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Saving Concepts in Supply Chain Management: A Study on Inventory and Transportation Costs

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Abstract

Supply chain is a systematic and strategic coordination of the traditional business function to across business function within supply chain for the purpose of improving the long-term performance of the business. The objective of the paper is to understand the saving concepts are used in operational path to achieve optimization in term of cost saving. Business nowadays going towards to minimizing the operational in order to compete with others The purpose is to achieve the minimization in inventory routing problem (IRP) with cost minimization consists inventory and transportation costs focus on the single warehouse with multiple customers. The operational costs can be reduced by solving the inventory management and transportation process for vehicle to replenish the inventory. In this paper, a mathematical model was developed and simulated by using an optimization software package to achieve the optimization. The findings show that the optimization can be achieved by reducing the movement of the vehicle To conclude, the bigger the vehicle's capacity, much capacity can add and less routes taken by the vehicle to supply the inventory to the customers.

Introduction

Basically, inventory routing problem consists of two elements known as inventory management and transportation process focus on vehicle routing. Vehicle routing problem (VRP) is defined as a routing problem with a single warehouse for a set of customers, using a vehicle to achieve the objective of minimizing the overall cost while serving the customers. Due to the different optimization solutions and technologies used in solving the logistic problem, VRP continues to attract a lot of attention. Many logistics companies are trying to be the best at organizing product delivery by implementing the technology available today. There is various technology in logistics systems, and it is commonly used in systems positioning. Addressing vehicle routing is one of the most important aspects of reducing and save the transportation costs (Rahim et al., 2014). For example, an accurate determination in placing the routes in multiple locations for distribution of product to the customers can avoid time waste, total inventory, and transportation costs. In a few instances, improving the outcome does not depend on implementing vendor managed inventory (VMI) itself.

Literature Review

The primary goal of distribution management is to find a solution to the inventory routing problem. Businesses regularly perform delivery and collection tasks. Making a plan that considers a trip from a warehouse, a customer whose demand is variable, and predicting the absolute minimum number of trucks required to minimize the cost of the route chosen is tough. VRP is used to create optimum routes for a vehicle to serve each customer (Comert et al., 2018). With the aim of reducing transportation costs while still meeting customer expectations, a vehicle routing problem (VRP) is simply a routing problem from a single warehouse to a group of consumers (Miranda-Bront et al., 2017). Still being worked on is the logistic issue.

The problem is solved by using the vehicle routing problem (VRP) approach (Oppen et al., 2010). The inventory routing problem, which determines how much inventory is required and where deliveries will be made in order to construct the best delivery routes, was tackled by Abidin, et al (2016); Harahap & Abdul Rahim (2022) using their studies. They came up with a two-phase optimization technique for optimizing inventory routing problems. The advantage of resolving the IRP is the decrease in overall inventory and transportation costs. Previously, an algorithm to build a vehicle route for the distribution process to carry the product to the clients. The VRP includes the creation of a collection of mostly delivery or collection routes based on these assumptions in Figure 2.1.

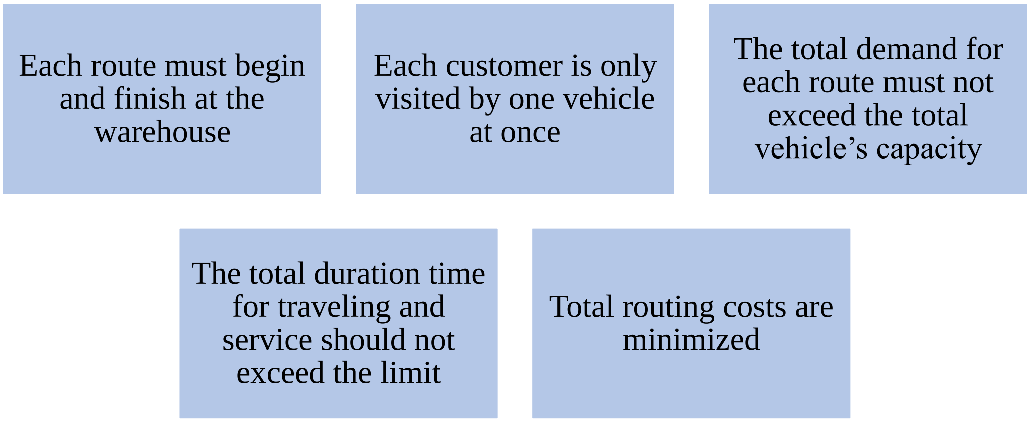

Figure 2.1 *The assumptions in VRP* Sources: (Abidin, et al., 2016)

