ABSTRACT

OPTIMIZATION OF VEHICLE ROUTING AND SCHEDULING WITH TRAVEL TIME VARIABILITY - APPLICATION IN WINTER ROAD MAINTENANCE

by
Haifeng Yu

This study developed a mathematical model for optimizing vehicle routing and scheduling, which can be used to collect travel time information, and also to perform winter road maintenance operations (e.g., salting, plowing). The objective of this research was to minimize the total vehicle travel time to complete a given set of service tasks, subject to resource constraints (e.g., truck capacity, fleet size) and operational constraints (e.g., service time windows, service time limit).

The nature of the problem is to design vehicle routes and schedules to perform the required service on predetermined road segments, which can be interpreted as an arc routing problem (ARP). By using a network transformation technique, an ARP can be transformed into a well-studied node routing problem (NRP). A set-partitioning (SP) approach was introduced to formulate the problem into an integer programming problem (IPP). To solve this problem, firstly, a number of feasible routes were generated, subject to resources and operational constraints. A genetic algorithm based heuristic was developed to improve the efficiency of generating feasible routes. Secondly, the corresponding travel time of each route was computed. Finally, the feasible routes were entered into the linear programming solver (CPLEX) to obtain final optimized results.

The impact of travel time variability on vehicle routing and scheduling for transportation planning was also considered in this study. Usually in the concern of vehicle and pedestrian’s safety, federal, state governments and local agencies are more

leaning towards using a conservative approach with constant travel time for the planning of winter roadway maintenance than an aggressive approach, which means that they would rather have a redundancy of plow trucks than a shortage. The proposed model and solution algorithm were validated with an empirical case study of 41 snow sections in the northwest area of New Jersey. Comprehensive analysis based on a deterministic travel time setting and a time-dependent travel time setting were both performed. The results show that a model that includes time dependent travel time produces better results than travel time being underestimated and being overestimated in transportation planning

In addition, a scenario-based analysis suggests that the current NJDOT operation based on given snow sector design, service routes and fleet size can be improved by the proposed model that considers time dependent travel time and the geometry of the road network to optimize vehicle routing and scheduling. In general, the benefit of better routing and scheduling design for snow plowing could be reflected in smaller minimum required fleet size and shorter total vehicle travel time. The depot location and number of service routes also have an impact on the final optimized results. This suggests that managers should consider the depot location, vehicle fleet sizing and the routing design problem simultaneously at the planning stage to minimize the total cost for snow plowing operations.

OPTIMIZATION OF VEHICLE ROUTING AND SCHEDULING WITH TRAVEL TIME VARIABILITY – APPLICATION IN WINTER ROAD MAINTENANCE

by
Haifeng Yu

A Dissertation
Submitted to the Faculty of
New Jersey Institute of Technology
in Partial Fulfillment of the Requirements for the Degree of
Doctor of Philosophy in Transportation

Department of Civil and Environmental Engineering

May 2014

.

APPROVAL PAGE

OPTIMIZATION OF VEHICLE ROUTING AND SCHEDULING WITH TRAVEL TIME VARIABILITY- APPLICATION IN WINTER ROAD MAINTENANCE

Haifeng Yu

Dr. Steven I-Jy Chien, Dissertation Advisor Date
Professor of John A. Reif, Jr. Department of Civil Environmental Engineering, NJIT

Dr. Lazar N. Spasovic, Committee Member Date
Professor of John A. Reif, Jr. Department of Civil Environmental Engineering, NJIT

Dr. Athanassios K. Bladikas, Committee Member Date
Associate Professor of Department of Mechanical and Industrial Engineering, NJIT

Dr. Janice R. Daniel, Committee Member Date
Associate Professor of John A. Reif, Jr. Department of Civil Environmental Engineering, NJIT

Dr. Jian Yang, Committee Member Date
Associate Professor of Management Science & Information System, Rutgers University

BIOGRAPHICAL SKETCH

Author: Haifeng Yu

Degree: Doctor of Philosophy

Date: May 2014

Undergraduate and Graduate Education:

- Doctor of Philosophy in Transportation Engineering,
  New Jersey Institute of Technology, Newark, NJ, 2014
- Master of Science in Manufacturing System Engineering,
  New Jersey Institute of Technology, Newark, NJ, 2009
- Bachelor of Science in Electrical Engineering,
  Guangdong University of Technology, Guangzhou, P. R. China, 2006

Major: Transportation Engineering

Presentations and Publications:

Yu, Haifeng, Steven I-Jy Chien, and Ching-Jung Ting. "Bilevel Programming Model for Minimum-Cost Travel Time Data Collection with Time Windows." Transportation Research Record: Journal of the Transportation Research Board 2197.-1 (2010): 29-35.

Yu, Haifeng, Steven I-Jy Chien, and Ching-Jung Ting. "Optimal Routing for Minimum Service Time of Winter Road Maintenance with Truck Capacity and Fleet Size Constraints." Transportation Research Board Annual Meeting, 2013, Washington DC.

Abdel-Malek, Layek L., Steven I. Chien, Jay N. Meegoda, and Haifeng Yu. "A Fleet Contracting Model for Snow Plowing Operations." Journal of Infrastructure System, American Society of Civil Engineering, 2014

This dissertation is dedicated to
my beloved family:
my mother, Manhong Xiao;
my father, Guoqiang Yu;
my girl friend, Chiewsze Cheah;
for their love and support.

ACKNOWLEDGMENT

I owe a great debt of gratitude to my advisor, Dr. Steven (I-Jy) Chien, who made this dissertation possible. He made outstanding contributions to my research by spending tons of time and effort turning my manuscript drafts into a high quality dissertation. During my five-year graduate study at NJIT, I had the privilege of having him as my instructor and mentor, and learned from him to be an independent thinker and excellent problem solver.

A special note of thanks goes to Dr. Athanassios K.Bladikas, Dr. Janice R. Daniel, Dr. Lazar N. Spasovic and Dr. Jian Yang in my Committee for their teaching, assistance, comments and suggestions.

Finally, I want to express my deep appreciation for the support and encouragement of my girlfriend, Chiewsze Cheah. Without her support and patience, this dissertation would not have been possible. I am also profoundly grateful to my parents for having faith on me and always encouraging me to challenge myself to move forward.

TABLE OF CONTENTS

Chapter	Page
1 INTRODUCTION	1
1.1 Background	1
1.2 The Nature of the Problem	2
1.3 Objective and Work Scope	4
1.4 Dissertation Organization	5
2 LITERATURE REVIEW	7
2.1 Variability of Travel Time (VTT)	7
2.1.1 Impacts of VTT on Routing and Scheduling	9
2.1.2 Technologies for Collecting Travel Time Data	12
2.2 Node Routing Problem	15
2.2.1 Vehicle Routing Problem with Pickup and Delivery (VRPPD)	15
2.2.2 Vehicle Routing Problem with Time Windows (VRPTW)	16
2.2.3 Vehicle Routing Problem with Time-dependent Travel Time	18
2.3 Arc Routing Problem	22
2.4 Transformation between NRP and ARP	24
2.4.1 Transformation of NRP to ARP	24

TABLE OF CONTENTS
(Continued)

Chapter	Page
2.4.2 Transformation of ARP to NRP ……………………………….…..….…	25
2.5 Vehicle Routing in Winter Road Maintenance ………………………....……	26
2.5.1 Vehicle Routing Problems for Spreading ……………………..…..…..	27
2.5.2 Vehicle Routing Problems for Snow Plowing ……………………….……..	29
2.6 Solution Algorithms …………………………………………………………….	32
2.6.1 Exact Algorithms …………………………………………………….…..…	32
2.6.2 Heuristic Algorithms ………………………………………………….……	37
2.7 Summary …………………………………………………..…………….....	42
3 MODEL DEVELOPMENT ………………………………………………………	44
3.1 Problem Description …………………………..…………….…………………	47
3.2 Network Transformation …………………………....…………………	48
3.3 The Basic Model …………………………………………………………….	50
3.3.1 Assumptions ……………………………………….................…..	51
3.3.2 Model Formulation ……………………………………………………	51
3.4 The Enhanced Model ……………………………………….....……….	53
3.4.1 Model Formulation ……………………………………………………	53

TABLE OF CONTENTS
(Continued)

Chapter		Page
	3.4.2 Time-Dependent Travel Time ………………………………………...	54
3.5	Set Partitioning Formulation ……………………………………….……..	56
3.6	Summary …………………………………………………………….…….	58
4	SOLUTION ALGORITHM ……………………………………….………..	60
4.1	Exhaustive Numeration …………………………….………………….….....	60
4.2	The Genetic Algorithm Based Heuristic ………………….……………..………..	62
4.3	Summary ………………………………………………………………………..	68
5	MODEL TESTING AND EVALUATION ……………..……………………...	70
5.1	Example I-Travel Time Data Collection...……………………………..……….	70
	5.1.1 Numerical Results ……………………………………………………….	72
	5.1.2 Scenario Analysis ………………………………………………………..	77
	5.1.3 Sensitivity Analysis ……………………………………………………	78
5.2	Example II- Winter Road Maintenance …….……………………….……..…	82
	5.2.1 Numerical Results ……………….……………………………..……...	84
	5.2.2 Scenario Analysis ………………………………………………………..	90
5.3	Summary ………………………………………………………………………..	92

TABLE OF CONTENTS
(Continued)

Chapter **Page**

6 CASE STUDY ………………………………………………………..……….. 93

6.1 Objective …………………………….…………………….……………...... 93

6.2 Current Winter Roadway Maintenance in New Jersey ………….……….. 94

6.3 Data Preparation …………………………………………………………….. 96

6.3.1 Geometric Data …………………………………………………….. 98

6.3.2 Weather Data ………………………………………………………. 100

6.3.3 Speed Data …………………………………………………………. 100

6.4 Results Discussion ……………………………………………………….... 102

6.4.1 Scenario Analysis ………………………………………………... 103

6.4.2 Sensitivity Analysis on Plowing Speed ………………………………. 113

6.5 Summary …………………………………………………………………….. 115

7 COMPUTATIONAL ANALYSIS ……………….…………….…….……….. 117

7.1 Optimal Results and Calulation Time ………………………….………… 117

7.2 Analysis on Population Size …………………………………………………. 120

8 CONCLUSIONS AND FUTURE WORK ………………………………………. 122

8.1 Contributions ………………………….………...……………..…. 123

TABLE OF CONTENTS
(Continued)

Chapter	Page
8.2 Future Work ……………………………………………………………………	124
REFERENCES …………………………………………………………………………	126

LIST OF TABLES

Table		Page
3.1	Glossary of Mathematical Notations (Alphabetical Order) ………………………...	46
3.2	The Adjacency Matrix ……………………………………………………………...	49
4.1	Sample of Chromosome Representation …………………………………………	64
5.1	Characteristics of the Study Road Segments …………………………………….	71
5.2	Travel Time and Distance Between Nodes ………………………………………	72
5.3	Cost of Travel between Nodes (Unit: $) …………………………………………	73
5.4	Node Assignment Travel Time/Cost Matrix for Time Window T_2 ……………...	74
5.5	Vehicle Availability Matrix for T_2 ……………………………………………….	74
5.6	Feasible Routes and Schedules for Vehicles (Fleet Size = 5) ……………………	75
5.7	Optimal Vehicle Schedule/Route Arrangement and the Minimized Cost ……….	76
5.8	Characteristics of Scenario A and B ……………………………………………..	77
5.9	Optimal Vehicle Schedule and Minimized Cost (Fleet Size: 3) …………………	78
5.10	List of Required Arcs and Unrequired Arcs ……………………………………..	85
5.11	Travel Distances Matrix ………………………………………………………….	86
5.12	Parameters and Notations (Alphabetical Order) ………………………………....	87
5.13	Results of Scenario I and Scenario II …………………………………………….	90
5.14	Results of Scenario III …………………………………………………………...	91
6.1	Expenditures in New Jersey for Winter Roadway Maintenance ………………...	96
6.2	Selected Snow Sections and Maintenance Yards ………………………………..	98
6.3	Snow Intensity Level …………………………………………………………….	100

LIST OF TABLES
(Continued)

Table		Page
6.4	Speed Profile of Road Type III at Different Time Period of PM peak …………..	102
6.5	Definitions of Common Terms ………………………………………………..	103
6.6	Definitions of Scenarios ………………………………………………..…..	104
6.7	Summary of Service Routes in Sussex ………………………………………..	107
6.8	Summary of Results for Scenario-I ……………………………………………	108
6.9	Summary of Results for Scenario-II …………………………………………	110
6.10	Results and Analyses for Various Plow Speed …………………………………..	114
7.1	Parameters of the GA Based Heuristic ………………………………………..	118
7.2	Result comparison of Small Size Problems …………………………………...	118
7.3	Results of scenario II with Different Population Sizes ………………………..…	120

LIST OF FIGURES

Table **Page**

1.1 "Requests" at multiple time windows ……….…………………………………….. 3

3.1 Implementation of model development …………………………………………. 45

3.2 The original network …………………………………………………………….. 49

3.3 The transformed network from the original network ……………………………. 50

3.4 Temporal traffic speed distribution ……………………………………………… 55

3.5 Corresponding travel time for a link of length 2 miles ………………………….. 56

4.1 Example of generating service routes …………………………………………… 62

4.2 An example of roulette wheel …………………………………………………… 66

4.3 Example of one-point crossover ………………………………………………… 67

5.1 The study network for traffic data collection ……………………………………. 71

5.2 The transformed route network for traffic data collection ………………………. 72

5.3 Minimum required fleet sizes vs. various numbers of sample size ……………... 80

5.4 Minimum required fleet sizes vs. various time window durations ……………… 81

5.5 Fleet size vs total vehicle travel time ……………………………………………. 82

5.6 Example network of winter road maintenance ………………………………….. 84

5.7 Example of plow tasks …………………………………………………………... 85

6.1 New Jersey snow sections and maintenance yards ……………………………… 95

6.2 Selected snow sections in the northern New Jersey roadway network ………….. 97

6.3 Sample of the studied transportation network in ArcGIS ……………………….. 99

6.4 Plowing speed vs snow accumulation rate and moisture content ……………….. 101

LIST OF FIGURES
(Continued)

Table **Page**

6.5 (a) Existing snow sections and maintenance yard in Sussex ………………………. 106

6.5 (b) Optimized service routes for Sussex ………………………………………… 106

6.6 Service route details ……………………………………………………………... 106

6.7 Service routes developed for Scenario I ………………………………………… 109

6.8 Service routes developed for Scenario-II ……………………………………….... 111

6.9 Cycle time distribution ………………………………………………………….... 112

6.10 Deadhead travel distance distribution …………………………………………… 113

7.1 Comparison of calculation time …………………………………………………. 119

CHAPTER 1

INTRODUCTION

1.1 Background

Routing and scheduling vehicles to perform the required service within a transportation network play an important role in the area of transportation planning and engineering. It is challenging for transportation planners to represent real-life conditions closely with traditional modeling approaches either with strict assumptions that make them limited or not applicable in real-world application, or complex formulations that make them difficult and inefficient to be implemented. One practical aspect that needs to be addressed is the travel time variability. Most of the models for vehicle routing and scheduling reported in the literature assumed constant travel time by ignoring its variation. Unfortunately, constant travel time is a weak assumption for congested conditions that can result from recurring (e.g., congestion during peak hours, work zone, etc.) or non-recurring (e.g., accidents, vehicle breakdowns, etc.) events. Therefore, the optimal solution subject to constant travel time may be suboptimal or even infeasible for time-dependent cases (e.g., snow emergency salting and plowing operations).

Travel time is a fundamental measure in transportation planning and engineering, whose variability and reliability are always of concern to travelers and transportation professionals. With the rapid development of Intelligent Transportation Systems (ITS), traveler information (e.g., travel time and delay) can be delivered to motorists through various communication technologies deployed on the transportation infrastructure and in vehicles. Many roadways have traffic sensors (i.e., inductive loops, acoustic sensors, etc.) for counting spatial as well as temporal traffic volume and speed, and apply new technologies (e.g., cell phones, GPS, and Bluetooth, etc.) for approximating travel times. In order to validate the travel time estimates with data collected by different sources, probe vehicles are commonly used for collecting ground truth O-D (Origin-Destination) based travel time. Because obtaining accurate O-D travel time for a transportation network with sufficient probe vehicles is expensive, it is desirable to develop a cost-effective data collection plan with optimized routes and schedules for vehicles considering practical constraints.

Vehicle routing and scheduling with time dependent travel time makes it possible to model the problem of winter road maintenance, where the timing of an intervention is of prime importance. If the intervention is too early or too late, the cost in material and time varies. In addition to the material cost, the state governments contract third-party trucks to support their operations during winter storms to make their operations more flexible and reduce truck maintenance cost. The payment rule used for these third-party trucks can be based on total travel time. In this case, the total travel time contributes majorly to total spending, which motivated this study to design efficient routes and schedules for winter maintenance operations to reduce the total cost while maintaining good level of service.

1.2 The Nature of the Problem

The nature of the research problem discussed in this study is a network optimization problem, involving efficient routing and scheduling of a number of vehicles engaged in practical transportation applications (e.g., data collection, winter road maintenance) on a predetermined directed graph $\boldsymbol{G=(V, A)}$,where $\boldsymbol{V}$ is a set of nodes, and $\boldsymbol{A}$ is a set of arcs connecting pairs of nodes in $\boldsymbol{V}$. It is assumed that $\boldsymbol{A}$ is partitioned into a subset of required arcs $\boldsymbol{A_1}$, and a complementary subset of arcs $\boldsymbol{A_2}$. $\boldsymbol{A_1}$ known as “requests” or “demands” must be serviced. The pickup and delivery locations are analogous to the start and end nodes of each arc. Because time windows are imposed for each arc belonging to $\boldsymbol{A_1}$, requiring vehicles to serve required arcs within pre-specified time periods based on the project needs. In other words, each “request” may occur in multiple time windows within a project duration (see Figure 1.1), which can be formulated as the arc routing problem with multiple time windows (Dumas et al., 1991 and Desroisers et al., 1995).

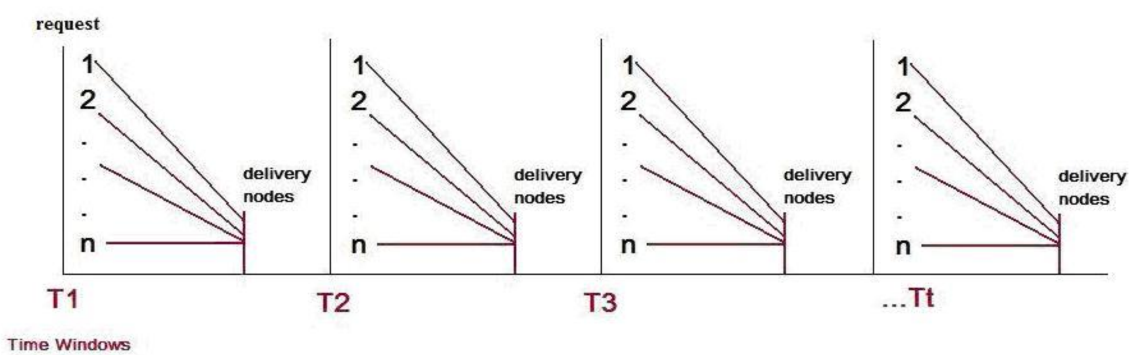


Figure 1.1 "Requests" at multiple time windows.

This study was considered in the context of the network optimization problem involving vehicle routing and scheduling. A generalized mathematical model was developed, which can be used to minimize either the total operating cost or travel time for vehicle routing and scheduling problems, subject to a set of practical constraints (e.g., limited budget, fleet size, number of demands, and project duration, etc.).

A set-partition approach was proposed to formulate the problem. Firstly, a number of promising feasible routes were generated by taking resource constraints or operational constraints into account. Secondly, these routes were treated as input to a mathematically formulated model that gives a solution of optimized routes and schedules that tells where and when to deploy vehicles. The exhaustive enumeration method was used to generate candidate routes for problems with a small size of demand. Then a genetic algorithm based heuristic was developed for solving problems with large size of demand. By using this efficient heuristic with adjustments, the proposed optimization model is able to solve the studied problem with consideration of time-dependent travel time.

1.3 Objective and Work Scope

Travel time and its variability are important indicators of roadway level of service. Various technologies (e.g., GPS, Bluetooth, etc.) have been widely applied for collecting speed data to approximate travel time. It is challenging to design a cost-effective plan including the routing and scheduling of vehicles to fulfill required service while considering time-dependent travel time. Because the nature of routing and scheduling vehicles for winter road maintenance makes the problem itself can be mathematically formulated as an Arc Routing Problem (ARP), thus the objectives of this study are:

1. To develop a mathematical model considering travel time variability for the winter road maintenance problem to minimize total vehicle travel time. Small size problems will be solved using an exact algorithm.
2. To develop an efficient solution algorithm to find good solutions for larger size problems, since the research problem is NP-hard.

3. To study the impact of travel time variability on vehicle routing and scheduling by comparing results obtained with constant travel time and time-dependent travel time.

To satisfy the above objectives, the nature of the routing and scheduling problem, its variants and solution algorithms were reviewed. Then the research problem was formulated and solved using the developed modeling approach and the solution algorithm. Later, two numerical examples based on applications of travel time data collection and winter snow plowing operation were provided to demonstrate the effectiveness of the developed model and solution algorithm. To extend this study's applicability to address the impact of travel time variability, constant travel time inputs were replaced by time-dependent ones. A complete case study based on 41 snow Sections in the northwest area of New Jersey was undertaken to evaluate the performance of the proposed model in both the constant travel time and time-dependent travel time setting.

1.4 Dissertation Organization

This dissertation was organized into seven chapters. Chapter 1 introduces the background of travel time data collection and presents the research objective and work scope. Chapter 2 summarizes the efforts of previous studies related to vehicle routing and scheduling problems, solution algorithms and applications. Chapter 3 presents the model development with the set partition approach， which was used to mathematically formulate the studied problem considering travel time variability. Chapter 4 introduces the exhaustive enumeration and the genetic algorithm based heuristic for solving the mathematical model that was developed in Chapter 3. Chapter 5 presents two numerical examples on travel time data collection and winter road maintenance to demonstrate the applicability of the present model. Chapter 6 presents a case study based on snow Sections in the state of New Jersey. Chapter 7 presents computational analysis by comparing results obtained by using the exact algorithm and results obtained by using the GA based heuristic. Finally, Chapter 8 concludes the findings of this study and suggests the directions of future research.

CHAPTER 2

LITERATURE REVIEW

This chapter discusses the literature review results in the area of vehicle routing and scheduling and its related variants and applications in winter road maintenance. In Section 2.1, the definition of Variability of Travel Time (VTT), its impact on vehicle routing and scheduling and the current technologies for travel time collection are reviewed. Later, the original problem of vehicle routing and scheduling is reviewed in the context of network optimization problem, which can be categorized and reviewed in details as two major related problems: Node Routing Problems (NRP) (Section 2.2) and Arc Routing Problems (ARP) (Section 2.3). The relationship between NRP and ARP and techniques of how one can be transformed to the other are discussed in Section 2.4. In Section2.5, research related to winter roadway maintenance is reviewed. After reviewing these problems, a brief discussion of solution algorithms including exact algorithms and heuristic algorithms are presented in Section 2.6. Finally, Section 2.7 summarizes the findings of the literature review.

2.1 Variability of Travel Time (VTT)

The Variability of Travel Time (VTT) in transportation systems has been the focus of many transportation agencies, because it affects transportation planning, design and operation, and system evaluation. Examples of planning and design applications include: 1) Develop transportation policies and programs; 2) Perform needs studies or assessments (Lyman and Bertini, 2008); 3) Rank and prioritize transportation improvements (Lyman and Bertini, 2008); 4) Evaluate transportation improvement strategies (Chen et al., 2003); and 5) Calculate road user costs for economic analyses (Chen et al., 2003). VTT can result from traveler behaviors (i.e., departure time, route choice, and driving characteristics) of traffic mix (i.e., passenger cars, transit vehicles, and trucks) and the transportation network topology, geometry and traffic control. VTT has increasingly been recognized as a major factor influencing travel decision making and, consequently, serves as an important performance measure in transportation management (Recker et al., 2005).

The Texas Transportation Institute's Urban Mobility Report (2012) defined reliability and variability of travel time separately. Reliability is commonly used in reference to the level of consistency in transportation service; and variability is the amount of operating inconsistency. To quantify reliability and variability, travel conditions in the peak period were compared to free-flow conditions and two measures were defined: Travel Time Index (TTI) and Buffer Time. The TTI can be used in various systems with different free-flow speeds. Values of the TTI can used by the general public as an indicator of extra time spent in a transportation system during a trip. Buffer Time is the amount of extra time that must be allowed by a traveler to reach his or her destination on time in 95% of the time. Back in 2000, Florida DOT developed and documented the Florida Reliability Method. Similar to the Texas Transportation Institute's definition of travel time reliability, they defined reliability on a highway segment as 95% of travel that takes no more than the expected travel time plus a certain acceptable additional time. These measures provide transportation planners and modelers a quantifiable basis to investigate and explore causes of travel time variability.

2.1.1 Impacts of VTT on Routing and Scheduling

VTT significantly impacts vehicle routing as well as scheduling when delivery times are heavily restricted by customers' time windows and schedules. For example, Holguin-Veras et al. (2006) investigated the effects of New York City's congestion pricing on commercial vehicles' delivery schedules and found little changes because delivery times were set by customer time windows and schedules. It was also found that a large proportion of carriers do not worry about the toll increase change since customers are willing to take the extra cost rather than to compromise the scheduled delivery times. In contrast, carriers pay more attention on traffic conditions that could be interpreted as travel time variability.

Figliozzi (2010) analyzed the impact of congestion on commercial vehicle tours. The paper suggested that VTT is significant when the travel time between the depot and customers is long in relation to the maximum tour duration and when the routes are highly constrained by travel time. Also VTT impacts carriers' productivity that can be measured in terms of tour time and distance required to serve a customer. Percentage of time driving and the average distance traveled per customer are usually used to indicate the efficiency of an individual tour because they are directly related to carriers' operating cost. Quak and De Koster (2009) utilized a fractional factorial design and regression analysis to quantify the impacts of delivery constraints and urban freight policies. Their findings confirmed previous results from Holgun-Veras's study showing that the cost impact of time windows is the largest for retailers who combine many deliveries in one vehicle round-trip. In summary, when a time window constraint for vehicle pickup and delivery comes into consideration, VTT has a significant impact on vehicle routing and scheduling decisions.

Evidence on the behavioral response to VTT has also been obtained by analyzing route choice decisions. Abdel-Aty et al. (1993) analyzed state preference data from Los Angeles, CA, where respondents were provided with five hypothetical choices based on the traffic report accuracy. The degree of accuracy was described as: 1) extremely accurate, 2) very accurate, 3) somewhat accurate, 4) not very accurate and 5) not accurate at all. These choices gave the option of two alternative routes with different means and variances of travel time. The results revealed the important relationship between the use of travel time information and the propensity of route changes. From the commuters' standing point, traffic conditions, perceptions of information accuracy and traffic variation were among the variables influencing the frequency of route changes based on en-route traffic information. From the planner's standing point, problems involving vehicle routing and scheduling should take those variables into consideration.

Noland (2002) developed a schedule delay framework in a simulation experiment for a hypothetical network with two routes. By varying the degree of travel time variation due to non-recurring congestion on one route, it was possible to observe the changes on commuters' route and departure time choices. The results showed that trips made by models with fixed schedules are subject to scheduling costs regardless of congestion with consequent implications. The change in travel activities is a major factor in valuing the costs and benefits of travel time variability. This work suggested that the modeling of route choice needs to consider scheduling effects if VTT becomes a major factor.

Recker et al. (2005) stated that VTT is increasingly being recognized as a major factor influencing travel decisions and, consequently, is an important performance measure in transportation management. The authors provide an analysis of segment travel time variability, which was first measured using a traffic database from GIS. The variability was measured from two different aspects, the first is the variability of day-to-day travel time, and the second one was within-day variability. The standard deviation and normalized standard deviation were used as measures of variability. Numerical experiments were carried out to examine the effects of route choice models on network assignment results. By incorporating travel time variability into the route choice models, the predictive capability of the route choice models was enhanced and could potentially lead to better means of reducing traffic congestion, wasteful travel, and loss of productivity, and at the same time, improve network capacity utilization and travel time reliability.

Hollander (2006) described two distinguishable modeling approaches based on modeling the attitudes of travelers to the unexpected day-to-day variability of travel times. In his study, the direct approach sees the extent of VTT as the variable that travelers react to, whereas the indirect approach claims that VTT effects are fully explained by trip scheduling considerations. In this, factors affecting bus users' scheduling behavior and attitudes to VTT are investigated through a survey among bus users in the city of York, England. The results confirm that the influence of VTT on bus users was best explained indirectly through scheduling considerations. The considerations of scheduling should be addressed by taking VTT into consideration so that planners could better utilize the available bus fleet and reduce waiting time for bus users.

