

**SIMULATED ANNEALING ALGORITHM FOR
VEHICLE ROUTING PROBLEM WITH
TRANSSHIPMENT**

BY

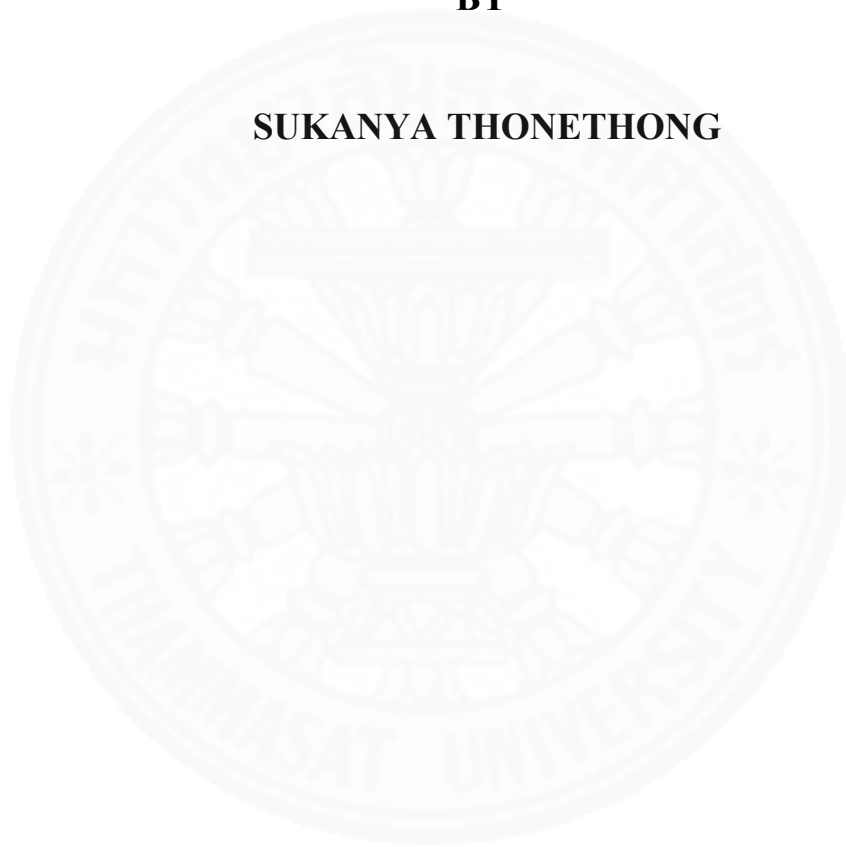
SUKANYA THONETHONG

**A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF MASTER OF
ENGINEERING (LOGISTICS AND SUPPLY CHAIN SYSTEMS
ENGINEERING)
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A Thesis Presented

By
SUKANYA THONETHONG

Submitted to
Sirindhorn International Institute of Technology
Thammasat University
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Approved as to style and content by

Advisor and Chairperson of Thesis Committee


(Assoc. Prof. Dr. Jirachai Buddhakulsomsiri)

Committee Member and

Chairperson of Examination Committee


(Asst. Prof. Dr. Narameth Nananukul)

Committee Member


(Assoc. Prof. Dr. Huynh Trung Luong)

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Abstract

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by

SUKANYA THONETHONG

Bachelor of Engineering. (Industrial Engineering) Naresuan University, 2012.

Master of Engineering. (Logistics and Supply Chain Systems Engineering),

Sirindhorn International Institute of Technology, 2016.

A vehicle routing problem (VRP) involves a problem of determining transportation routes for a fleet of vehicles that exist to provide delivery services from a depot to satisfy a set of geographically dispersed customers' demands. The vehicle routing problem with transshipment (VRPT) defined in this study is the VRP that includes transshipment demand between pairs of customers, in addition to the regular demand. Transshipment demands are demands for seasonal product that change model or design every season such that the depot can only place a one-time order for the item before the selling season. At the middle towards the end of a selling season, inventories of the item are already distributed to all the retail stores, i.e. the depot no longer has the item. As end customer demands for the item arrive at a retail store that already sold out the item, one way to satisfy the end customer demand is to transship the from another retail store that still has the item. Motivation for the VRPT is from a real world problem found in one of the largest retail chains in Thailand. The current practice at the depot of this retail chain is that when transshipment demand is requested, a delivery vehicle will pick-up the item from one retail store, bring it back to the depot and store it, then deliver to the retail store that request the item in the next delivery trip. In order to improve customer service by reducing the delivery time of transshipment demand, the objective is to determine delivery routes for vehicles that can pick up the item at one store and deliver it to another store on the same trip. In other words, the pick-up and drop-off of transshipment demand must be performed in addition to the delivery of

regular demand from the depot to the retail stores by the same vehicle. A simulated annealing (SA) algorithm is developed to generate delivery routes in which both demands can be satisfied in the same delivery routes while minimizing the transportation cost. The algorithm was tested with standard problem instances of capacitated vehicle routing (CVRP). The results from testing the algorithm using numerical examples shows that there is a tradeoff between additional cost of allowing delivery of transshipment demands on the same trip and the benefit of reducing delivery lead time of transshipment demand.

Keywords: Vehicle Routing Problem; Transshipment; Simulated Annealing

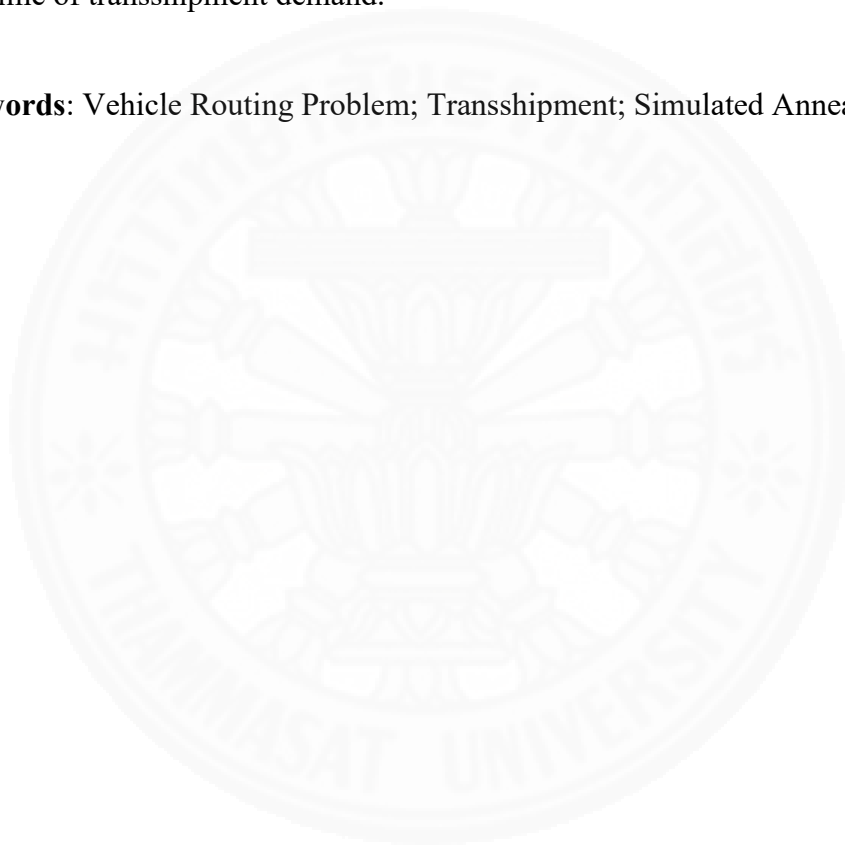


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Chapter 1

Introduction

Dantzig and Ramser (1959) firstly introduced the Vehicle Routing Problem (VRP). The problem was modelled after a routing optimization problem for petrol deliveries by truck. The objective is to find the optimal set of routes for a fleet of vehicles to perform delivery services to a set of customers so as to minimize the total transportation cost. Since then, numerous research studies have been conducted to solve the VRP using exact and heuristics algorithms. There are also many variants of the VRP, such as VRP with time windows (VRPTW), VRP with pickup and delivery (VRPPD), etc.

