MULTI-START SIMULATED ANNEALING APPROACH FOR WAREHOUSE NETWORK REDESIGNING PROBLEM WITH ZONE DEPENDENT FIXED COST

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DEDICATION

Specially dedicated to my lovely and supporting parents, Khairuddin Mahmud and Zainab Likam and family members, Khairuza Wawiyah and family, Khairuza Izyani and family, Nozieana, Nur Bahariyah and family and Mohd Jamal Idzuan and family.

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ABSTRACT

The warehouse location model is one of the important researches in the location analysis field, but it is different from other types of location problems such as the facility location problem and also the location and allocation problem since it is strongly affected by the current economic situation. In addition, existing warehouse network redesign models and mathematical programming models do not consider the consolidation, elimination, and addition of a new warehouse simultaneously in one model but only consider one or a combination of two of them only. However, these three redesign techniques namely addition, closure, and consolidation of a new warehouse should be considered in the model to optimize the cost. Therefore, this study aims to construct a warehouse network model that minimizes the total supply chain costs by consolidating, eliminating, and adding new sites. It is done through the implementation of Simulated Annealing (SA) optimization method that adopts cooling schedule variants, dynamic stopping criteria, and multi-start. A study of SA parameters such as cooling strategies, initial temperature, and stopping criteria is conducted to ensure a more efficient SA procedure. The study is carried out on three types of network data types: data type 1 – uniform, data type 2 – cluster, and data type 3 – compact. The performance comparisons are done among three different SA cooling schedules: geometric, logarithmic, and linear on the three different sets of data. Dynamic stopping criteria has been chosen such that the algorithm will stop after finding five consecutive best solutions or when there was no improvement in the cost after hundred successive iterations. The computational experiments showed that the geometric cooling schedule produced consistently better-quality solutions in a shorter time than the other schemes' solution. The best initial temperature was found to vary for all three sets of data. This research found that when the number of multi starts increases, the average cost is also proportionally decreasing. On the additional redesign network factors such as the zone dependent fixed cost and capacity constraint, the results showed that when the cost of the zone is introduced, the model suggested the warehouse to be opened in low-value zones. Warehouses in the high-value zone will be closed, and its operations combined with nearby warehouses in the low-value zone. Consequently, warehouses that are in the low-value zone will usually receive a lot of customers from the high-value zone causing increased merger costs for nearby warehouses. The capacity constraint is also considered in the model to control the number of customers that need to be supplied by a warehouse so that the model will represent the real problem more closely. With the addition of this constraint, the customers are not necessarily served by the nearest warehouse hence will increase the transportation cost.

ABSTRAK

Model lokasi gudang adalah salah satu penyelidikan penting dalam bidang analisis lokasi, tetapi berbeza dengan jenis masalah lokasi lain seperti masalah lokasi kemudahan dan juga masalah lokasi dan peruntukan kerana ia sangat dipengaruhi oleh keadaan ekonomi semasa. Sebagai tambahan, model reka bentuk semula rangkaian gudang dan model pengaturcaraan matematik yang sedia ada tidak mempertimbangkan penggabungan, penghapusan dan penambahan gudang baru secara serentak dalam model yang sama tetapi hanya mempertimbangkan satu atau gabungan dua daripadanya. Walau bagaimanapun, tiga teknik reka bentuk semula ini iaitu penambahan, penutupan, dan penyatuan gudang baharu harus dipertimbangkan dalam model untuk mengoptimumkan kos. Oleh itu, kajian ini bertujuan untuk membina model rangkaian gudang yang meminimumkan jumlah kos rantaian bekalan dengan menggabungkan, menghapuskan, dan menambah bahagian baharu. Ini dilakukan melalui penerapan kaedah pengoptimuman Simulasi Penyepuhlindapan (SP) yang menggunakan varian jadual penyejukan, kriteria berhenti dinamik, dan kaedah berbilang permulaan. Kajian parameter SP seperti strategi penyejukan, penetapan suhu awal, dan kriteria berhenti dilakukan untuk memastikan prosedur SP yang lebih cekap. Kajian ini dilakukan pada tiga jenis data yang berbeza: jenis data 1 - seragam, jenis data 2 - kelompok, dan jenis data 3 - padat. Berdasarkan kepada tiga jenis data ini, perbandingan prestasi dilakukan di antara tiga jadual penyejukan SP yang berbeza: geometri, logaritma, dan linear. Kriteria penghenti dinamik telah dipilih sehingga algoritma akan berhenti selepas ia menemukan penyelesaian terbaik untuk lima kali berturut-turut atau apabila tiada peningkatan dalam kos selepas seratus lelaran berturut-turut. Eksperimen pengiraan menunjukkan bahawa jadual penyejukan geometri menghasilkan penyelesaian yang berkualiti secara konsisten dan lebih baik dalam waktu yang lebih singkat daripada jadual penyejukan yang lain. Suhu awal terbaik telah didapati berbeza untuk ketiga-tiga set data. Kajian mendapati apabila bilangan permulaan meningkat, purata kos keseluruhan berkurang secara berkadar. Hasil kajian faktor tambahan yang direka semula seperti kos zon tetap dan had kapasiti, menunjukkan bahawa apabila kos zon diperkenalkan, model mencadangkan gudang yang terletak di zon bernilai rendah untuk dibuka. Gudang di dalam zon bernilai tinggi akan ditutup, operasinya akan digabungkan dengan gudang dalam zon bernilai rendah yang berhampiran. Akibatnya, gudang yang berada dalam zon bernilai rendah akan menerima pelanggan yang sangat banyak dari zon bernilai tinggi menyebabkan kos penggabungan meningkat untuk gudang tersebut. Kekangan kapasiti juga dipertimbangkan dalam model untuk mengawal jumlah pelanggan yang perlu dibekalkan oleh gudang supaya model dapat mewakili masalah sebenar dengan lebih dekat. Dengan penambahan kekangan ini, pelanggan tidak semestinya dilayan oleh gudang terdekat sekaligus akan menaikkan kos pengangkutan.