2.1.2 Technologies for Collecting Travel Time Data

The rapid progress of information technology (IT) may provide new insights to the understanding of traffic phenomena. Many technologies including the ITS probe vehicle have been used in travel time data collection. The Automatic Vehicle Identification (AVI) transponder [e.g., TRANSCOM's System for Managing Incidents and Traffic (TRANSMIT)], which is located inside a vehicle and is used in electronic toll collection applications, is an example. This system utilizes antenna readers installed at regular intervals along the highway to identify the time when each transponder-equipped vehicle passes by. The detection of an equipped vehicle at successive readers downstream produces estimates of link travel times.

Various research studies and operational tests were conducted in regards to measure travel times through the use of electronic toll collection (ETC) system. Wright and Dahlgren (2001) discussed that ETC on the eight bridges crossing San Francisco Bay provided the means for a relatively simple and low cost system for measuring travel times on bridges and roads. Readers at various locations could recognize the toll tags used for ETC. The time of reading was recorded so that the time difference between when a vehicle passes one reader and another could be obtained. It was found that the application of ETC data improved facilities efficiency and reduced users delay. Saka and Agboh (2002) discussed the aggregated impact of ETC (also called M-Tag) deployment at three toll plazas in the Baltimore Metropolitan Area. The toll plazas were treated as multi-server queuing systems. The delay as well as travel time data were used to estimate mean vehicular travel speed at the toll facilities. The analysis involved the development of simulation and deterministic models used to generate traffic flow parameters, including speed and driving cycles for the study areas.

<u>GPS Based Probe Vehicle:</u>

In this section, the GPS based probe vehicle was mainly discussed in terms of the technology itself, its advantages and disadvantages, and its popularity in real practice of travel time data collection. One of the key applications of IT to traffic and transport analysis is the identification of the location of moving objects using the global positioning system (GPS). It is expected that detailed traffic analysis could be carried out using these data. Zito et al. (1995) were the first to address the use of GPS data for traffic engineering. They discussed the accuracy of the GPS and its potential for traffic analysis, and suggested that geographical information systems (GIS) could be used efficiently for managing the data obtained by the GPS. A study that estimated VTT on New Jersey (NJ) highways was conducted by collecting travel times with probe vehicles carrying GPS devices (Chien et al., 2010). The results include estimated travel time and its variability on selected NJ highways by departure time of day and day of the week. The travel time data were collected through the use of an in-vehicle navigation device equipped with a GPS-receiver. The use of GPS-based link/path travel time data collection could produce the corresponding distributions and buffer index to assist real-time traffic operations (e.g., signal timing) traveler information (e.g., real-time route planning), and transportation short term and long term planning (e.g., infrastructure and traffic management strategies).

<u>Number of Probe vehicles:</u>

Travel times are generally estimated by roadside detectors. Travel time cannot be observed on a road without any onsite observation instruments, although some estimation techniques have been proposed. The probe vehicle approach is one efficient method of collecting LOS information and data about the source of traffic congestion. The reliability of probe vehicle data for estimating the travel time should be investigated. Karthik et al. (1996) implemented an algorithm to determine the number of probe vehicles required for reliable travel time measurement by using a simulation of the Sacramento network for the morning peak period. The results indicated that the number of probe vehicles required increases nonlinearly as the reliability criterion is made more stringent. More probes are required for shorter measurement periods. As the desired proportion of link coverage in the network increases, the number of probes required increases. With a given number of probes a greater proportion of freeway links than of major arterials can reliably be covered. Probe vehicles appear to be an attractive source of real time traffic information in heavily traveled, high speed corridors such as freeways and major arterials during peak periods, but not recommended for coverage of minor arterials or local streets during off-peak hours.

Lee et al. (2006) examined the relationship between the number of probe vehicles and the travel time collection reliability using both simulated and field data. Their results suggested that the operational characteristics of probe vehicles are very important when constructing a reliable information system that needs to meet network coverage requirements. Cheu et al. (2002) also discussed the population and size of probe vehicles using a simulation-based analysis. They concluded that the improvement in the accuracy of link speed estimation diminishes when the probe vehicle population in the network reaches the threshold of 15% of the total network traffic network volume. They further concluded that to achieve an absolute error in the estimated average link speed of less than 5.0 km/h at least 95% of the time, there should at least 4 to 5% active probes in the total network traffic volume, or at least 10 probes that have successfully traversed a link. As stated in the above studies, viewing the travel time data collection from a statistical perspective, having enough probe vehicles is crucial because the sample size determines the accuracy of the travel time estimation. But standing from the viewpoint of the cost control, it is costly to schedule and route vehicles to collect enough data samples without compromising data accuracy. Thus, it is important to develop a mathematical model to optimize routes and schedules based on minimum cost.

2.2 Node Routing Problem

Node routing problems try to find the minimum cost routes that service the nodes in the network. There are two main problems in this category, one is the travelling salesman problem (TSP), which does not have the capacity constraint, and the other is the vehicle routing problem (VRP), which considers the capacity constraint. In the classical node routing problem if there is only one vehicle and there is no capacity constraint, the problem simplifies into a traveling salesman problem. This section focuses on the capacitated VRP and its variations.

2.2.1 Vehicle Routing Problem with Pickup and Delivery (VRPPD)

The classical VRP can be described as follows: A fleet of m capacitated vehicles localized at one or more depots have to serve n customers with demand d. The problem is to find the minimum cost route for all vehicles so that all customer demands are satisfied.

The VRP with pickup and delivery (VRPPD) is an extension of VRP. In addition to the traits of VRP each customer i now has both an origin (pick-up point), as well as a destination (drop-off point) and the demand. Typical applications can be found in the fields of parcel and para-transit services. The VRPPD is a generalization of the classical VRP, which also belongs to a larger family of pickup and delivery problems (PDPs). One can distinguish between three well-known types of pickup and delivery problems that have been studied in the literature. 1) One is the single-commodity PDP in which a single type of good is either picked up or delivered at each node (Hernandez-Perez and Salazar-Gonzalez, 2004). This is the case, for example, when an armored vehicle transports money between the branch offices of a bank. 2) Another variant is the two-commodity PDP where two types of goods are considered and each node may act as both a pickup and a delivery node (Angelelli and Mansini, 2002). This problem arises in beer or soft drink delivery where vehicles deliver full bottles and collect empty ones. A variant of this problem is the VRP with backhauls in which all deliveries must be performed before any pickup. 3) Finally, the n-commodity problem occurs when each commodity is associated with a single pickup node and a single delivery node. This is the case when passengers or goods must be transported from an origin to a destination.

2.2.2 Vehicle Routing Problem with Time Windows (VRPTW)

Because most practical applications of the VRPPD include restrictions on visiting time at each location that may be visited by a vehicle, it is convenient to present a more general variant of the problem, called the VRPPD with time windows (VRPPDTW). The VRPPDTW is NP-hard since it generalizes the TSP that is also known to be NP-hard (Garey and Johnson, 1979). With the presence of time windows, even finding a feasible solution to the problem is NP-hard since the feasibility problem for the TSP with time windows is itself NP-complete (Savelsbergh, 1985). Savelsbergh and Sol (1995) considered a more general formulation of the pickup and delivery problem and reviewed the relevant literature on this problem. A more recent survey on pickup and delivery problems with time windows was also prepared by Desaulniers et al. (2001). In this study, empirical applications in winter road maintenance and travel time data collection can have multiple time windows on each demand that located on either arcs or nodes.

Time windows can be classified into two types: hard time windows (HTW) and soft time windows (STW). In the first case, if the vehicle arrives early, it must wait until the lower bound of the window, and it is strictly forbidden to arrive late. In the case of STW, the violation of the constraint is permitted but leads to an objective function penalty. As discussed by Chiang and Russell (2004), VRP with soft time windows (VRPSTW) has been practically applied for the following reasons: 1) relaxing HTW constraints to reduce total cost without compromising customer satisfaction; 2) relaxing unnecessary HTW constraints for particular applications (e.g. the delivery of fuel/gas to service stations); 3) dealing with issues related to travel time uncertainty; 4) solving VRPHTW with proper penalty setups. The solution of VRPSTW was used as an alternative answer when the solution of VRPHTW is infeasible.

Replacing HTW constraints with STW ones will increase computation time because of the increase in feasible solution spaces. Thus, an efficient solution algorithm is desirable to improve the computational efficiency. Qureshi et al. (2009) presented a new column-generation-based approach to find exact optimal solutions for vehicle scheduling problems with STW constraints. An elementary shortest path problem with resource constraints and late arrival penalty was solved as a sub-problem. It was found that the VRPSTW solution results in fewer routes and lower cost while a late arrival penalty has a small impact on total cost. Figliozzi (2010) developed an iterative route construction and improvement algorithm for solving VRPSTW, which was able to accommodate general cost and penalty functions. Experimental results indicated that the average run time performance was significantly improved. Even though the increased computation time can be handled by some solution algorithms, there is still case that HTW is more preferable. In winter gritting operations, where a subset of road segments must be serviced at a cost that depends on the time service begins, if the intervention is too late, the cost in material and time sharply increases. Therefore, planners would rather have vehicles arrive early than fine vehicles for arriving late.

2.2.3 Vehicle Routing Problem with Time-dependent Travel Time

Most of the VRP models and their solution approaches assume that all characteristics are independent of the time of day. Therefore, these models may have problems to deal with real-life applications where travel time can be influenced by congestion or incidents occur on the road network. The literature related to vehicle routing with time-dependent travel times is relatively scarce.

Malandraki and Daskin (1992) examined both the time-dependent vehicle routing problem (TDVRP), and the time-dependent traveling salesman problem (TDTSP) which is a special case of the TDVRP, where the feet size is equal to one. They provided mixed integer linear programming formulations that included capacities and time windows constraints. The travel times were computed using step functions. The travel time between two customers or between a customer and the depot depends on the travel distance and time of day. The Nearest-neighbor (greedy) heuristics for TDTSP and TDVRP without time windows were proposed, as well as a branch-and-cut algorithm for solving small problems with 10 to 25 nodes. In Malandraki and Dial's following work (1996), a dynamic programming algorithm was developed to solve the TDTSP. Although it was argued that this algorithm can handle many different types of travel time functions, no results comparison was done between different types of travel time functions. Results were only reported for step functions found in their previous work (1992).

Hill and Benton (1992) considered a TDVRP (without time windows) and proposed a model based on time-dependent travel speeds. In their formulation, the travel time on a given link is dependent on the average travel speed during the period that a vehicle starts travelling. Computational results were reported on a small example with a single vehicle and five locations. The authors implemented a simple greedy heuristic for the multi-vehicle traveling salesman problem with capacity constraints and no time windows for a city with 210 locations. A validation of the model was conducted in a commercial courier vehicle scheduling system and was judged to be very useful by users in a number of different metropolitan areas in the United States.

Donati et al. (2008) considered variable traffic conditions in VRP to perform realistic optimization. TDVRP consists of finding optimal routes by considering the time it takes to traverse each given arc depending on the time of day travel starts. This variant of the classic VRP is motivated by the fact that in urban contexts variable traffic conditions play an essential role and cannot be ignored in order to perform a realistic optimization. The paper showed that when dealing with time constraints, like hard delivery time windows for customers, the known solutions for the classic case become unfeasible and the degree of unfeasibility increases with the variability of traffic conditions.

The TDVRP is more difficult to model and to solve than the VRP with constant travel time. The major issue is how to model the variation of travel time during a certain time period. Available models often discretized a time period into a limited fixed number of time intervals (e.g., morning, midday and afternoon) with a distinct associated fixed mean speed. Ichoua et al. (2003) used a model based on discrete travel speeds by adding correction factors to model congestion. It is a simple way to take time-dependency into account by working with time-dependent travel speeds and to adjust the speed when the vehicle crosses a boundary between two time periods. In contrast with the formulation proposed by Hill and Benton (1992) where travel speeds corresponded to time periods and nodes, the travel speeds were associated with different time periods and arcs in Ichoua et al.'s study. This reduced the computational effort at the cost of storing speed data. Hill and Benton's model was implemented in a static and a dynamic environment, respectively. The results showed that the time-dependent model provided significant improvement over the model with fixed travel times, which indicated the usefulness of time-dependent travel speed information.

Donati et al. (2006) expressed the total distance between any two nodes in terms of the time taken to traverse an arc. Travel speed was inversely proportional to the time taken to traverse the distance. A step function was used for representing the speed distribution, from which the travel time distribution was derived. By applying this travel speed modeling approach to a real road network with 1522 nodes and 2579 arcs, the authors concluded that the time dependent models can provide a better modeling of travel time when variable traffic conditions have a considerable influence on travel time. In general, time dependent travel time can be modeled in two ways: deterministically or stochastically (Van Woensel et al., 2008). In the deterministic case, the travel time is known in advance. The travel time is then a function of distance and mean speed. For instance, Ichoua et al. (2003) considered three distinct time periods (where the first and third periods stand for the morning and evening rush hours, respectively, and the second period corresponds to the middle part of the day) and three different types of road links. This approach has been implemented within a parallel Tabu search developed by Taillard et al. (1995) for the fixed travel time version. It provided a simple way to take time-dependency into account by working with time-dependent travel speed that could be obtained from different sources of traffic data collection.

In the stochastic time-dependent models, the solution procedure takes into account the stochastic nature of travel time. Travel time is the result of taking into account not only mean travel time but ideally the travel time distribution itself. As the travel time distribution is derived from the speed distribution and the known distances, the approach requires realistic speed distributions. He et al. (2005) indicated that although mean and variance contain the most important information about path travel time, finding the single route with expected shortest travel time is not appropriate for routing when planners are not risk neutral. The entire travel time distribution contributes to the routing choice. A stochastic model usually involves two stages. In the first stage, a route is planned a priori, followed by a realization of the random variables. In the second stage, a recourse or corrective action is then applied to the solution of the first stage. The cost/saving generated though the recourse action may have to be considered when designing the first stage solution.

In this dissertation, to include time-dependency into vehicle routing and scheduling, a predefined service time period was discretized into a limited fixed number of time intervals (e.g., 15-minute intervals) with a distinct associated fixed mean speed that was extracted from historical speed data or proper estimation. Future work will be focused on the integration of the real-time information (traffic conditions) and the speed profile provided by historical data. The general idea is to modify in real time, the speed profiles to accommodate traffic and thus to provide more realistic travel times.

2.3 Arc Routing Problem

The arc routing problems belong to another subset of the network optimization problems. While in node routing problems one tries to visit the nodes of the network, in arc routing problems the objective is to traverse the arcs of the network. The Chinese Postman Problem (CPP) and the Rural Postman Problem (RPP) are two popular arc routing problems.

CPP was simply stated by Kwan (1962) as the problem of finding the shortest walking distance for a mailman who has to cover his assigned segment before returning to the post office. Two extensions of CPP were described as follows. One is the windy postman problem (WPP), in which the underlying network is an undirected graph, but the cost of traversing an arc depends on the direction of travel. Another form of CPP is the hierarchical CPP where a precedence relation is defined on arcs of the graph, and the order in which the arcs are serviced must respect this relation. CPP can be viewed as the counter part of the traveling salesman problem in the category of arc routing problems. The capacitated CPP is a counterpart of the VRP in the ARP and deals with a more realistic case than CPP. Given the demand for each arc that must be satisfied by vehicles with given capacities, find a set of cycles that all pass through a domicile and satisfy demands at minimal total cost. Just like that CPP is more likely to arise in urban areas, RPP is commonly associated with mail delivery in rural areas. There are a number of areas whose set of streets has to be serviced by a postman, and the other set of links between those areas that do not have to be served, but may be used for traveling between those areas. This problem is to find the minimum cost route to service those arcs that must be served.

Christofides and Beasley (1984) introduced the periodic arc routing problem (PARP), the problem of designing vehicle routes to meet required service levels for customers and minimize distribution costs over a given several-day period of time. A typical PARP in real life is the waste collection problem. Waste management companies gather statistics and know the average daily waste production in each street. This amount depends on the region, the population and the habitat. Apartment blocks in town centers cannot store waste for a long time in their basements so that it needs to be collected everyday generally. Houses in residential areas may keep waste for a few days in a container located in a garage or a garden and do not need a daily removal. This is why the collection process must be planned over a multi-period horizon. In practice, planners translate these waste productions into one service frequency for each street, for instance “everyday” or “twice a week”. Like location and districting, these computations depend upon the strategic decision level, because frequencies must remain constant for at least one year, to avoid upsetting the residents. It is assumed in the sequel that all strategic decisions have been already taken.

PARP in waste collection consists of selecting for each street a number of treatment days equal to its frequency (tactical decisions), and then of computing the trips for the streets assigned to each day (operational decisions). Obviously, the total cost over the horizon depends on this combination of assignment and routing decisions. Waste collection is just one example. A similar organization can be found in other applications like winter gritting, sweeping, inspection of power lines, or spraying herbicides on rails or roads to kill weeds.

2.4 Transformation between NRP and ARP

It can be shown that a VRP can be transformed into an ARP, and that an ARP can be transformed into a VRP, making the two classes of problems equivalent. For transformations of ARP into VRP, the resulting VRP instance requires either adjustment of variables or the use of arcs with infinite cost. In this Section, the relationship between NRP and ARP is reviewed.

2.4.1 Transformation of NRP to ARP

Relatively Very few studies addressed the transformation from NRP to ARP, because the transformation usually is accompanied by a significant increase in the size of the problem. Golden and Wong (1981) showed how NRP can be transformed into a capacitated ARP by slitting each nodes into two nodes joined by an arc, and by assigning the original node demand to that arc. Ghiani and Improta (2000) developed an efficient transformation of VRP into a capacitated ARP with only increasing the number of nodes by not much. The number of nodes increased after transformation was dependent on the number of multiple membership nodes in the original problem. They proposed a transformation that can be divided into three main stages. In the first stage, the general problem was transformed to a general TSP having mutually exclusive node sets. In the second stage, the intraset arcs were eliminated. In the third stage, the problem was transformed to a clustered TSP and then finally into a standard TSP. The resulting TSP has an arc and arc cost structure, which can be optimally solved by an approach based on integer linear programming.

2.4.2 Transformation of ARP to NRP

The field of arc routing is gaining momentum. However, since more literature is available on Node Routing Problems, some have ventured to turn ARP into VRP. The first and most generally used method for converting ARP into VRP was done by Pearn et al. (1987). They transformed the capacitated ARP into a capacitated VPR by replacing each arc with positive demand with three vertices, each having a demand equal to one third of the original demand. In this formulation the distances between vertex pairs were defined to enforce the constraint that a customer can only be visited by a single vehicle in the VRP and to guarantee that the three arcs appear consecutively on the same route in any capacitated VPR solution. Laporte (1997) transformed several types of ARP such as the Rural Postman Problem. Instances involving up to 220 vertices, 660 directed arcs and a few undirected arcs were solved to optimality on low density graphs. The transformation includes three steps:

1. Replace each edge by two arcs;
2. Create a transformed network. The nodes in the transformed network are the arcs in the original network; the arcs in the transformed network are the length of the shortest path between two arcs in the original network;
3. Transform the Generalized Traveling Salesman Problem into TSP.

However, the transformation is regarded as unpractical, since an original instance with r required edges was turned into a CVRP over a complete graph with $3r+1$ vertices. Longo et al. (2004) proposed a similar transformation that reduces this graph to $2r+1$ vertices, with the additional restriction that r edges were already fixed to 1. Using a recent branch-and-cut-and-price algorithm for the CVRP, it was observed that it yields an effective way of attacking the CARP and computational experiments obtained improved lower bounds for almost all open instances. But, the transformation entails certain drawbacks summarized by Letchford and Oukil (2009):

1. A huge amount of memory is needed to perform the transformation.
2. The transformation method is not suitable for all types of graphs.

To address these two drawbacks, it is worth noticing that as the information techniques have been developing in a fast pace, the memory capacity should not be a barrier for transforming ARP to VRP. Also, with appropriate adjustments on network graphs, the applications of ARP in waste collection, winter plowing and spreading can be formulated in the context of VRP.

2.5 Vehicle Routing in Winter Road Maintenance

VRP is one of the most well studied problems in operations research, both in real life problems and for scientific research purposes. Many practical transportation problems including the winter road maintenance routing problem can be formulated as a VRP. Winter road maintenance operations involve challenging vehicle routing that can be addressed using operations research (OR) techniques. Key problems such as routing trucks and specialized vehicles for spreading chemicals and abrasives on roadways, snow plowing, and snow disposal, all of which are undertaken in a difficult and dynamic operating environment with strict level of service constraints. There is an extensive literature of academic research on various issues related to the planning, design and management of winter road maintenance operations summarized by Perrier et al. (2006a,b, 2007a,b).

2.5.1 Vehicle Routing Problems for Spreading

Consider a road network consisting of a set of predetermined maintenance segments with each representing an itinerary that a service vehicle may follow. A fleet of vehicles is available to provide winter maintenance services such as salting during a snowstorm event. The problem is to develop an operation plan for the available service vehicles that specify a route assignment to take into account the following requirements:

1) The total operating cost is minimized;
2) The total service time is minimized;
3) The level of service for the network is maximized;
4) Total negative environmental effects (e.g., salt usage) are minimized.

Early studies generally formulated the routing problem related to spreading operations as ARP. Evans and Weant (1990) formulated salt spreading operations as the capacitated ARP and used the path-scanning algorithm to search for the optimal solution that satisfied the constraints of maximum service time for spreading completion, maximum route duration and vehicle capacities. Campbell and Langevin (2000) provided a detailed description of the snow removal and disposal operation in Montreal. They listed major arc routing theories, solutions and applications related to snow operations. These problems include site location, Section design, Section assignment, fleet mix and routing. An integer programming formulation for snow disposal site location and the vehicle assignment problem was given.

Compared to early studies, researchers gradually incorporated more practical constraints and techniques into their models. Thus, the spreading problem cannot be only limited to the context of ARP. To reduce the operation cost that is dominated by total travel distance or total travel time of the entire fleet, Haghani and Qiao (2001) developed a model that incorporated the constraints of maximum route distance and truck capacities to optimize snow emergency routes for Calvert County, MD. Later, the model was enhanced (2002) by considering the link continuity constraint into the optimization processes. A heuristic approach was applied, which decomposes the problem into two components: “allocation of road Sections to salt spreaders” and “vehicle routing”. In the first component, the network transformation technique was used to convert an ARP to a NRP, and the minimum spanning tree formulation was used to calculate the minimum required fleet size to complete the entire spreading operation; and in the second one, the total deadhead cost was minimized by optimizing routes with the fleet size obtained from the first component.

Yu and Chien (2013) applied a similar network transformation technique to formulate a routing problem related to anti-icing and de-icing operations as a NRP. The objective was to minimize the service time needed for anti-icing/de-icing operations, subject to truck capacity, truck operating speed and fleet size constraints. After the vehicle routing network was converted from an ARP to a NRP, the study vehicle routing problem can be solved via dynamic programming (DP). The solution approach was tested on a general network with practical operational data. The results were promising and computationally efficient.

In summary, despite of the difficulty of routing and scheduling vehicles for road maintenance, recently proposed models tended to take into account a larger variety of problem characteristics (e.g., roadway characteristics, snow sectors, level of service) arising in real-world applications. Recent developments in modeling and algorithmic tools, the increased performance of computers, and the increased desire from state and local agencies to reduce expenditures on winter road maintenance operations, while maintaining or enhancing service levels and minimizing environmental impacts, all motivate the more widespread use of optimization models.

2.5.2 Vehicle Routing Problems for Snow Plowing

Plowing operations involve a number of VRP where streets or roads have to be traversed by plows or trucks. The plow routing and scheduling problems consist of determining a set of routes, each traveled by a vehicle that starts and ends at its own depot, such that all road segments are serviced, all the operational constraints are satisfied, and the global cost is minimized. Similar to routing problems related to spreading operations, routing problems related to plowing operations were generally formulated as arc routing problems.

Marks and Stricker (1971) modeled the plow routing problem as a multiple vehicle CPP, which is a special case of ARP. The authors attempted to minimize deadhead distance while respecting the service requirements and vehicle capacity constraints. Haslam and Wright (1991) and Wang and Wright (1994) developed a maintenance decision support system for the Indiana Department of Transportation planners to determine snow plowing routes with minimized deadheading, service time window violation and the total distance of class upgraded road segments. The system can handle plow routing problems with service time windows, class continuity and class upgrading constraints.

Perrier et al. (2008) proposed a formulation and two solution approaches based on mathematical optimization techniques for the routing of snow plowing vehicles in urban areas. Given a district and a single depot where a number of plows are based, the problem is to determine a set of routes, each performed by a single vehicle that starts and ends at the district's depot, such that all road segments are serviced while satisfying a set of operational constraints and minimizing a service completion time. The model contained general precedence relation constraints with no assumption on class connectivity, different service and deadhead speed possibilities, and vehicle road segment dependencies. The author proposed a model based on a multi-commodity network flow structure to impose the connectivity of the route performed by each vehicle, as well as constraints to model a hierarchical objective. The problem was solved by means of two constructive algorithms. The first one constructed several routes in parallel by sequentially solving a multiple vehicle rural postman problem with side constraints. The second was a cluster-first, route-second algorithm, which first determines a partition of the arcs into clusters, each having approximately the same work load. A hierarchical rural postman problem with class upgrading possibilities, vehicle road segment dependencies, and turn restrictions was then solved on each cluster.

Similarly, Dali (2009) proposed a sequential constructive heuristic for designing snowplow routes in a multi-depot network. The problem was modeled as a capacitated arc routing problem. The research was helpful in planning the optimum plowing routes; however, this problem was not applicable to predefined snow Sections in which the service routes were predetermined.

Fu et al. (2009) developed a real-time optimization model to evaluate the alternative resources allocation plan for winter road maintenance operations. Given a fleet of plowing vehicles and a set of predefined maintenance routes, the problem consisted of developing an operations plan for the available service vehicles that specify for each of them a route assignment including service type and service starting time. The scheduling model took into account both operation costs and quality of service requirements, as well as road network topology, road classes, and weather forecasts.

Salazar et al. (2011) studied the synchronized arc routing problem for snow plowing operations. In their research, the routes were designed in such a way that different synchronized vehicles plow street segments with two or more lanes in the same direction simultaneously. This research solved the problem of an important practical consideration absent from the literature on the planning of snow plowing operation. Namely, that plowing may need to be synchronized at the same time on the same street segment. The synchronized arc routing problem consists of determining a set of routes such that all street segments are serviced within the least possible time, subject to a synchronization constraint.

In summary, winter road plowing operations involve a host of system design and vehicle routing problems that can be addressed with operations research techniques. VRP for winter road maintenance are site specific because of the diversity of operating conditions and the wide variety of operational constraints. Hence, most algorithms developed for the routing of vehicles for winter road maintenance are heuristics (Perrier et al., 2007). Early models were generally solved with simple constructive methods for undirected and directed versions of CPP (a special case of ARP), and used simulation models to evaluate benefits. Implementation details and operational constraints were rarely considered. But lately it is a trend of gradual consideration of more realistic vehicle routing problems and a gradual introduction of local search techniques. While some recent models were solved with composite heuristic methods, others are solved using meta-heuristics, which have proven to be very effective for several classes of discrete optimization problems.

2.6 Solution Algorithms

A good algorithm for Vehicle Routing Problem should have four attributes, which are accuracy, speed, simplicity and flexibility. In general, there are two major categories of solution algorithms. One is the exact algorithms that provide global optimal solutions, the other one is the heuristics that give approximate solutions. In the following Section, algorithms in each category are reviewed based on the four attributes of a good algorithm.

2.6.1 Exact Algorithms

Most VRPs are difficult to solve exactly, even for problems of small size. The first optimization algorithm for the VRPTW can be attributed to Kolen et al. (1987) who used dynamic programming coupled with state space relaxation (Christofides et al., 1981b) to compute lower bounds within a branch-and-bound algorithm. Instances with $n <= 15$ were solved using this approach. Most subsequent algorithms rely either on the generation of valid inequalities to strengthen the linear programming relaxation or on mathematical decomposition techniques. This Section reviews the two main available approaches that have been prove efficient and effective in solving VRP: the column generation and the branch-and-cut.