The basic routing problem has been studied in many different ways recently (Harahap & Rahim, 2017). Algorithms for the ideal formulation and precise decomposition have been proposed (Rahimi, 2017; Suraraksa & Shin, 2019). A variety of heuristics have also been published in order to solve the VRP. The optimal strategy for enhancing the objective function must be chosen carefully in order to resolve VRP. As a result, this research contributes to the body of knowledge regarding the ideal heuristic technique for VRP. The constructive technique, two-phase algorithms, and tour improvement heuristics are the three main categories of basic heuristics approaches (Oliver, 2013), as shown in Table 2.1.

Table 2.1
A heuristic approach for vehicle routing problems (VRP)

Method	Function
Constructive method	Produce and approximately optimal tour of the distance matrix
Two-phase algorithms	Is to cluster the first route and second procedures. (Improvement route from normal route to optimal routes
Tour improvement heuristics	Discover a better tour given the initial one

Source: (Oliver, 2013)

Constructive Method

Construction approaches are the first heuristic approach for the VRP. For any routing application, this technique continues to be the best across numerous software implementations (Ahmad, 2017) The algorithm is developed by starting with an empty solution and repeatedly creating routes until the customers are routed. Depending on the number of accessible routes to connect with the clients, the construction algorithm is split into two parts: a sequential technique and a parallel way. While parallel methods consider several routes, sequential methods only evaluate one route at a time.

Clients are divided into groups according to each replenishment period throughout the vehicle routing phase. For each group, a technique suggested by Clark and Wright's (1964) is employed (Ouelhadj & Wall, 2017). The savings notion in Figure 2.2 serves as the foundation for the algorithm. Figure 2.2 (a) shows that two routes are required for the distribution process to deliver the goods to two clients. In order to satisfy the customer's request, the delivery procedure can be condensed to just one route, as shown in Figure 2.2 (b). Certainly, this condition can lower transportation expenses, which is in accordance with the goals. Each consumer can only come once, so the solution must determine where the necessary quantity is supplied and how much demand there is overall for each route utilizing the maximum vehicle's capacity.

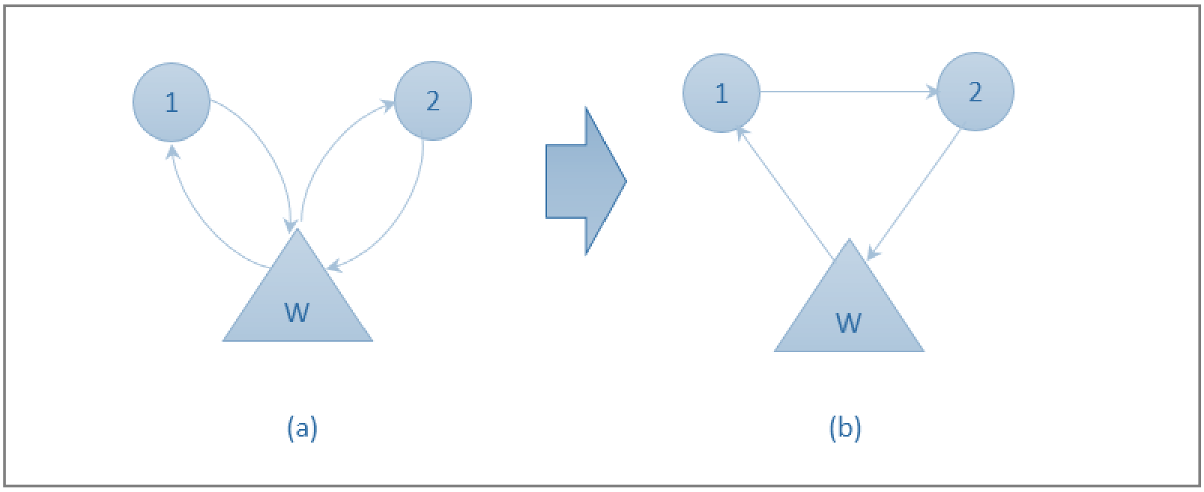

Figure 2.2
An example of a savings concept illustration (cost minimization)
Sources: (Ouelhadj & Wall, 2017)

The following are the saving concept procedure for each of the customers which have the same replenishment interval after implementing the previous step

a) The savings are computed using the formula Sij = $\tau i0 + \tau 0j - \tau ij$ to find the possible pair of customers i and j in a cluster and sorted them in decreasing order.
b) Find the first possible connection in the list that can be used to extend the route to one of two ends of the current route.
c) The route should be terminated if cannot be extended.
d) Steps (b) and (c) are repeated until there is no further feasible connection that can be chosen.