1.1 Problem Statement

This study presents one of the variants of vehicle routing problem (VRP), so-called, vehicle routing problem with transshipment (VRPT) in this study. Customer demands are of two types: regular demands that can be satisfied by inventories at the depot and transshipment demands that request of items from other customers. The motivation for the VRPT is from a real world problem found in one of the largest retail chains in Thailand. In this problem, a depot exists to satisfy daily demand from many retail stores, all of which are in the same retail chain under a single ownership. The retail chain offers products that are both continuously stocked and seasonal products. The focus is on seasonal products, which are usually ordered once a year from both domestics and international suppliers. These items arrive before the beginning of the selling season, and are kept at the depot, and the retail stores would order these items according to the store's projected sale figure.

By the middle of a season, all inventories of a seasonal item would be ordered and kept at the retail stores, and the depot would no longer have inventory of the item available. At this point, there are many occurrences when demands from end customers arise at a retail store that already has the items sold out, while the desired items are available at some other retail stores. The current practice of the company is

as follows: (1) The store, so-called delivery customer, that needs the items would issue a request to the depot. (2) Delivery truck that visits another store that has the item, so-called pick-up customer, would pick up the item and bring it back to the depot. (3) The depot then sends the item to the delivery store in the next delivery cycle. The process usually takes at least as long as the length of the delivery cycle. For example, the process takes at least one day if the deliveries to both the pick-up and delivery stores are performed on a daily basis, or it takes at least two days, if delivery cycle is on alternate day basis.

The company is considering changing this process in order to satisfy the end customer demand in a shorter time. Specifically, the depot would like to design delivery routes that take into account the pick-up / delivery demands between stores, which is called transshipment demand in this study. The delivery routes that can satisfy the transshipment demand in addition to the regular demand from the depot must have the truck visits the pick-up store prior to the delivery store on the same route. In other words, the pick-up item from one store will be delivered to another store on the same trip. Benefit from the same day delivery would give the retail stores a significant advantage in terms of customer service in the highly competitive retail business environment. The company would like to incorporate this change without having to incur too much additional delivery cost.

This study presents an algorithm development for the VRPT that can generate good routing solution that allows both regular demand and transshipment demand deliveries on the same trip. The objective function is to minimize the total transportation cost. The algorithm is based on the well-known simulated annealing (SA) algorithm with solution generation mechanism that forces transshipment delivery.

Specifically, the VRPT under study has the following characteristics:

1. There is one central depot.
2. There are many retail stores (customers), each of which may have up to two types of demand: regular demand that must be satisfied directly by the depot, and transshipment demand that can only be satisfied from inventory at another customer.
3. Trucks are of the same type and have the same limited capacity.

4. All trips start at the depot and must return to the depot after the end of the trips.
5. Distance (or travel time) from one node (i.e. depot or retail stores) to another node is assumed known and constant.

1.2 Research Objectives

The objectives for this study can be stated as follows:

- To develop an efficient simulated annealing (SA) algorithm for the Vehicle Routing Problem with Transshipment (VRPT) under study.
- To test the algorithm on problem instances of the VRPT to gain some fundamental insights on satisfying transshipment demand.

1.3 Research Overview

The remainder of this thesis is organized as follows. Chapter 2 provides a literature review, including VRP, solution techniques, and related problems to VRPT. The developed methodology is described in Chapter 3, which includes the VRPT, simulated annealing (SA) and a numerical example. Then, in Chapter 4 computational experiment, analysis results and discussion are presented. Finally, conclusion and recommendations are given in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

This chapter contains the literature review of previous research related to this thesis's topic. Firstly, an overview of the vehicle routing problem (VRP) is provided, followed by reviews of the solution techniques available for VRP. Finally, the literature review of related research studies to the vehicle routing problem with transshipment.

2.1 Vehicle Routing Problems

The Vehicle Routing Problem was first introduced by Dantzig & Ramser (1959). The problem was modelled after a routing optimization problem for petrol deliveries by truck. The objective is to find the optimal set of routes for a fleet of vehicles to perform deliver services to a set of customers so as to minimize the total transportation cost. Since then, numerous research studies have been conducted to solve the VRP using exact and heuristics algorithms. There are also many variants of the VRP, such as the capacitated VRP (CVRP), VRP with time window (VRPTW), VRP with backhaul (VRPB), VRP with pickup and delivery (VRPPD), and stochastic VRP (SVRP). Due to the vast literature review on VRP, each variant of VRP will be briefly described, and followed by recent research studies of the problem.

2.1.1 Capacitated VRP

The capacitated vehicle routing problem (CVRP) is a VRP in which a homogenous fleet of delivery vehicles with the same capacity must provide delivery service to known customer demands. The objective is to minimize the total cost, while the total demands delivered in each trip cannot exceed vehicle's capacity.

Recent studies in CVRP by using heuristic and metaheuristic are from W.Y. et al. (2011), Yiyong et al. (2012), Jianyong et al. (2014), Kenneth and Patrick (2013), and Yiyong et al. (2014). W.Y. et al. (2011) proposed enhanced version of the artificial bee colony heuristic. Yiyong et al. (2012) developed a mathematical optimization model, and proposed SA algorithm with a hybrid exchange rule to solve CVRP and the

FCVRP. Kenneth and Patrick (2013) developed an intelligent path relinking procedure based on the relocate distance. Jianyong et al. (2014) proposed a cooperative parallel metaheuristic, which consists of multiple parallel tabu search threads. Yiyong et al. (2014) presented the variable neighbourhood simulated annealing (VNSA) algorithm, which combined VNS with SA.

2.1.2 VRP with backhauls

Vehicle routing problem with backhauls (VRPB) is a VRP that considers both delivery of items from the depot (line-haul) and pickup of items back to the depot (backhaul). VRPB assumes that all deliveries must be made on the route before pickups can be performed.

Recent studies on VRPB are from Ismail and Fulya (2015), Ilker and Nursel (2015), and Daniel et al. (2014). Ismail and Fulya (2015) proposed a memetic algorithm to solve the Capacitated Location-Routing Problem with Mixed Backhauls (CLRPMB), which finds locations of the depots and designs route that pickup and delivery demands of each customer must be served with the same vehicle. Ilker and Nursel (2015) presented an advanced algorithm to solve the VRP with backhauls and time windows (VRPBTW) that includes capacity, backhaul and time window constraints, is a hybrid meta-heuristic algorithm (HMA). The objective is to minimize the total distance. Lastly, Daniel et al. (2014) proposed a simple iterated local search algorithm for the VRPB.

2.1.3 VRP with pick-up and delivery

Vehicle routing problem with pickup and delivery (VRPPD, sometimes denoted as PDP) is an extension of VRPB. Pure pickup or delivery only performs pickup or delivery in the routes. Mixed pickup and delivery has two types: (1) a route is not interspersed, which means the vehicle must finish all delivery demands before performing the pick-up on the same route, and (2) interspersed route that mixes pickup and delivery on the same route. Another variant of the VRPPD is the VRP with simultaneous pick-up and delivery (VRPSPD), where delivery and pickup demands are required to be made simultaneously at each customer stop.