Approaches Based on Column Generation (CG)

The CG method, similar to the nature of the set partitioning (SP) approach, has been widely used to optimally solve various types of vehicle routing and scheduling problems with time windows. CG is intimately related to constraint generation and can be seen as special way of updating the multipliers associated with the relaxed constraints. Let Ω^k denote the set of feasible routes for vehicle $k \in K$. For each route $w \in \Omega^k$, let c_w^k be the cost of this route and let x_w^k be a binary variable equal to *1* if and only if vehicle *k* uses path *w*, and *0* other wise. As first suggested by Balinski and Quandt (1964), the objective function of VRPWT can be sated as follows:

$$\text{Minimize} \sum_{k \in K} \sum_{w \in \Omega^k} c_w^k x_w^k$$

Because the sets Ω^k are likely to have a large cardinality, this problem can be tackled by a branch-and-bound algorithm in which the linear relaxations are solved by CG. At each node of the enumeration tree, a restricted column generation master problem is solved over the current set of columns. New columns of negative reduced cost are generated by solving a resource constrained shortest path problem with modified costs reflecting the current values of the dual variables associated with the constraints of the column generation master problem. This process stops when no negative reduced cost column can be generated.

CG was used by Dumas et al. (1991) to solve a VRPPD problem with time windows and multi-vehicle cases, which worked efficiently under restrictive capacity and hard time window constraints. Because of the reduced solution spaces, the CG method is computationally tractable to find optimal solutions for small to moderate size problems. Fagerholt (2000) proposed an optimization approach based on the SP approach to solve a ship-scheduling problem with time windows. First, the traditional VRP formulation was partitioned into a master problem and a brunch of sub-problems of the shortest path or the least cost. Second, all or a number of promising feasible routes were enumerated and the various possible schedules of each route were computed for each sub-problem. Finally, the schedules were given as input to the master problem to find the optimal schedule for a fleet of ships.

By adding some valid inequalities, a VRP can be efficiently formulated with the SP approach. Some of the most successful implementations by Fukasawa et al. (2006) and by Baldacci et al. (2008), were based on this methodology. Baldacci et al. (2008) presented a new exact algorithm for the capacitated VRP based on the SP formulation with additional cuts that correspond to capacity and clique inequalities. The exact algorithm used a bounding procedure that finds a near optimal dual solution of the LP-relaxation of the resulting mathematical formulation by combining three dual ascent heuristics. The first dual heuristic was based on the q-route relaxation of the set partitioning formulation of the CVRP. The second one combined Lagrangean relaxation, pricing and cut generation. The third attempted to close the duality gap left by the first two procedures using a classical pricing and cut generation technique. The final dual solution was used to generate a reduced problem containing only the routes whose reduced costs are smaller than the gap between an upper bound and the lower bound achieved. The resulting problem was solved by an integer programming solver. Computational results over the main problems from the literature showed the effectiveness of the proposed algorithm.

Wilhelm (2001) did a technical review of CG in integer programming, and he stated that the success of work on the VRPTW was pivotal in motivating the use of CG methods as modern tools for solving large-scale integer programming problems. Not only for VRPTW, but also CG was proved to be an effective and efficient solution approach for miscellaneous applications such as job scheduling, machine assembling, and cutting stock.

Approaches Based on Branch and Cut

Branch-and-cut algorithms currently constitute one of the best available exact approaches for the solution of the VRP (Laporte, 2009). The use of branch-and-cut for the capacitated VRP (CVRP) was rooted in the exact algorithm of Laporte et al. (1985). This algorithm used the Linear Programming (LP) relaxation result of the CVRP without capacity constraints as a basis for the solution of the VRP with capacity and maximum distance restrictions. This initial relaxation was iteratively strengthened by adding violated capacity constraints in the current LP solution. The algorithm was capable of solving randomly generated problems with two or three vehicles and up to 60 customers.

The key to Branch-and-Cut algorithm is to separate the capacity constrain to generate the initial solution. Thus, researchers have been focusing on developing separation procedures of capacity inequalities. Augerat et al. (1995) developed the first complete branch-and-cut approach for the CVRP. They described several heuristic separation procedures for the classes of valid inequalities, as well as four new classes of valid inequalities. Separation procedures were further investigated by Augerat et al. (1998). The resulting approach was able to solve several CVRP problems containing up to 134 customers. Ralphs et al. (2003) have presented a branch-and-cut algorithm for the CVRP in which an exact separation of valid m-TSP inequalities was used in addition to heuristic separation of capacity inequalities. The resulting algorithm was implemented within the parallel branch-and-cut-and-price framework and was able to solve several instances involving fewer than 100 vertices. Lysgaard et al. (2004) have developed new separation procedures for most of the families of valid inequalities proposed so far. Their overall branch-and-cut approach, which was further enhanced by the use of Gomory cuts, was able to solve previously solved problems within moderate computing time.

Baldacci et al. (2004) put forward a branch-and-cut algorithm based on a two-commodity network flow formulation of the CVRP and requiring a polynomial number of integer variables. It provided an interesting alternative to other classical formulations. The overall algorithm strengthened the LP relaxation by adding violated capacity inequalities and implementing various variable reduction and branching rules. The results obtained with this approach are comparable with those of the other branch-and-cut algorithms just described.

Another key issue to the branch-and-cut approach is to define bounds of branches. Fukasawa et al. (2006) proposed a successful branch-and-cut and- price algorithm combining branch-and-cut with the column generation approach to derive a tighter bound than other branch-and-cut algorithms. The proposed algorithm was capable of solving several previously unsolved problems with up to 135 vertices, which doubled the size of the problems that can be consistently solved.

2.6.2 Heuristic Algorithms

The development of modern heuristics for the VRP really started in the 1980s. It is fair to say that the study of the VRP has stimulated the growth and understanding of several heuristic concepts we now know. The early research in this area was quite fragmented, with a notable bias towards tabu search-based approaches and some of the algorithms were over engineered, but some rationalization has started to take place in recent years. The best heuristics are those that simultaneously perform a wide and deep search of the solution space and can solve several variants of the VRP. In the following Section, several heuristics were reviewed.

<u>Savings-based Methods and Modifications</u>

It has been argued (Cordeau et al., 2002b) that four attributes of good VRP heuristics are accuracy, speed, simplicity and flexibility. The savings-based method scores highly on speed and simplicity, because it contains no parameters and is easy to code.

Clarke and Wright (1964) developed a heuristic solution method which became known as the savings method and was the first algorithm that became widely used. The algorithm was used to solve a TSP, which is a special case of VRP without capacity constraint. This simple heuristic works as follows. At the start, it is assumed that each customer is serviced by a single route. Then, at each iteration, a pair of routes is selected and merged together on the basis of the best cost saving that can be achieved. This is repeated until a single route is obtained or no feasible merge exits. This is the most basic form of the savings-based method. Many authors proposed developments of this algorithm by proposing new parameters into the original CW formula, such as an estimate of the maximum savings value (Tillman, 1969), a penalty multiplier for solving CVRP with backhauls (Deif and Bodin, 1984), the route shape parameter for solving CVRP (Yellow, 1970), and the customer demand (Altinel and Oncan, 2005).

Above developments could be categorized as adaptations to the savings formula, there are also methods to speed up computation time and improvements to the route merging process. Altinkemer and Gavish (1991) sought to optimize the route merging process. They proposed to replace the merging procedure of the savings method by a matching procedure which merges partial solutions at each step. At each iteration of the algorithm, multiple clusters of nodes were merged. The number of clusters was determined by solving a matching problem, which can maximize the savings obtained. Their algorithm was polynomial, with a time complexity of $O(n^3)$, where n denotes the number of demands.

The recent development has been the application of Ant Systems to the VRP, using modifications of the savings method (Reimann et al., 2004). In such systems, a population of artificial agents repeatedly constructs solutions to the problem using a joint population memory and some heuristic information. After each member of the population has constructed its next solution, the memory is updated with a bias towards. The better solutions were found. Gradually, the memory will build up, thus giving stronger influence to the solutions built by the artificial agents, and the solutions will evolve towards the global optimum. Reimann et al. (2004) modified the savings method to create a savings-based ant system that not only improves the efficiency, but also improves the effectiveness of the algorithm leading to a fast and powerful problem solving tool for real world sized Vehicle Routing Problems. Juan et al. (2011) has proposed a new probabilistic approach to the CW procedure by composing of Monte Carlo Simulation, cache, and splitting techniques. The algorithm was validated through a set of CVRP standard benchmarks and competitive results were obtained in all tested cases.

Simulated Annealing (SA)

SA is a technique that works by searching through the set of all possible solutions, and reducing the chance of getting stuck in a poor local optimum solution. Cerny (1985) proposed an analogy of statistical thermodynamics with SA and illustrated its application in solving a TSP. The results obtained by SA were very close to the optimal solution and even sometimes the optimal solution was obtained. Eglese (1990) stated various modifications such as storing the best solution, sampling the neighborhood without replacement, and alternative acceptance probabilities for the SA algorithm to improve its efficiency. Connolly (1990) used simulated annealing to the Quadratic Assignment Problem. In the paper, the author developed an improved annealing scheme that gives better results for a given range of problems.

Even though SA is a simple procedure to use, there are several decisions that need to be made while applying it. Usually, the SA can be implemented with a simple neighborhood suggested by some small scale initial experiments. Then further improvements can be made by more detailed analysis of the problem characteristics or by combining simulated annealing with other techniques. In general, SA is often used when the search space is discrete. For certain problems, simulated annealing may be efficient when the goal is merely to find an acceptably good solution in a fixed amount of time, rather than the best possible solution.

Genetic Algorithm (GA)

The GA is inspired by the population genetics. GA uses a collection of solutions, from which using selective breeding and recombination strategies, better solutions can be produced. Simple genetic operators such as crossover and mutation are used to construct new solutions form pieces of old ones. Crossover and mutation are the basic tools for creating new solutions. However, the chromosomes that are selected as a basis for the reproductive step are clearly critical in what happens to a population as a whole. Thus, Holland (1992) suggested that at least one parent should always be chosen on the basis of its fitness in terms of combinational problems.

Like SA, GA provides the user with several parameters to adjust. Zhao et al. (2008) developed an online genetic algorithm to solve the dynamic VRPTW with variable travel times. In the case of the dynamic VRP with time-dependent travel times, the speed of a route is no more constant but variable. The travel time of vehicles between two customers relates to its departure time. Thus, Zhao et al. (2008) set the fitness of the chromosomes not only based on the distance but speed and departure time. The result showed that the variable speed model gives better results than the constant speed model.

In General, problems which appear to be particularly appropriate for solution by GA include timetabling and scheduling problems, and many scheduling software packages are based on GA.

Tabu Search (TS)

TS was first introduced by Fred Glover in 1993 and has been used to solve many practical problems that arise in real-world application like the VRP. TS uses a local or neighborhood search procedure to iteratively move from one potential solution *x* to an improved solution *x'* in the neighborhood of *x*, until some stopping criterion has been satisfied. Local search procedures often become stuck in poor-scoring areas or areas where scores plateau. To avoid these pitfalls and explore regions of the search space that would be left unexplored by other local search procedures, TS carefully explores the neighborhood of each solution as the search progresses.

A TS heuristic for a PDP with time windows was developed by Nanry and Barnes (2000). Solutions that violate time window and vehicle capacity constraints are allowed during the search. These authors have considered three move types. 1) to remove a node pair $(i, n + i)$ from its current route and reinsert it in a different route; 2) to swap two pairs of nodes between two distinct routes. 3) to move a single node within its current route. A hierarchical search mechanism was used to dynamically alternate these neighborhoods according to problem difficulty. Computational results were reported on random instances involving up to 100 requests. A similar TS heuristic was also developed by Lau and Liang (2002).

TS is similar to SA in that both traverse the solution space by testing mutations of an individual solution. While simulated annealing generates only one mutated solution, TS generates many mutated solutions and moves to the solution with the lowest energy of those generated. To prevent cycling and encourage greater movement through the solution space, a tabu list is maintained of partial or complete solutions. It is forbidden to move to a solution that contains elements of the tabu list, which is updated as the solution traverses the solution space.

2.7 Summary

The vehicle routing and scheduling problem consists of designing least cost delivery routes through a set of geographically scattered customers, subject to a number of side constraints. This problem holds a central place in distribution management and is faced on a daily basis by tens of thousands of carriers worldwide. The problem arises in several forms because of the variety of constraints encountered in practice. For over 50 years, the vehicle routing and scheduling problem has been extensively studied by the operations research community. Initially, in a more practical aspect, this problem contributes directly to a real opportunity to reduce costs in the important area of logistics. Secondly, because it is still one of the most difficult problems in combinatorial optimization and consequently presents a great challenge. For example, a TSP, which is a special case of the VRP, can now be solved for thousands and even tens of thousands of vertices (Laporte et al., 2013). In contrast, VRP is much more difficult to solve. For example, in the relatively simple case where only capacity constraints are present (called the capacitated VRP, or CVRP), it is still difficult to solve problems with one or two hundred customers by means of exact algorithms.

In this chapter, the problems relevant to the topic of vehicle routing and scheduling and its variants and solution procedures were reviewed. It is clear that the ideas behind designing algorithms for these problems are closed related to each other. One problem can be transformed to another problem. Because of the difficulties of these problems (NP-Completeness), the proposed algorithms for these are mostly heuristic methods. However, as pointed out by Fisher (1995), heuristics usually lack robustness and their performance is very much problem specific. Fisher states “It’s not uncommon that a heuristic developed for a particular geographic region of a company's operation will perform poorly in another region served by the same company."

In general, when heuristic methods were used, the number of vehicles was chosen as the first objective and the total travel distance only as the second. In fact, the choice of the most appropriate objective depends on specific rules and peculiarities of each individual business. For example, if a company limits the number of vehicles in their own fleet to a certain percentage of their actual requirement, a large amount of goods will be delivered by third-parties, usually small businesses or even self-employed owners of individual trucks. The payment rule used to these third-party trucks is normally based on the total travelled distance. In this case, minimization of travel distance is the most attractive and primary objective for the company. Another example is government contracting of third-party trucks to provide service during winter storms. The total travelled distance or travel time dominates this spending. Consequently, many real-life situations justify the study of new algorithms and techniques to improve the vehicle routing results in terms of total travelled distance.

In summary, when it comes to algorithm design, this research should not be confined either to exact algorithms or heuristic methods. Ideas from different algorithms for vehicle routing problems should be considered.

CHAPTER 3

MODEL DEVELOPMENT

Real world transportation problems such as travel time data collection and winter roadway maintenance discussed earlier can be classified as a vehicle routing and scheduling problem. To solve these problems, a basic model without considering travel time variability was developed first. Then, an enhanced model was developed to deal with time dependent travel time issue existing in a transportation network.

The study problem was formulated as an integer programming problem. Detailed descriptions about model preparation are discussed in Section 3.1. Additionally, a network transformation technique described in Section 3.2 was used to convert an arc routing problem (ARP) to a node routing problem (NRP), so that the proposed set-partitioning (SP) approach can be used to formulate the research problem. The formulation of the proposed models and associated parameters are discussed in Sections 3.3 and 3.4.

To ensure that the study problem is properly formulated with realistic conditions and solved efficiently, the implementation for the model development considered a number of operational constraints, including limited fleet size, pre-specified time windows and level of service (e.g., service time limit). The framework of this implementation is illustrated in Figure 3.1.

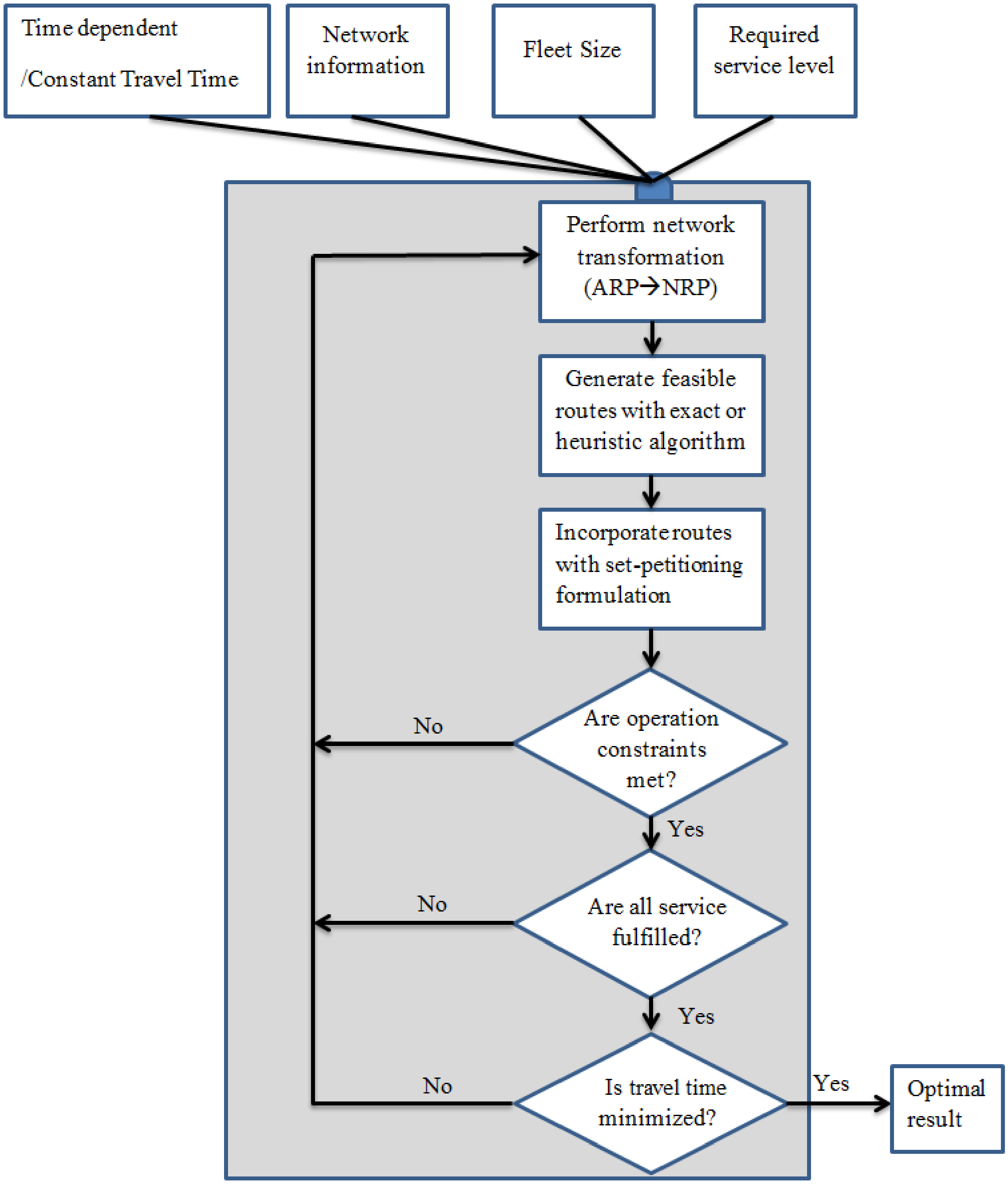


Figure 3.1 Implementation of model development.

From the mathematical perspective, variables that used to represent optimal routing and scheduling results are restricted to be integers, thus the study problem is formulated as an integer programing problem, which takes inputs of a set of travel times and network information, and is subject to constraints of fleet size and service time limit. Then the network transformation technique and SP approach is used with adjustments to serve the purpose of model development. After the model is developed, a solution algorithm comes in to solve the model and produces output a dispatch list describing when and where to deploy vehicles. Before getting into the details of the mathematical model, the indexes, parameters and decision variables used in this chapter are defined in Table 3.1.

Table 3.1 Glossary of Mathematical Notations (Alphabetical Order)

Types of Variable	Notation	Meaning	Unit
Parameters	δ_{rd}	1, if route *r* starts at depot *d*; 0, otherwise.	/
	α_r^{it}	1, if service route *r* covers service node *i* at time window *t*; 0, otherwise	/
	$\boldsymbol{A}$	Set of directed arcs in the original network	/
	$\boldsymbol{A}'$	Set of directed arcs in the transformed network	/
	$\boldsymbol{A^1}$	Set of directed arcs that need to be serviced in the original network	/
	$\boldsymbol{A^2}$	Set of directed arcs that don't need to be serviced in the original network	/
	b_i^v	The beginning service time of vehicle *v* at node *i*, $i \in \boldsymbol{I}$	/
	C_r	The cycle time for service route *r*, the sum of deadhead travel time and service time	
	D	Set of depots, indexed by *d*	
	e_{ti}	The earliest departure time from node *i* at time window *t*, $i \in \boldsymbol{I}$	/
	k_d	Number of available of vehicles at depot *d*	

		Continued	
	l_{ti}	The latest departure time from node *i* at time window $t, {}_{,}\ i \in \boldsymbol{I}$	/
	m	Number of designated time windows	/
	n	Number of nodes to be serviced	
	$\boldsymbol{I}$	Set of nodes to be serviced	/
	$\boldsymbol{N}$	Set of all nodes except depots in the original network	/
	$\boldsymbol{N}'$	Set of all nodes except depots in the transformed network, $\boldsymbol{I} \subset \boldsymbol{N}'$	/
	$\boldsymbol{R}$	A set of service routes, indexed by *r*, a service route is a sequence of nodes that a vehicle visit along with	/
	s_i	The service time of node *i*, $i \in \boldsymbol{I}$	Minute
	$s_i(b_i^v)$	A time-dependent service time of the required node *i* while beginning at time b_i^v	Minute
	$t_{ij}(b_i^v)$	A time-dependent travel time from node *i* to node *j* while beginning at time b_i^v	Minute
	$\boldsymbol{T}$	Set of designated time windows, indexed by *t*	/
	t_{ij}	Travel time for traveling arc $(i, j) \in \boldsymbol{A}'$	Minute
	$\boldsymbol{V}$	Set of probe vehicles, indexed by *v*	/
Decision Variables	X_{vr}	1, if vehicle *v* travels on service route *r*; 0, otherwise	/
	x_{ij}^{vt}	*1* if (*i*,*j*) is traveled by vehicle *v* within time window *t*, *0* otherwise	/

3.1 Problem Description

Let $\boldsymbol{G = (N, A)}$ be a directed graph where $\boldsymbol{N}$ is the node set and $\boldsymbol{A}$ is the arc set. It is assumed that $\boldsymbol{A}$ is partitioned into a subset of required arcs $\boldsymbol{A_1}$, which must be serviced, and a complementary subset $\boldsymbol{A_2}$. Each required arc $i \in \boldsymbol{A_1}$ is associated with parameters that can be constant and time-dependent, including demand, travel time, service time and travel cost. A service time window indexed by t is imposed to ensure that each required arc i is serviced by a vehicle within a time period from e_{ti} to l_{ti}. The other arcs in subset $\boldsymbol{A_2}$ have values of travel time and travel cost only. Also it is noted that service time is typically larger than the travel time because it takes more time to service an arc than to simply travel along the arc. A set $\boldsymbol{V}=\{1,2.....k\}$ of identical vehicles (assumed the fleet size is k) is available to service the required arcs. These vehicles are required to start and end their services at a predetermined depot. The objective is to service all required arcs within the associated time windows at least cost or at least travel time.

3.2 Network Transformation

Both arc and node routing problems have received continuous research attention. The connections between these two classes of problems have been underlined by the transformation techniques that can translate an instance of one problem into an instance of the other problem. As mentioned in the literature review, compared to the well-known NRP, the ARP had been neglected for a period of time (Lacomme et al., 2004). NRPs have received relatively more attention because of their computational efficiency when compared with the arc routing ones, and there are problems for which research results are much more impressive for node routing than for their arc routing counterparts (Baldacci and Maniezzo, 2006).

Before formulating the studied problem, a network transformation approach (Pearn et al., 1987) was introduced to transform the arc routing problem denoted as $\boldsymbol{G = (N, A)}$

into a node routing problem denoted as $\boldsymbol{G}' = (\boldsymbol{N}', \boldsymbol{A}')$. Each arc $i \in \boldsymbol{A_1}$ in graph $\boldsymbol{G}$ corresponds to a node i in graph $\boldsymbol{G}'$, with service time s_i and time window $[e_i,l_i]$. Each pair of nodes i and j in $\boldsymbol{G}'$ is connected by an arc $(i,j) \in \boldsymbol{A}'$ with travel time t_{ij}. The travel time is based on the shortest path between the two corresponding required arcs in $\boldsymbol{G}$. These shortest paths were calculated from the end node of the first arc to the start node of the second arc. Finally, a depot was assumed to be connected to all other nodes in G'. A general road network is illustrated in Figure 3.2, the numbers next to the arcs were denoted as arc IDs.

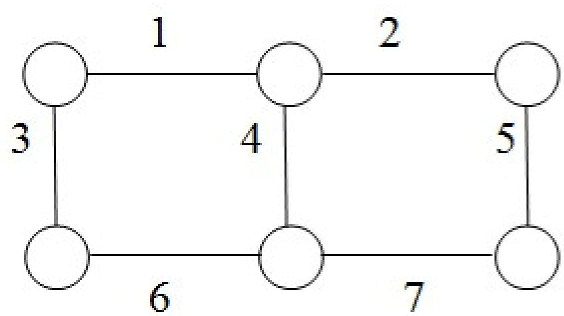


Figure 3.2 The original network.

An adjacency matrix was established and showed in Table 3.2, which is symmetric and associated with the original network.

Table 3.2 The Adjacency Matrix

From/To	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	0	1	1	1	0	0	0
2	1	0	0	1	1	0	0
3	1	0	0	0	0	1	0
4	1	1	0	0	0	1	1
5	0	1	0	0	0	0	1
6	0	0	1	1	0	0	1
7	0	0	0	1	1	1	0

Since arc 3 connects with arcs 1 and 6, the entries for (3,1) and (3,6) were designated as "1" and all others designated as "0", since there are no direct connections between them.

Thus, the original network can be transformed in such a way that the arcs in the original network are the nodes in the transformed network as shown in Figure 3.3. Note that the arcs in the transformed network indicate the adjacency relationship among the arcs in the original network. The main contribution of this transformation is to turn an ARP into a NRP. So the study problem can be effectively formulated by the SP approach introduced in a later section.

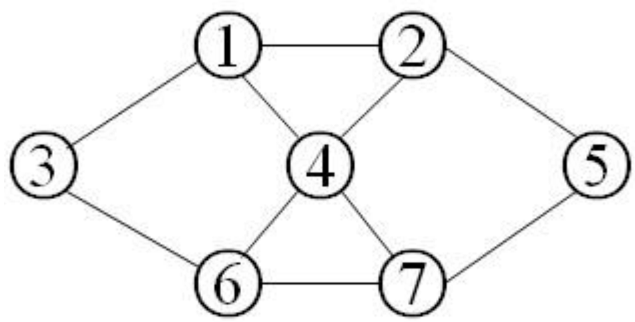


Figure 3.3 The transformed network from the original network.

3.3 The Basic Model

After the network transformation, a NRP model was developed that takes input including number of vehicles, constant travel time, time windows and transportation network information. The model then output a summary of the optimal vehicle dispatch schedule describing when and where to collect traffic data subject to constrains of fleet size and time windows. For developing the basic model, the required assumptions to formulate the objective function and constraints are presented next.

3.3.1 Assumptions

To formulate the research problem, some assumptions are made and are discussed below:

- It could be a single depot problem or a multiple-depot problem based on real operations. But each vehicle's trip must start and end at the same depot.
- Every vehicle must depart from a starting node of a required service arc within the designated time windows. In this study, each required service arc can have multiple service time windows.
- The required service arcs are known in advance.
- The travel times are constant and known in advance.

3.3.2 Model Formulation

A vehicle routing problem with multiple time windows is defined on a directed graph $\boldsymbol{G'} = (\boldsymbol{N'}, \boldsymbol{A'})$, which was transformed from $\boldsymbol{G} = (\boldsymbol{N}, \boldsymbol{A})$ as defined in Section 3.1.

<u>Objective functions and constraints:</u>

$$\text{Min } Z = \sum_{v \in \boldsymbol{V}} \sum_{t \in \boldsymbol{T}} \Big(\sum_{(i,j) \in \boldsymbol{A}'} t_{ij} x_{ij}^{vt} + \sum_{i \in \boldsymbol{I}} s_i \sum_{j \in \boldsymbol{N}' \cup \{\boldsymbol{D}\}} x_{ji}^{vt} \Big) \qquad (3.1)$$

The objective is to minimize the total vehicle travel time. Eq. (3.1) has two components, the first one is the sum of deadheading travel time and the second one is the sum of service time. The deadheading travel time captures the travel time that is incurred by traveling between nodes without providing service. Service time is only incurred at the nodes that require service (set $\boldsymbol{I}$).