Finally, the last step is to achieve the lowest cost for routing using an improved heuristic that attempts to make an elementary modification depending on the current situation. Thus, the most well-known improvement heuristic for vehicle routing problem (VRP) called 2-opt is implemented to reduce transportation costs. The 2-opt exchange is a simple method applied but it has a very high impact globally. This involves completely considering that the two customers are exchanged in different ways in Figure 2.1. This includes the process of removing and re-entering routes. The potential sub-route is inserted into the existing solution and the cheapest options remain. If no cheapest route exists, the solution route is restored and there is no improvement in the results. However, the solution can be improved if the cheapest route has been found. Hence, lower costs for routing plans can be achieved by implementing the correct approach that applies changes to the existing solution. Specific steps were developed to transform the information into a mathematical formulation for optimization purposes for the next phase.

Two-phase Algorithms

The literature on the two-phase heuristics employed in this study is presented in this subsection. The two phases of the VRP solution approach are customer clustering into groups connected by routes and customer routing inside each group (Rahim et al., 2014). There are two ways to separate the heuristics:

a) Cluster-first, Route-second Approach

A well-known heuristic is the cluster-first route-second technique. When customers are organized into clusters and the routes are chosen based on the customers in each cluster, this condition is referred to (Iassinovskaia et al., 2017). A distinct clustering approach was put forth by certain writers and presented in the literature.

Gillet and Miller (1974) designed a sweep algorithm that served as the initial algorithm that divides warehouses into clusters by spinning a ray centered at the warehouse. The procedure looks at a solution in two steps. It starts by assigning clients to specific vehicles, and after that decides the sequence in which each vehicle must visit the customers it has been given. Until the vehicle constraint is met, each client will be successfully linked in this scenario at the end of the existing route. If this insertion cannot be made, another path is suggested. Solving the comparable TSP results in the optimization of the applicable vehicle route. Fisher and Jaikumar (1984) created the most well-known cluster-first route-second algorithm. The algorithm selects which consumers to serve in the initial stage.
The algorithm selects which consumers to place first in the cluster zone and then allots a car to each of these customers in the first phase. The insertion costs of each customer's addition

to each cluster's k are then calculated. The clusters are then produced by solving a generalized assignment problem based on the customer weights (GAP). TSPs are solved optimally using a constraint relaxation-based methodology after the cluster has been terminated. The most recent example algorithm can be found in (Miranda-Bront et al., 2017; Comert et al., 2018).

b) Route-first, cluster-second

Route-first cluster-second approaches typically provide a sizable TSP tour consumer base. After that, it will disintegrate into drivable vehicle routes. Beasly (1983) investigated the fundamentals of the route-first cluster-second technique, which places the warehouse in the middle and surrounds it with a number of clients. Figure 2.3 illustrates the fundamental dividing process (split).

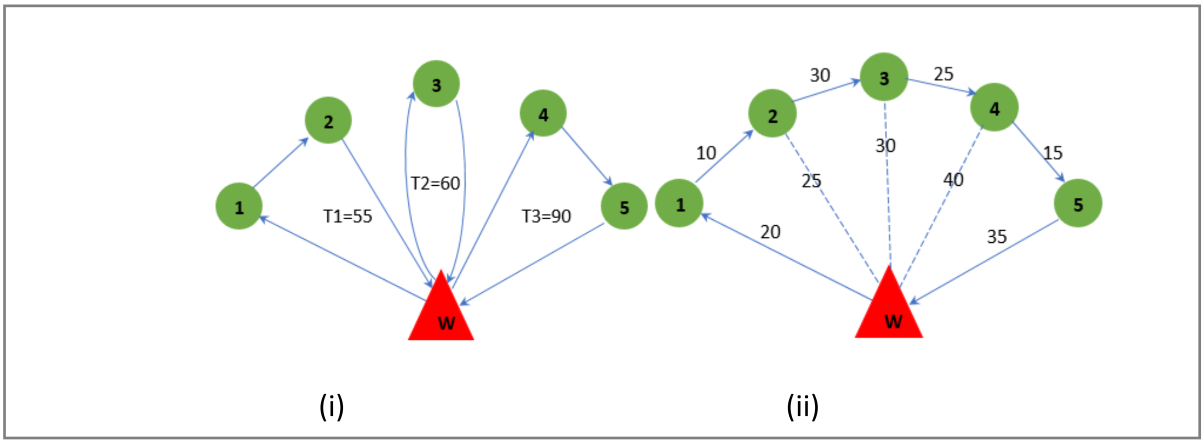

Figure 2.3
(i) Giant tour T = {1,2,3,4,5}, (ii) Optimal Splitting
Adapted from (Markov et al., 2016)

The author created a "big tour" in the first phase, travelling from the warehouse to each customer before returning to the warehouse. It is necessary to divide the route into a number of doable vehicle routes in order to optimize it. Additional examples of algorithms can be found in (Bertsimas and Simchi-Levi, 1996; Haimovich and Kan, 1985).