Recent studies on VRPPD are from Tajik et al. (2014), who proposed a new mixed integer linear programming (MILP) for a new time window pickup-delivery

pollution routing problem (TWPDPRP) to manage with unsteady input data. Mustafa and Qingfeng et al. (2014) developed an easy-to-implement heuristic for the routing problem with unpaired pickup and delivery with split loads. Mustafa and Seyda (2015) developed an adaptable local search solution method, which a SA inspired algorithm with Variable Neighborhood Descent for both the VRP with Mixed Pickup and Delivery (VRPMPD) and the VRP with Simultaneous Pickup and Delivery (VRPSPD), which are different in that the customers may have pickup or delivery demand. Olcay et al. (2015) proposed a mixed-integer mathematical optimization model and a perturbation based neighborhood search algorithm that mixed with the classic savings heuristic. Monirehalsadat and Xuesong (2016) proposed a new time-discretized multi-commodity network flow model based on the integration of vehicles' carrying states within space–time transportation networks for the VRPPDTW.

2.1.4 VRP with time windows

Vehicle routing problem with time windows, or VRPTW, is a VRP where customers have specified time windows constraint in which the delivery must be made. Thibaut et al. (2013) presented an efficient Hybrid Genetic Search with Advanced Diversity Control for a large class of time-constrained vehicle routing problems, introducing several new features to manage the temporal dimension. Phuong et al. (2013) proposed a tabu search meta-heuristic for the Time-dependent Multi-zone Multi-trip Vehicle Routing Problem with Time Windows. Ran et al. (2013) proposed Genetic algorithm (GA) and a Tabu Search (TS) for a vehicle routing problem with simultaneous delivery and pickup and time windows in home health care. Raúl et al. (2013) proposed a Pareto-based hybrid algorithm that combines evolutionary computation and simulated annealing for solving the VRPTW, which also considered the workload imbalance in terms of the distances travelled by the used vehicles and their loads. Duygu et al. (2013) proposed Tabu Search to solve a VRP with soft time windows and stochastic travel times. Chao et al. (2015) developed and applied a parallel Simulated Annealing algorithm to solve the vehicle routing problem in which customers require simultaneous pickup and delivery of goods during specific individual time windows (VRPSPDTW).

2.1.5 Stochastic VRP

Stochastic vehicle routing problem (SVRP) is a VRP where one or several components of the problem are random, such as stochastic demands, and stochastic travel times. Charles et al. (2014) proposed a state-of-the-art branch-cut-and-price algorithm for the vehicle routing problem with stochastic demands (VRPSD). Justin (2015) developed simulated annealing algorithm to estimate and exactly calculate the expected cost of a priori policies for the multi-compartment vehicle routing problem with stochastic demands. Lin et al. (2014) developed a paired cooperative re-optimization (PCR) strategy, which can realize re-optimization policy under cooperation between a pair of vehicles, and it can be applied in the multi-vehicle situation to solve the vehicle routing problem with stochastic demands (VRPSD).

2.2 Solution Techniques for VRP

Solution techniques for VRP can be classified into three categories; 1) exact algorithm 2) heuristics 3) meta-heuristics. Exact algorithms, such as branch and bound algorithm and branch and cut algorithm, are methods that solve the problem to optimality. These algorithms have a limited size of VRP that they can solve due to the non-polynomial nature of VRP.

Heuristics are methods that produce a good solution in a reasonable time. The solution obtained is neither guaranteed to be an optimal nor a feasible solution. These are the methods available to solve large-scale VRP effectively. Meta-heuristics have been developed over the last two decades. They are similar to the heuristics, but have more sophisticated procedures that enable them to escape the local optimal. Examples are such as tabu search, genetic algorithm, and simulated annealing algorithm.

2.3 Vehicle Routing Problem featuring Transshipment

One of the studies in the literature by Yang and Xiao (2007) consider the transshipment characteristic of the problem. In their study, the VRP considers a multi-period single-product logistics system with transshipment centers. The transshipment

centers can receive items from the depot and act as the second depot, after the transshipment of items from the main depot is made. In other words, the problem is similar to multi-depot problem, where additional depot is created from transshipment of items from the original depot. Although their problem is denoted with “transshipment,” the problem is much different from the transshipment demand that is defined in this study. To the best of our knowledge, as of this writing, there is no study that consider the transshipment demand in a VRP and mix them with the regular demand from the depot in the same way that is considered in this study.



Chapter 3

Methodology

3.1 Method of Approach

The method of approach is summarized as shown in Figure 3.1.

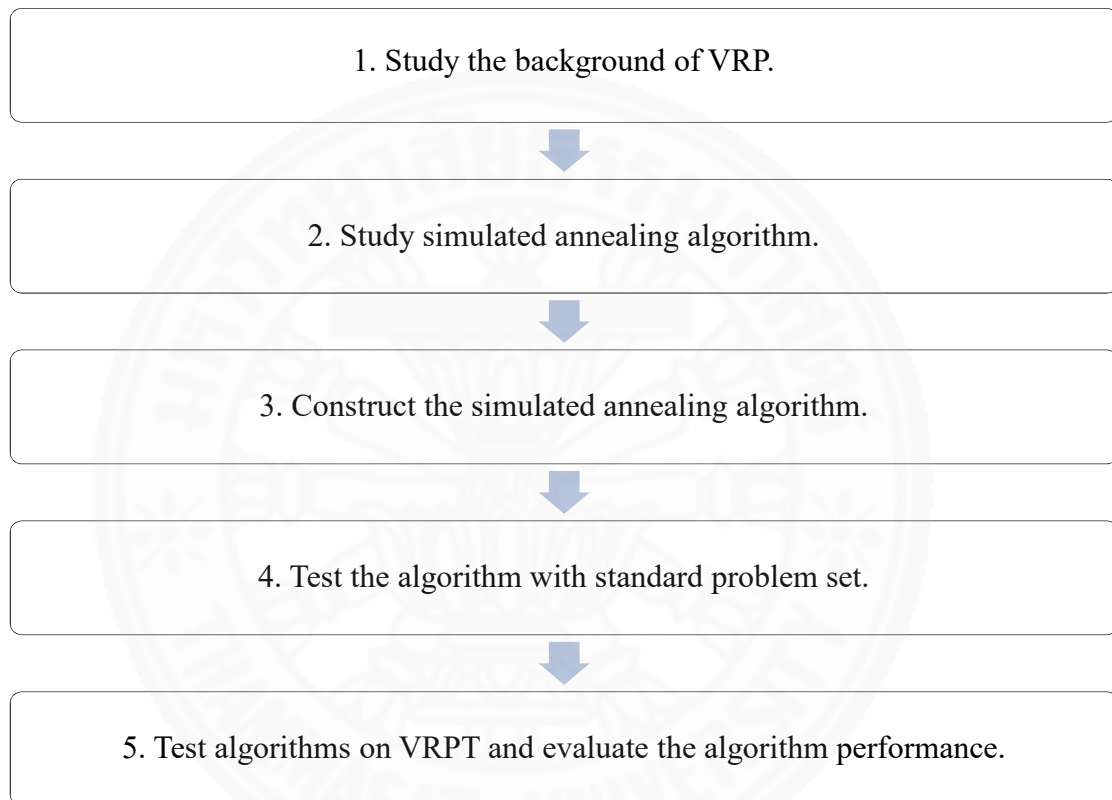


Figure 3.1 Method of approach diagram

In Step 1, general characteristics of the vehicle routing problem (VRP) is studied including the number of depot, capacity of the truck, the objective function, and solution techniques for VRP. The well-known simulated annealing (SA), first introduced by Kirkpatrick et al., is chosen in Step 2 due to its simplicity to implement. The parameters of the simulated annealing algorithm are starting temperature, final temperature, cooling rate and the number of iterations in each temperature. The SA was developed in Step 3 as a spreadsheet-based decision support tool using visual basic for applications (VBA) programming language. Then, the algorithm was tested using one

of the standard problem sets, set A from Augerat et al. The algorithm performance results are compared with the best known solution. Finally, in Step 5 the algorithm is used to solve the problem of interest under study, the VRPT.