<u>Subject to:</u>

$$\sum_{v \in \boldsymbol{V}} \sum_{i \in \boldsymbol{N}' \cup \{\boldsymbol{D}\}} x_{ij}^{vt} = 1, \forall t \in \boldsymbol{T}, \forall j \in \boldsymbol{I} \qquad (3.2)$$

Equation (3.2) requires that each node j belonging to $\boldsymbol{I}$ must be serviced only once at each time window t.

$$\sum_{v \in \boldsymbol{V}} \sum_{j \in \boldsymbol{I}} x_{dj}^{vt} \leq k_d, \forall t \in \boldsymbol{T}, \forall d \in \boldsymbol{D} \tag{3.3}$$

Equation (3.3) imposes the fleet size limit at each time period t.

$$\sum_{j \in \boldsymbol{I}} x_{dj}^{v1} = 1, \forall v \in \boldsymbol{V}, \forall d \in \boldsymbol{D} \tag{3.4}$$

Equation (3.4) ensures all vehicles start their trips from a depot.

$$\sum_{j \in \boldsymbol{I}} x_{jd}^{vm} = 1, \forall v \in \boldsymbol{V}, \forall d \in \boldsymbol{D} \tag{3.5}$$

Equation (3.5) ensures all vehicles end their trips at a depot; m represents the last time window.

$$e_{ti} \leq b_i^v \leq l_{ti}, \forall t \in \boldsymbol{T}, \forall i \in \boldsymbol{I}, \forall v \in \boldsymbol{V} \tag{3.6}$$

Equation (3.6) ensures that the beginning service time at each required node must be within the corresponding time windows. If vehicles arrive early, they have to wait till the earliest beginning service time to depart. e_{ti}, l_{ti} represent the lower bound and the upper bound of the designated time window, which are predetermined by users.

$$b_i^v + s_i + t_{ij} \leq b_j^v, \forall i, j \in \boldsymbol{I}, \forall v \in \boldsymbol{V} \tag{3.7}$$

Equation (3.7) is the time flow constraint that ensures vehicles to service node i before servicing node j.

The basic model presented above is able to mathematically represent a vehicle routing problem with time windows. The objective function of the basic model strategically divides the total vehicle travel time into two components, which are the deadhead travel time and the service time. The service time is inevitable because all the service demand has to be satisfied, thus the major optimization for the basic model turned into finding a feasible route to minimize deadhead travelling between nodes in the study network. The constraints of fleet size and time windows were addressed in the basic model. However, the basic model was based on the already known constant travel times, which may restrict its applicability to real-world problems where travel times are subject to more subtle variations over time. Therefore, an enhanced model considering time-dependent travel times was developed and is discussed in the next section.

3.4 The Enhanced Model

The basic model presented above assumed that the travel times each pair of nodes in the study network are constant. Unfortunately, this assumption may not be practical for most real-world problems because travel times are not constant but vary from predictable events like congestion during peak hours or from unpredictable events like snow storms. Therefore, an enhanced model is proposed here considering time-dependent travel time.

3.4.1 Model Formulation

In the basic model, the objective function was calculated in terms of travel cost that can be interpreted as mean travel time multiplied by the cost coefficient c_{ij} (Eq. 3.1). The major change in the formulation of the enhanced model is to replace the total travel cost by the total travel time which is affected by traffic conditions in different time periods.

<u>Objective function:</u>

$$\text{Min } Z = \sum_{v \in \boldsymbol{V}} \sum_{t \in \boldsymbol{T}} \left(\sum_{(i,j) \in \boldsymbol{A}'} t_{ij}(b_i^v) x_{ij}^{vt} + \sum_{i \in \boldsymbol{I}} s_i(b_i^v) \sum_{j \in \boldsymbol{N}' \cup \{0\}} x_{ji}^{vt} \right) \tag{3.8}$$

Similar to the objective function of the basic model, Eq. (3.8) has two components. The first one is the sum of deadheading travel times and the second one is the sum of service times. However, compared to the basic model, both components in the enhanced model cannot be calculated by adding up constant travel time values, but have to take the time dependency of travel time into account.

3.4.2 Time-Dependent Travel Time

In real world vehicle routing problems, the speed is not constant. Thus, it is necessary to model the speed profile to get more realistic solutions. As defined in the objective function Eq. 3.8, the time dependent parameters $s_i(b_i^v)$ and $t_{ij}(b_i^v)$ can be calculated as a time dependent function of travel speed.

A model was developed here to consider that travel is not carried out at constant speed all day, but only on different and shorter time periods. This model considered speed profiles that correspond to various time periods of a day (e.g., peak hours). For simplicity, this dissertation considered a planning horizon that can be discretized into a number of time intervals. For example, each time interval is 15 minutes in length. For more accuracy, the time distribution using shorter time intervals can be considered.

Considering a graph ***G (N, A)*** representing a transportation network, where ***N*** is a set of nodes and ***A*** is a set of arcs, vehicles on link (i, j) travel at the same speed within each time interval. Let s_{ij}^t be the speed of the vehicle during the t^{th} period of the day for a particular link (i, j). The speed distribution $s(h)$ is assumed to be a step function of time h as below.

$$s(h) = s_{ij}^t \text{, if } t \leq h \leq t+1;$$

$$s(h) = s_{ij}^{t+1}, \text{ if } t+1 \leq h \leq t+2$$

Figure 3.4 shows an arbitrary speed distribution. For example, the traffic speed on link (i, j) varies over time; therefore a vehicle may travel with a speed of 40 mph between 7:00–8:00 a.m. and 50 mph between 8:00–9:00 a.m. Similarly, travel speeds also vary over links in the study network. The travel time distribution on link (i, j) is a step function of the time of departure from node i and it can be derived from the speed distribution. Assume the length of arc (i, j) is two miles, the time to reach node j depends on the time of departure from node i. Figure 3.5 shows the corresponding travel time based on the speed variation over time periods.

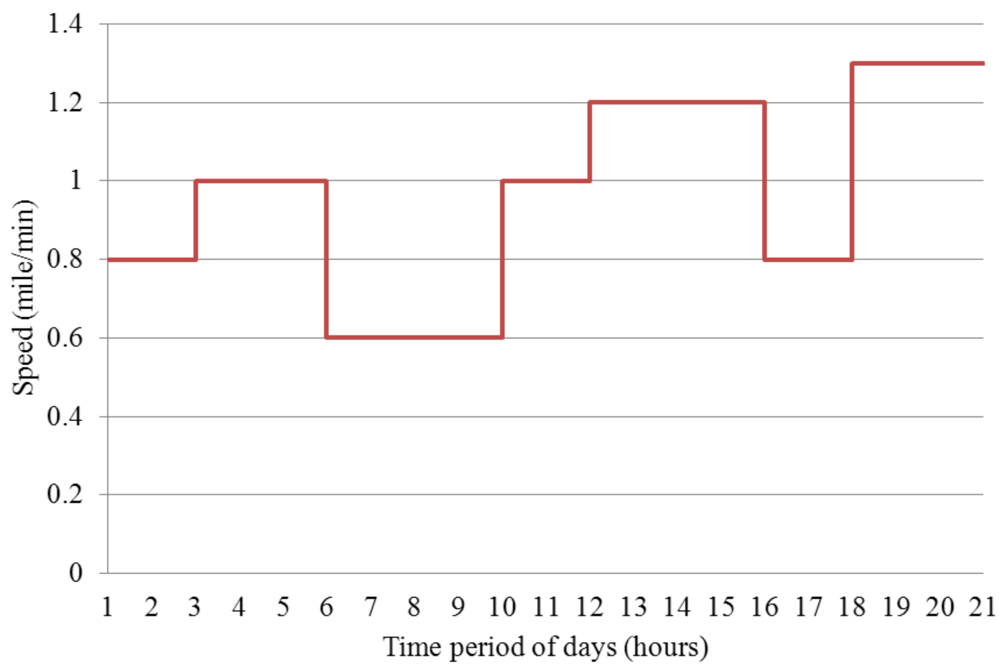


Figure 3.4 Temporal traffic speed distribution.

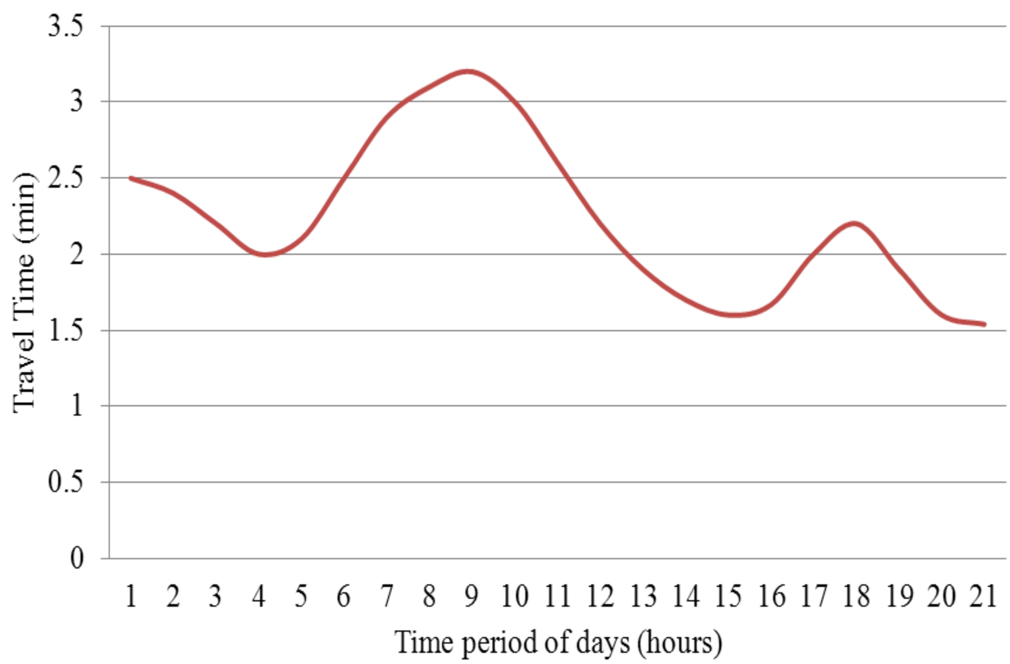


Figure 3.5 Corresponding travel time for a link of length 2 miles.

3.5 Set Partitioning Formulation

The SP approach has been widely used to solve various vehicle routing and scheduling problems with time windows. Models formulated by SP approach often consist of two problems: a master problem and a sub-problem. Since large numbers of variables are involved, a restricted master problem is used instead of working with the complete master problem. This restricted master problem is much smaller, containing only a subset of columns, thus is easier to solve. In each iteration, the restricted master problem is solved by calling the commercial optimization package software CPLEX. Additional columns are generated in the sub-problem where the objective is to find columns with a negative reduced cost (for a minimization problem). These columns represent service routes in this study. If the reduced cost is negative, the generated column is added to the restricted master problem.

In this Section, the SP approach is used to reformulate the proposed basic and enhanced model developed in previous Sections. The master problem corresponds to the objective function and Equations (3.2) and (3.3) in the original VRP formulation is reformulated as follows:

Objective function and constraints:

$$\min Z = \sum_{r \in \boldsymbol{R}} \sum_{v \in \boldsymbol{V}} C_r X_{vr} \tag{3.9}$$

Compared to Equation (3.1) that has two cost components to represent the total travel time for each time period, Equation (3.9) uses one parameter (the cycle time of service route r, C_r) to represent the total travel time associated to each service route that is generated by sub problems. C_r also includes the deadhead travel time and the service time incurred by traveling through the entire service route.

Subject to:

$$\sum_{r \in \boldsymbol{R}} \sum_{v \in \boldsymbol{V}} \alpha_r^{it} X_{vr} = 1, \forall t \in \boldsymbol{T}, \forall i \in \boldsymbol{I} \tag{3.10}$$

Equation (3.10) corresponds to the service constraint (3.2) that every required node i must be serviced once at each time window t.

$$\sum_{r \in \boldsymbol{R}} \delta_{rd} X_{vr} \le k_d, \forall d \in \boldsymbol{D} \tag{3.11}$$

Equation (3.11) limits the number of available vehicles for each depot. It corresponds to the fleet size constraint, which is Equation (3.3) in the original VRP formulation.

$$\sum_{r \in \boldsymbol{R}} X_{vr} = 1, \forall v \in \boldsymbol{V} \quad (3.12)$$

Equation (3.12) ensures that each vehicle must travel on one service route.

$$X_{vr} \in \{0,1\}, \forall v \in \boldsymbol{V}, \forall r \in \boldsymbol{R} \quad (3.13)$$

Equation (3.13) imposes binary requirements on the X_{vr} variables.

The sub-problem, for each vehicle, is an elementary shortest path problem with time-window constraint that corresponds to the original VRP formulation. It can be expressed as follows and subject to Equations (3.4) through (3.7):

$$\min Z = \sum_{(i,j) \in \boldsymbol{A}'} t_{ij} x_{ij}^{vt} + \sum_{i \in \boldsymbol{I}} s_i \sum_{j \in \boldsymbol{N}' \cup \boldsymbol{D}} x_{ji}^{vt} \quad (3.14)$$

All feasible service routes generated from sup-problems were then utilized as inputs for the restricted master problem, which can be solved efficiently with linear programming solvers (e.g., CPLEX, Excel Solver) to obtain the decision variables defined in the SP formulation. The program was implemented in *CPLEX*.

3.6 Summary

In this chapter, a basic model was developed first to formulate a vehicle routing and scheduling problem with constant travel time, and then an enhanced model was proposed to include travel time variability to the basic model. To solve these two models in an effective and efficient way, the network transformation technique and the SP approach were introduced to serve this purpose. The network transformation technique was used to transform an ARP to a VRP so that the network can be easily described and more solution algorithms for the VRP can be utilized. After network transformation, the research problem was divided into a master problem and a sub-problem and formulated with the SP approach. The optimal solution of the master problem depends on the number of service routes generated by solving the sub problem. Because of the fact that the more feasible service routes to be incorporated into the master problem, the better the solution quality of the master problem will be. Thus how to efficiently generate those paths became the major challenge for this study. In the next chapter, different solution algorithms that can be used to address this challenge are discussed.

CHAPTER 4

SOLUTION ALGORITHM

Using the set-partitioning (SP) formulation approach, the study problem was formulated into a master problem and a number of sub-problems of shortest travel time with operation constraints as discussed in Chapter 3. This basic formulation was selected because the specific problem in this study requires complex constraints. The SP formulation allows the constraints to be simply modeled as part of the cost and binary constraint matrix. Compared with the shortest path sub-problem, the master problem was relatively easy to solve. The optimal solution of the master problem was derived based on searching for the feasible service routes which were the outcome of the sub-problems. By incorporating sufficient service routes into the master problem, the solution quality will be improved. Therefore, the major challenge of solving the mathematical model that formulated in Chapter 3 is to develop a solution algorithm to efficiently generate the required service routes.

In this chapter, the exhaustive search method is developed and illustrated first in Section 4.1. An example is given to demonstrate its performance for a small network. In Section 4.2, a genetic algorithm (GA) based heuristic is introduced to manage larger scale problems.

4.1 Exhaustive Numeration

Exhaustive numeration, also known as brute-force search, is a very general problem-solving technique that consists of systematically enumerating all possible candidates for the solution and checking whether each candidate satisfies the problem's constraints. While a brute-force search is simple to implement and will always find a solution if it exists, its computation cost is proportional to the number of candidate solutions, which in many practical problems tends to grow very quickly as the size of the problem increases. Therefore, an exhaustive search is typically used when the problem size is limited or it is integrated with heuristics so that it can be used to reduce the space of candidate solutions to a manageable size. An exhaustive search is also used when simplicity of implementation is more important than computation speed.

An exhaustive search can be used to search for the optimal integer solution in this study by using the proposed set partitioning model discussed in Chapter 3 where a small number of service routes in a set $\boldsymbol{R}$ can be exhaustively enumerated and are well restricted by the time windows and resources constraints. An array $[i, j, \ldots]$ $(i, j \in \boldsymbol{I})$ represents a feasible service route for visiting the nodes belonging to set $\boldsymbol{I}$, which is bounded by Equations (3.4) to (3.7). An example follows that illustrates how candidate schedules can be enumerated.

There is a transformed graph $(\boldsymbol{G}', \boldsymbol{A}')$ with m designated time windows imposed on four required nodes for required services (i.e., travel time data collection, roadway maintenance). Suppose that vehicles departing from a depot (node 0) can serve all four required nodes belonging to $\boldsymbol{I}$ within the first time window denoted as T_1. The availability of vehicles to continue servicing any required nodes within the next $(m-1)$ time windows (i.e., T_2, T_3, … T_m) could be obtained via the two constraints formulated as Equations. (3.6) and (3.7).

Figure 4.1 illustrates feasible service routes for a vehicle departing from a depot to serve the required nodes within specified time windows, in which "⊗" indicates that the vehicle was unable to arrive at the node within its time window. This vehicle would be assigned to the next node that satisfies the time window constraint. c_{ij} indicates the least cost for travelling though the arc ($i, j \in \boldsymbol{A}'$).

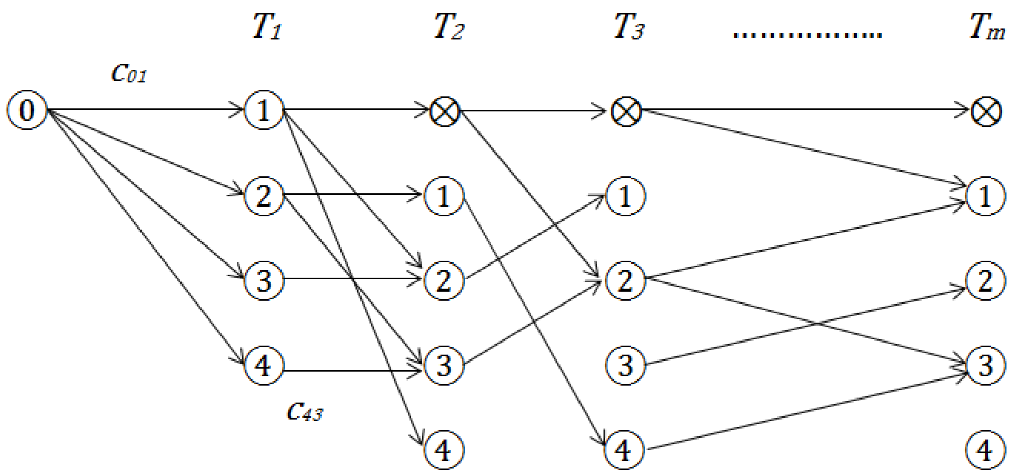


Figure 4.1 Example of generating service routes.

4.2 The Genetic Algorithm Based Heuristic

Compared to the exhaustive search method, a heuristic algorithm is designed for solving a problem more quickly or for finding an approximate solution when classic methods fail to find an exact solution. This is achieved by trading optimality, completeness, or accuracy for computational speed. The objective of a heuristic is to quickly search for a solution that is good enough for solving the problem at hand. This solution may not be the best one for this problem, or it may simply is an approximation to the exact solution. However, it is still valuable because finding it does not require a prohibitively long time.

For vehicle routing and scheduling problems with a large network size or relaxed time window constraints, the number of feasible routes for the fleet may significantly increase. For such problems, it is more computationally efficient to generate promising routes with heuristics than with exhaustive numeration. In Chapter 2, several heuristic algorithms were discussed. As indicated by Laporte and Gendreau (2001), metaheuristics (i.e., Tabu Search, Simulated Annealing and Genetic Algorithm) perform better than classical heuristics (i.e., Saving Heuristic) for solving the VRP. The GA was utilized in this dissertation due to its ease of implementation and good fit for problems that include timetabling and scheduling.

A GA is a problem solving algorithm which imitates natural selection or natural genetics. It is a search technique to find optimal or nearly optimal solutions of search problems. In 1975, Holland invented GA as a heuristic search based on "Survival of the fittest", a biological idea. He introduced not only mutation, but also reproduction into the artificial system. Hence the terms gene, chromosome, individual, population, crossover and mutation are used in this search technique. Also, the critical issue in developing a GA is that the representations of chromosome, initialization, the fitness function, the selection process, and the termination condition need to be determined in advanced. The below sections explain the common genetic algorithm terms and associated procedures.

<u>Steps of GA:</u>

The algorithm uses a bottom up approach. This means that it starts with a set of solutions and ends with the optimal one. The general steps used by genetic algorithm are described below:

Step 1: Create the initial population by producing a set of individuals or chromosomes;

Step 2: Evaluate the fitness value of each individual in the population;

Step 3: Repeat (creating a new generation of population)

a. Select a parent from individuals in population

b. Perform recombination or mutation to generate new individual

c. Add new individuals into the population

d. Remove individual considering low fitness or randomness;

Step 4: Go to step 3 until termination criteria are satisfied.

<u>Chromosome representation and the fitness function:</u>

In this study, a service route was stored as an array with a binary chromosome (Table 4.1). If the problem has *n* total nodes required to be serviced, the chromosome will contain *n* genes. For example, the sample service route for a crew based at depot 9 was required to service nodes 1, 2, and 5 out of a total five required nodes, before returning the depot. Then, a "*1*" in a gene represents a selected node, and a "0" represents a non-selected node.

Table 4.1 Sample of Chromosome Representation

Sample Service Route				
Depot →	Node 1 →	Node 2 →	Node 5 →	Depot
Sample Chromosome				
Node 1	Node 2	Node 3	Node 4	Node 5
1	1	0	0	1

This chromosome representation of a service route corresponds to a column in the binary matrix of the set-partitioning formulation that mentioned in the model formulation section. In addition to storing the chromosome, two separate arrays are used to keep record of the depot of each service route and keep track of the beginning service time of each required node.

The fitness value is the measure of goodness of a solution with respect to the original objective function. In this study, candidate solutions with lower total travel time imply better solutions. Thus, the fitness function for each chromosome was defined as the inverse of its total travel time with the form in Equation (3.14).

$$F(n) = 1/Z \qquad (4.1)$$

In Equation (4.1), n is the chromosome index, and Z is the value calculated from Equation (3.14). In conclusion, the higher the fitness value, the more chances the individuals have to be selected.

<u>Initialization</u>

As previously stated, the genetic algorithm initializes with the current subset of routes in the restricted problem using a solution construction approach based on the savings heuristic of Clarke and Wright (1964). This simple heuristic works as follows. At the start, it is assumed that each node is serviced by a single route. Then at each iteration, a pair of routes is selected and merged together on the basis of the best cost saving that can be achieved. This is repeated until a single route is obtained or no feasible merge exits. It is worth noting that the evaluation of the savings is based on the true time-dependent costs.

<u>Selection Process:</u>

To produce “offspring”, parents for recombination need to be selected from the population via a well-designed selection process. The purpose of having an appropriate selection process is to have better offspring and to lead the genetic algorithm to a global optimal solution. Though selection process pick individuals randomly, the higher its fitness value the more likely it is for the individual to be selected. Diversified gene randomness and good chromosome fitness values are important to reach in global convergence. There are several techniques of choosing parents like the Roulette wheel method, the random selection method, and the ranking selection method. Random selection is simple to implement but may produce a population of weak fitness. Also, the randomness of ranking selection prevents early convergence but yields slow convergence. Thus, in this study, the Roulette wheel method was used with the selection probability being equal to the fitness value of each chromosome.

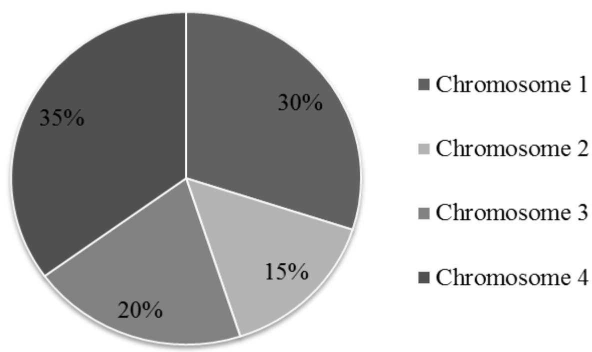


Figure 4.2 An example of roulette wheel.

To create a roulette wheel (as Figure 4.2 shows), the selection probability (p_n) and the cumulative probability (q_n) associated with the fitness value (f_n) for each individual chromosome (n) are calculated by the following equations:

$$p_n = \frac{f_n}{\sum_{i=n} f_i} \qquad (4.2)$$

$$q_n = \sum_{i=n} p_i \qquad (4.3)$$

After calculations for p_n and q_n are done, by spinning the "roulette wheel", a random number r between *0* and *1* is generated. A parent is selected by comparing r and q_n. If $r \le q_1$, then select the parent having the first fitness value s_1; otherwise, the *n*th fitness value would be selected ($2 \le n$), so that $q_{n-1} < r \le q_n$. Like the analogy of gambling wheel, any of chromosomes can be selected. But, the higher the fitness, the higher the chance of selection is.

Crossover

Once parents are selected, they reproduce to create "children". Even though there has been some recent interest in multiple-point crossover, it is relatively difficult to code and the improvement is not immediately apparent (Epstein, R., 1992). In this solution approach, reproduction occurs through a simple one-point crossover. The crossover point is selected randomly for this approach. In Figure 4.3, two routes, Route A and Route B, were the parents. The crossover point is in between the fifth and sixth gene in the chromosome for this example. The two new routes that are created then share genes from each parent.

Figure 4.3 Example of one-point crossover.

The crossover created a possible route, and a subsequent feasibility operator would test it to ensure that the route is feasible. A route is considered feasible if it meets resources and operational constraints, and it is not already in the subset of routes in the restricted problem. In the application of this study, a large number of routes are infeasible due to the constraints. An additional mutation operator facilitated the genetic diversity of subsequent populations. This reproduction process iterates to create many new populations of routes for the restricted problem.

Termination condition:

The GA terminates when a fixed number of feasible routes are created. The population size, *n*, is limited to a defined number to prevent the problem from becoming excessively large. These candidate routes are added to the restricted problem. The algorithm also terminates if no new feasible routes can be found within a given amount of time. The latter stopping criterion makes the solution approach more efficient and prevents the program from searching for feasible pairings for an excessive amount of time.

4.3 Summary

In this chapter, an exact exhaustive algorithm and a GA based heuristic were discussed. Between these two algorithms, the exhaustive method is easy to implement and has no parameters to adjust, which is particularly appropriate to be used when the problem size is limited or strictly constrained by time windows or service constraints. On the other hand, the GA has lots of options in its implementation in terms of the design of the fitness function, selection process and other operators. Past researchers showed that the GA has been particularly successful in solving large size vehicle routing problems that includes timetabling and scheduling. In next chapter, the exhaustive method and the GA are tested and evaluated based on two numerical examples.

CHAPTER 5

MODEL TESTING AND EVALUATION

In this chapter, two numerical examples are presented to demonstrate how the proposed model and algorithms can be used to resolve real transportation planning problems, including a traffic data collection problem and a winter roadway maintenance problem.

5.1 Example I-Travel Time Data Collection

Travel time information is essential for road users to make travel decisions and for transportation agencies to manage traffic effectively. There are various methods and equations for collecting and estimating travel time information. Inductive loop detectors were the most commonly used technology to collect traffic count and speed data for freeways, arterials, and streets, but are expensive to install and maintain. Floating car technologies, using toll tags, license plate matching, cellular phones, and automated vehicle identification units became popular in recent years.

A study for estimating travel time variability on New Jersey highways was conducted by Chien et al. (2010). Travel time data were collected by probe vehicles carrying GPS-based in-vehicle navigation devices in the morning peak period on weekdays. As shown in Figure 5.1, the study network included four road segments of US-46, NJ-3, NJ-4, I-280, NJ-17 and NJ-208 for travel time data collection, denoted as tasks 1 through 4. The characteristics of each segment including length as well as starting and ending locations are summarized in Table 5.1. A number of probe vehicles carrying navigation devices which record locations of vehicles over time, and the dispatching schedule and routing plan must be determined before collecting data, such that the total cost may be minimized. The depot is located at coordinates (40.740039,-74.179001), the campus of New Jersey Institute of Technology.

Table 5.1 Characteristics of the Study Road Segments

No.	Segment	Length(mi)	Start Node	End Node
1	US46-NJ3	13.0	40.894883,-74.240614	40.787892,-74.049948
2	I-280	8.5	40.797041,-74.251397	40.750210,-74.128366
3	NJ4-NJ208	17.4	41.017236,-74.216496	40.864962,-73.974483
4	NJ-17	12.8	41.000399,-74.100959	40.864962,-73.974483

Every probe vehicle departed from and ended its trip at the depot. Travel time data has to be collected in each segment during the following four time windows: T_1: 6:55 a.m. ~ 7:05 a.m., T_2: 7:25 a.m. ~ 7:35 a.m., T_3: 7:55 a.m. ~ 8:05 a.m., T_4: 8:25 a.m. ~ 8:35 a.m.