Tour Improvement Heuristic

The routes have improved Heuristic describes an enhancement of the routes through the introduction of inexpensive ways. 2-opt route improvement, according to Lin (1965), is a heuristic technique that alludes to the intra-route optimization process. In order to determine whether an overall improvement in the goal function can be achieved, this heuristic technique examines the possibilities of changes in the vehicle capacity. The first local search, called "swap customer," focuses on modifications of the vehicle's capacity (Prins et al., 2014). It is possible to shorten the distribution routes by increasing the vehicle's capacity (Lee et al., 2020). This is so that more can be sent directly to a group of clients without having to go back to the warehouse, and the more the vehicle can carry (Karagul et al., 2016; Chen et al., 2017)

Solution Approach

This section will explain the method used in solving the problem. First, the algorithm will develop and then the variable will be used and simulate using the optimization solver package known as A Mathematical Programming Language (AMPL).

Algorithm Development

The single-period inventory routing problem (SP-DIRP) involves a single warehouse (W) to distribute a product to a set of customers over a given planning horizon. The objective is to find the optimal demand quantities required to be delivered to a set of customers, delivery time and the vehicle delivery routes to deliver the product to each customer, so that the total inventory and transportation costs can achieve the optimization during the entire planning horizon. The solving model used in this research is develop from previous paper (Rahim et al., 2017). We design a layout which include warehouse (W) as a supplier to distribute the product to a set of customers by using a fleet of homogeneous vehicle. To solve the SP-DIRP, there are condition has to follow

- The customer demand is known.
- The vehicle's capacity must be set enough in order to deliver the customer's requirement.
- The cost of transportation must be proportional to vehicle travelling times.
- Only a fleet of homogeneous vehicles are used to replenish the customers
- Split delivery is not allowed in the model

In addition, there are some relevant parameters and variables are used to develop the model as shown in Table 3.1.

Table 3.1
Parameters and variables are used in solving IRP

Parameters	
Label	**Description**
φ_j	Fixed handling cost per delivery (in RM) at location *j* ∈ S^+ (customers and DC)
n_j	Product holding cost per period at location *j* ∈ S^+ (in RM/kg)
ψ^v	Vehicle's operating fixed cost *v* ∈ *V* (in RM/vehicle)
δ_v	Vehicle's traveling cost *v* ∈ *V* (in RM/km)
k^v	Vehicle's capacity *v* ∈ *V* (in kg)
v_v	Vehicle's average speed *v* ∈ *V* (in km/hour)
θ_{ij}	The duration trip from customer *i* ∈ S^+ to customer *j* ∈ S^+ (in hour)
d_j	The constant demand rate at customer *j* (in kg/hour).
I_{j0}	The levels of initial product (in kg) at each customer *j* ∈ *S*
Variables	
Label	**Description**
Q_{ij}^v	The product quantity remaining in vehicle (in kg) *v* ∈ *V* when the vehicle travels directly to location *j* ∈ S^+ from location *i* ∈ S^+. The quantity will become zero (0) when the trip (*i, j*) is not having a tour by the vehicle *v* ∈ *V*
q_j	The delivery quantity (in kg) to the location *j* ∈ *S*, and 0
I_j	The level of the product at the location (customers and W) *j* ∈ S^+
x_{ij}^v	If location *j* ∈ S^+ is visited immediately after location *i* ∈ S^+ by vehicle *v* ∈ *V*, and 0 (A binary variable set to 1)
y^v	If vehicle *v* ∈ *V*, and 0 (A binary variable set to 1)

Minimize

$$CV = \sum_{v \in V} \left[\psi^v y^v + \sum_{i \in S^+} \sum_{j \in S^+} (\delta_v v_v \theta_{ij} + \varphi_j) x_{ij}^v \right] + \sum_{j \in S^+} \eta_j I_j \tag{1}$$