3.2 Simulated Annealing Algorithm

SA is a metaheuristic method featuring a local search based on the concept of metal annealing process. Numerous research studies have used SA to solve many combinatorial optimization problems effectively. The developed algorithm begins by generating an initial solution, and performing a local search within neighbour solutions. A better neighbour solution that improves the objective function is accepted and replaces the current solution, whereas the worse solution may be accepted with a probability in order to escape the local minimum. This probability is computed from the Boltzmann function, $e^{-\Delta/kT}$, which consists of three components: (1) the difference between the current and the new solution, Δ ; (2) a constant, k ; and (3) a temperature, T .

At the beginning of the search, the temperature is set to a high initial temperature, T_s , which makes it easier to accept a worse solution. The algorithm continues to perform a local search until it reaches a specified number of iterations. Then, the temperature is reduced by a cooling rate, α , and the local search resumes. The search is repeated until the temperature falls below the final temperature, T_f , at which the algorithm terminates and the best solution is reported.

Notation

T_s	Starting temperature
T_f	Final temperature
α	Cooling rate
S	Current solution
S_b	Best neighbour solution found from the local search
$C(S)$	Objective function value of solution S
N	Number of iterations in each temperature

The algorithm can be described as follows:

Step 1: Set the algorithm parameters: T_s , T_f , α , N , and initialize $T = T_s$.

Step 2: Generate an initial solution and keep it as the current solution S and the best solution S_b .

Step 3: Perform a local search in the neighbourhood of the current solution S . The best solution found is the new solution S' .

Step 4: Compute $\Delta = C(S') - C(S)$.

Step 5:

- If $\Delta < 0$, then set $S = S'$.
- Otherwise, compute the probability, $p = e^{-\Delta/T}$. Then, generate a random number θ from $U[0, 1]$; and set $S = S'$ if $\theta \leq p$.
- Update $S_b = S'$ if $C(S') - C(S_b) < 0$.

Step 6: Repeat Steps 3-5, until the number of iterations reach N . If the terminating condition $T = T_f$ is met, then stop. Otherwise, let $T = \alpha T$, and go to step 3.

3.2.1 Algorithm Parameter Tuning

The developed simulated annealing algorithm was constructed in visual basic for applications (VBA) and was tested on a Core(TM) i3-3227U processor 1.90GHz with 4.00GB of RAM laptop computer. In order to fine tune the parameters of the algorithm and improve its performance, a standard problem set A from Augerat et al. is selected.

This benchmark problem set contains problem instances where both customer locations are uniformly scattered around the depot and demands are generated from a uniform distribution. The size of the problem instances ranges from 31 to 79 customers. The best-known solutions have been proved to be the optimal ones for every instance of this benchmark. After fine tuning, the parameters were set at $T_s = 1000$, $T_f = 0.00001$, $\alpha = 0.98$, and $N = 1,000$. Performance of the algorithms in all 27 problem

instances on problem set A is given in Table 3.1. The average % off-optimal is 6.75 and the SD is 4.42.

Table 3.1 Comparison of results for instance set A

Instance	Best known (optimal)	Best found	CPU time (Sec.)	% off optimal
A-n32-k5	784	814	512	3.83
A-n33-k5	661	662	834	0.15
A-n33-k6	742	744	845	0.27
A-n34-k5	778	799	862	2.70
A-n36-k5	799	834	874	4.38
A-n37-k5	669	697	1056	4.19
A-n37-k6	949	974	1061	2.63
A-n38-k5	730	768	1086	5.21
A-n39-k5	822	857	1089	4.26
A-n39-k6	831	842	1278	1.32
A-n44-k7	937	963	1467	2.77
A-n45-k6	944	1032	1701	9.32
A-n45-k7	1146	1179	1718	2.88
A-n46-k7	914	996	1798	8.97
A-n48-k7	1073	1146	1945	6.80
A-n53-k7	1010	1130	2105	11.88
A-n54-k7	1167	1276	2164	9.34
A-n55-k9	1073	1159	2250	8.01
A-n60-k9	1408	1470	2620	4.40
A-n61-k9	1035	1128	2684	8.99
A-n62-k8	1290	1434	2509	11.16
A-n63-k9	1634	1704	3087	4.28
A-n63-k10	1315	1450	3115	10.27
A-n64-k9	1402	1562	3135	11.41
A-n65-k9	1177	1373	3218	16.65
A-n69-k9	1168	1338	3273	14.55
A-n80-k10	1764	1970	4425	11.68
			Average	6.75
			S.D.	4.42
			Min	0.15
			Max	16.65

3.3 Vehicle Routing Problem with Transshipment (VRPT)

Consider the VRP consisting of a set of customer nodes, a central depot node, a set of vehicles, and a network connecting the depot and customers. The customer nodes are denoted as 1, 2, ... and the depot corresponding to node 0. The depot acts as the distribution center. The customer demand nodes have up to two types of demand: regular demand that must be satisfied directly by inventories at the depot, and transshipment demand that can only be satisfied from inventory at another customer node. A fleet of homogenous vehicles with limited capacity is available. Each vehicle must start and end the trip at the depot. Distance between customers is based on the Euclidean distance. A route starts at the depot, visits a number of customers (at most once for each customer), and then returns to the depot. The objective function is to minimize the total transportation cost or distance of all routes to serve all customer demand. The purpose is to generate good delivery routes for a fleet of homogenous capacitated trucks that allow deliveries of both demands on the same trip.

An example of VRPT can be described as follows. Suppose there are 10 customers that must be served by depot. The depot has two delivery vehicles of same type and capacity. Each customer has daily demand that can be satisfied by the depot. These are considered regular demand in this study. Some of the items carried at the depot are seasonal items that change model every season, e.g. fashion items, luxury bags. These are items that the depot must place a one-time order to the supplier before the season. At the middle of the season towards the end of the season, for some items that are sold very well, the depot would have no inventory leftover to satisfy the demand requested by a particular customer, say Customer 5, i.e. a retail store that already sold out the item. However, inventories of the item are available at another retail store, say Customer 3. Thus, the retail store that makes a request of this item can be satisfied by inventory at another retail store. Under the general VRP, the item would be picked up from Customer 3 after the regular demand at that customer is delivered during a trip. Then, the vehicle would bring the item back to the depot, store the item, and wait for the next trip to Customer 5 before the item can be delivered.

A VRPT is the VRP that incorporates the demand from one customer to another customer, a so-called transshipment demand in this study, to be picked up and

delivered in the same delivery route. Example of a solution for the two trucks is as illustrated in Figure 3.2-3. The first route is the one that visits both Customer 3 and Customer 5, with Customer 3 being visited first, which enables delivery of the transshipment demand from Customer 3 to Customer 5.

Two important benefits from extending the problem to VRPT is the reduction in both the lead time to deliver the item and the carryover demand from day-to-day. This is because without allowing transshipment demand to be delivered on the same trip, the truck would have to pick-up the item from Customer 3, bring it back to the depot, and deliver to Customer 5 on the next delivery cycle.

