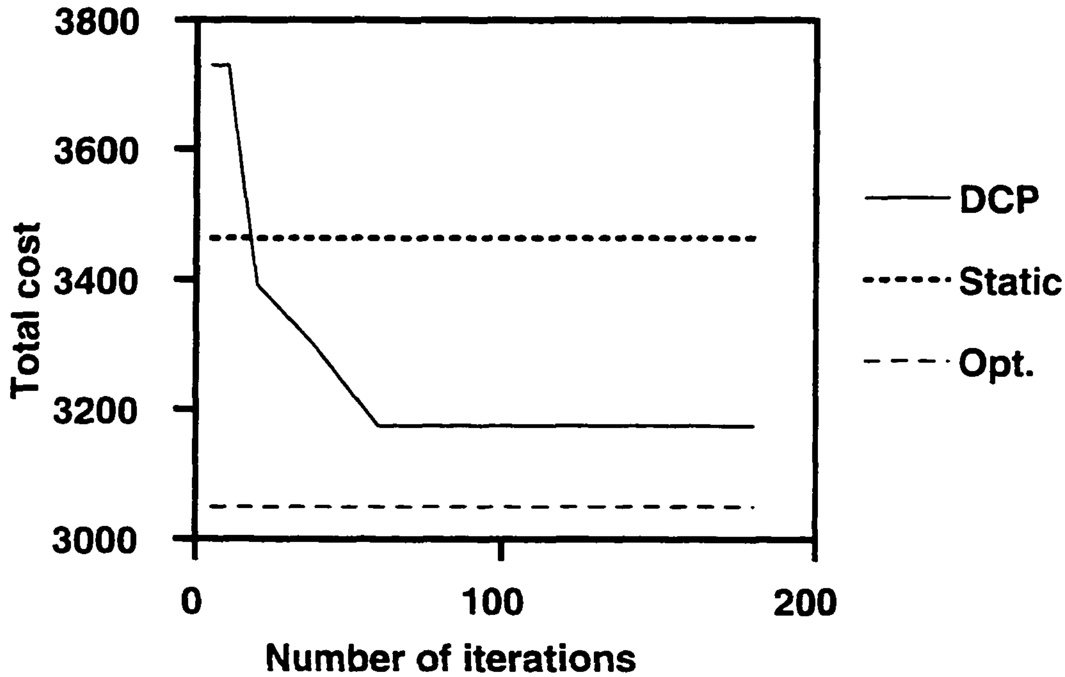


Figure 5.14 Comparison of dynamic, stationary, and optimal solutions for $F = 100$, $h = 1$, $\alpha = 0.96$

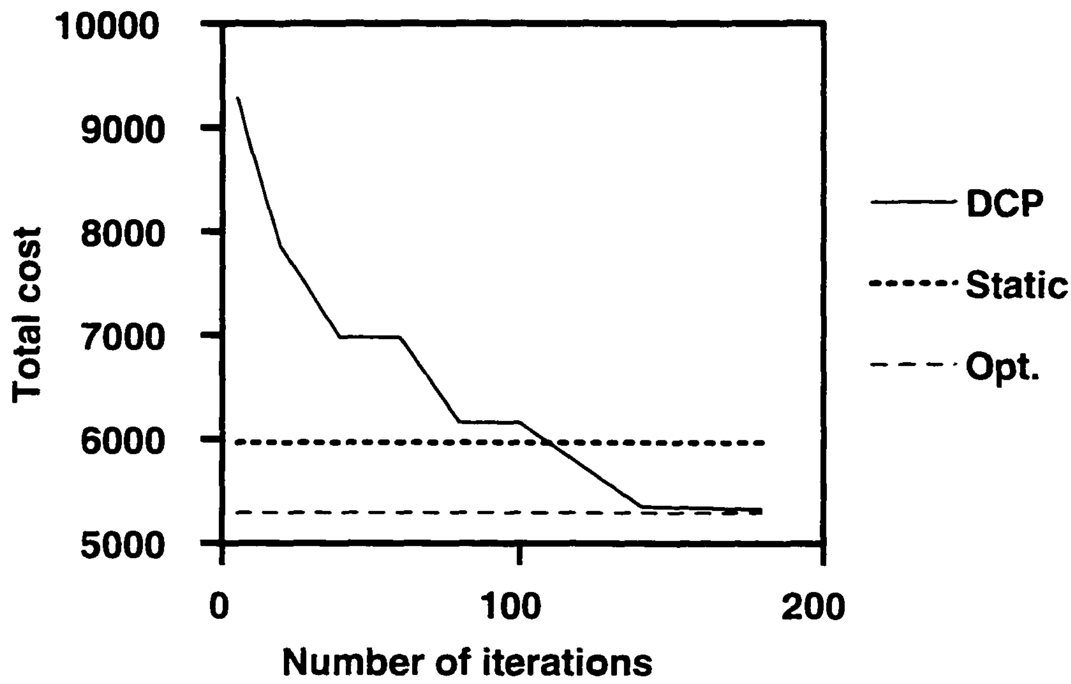


Figure 5.15 Comparison of dynamic, stationary, and optimal solutions for $F = 500$, $h = 0.5$, $\alpha = 0.96$