Subject to:

$$\sum_{v \in V} \sum_{i \in S^+} x_{ij}^v \leq 1, \quad \forall j \in S \tag{2}$$

$$\sum_{i \in S^+} x_{ij}^v - \sum_{k \in S^+} x_{jk}^v = 0, \forall j \in S^+, v = V$$

$$\sum_{i \in S^+} \sum_{j \in S^+} \theta_{ij} x_{ij}^v \leq \tau_t, v = V \quad (4)$$

$$\sum_{v \in V} \sum_{i \in S^+} Q_{ij}^v - \sum_{v \in V} \sum_{k \in S^+} Q_{jk}^v = q_{jt}, \forall j \in S \quad (5)$$

(6) $$Q_{ij}^v \leq k^v x_{ij}^v, \quad \forall i,j \in S^+, \ v \in V$$

$$I_{j-1} + q_r - I_r = d_j \tau_t, \forall j \in S$$

$$I_{j0} \leq I_j \quad \forall j \in S$$

$$x_{rj}^v \leq y^v, \ \forall j \in S, v \in V$$

$$x_{rj}^v, \ y^v \in \{0,1\}, I_{j0}, \ I_j \geq 0, \ Q_{ij}^v \geq 0, q_j \geq 0, \quad \forall i,j \in S^+, v \in V$$

Constraint (1) is the objective function which is has four cost components (total vehicle 's fixed operating, total transportation cost, total delivery handling cost and total inventory holding cost) at the warehouse (W) and customers. Constraints (2) ensure that the vehicle must visit each customer at once not more. Constraints (3) make sure that the vehicle must leave after it has served it and then go to a next customer or return to the W. Constraints (4) ensure that vehicles complete their routes within one travel period, so that the total vehicle's travelling time should not exceed the total working hours. Constraints (5) estimate the customer's quantity requirement to be delivered. Constraint (6) assure that the quantity carried cannot exceed the maximum loading capacity of the vehicle. The product balance equation at the customers in constraint (7). To indicate the final level of product at customer *j* at the end of period is of the same magnitude as its initial product shows in constraints (8). Constraints (9) ensure that a vehicle cannot be used to serve any customer only if the customers are selected. Constraint (10) are the entireness and sign constraint to be imposed on the variables.

Simulation Processes (AMPL)
In the AMPL application, the information needs to be written on different files. Three files need to be developed using AMPL simulation applications as shown in figure 2.3. First, the *model file* is developed with all the sets and parameters that are coded inside the file. Second, all the data are inserted into a *data file* where all the data contains all the information variables. Finally, the running file is created which is a *run file* that is used to run the developed AMPL model in both files. Figure 3.1 shows the process of using the optimization AMPL software.