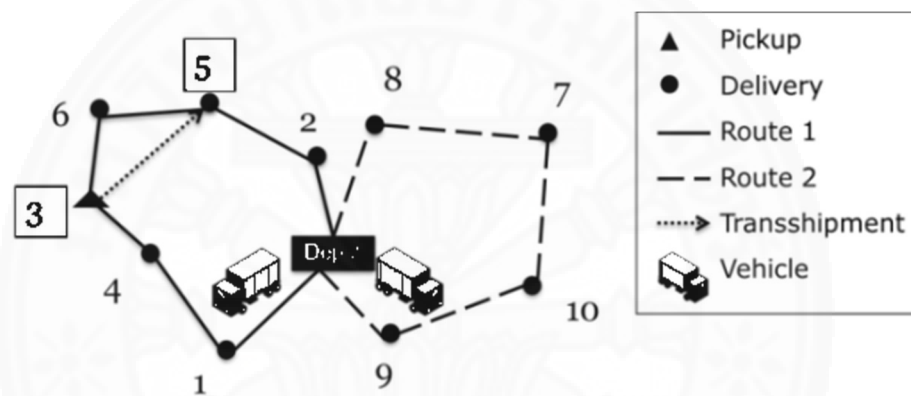


Figure 3.2 An illustration of the vehicle routing problem with transshipment (VRPT)

0	1	4	3	6	5	2	0	0	9	10	7	8	0
Route 1							Route 2						

Figure 3.3 The VRPT solution representation

3.4 A Numerical Example

3.4.1 Problem Instance

Consider a VRPT instance with 15 customers. Each customer has a daily demand that must be satisfied directly from the depot, so-called regular demand; and transshipment demand that can be satisfied from inventory at another customer. The problem instance is to be solved in two consecutive days (Day 1 and Day 2) in order to

evaluate the impact of satisfying the transshipment demand. The depot has three delivery vehicles of same type, each with a capacity of 100 units. Distance between a pair of customers is estimated from (X, Y) coordinate. Regular demands are randomly generated from a uniform distribution. The customer locations and regular demand data are shown in Table 3.2. In addition, there are three levels of transshipment: 1, 2, and 3 customers that require transshipment demand. Table 3.3 provides the transshipment demand data. The problem instance with one transshipment demand only contains transshipment demand No.1. The instance with two transshipment demand has transshipment demands No. 1 and No. 2. Finally, the three transshipment demand instance contains all three transshipment demands (No.1-3).

The problem instance is solved twice. The first time is when only regular demands from the depot can be delivered, while transshipment demands on the same trip are not allowed. That is, the transshipment demands are picked up and brought back to the depot. Then, the transshipment demand from Day 1 will be added to the regular demand to be delivered in Day 2. The second time is when both regular and transshipment demands of Day 1 must be delivered in the same trip. That is, the generated delivery routes must contain both customer 3 and customer 8 and that customer 3 must be visited first.

The difference in the total cost between allowing and not allowing transshipment demand delivery can provide the impact of including transshipment demand in the delivery route.

Table 3.2 Locations considered in this case study and a set of regular demand

<i>Node</i>	<i>Location</i>		<i>Regular Demand</i>	
<i>Depot</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>
0	14	68	-	-
<i>Customer</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>
1	96	44	17	18
2	50	5	12	15
3	49	8	7	15
4	13	7	8	10
5	29	89	5	8
6	58	30	12	17
7	84	39	5	6
8	14	24	6	7
9	2	39	19	13
10	3	82	10	16
11	5	10	12	10
12	98	52	11	9
13	84	25	8	10
14	61	59	12	15
15	1	65	19	12

Table 3.3 Transshipment demand

<i>Transshipment</i>	<i>Day1</i>		
<i>No.</i>	<i>Pick-up customer</i>	<i>Delivery customer</i>	<i>Demand</i>
1	3	8	2
2	8	6	1
3	5	14	2

3.4.2 Results and Discussion

Results from numerical example are shown in Table 3.4. The results indicate that allowing transshipment demand to be delivered on the same day could incur additional cost of 1 (i.e. 0.1%) for the case when there is one customer requiring the transshipment demand. A closer look reveals that there is a cost savings of 15 on Day 2, which is almost enough savings to offset the additional cost of 16 that incurs on Day 1 for delivery of the transshipment demand. This suggests that allowing transshipment delivery could lead to cost savings in some cases, which remains to be investigated further. The same results can be seen for satisfying the cases of 2 and 3 transshipment demands, i.e. additional cost of 46 (i.e. 5.2%) and 46 (i.e. 5.2%), respectively.

Table 3.4 Test results satisfying the transshipment demands

	<i>1 Transshipment</i>		<i>2 Transshipments</i>		<i>3 Transshipments</i>	
	<i>Not allowed</i>	<i>allowed</i>	<i>Not allowed</i>	<i>allowed</i>	<i>Not allowed</i>	<i>Allowed</i>
Day 1	424	440	424	485	424	485
Day 2	454	439	454	439	454	439
Total cost	878	879	878	924	878	924
Difference		1		46		46
% Difference		0.1%		5.2%		5.2%

The benefit from allowing same day delivery of transshipment is the reduction in the carryover demand from day-to-day that is caused by having to bring the transshipment demand back to the depot on Day 1 to be delivered on Day 2. More importantly, this benefit can be significant from the service level to the end customer standpoint. Being able to deliver on the same day implies that the end customer would receive the item faster. This reduction in the lead time is especially important because it is the lead time for the item that was previously unavailable to the end customer, i.e. the very reason of performing transshipment. In other words, it is a tradeoff between a higher cost and better customer service.

Chapter 4

Computational Experiment, Result and Discussion

4.1 Test Problems

In this section, we have created six problem instances, which are divided into three categories; 1) two small problems 2) two medium size problems and 3) two large problems. The results are shown in terms of the total cost. The problem instance is to be solved in six consecutive days (Day 1 to Day 6). Each customer has regular demand and may have transshipment demand. All delivery vehicles are of the same type and the same capacity (100 units). The average delivery vehicle speed is assumed at 80 km/hr. Transportation cost is assumed to be proportional to the distance traveled in each trip. Transportation rate is set at 5 THB/km. The distance between a pair of customers is estimated from (X,Y) coordinates, with an appropriate circuitry factor for distance adjustment of 1.3. Regular demands are randomly generated from a uniform distribution. In addition, the percentage of customers that require transshipment demand is of two levels.

The problem is solved twice. The first time is when only regular demands from the depot can be delivered, while transshipment demands on the same trip are not allowed. That is, the transshipment demands are picked up and brought back to the depot. Then, the transshipment demand from one day will be added to the regular demand to be delivered on the next day. The second time is when both regular and transshipment demands must be delivered in the same trip.

The small problem instances contain 30 customers. The two instances are denoted S1 and S2 with three transshipment demands and seven transshipment demands, respectively. For medium problem instances, there are 80 customers. The two instances are denoted M1 and M2 with eight transshipment demands and twenty transshipment demands. Finally, the two large problem instances 100 customers are L1 with ten transshipment demands and L2 with twenty-five transshipment demands.

4.2 Simulated annealing for vehicle routing problem with transshipment

The simulated annealing for VRPT is developed as a spreadsheet-based decision support tool using visual basic for applications (VBA). The tool requires the following input data: the number of customers, the number and capacity of vehicles, customers' demand (regular and transshipment), locations of customers and depot, circuitry factor, and the transportation rate (THB/km). Outputs are delivery routes and the total cost. The VRPT input sheet is as shown in Figure 4.1.

Please fill in data			Customer	X Coord	Y Coord	Demand (Ton.)	Demand Pick up and Delivery (Ton.)	Delivery Customer
Number of Customer	30	Customer	1	-97	52	11		
Number of Vehicle	3	Vehicle	2	-25	92	12		
Capacity of Vehicle	100.00	Ton.	3	-89	18	12		
Start Time of Vehicle	8.00	Hr.	4	66	65	9		
End Time of Vehicle	18.00	Hr.	5	-51	7	10		
Speed of Vehicle	80.00	Km./Hr.	6	-79	60	6		
Cost of Vehicle	5.00	Thb./Km.	7	96	-20	7	7	6
Circuitry Factor	1.30		8	43	-35	7		
		X Coord.	9	81	-48	10		
		Y Coord.	10	-14	-80	11		
Depot	0	0	11	83	-14	9		

Figure 4.1 Input sheet

4.3 Result and discussion

The results from solving the small, medium and large problem instances of VRPT (two instance for each problem size) are shown in Table 4.1. Each instance contains one week of demand (six business days).