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LIST OF ABBREVIATIONS

CO	-	Combinatorial Optimization
LA	-	Location Analysis
MFA	-	Mean-Field Annealing
MILP	-	Mixed Integer Linear Programming
MILP-DIPO	-	MILP-based dynamic iterative partial optimization
MODI	-	Modified Distribution Method
NP	-	Non-Polynomial
QM	-	Quality Management
SA	-	Simulated Annealing
SSM	-	Stepping Stone Method
TOM	-	Total Opportunity Cost Method
TORA	-	Temporary-Ordered Routing Algorithm
TP	-	Transportation Problem
VAM	-	Vogel’s Approximation Method

LIST OF SYMBOLS

i	-	index for existing warehouses and new candidate sites for relocation and consolidation; $i \in A$. $A = E \cup N$; $(j,i) \in (E \times A)$,
j	-	index for warehouse $(j = 1, 2, \ldots, n)$
k	-	index for customer $(k = 1, 2, \ldots, q)$
p	-	index for plant $(i = 1, 2, \ldots, P)$
q	-	total number of customers
n	-	total number of warehouses
P	-	total number of plants
C_{ijk}	-	cost of the shipment (from factory *i* to customer *k* through warehouse *j* including the relevant inventory cost
Q_i	-	quantity shipped from factory *i*
R_j	-	capacity of warehouse *j*
S_k	-	quantity required at destination *k*
X_{ijk}	-	quantity shipped from factory *i* via warehouse *j* to customer *k*
A_{ijk}	-	amount of inventory remained in warehouse *j* from the flow X_{ijk}
f_j	-	cost of locating a warehouse in point *j*
d_k	-	customer's demand
v_{kj}	-	the cost of one unit shipment to customer *k* from point *j* for each unit
x_{kj}	-	a fraction of r_k which is transported from *j* to customer *k*
y_i	-	will be equal to one if the candidate point *j* is selected, otherwise it will be equal to zero
c_{kj}	-	a table containing the cost associated to the supply
c_f	-	the fixed cost

cap_j	-	the max number of customer that it can supply
O_j	-	A Boolean vector indicating what warehouses has been opened or otherwise
S_{kj}	-	a matrix of Booleans indicating if customer *k* is supplied by warehouse *j*
D_k	-	$\frac{d_k}{\sum d_k}$ demand at market *k* as a fraction of total customer demand
S_i	-	supply available at plant *i*
s_i	-	$\frac{S_i}{\sum d_k}$ supply available at plant *i* as a fraction of total customer demand
s_j		supply available at warehouse *j* as a fraction of total customer demand
f_j	-	fixed cost of locating a warehouse at *j*
CAP_j	-	$\frac{cap_j}{\sum d_k}$ capacity of the warehouse at location *j* as a fraction of total customer demand
X_{ijk}	-	quantity of commodity transported from plant *i* to warehouse *j* to customer *k*
x_{ijk}	-	$\frac{X_{ijk}}{\sum d_k}$ quantity transported as a fraction of total customer demand
E	-	set of existing warehouses
N	-	set of new candidate sites for relocation and consolidation.
v_{pi}	-	unit production cost (including storage cost) at manufacturing plant p plus unit transhipment cost between manufacturing plant p and warehouse i
s_{ik}	-	unit warehousing cost at warehouse *i* and unit transportation cost between warehouse *i* and customer *k*

r_{ji} - cost of moving and relocating unit capacity j to consolidated site i $(j \neq i)$

c_j - throughput capacity of existing warehouse j

q_p - production capacity of manufacturing plant p

d_k - demand of customer k

f_i^c - cost per unit capacity of warehouse i,

f_i^m - fixed cost of maintaining warehouse i, excluding capacity cost.

f_i^s - cost saving resulted from the closure of existing warehouse i,

x_{ik} - volume of products shipped from warehouse i to customer k,

y_{pi} - volume of products supplied plant p to warehouse i,

vw_i. - throughput volume

o_b - the unit outbound shipping cost per unit product and mile

d_{ik} - the distance (unit) between warehouse i and customer k.

i_b - the inbound shipping cost per unit of product and mile

d_{pi} - the distance (unit) between manufacturing plant p and warehouse i.

rf_{ji} - fixed cost of relocation that is independent of capacity and distance but dependent onsite j and i

d_{ji} - the distance from the current location to site i at which it is relocated (consolidated)

rc_{ji} - the relocation cost per unit of capacity

r_d - the cost of moving a unit of capacity one mile away from the current location

a - represent the savings per unit of capacity released.

$F(x)$ - the objective function for the existing trial result

$F(x')$ - the objective function of the current entrant in the subsequent trial result.

T_0 - initial temperature

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Large scale manufacturing and distribution companies that deal with import and export, venders, transportation, and customs require large buildings for the storage of their properties. These large buildings are also known as warehouses and they can be found in industrial areas either in rural or urban areas.

Warehousing facilities are important to the overall supply chain development. Due to the continuous globalization and changes, there have been developments in the responsibilities, roles and strategies for warehouses. These developments cut across overall supply chain integration, ecological sustainability, information technology, and reverse logistics.

In recent times, the globalization and development of the trading scene has changed the commerce scene and the status quo. Thomas and Griffin (1996) suggested that the supply chain administration controls fabric stream among distribution centres, plants, providers, and clients effectively to destroy the supply chain. Shapiro (2000) stated that arranging, acquiring, fabricating, dispersing, and showcasing organizations along the supply chain have worked autonomously, but presently it may only be a procedure through which integration can be accomplished. The concurrent optimization of diverse capacities such as generation and dissemination, produce an effective stage which can assist companies to attain an assortment of logistics goals extending from low cost to high responsiveness.

The satisfaction of the demand from retailers involves a few decisions on the number, location, capacity, and shipping quantity between production centres and warehouses. According to Simchi-Levi et al. (2004), those decisions could consequently affect the companies design of supply chain network configurations which are considered as strategic decisions. The planned and long-term decisions are generally for corporations' engagement to launch facilities and therefore are not intended to be changed rapidly.

Nevertheless, both internal and external changes of the world have forced some companies to re-evaluate and face decisions to reposition the facilities or reallocate the functions to different facilities. Moreover, the redesigning must deal with simultaneous constraints and find an easy transition with a significant cost reduction and service improvement (Xu et al. 2009).

The relocation, capacity expansion or reduction decisions for existing facilities are included in the supply chain network redesign which also comprises the numbers, location, and capacity decisions for new facilities (Kiya and Davoudpour, 2012). This procedure involves the process of elimination (phase out), transfer or consolidation of existing facilities, which consist of network design events for both new and old facilities. Two factors distinguish between a primary design and a redesign project for a supply chain network. Firstly, the state of the existing facilities (i.e., the number, location, and capacity level of the facilities) that affect potential new sites. Additionally, every single change in the network state (phase out, capacity transfer, etc.) requires substantial capital investment and has a continuous effect on the efficiency of the supply chain events. Secondly, a redesign project should progressively be applied such that changing the state of existing facilities does not disrupt the typical activities of the supply chain. Henceforth, a redesign is more complex compared with the primary design of a supply chain network.