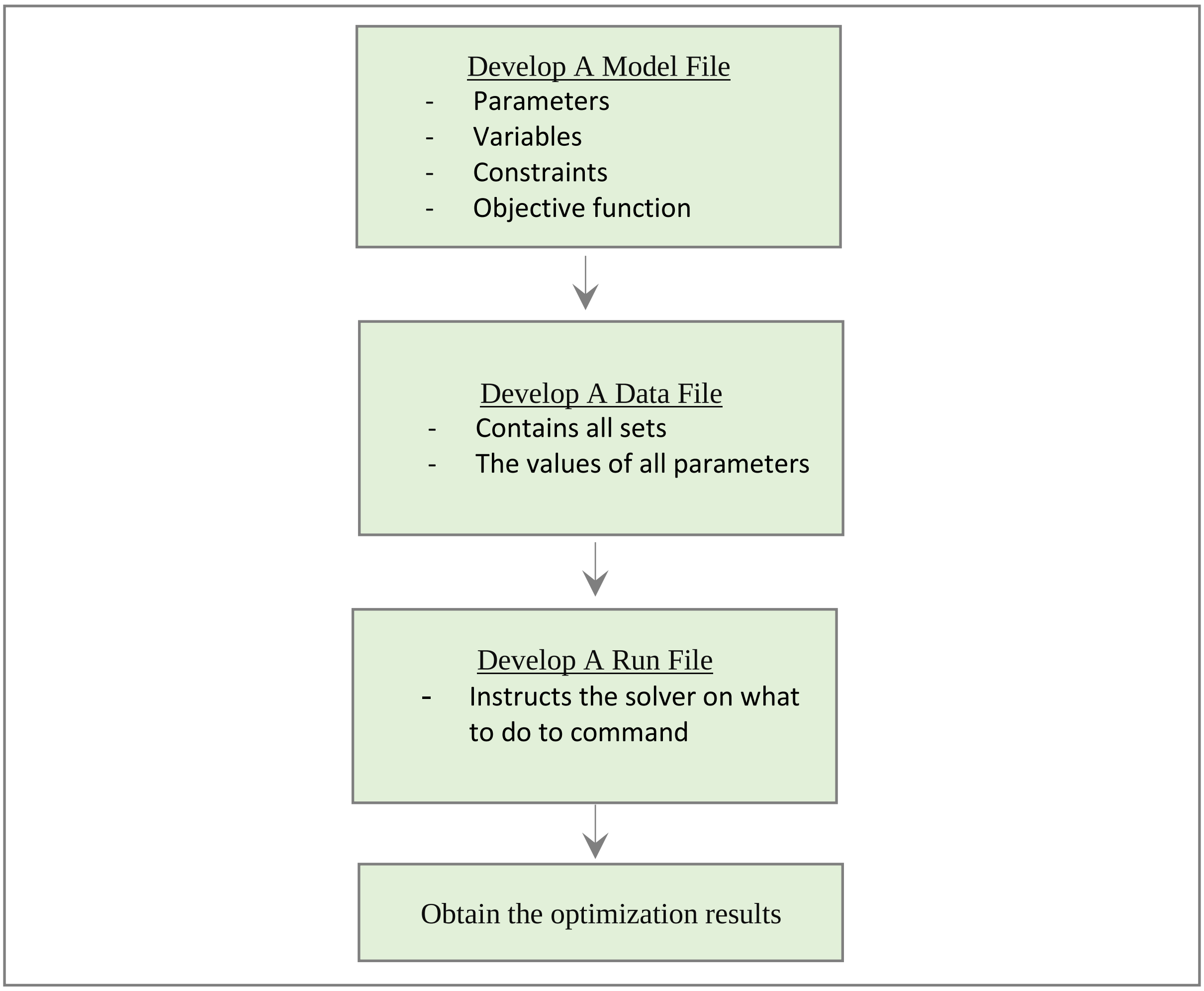

Figure 3.1
Simulation process (AMPL)

The *model file* is the main file that contains all the sets and parameters, as well as variables, constraints, and the objective function. AMPL is a complex software, so the description must be written correctly because all the running processes will be based on this file. Once the AMPL processes the *model file*, it is ready to read the data file. However, it would be useful to have a standard data format for the translator to accept all versions

The *data file* contains all sets, and the values of all parameters are known. After that, the AMPL application can identify and display the result, as well as calculate the coefficients as set in the objective function and constraints. In addition, the AMPL also views the suitable output for the algorithm. In order to determine which customers, need to be visited and the available capacity, there is an input format that is used to allow the set, and one or more parameters must be specified together such as period, vehicle capacity, vehicle speed, number of the vehicle used and delivery cost.
The *run file* instructs the solver on what to do to command to obtain a result. It specifies which model file should be read and which data file is related to the model file. In addition, it is possible to specify the type of solver that is used in solving the problem using the model. In this case, the option solver CPLEX was also utilized. Then the data is created to obtain the

result for this transportation problem. Finally, after the solve statement, any of the variables that need can be viewed.

IRP Analysis and Results

First, to introduce a single-period deterministic inventory routing problem (SP-DIRP) problem solving, a simple instance case of 10 customers is developed. This provides the reader with a better understanding of how the proposed model works. Furthermore, this thesis focuses on the multi-period inventory routing problem, this section also shows a concept to solve the MP-DIRP before moving on to the stochastic problem which is related to this thesis in the following section.

Figure 4.1 shows the illustration of a location for a simple instance case of 10 customers to solve the SP-DIRP. In this case, only one vehicle is used as a condition to replenish the inventory for each of the customers over the planning horizon.