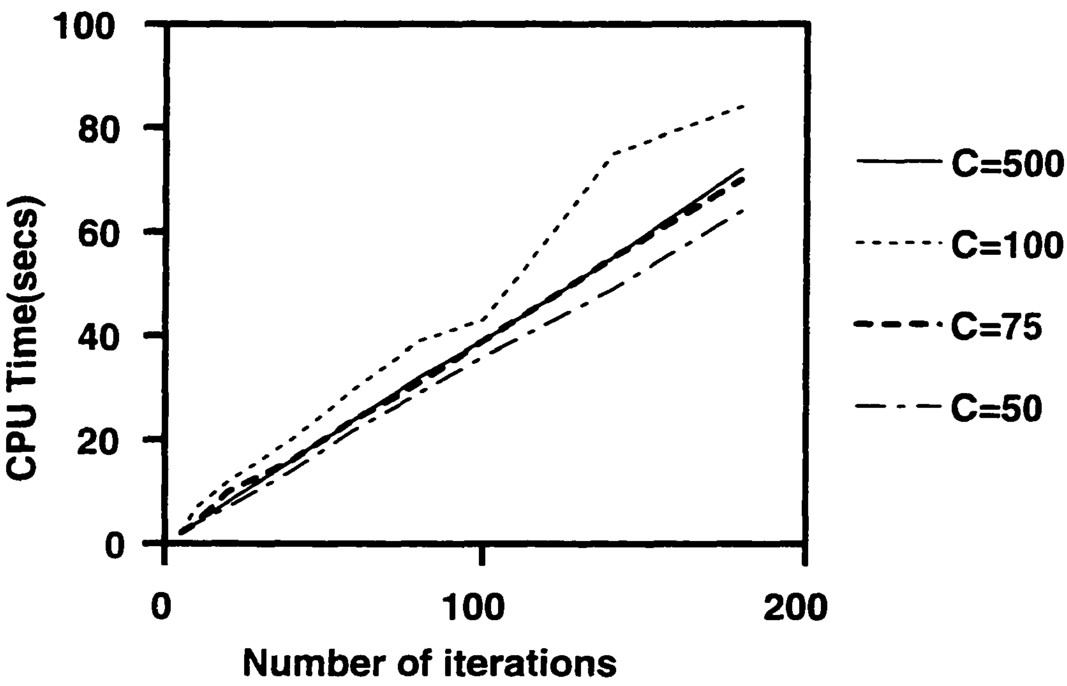


Figure 5.16 Solution times for dynamic dispatch strategy at different values of F, h, α

6 CONCLUSION

The research investigated the impact of opportunisitic direct service. direct service. holding time. TTMS. and closing capacity on total cost of the system and on the number of bills delayed. The simulation model pointed out that decreasing the minimum capacity that needs to be filled for dispatch or decreasing the holding time at a terminal did not necessarily decrease the number of delayed shipments. The number of delayed shipments was only affected by TTMS. The experiments also showed that adding opportunistic direct service to regular service reduced the number of bills delayed. The simulation model was also able to identify the most congested/underutilized breaks so that EOLs could be reassigned. These experiments in changing policies/loadplans to reduce congestion or to increase utilization are costly to implement in the actual operations of an LTL carrier without knowing their total impact on the cost/service of the whole system. The simulation model developed could also be used by LTL managers for planning day-to-day operations in estimating the number of empty trailers that had to be moved to a terminal and number of drivers that had to be sent to a terminal to meet the demand.

Although. abundant literature is available in railroad and shipping operations simulation. none has been found in LTL operation simulation. It is therefore assumed that. the simulation model will serve as a valuable tool for large LTL carriers to improve the level of service provided to the customers and to reduce the cost. The simulation model will be more acceptable by LTL managers as they can manipulate and conduct sensitivity analysis on it easily when compared to complicated analytical formulation that they cannot work with on a regular basis. This research has demonstrated the use of simulation in a real world application. The simulation model and the approach described in this research are considered to be very useful to the LTL company analysts to explore many other operating options in the future.