1.2 Background of the Problem

Many studies have been performed on facility location problems. These studies began by Weber (1909) who noted the effect of industrial location on transportation costs of raw material and final product. Baumol and Wolfe (1958) constructed the model for warehouse location problem without fixing the installation costs which resulted to deviations in the problem variables. In reality, fixed costs such as the cost to build or to rent the warehouse do relate to the location model. Akinc and Khumawala (1977) minimized the total costs of the system by including the fixed and variable costs allied with locating and operating a warehouse.

By looking at the role of a warehouse and the operations involved, there must be other costs that should be considered such as the zone dependent fixed cost. There were studies found in literature for zone dependent fixed cost in location theory but in redesigning a warehouse network problem this factor has never been considered. Zone dependent fixed cost has been widely discussed and shown its importance in location-allocation studies such as in Lim et al. (2011) and Irawan et al. (2017). Napolitano (2010) discussed the need to redesign a warehouse network and also listed dependent zones factors.

The idea for the warehouse redesign network began in 2000, when Melachrinoudis and Min (2007) proposed a Mix Integer Programming to help a firm called Beta who planned to consolidate their warehouses while offering a one-day delivery service to their customers. The proposal involved a consolidation of two or more existing warehouses to help the firm save the transportation, inventory, and warehousing cost due to economies of scale. The redesign strategy by Melachrinoudis et al. (2005), involved improvement by not only consolidating but also eliminating or closing sites (and its capacity lost) or its whole capacity is relocated and consolidated into other existing warehouses.

Based on the works discussed earlier, it can be seen that most of the problems are solved by consolidating and eliminating the existing warehouse. Consolidating the network should reduce inventory and fixed cost (see Figure 1.1a and 1.1b for examples of warehouse redesign network). Unfortunately, having fewer sites will also increase transportation costs and adding a new site might help to solve this problem. Figure 1.2 presents the scenario leading to the research problem considered in this study.

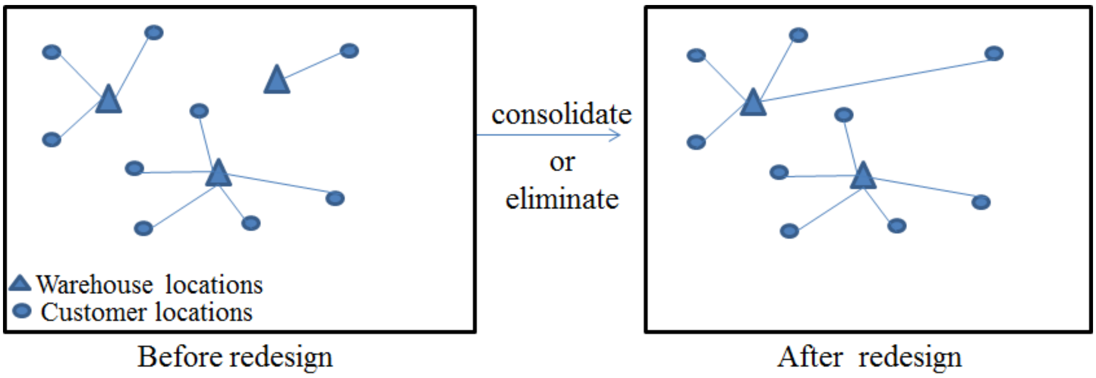

Figure 1.1a Example of warehouse redesign network using (a) consolidation or elimination strategies

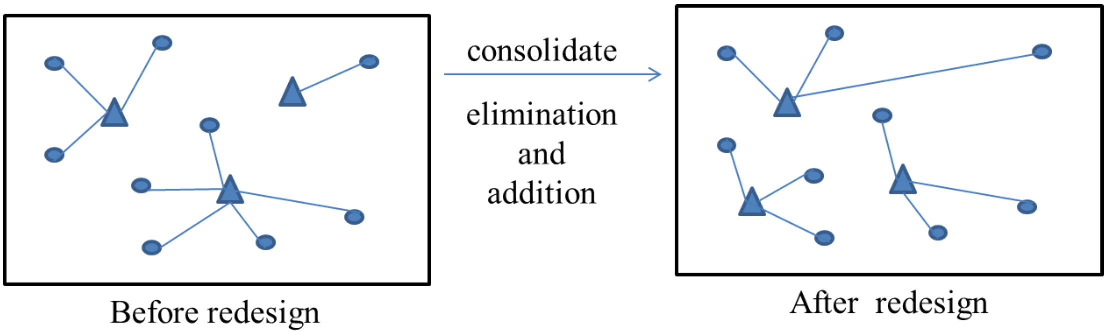

Figure 1.1b Example of warehouse redesign network using consolidation, elimination and addition strategies.

1.3 Problem Statement

Warehouse location model is one of the important researches in the location analysis field, but it is different from other types of locations because it is strongly affected by the current economic situation. However, if the economic situation changes after a certain period, the existing network model will need to be changed to get the ideal cost under the current economic situations. The current warehouse network redesign model does not include the consolidation, elimination, and addition of new warehouse. Therefore, the addition of a new warehouse, the closure of