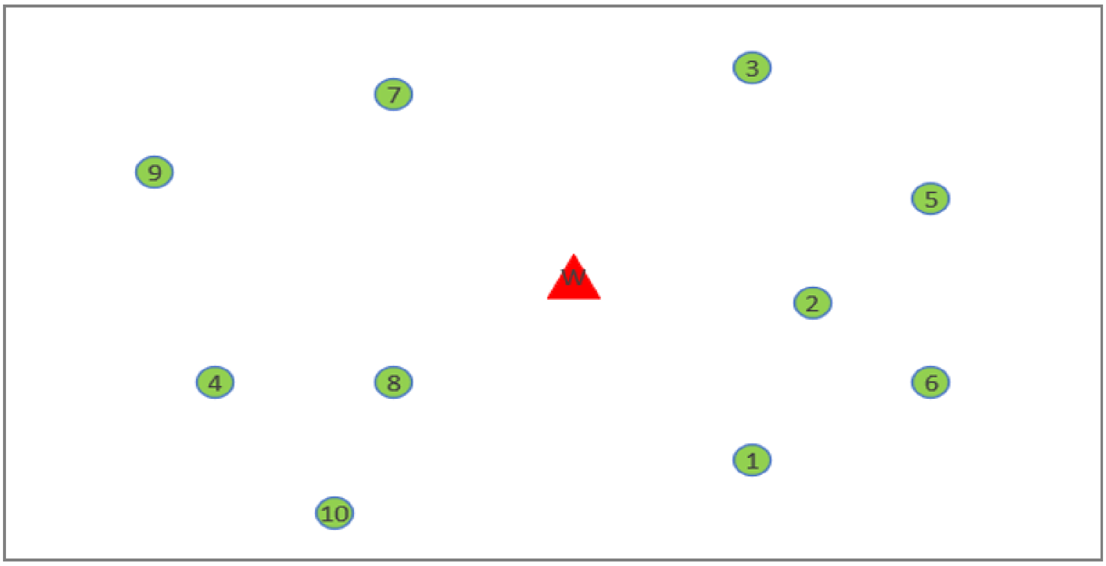

Figure 4.1
Illustrative instances for 10 customers (SP-DIRP)

For this instance, 10 customers were developed which are sketched around the warehouse in a square of 30 by 30 km, with an average demand rate known in advance (deterministic) between 0.1 to 3 tons per hour. The vehicle loading capacity, k^v = 40 tons for a fleet homogeneous vehicle, V. The operating fixed cost for the vehicle, ψ^v = RM200 per vehicle. The average speed for the vehicle is 60 km per hour and the travel cost, δ_{v} = RM4 per kilometer. The handling fixed cost per delivery, φ_{jt} = RM100 for all customers and considered the same with the time units, τ_{t} = 8 hours.

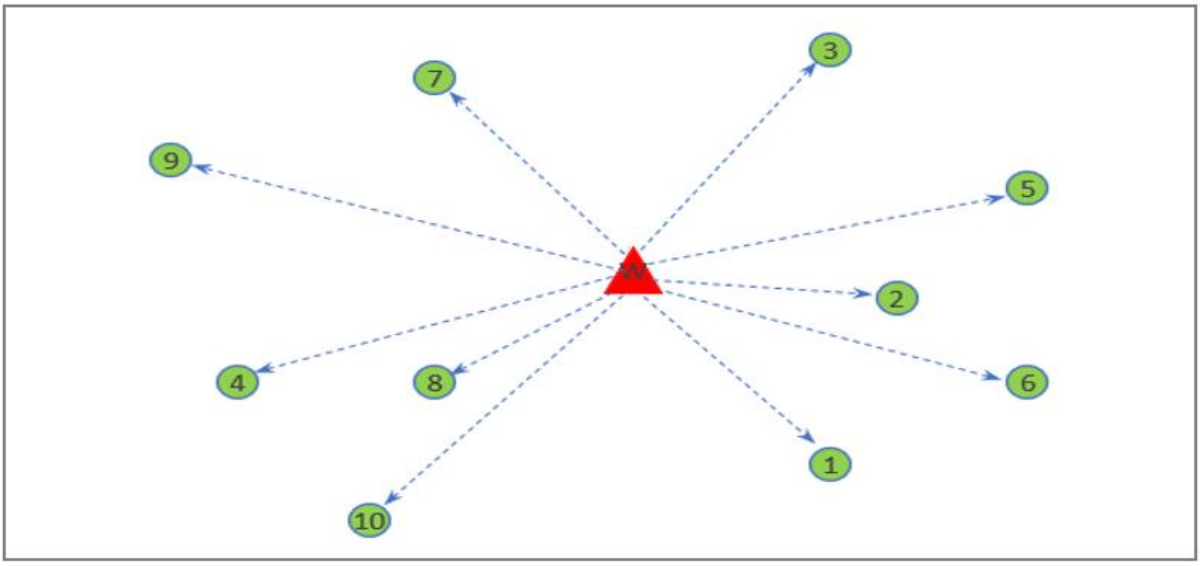

Figure 4.2
Illustrative instances for a direct tour of SP-DIRP (10 customers)

Figure 4.2 shows the possible directions for the vehicle to serve the customers one by one without having a multi-tour. This pattern illustrates the movement of the vehicle starts from the warehouse directly to each of the customers and then returns to the warehouse. By adding a variable solve by using a computational solving method AMPL, the delivery quantity can be obtained. Also, the optimum total operational costs can be defined by illustrating the delivery routes that need to be taken by the vehicle to serve the customers.