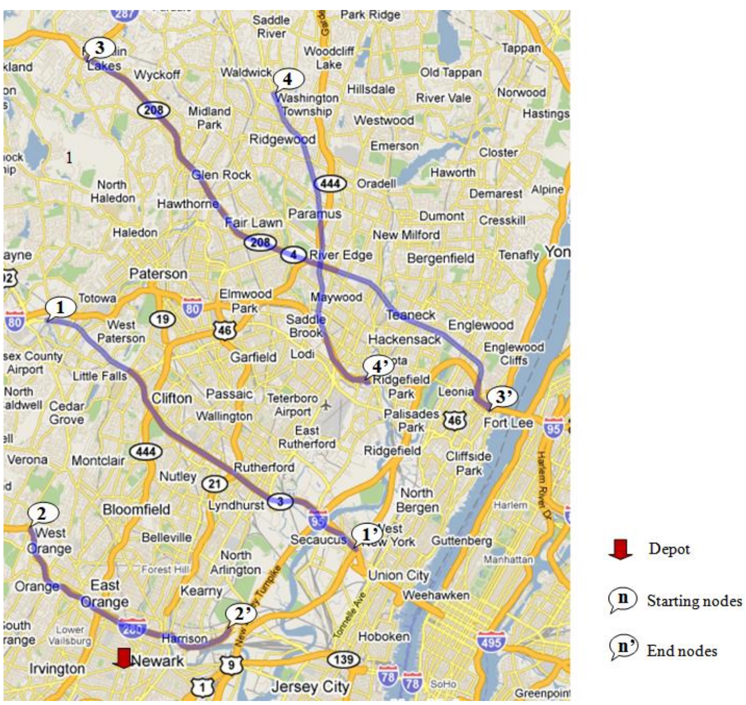


Figure 5.1 The study network for traffic data collection.

5.1.1 Numerical Results

By using the network transformation technique introduced in Section 3.2, a transformed network (***G'*****=*****A'*****, *****N'***) is presented in Figure 5.2. Note that nodes 1, 2, 3 and 4 represent the road segments of Table 5.1 that require data collection service. The depot (node 0) is assumed to be able to connect to all nodes.

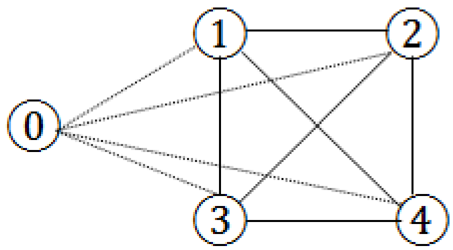


Figure 5.2 The transformed route network for traffic data collection.

With all the information of physical locations for each node in the network, the shortest path distance/travel time between each pair of nodes was calculated using the fast routing planning tool in Google Map (2009) and summarized in Table 5.2. The service times for each required node are highlighted in red.

Table 5.2 Travel Time and Distance Between Nodes

From\To	1	2	3	4
0	10(07)*	15(13)	25(21)	23(20)
1	18(15)	12(14)	39(29)	30(23)
2	20(17)	09(09)	38(30)	21(17)
3	33(26)	36(27)	28(22)	22(16)
4	26(20)	36(25)	16(14)	14(13)

*: X(Y) represents that the travel time (distance) are X minutes (Y miles)

The cost of the travel time data collection defined in this example included the labor cost and fuel expenses. The labor cost was equal to the hours of travel per vehicle multiplied by the hourly salary rate (e.g., 20 $/hour), while the fuel cost was equal to the total miles of travel multiplied by the unit cost per travel mile (e.g., 0.35 $/mi). The cost matrix is generated and summarized in Table 5.3. The service costs for each required nodes are highlighted in red as well.

Table 5.3 Cost of Travel between Nodes (Unit: $)

From\To	1	2	3	4
0	5.8	9.6	15.7	14.7
1	11.3	8.9	23.2	18.1
2	9.3	6.2	23.2	13.0
3	20.1	21.5	17.0	12.9
4	15.7	20.8	10.2	9.2

To better index this numerical example, a binary variable $V_k(i,\ t,\ t')$ was used to represent a probe vehicle *k* that collects data at node *i* within time window *t*, and could be available for another task of data collection at the following time window *t'*. If vehicle *k* was available at *t'*, $V_k(i,\ t,\ t')$ will be assigned 1; otherwise, it will be 0. In this example, there were 4 required nodes in the study network. Thus, 4 vehicles, denoted as V_1 (*0, 0, 1*), V_2 (*0, 0, 1*), V_3 (*0, 0, 1*), and V_4 (*0, 0, 1*) at the initial time point ($t = 0$), are available at the 1^{st} time window ($t' = 1$), where *0* represents leaving from node 0, which is the depot. The derivation of results for this problem is illustrated and discussed below:

<u>Time Window T_1:</u> Vehicle must arrive at the required node between 6:55 a.m.-7:05 a.m.

As discussed above, the fleet size of available probe vehicles and their schedules at time window *1* noted as T_1 were initialized as: V_1 (*0, 0, 1*), V_2 (*0, 0, 1*), V_3 (*0, 0, 1*), and V_4 (*0, 0, 1*), and the associated travel times and costs were calculated and presented in Table 5.4. For example, the time/cost for assigning vehicle V_1 to collect data for node 1 was the sum of travelling time/cost from node *0* to node *1* and the required service time/cost for node *1*. According to Table 5.2 and Table 5.3 the total travel time was 28 (i.e.10+18=28) minutes and the total cost was 13.9 (i.e. 5.8+11.3=17.1) dollars.

Table 5.4 Node Assignment Travel Time/Cost Matrix for Time Window T_1

Vehicle\Node	1	2	3	4
V_1 **(0,0,1)**	28/17.1	-	-	-
V_2 **(0,0,1)**	-	24/15.8	-	-
V_3 **(0,0,1)**	-	-	53/32.7	-
V_4 **(0,0,1)**	-	-	-	37/23.9

(-):There is no vehicle assigned to service node#.

Time Window T_2: Vehicle must arrive at the required node between 7:25 a.m.-7:35 a.m. Based on the travel time information calculated in Table 5.4, the time window constraints were formulated as Equations (3.4) to (3.7) and used to generate the vehicle availability matrix (Table 5.5). If a vehicle was available to service any required nodes in the next time window, *1* will be assigned to those nodes, and otherwise, *0*.

Table 5.5 Vehicle Availability Matrix for T_2

Vehicle\Node	1	2	3	4
V_1 **(1,1,2)**	0	1	0	0
V_2 **(2,1,2)**	1	1	0	1
V_3 **(3,1,2)**	0	0	0	0
V_4 **(4,1,2)**	0	0	1	1
V_5 **(0,2,2)**	1	1	1	1

1 – available; 0 – not available

As showed in Table 5.5, the binary variables $V_3(i, t, t')$ for Vehicle *3* were zeroes for all nodes, which means that Vehicle *3* is not able to undertake any data collection task within time window T_2 (7:25 a.m.-7:35 a.m.) after servicing node *3* in time window T_1; and therefore an additional vehicle labeled as V_5 (*0*, *2*, *2*) has to be assigned. Because Vehicle 5 is departing from the depot (node 0), it will be able to arrive at any one of the required nodes within time window T_2. Therefore, by looking up all the entries with a value of "1" in each row of the matrix, there will be 24 (=1*3*2*4) candidate schedules for T_2 in total.

The same procedure of finding vehicle availability is performed for the remaining time windows. It was found that there were a total of 45 feasible schedules for *5* probe vehicles to choose from to complete their travel time data collection (Table 5.6).

Table 5.6 Feasible Routes and Schedules for Vehicles (Fleet Size = 5)

Routes\Time window	T_1	T_2	T_3	T_4
R_1	1	2	1	2
R_2	2	4	3	-
R_3	3	-	4	3
R_4	4	3	-	4
R_5	2	1	2	1
R_6	-	1	2	1
.				
.				
.				
R_{44}				
R_{45}	-	2	3	-

"-" vehicle was not assigned to serve required nodes.

The SP formulation took Table 5.6 as input and solved by CPLEX (6.0), which yielded a least cost of $402.2 to collect travel time data. The optimized vehicle schedule and minimized cost for the minimum required fleet size of five are summarized in Table 5.7.

Table 5.7 Optimal Vehicle Schedule/Route Arrangement and the Minimized Cost

Vehicle\Time window	T_1	T_2	T_3	T_4	**Cost ($)**
V_1	1	2	1	2	77.2
V_2	2	4	3	-	80.8
V_3	3	-	4	3	97.8
V_4	4	3	-	4	88.0
V_5	-	1	2	1	58.4
Total Cost ($)	89.3	81.5	100.7	130.7	402.2

(-): Vehicle was not assigned for data collection.

In this example, a minimum five probe vehicles was required to collect travel time data on four road segments within four different time windows of departure. Because of the network characteristics, the optimized schedule only allowed one out of five vehicles to perform data collection service on every time window. This numerical example has demonstrated the proposed mathematical formulation and the exhaustive method are able to find the optimal route and schedule for probe vehicles. The total cost for collecting traffic data on New Jersey roadways was minimized. However, it was found that the exhaustive enumeration can be only efficient for solving small to medium size cases. When it comes to a large scale network with more number of road segments need to be serviced, the exhaustive method would be less attractive, because the number of iterations for optimal solution searching would be exponentially increased as the demand increases. Thus, heuristics would be preferable. In Chapter 6, a case study of a large scale network was solved by the genetic algorithm based heuristic.

5.1.2 Scenario Analysis

In Section 5.1.1, the optimal solution that minimized the total cost was obtained by using the proposed methodology. However, due to budget and resources constraints, the number of operable probe vehicles might be limited. To collect sufficient traffic data with a limited number of vehicles, the duration of the data collection project has to increase. Two scenarios were conducted and compared based on different project durations and fleet sizes (Table 5.8).

Table 5.8 Characteristics of Scenario A and B

	Scenario A	**Scenario B**
Objective	To minimize total cost	To minimize total cost
Study Network	4 required tasks	4 required tasks
Project Duration	1 day	2 days
Time Windows per day	4 time windows	4 time windows
Flee Size	The minimum required	3 Vehicles

For collecting travel time data in the study network, a constraint was introduced to ensure that probe vehicles service each required node four times per day, once per time window. Given a fleet size constraint (i.e. F = 3 vehicles), which is smaller than the minimum required fleet size (i.e. 5 vehicles) found in Scenario A, the data collection cannot be completed within one day. Table 5.9 showed the optimal vehicle schedule for Scenario B. With a limited fleet size, the project duration has to be increased from one day to two days, so that the required data can be collected. It was found that the total operating cost in terms of travel time and travel distance for Scenario B is higher than that of Scenario A, because a smaller fleet size means few vehicles dispatched on the network for data collection service, resulting in an increase in travel time and travel distance.

Table 5.9 Optimal Vehicle Schedule and Minimized Cost (Fleet Size: 3)

Day	Vehicle\Time window	T_1	T_2	T_3	T_4	Cost ($)
1	V_1	1	2	1	2	77.2
	V_2	2	1	2	1	75.6
2	V_1	3	-	4	3	97.8
	V_2	4	3	-	4	88.0
	V_3	-	4	3	-	69.3
Total Cost ($)						407.9

(-): Vehicle was not assigned for data collection

5.1.3 Sensitivity Analysis

In this Section, a sensitivity analysis is conducted to explore the relationship between optimal results and model parameters. It is very common for decision makers to debate how long the duration of the data collection project should be, how many data samples should be collected and what the fleet size should be. The results useful to decision makers would be the optimal scheduling and routing plan subject to fleet size, project duration and required sample size of travel data.

1) Minimum required fleet size vs. sample size:

Viewing the travel time data collection from a statistical perspective, collecting sufficient samples is crucial because the sample size determines the accuracy of the travel time estimation. But from the viewpoint of cost control, it is necessary to collect the required data samples with a cost as little as possible. In addition, when historical travel time data are available for computing the shortest path travel time between each pair of nodes in the network, the percentile of travel time that is chosen to be used has a big impact on cost control as well. A conservative decision maker tends to choose a high percentile of travel time to give more buffer room for transportation planning, but this would lead to an increase in total vehicle travel time in comparison with choosing mean travel time. In opposite, if an aggressive decision maker prefers choosing a low percentile travel time, then less total travel time would be needed to complete the required service. Thus, a sensitivity analysis to reveal the relationship among fleet size, percentile travel time and the sample size could be helpful for decision makers to understand the trade-off between these parameters.

In an example of collecting travel time data in four different time windows in one day at a network with *15* required service road segments, Figure 5.3 indicates that the minimum required fleet size increases as a higher percentile of travel time is used, and is reduced as a lower travel time percentile is used. Also there is an obvious trend showing that the minimum required fleet size increases with an increasing number of samples. It is easy to understand that the more samples are needed, the more vehicles have to be dispatched on the network.

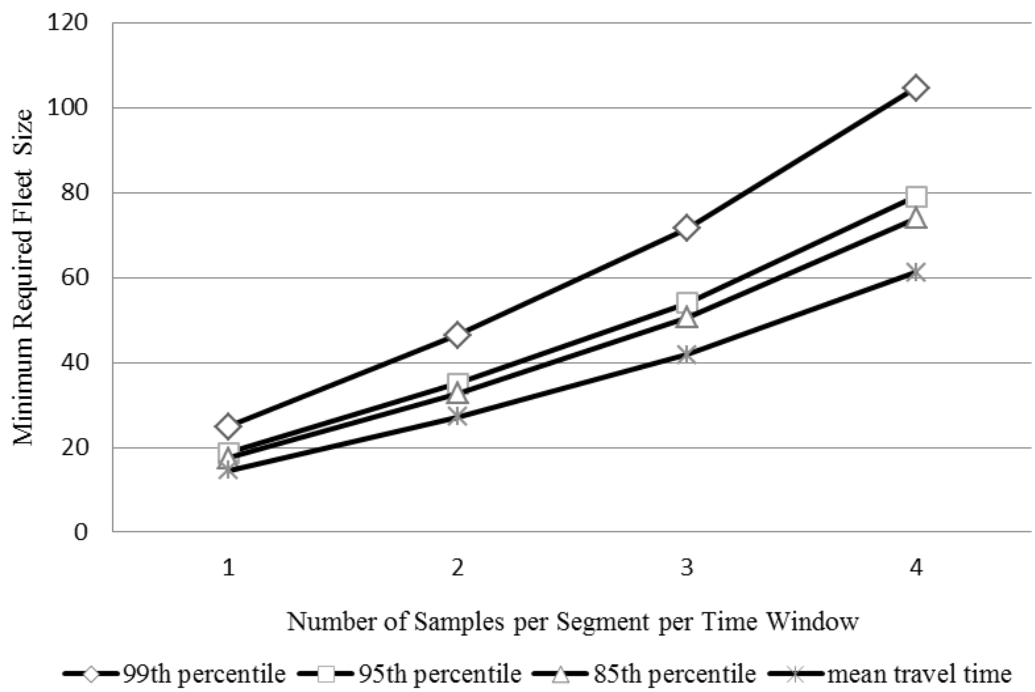


Figure 5.3 Minimum required fleet sizes vs. various numbers of sample size.

2) Minimum required fleet size vs. durations of time window:

As discussed in the literature review, the time windows can be divided into two types: hard time windows (HTW) and soft time windows (STW). In the first case, if the vehicle arrives early, it must wait until the earliest arrival time of the time window, and it is strictly forbidden to arrive late. In the case of soft time windows, the violation of the constraint is permitted but it leads to a penalty of the objective function. In this example of travel time data collection, only HTW was considered because for research purposes, the sample data has to be collected in a certain time window.

When a subset of road segments must be serviced at a cost that is dependent on the time service begins, the duration of time window could affect the results of vehicle routing and scheduling. For example, if the intervention of winter roadway maintenance for a snow storm emergency was too late, the cost in material and time could sharply increase. Therefore, planners would rather have vehicles arrive early than have a penalty for vehicles arriving late. It is useful to reveal the relationship between the duration of the time window and the optimal fleet size needed. Figure 5.4 indicates that the needed fleet size decreases as the duration of the time window increases. Because longer time windows give more room to allow vehicles to arrive “late” when compared to cases with tighter time windows. In other words, fewer vehicles are needed to meet a time window that has longer duration.

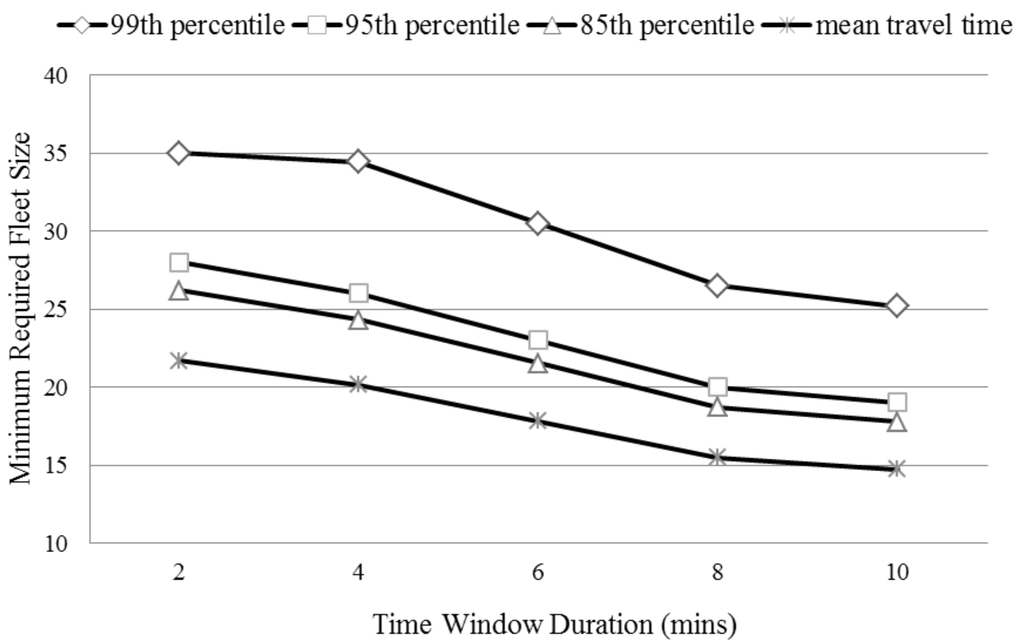


Figure 5.4 Minimum required fleet sizes vs. various time window durations.

3) Fleet sizes vs. total vehicle travel time:

Figure 5.5 shows the total vehicle travel time needed for all the data collection tasks under different percentiles of travel time and fleet size. Initially, there is an obvious trend showing that the total travel time decreases significantly with the increase of fleet size. It is easy to understand that more probe vehicles dispatched on the road for travel time data collection could result in a decrease in the required service time. Although the traffic data can be collected in a shorter time frame by using more vehicles, this strategy could also result in a significant incremental cost of equipment and labor costs. Therefore, a combined model for the fleet sizing and routing assignment is needed to determine simultaneously the optimal fleet size and routing.

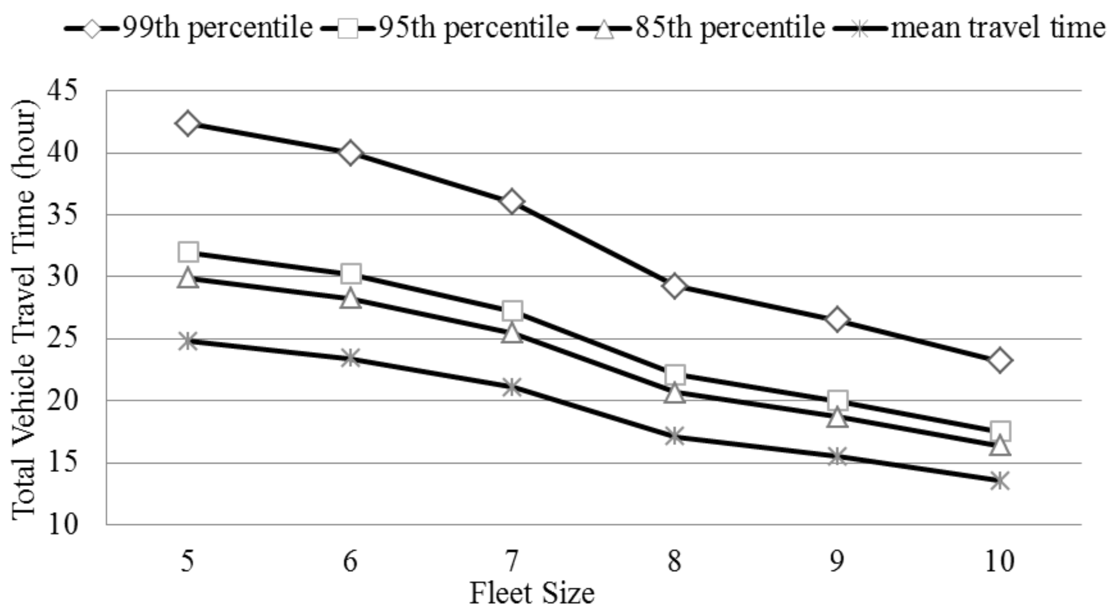


Figure 5.5 Fleet size vs total vehicle travel time.

5.2 Example II- Winter Road Maintenance

Winter road maintenance involves costly operations, including spreading of chemicals and abrasives, snow plowing, loading snow into trucks, and hauling snow to disposal sites. In the United States, winter road maintenance operations consume over $2.3 billion each year to ensure a safe road network (FHWA-USDOT, 2011). Winter storms act through precipitation, visibility impairments, high winds, and temperature extremes to affect driver capabilities, vehicle performance, pavement friction, roadway infrastructure, crash risk, traffic flow and agency productivity.

Given the present economic climate of shrinking monetary and manpower resources, it is important for all public and/or private sectors to make the most efficient use of their resources, such as allocating and routing snow plows and salt spreaders to serve a transportation network for a given snow event. In recent years, new technologies in the applications of road weather information systems, weather forecasting services, maintenance decision systems, and intelligent transportation systems have been implemented in many agencies in Europe (e.g., Switzerland, England), Asia (e.g., Japan, China) and United States to reduce the operating cost as well as to improve effectiveness and efficiency (Perrier et al., 2007). However, the progress in the development of optimization models for the routing and scheduling of vehicles has grown slowly compared to improvements of new technologies. Many agencies still rely on field experiences in making vehicle routing and scheduling decisions for winter road maintenance (Campbell and Langevin, 2000). Currently, most agencies do not have predetermined routes to guide the winter road maintenance operations. Once a driver has completed the assignment, he or she returns to the depot to refill the vehicle and receive another assignment. An experienced supervisor makes the operator assignments based his or her knowledge of the operating environment, the storm conditions, and the desire to service higher priority roadways prior to lower priority ones. The operator assignments vary from one storm event to another.

The primary goal of winter road maintenance is to provide a safe and dependable transportation infrastructure for moving people and goods. Snow emergency procedures strive to reduce the time necessary to clear a designated network of roadways. During winter road maintenance operations, trucks are assigned to de-ice the road surface by spreading chemical materials. Depending on the location, traffic condition and forecasted temperature and snowfall rate, roads shall be treated within given time intervals.

In US, state governments contract third-party trucks whose payment is normally based on the total travelled time to maintain roadway service during winter storms. The total cost in this study is defined in terms of the amounts of travel time spent in servicing required road segments. Consequently, the objective in this numerical example is to develop a routing and scheduling plan to minimize the time it takes for a given number of maintenance trucks to service a designated road network, subject to fleet size and service time limit constraints.

5.2.1 Numerical Results

Consider a maintenance region as illustrated in Figure 5.6, with two maintenance yards (at node 4 & 5) and six required arcs (bold black line, one lane each direction).The term “required arc” in this study is used for an arc that needs to be serviced by a vehicle. An “unrequired arc” is an arc used for traveling but does not need to be serviced.

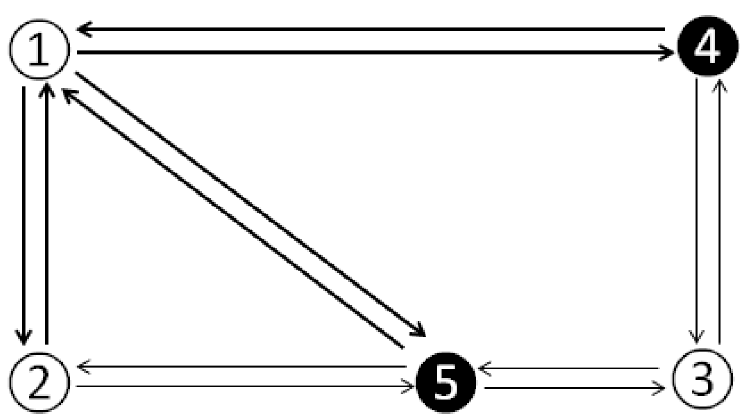


Figure 5.6 Example network of winter road maintenance.

In this example, a plowing task is defined as a single one direction pass on a segment, and therefore a one-way road segment may generate one task and a two-way road segment may generate two. This definition was illustrated in Figure 5.7. It is also assumed that each lane can be serviced in a single pass, and that there are two plows available for dispatch.

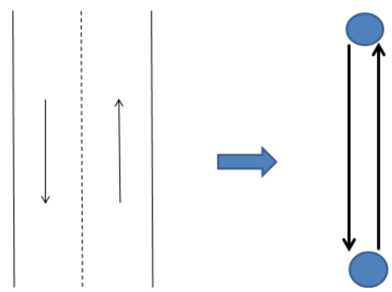


Figure 5.7 Example of plow tasks.

The concept of network transformation described in Section 3.2 is to use a single node to denote an arc. Transforming the required arcs in the example network can produce the tasks shown in Table 5.10.

Table 5.10 List of Required Arcs and Unrequired Arcs

Required Arcs (from node *i* to node *j*)	**Denoted As Task**	**Length (mile)**	**Unrequired Arcs (from node *i* to node *j*)**	**Length (mile)**
1-2	I1	6	2-5	6
2-1	I2	6	5-2	6
1-5	I3	9	3-5	5
4-1	I4	10	5-3	5
1-4	I5	10	4-3	7
5-1	I6	9	3-4	7

With the network information provided in the Table 5.10, a travel distance matrix can be created as shown in Table 5.11, where each cell represents the distance from the row element to the column element for that cell. Each cell in the first two rows denotes the distance from depot nodes (node 4 and 5) to the beginning of every plowing task and each cell in the first two columns denotes the distance from the end of every plowing task to the depot nodes. All other cells consist of distance values from the end of a plowing task to the beginning of every other plowing task.

Table 5.11 Travel Distances Matrix

From\To	4	5	I1	I2	I3	I4	I5	I6
4	-	12	10	16	10	0	10	12
5	12	-	9	6	9	12	9	0
I1	18	6	-	0	6	16	6	6
I2	10	9	0	-	0	10	0	9
I3	12	0	9	6	-	12	9	0
I4	10	9	0	6	0	-	0	9
I5	0	12	10	16	10	0	-	12
I6	10	9	0	6	0	10	0	-

After creating the distance matrix, the next step is to include time-dependent travel time into the model. Assuming that a planning horizon of two hours is divided into four time periods, each period is half hour in length. A time dependent travel time is incurred at each time period for each road segment due to snow accumulation. A “natural” and simple way to take time-dependency into account is to work with time-dependent travel speeds and to adjust the speed when the vehicle crosses a boundary between two time periods. In this example, the plowing speed was assumed to decrease from the beginning to the end of the planning horizon due to the fact that a driver’s visibility would be affected by snow accumulation.

With all the data ready to be used as input for the integer programming problem that is formulated below, a final solution of deployment route and schedule is expected to be generated. If there was no feasible solution to this initial problem, it means that there are not sufficient resources to operational requirements. In this case, the only course of action is to add more service plows, or relax operational constraints until a feasible solution can be found.

Table 5.12 Parameters and Notations (Alphabetical Order)

Notation	Meaning	Unit
B_{ir}	1 if task $i \in \boldsymbol{I}$ is assigned to route r, and 0 otherwise	/
C_r	Total cycle time of route r	Minute
C_m	Maximum cycle time limit	Minute
$\boldsymbol{D}$	Set of nodes of depots (maintenance yards), indexed by d	/
$\boldsymbol{I}$	Set of plowing tasks	/
k_d	The fleet size for depot d	/
l_{ij}	Length of arc (i,j)	Mile
$\boldsymbol{R}$	Set of candidate routes, indexed by r	/
$\boldsymbol{T}$	Time periods, indexed by t	Hour
x_{ij}^{v}	*1* if (i,j) is traveled by vehicle v, *0* otherwise	
z^t	Travel speed at time period t, $t \in \boldsymbol{T}$	MPH

As stated in the model development section, this example can be numerically described as a master problem and a sub-problem by using the set-partitioning approach. Table 3.1 and 5.12 can be used as quick references for the notation used in below formulation.