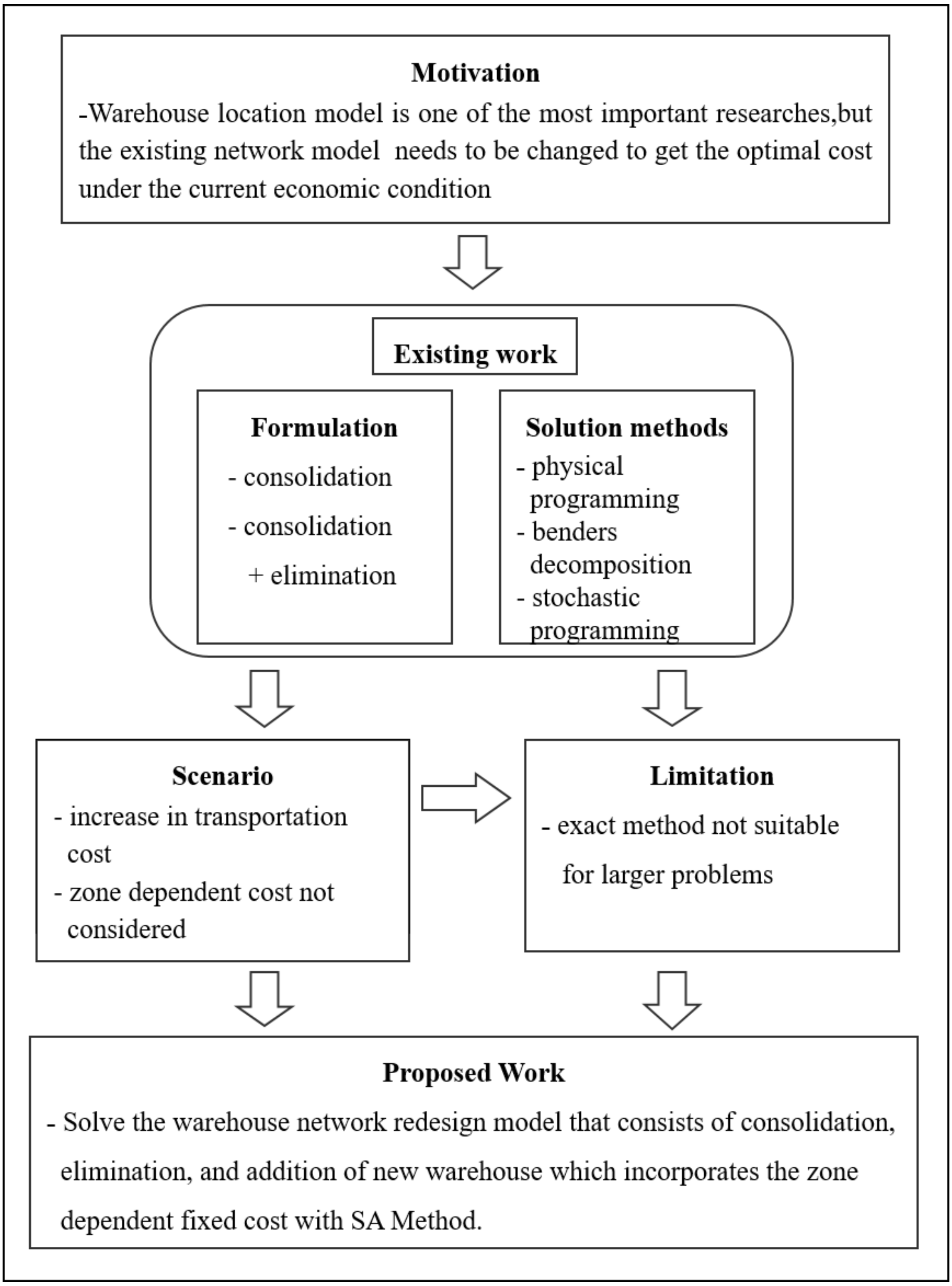

Figure 1.2 Scenario leading to the statement of the problem.

an existing warehouse or the consolidation should be considered in the original model to get a better cost. In addition, the current mathematical programming model for the warehouse network redesign problem also does not include consolidation, elimination, and addition of new warehouse.

Referring to Simulated Annealing method implemented in solving warehouse network redesign problem before, they did not consider investigating on variants cooling schedules. Dynamic stopping criteria and multi-start implementation in Simulated Annealing were also not considered. Moreover, previous warehouse network redesign models have never considered the network redesign factor involving the changes in zone network which includes the zone dependent fixed cost and capacity constraint. Zone dependent fixed cost is also crucial in the warehouse problem, so it should also be included in the warehouse network redesign model. Therefore, in this study, we will consider the warehouse network redesign model based on the additional criteria set above.

1.4 Research Questions

The problem statement raises several research challenges. These challenges will be addressed by providing answers to the following questions:

1) How can the consolidation, elimination, and addition of new warehouse be included in the current warehouse network redesign model, specifically for Mixed Integer Liner Programming model (MILP)?

2) What are the best initial temperature, cooling schedule, and stopping criterion to be implemented in Simulated Annealing?

3) How can the suggested dynamic stopping criterion and multi-start function be best embeded in the SA procedure so as to improve the overall result convergence?

4) How can the zone dependent fixed cost and capacity constraint criteria be included into the formulated MILP model?

1.5 Objectives of the Study

The objectives of the study are as follows:

i) To construct a Mixed Integer Linear Programming (MILP) model for warehouse network redesigning that minimizes the total supply chain costs by considering three strategies which are consolidation, elimination, and addition of a new site.
ii) To establish solution procedure for SA which includes variants of cooling schedules, dynamic stopping criteria and multi-start SA for solving the formulated MILP model.
iii) To modify the formulated MILP model by incorporating the zone dependent fixed cost and capacity constraint.
iv) To determine the optimal solution by solving the MILP model using the established SA solution procedures; and
v) To propose optimal strategies for warehouse network redesign problem based on analysis of the solutions.

1.6 Scope and Limitation of the Study

This study focuses on the redesigning of a warehouse network and also takes into account the zone dependent involved. This study will only consider a deterministic warehouse network redesign model. Redesign strategies that will be used for this study are elimination, consolidation, and addition of new sites. Private warehouse data from Eilon et al. (1971) and Khairuddin et al. (2007) will be used for testing purposes.

In the mathematical programming, single objective function will be used where the constraints will be modified accordingly. The solution method is from Simulated Annealing (SA) method while imposing dynamic stopping criteria and multi-start technique. When running the simulation, it is assumed that when a warehouse is consolidated into another warehouse, its total capacity is relocated to the nearest warehouse. It is also assumed no substantial changes in customer demands and the transportation infrastructure. For the baseline study, the manufacturing plant is given an equal capacity to serve the warehouse and such that there is an incapacitated allocation for any warehouse to serve the customer.

1.7 Novelties and Significance of the Study

This study focuses on developing a new Multi-start Simulated Annealing (SA) approach for warehouse redesigning model with zone dependent fixed cost and capacity constraint. Large size problem is solved with the heuristic method. In this study, warehouse network will be redesigned by using some selected parameters such as cooling schedule, probability ratio in geometric schemes, initial temperature, and stopping limit. These parameters will be implemented in such a way that it will produce the best SA algorithm applicable to the warehouse network redesign. Multi-start technique is introduced to improve the values of average cost and standard deviation while at the same time imposing the dynamic stopping limit to the algorithm.

The solution procedure is developed for solving the warehouse redesign model with consolidation, elimination and addition of new site. Finally, zone dependent fixed cost is introduced as one of the factors for redesigning the warehouse network. The effect of introducing zone dependent fixed cost will be analysed using literature data.

Three different distribution data sets are used in this study consisting of normal, clustered and dense data. For these three data types, it is found that initial temperature would be different for each of them, using various cooling schedules. All data types are suitable to be imposed with dynamic stopping limit than static stopping limit, since it gives more searching area for finding the best solution. Multi-start method introduced, being a population based heuristic method, will be able to improve the standard Simulated Annealing algorithm. Multi-start method is also used to avoid being trap in local minimum due to its function to start multiple times depending on the defined setting, thus giving better searching ability and area for finding the best solution.

The heuristic method used in this study is able to solve for best solution even in multitudes of data. The model introduced improves the former objective function by taking into account a more realistic costing, such as cost saving that can be achieved due to existing warehouse closure and consolidation as well as new warehouse opening. In addition, the proposed model is also able to suggest new strategic location because of the combination of location and allocation problem for placing a new warehouse. Furthermore, a new factor is introduced in the model which is zone dependent fixed cost which is suitable to redesign network problem. Companies that want to redesign their warehouse network ought to consider this factor because the new warehouse locations may be located in certain economic zones with different cost attributes.