Table 4.1
The parameters and delivery quantity for each customer (SP-DIRP)

Customers	Demand rate (ton/hour)	Delivery cost (RM)	Delivery quantity (ton)
1	1.83	100	14.64
2	2.04	100	16.32
3	2.55	100	20.40
4	1.35	100	10.80
5	1.62	100	12.96
6	2.51	100	20.08
7	1.41	100	11.28
8	2.25	100	18.00
9	1.52	100	12.16
10	1.82	100	14.56

The quantity delivered for each customer is presented in Table 4.1. For this solution, a fleet of homogeneous vehicles is used to replenish the inventory for each customer. AMPL will generate the optimization results in a binary number as shown in Table 4.2. Then, the binary number shows the results where the vehicles serve the customers optimally using the best routes.

Table 4.2
Binary number results output (AMPL)

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

Then, from the binary number the results can be analyzed the results for the instance as illustrated in Figure 4.3, the customer's routes have been assigned into {(1,10,4), (5,3), (2,6), (8), (9,7} with the optimum cost is RM 1562.40 which is lower than a direct tour for each customer which is RM1756.80. In this solution method, the cost can be reduced by having a multi-tour for the vehicle to deliver the inventory to the customers.

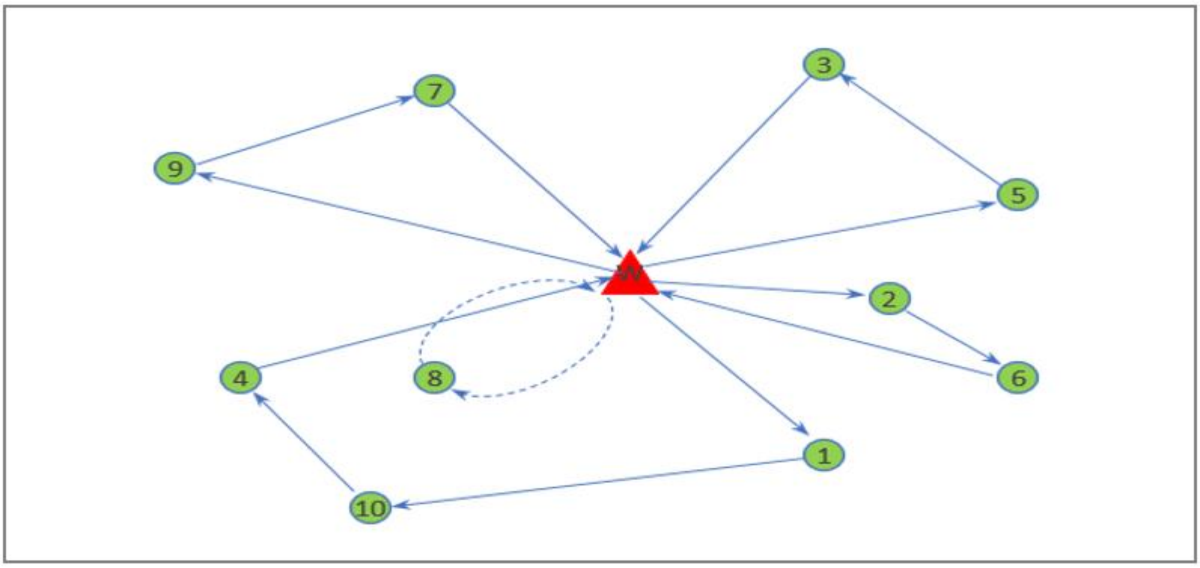

Figure 4.3
Illustrative instances for multi-tour of SP-DIRP (10 customers)

Conclusion
In this article, deterministic IRP are taken into consideration when demand is already known in advanced. The goal is to determine the customer's optimal amount of safety stock allocation in order to maximize savings and provide the desired level of service. Finally, we might conclusion that operational research faces a complicated situation. Since non-linear issues can be solved using mathematical modelling, even with integrality constraints, it is crucial to have knowledge of a variety of methods. The majority of research attempts to find a faster and easier way to handle the problem, despite the risk of losing accuracy in doing so.

Additionally, it is advised to use these modelling approaches to carry out additional study on the various IRP variants.

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