An alternative shipment routing strategy is considered for the priority shipments on an LTL line-haul network. By using a network formulation. this strategy can be represented by finding a dynamic shortest path over a stochastic network. A label-setting algorithm was developed to find the expected travel time from each node to the destination when using this strategy. The algorithm was found to be quite efficient to be used in real time. Numerical experiments indicated that this adaptive routing strategy allowed the priority shipments to reach their destination at a fast rate. Therefore. considering the stochastic and dynamic aspects in LTL routing is worthwhile.

While the results are encouraging. several issues remain to be addressed. First. the assumption that perfect information about a terminal is given when the terminal is reached may not be valid. In practice. only partial information can be obtained. In fact. transforming real-time information to a form that can be used mathematically requires further investigation. Second. in the experiments. the waiting time for a closed trailer to be dispatched at a terminal was not considered a random variable. The waiting time depends on the availability of drivers who can handle this trailer. However. dealing with this issue is not trivial. For example. even when a driver is available to handle a closed trailer. he can take a "future" trailer on which many shipments have missed the deadline. Third. since priority shipments constitute only relatively small portion of the total shipments. the total cost increase due to the violation of using the load plan is small. If the same dynamic routing strategy is applied to regular shipments. it is unclear at this stage whether the total cost would increase substantially or not.

A dynamic control policy was developed for dispatching trailers on a single link. A recourse function was developed which estimates the total future cost from current time

t given state S_t at current time. The dynamic control policy exploited the linearity of the recourse function in solving the trailer dispatching problem efficiently. Though an infinite horizon with stationary arrivals and a finite horizon with dynamic arrivals could be solved easily, most of the real world problems occur in an infinite horizon and dynamic setting. Therefore, the solution obtained for infinite horizon and finite horizon models will be approximate for real world problems. This research finds an approximate solution for infinite horizon and dynamic setting and shows that the quality of solution obtained is close to the optimal. Numerical experiments show that the dynamic control policy reduced the cost when compared to the static dispatch strategy. Therefore, this research shows that considering dynamic control policy for dispatching trucks in LTL networks is worthwhile. Since, the algorithm is simple and fast and hence, could be extended easily to large LTL networks.

Several of the following issues remains to be addressed in the future. First, though the numerical results showed that the dynamic control policy was effective, it was not proved to be optimal. Second, this research assumed the demand to be deterministic. Therefore, further research is recommended to extend the dynamic control policy to the dispatch problem with stochastic demands. Third, this research mainly considered vehicle dispatching problem over a single link. However, application and effectiveness of this strategy on a large LTL network needs to be tested. Fourth, in this research regardless of the time the shipment is delayed, the penalty cost is assumed to be the same during each period. Future research needs to consider non-linear penalty costs with increasing waiting time. However, dealing with non-linear penalty costs is not trivial.

BIBLIOGRAPHY

[1] M. O. Akyilmaz. An algorithmic framework for routing LTL shipments. *Journal of Operational Research Society*. 45(5):529–538. 1994.

[2] A. A. Assad. Models for rail transportation. *Transportation Research*. 14A:205–220. 1980.

[3] C. Barnhart. and Y. Sheffi. A network-based primal-dual heuristic for the solution of multicommodity network flow problem. *Transportation Science*. 27(2):102–117. 1993.

[4] D. Bertsekas. and J. N. Tsitsiklis. An analysis of stochastic shortest path problems. *Mathematics of Operations Research*. 16:580–595. 1991.

[5] M. Bronzini. and D. Sherman. The rail carrier route choice model. *Transportation Research A*. 17A(6):463–469. 1983.

[6] J. F. Campbell. Freight consolidation and routing with transportation economies of scale. *Transportation Research B*. 24B:345–361. 1990.

[7] J. F. Campbell. Continuous and discrete demand hub location problems. *Transportation Research B*. 27B(6):473–482. 1993.

[8] R. K. Cheung and B. Muralidharan. Dynamic routing for priority shipments in LTL service network. *IMSE Technical Report*. Iowa State University. Ames. IA 50011. September 1995.

[9] T. G. Crainic. and J. Leal. A model for the strategic planning of national freight transportation by rail. *Transportation Science*. 24(1):1–24. February 1990.

[10] T. G. Crainic. Operations research models of intercity freight transportation: The current state and future research issues. *Logistics and Transportation Review*. 23(2):189–206. 1987.

[11] T. G. Crainic. and J. M. Rousseau. Multicommodity. multimode freight transportation: A general modeling and algorithmic framework for the service network design problem. *Transportation Research-B*. 20B(3):225–242. 1986.