<u>Master Problem:</u>

$$Min \sum_{r \in \boldsymbol{R}} \sum_{v \in \boldsymbol{V}} C_r X_{vr}$$

Subject to

$$\sum_{r \in \boldsymbol{R}} \sum_{v \in \boldsymbol{V}} B_{ir} X_{vr} = 1, \forall i \in I \qquad (5.1)$$

$$\sum_{r \in \boldsymbol{R}} \delta_{rd} X_{vr} \leq k_d, \forall d \in \boldsymbol{D} \qquad (5.2)$$

$$\sum_{r \in \boldsymbol{R}} X_{vr} = 1 \quad \forall v \in \boldsymbol{V} \qquad (5.3)$$

$$X_{vr} \in \{0,1\} \qquad \forall v \in \boldsymbol{V}, \forall r \in \boldsymbol{R} \qquad (5.4)$$

The objective is to minimize the sum of two component costs, one is the deadhead travel time and the other one is the service time. The constraint of Equation (5.1) ensures that every plowing task should be performed exactly once. The constraint formulated as Equation (5.2) imposes a limit on the fleet size. The constraints formulated in Equation (5.3) and Equation (5.4) ensure that each vehicle travels at least on only one route.

<u>Sub problem:</u>

For a given plow *v*:

$$\text{Minimize} \sum_{(i,j) \in \boldsymbol{A}'} t_{ij}(b_i^v) x_{ij}^v + \sum_{i \in \boldsymbol{I}} s_i(b_i^v) \sum_{j \in \boldsymbol{N}' \cup \boldsymbol{D}} x_{ij}^v \quad , \qquad (5.5)$$

Subject to

$$\sum_{(i,j) \in \boldsymbol{A}'} t_{ij}(b_i^v) x_{ij}^v + \sum_{i \in \boldsymbol{I}} s_i(b_i^v) \sum_{j \in \boldsymbol{N}' \cup \boldsymbol{D}} x_{ij}^v \leq C_m, \forall v \in \boldsymbol{V} \qquad (5.6)$$

$$\sum_{j \in N'} x_{dj}^{v} = k_d, \forall d \in \boldsymbol{D}, \forall v \in \boldsymbol{V} \tag{5.7}$$

$$\sum_{j \in N'} x_{jd}^{v} = k_d, \forall d \in \boldsymbol{D}, \forall v \in \boldsymbol{V} \tag{5.8}$$

The objective of the sub-problem is to find feasible service routes that minimize the total travel time for a given plow. The constraints guarantee that 1) there is a limit on the service time for each plow, 2) each plow starts and ends its route at the depot it belongs. The sub-problem is an elementary shortest path problem with operation constraints, which is solved with the exhaustive numeration method. All feasible routes are then added to the master program and the latter was solved with a standard ILP solver (CPLEX 6.0) to obtain an integer solution for decision variable X_{vr}. The final decision matrix of X_{vr} represents the selected dispatch schedule that should be followed, where the rows correspond to the numbered snow plow, and the columns correspond to the number routes. The data and the solution of the example are as follows:

<u>Parameters:</u>

$z^t = (20,18,15,12)$, represents the plowing speed profile at time period t;

C_m=2, the maximum service time for each plow is two hour.

<u>Results:</u>

1) In the case of only one available plow for six required segments, there is no feasible solution found with given maximum service time limit for each plow;

2) In the case of two or more available plows for six required tasks, feasible solution are found;

5.2.2 Scenario Analysis

A set of scenarios were analyzed to test the impact of various fleet size and maintenance yard (depot) locations on final results. Each scenario produced results including the total deadheading travel distance (denoted by DH), the longest cycle time of optimized service route (denoted by CT) and the total vehicle travel time (denoted by TT).

First, it was assumed that all vehicles depart from the same depot, which is node 4 in Scenario I and node 5 in Scenario II, respectively. The results as shown in Table 5.13 indicate that DH and the TT are sensitive to the depot locations. For example, when it is assumed that there are three available vehicles, the TT and DH with node 5 as the depot are both higher than they are with node 4 as the depot. However, when there are only two available vehicles, the result with node 5 as depot is slightly lower than it is with node 4 as the depot. This reveals that the optimal depot location and fleet size are correlated with each other, as both factors are related to the geometry of the road network. In general, the fleet size and depot location both are important factors that have impacts on the final solution of routing and scheduling.

Table 5.13 Results of Scenario I and Scenario II

Scenario	Fleet Size	DH (mile)	CT (min)	TT (min)	Depart from depot
I	1	n/a	n/a	n/a	4
	2	22	117	202	4
	3	40	104	245	4
II	1	n/a	n/a	n/a	5
	2	18	112	194	5
	3	42	93	259	5

A later Scenario III, where it was assumed that vehicles depart from different depots, provides better results (Table 5.14) in terms of TT and DH than Scenario I and II. This is because the multi-depot setup allows vehicles to perform plowing tasks that are close by their corresponding depot.

Table 5.14 Results of Scenario III

Scenario	Fleet Size	DH (mile)	CT (min)	TT (min)	Depart from depot
III	2	0	87	137	one from 4, one from 5
	3	10	92	156	one from 4, two from 5

Lastly, by viewing the results of all three scenarios together, it is showed that no feasible solution is founded when there is only one vehicle available. A fleet of two vehicles outperformed a fleet of three vehicles in terms of total deadheading travel distance and total vehicle travel time. The reason is that with a given depot location and the geometry of the road network, a vehicle is able to continuously perform plowing service for multiple tasks and end its trip at its depot without having too much deadheading travel. On the other hand, adding an extra vehicle to take over plowing tasks from other existing vehicles can lead to more deadheading travel because all vehicles have to start and end their trips at the same depot.

Decision makers need to make decisions about the fleet size and depot location at the planning stage simultaneously based on different objectives and available resources. In the next chapter, a real-world case study based on a large scale road network is analyzed to help transportation planners optimize snow service routes and evaluate resource allocation options.

5.3 Summary

In this chapter, a numerical example of travel time data collection was provided to test the basic model developed in Section 3.3, which was solved via an exhaustive enumeration method. It was found that the exhaustive enumeration can be simple to implement but it is only efficient for solving small size problems. Also, sensitivity analysis shows that the optimal results of the basic model vary significantly as different percentiles of travel time was used as model input, due to the lack of consideration of travel time variability. Another numerical example of winter road maintenance was used to test the enhanced model that uses time dependent travel time as model input. The results prove that the model with consideration of travel time variability can better describe real world applications when demand must be satisfied at a cost that depends on the timing of intervention. Also, scenario analysis shows that, not only the beginning time of service has an impact on the final results, but also the depot location and fleet size.

CHAPTER 6

CASE STUDY

In this Chapter, a case study is presented based on actual winter road maintenance operating in the state of New Jersey. The objective and related background of the current NJDOT winter road maintenance operations are introduced in Section 6.1 and 6.2, respectively. The data preparation, optimized results, and scenario analysis for different operations and the computational complexity analysis are discussed in Sections 6.3 to 6.5.

6.1 Objective

To achieve effective Winter road maintenance operations (i.e., salt spreading, snow plowing) requires many complex planning decisions to be made including complying with a service level policy (e.g., roadway level of service, snow accumulation level), locating depots, routing/scheduling service vehicles, and configuring the vehicle fleet with various capacity for various workload shall be made. Since the definition of a service level policy is a prerequisite for later planning decisions, it can be handled separately. However, the remaining decisions are all interrelated and affect the agency's ability to ensure a desired level of service.

This case study considered problems of routing and scheduling vehicles (i.e., maintenance trucks), locating depots and configuring fleet size to provide higher quality service on winter roadway maintenance. Additionally, the impact of travel time variability was taken into account to address the requirement of service time limit. State and local governments contract third-party trucks to maintain roadway conditions during the winter season. The payment rule used to these third-party trucks is normally based on the total travelled time of all vehicles (NJDOT Contract Agreement for Snow Plowing & Hauling Service, 2011-2013). To this end, the total travel time of maintenance vehicles dominates total spending.

The case study discussed in this dissertation considers a real transportation network operated under the New Jersey Department of Transportation's policy on winter road maintenance operations and planning. The detailed description of the case study follows.

6.2 Current Winter Roadway Maintenance in New Jersey

In a winter, the New Jersey Department of Transportation (NJDOT) is prepared to clear snow and ice from roadways statewide, by filling salt and liquid calcium inventories, fitting trucks with plows and deploying personnel to ensure motorist safety. NJDOT maintains *37* remote roadway weather sensing stations to help keep crews informed on road conditions on the state highway system. These stations provide detailed information on weather and road conditions in specific regions of the state, including air temperature, humidity, wind speed and direction and road and bridge surface temperatures. Material is housed in *70* salt storage facilities, 49 salt domes and 21 sheds at 68 maintenance yards (including winter-only yards). Figure 6.1 shows the current snow sections and the locations of maintenance yards in the state of New Jersey.

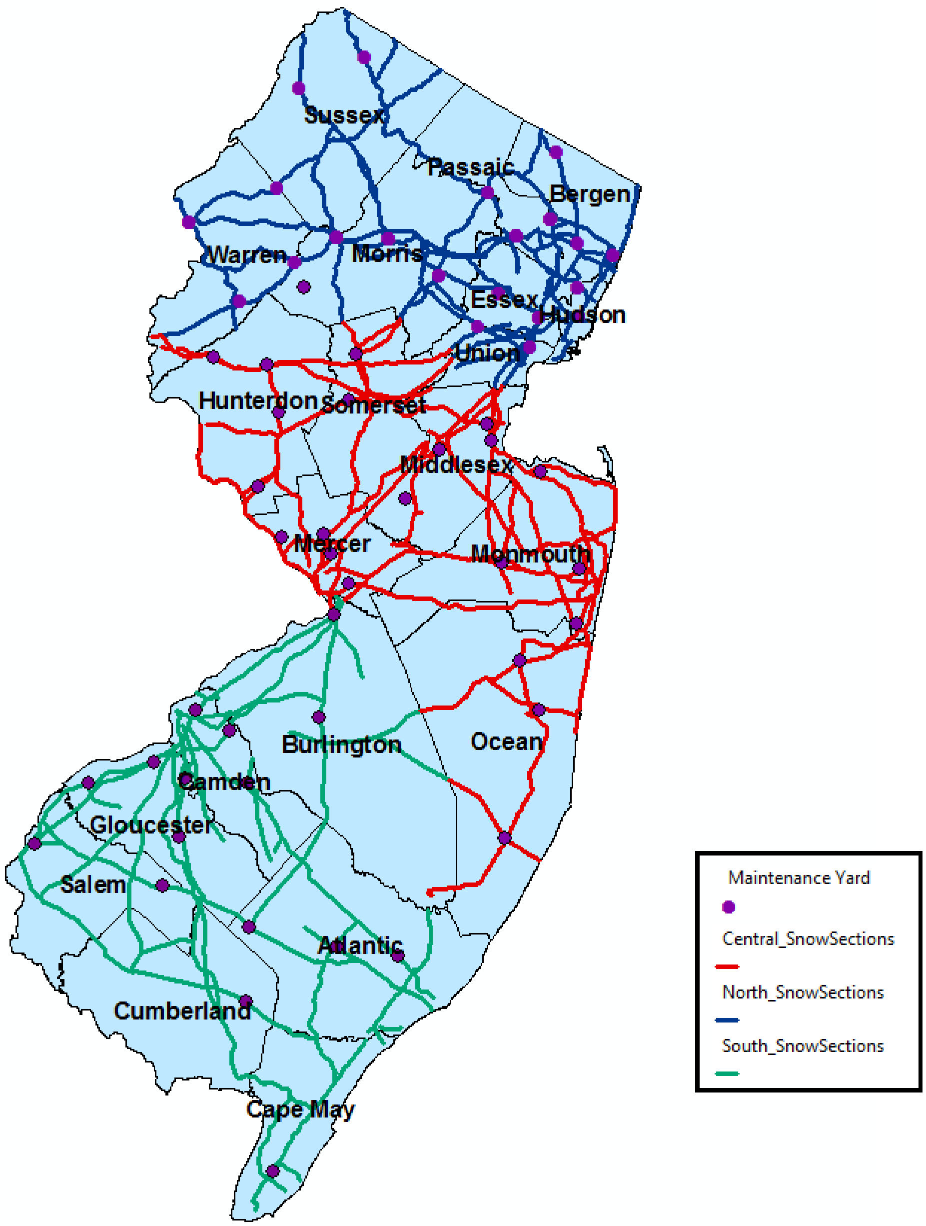


Figure 6.1 New Jersey snow Sections and maintenance yards.

Table 6.1 summarizes the expenditures of past two winter seasons that were necessary to successfully combat winter weather on the 13,295 lane-miles of over 300 snow Sections in New Jersey.

Table 6.1 Expenditures in New Jersey for Winter Roadway Maintenance

Material Usage	**2012-2013**	**2013-2014 (though Dec. 11, 2013)**
Salt	28,201 tons	48,875 tons
Liquid Calcium Chloride	895,532 gallons	154,231 gallons
Brine	828,805 gallons	46,310 gallons
Total Expenditures	$62,543,773	$14,231,881

*source: http://www.state.nj.us/transportation/about/winter/expenditures.shtm, accessed on Jan. 22, 2014

6.3 Data Preparation

To use the developed model and the solution algorithm to optimize a winter road maintenance problem based on the roadway network of New Jersey, the geometric data of the study transportation network, information of current plow operations and fleet configuration should be collected.

Because roadways in urban areas have more complicated lane configurations, pavement characteristics and winter operation guidelines than roadways in suburban areas, in this case study, a network consist of 41 snow sections associated with 10 maintenance yards located in northwest New Jersey was selected. As show in Figure 6.2, the selected roadway network (snow Sections highlighted in Blue) has much less road density than that in the northeast area of New Jersey (snow Sections highlighted in green), where population density is higher due to its adjacency to the New York metropolitan area. Table 6.2 summarizes the snow section data of the 10 maintenance yards.

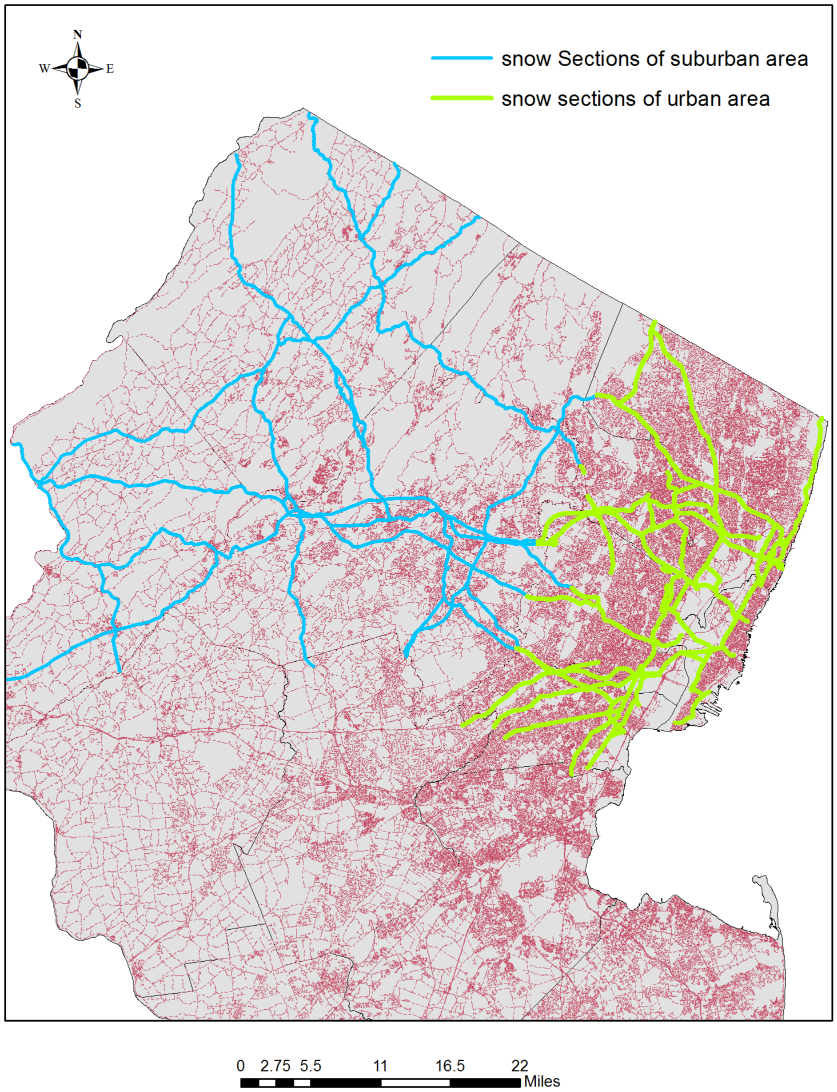


Figure 6.2 Selected snow Sections in the northern New Jersey roadway network.

The key data needed for the selected snow Sections are geometric data, weather information, and snowplow speeds. Sections 6.3.1 through 6.3.3 present three types of information for each major data category: 1) the data type; 2) the source of the data and; 3) how relevant information can be extracted from the data.

Table 6.2 Selected Snow Sections and Maintenance Yards

Maintenance Yard	No. of Snow Sections	Total Lane Miles
Branchville	3	80.6
Columbia	3	237.45
Hackettstown	2	88.4
Hanover	8	351.5
Netcong	6	157.6
Port Colden	3	71.6
Riverdale	5	225.6
Rockaway	4	212.9
Sussex	4	116.7
Yellow Frame	3	78.5
Total	41	1620.85

*source: NJDOT strategic deployment plan winter 2012-2013

6.3.1 Geometric Data

The roadway geometric data can be obtained from the NJDOT 2010 Straight Line Diagrams (SLDs) (http://www.state.nj.us/transportation/refdata/sldiag/). The SLD network presents approximately 12,000 miles of State (Interstate, US and NJ numbered roads), National Highway System (NHS), Surface Transportation Program (STP) and all County routes. After mapping each snow Section to the SLD database, the information, highway pavement width, shoulder width, ramp width, centerline mile of mainline, ramp length, and *etc*. can be obtained. According to a report by Chien et al. (2013) the NJ roadways can be classified into four categories: I - Urban Interstate; II - Urban Arterial; III - Rural Interstate; and IV - Rural Arterial.

To identify the roadway types of selected 41 snow Sections and calculate the shortest distances between pairs of snow Sections, the roadway network of the study area was created using ArcGIS software based on the shape file of the New Jersey roadway network, as shown in Figure 6.3, where each node represents a road intersection, and connections between nodes (i.e., links) represent road segments. The road segments that require plowing service, also known as snow Sections are highlighted in blue.

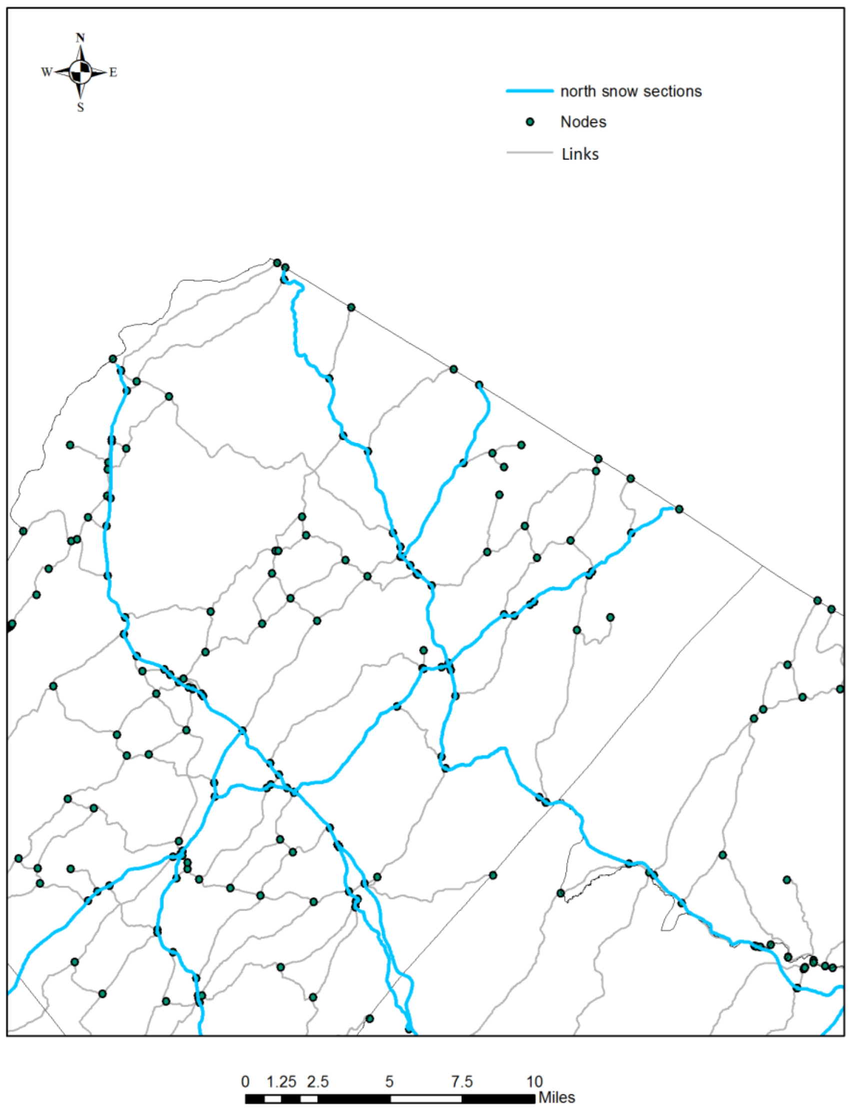


Figure 6.3 Sample of the studied transportation network in ArcGIS.

6.3.2 Weather Data

Travel speed is not only affected by roadway type, but also by snow intensity. Agrawal *et al.* (8) quantified the impact of different levels of snow intensities and pavement surface conditions on freeway traffic flow for the metro freeway region around the Twin Cities in Iowa. Four different levels of snowfall intensity were defined in the research: Trace (<0.05inch/hour), light (0.06-0.1inch/hour), moderate (0.11-0.5 inch/hour) and heavy (>0.5 inch/hour). In this case study, snow intensity was chosen as the index of weather information and three levels of snow intensity were as shown in Table 6.3.

Table 6.3 Snow Intensity Level

Snow Intensity Level	Snow Fall Rate (inch/hour)	Description
1	0-0.5	Light
2	0.5-1.0	Medium
3	≥1.0	Heavy

Weather data is available from *Clarus* (http://www.its.dot.gov/clarus/). *Clarus* records weather data including relative humidity, snow intensity, wind speed, and pavement surface temperature etc. All data used in this dissertation were stored on a 20-minute interval basis in *Clarus*.

6.3.3 Speed Data

The key factors that affect plow speed include traffic density, snow depth, visibility, and moisture content of falling snow. Other variables affecting snow and ice removal from the surface are snow accumulation rate, humidity, air temperature, pavement temperature, wind speed and direction, time of day, and the sun is present. Zhang et.al (2006) indicated that in the state of Missouri, for combined spreading and plowing the average speed while servicing is 40 mph on the interstates and highways and 30 mph on all other state roadways. While deadheading vehicles travel approximately 10 mph faster than they do while servicing, combined spreading and plowing. An average plowing speed chart based on storm conditions is displayed in Figure 6.4 below. These rates come from a study done by Wilson, Dadie-Amoah, and Zhang (2003). They stated that plow speed is a result of the combined effect of moisture content and snow accumulation rates. The plow speed decreases as the snow accumulation rate increases, the higher the moisture content the lower the plow speed would be.

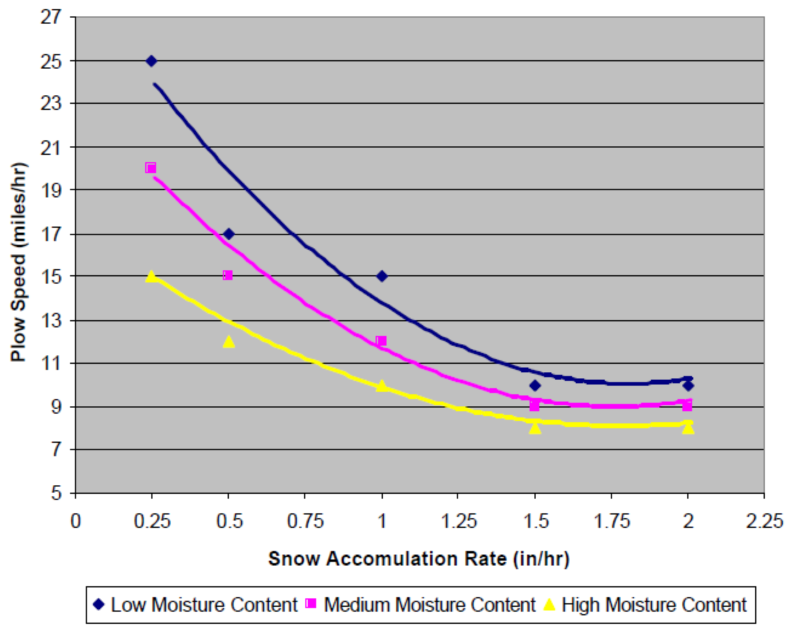


Figure 6.4 Plowing speed vs snow accumulation rate and moisture content.

As the selected snow Sections are composed majorly by type III roadways (rural interstate highway), the speed profile of the PM peak (4 p.m.-6 p.m.) was discretized into four time periods $(T_t)_{1\leq t\leq 4}$ as summarized in Table 6.4. It was assumed that the plowing speed decreases as the snow continues to accumulate and affects roadway surface condition and driver's visibility. So there is a decreasing trend in plowing speed as shown in Table 6.4.A maximum plowing speed of 25 mph was recommended by Chien et.al (2012). And the average speed of plow trucks were assumed to be 30 mph while not performing plowing operation.

Table 6.4 Speed Profile of Road Type III at Different Time Period of PM peak

Speed Type\Period	T_1	T_2	T_3	T_4
Deadheading Speed (mph)	30	30	30	30
Plowing Speed (mph)	25	17	15	10

6.4 Results Discussion

This Section includes an illustration of the solution methodology developed in this research, which solved the problems of service route design, vehicle scheduling, and fleet configuration for the selected snow Sections in New Jersey. The problem presented in this chapter is to minimize the total vehicle travel time including total deadhead travel, subject to resource and operational constraints.

A plowing operation was assumed to take place during a predicted snow storm that started from 4 to 6 pm at the maximum intensity level of 3 (>1.0 inch/hour). First, the input data for the optimization model including the geometric data of the snow Sections and time-dependent traffic speed information are presented. Then, the developed model was used to route and schedule a fleet of plows for clearing all 41 snow Sections within the two hour service time limit. In this case study, the following assumptions were made:

1) Only Class A vehicles- Gross Vehicle Weight (GVW) of 45,000 pounds or over) were considered. (http://www.state.nj.us/transportation/about/winter/contractor.shtm)

2) The plowing speed was considered to vary by roadway type, snow intensity, starting service time.

3) Each direction of a snow Section would be plowed once.

4) All drivers are assumed to be familiar with the study road network and alternative routes.

Finally, different scenarios with respect to different operational situations were evaluated.

6.4.1 Scenario Analysis

The main strategic and operational problems for winter roadway maintenance include decisions of locating depots, designing sectors, routing and scheduling service vehicles, and configuring the vehicle fleet. All these decisions are interrelated. The common terms used in winter road maintenance are presented in Table 6.5.

Table 6.5 Definitions of Common Terms

Term	Definition
Maintenance Yard	Known as a depot, where maintenance trucks start and end their trips
Snow Section	A road segment that needs to be serviced
Snow Sector	A service area that consists of a maintenance yard and a number of snow sections
Service Route	A sequence of consecutive nodes that a vehicle travels though

Table 6.7 indicates that, two scenarios are constructed with unconstrained fleet size and optimized service route (as Table 6.6 showed) and then their results are compared with the base scenario, which consists of the current NJDOT winter operation.