Table 4.1 Test results

	S1		S2		M1		M2		L1		L2	
	Not allowed	Allowed	Not allowed	Allowed	Not allowed	Allowed	Not allowed	Allowed	Not allowed	Allowed	Not allowed	Allowed
Day 1	1,093	1,242	1,093	1,454	2,148	2,826	2,148	3,680	2,641	3,666	2,747	4,562
Day 2	1,093	1,355	1,113	1,253	2,231	2,932	2,410	3,715	2,597	3,780	2,703	5,151
Day 3	1,087	1,246	1,108	1,450	2,157	3,124	2,302	3,997	2,585	3,666	2,628	4,791
Day 4	1,060	1,241	1,102	1,358	2,197	2,912	2,261	3,817	2,588	3,799	2,654	4,864
Day 5	1,087	1,192	1,104	1,398	2,170	3,162	2,321	3,591	2,590	3,899	2,660	14,557
Day 6	1,068	1,434	1,069	1,434	2,191	2,233	2,307	2,233	2,620	2,792	2,561	2,792
Total cost	6,488	7,710	6,589	8,347	13,094	17,189	13,749	21,033	15,621	21,602	15,953	36,717
Difference		1,222		1,758		4,095		7,284		5,981		20,764
% Difference		19%		27%		31%		53%		38%		130%

For the small size problem instances, the results indicate that the allowing transshipment demand to be delivered on the same day could incur additional cost 19% or 1,222 THB for S1 problem with three transshipment demands, and additional cost 27% or 1,758 THB for S2 problem with seven transshipment demands. There are three delivery vehicles for both problem instances. As expected, the more the number of transshipment demand, the higher the transportation cost. Similar results can be seen for the M1, M2, L1, and L2 problem instances with additional cost of 4,095 THB, 7,284 THB, 5,981 THB and 20,764 THB, respectively. Also, the larger the problem, the higher the total cost.

Based on the results, it can be seen that there is a tradeoff between additional transportation cost and the benefit from allowing same day delivery of transshipment demand, i.e. shorter lead time to satisfy the end customer demand and lower carryover demand from one day to the next. This benefit can be significant from the service level to end customer standpoint. Being able to deliver on the same day implies that the end customer would receive the item faster. This reduction in the lead time is especially important because it is the lead time for the item that was previously unavailable to the end customer, i.e. the very reason to perform transshipment. Therefore, the decision to satisfy transshipment demands on the same trip is a managerial decision that depends on whether the company focuses on being responsive or being cost efficient.

Finally, the computational time is approximately 20 minutes for small problem instances, 93 minutes for medium problem instances, and 150 minutes for large problem instances.

Chapter 5

Conclusions

In this study, a simulated annealing algorithm for vehicle routing problem with transshipment has been developed. The VRPT considers both regular demands that can be satisfied directly by inventories at the depot and transshipment demands of items that can only be satisfied from another customer.

Parameters of SA are fine-tuned with a standard problem set to improve its performance. The developed algorithm is embedded in a spreadsheet based decision support tool that is written using visual basic for applications (VBA). A numerical example is provided to demonstrate the VRPT, benefit of allowing same day transshipment delivery, and the performance of the algorithm.

The algorithm are tested on six problem instances. Each instance contains demand data for six consecutive days (Day 1 to Day 6) where each customer has regular demand and may have transshipment demand. Each problem instance is solved twice, without allowing delivery of transshipment demand in the same trip and allowing them to be delivered on the same trip. The results indicate an important tradeoff between allowing same day delivery of transshipment demands to improve end customer service and incurring additional transportation cost.

The results of this study point to further research directions: 1) formulating a mathematical representation of the VRPT so that small problem instances can be solved to optimality using standard solver, and 2) develop and improve the performance of the metaheuristics for the VRPT.

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Appendices

Appendix A

Problem instances for test the algorithm

1. The small problem instances: S1 and S2 problem

Contain 30 customers. All delivery vehicles are of the same type and the same capacity (100 units). The customer locations and regular demand data are shown in Table A.1. Transshipment demand data are shown in Table A.2 and Table A.3.

2. The medium problem instances: M1 and M2 problem

Contain 80 customers. All delivery vehicles are of the same type and the same capacity (100 units). The customer locations and regular demand data are shown in Table A.4. Transshipment demand data are shown in Table A.5 and Table A.6.

3. The large problem instances: L1 and L2 problem

Contain 100 customers. All delivery vehicles are of the same type and the same capacity (100 units). The customer locations and regular demand data are shown in Table A.7. Transshipment demand data are shown in Table A.8 and Table A.9.

Table A.1 Locations and a set of regular demand for S1 and S2 problem

<i>Node</i>	<i>Location</i>		<i>Regular Demand</i>					
<i>Depot</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>	<i>Day3</i>	<i>Day4</i>	<i>Day5</i>	<i>Day6</i>
0	14	68	-	-	-	-	-	-
<i>Customer</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>	<i>Day3</i>	<i>Day4</i>	<i>Day5</i>	<i>Day6</i>
1	-97	52	11	9	10	7	7	11
2	-25	92	12	11	5	8	12	2
3	-89	18	12	5	13	8	9	11
4	66	65	9	7	10	10	7	7
5	-51	7	10	13	12	7	11	13
6	-79	60	6	13	10	5	10	6
7	96	-20	7	5	7	8	7	13
8	43	-35	7	6	6	10	8	8
9	81	-48	10	7	6	10	6	9
10	-14	-80	11	8	7	12	10	10
11	83	-14	9	11	12	12	5	9
12	-46	-89	10	9	9	9	8	8
13	-69	-5	7	13	5	8	8	4
14	1	-22	7	10	9	6	13	10
15	-96	-58	6	11	9	11	10	12
16	31	9	6	6	8	6	5	9
17	-70	41	12	6	7	10	9	8
18	-2	-58	12	9	6	11	8	9
19	-11	-45	8	6	10	6	12	6
20	-94	-35	12	11	7	10	7	6
21	-91	-4	11	7	7	9	7	8
22	9	-84	7	12	10	11	12	8
23	-30	-70	10	8	13	6	12	10
24	10	85	9	7	13	6	5	8
25	99	-32	9	8	12	12	10	11
26	63	8	9	8	11	6	8	9
27	77	-26	8	9	7	10	9	10
28	-27	75	7	7	6	9	7	5
29	-68	62	9	7	10	11	10	11
30	-7	-76	7	13	6	5	11	8

Table A.2 Transshipment demand for S1 problem

<i>Day1</i>			<i>Day2</i>			<i>Day3</i>			<i>Day4</i>			<i>Day5</i>		
<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>
7	6	7	10	24	4	1	8	4	8	21	6	9	23	2
12	27	4	13	26	5	3	17	3	15	30	2	18	29	4
26	29	2	25	21	7	29	18	1	17	20	5	27	19	1

Table A.3 Transshipment demand for S2 problem

<i>Day1</i>			<i>Day2</i>			<i>Day3</i>			<i>Day4</i>			<i>Day5</i>		
<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>
2	22	1	5	29	2	2	22	1	5	29	2	1	20	5
5	1	6	9	16	7	5	1	6	9	16	7	5	14	6
8	30	7	12	6	1	8	30	7	12	6	1	10	15	1
11	2	3	13	11	6	11	2	3	13	11	6	14	30	7
13	18	1	18	30	6	13	18	1	18	30	6	18	17	5
19	17	6	25	18	2	19	17	6	25	18	2	25	7	5
29	18	6	28	29	4	29	18	6	28	29	4	27	29	4