When the zone dependent fixed cost considered in this study, the warehouse closest to the closed warehouse will be served a large number of customers due to their close proximity and this creates an unrealistic situation. Taking into account zone dependent fixed cost in the model solution, it would resolve to the warehouse with the most customers since it will be the optimum case. To solve this, a restriction is introduced called capacity constraint to limit the number of customers for a more realistic model.

1.8 Outline of the Thesis

This thesis contains seven chapters. The first chapter is the introduction. This chapter introduces the background of the problem, the statement of the problem, objectives, scope of study and significant of study.

Chapter 2 is the literature review. This chapter presents a literature review about the warehouse location problem, redesign a warehouse network, related works on warehouse redesign network, inventory cost on warehouse location problem, and review on solution methods for solving warehouse location problem.

Chapter 3 is the research methodology. This chapter presents the direction of the study and an overview of the method used. It begins with the general step of the research framework.

Chapter 4 until 6 presents the results of the research study. Whilst, Chapter 7 is the last chapter of this thesis which summarized all the conclusions of the presented work.

1.9 Summary

This chapter introduces the background of warehouse network relocation model and identify the opportunity to redesign it in order to minimize the total supply chain costs. The suggestion to include the consolidation, elimination, and addition of new sites by way of Simulated Annealing optimization method is emphasized. The Simulated Annealing method will incorporate variant cooling schedule, dynamic stopping criteria, and multi-start in order to optimize the solution. Other consideration is the addition of zone dependent fixed cost and capacity constraint in order to further refine the optimal solution. Next chapter will explore the literature in order to identify and understand the concept of warehouse location problem and warehouse redesign network.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter presents previous research on the warehouse location problem, warehouse network redesign, and zone dependency for addressing facility location problems in the literature. The issues and challenges, past models, methods and approaches will be identified. Main characteristics of the past warehouse location problem will be discussed and lastly, the research gap will be addressed.

2.2 Warehouse Location Problem

The problem of locating warehouses includes determining the number and magnitude of warehouses required to cater to various demand centres. The goal is to allot or quantify the number of warehouses and determine suitable warehouses to supply the demand centres at minimal total costs of distribution. The cost of distribution is the sum of the overall cost of transportation. This is supposedly conventional along with the warehouse building and operational costs Feldman et al., (1966). The problems of locating facilities are designed either to account for the location problem or a collection of encompassing location challenges.

Baclik and Beamon (2008) examined the challenges of designing robust models for locating suitable centres for distribution in a relief network. The study also evaluated the magnitude of relief supplies that should be stowed at respective distribution centres using an alternative to the optimal covering model for location. An approximate model using linear programming to determine appropriate environments was the subject of research carried out by Canel and Khumawala (2001). The study also highlighted that factors such as warehouse location that affect profit maximisation.

Typically, the problems associated with client-based warehouse management differ based on geographical location and the warehouses responsible for handling stocks. According to Sweeney and Tatham (1976), the suitable technique for addressing warehouse location challenges are based on the following ideals:

(a) possess the competency to practically assess the potential number, locations, and configurations of warehouses.
(b) possess the competency to timely assess various configurations of warehouses and flexibility to alter the desired configurations based on ever-changing patterns of demand and costs of supply.
(c) permits cost dependency between the site's warehouse through solitary and multiple periods. Consequently, the selection of sites is autonomous irrespective of the sites selected from previous periods of planning.
(d) manage non-linear factors based on the fixed and variable costs related to the substitute alignments and throughput of the system, respectively.
(e) permit practicable and effective computations during analyses.

2.2.1 Mathematical Modelling of warehouse location problem

This section presents the developments on mathematical modelling of warehouse location problems. In early 1958, Baumol and Wolfe (1958) introduced the first warehouse location model along with the parametric variations required to adapt such problems to the field of transportation. The objective function of the problem aims to reduce the total cost of delivery. The similarity to the current challenges of transportation is noticeable due to three (3) modifications. These changes typically include; the potential multi-dimensions of the objective function, warehouse volume occurrences, and the three subscript notation requirements for the variable X_{ijk}. Typically, this arises due to the need to channel separate flows via a warehouse. Statistically, the problem could be expressed by the relation:

Given

$i =$ index for plant $(i = 1, 2, \ldots, m)$

$j =$ index for warehouse $(j = 1, 2, \ldots, n)$

$k =$ index for customer $(k = 1, 2, \ldots, q)$

C_{ijk} = shipment costs (between the plant *i* and the customer *k* via warehouse *j*), which includes the applicable cost of the inventory.

Q_i = volume shipped out of plant *i*

R_j = size of the warehouse *j*

S_k = capacity required at destination *k*

Decision variables

X_{ijk} = Volume shipped out of factory *i* using warehouse *j* to the seller *k*

A_{ijk} = Volume of inventory outstanding at the warehouse *j* out of the flow X_{ijk}

$$\text{Min } \sum_i \sum_j \sum_k C_{ijk}\left(X_{ijk}\right) \tag{2.1}$$

subject to

$$\sum_j \sum_k X_{ijk} = Q_i, \quad i = 1, 2, \ldots, m \tag{2.2}$$

$$\sum_i \sum_k A_{ijk}\left(X_{ijk}\right) \leq R_j, \quad j = 1, 2, \ldots, n \tag{2.3}$$

$$\sum_i \sum_j X_{ijk} = S_k, \quad k = 1, 2, \ldots, q \tag{2.4}$$

$$x_{ijk} \geq 0, \quad \forall i, j, k. \tag{2.5}$$

The objective function (2.1) yields the total cost of delivery. Equation (2.2) ensures the total goods are shipped from the selected factory. Furthermore, Equation (2.3) ensures the capacity of each warehouse is not surpassed, whereas Equation (2.4) ensures that all the demands of the customers are satisfied and Equation (2.5) are nonnegativity constraints. However, the fixed costs such as the setting up of the warehouse are neglected during problems of warehouse location. Therefore, there are parametric variations that transform the problem into a transportation problem.

Akinc and Khumawala (1977), improved the model by integrating fixed cost into the problem of locating warehouses. All the assumptions in Akinc and Khumawala (1977) are comparable to earlier problems described in other works. However, the evident alteration is the introduction of the fixed cost of the location. Hence, the problem of warehouse location combined with fixed costs can be computed mathematically based on the relation:

Given

$j =$ index for warehouse $(j = 1, 2, \ldots, n)$,

$k =$ index for customer (k = 1, 2…q),

$f_j =$ fixed operating cost for warehouse j,

$d_k =$ customer's demand,

$s_j =$ an upper limit on the capacity of warehouse j

$v_{kj} =$ unit costs of shipment to the customer k from point j,

$c_{kj} =$ the per unit cost which includes the FOB cost at warehouse j, the warehouse handling cost and the outbound transportation cost from warehouse j to customer k.