Table 6.6 Definitions of Scenarios

	Depot Location	**Fleet Size**	**Service Route**
Base Scenario (Current NJDOT Operation)	Fixed	Fixed	Fixed
Scenario-I	Fixed	Minimized	Optimized within predefined snow sectors
Scenario-II	Fixed	Minimized	Optimized without predefined snow sectors

Base Scenario:

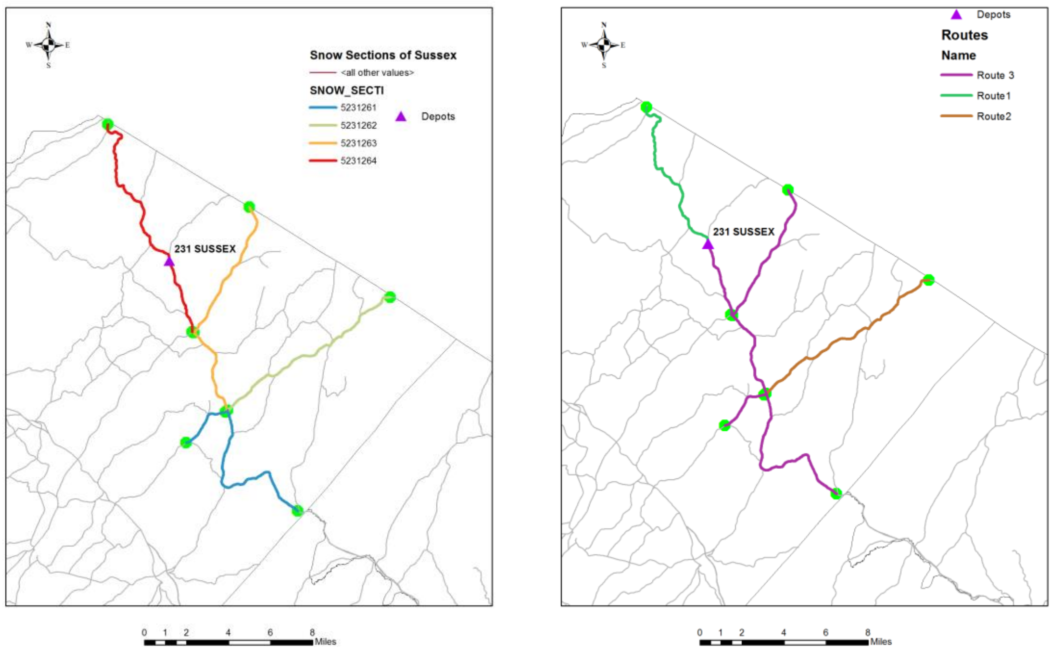
Currently, NJDOT does not have an optimization model to guide the winter road maintenance operations. Usually a supervisor assigns each driver a set of snow Sections to service, and the order in which they should be serviced is not optimized. Once a driver has completed the assignment, he or she returns to the depot to refill the vehicle or receive another assignment. An experienced supervisor arranges the operator assignments based on his or her knowledge of the operating environment, the storm conditions, and the desire to service higher priority roadways before lower priority ones. Thus, the snow Section assignments may vary from one storm event to another, and from one supervisor to another.

The current number of plows required for each snow Section was estimated by a formula that was developed in 1978. The formulate took into account the applicable speed of the plow, the two-hour service completion time limit, and the total lane miles of snow Sections. However, it did not consider the impact of roadway type, traffic peak period and weather condition on snow plow speed. Moreover, it did not consider that the plowing speed could be time dependent instead of being constant throughout the operating period.

Scenario-I:

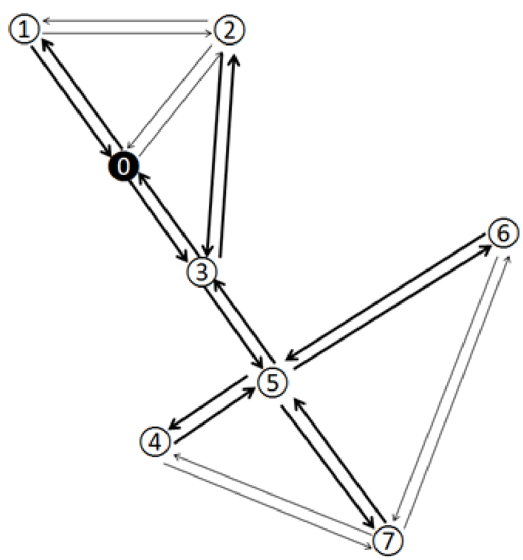
In this scenario, there are 10 maintenance yards that are also considered as depots of snow plows according to the actual winter operations in New Jersey. In New Jersey, a "snow sector" with a pre-assigned maintenance yard and various snow sections is defined based on available personnel, plow trucks, service equipment and materials. The service route for snow plows is constructed to start at a maintenance yard and then to service snow sections that belong to its corresponding snow sector before returning to the maintenance yard. Compared to the current NJDOT operation, Scenario-I optimized the service routes for each snow sector based on existing divided snow Sections, with an attempt to minimize total travel time with a minimum number of required vehicles.

The Sussex snow sector is used as an example to illustrate this scenario. Figure 6.5(a) shows the maintenance yard location and the exiting 4 snow Sections in Sussex County. Figure 6.5(b) shows that there were three service routes constructed by the proposed methodology, which means at least three groups of plows would be needed to service all four snow Sections within the two hour service time limit. Figure 6.6 illustrates the service sequences of snow Sections for each service route. Deadhead travelling is indicated by underscored arrows.



(a) (b)

Figure 6.5 (a) Existing snow Sections and maintenance yard in Sussex (b) Optimized service routes for Sussex.



Route 1:
0→3→0 →1→3→0

Route 2:
0→3→2→3→5→6→5→3→0

Route 3:
0→3→5→4→5→7→5→4→5→
3→2→0

Figure 6.6 Service route details.

After generating service routes, the next step is to develop a plow truck assignment rule. Chien and Gao (2013) developed a model to estimate the needed fleet size for snow plowing operations based on the geometric details of snow Sections in New Jersey. The results of their model were used in this study as a reference to assign the minimum required number of plow trucks to each generated service route. However, their model is based on the assumption that all plow vehicles are available when needed. In reality vehicles can be unavailable to due to breakdowns, maintenance or other reasons. Thus, in the base scenario, NJDOT has further modified the formula to reflect the age of the existing fleet. The data supplied indicated an average 80% up time for their truck fleet. Thus, extra vehicles were needed. The minimum required fleet sizes obtained in Scenario I and Scenario II were adjusted by increasing 20%. Table 6.7 summarizes the needed fleet size, total deadhead distance and total travel time, cycle time for each route.

Table 6.7 Summary of Service Routes in Sussex

Snow Section	No. of Trucks assigned by NJDOT (1978)	Serviced by Service Route	Cycle Time per Route	No. of Trucks assigned per service route	Total Vehicle Deadhead Distance (vehicle*mile)	Total Vehicle Travel Time (vehicle*minute)
5231261	3	3	116.34	3	65.09	388.56
5231262	3	2	102.13	3	57.3	340.53
5231263	3	2&3	-	-	0	-
5231264	3	1	77.18	3	22.2	214.34
Total	**12**	**-**	**295.65**	**9**	**144.59**	**943.43**

By using the same optimization procedure, the service routes for each snow sector were developed. Table 6.8 summarizes the results of the rest of the considered snow sectors. It indicates that the optimized routes and corresponding vehicle schedules for each of the existing snow sector did decrease the total number of required plows from the current NJDOT level of 197 to 123 plows. The decrease in the number of required plows in Scenario-I suggests a reasonable quality solution to the routing and scheduling problem. The total deadhead travel distance for all routes is 581 miles.

Table 6.8 Summary of Results for Scenario-I

Snow Sector	**No. of Plows Assigned by NJDOT (1978 model)**	**No. of Optimized Service Routes**	**Minimum Required Fleet Size**	**Total Vehicle Deadheading Distance (vehicle*mile)**	**Total Vehicle Travel Time (vehicle*minute)**
Branchville	10	3	5	34	290
Columbia	21	2	9	8	658
Hackettstown	6	2	4	9	188
Hangover	35	6	30	111	1119
Netcong	33	4	16	101	1293
Port Colden	9	2	6	20	500
Riverdale	39	3	15	39	688
Rockaway	22	2	6	86	511
Sussex	12	3	9	145	889
Yellow Frame	10	2	2	27	206
Total	**197**	**29**	**102/123***	**581**	**6341**

*the adjusted fleet size in case of 20% unavailability

Figure 6.7 shows that the snow Sections that covered by all the new designed service routes highlighted in blue, and the deadhead segments are highlighted in red.

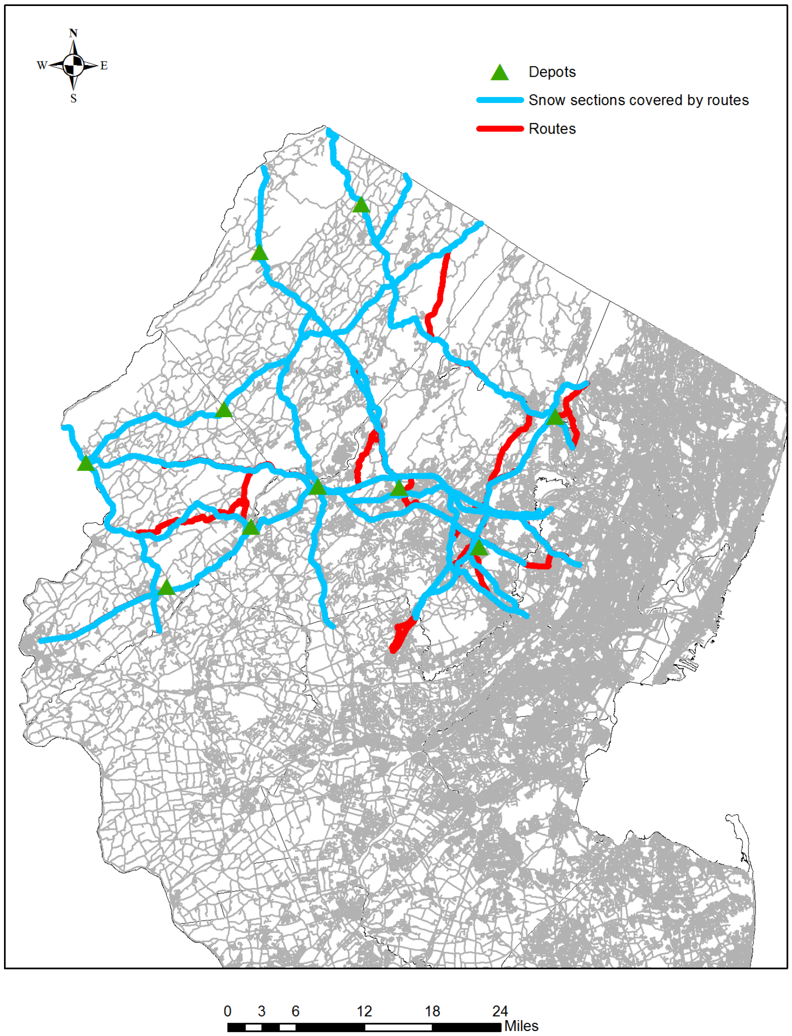


Figure 6.7 Service routes developed for Scenario I.

Scenario-II:

In this scenario, the locations of the maintenance yards were still predefined. Relocating of maintenance yards or adding new ones is not considered in this scenario because of budget limit options or geographic constraints. However, the service routes would not be constrained any more within their corresponding snow sectors and inter-sector routes would be considered. In other words, a service route can contain snow Sections that belong to different snow sectors. Instead of finding the best service routes for each snow sector, the proposed optimization model finds the best service routes that crossing different snow sectors.

Table 6.9 Summary of results for Scenario-II

Snow Sector	No. of Plows Assigned by NJDOT (1978 model)	No. of Optimized Service Routes	Minimum Required Fleet Size	Total Vehicle Deadheading Distance (vehicle*mile)	Total Vehicle Travel Time (vehicle*minute)
Branchville	10	2	5	31	490
Columbia	21	1	4	6	408
Hackettstown	6	1	2	9	220
Hangover	35	7	35	205	2592
Netcong	33	5	15	176	1545
Port Colden	9	2	6	22	666
Riverdale	39	1	4	12	380
Rockaway	22	3	9	134	927
Sussex	12	2	6	60	672
Yellow Frame	10	1	2	27	178
Total	**197**	**25**	**88/106***	**683**	**8078**

*the adjusted fleet size in case of 20% unavailability

Compared to the result of scenario-I, the result of scenario-II (Table 6.9) shows that the number of service routes and the minimum required fleet size are decreased from the Scenario I level of 29 service routes with 123 plows to 25 service routes with 106 plows, but at the cost of increasing the total deadheading distances of all vehicles required to cover all snow sections.

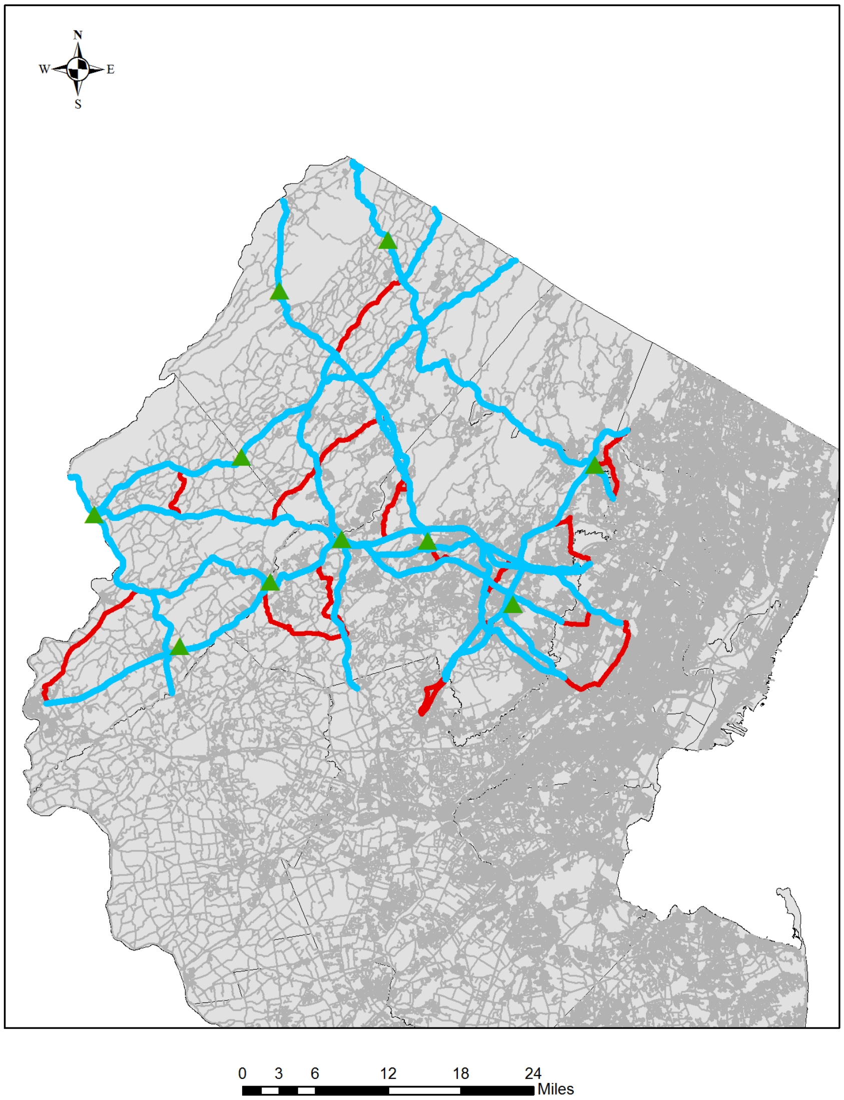


Figure 6.8 Service routes developed for Scenario-II.

As show in Figure 6.8, there are more red-highlighted deadhead traveling segments than show in Figure 6.7. This is not surprising, as scenario-II still maintained the existing maintenance yard locations and snow section design, so there is effectively a larger area to cover with a smaller number of plow trucks and total vehicle travel time for each service route increases.

In addition, a closer look at the plows at each of the 10 maintenance yards indicates that there were more routes starting from yards of Netcong, Hanover and Rockaway than in Scenario-I, because the locations of those yards allow plows to maximize their utilization by covering more snow sections within a two hour service time limit.

Comparisons:

The quality of routes developed in Scenario-I and II can be measured by cycle time and deadhead traveling miles per route. As seen in Figure 6.9, where the distribution of cycle time for the two scenarios is presented, most cycle times for scenario-I are less than 100 minutes.

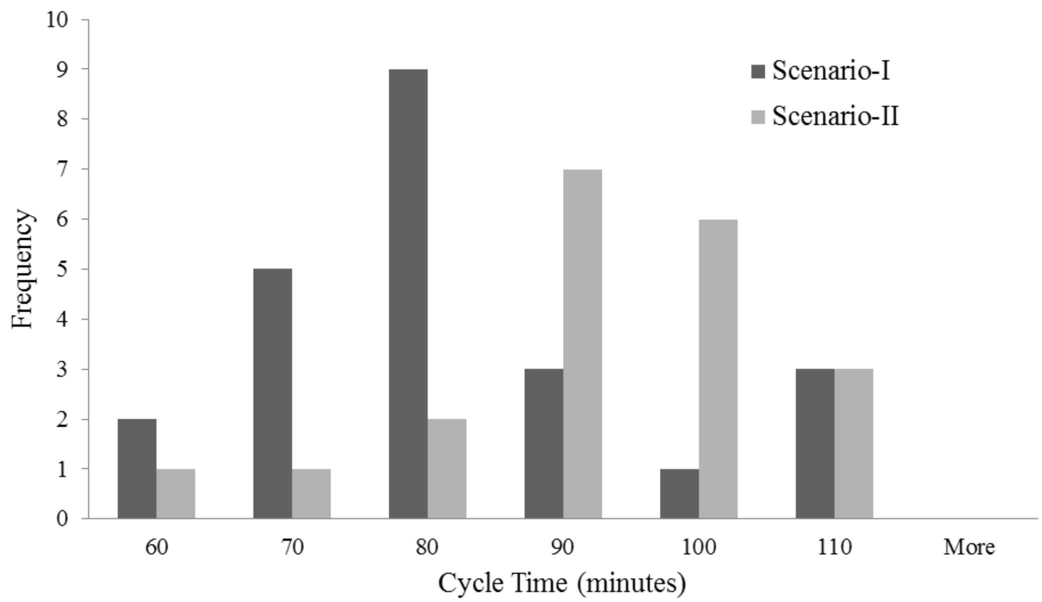


Figure 6.9 Cycle time distribution.

The average travel time is 89 minutes for all service routes. In contrast, most ravel times for scenario-II are over 100 minutes. The average travel time is 104 minutes for all service routes, which indicates a high utilization of snow plows. This high utilization is the direct result of the optimized service routes that are using fewer plows to cover more snow Sections.

However, more deadhead travelling was incurred in Scenario-II. Figure 6.10 shows the distribution of deadhead travelling miles. The deadhead travelling miles in most routes are less than 15 miles for Scenario-I. In contrast, more service routes with more than 15 miles in deadhead travelling were generated under Scenario-II. The distribution of deadhead travel distance is consistent with the distribution of cycle time.

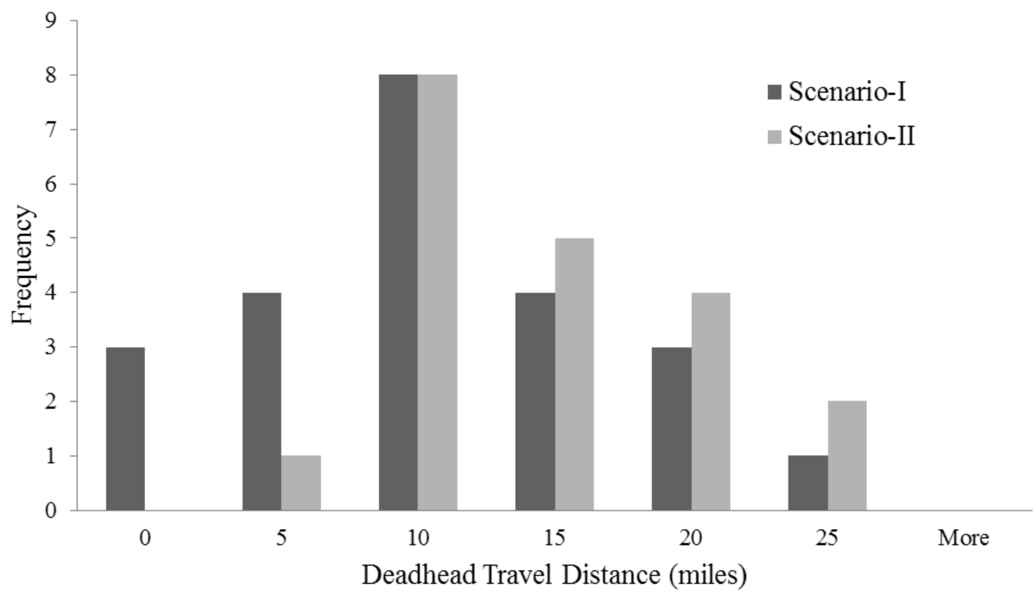


Figure 6.10 Deadhead travel distance distribution.

6.4.2 Sensitivity Analysis on Plowing Speed

To evaluate the contribution of the enhanced model that takes travel time variability into account, the results based on time-dependent plow speed and constant plow speed were compared and analyzed. The proposed model and the genetic algorithm were performed in the following three settings:

<u>Set-I:</u> The process considered impact of roadway type, weather condition and starting time of plowing service on plow speed. The plow speed profile was as summarized in Table 6.4.

<u>Set-II:</u> A constant plow speed of 25 mph was assumed, a more aggressive planner who uses a higher plow speed.

<u>Set-III:</u> A constant plow speed of 15 mph was assumed, a more risk-averse planner who uses a lower plow speed.

Table 6.10 Results and Analyses for Various Plow Speed

	Total Service Routes Needed				**Total Plows Needed**			
Snow Sector	**NJDOT**	**Set-I**	**Set-II**	**Set-III**	**NJDOT**	**Set-I**	**Set-II**	**Set-III**
Branchville	3	3	3	2	10	5	3	5
Columbia	3	2	3	2	21	9	9	12
Hackettstown	2	2	2	1	6	4	2	4
Hangover	8	6	7	4	35	30	16	35
Netcong	6	4	6	4	33	16	16	24
Port Colden	3	2	3	2	9	6	6	9
Riverdale	5	3	4	3	39	15	12	16
Rockaway	4	2	4	2	22	6	6	12
Sussex	4	3	3	3	12	9	9	9
Yellow Frame	3	2	3	2	10	2	2	3
Total	**41**	**29**	**38**	**25**	**197**	**102**	**81**	**129**

Table 6.10 suggests that all three sets require fewer service routes and plow trucks than current used by NJDOT. It also appears that S-I, having a variable speed profile, produce a result sitting in the middle between results for S-II and S-III. It needs fewer

routes and plow trucks than S-III that uses a constant speed with a conservative value, but more than S-II that uses a more aggressive speed.

In the intent of safety, governments and local agencies are leaning more towards using a conservative approach for the planning of winter roadway maintenance than an aggressive approach, which means that they would rather have a redundancy of plow trucks than a shortage. However, a model with the proper formulation to reflect time-dependent travel time is proved to be able to provide better results than travel time being underestimated and being overestimated in transportation planning. In the future, more work should be focused on using the real-time information (traffic conditions) instead of historical speed data. The general idea is to route and schedule vehicles in a dynamic travel time environment.

6.5 Summary

In this chapter, a case study used the set-partitioning mathematical model and one genetic algorithm based heuristic to solve the vehicle routing and scheduling problem for snow plowing operations. A transportation network selected from the northwest part of the state of New Jersey was used to test the model and algorithm. Comprehensive analysis based on a deterministic travel time setting and a time-dependent travel time setting was conducted. The results show that a model with proper formulation to reflect time-dependent travel time generates better results than being too aggressive or being too conservative in travel time estimation. A smaller fleet size and less total vehicle travel time were needed to complete the plowing operation within service time limit with the optimized routes and schedules.

In addition, scenario analysis suggest that the current NJDOT operation with fixed snow sector design and service routes uses more plow trucks than operations with optimized routes and schedules. In general, there is a trade-off between fleet size and deadhead travelling distance, which is important for planners who optimize service routes and evaluate resources allocation options.

CHAPTER 7

COMPUTATIONAL ANALYSIS

Using the set partitioning formulation described in Section 3.5 to search for the optimal integer solution for a vehicle routing and scheduling problem, it could be doable to enumerate all possible routes for problems with a small number of snow sections to service. According to Alvarenga et al. (2007), for a problem with five demands where time and capacity constraints are strict or sufficient enough to restrain possible routings up to two, the number of possible routes would be:

$$\sum_{n=1}^{2}\left(\frac{5!}{(5-n)!}\right)=25 \tag{7.1}$$

However, when the number of demands increases, the number of possible routes increases significantly as well. Alvarenga et al. (2007) stated that around $3.8*10^{16}$ possible routes can be generated for a problem with 50 demand nodes. Consequently, heuristic approaches come in to help reduce the number of possible routes. In this Chapter, the computational efficiency of the developed GA algorithm was studied.

7.1 Optimal Result and Calculation Time

In order to determine how much the developed heuristic can improve the computational efficiency, a few small size problems were solved using the exhaustive method described in Section 4.1 and the GA based heuristic developed in Section 4.2, respectively. To make sure the solution searching space is reasonable, the test was performed on a simple network as presented in Section 5.2 and operated on an Intel Core i5 CPU clocked at 2.40

GHZ with 2 GB of RAM under Windows 7 platform. Parameters for the GA algorithm were summarized in Table 6.12.

Table 7.1 Parameters of the GA Based Heuristic

Parameters	Values
Crossover rate	0.98
Mutation rate	0.10
Population size	100

Table 7.2 summarized the total vehicle travel time and the computation times of various small size problems obtained by the using the exact algorithm and the heuristic, respectively. The solutions produced by the proposed GA based heuristic were the final results have converged and the calculation time was calculated by the summing the running times of each iteration. As shown in Table 7.1, for problems with 6 to 9 required arcs, the heuristic solved the problem to global optimality in two seconds, which is far less than the time required for the exact algorithm.

Table 7.2 Result comparison of Small Size Problems

No. of Required Arcs	Total Vehicle Travel Time (min)		Calculation Time (sec)	
	Heuristic	Exact	Heuristic	Exact
6	137	137	1	3
7	156	156	1	15
8	176	176	2	70
9	223	223	2	247
10	246	237	5	654
11	288	275	11	1389
12	321	317	27	2790
13	378	372	34	4569

As the number of required arcs increases beyond 10, it is expected that the proposed heuristic solution would be increasingly less optimal. However, the savings in calculation time appears to increase exponentially as the number of required arcs increases. As shown in Figure 7.1, the total calculation time using the heuristic appears to increase linearly as number of duties increases. The calculation time for using the exalt algorithm to achieve optimality increases exponentially as the number of required arcs increases.

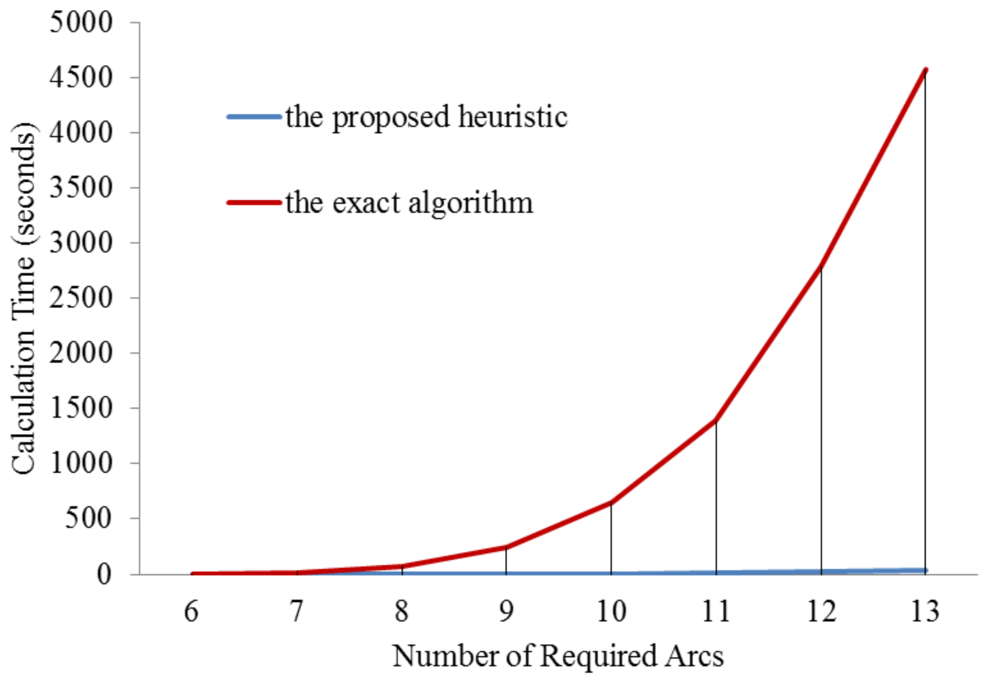


Figure 7.1 Computation time vs. number of required arcs.

Based on this the calculation times of the small problems, the problem with 13 required arcs approximately required 76 minutes (4569 seconds) to solve with the exact algorithm. The excessive calculation time required to find optimal solutions for the real world-sized problems demonstrates the need for more an efficient solution method. For the problems with over 100 required arcs, generating all feasible duties and then solving the problem to optimality becomes nearly impossible due to computer memory and calculation time constraints.

7.2 Analysis on Population Size

As previously discussed in Section 4.2, the improvement in objective function, calculation time and memory usage all vary with the population size. As the population size increases, the formulated sub-problem of travel salesman problem becomes more difficult to solve due to several reasons. First, increasing the population size makes it more difficult to find feasible routes. Since many potential “good” routes are likely to have been found and have entered the restricted subset in later iterations, it becomes increasingly harder to find new routes to enter to subset. Second, a larger population size means that the restricted subset is also larger.