Table A.4 Locations and a set of regular demand for M1 and M2 problem

<i>Node</i>	<i>Location</i>		<i>Regular Demand</i>					
<i>Depot</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>	<i>Day3</i>	<i>Day4</i>	<i>Day5</i>	<i>Day6</i>
0	14	68	-	-	-	-	-	-
<i>Customer</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>	<i>Day3</i>	<i>Day4</i>	<i>Day5</i>	<i>Day6</i>
1	-97	52	11	9	10	7	7	11
2	-25	92	12	11	5	8	12	11
3	-89	18	12	5	13	8	9	11
4	66	65	9	7	10	10	7	7
5	-51	7	10	13	12	7	11	13
6	-79	60	6	13	10	5	10	6
7	96	-20	7	5	7	8	7	13
8	43	-35	7	6	6	10	8	8
9	81	-48	10	7	6	10	6	9
10	-14	-80	11	8	7	12	10	10
11	83	-14	9	11	12	12	5	9
12	-46	-89	10	9	9	9	8	8
13	-69	-5	7	13	5	8	8	9
14	1	-22	7	10	9	6	13	10
15	-96	-58	6	11	9	11	10	12
16	31	9	6	6	8	6	5	9
17	-70	41	12	6	7	10	9	8
18	-2	-58	12	9	6	11	8	9
19	-11	-45	8	6	10	6	12	6
20	-94	-35	12	11	7	10	7	6
21	-91	-4	11	7	7	9	7	8
22	9	-84	7	12	10	11	12	8
23	-30	-70	10	8	13	6	12	10
24	10	85	9	7	13	6	5	8
25	99	-32	9	8	12	12	10	11
26	63	8	9	8	11	6	8	9
27	77	-26	8	9	7	10	9	10
28	-27	75	7	7	6	9	7	10
29	-68	62	9	7	10	11	10	11
30	-7	-76	7	13	6	5	11	8

Table A.4 (Continue) Locations and a set of regular demand for M1 and M2 problem

<i>Node</i>	<i>Location</i>		<i>Regular Demand</i>					
<i>Customer</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>	<i>Day3</i>	<i>Day4</i>	<i>Day5</i>	<i>Day6</i>
31	-57	-6	6	6	5	11	9	9
32	27	43	11	11	8	12	11	6
33	39	-16	5	8	8	7	13	11
34	29	-30	11	7	2	8	13	6
35	-1	95	6	6	6	8	13	9
36	3	93	7	8	8	7	9	6
37	51	40	9	12	10	9	11	6
38	4	51	9	6	7	8	11	5
39	75	-17	11	8	13	11	10	12
40	-66	-67	6	13	11	11	8	5
41	0	-62	9	8	6	7	10	2
42	-53	76	12	8	8	11	7	9
43	3	-34	10	8	8	12	10	12
44	48	68	12	7	7	6	8	5
45	-84	-18	7	11	8	11	11	9
46	91	-51	8	11	7	3	6	10
47	15	-51	13	6	13	10	10	12
48	-21	5	12	6	9	11	7	8
49	30	80	7	10	7	6	12	6
50	67	-23	7	13	12	9	9	11
51	-59	39	7	8	8	6	10	6
52	-42	51	9	6	13	9	5	8
53	-25	-62	12	12	6	6	5	6
54	-94	66	13	12	10	11	6	7
55	13	-59	11	11	8	9	9	11
56	15	-90	7	8	10	8	9	8
57	-18	61	9	7	13	12	13	12
58	39	-78	13	7	6	11	5	8
59	62	-38	6	7	8	9	7	7
60	-19	90	8	8	12	4	8	10

Table A.4 (Continue) Locations and a set of regular demand for M1 and M2 problem

<i>Node</i>	<i>Location</i>		<i>Regular Demand</i>					
<i>Customer</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>	<i>Day3</i>	<i>Day4</i>	<i>Day5</i>	<i>Day6</i>
61	81	-43	10	9	7	10	11	9
62	97	52	10	12	7	8	5	7
63	-81	8	10	10	7	9	11	12
64	89	97	8	6	9	11	9	8
65	-96	-69	10	9	10	6	6	7
66	-88	-38	8	9	9	10	5	8
67	15	-14	10	9	10	8	12	11
68	-31	37	11	6	5	7	11	13
69	82	89	11	5	11	9	7	10
70	-85	-41	10	5	10	13	5	13
71	-18	2	10	11	5	5	10	8
72	53	16	11	9	8	6	8	10
73	46	-62	10	11	8	11	7	11
74	-63	-53	11	6	7	5	12	7
75	52	-38	12	7	7	11	10	11
76	-29	-59	12	11	12	7	8	9
77	28	-15	10	10	6	3	10	12
78	9	35	6	9	13	11	8	9
79	54	-28	5	10	12	8	6	8
80	-44	-83	8	11	8	11	9	6

Table A.5 Transshipment demand for M1 problem

<i>Day1</i>			<i>Day2</i>			<i>Day3</i>			<i>Day4</i>			<i>Day5</i>		
<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>
10	47	3	5	3	4	5	52	4	5	11	2	12	35	6
16	2	6	15	21	5	13	25	1	7	73	7	14	52	1
33	37	1	21	39	4	18	72	6	18	23	6	15	44	6
42	60	1	22	9	7	26	12	5	30	4	3	27	47	2
43	40	4	27	69	3	38	54	7	34	69	1	41	36	5
46	39	7	42	40	2	48	78	1	57	61	6	49	63	3
59	63	6	77	61	2	66	61	5	62	8	3	52	69	2
73	46	6	80	10	1	73	19	3	76	30	6	57	3	6

Table A.6 Transshipment demand for M2 problem

<i>Day1</i>			<i>Day2</i>			<i>Day3</i>			<i>Day4</i>			<i>Day5</i>		
<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>
2	45	4	7	8	1	9	40	6	1	52	1	5	70	5
4	63	1	12	20	3	10	78	3	4	29	3	6	4	7
11	7	5	15	23	1	13	57	4	8	19	6	9	24	6
14	29	7	21	73	2	15	21	3	14	19	7	12	40	2
19	16	6	22	5	4	16	36	7	21	49	2	13	60	4
20	11	1	23	53	3	24	47	5	24	76	6	18	63	7
28	53	7	25	2	1	28	9	1	27	5	6	22	58	1
29	59	6	27	66	7	32	34	1	29	37	2	26	61	5
30	27	4	28	9	6	48	35	3	33	12	3	29	71	2
31	42	1	29	34	7	52	80	1	35	11	2	39	2	5
33	42	7	38	54	7	55	74	4	38	33	7	40	55	1
38	24	5	41	13	7	58	37	6	41	73	4	48	50	4
42	1	2	47	9	4	59	20	3	44	51	3	50	14	7
44	22	5	50	45	4	62	41	1	49	43	3	51	1	1
46	8	5	51	80	7	65	58	6	50	35	7	54	9	1
50	64	2	57	77	5	70	65	3	53	55	2	56	73	4
52	29	6	67	9	4	71	53	6	57	23	2	62	78	5
59	41	5	73	65	5	73	56	1	59	80	5	67	13	4
61	56	6	75	45	2	75	65	5	66	21	1	71	19	3
78	54	2	77	70	7	79	27	1	69	18	4	79	39	6

Table A.7 Locations and a set of regular demand for L1 and L2 problem

<i>Node</i>	<i>Location</i>		<i>Regular Demand</i>					
<i>Depot</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>	<i>Day3</i>	<i>Day4</i>	<i>Day5</i>	<i>Day6</i>
0	14	68	-	-	-	-	-	-
<i>Customer</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>	<i>Day3</i>	<i>Day4</i>	<i>Day5</i>	<i>Day6</i>
1	59	-65	13	7	10	7	12	8
2	-36	-73	7	6	9	9	10	5
3	21	-62	8	11	10	13	12	9
4	37	52	12	8	10	10	11	11
5	-30	94	7	9	9	10	7	8
6	31	-69	9	10	9	5	8	6
7	-16	-33	7	8	6	10	11	9
8	48	51	11	7	5	12	5	9
9	-7	-30	12	7	9	12	12	8
10	42	-48	7	11	9	9	10	6
11	-26	-35	5	7	13	8	10	8
12	18	21	7	7	8	10	7	10
13	-42	67	6	5	6	7	8	10
14	29	96	12	9	8	5	7	6
15	22	39	7	7	12	6	10	10
16	-21	67	12	6	8	12	7	10
17	96	93	8	12	7	11	12	7
18	23	71	12	9	10	9	6	10
19	-40	94	8	5	9	5	8	9
20	-37	96	5	10	10	9	5	11
21	40	-46	7	8	8	8	7	10
22	54	-18	10	10	13	12	7	11
23	18	36	10	9	9	6	13	6
24	0	15	6	10	11	11	8	6
25	21	-45	5	8	6	6	8	13
26	-45	-65	8	9	6	9	8	13
27	28	-27	9	8	9	8	7	6
28	-78	-71	9	12	8	10	8	5
29	69	3	6	11	7	6	5	11
30	-44	37	11	13	9	6	10	8