Decision variables

$x_{kj} =$ amount to be sent from warehouse j to customer k

$y_i =$ equivalent to 1 for the selected contending point j, or else it is equivalent to zero.

$$\text{Min } \sum_{j=1}^{n} f_j y_j + \sum_{j=1}^{n}\sum_{k=1}^{q} c_{kj} x_{kj} \tag{2.6}$$

subject to

$$\sum_{j=1}^{n} x_{kj} = d_k, \quad k = 1, 2, \ldots, q \tag{2.7}$$

$$\sum_{j=1}^{n} x_{kj} \le s_j y_j, \quad j = 1, 2, \ldots, n \tag{2.8}$$

$$0 \le x_{kj} \le 1 \tag{2.9}$$

$$y_j = \{0,1\} \tag{2.10}$$

In theory, Equation (2.6) guarantees that the buyer's request is fulfilled based on the maximum quantity of x_{kj} which is unity (1). In addition, Equation (2.7) guarantees that the warehouse at point *j* attends to the buyer *k* provided a warehouse is sited at the location. Furthermore, Equation (2.8) and Equation (2.9) guarantee the buyers' demands are precisely fulfilled from a single operational facility and ensure that the facility is either opened or closed respectively.

Earlier models revealed that the demand of a buyer could be fulfilled by various warehouses. Subsequently, Naggy (2004) proposed a novel model with a constraint on the warehouses. Based on the model, a specific warehouse can only serve a selected number of customers. Therefore, every customer can only be serviced by a specific warehouse. This concept aims to ascertain the warehouse to open, and the distribution of the customers to these unlocked warehouses, so that the overall costs of maintenance and supply are reduced. The mathematical formulation is as follows:

Given

$j =$ index for warehouse $(j = 1, 2, \ldots, n)$

$k =$ index for customer $(k = 1, 2, \ldots, q)$

$c_{kj} =$ table of associated costs of the supply,

$c_f =$ is the fixed cost

$cap_j =$ the maximum number of customers that warehouse *j* can supply

Decision variables

$O_j =$ is a Booleans vector showing the open warehouses

$S_{kj} =$ is a Booleans matrices indicating if customer *k* is served by warehouse *j*

$$\text{Min } \sum_{k,j} S_{kj} c_{kj} + c_f \sum_j O_j \tag{2.10}$$

subject to

$$\sum_j S_{kj} = 1, \quad \forall k \tag{2.11}$$

$$\sum_{k} S_{kj} \leq cap_j, \quad \forall j \tag{2.12}$$

$$\sum_{k} S_{kj} \leq O_j, \quad \forall k, j \tag{2.13}$$

Hence, Equation 2.11 confirms that each buyer is supplied by a specific warehouse. However, Equation 2.12 guarantees that the capacity of each warehouse is static. Finally, Equation 2.13 guarantees that each buyer is only supplied by an open warehouse. The study by Sharma and Berry (2007) introduced a novel idea on the formulation and reduction of the single-stage capacity difficulties of locating warehouses. In this model, the multi-echelon logistics network comprising the plant, warehouse, and market (customer) are considered. The problem can be mathematically formulated as:

Given

i = index for plant $(i = 1, 2, \ldots, m)$

j = index for warehouse $(j = 1, 2, \ldots, n)$

k = index for customer $(k = 1, 2, \ldots, q)$

$d_k =$ commodity demand of customer, k

$D_k = \dfrac{d_k}{\sum d_k}$ Customer k demand based on the fraction of the total demands of the customer,

$S_i =$ Existing supply at plant i

$s_i = \dfrac{S_i}{\sum d_k}$ Existing supply at plant i based on the fraction of total demands of the customer.

$f_j =$ fixed costs of locating the warehouse j,

C_{ijk} = transportation cost of various goods from i to j and finally to the customer k,

$cap_j =$ volume of warehouse j,

\` $CAP_j = \dfrac{cap_j}{\sum d_k}$ capacity of the warehouse at location *j* as a portion of the total demand of the customer.

Decision variables

$X_{ijk} =$ Magnitude of the commodities transported from *i* (plant) to *j* (warehouse) and to *k* (customer).

$x_{ijk} = \dfrac{X_{ijk}}{\sum d_k}$ quantity transported as a portion of the total demand of the customer.

$y_j =$ will be equal to 1 if warehouse is located at *j*, 0 otherwise.

$$\text{Min } \sum_i \sum_j \sum_k c_{ijk} x_{ijk} + \sum_j f_j y_j \tag{2.14}$$

subject to

$$\sum_i \sum_j \sum_k x_{ijk} = 1 \tag{2.15}$$

$$\sum_j \sum_k x_{ijk} \le s_i, \quad \forall i \tag{2.16}$$

$$\sum_i \sum_j x_{ijk} \ge d_k, \quad \forall k \tag{2.17}$$

$$\sum_i \sum_k x_{ijk} \le cap_j, \quad \forall j \tag{2.18}$$

$$x_{ijk} \ge 0, \quad \forall i, j, k. \tag{2.19}$$

Equation 2.15 guarantees that the entire network flow of goods is equal to the entire market demand. Equation 2.16 confirms that the flow out of the supply is less than the total stock. In addition, Equation 2.17 guarantees the influx of goods at the selected market meets the point of specific demand. Lastly, Equation 2.18 ensure that each warehouse has a fixed capacity, whereas Equation 2.19 introduces the non-negativity constraints.

The entire models presented are fundamental to the development of future models for warehouse location problems proposed in the literature (Demirel et al., 2010; Jacyna-Golda et al., 2016; Jacyna-Golda 2013; Dey et al., 2015; Izdebski et al., 2016; Wasiak et al., 2016). However, additional constraints were introduced by Jacyna-Golda et al. (2017) to improve the studied models.

2.2.2 Related Works on Warehouse Location.

Murari (2010) suggested that determining the optimal location and applying this to the supply chain facilities is time-consuming. The objective function of the problem is to reduce the total costs of delivery. Therefore, the similarity to the customary problems associated with transportation is indisputable. However, there are three (3) changes, namely; the potential non-linear attributes of the objective function, existing capacity of the warehouse, and the three subscript notation requirements for X_{ijk}. This variable arises from the need to channel the flow into or out of each warehouse. Therefore, there is an evident need to approach the location problem by bearing in mind the collective effect of qualitative and quantitative factors Ada and Ozkan (2005). The location features are categorised into three (3) broad functional groups, namely; site, accessibility, and socio-economic environment.