[12] T. G. Crainic. and J. Roy. Design of regular intercity driver routes for the LTL motor carrier industry. *Transportation Science*. 26(4):280–295. November 1992.

[13] J. Croucher. A note on stochastic shortest route problem. *Naval Research Logistics Quarterly*. 25:729–732. 1978.

[14] C. F. Daganzo. The break-bulk role of terminals in many to many logistic networks. *Operations Research*. 35:543–555. 1987.

[15] C. F. Daganzo. A comparison of in-vehicle and out-of-vehicle freight consolidation strategies. *Transportation Research B*. 22B(3):173–180. 1988.

[16] A. F. Daughety. M. A. Turnquist. and S. L. Griesbach. Estimating origin-destination specific railroad marginal operating cost functions. *Transportation Research A*. 17A(6):451–462. 1983.

[17] R. Deb. Optimal control of batch service queues with switching costs. *Advances in Applied Probability*. 8:177-194.1978.

[18] R. Deb. and R. Serfozo. Optimal dispatch of batch service queues. *Advances in Applied Probability*. 5:340-361. 1973.

[19] P. J. Dejax. and T. G. Crainic. A review of empty flows and fleet management models in freight transportation. *Transportation Science*. 21(4):227–247. November 1987.

[20] N. Deo. and C. Pang. Shortest-path algorithms: Taxonomy and annotations. *Networks*. 14:275–323. 1984.

[21] S. E. Dreyfus. An appraisal of some shortest path algorithms. *Operations Research*. 17:395–412. 1969.

[22] J. M. Farvolden. and W. B. Powell. Subgradients for service network design. *Transportation Science*. 28(3):256–272. 1994.

[23] L. F. Frantzeskakis. and W. B. Powell. A successive linear approximation procedure for stochastic. dynamic vehicle allocation problems. *Transportation Science*. 24(1). February 1990.

[24] A. Frieze. and G. Grimmet. The shortest path problem for graphs with random arc lengths. *Discrete Applied Mathematics*. 10:57–77. 1985.

[25] J. Guelat. M. Florian. and T. G. Crainic. A multimode multiproduct network assignment model for strategic planning of freight flows. *Transportation Science*. 24(1):25–39. February 1990.

[26] A. E. Haghani. Formulation and solution of a combined train routing and makeup. and empty car distribution model. *Transportation Research B*. 23B:433–452. 1989.

[27] R. W. Hall. The fastest path through a network with random time-dependent travel times. *Transportation Science*. 20:182–188. 1986.

[28] R. W. Hall. Comparison of strategies for routing shipments through transportation terminals. *Transportation Research A*. 21A:421–429. 1987.

[29] R. W. Hall. Route choice on freight networks with concave costs and exclusive arcs. *Transportation Research B*. 23B(3):177–194. 1989.

[30] R. W. Hall. and M. Racer. Transportation with common carrier and private fleets: System assignment and shipment frequency optimization. *IIE Transactions*. 27:217–225. 1995.

[31] W. C. Jordan. Truck backhauling on networks with many terminals. *Transportation Research B*. 21B:183–193. 1987.

[32] J. Kamburowski. An overview of the computational complexity of the PERT shortest route and maximum flow problems in stochastic networks. In G. Andreatta. F. Mason. and P. Serafini. editors. *Stochastics in Combinatorial Optimization*. World Scientific Publishing Co., Singapore. 1987.

[33] M. H. Keaton. Are there economies of traffic density in the less-than-truckload motor carrier industry? An operations planning analysis. *Transportation Research-A*. 27A(5):343–358. 1993.

[34] W. D. Kelton. Perspectives on Simulation Research and Practice. *ORSA Journal on Computing*. 6(4):318–328. 1994.

[35] L. Kosten. The custodian problem. *Queueing Theory. Recent Developments and Applications*. 65-70. London. 1967. English Press Ltd.

[36] L. Kosten. *Stochastic Theory of Service Systems*. Pergamon Press. New York. 1973.

[37] J. Medhi. *Recent Developments in Bulk Queueing Models*. Wiley Eastern Limited. New Delhi. 1984.

[38] K. K. Lai. K. Lam. and W. K. Chan. Shipping container logistics and allocation. *Journal of Operational Research Society*. 46:687–697. 1995.

[39] J. Lysgaard. Dynamic transportation networks in vehicle routing and scheduling. *Interfaces*. 22(3):45–55. May-June 1992.

[40] M. A. McGinnis. A comparitive evaluation of freight transportation choice models. *Transportation Journal*. 36–46. 1989.

[41] P. Mirchandani. and M. H. Veatch. 'Hot job' routing through a stochastic job-shop network. *Large Scale Systems*. 11:131–148. 1986.