Table 7.3 Results of scenario II with different population sizes

Population size	generations	Total Vehicle Travel Time (vehicle*minute)	Improvement	Calculation Time (sec)	Memory Space (MB)
80	14	8955	-	870	31
100	16	8328	7%	1305	58
120	20	8078	3%	2030	97

A numerical experiment was tested on the scenario II of the case study presented in Section 6.1 to show how population size affect the computational efficiency. All the parameters were taken from Table 6.12. The results were summarized in Table 7.3 and suggest that the final integer program that needs to be solved by CPLEX has a larger search space and results in more calculation time when the population size increases.

Also, since increasing the population size can lead more feasible routes that must be stored in record; the overall computer program requires more intensive memory usage.

To illustrate that how solutions from the GA based heuristic converge to optimum given different population sizes, by comparing the results that summarized in Table 7.2, three conclusions can be drawn. First, the greater the population size the greater the chance that the initial state of the population will contain a chromosome representing the optimal solution. Second, the increase in population size causes the number of generations to converge to increase as well. This is because if mutation occurs for large population sizes, more generations are needed to eliminate the mutated chromosomes. Third, although increasing the population size makes the sub-problem of the travel salesman problem more difficult to solve, the solutions also get improved. The results suggest that the population size should be set at approximately 100. There does not appear to be a strong relationship between the number of snow Sections and a good population size limit. It is possible that the population size depends on the existing routes and schedules, and how much potential there is for improvement.

CHAPTER 8

CONCLUSIONS AND FUTURE WORK

In this dissertation, a comprehensive summary of exiting research, both theoretical and practical, regarding vehicle routing and scheduling was undertaken and presented in the literature review chapter. This summary explored existing research in three major areas: variability of travel time, network optimization and winter road maintenance. These three areas form the foundation for a vehicle routing and scheduling model considering variability of travel time. A genetic algorithm based heuristic was developed to generate good feasible solutions to the problem, and they were further solved by a set-partitioning approach.

The developed model accepts inputs describing constant or time-dependent travel time, road network information, service demand and service time limits, fleet size restrictions, and time windows restrictions. The output of the model describes when and on which routes service vehicles should depart to fulfill the service of traffic data collection or winter road maintenance. This information is useful as a visualization tool for project managers and maintenance supervisors.

To illustrate the proposed model and the solution algorithm in a real life transportation network, two realistic examples were used to solve a traffic data collection problem and a winter road maintenance problem, respectably. To assess the quality of the solutions derived by the heuristic, exhaustive enumeration was used to find the optimal solution for small size problems. The enumeration method takes much more time than the heuristic method to solve problems with large size of demands. The comparison showed that the heuristic approach provides near optimal solutions in a reasonable amount of time. The computational efficiency and accuracy of the heuristic depends on the quality of the initial solution and population size used to solve the problem.

8.1 Contributions

This dissertation produced a model to solve vehicle routing and scheduling problems considering the variability of travel time in a formal mathematical context. This model is flexible in terms of the operations it models, and also the metrics that it uses to establish optimal routes and schedules. Such a model is believed to be a useful contribution to the field of network optimization.

The developed model proves useful both for developing a plan of action during a snow event, and for estimating the effects of altering various system parameters such as fleet size, depot locations and service routes. In addition to providing recommended schedules for vehicle dispatch, total vehicle travel time estimates are also provided, which can prove useful for emergency response purposes.

From an application standpoint, the developed model has the potential to be adapted for applications with similar vehicle/arc routing and schedule features, such as waste collection or ship scheduling problems. This research has provided a general model towards this eventual goal. However, a great deal of modifications in terms of model objective function and constraints remains to be done before such applications could become a reality. Accordingly, the Future Work Section is concerned primarily with extensions of the model in the direction of real-world applicability.

The principal contribution of this model to current research is the mathematical system that takes time dependent travel time into account. This work contributes in the literature that explicitly models the problem of traffic data collection as a direct consequence of vehicle routing and scheduling decisions. In addition, the network based structure of winter maintenance operations is presented in this dissertation to prove this mathematical system's applicability in the transportation planning area, an aspect that is lacking in most existing research in the field to date.

8.2 Future Work

This research attempted to produce a model that is extendable for future applications and whose accuracy is also quantifiable. Such quantification is a necessary step for making this model deployable in a production setting. A formal validation of the model's fidelity to real-world operations should be undertaken. This way, the model can be brought into closer alignment with the reality it seeks to represent. The following recommendations were made for future work:

- The model can be enhanced by taking into account the stochastic nature of the travel time. Travel time is the result of taking into account not only mean travel time but ideally the travel time distribution itself. As the travel time distribution is derived from the speed distribution and the known distances, the approach requires realistic speed distributions. The deviations or variations of plowing speed at different traffic time period for heterogeneous road geometry should be determined. If the deviations were known, then the plow speeds could be stochastically modeled to reflect what will happen in the real snowplow system.

- The developed model can be extended by addressing the fleet contracting issue in the application of winter road maintenance. In reality, most departments of transportation do not maintain sufficient vehicles and hence they may resort to contract additional equipment to make up for the shortfall. It is critical to determine the number of maintenance vehicles that should be contracted prior to a snow season to minimize the total cost, considering the frequency and distribution of various intensities of snow events, geometry of the roadways and traffic speeds.
- The developed model can be improved by adding extensions to the study problem such as different vehicle types, road priorities, intermediate facilities for refilling the vehicles, etc. And modify the formulation and the developed heuristic for those cases.
- The developed GA based heuristic can be enhanced by incorporating other meta-heuristics such as Tabu Search, Ants Colony, and combination of meta-heuristics (hybrid meta-heuristics) that may be used to improve the searching process on the optimized results.

REFERENCES

Abdel-Aty, M. A., Vaughn, K. M., Kitamura, R., Jovanis, P. P., & Mannering, F. L. (1993). Models of commuters' information use and route choice: Initial results based on a southern California commuter route choice survey. *California Partners for Advanced Transit and Highways (PATH)*.

Adams, T. M., Danijarsa, M., Martinelli, T., Stanuch, G., & Vonderohe, A. (2003). Performance measures for winter operations. *Transportation Research Record: Journal of the Transportation Research Board*, *1824*(1), 87-97.

Altinkemer, K., & Gavish, B. (1991). Parallel savings based heuristics for the delivery problem. *Operations Research*, *39*(3), 456-469.

Alvarenga, G. B., Mateus, G. R., & De Tomi, G. (2007). A genetic and set partitioning two-phase approach for the vehicle routing problem with time windows. *Computers & Operations Research*, *34*(6), 1561-1584.

Angelelli, E., & Mansini, R. (2002). The vehicle routing problem with time windows and simultaneous pick-up and delivery. In *Quantitative approaches to distribution logistics and supply chain management* (pp. 249-267). Springer Berlin Heidelberg.

Augerat, P., Belenguer, J. M., Benavent, E., Corbéran, A., & Naddef, D. (1998). Separating capacity constraints in the CVRP using tabu search. *European Journal of Operational Research*, *106*(2), 546-557.

Augerat, P., Belenguer, J. M., Benavent, E., Corberán, A., Naddef, D., & Rinaldi, G. (1995). Computational results with a branch and cut code for the capacitated vehicle routing problem. *Rapport de recherche*, *1*.

Baldacci, R., Christofides, N., & Mingozzi, A. (2008). An exact algorithm for the vehicle routing problem based on the set partitioning formulation with additional cuts. *Mathematical Programming*, *115*(2), 351-385.

Bektas, T., Erdogan, G., & Røpke, S. (2011). Formulations and branch-and-cut algorithms for the generalized vehicle routing problem. *Transportation Science*,*45*(3), 299-316.

Benson, D. E., Bander, J. L., & White, C. C. (1998). A planning and operational decision support system for winter storm maintenance in an ITS environment. In*IEEE International Conference on Intelligent Vehicles. Proceedings of the 1998 IEEE International Conference on Intelligent Vehicles* (Vol. 2).

Blackburn, R. R., Amsler Sr, D. E., Bauer, K. M., & Transportation Research Board. (2004). Guidelines for Snow and Ice Control Materials and Methods.*Transportation Research Circular*, 31-49.

Brown, G. G., Ellis, C. J., Graves, G. W., & Ronen, D. (1987). Real-time, wide area dispatch of mobil tank trucks. *Interfaces*, *17*(1), 107-120.

Campbell, J. F., & Langevin, A. (2000). Roadway snow and ice control. In *Arc Routing* (pp. 389-418). Springer US.

Chiang, W. C., & Russell, R. A. (1997). A reactive tabu search metaheuristic for the vehicle routing problem with time windows. *INFORMS Journal on computing*, *9*(4), 417-430.

Christofides, N., & Beasley, J. E. (1984). The period routing problem. *Networks*,*14*(2), 237-256.

Cordeau, J. F., & Laporte, G. (2003). A tabu search heuristic for the static multi-vehicle dial-a-ride problem. *Transportation Research Part B: Methodological*, *37*(6), 579-594.

Cook, T. M., & Alprin, B. S. (1976). Snow and ice removal in an urban environment. *Management Science*, *23*(3), 227-234.

Chen, C., Skabardonis, A., & Varaiya, P. (2003). Travel-time reliability as a measure of service. *Transportation Research Record: Journal of the Transportation Research Board*, *1855*(1), 74-79.

Chien, Steven. "Implementation of Maintenance Decision Support System in New Jersey. Final Report." (2012).

Chien, S. I., Gao, S., & Meegoda, J. N. (2013). Fleet Size Estimation for Snowplowing Operation Considering Road Geometry, Weather, and Traffic Speed. *Journal of Transportation Engineering*, *139*(9), 903-912.

Chiou, S. W. (2009). A bi-level programming for logistics network design with system-optimized flows. *Information Sciences*, *179*(14), 2434-2441.

Chiang, W. C., & Russell, R. A. (2004). A metaheuristic for the vehicle-routeing problem with soft time windows. *Journal of the Operational Research Society*,*55*(12), 1298-1310.

Chien,S., Mouskos, K., Boile, M., and Kim, K., “Variability of Travel Time on New Jersey Highways,” Final Report, New Jersey Department of Transportation, Trenton, New Jersey, Jan.2010

Christofides, N., Mingozzi, A., & Toth, P. (1981). State-space relaxation procedures for the computation of bounds to routing problems. *Networks*, *11*(2), 145-164.

Chabrier, A. (2006). Vehicle routing problem with elementary shortest path based column generation. *Computers & Operations Research*, *33*(10), 2972-2990.

Clarke, G. U., & Wright, J. W. (1964). Scheduling of vehicles from a central depot to a number of delivery points. *Operations research*, *12*(4), 568-581.

Connolly, D. T. (1990). An improved annealing scheme for the QAP. *European Journal of Operational Research*, *46*(1), 93-100.

Cordeau, J. F., Gendreau, M., Laporte, G., Potvin, J. Y., & Semet, F. (2002). A guide to vehicle routing heuristics. *Journal of the Operational Research society*, 512-522.

Černý, V. (1985). Thermodynamical approach to the traveling salesman problem: An efficient simulation algorithm. *Journal of optimization theory and applications*, *45*(1), 41-51.

Danna, E., & Le Pape, C. (2005). Branch-and-price heuristics: A case study on the vehicle routing problem with time windows. In *Column Generation* (pp. 99-129). Springer US.

Dali, Z. (2009). Optimization of Vehicle Routing for Plowing and Snow Disposal.

Desaulniers, G., Desrosiers, J., Erdmann, A., Solomon, M. M., & Soumis, F. (2002). VRP with pickup and delivery. *The vehicle routing problem*, *9*, 225-242.

Desrosiers, J., Dumas, Y., & Soumis, F. (1986). A dynamic programming solution of the large-scale single-vehicle dial-a-ride problem with time windows.*American Journal of Mathematical and Management Sciences*, *6*(3-4), 301-325.
Desrosiers, J., Dumas, Y., & Soumis, F. (1986). A dynamic programming solution of the large-scale single-vehicle dial-a-ride problem with time windows.*American Journal of Mathematical and Management Sciences*, *6*(3-4), 301-325.
Donati, A. V., Montemanni, R., Casagrande, N., Rizzoli, A. E., & Gambardella, L. M. (2008). Time dependent vehicle routing problem with a multi ant colony system. *European journal of operational research*, *185*(3), 1174-1191.

Dumas, Y., Desrosiers, J., & Soumis, F. (1991). The pickup and delivery problem with time windows. *European Journal of Operational Research*, *54*(1), 7-22.

Eiselt, H. A., Gendreau, M., & Laporte, G. (1995). Arc routing problems, part II: The rural postman problem. *Operations Research*, *43*(3), 399-414.

Eglese, R. W. (1990). Simulated annealing: a tool for operational research.*European journal of operational research*, *46*(3), 271-281.

Ettema, D., Tamminga, G., Timmermans, H., & Arentze, T. (2005). A micro-simulation model system of departure time using a perception updating model under travel time uncertainty. *Transportation Research Part A: Policy and Practice*, *39*(4), 325-344.

Evans, J. R., & Weant, M. (1990). Strategic planning for snow and ice control using computer-based routing software. *Public Works*, *121*(4).

Fagerholt, K., & Christiansen, M. (2000). A combined ship scheduling and allocation problem. *Journal of the Operational Research Society*, 834-842.

Figliozzi, M. A. (2010). An iterative route construction and improvement algorithm for the vehicle routing problem with soft time windows. *Transportation Research Part C: Emerging Technologies*, *18*(5), 668-679.

Fisher, M. 1995. Vehicle routing. M. O. Ball, T. L. Magnanti, C. L. Monma, G. L. Nemhauser, eds. Network Routing, *Handbooks in Operations Research and Management Science*, Vol. 8. North-Holland, Amsterdam, the Netherlands, 1–33.

Fleischmann, B., Gietz, M., & Gnutzmann, S. (2004). Time-varying travel times in vehicle routing. *Transportation science*, *38*(2), 160-173.

Figliozzi, M. A. (2010). The impacts of congestion on commercial vehicle tour characteristics and costs. *Transportation research part E: logistics and transportation review*, *46*(4), 496-506.

Fukasawa, R., Longo, H., Lysgaard, J., de Aragão, M. P., Reis, M., Uchoa, E., & Werneck, R. F. (2006). Robust branch-and-cut-and-price for the capacitated vehicle routing problem. *Mathematical programming*, *106*(3), 491-511.

Fu, L. (2002). Scheduling dial-a-ride paratransit under time-varying, stochastic congestion. *Transportation Research Part B: Methodological*, *36*(6), 485-506.

Fu, L., Trudel, M., & Kim, V. (2009). Optimizing winter road maintenance operations under real-time information. *European Journal of Operational Research*, *196*(1), 332-341.

FHWA, http://www-fars.nhtsa.dot.gov/Main/index.aspx, 2011

Ghiani, G., & Improta, G. (2000). An efficient transformation of the generalized vehicle routing problem. *European Journal of Operational Research*, *122*(1), 11-17.

Haghani, A., & Qiao, H. (2001). Decision support system for snow emergency vehicle routing: Algorithms and application. *Transportation Research Record: Journal of the Transportation Research Board*, *1771*(1), 172-178.

Haghani, A., & Qiao, H. (2002). Snow emergency vehicle routing with route continuity constraints. *Transportation Research Record: Journal of the Transportation Research Board*, *1783*(1), 119-124.

Haslam, E., & Wright, J. R. (1991). Application of routing technologies to rural snow and ice control. *Transportation Research Record*, (1304).

He, R. R., Kornhauser, A. L., & Ran, B. (2005). Essentially best routes in dynamic and stochastic transportation network. *International journal of vehicle information and communication systems*, *1*(1), 1-14.

Hernández-Pérez, H., & Salazar-González, J. J. (2004). Heuristics for the one-commodity pickup-and-delivery traveling salesman problem. *Transportation Science*, *38*(2), 245-255.

Hill, A. V., & Benton, W. C. (1992). Modelling intra-city time-dependent travel speeds for vehicle scheduling problems. *Journal of the Operational Research Society*, 343-351.

Highway Functional Classification: Concepts, Criteria and Procedures. Report No. FHWA-ED-90-006. Federal Highway Administration, U.S. Department of Transportation, Washington, DC, March 1989.

Hendricks, A., Fontaine, M., & Smith, B. (2005). Probe-based traffic monitoring: Nchrp project 70-01. *University of Virginia Center for Transportation Studies, Tech. Rep*.

Hollander, Y. (2006). Direct versus indirect models for the effects of unreliability. *Transportation Research Part A: Policy and Practice*, *40*(9), 699-711.

Holland, J. H. (1992). Genetic algorithms. *Scientific american*, *267*(1), 66-72.

Holguin-Veras, J., Wang, Q., Xu, N., Ozbay, K., Cetin, M., & Polimeni, J. (2006). The impacts of time of day pricing on the behavior of freight carriers in a congested urban area: Implications to road pricing. *Transportation Research Part A: Policy and Practice*, *40*(9), 744-766.

Huth, T., & Mattfeld, D. C. (2009). Integration of vehicle routing and resource allocation in a dynamic logistics network. *Transportation Research Part C: Emerging Technologies*, *17*(2), 149-162.

Ichoua, S., Gendreau, M., & Potvin, J. Y. (2003). Vehicle dispatching with time-dependent travel times. *European journal of operational research*, *144*(2), 379-396.

Irnich, S., & Villeneuve, D. (2006). The shortest-path problem with resource constraints and k-cycle elimination for k≥ 3. *INFORMS Journal on Computing*,*18*(3), 391-406.

Jang, W., Noble, J. S., & Hutsel, T. (2010). An integrated model to solve the winter asset and road maintenance problem. *Iie Transactions*, *42*(9), 675-689.

Kwan, M. K. (1962). Graphic programming using odd or even points. *Chinese Math*, *1*(273-277), 110.

Kenyon, A. S., & Morton, D. P. (2003). Stochastic vehicle routing with random travel times. *Transportation Science*, *37*(1), 69-82.

Kolen, A. W., Rinnooy Kan, A. H. G., & Trienekens, H. W. J. M. (1987). Vehicle routing with time windows. *Operations Research*, *35*(2), 266-273.

Laporte, G. (2009). Fifty years of vehicle routing. *Transportation Science*, *43*(4), 408-416.

Laporte, G., Toth, P., & Vigo, D. (2013). Vehicle routing: historical perspective and recent contributions. *EURO Journal on Transportation and Logistics*, 1-4.

Lambert, V., Laporte, G., & Louveaux, F. (1993). Designing collection routes through bank branches. *Computers & Operations Research*, 20(7), 783-791.

Lau, H. C., & Liang, Z. (2002). Pickup and delivery with time windows: Algorithms and test case generation. *International Journal on Artificial Intelligence Tools*, 11(03), 455-472.

Laporte, G., Nobert, Y., & Arpin, D. (1986). An exact algorithm for solving a capacitated location-routing problem. *Annals of Operations Research*, 6(9), 291-310.

Letchford, A. N., & Oukil, A. (2009). Exploiting sparsity in pricing routines for the capacitated arc routing problem. *Computers & Operations Research*, 36(7), 2320-2327.

Lianyyu Chu, Jun-Seok Oh, and Will Recker, "Adaptive Kalman Filter Based Freeway Travel time Estimation," *TRB Annual Meeting*, 2005

Liu, T.K. "Travel Time Data Needs, Applications, and Data Collection." In National Traffic Data Acquisition Conference (NATDAC '96) Proceedings, Volume II.

Report No. NM-NATDAC-96, *Alliance for Transportation Research*, Albuquerque, New Mexico, May 1996, pp. 402-418.

Longo, H., de Aragão, M. P., & Uchoa, E. (2006). Solving capacitated arc routing problems using a transformation to the CVRP. *Computers & Operations Research*, 33(6), 1823-1837.

Lomax, T., S. Turner, G. Shunk, H.S. Levinson, R.H. Pratt, P.N. Bay, and G.B. Douglas. Quantifying Congestion: User's Guide. NCHRP Report 398. Transportation Research Board, Washington, DC, November 1997.

Long Cheu, R., Xie, C., & Lee, D. H. (2002). Probe vehicle population and sample size for arterial speed estimation. *Computer‐Aided Civil and Infrastructure Engineering*, *17*(1), 53-60.

Lu, J., Yang, F., Ban, X., & Ran, B. (2006). Moments analysis for improving decision reliability based on travel time. *Transportation Research Record: Journal of the Transportation Research Board*, *1968*(1), 109-116.

Malandraki, C., & Daskin, M. S. (1992). Time dependent vehicle routing problems: Formulations, properties and heuristic algorithms. *Transportation science*, 26(3), 185-200.

Malandraki, C., & Dial, R. B. (1996). A restricted dynamic programming heuristic algorithm for the time dependent traveling salesman problem. *European Journal of Operational Research*, 90(1), 45-55.

Marks, D. H., & Stricker, R. (1971). Routing for public service vehicles. *Journal of the Urban Planning and Development Division*, 97(2), 165-178.

Michael, R. G., & David, S. J. (1979). Computers and intractability: a guide to the theory of NP-completeness. *WH Freeman & Co., San Francisco*.

Manual, H. C. (1985). Special report 209. *Transportation Research Board, Washington, DC*, *1*, 985.

Ngassa, C. K. (2006). *Estimation of Network Based Incident Delay in a Transportation Network Using Dynamic Traffic Assignment* (Doctoral dissertation, The City University of New York).

New Jersey Department of Transportation Model for Winter Equipment and Manpower Allocations, 2005 Strategic Highway Research Program. Snow and Ice control Showcasing and Implementation Task: A summary Report. FHWA, U.S. Department of Transportation, 1994

NCHRP Project 70-01, "Private Sector Provision of Congestion Data Probe-based Traffic Monitoring: State-of Practice Report," University of Virginia Center for Transportation Studies: Virginia Transportation Research Council, November 21, 2005

Nanry, W. P., & Wesley Barnes, J. (2000). Solving the pickup and delivery problem with time windows using reactive tabu search. *Transportation Research Part B: Methodological*, *34*(2), 107-121.

Noland, R. B., & Polak, J. W. (2002). Travel time variability: a review of theoretical and empirical issues. *Transport Reviews*, *22*(1), 39-54.

Ochieng, W. Y., & Sauer, K. (2002). Urban road transport navigation: performance of the global positioning system after selective availability.*Transportation Research Part C: Emerging Technologies*, *10*(3), 171-187.

Oppen, J., & Løkketangen, A. (2006). Arc routing in a node routing environment.Computers & operations research, 33(4), 1033-1055.

Osman, I. H., & Wassan, N. A. (2002). A reactive tabu search meta-heuristic for the vehicle routing problem with back-hauls. Journal of Scheduling, 5(4), 263-285.

Psaraftis, H. N. (1980). A dynamic programming solution to the single vehicle many-to-many immediate request dial-a-ride problem. *Transportation Science*,*14*(2), 130-154.

Pearn, W. L., Assad, A., & Golden, B. L. (1987). Transforming arc routing into node routing problems. *Computers & operations research*, 14(4), 285-288.

Perrier, N., Langevin, A., & Campbell, J. F. (2007). A survey of models and algorithms for winter road maintenance. Part IV: Vehicle routing and fleet sizing for plowing and snow disposal. *Computers & Operations Research*, 34(1), 258-294.

Perrier, N., Langevin, A., & Campbell, J. F. (2006). A survey of models and algorithms for winter road maintenance. Part I: system design for spreading and plowing. *Computers & Operations Research*, 33(1), 209-238.

Perrier, N., Langevin, A., & Campbell, J. F. (2006). A survey of models and algorithms for winter road maintenance. Part II: system design for snow disposal. *Computers & Operations Research*, 33(1), 239-262.

Perrier, N., Langevin, A., & Campbell, J. F. (2007). A survey of models and algorithms for winter road maintenance. Part III: Vehicle routing and depot location for spreading. *Computers & Operations Research*, 34(1), 211-257.

Perrier, N., Langevin, A., & Amaya, C. A. (2008). Vehicle routing for urban snow plowing operations. *Transportation Science*, 42(1), 44-56.

Qureshi, A. G., Taniguchi, E., & Yamada, T. (2009). An exact solution approach for vehicle routing and scheduling problems with soft time windows.*Transportation Research Part E: Logistics and Transportation Review*, *45*(6), 960-977.

Quak, H. J., & de Koster, M. R. B. (2009). Delivering goods in urban areas: how to deal with urban policy restrictions and the environment. *Transportation Science*, *43*(2), 211-227.

Rand, G. K. (2009). The life and times of the savings method for vehicle routing problems. ORiON: *The Journal of ORSSA*, 25(2).

Ralphs, T. K. (2003). Parallel branch and cut for capacitated vehicle routing.*Parallel Computing*, *29*(5), 607-629.

Reimann, M., Doerner, K., & Hartl, R. F. (2004). D-Ants: savings based ants divide and conquer the vehicle routing problem. *Computers & Operations Research*, 31(4), 563-591.

Recker, W., Chung, Y., Park, J., Wang, L., Chen, A., Ji, Z., ... & Oh, J. S. (2005). Considering risk-taking behavior in travel time reliability. *California Partners for Advanced Transit and Highways (PATH).*

Saka, Anthony Amos, Dennis K. Agboh, and D. Montebello. Assessment of the Impact of Electronic Toll Collection on Mobile Emissions in the Baltimore Metropolitan Area. National Transportation Center, Morgan State University, 2002.

Savelsbergh, M. W., & Sol, M. (1995). The general pickup and delivery problem.*Transportation science*, 29(1), 17-29.

Savelsbergh, M. W. (1985). Local search in routing problems with time windows. *Annals of Operations research*, 4(1), 285-305.

Salazar-Aguilar, M. A., Langevin, A., & Laporte, G. (2012). Synchronized arc routing for snow plowing operations. *Computers & Operations Research*, 39(7), 1432-1440.

Schrank, David, Bill Eisele, and Tim Lomax. "TTI's 2012 Urban Mobility Report."Texas A&M Transportation Institute. The Texas A&M University System (2012).

Srinivasan, K. K., & Jovanis, P. P. (1996). Determination of number of probe vehicles required for reliable travel time measurement in urban network.Transportation Research Record: *Journal of the Transportation Research Board*, 1537(1), 15-22.

Shen, Y., Potvin, J. Y., Rousseau, J. M., & Roy, S. (1995). A computer assistant for vehicle dispatching with learning capabilities. An*nals of Operations Research*, 61(1), 189-211.

Sun, Huijun, Ziyou Gao, and Jianjun Wu. "A bi-level programming model and solution algorithm for the location of logistics distribution centers." *Applied Mathematical Modelling* 32.4 (2008): 610-616.

Taillard, É., Badeau, P., Gendreau, M., Guertin, F., & Potvin, J. Y. (1997). A tabu search heuristic for the vehicle routing problem with soft time windows.*Transportation science*, *31*(2), 170-186.

Uno, N., Kurauchi, F., Tamura, H., & Iida, Y. (2009). Using bus probe data for analysis of travel time variability. *Journal of Intelligent Transportation Systems*,*13*(1), 2-15.

Van Woensel, T., Kerbache, L., Peremans, H., & Vandaele, N. (2008). Vehicle routing with dynamic travel times: A queueing approach. *European journal of operational research*, 186(3), 990-1007.

Wassan, N. A., Wassan, A. H., & Nagy, G. (2008). A reactive tabu search algorithm for the vehicle routing problem with simultaneous pickups and deliveries. *Journal of combinatorial optimization*, 15(4), 368-386.

Wilhelm, W. E. (2001). A technical review of column generation in integer programming. *Optimization and Engineering*, 2(2), 159-200.

Wright, J., & Dahlgren, J. (2001). *Using vehicles equipped with toll tags as probes for providing travel times*. California PATH Program, Institute of Transportation Studies, University of California at Berkeley.

Xu, H., Chen, Z. L., Rajagopal, S., & Arunapuram, S. (2003). Solving a practical pickup and delivery problem. *Transportation science*, *37*(3), 347-364.

Yang, J. S. (2006). A Nonlinear State Space Approach to Arterial Travel Time Prediction.

Yu, H., Chien, S. I. J., & Ting, C. J. (2010). Bilevel Programming Model for Minimum-Cost Travel Time Data Collection with Time Windows. *Transportation Research Record: Journal of the Transportation Research Board*, *2197*(1), 29-35.

Yu, Haifeng, I. Steven, and Jy Chien. "Optimal Routing for Minimum Service Time of Winter Road Maintenance with Truck Capacity and Fleet Size Constraints." Environment 23 (2013): 227-234.

Zito, R., d'Este, G., & Taylor, M. A. (1995). Global positioning systems in the time domain: how useful a tool for intelligent vehicle-highway systems. *Transportation Research Part C: Emerging Technologies*, *3*(4), 193-209.