Typically, the focus of the warehouse establishment is to incorporate the heuristic programme approach in solving the uncapacitated problem of warehouse location. Erlebacher and Meller (2000) highlighted that the formulated location-inventory problem is a non-linear integer programme that helps to reveal the different version of the heuristic algorithm for solving it. Subsequently, the authors compared their study findings with others obtained in the literature. The results were found to be equal to or better than those provided by the alternative methods considered. Furthermore, the authors stated that warehouse location is a non-convex programming problem that involves the geography and sizing of intermediate facilities in distribution studies. Lastly, the study stated that the non-convexities are caused by the economies of scale related to the building and operational costs of the facilities.

In practice, the techniques of integer programming optimisation can be used to address minor problems associated with locating warehouses. Conversely, heuristic or meta-heuristic approaches are employed for more complicated problems. Over the years, the problem of unoccupied warehouse location has garnered significant consideration in mathematical program design. Duran et al., (2011) examined the balance network structure for optimum supply at CARE International using an investment (inventory location, demand, and up-front) model based on mixed-integer programming. This system consists of the number of locations, the quantity, and type of aid supplies stocked by each registered warehouse.

According to Ravi (2005), dual and primal-dual processes are efficient for solving problems of uncapacitated warehouse location on the OR Library benchmarks. The dual-based algorithms can obtain a good approximation algorithm for the extraction of an excellent combinatorial. Lagrangian relaxation is a prominent procedure for computing the branched lower and algorithm bounds. The technique can also be employed to solve the problems associated with uncapacitated warehouse location. This method of relaxation is employed to create novel nonstop problems by relaxing the problem of matching that typically persists. Therefore, a post-optimisation (discretisation) step is introduced to gain the concluding discrete (binary) solution for mapping (Cour et al., 2006). Based on the selected location, the location of the warehouse can be detected and secured by the outlined technique. Besides, the technique introduces a minor guarantee for the problem of locating an uncapacitated warehouse according to the Lagrangian relaxation of a mixed-integer problem formulation. The study by Dupont (2008) proposed two algorithms (the branch and bound variants) to address the problem of locating a concave site facility with dependent costs.

Sharma and Berry (2007) introduced a novel design and reduction for a single-stage problem of locating a capacitated warehouse. In the study, the diverse interpretations and relaxations proposed were compared with one another. Due to the peculiarities of the warehouse location, conventional techniques cannot be used to solve these problems. Therefore, the use of heuristic and metaheuristic approaches are typically employed in the literature. The heuristics technique for warehouse location problem was pioneered by the Kuehn and Hamburger in the 1960s (Kuehn and Hamburger, 1963).

Subsequently, Whitaker (1985) proposed improvements to the original Kuehn and Hamburger (1963) algorithm. Whitaker (1985) developed the Greedy-Bump and Shift (Interchange) heuristic-based algorithms. Based on the greedy procedure, the warehouses are individually positioned at the most economically practical locations, provided no further warehouses can be included without raising the entire cost. However, the bump process guarantees that the uneconomic warehouses resulting from consequent warehouse placements are excluded. Lastly, the shifting process ensures that a warehouse at a separate feasible site in a similar region is shifted when the relocation reduces the total cost. Typically, such genetic algorithms have successfully addressed problems associated with locating the uncapacitated warehouse. Over the years, numerous studies such as Kratica et al. (2001) have revealed that the best results, which have excellent efficiency and high frequencies, can be deduced from the OR Library through genetic algorithms. Similarly, numerous explorative heuristic algorithms have been recommended, albeit with limited success.

The process of Simulated Annealing (SA) is an indigenous exploration technique developed by integrating statistical, mechanical, and optimisation principles. SA is a probabilistic technique. Therefore, SA is considered an influential instrument for deciphering numerous problems in the field of optimisation. Furthermore, SA is an algorithm typically implemented in computing global optimisation problems, particularly in computational chemistry and industrial engineering. However, the search for the best global values by SA is challenging, particularly in the absence of a logarithmic schedule for cooling. Deb (2011) previously reported that the technique provides an extensive review of early non-evolutionary and multi-objective techniques for optimisation. Therefore, its introductory algorithms for multi-objective are considered state of the art.

Typically, the two conventional approaches to evolutionary optimisation are generic algorithms and evolution strategies. These methods are concisely discoursed in general when selected as methods for consideration. However, the methods are regarded as elitist if the best solutions maintained are localized in the search, thereby allowing the flow of information Coello (2002). Typically, 5*n* neighbours are produced by the algorithm for every single iteration before migrating to the best neighbour that is neither forbidden nor add to the existing significance of the objective function. For every single iteration, the computational duration is significant, thereby hampering the practicality of the algorithm. Cura (2010) introduced an equivalent home-grown search approach to resolve the problems associated with locating uncapacitated warehouses. This robust yet straightforward algorithm is considered effective when applied in selected circumstances. Furthermore, the algorithm is designed for execution in either a multiple processor or multiple core system, which are standard configurations of any modern-day personal computer (PC).

In conclusion, the previous studies reviewed in this section of the thesis present a comprehensive understanding of the warehouse location problem. Therefore, most researchers have extended their work based on other methods. These works are described in the literature by Khumawala (1972), Davis and Ray (1969), Baker (1982), Kelly and Khumawala (1982) and Whitaker (1985) to provide better solutions to the problem of warehouse location.

2.3 Redesigning a Warehouse Network

The problems of warehouse network redesign comprise incorporating or eradicating issues associated with prevailing warehouses and the establishment of new sites. Typically, the redesign of a warehouse network includes the repositioning, enlargement or decrement of capacity and associated decisions for prevailing facilities. In addition, the redesign process includes decisions on the statistics, settings, and capacity of new structures. The process could lead to the abolition (removal), allocation or merging of prevailing amenities. Hence, a redesign venture involves network design actions required for both novel and longstanding facilities.