[42] P. B. Mirchandani. Shortest distance and reliability of probabilistic networks. *Computers and Operations Research*, 3:347–355, 1976.

[43] E. K. Morlok, and L. Nozick. A model of intermodal rail truck service for operations management, investment planning and costing. *Technical Report, Department of Systems, University of Pennsylvania, Philadelphia, PA 19106-6315*. January 1992.

[44] A. Orda, R. Rom, and M. Sidi. Minimum delay routing in stochastic networks. *IEEE/ACM Transactions on Networking*, 1(2):187–198, April 1993.

[45] J. D. Papastavrou, S. Rajagopalan and A. Kleywegt. The dynamic and stochastic knapsack problem with deadlines. *Management Science*, 42(12):1706–1718, December 1996.

[46] C. S. Park, and Y. D. Noh. A Port simulation model for bulk cargo operations. *Simulation*, 48(6):236–246, 1987.

[47] E. R. Petersen, and A. J. Taylor. A structured model for rail line simulation and optimization. *Transportation Science*, 16(2):192–206, May 1982.

[48] A. R. Pierce. Bibliography on algorithms for shortest path, shortest spanning tree, and related circuitry touring problems (1956-1974). *Networks*, 5:129–149, 1975.

[49] G. H. Polychronopoulos. Stochastic and dynamic shortest distance problems. Ph.D. Thesis, Department of Electrical Engineering and Computer Science, MIT, Cambridge, MA, 1992.

[50] W. Powell. A local improvement heuristic for the design of less-than-truckload motor carrier networks. *Transportation Science*, 20(4):246–257, November 1986.

[51] W. Powell, T. Carvalho, G. Godfrey, and H. P. Simao. Dynamic fleet management as a logistics queueing network. *Technical Report 94-18, Deparment of Civil Engineering and Operations Research*, Princeton University, December 1994.

[52] W. Powell, and P. Humblet. The bulk service queue with a general control strategy: Theoretical analysis and a new computational procedure. *Operations Research*, 34(2):267-275,1986.

[53] W. Powell, and H. P. Simao. Numerical simulation of transient bulk queues with general vehicle dispatching strategies. Transportation Research, 20(6):477-490, 1986.

[54] W. Powell, and Y. Sheffi. The load planning problem of motor carriers: Problem description and a proposed solution approach. *Transportaion Research-A*, 17A(6):471–480, 1983.

[55] W. Powell, and Y. Sheffi. Design and implementation of an interactive optimization system for the network design in the motor carrier industry. *Operations Research*, 37:12–29, 1989.

[56] W. B. Powell. Analysis of vehicle holding and cancellation strategies in bulk arrival, bulk service queues. *Transportation Science*, 19(4):352-277, 1985.

[57] W. B. Powell. A stochastic model of the dynamic vehicle allocation problem. *Transportation Science*, 20:117–129, 1986.

[58] W. B. Powell. An operational planning model for the dynamic vehicle allocation problem with uncertain demands. *Transportation Research*, 21B:217–232, 1987.

[59] H. N. Psaraftis, and J. N. Tsitsiklis. Dynamic shortest paths in acyclic networks with Markovian arc costs. *Operations Research*, 41:91–101, 1993.

[60] S. U. Randhawa, C. C. Brunner, J. W. Funck, and G. Zhang. A discrete event object oriented modeling environment for sawmill simulation. *Simulation*, 64(2):119–130, February 1994.

[61] J. Roy, and T. G. Crainic. Improving intercity freight routing with a tactical planning model. *Interfaces*, 22:31–44, May-June 1992.

[62] R. Semenzato, S. Lozano, and R. Valero. A discrete event simulation of sugar cane harvesting operations. *Simulation*, 46:1073–1078, 1995.

[63] G. Sharma, R. G. .S. Asthana, and S. Goel. A knowledge based simulation approach (K-sim) for train operation and planning. *Simulation*, 62(6):381–391, June 1994.

[64] A. A. R. EL Sheikh, R. J. Paul, A. S. Harding, and D. W. Balmer. A microcomputer based simulation study of a port. *Journal of Operational Research Society*, 38(8):673–681, 1987.

[65] H. Weiss, and S. Pliska. Optimal control of some Markov processes with applications to batch queueing and continuous review inventory systems. Discussion paper no. 214, The Center for Mathematical Studies in Economics and Management Science, Northwestern University, 1976.

IMAGE EVALUATION TEST TARGET (QA-3)

150mm

6"

APPLIED IMAGE, Inc
1653 East Main Street
Rochester, NY 14609 USA
Phone: 716/482-0300
Fax: 716/288-5989