Table A.7 (Continue) Locations and a set of regular demand for L1 and L2 problem

<i>Node</i>	<i>Location</i>		<i>Regular Demand</i>					
<i>Customer</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>	<i>Day3</i>	<i>Day4</i>	<i>Day5</i>	<i>Day6</i>
31	22	10	8	8	7	12	6	8
32	-40	-55	11	6	8	5	11	12
33	16	5	13	7	8	8	8	13
34	88	-7	6	12	5	11	11	7
35	30	53	11	8	7	10	9	9
36	-55	-31	6	6	6	5	9	13
37	93	67	12	9	7	12	6	6
38	-16	-89	12	13	7	10	10	13
39	84	9	12	6	7	10	8	9
40	-91	-92	13	11	8	11	10	9
41	-69	94	8	8	8	10	6	8
42	74	97	7	5	11	11	7	11
43	14	-16	7	9	12	12	9	12
44	83	67	12	11	12	6	11	10
45	-38	-6	11	11	9	11	10	6
46	-11	56	12	12	8	13	9	13
47	54	85	7	6	12	10	12	11
48	98	-48	5	12	7	7	5	12
49	17	71	9	8	7	7	6	10
50	-39	95	6	7	10	9	7	12
51	32	17	8	11	11	10	8	10
52	-15	71	5	12	5	6	8	8
53	-73	34	5	12	7	5	11	5
54	21	-80	7	12	7	7	9	7
55	-19	86	13	8	8	5	12	9
56	-25	-71	7	9	5	12	9	3
57	-76	-13	11	7	7	8	8	11
58	0	38	12	10	11	7	6	10
59	-67	0	8	10	6	12	8	12
60	-99	33	5	11	12	7	8	9

Table A.7 (Continue) Locations and a set of regular demand for L1 and L2 problem

<i>Node</i>	<i>Location</i>		<i>Regular Demand</i>					
<i>Customer</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>	<i>Day3</i>	<i>Day4</i>	<i>Day5</i>	<i>Day6</i>
61	38	38	13	6	11	5	13	13
62	-70	-46	6	6	13	11	12	6
63	-83	64	5	8	12	7	11	12
64	-8	89	12	7	6	10	6	10
65	-99	91	7	7	10	7	8	6
66	41	-25	11	8	9	9	12	8
67	-34	-16	8	7	7	6	11	12
68	81	2	13	11	9	12	8	6
69	-56	55	11	10	8	13	8	7
70	-34	8	12	6	12	10	12	11
71	-89	67	12	6	11	8	9	6
72	-1	80	13	5	10	13	6	2
73	-2	34	6	12	10	7	5	12
74	-66	-42	6	5	13	7	12	9
75	-17	19	11	12	7	8	12	12
76	-24	28	7	13	7	5	8	10
77	95	-65	11	11	6	5	7	7
78	-22	-69	10	12	7	7	11	11
79	13	-54	10	6	7	12	10	9
80	44	-46	5	7	13	5	12	6
81	66	65	12	5	10	9	12	9
82	-72	35	6	10	9	11	8	13
83	33	-45	11	11	9	13	12	6
84	35	-38	12	11	8	6	10	6
85	-58	-70	6	10	9	10	12	12
86	17	-26	11	11	8	12	11	8
87	73	-48	9	9	10	11	8	7
88	-21	-40	6	6	7	6	9	6
89	-45	35	10	7	11	8	5	13
90	75	56	13	8	8	9	11	7

Table A.7 (Continue) Locations and a set of regular demand for L1 and L2 problem

<i>Node</i>	<i>Location</i>		<i>Regular Demand</i>					
<i>Customer</i>	<i>X Cord.</i>	<i>Y Cord.</i>	<i>Day1</i>	<i>Day2</i>	<i>Day3</i>	<i>Day4</i>	<i>Day5</i>	<i>Day6</i>
91	-34	42	9	6	7	7	13	5
92	-92	53	7	8	6	8	9	12
93	-65	87	6	10	10	11	8	4
94	-67	-13	8	6	7	10	6	5
95	-59	-67	12	9	13	8	11	11
96	53	-52	10	13	11	10	8	7
97	-86	-7	11	10	6	13	12	10
98	22	73	6	10	11	9	5	5
99	31	-70	8	7	10	8	9	10
100	45	-49	11	13	11	13	6	5

Table A.8 Transshipment demand for L1 problem

<i>Day1</i>			<i>Day2</i>			<i>Day3</i>			<i>Day4</i>			<i>Day5</i>		
<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>
22	77	2	1	24	6	1	71	4	4	99	6	4	53	2
39	78	6	16	95	4	3	56	3	8	40	5	22	14	7
40	3	2	36	18	1	17	76	3	40	84	4	28	37	2
54	1	5	44	83	3	38	25	7	42	53	7	51	96	6
62	57	5	47	16	2	40	69	4	47	26	2	70	48	6
85	46	5	56	4	2	48	47	6	48	31	3	80	46	6
88	95	2	87	99	6	55	13	1	55	7	5	82	3	1
93	87	5	90	78	5	67	22	5	73	61	4	92	40	4
96	7	3	93	74	4	97	38	2	77	68	5	95	50	4
100	63	6	98	12	5	98	79	1	79	51	4	99	66	5

Table A.9 Transshipment demand for L2 problem

<i>Day1</i>			<i>Day2</i>			<i>Day3</i>			<i>Day4</i>			<i>Day5</i>		
<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>	<i>Pick-up</i>	<i>Delivery</i>	<i>Demand</i>
5	72	4	6	6	9	2	5	85	10	2	45	3	6	41
9	64	1	9	4	32	6	2	90	11	6	24	10	7	55
12	26	2	11	2	28	10	6	9	17	3	89	11	3	49
14	34	4	16	2	47	13	4	80	21	5	74	14	5	74
19	60	7	18	4	27	31	7	18	29	1	1	19	7	33
21	97	7	20	6	38	33	2	92	35	3	68	20	3	99
24	1	1	21	5	18	37	4	46	41	2	32	24	6	85
26	3	6	25	7	8	39	2	60	42	6	39	32	3	29
33	30	7	26	7	13	40	6	46	46	7	70	35	5	99
39	8	5	28	2	15	41	2	68	50	3	70	39	3	30
50	51	3	34	1	93	47	7	38	53	1	27	41	2	99
54	92	7	35	7	7	51	7	64	57	7	71	43	3	3
60	1	5	39	4	31	53	6	44	61	3	97	49	1	20
61	45	2	40	7	41	56	4	87	69	5	77	54	6	1
62	28	3	42	2	19	57	1	54	70	6	100	55	7	2
64	2	2	49	4	78	59	1	40	71	3	37	58	2	74
68	97	7	52	2	26	67	5	71	74	4	14	63	4	49
71	45	2	59	1	56	75	1	54	77	2	90	64	4	33
74	62	2	63	7	90	79	3	11	78	6	10	70	5	9
77	84	6	71	7	77	80	4	95	79	6	35	74	3	96
81	11	5	77	3	81	82	3	28	80	6	67	80	1	74
82	95	6	82	2	83	88	4	98	84	7	51	84	7	56
86	56	5	85	5	97	92	1	65	87	1	73	88	7	96
87	62	6	89	6	52	96	1	99	89	3	25	91	1	45
91	17	4	96	3	56	98	5	14	98	2	76	97	6	48