2.3.1 Mathematical Modeling of Warehouse Redesign Network

Before the development of the scientific model, several fundamental assumptions and modifications of preceding techniques are required. These include (1) The warehouse is isolated, and (2) The total capacity of a consolidated warehouse is transferred. Therefore, the redesign network problem of an uncapacitated warehouse could be expressed by Melachrinoudis and Min (2007) is as the following:

Given

i = index for plant $(i = 1, 2, \ldots, m)$

j = index for warehouse $(j = 1, 2, \ldots, n)$

k = index for customer $(k = 1, 2, \ldots, q)$

$A = E \cup N$; $(j,i) \in (E \times A)$, where E = set of existing warehouses, and N = set of new candidate sites for relocation and consolidation.

v_{pi} = Component costs of production (including storage cost) at an manufacturing plant. The term *p* is the additional unit cost for transhipment from manufacturing plant *p* to the warehouse *i*,

s_{ik} = Unit cost for warehousing at the warehouse *i* and unit cost of transportation from warehouse *i* to the customer *k*,

r_{ji} = Moving costs for moving a unit volume *j* to the merged site $i\ (j \neq i)$,

c_j = Output volume of the current warehouse *j*,

q_p = Output volume for the industrial plant *p*,

d_k = Buyers demand *k*,

f_i^c = Cost of a unit volume of the warehouse *i*,

f_i^m = Static cost of warehouse *i*, maintenance exclusive of volume cost,

f_i^s = Saved costs from the shutting of the current warehouse *i*.

Decision variables

x_{ik} = Total products transported to customer *k*, from the warehouse, *i*

$y_{pi} =$ Total products delivered to the warehouse i, from the plant p,

$$z_{ji} = \begin{cases} 1, & \text{if capacity of warehouse } j\left(j \in E\right) \text{ is relocated to site} \\ & i\left(i \in A, i \neq j\right) \text{or if existing warehouse } j\left(j \in E, i = j\right) \text{ remains open} \\ 0, & \text{otherwise.} \end{cases}$$

$$w_i = \begin{cases} 1, & \text{if a new warehouse is established at site } i\left(i \in N\right), \\ 0, & \text{otherwise.} \end{cases}$$

$$\text{Min} \sum_{p \in P} \sum_{i \in A} v_{pi} y_{pi} + \sum_{i \in A} \sum_{k \in C(i)} s_{ik} x_{ik} + \sum_{p \in P} \sum_{i \in A} r_{ji} z_{ji} + \sum_{i \in A} f_i^c \sum_{j \in E} c_j z_{ji} + \sum_{i \in E} f_i^m z_{ii}$$
$$+ \sum_{i \in N} f_i^m w_i - \sum_{j \in E} \left[f_j^s \left(1 - \sum_{i \in A} z_{jk} \right) + f_i^m \sum_{\{i \in E, i \neq j\}} z_{ji} \right] \qquad (2.20)$$

subject to

$$\sum_{i \in A} y_{pi} \leq q_p \quad \forall p \in P, \qquad (2.21)$$

$$\sum_{p \in P} y_{pi} \leq \sum_{k \in C(i)} x_{ik} \quad \forall i \in A, \qquad (2.22)$$

$$\sum_{k \in C(i)} x_{ik} \leq \sum_{j \in E} c_j x_{ji} \quad \forall i \in A, \qquad (2.23)$$

$$\sum_{i \in D(k)} x_{ik} = d_k \quad \forall k \in K, \qquad (2.24)$$

$$\sum_{j \in E} z_{ji} \leq |E| z_{ii} \quad \forall i \in E, \qquad (2.25)$$

$$\sum_{j \in E} z_{ji} \leq |E| w_i \quad \forall i \in N, \qquad (2.26)$$

$$\sum_{i \in A} z_{ji} \leq 1 \quad \forall j \in E, \qquad (2.27)$$

$$x_{ik} \geq 0 \quad \forall i \in A, k \in K, \qquad (2.28)$$

$$y_{pi} \geq 0 \quad \forall p \in P, i \in A, \qquad (2.29)$$

$$z_{ji}, w_i \in \{0,1\} \quad \forall j \in E, i \in A, \qquad (2.30)$$

The objective function Equation 2.20 reduces the total cost for the supply chain, which consists of manufacture, passage, storage and transfer. This occurs while exploiting the savings cost ensuing from the shutting or merging of empty warehouses. The constraint Equation 2.21 verifies the dispatch of the cumulative volume of items to the delivery centres or storerooms does not exceed the boundary of the industrial plant delivering such items. Constraint Equation 2.22 confirms that the entire bulk of the goods delivered to every warehouse by the production plant equals the total bulk of goods distributed to buyers from a specific warehouse. Consequently, the arriving volume of shipment for respective warehouses must correspond to the departing shipment.

Constraint Equation 2.23 ensures that the overall bulk of goods transported does not surpass the output capacity (after merging) of the warehouse serving the buyers. Constraint Equation 2.24 aims to accomplish the requests of the customer. However, constraint Equation 2.25 states that the prevailing capacity (or assets) of an existing warehouse must not be combined with another warehouse except the combined warehouse remains open. In this case, the term $|E|$ represents the cardinality of set *E*. Likewise, constraint Equation 2.26 states the boundaries of any existing warehouse or centre of distribution will not be transferred to an alternative location except the warehouse is constructed on a fresh site. Lastly, the constraint Equation 2.27 ruminates on numerous selections for the prevailing warehouse, *j*. The available selections are the warehouse stays open$\left(z_{jj}=1\right)$, or its bulk is merged with a current standing warehouse $i \in E,\ i \neq j\ \left(z_{ji}=1\right)$. However, its bulk could also be repositioned to a novel location $i \in N\ \left(z_{ji}=1\right)$, or a standing warehouse *j* is shut $\left(z_{ji}=0,\ \forall i \in A\right)$. The constraints in Equation 2.28 and Equation 2.29 confirm the non-negativity or decision factors x_{ik}, y_{pi}. Lastly, the constraint Equation 2.30 state that the factors z_{ji} and w_i are zero-one integer variables.

2.3.2 Estimation of Cost Parameters

Based on Melachrinoudis and Min (2007), the consolidation decision was suitably modelled by openly splitting the factor of costs into two constituents. These include; the costs of capacity and direct throughput. Therefore, the warehouse costs are categorized as;

(a) Fixed costs, which is autonomous from output volume as previously described,

(b) The bulk costs such as the depreciation of various infrastructure and equipment in the warehouse, along with other factors such as labour and ancillary costs, which are autonomous to the output volume.

(c) The proportional costs to output volume.

For instance, the merging of a warehouse with another of similar volume requires that the resulting cost of the capacity is greater than or double the costs before the merger. Likewise, it is expected that the fixed and direct unit output costs are unaffected by any measure to the freshly merged warehouses.

Consequently, the elemental costs of the warehouse *i* include the fixed cost, f_i^m, unit capacity cost, f_i^c, and warehousing cost per unit of output volume, vw_i. The initial terms were previously described in Section 2.3.1. The third element of cost is included in the cost parameter s_{ik}. i.e., $s_{ik} = vw_i + o_b\left(d_{ik}\right)$, where o_b is the unit departing unit cost per mile for each shipment and, d_{ik} is the distance (in miles) from the warehouse i to the buyer *k*. Similarly, the parameter v_{pi} integrates the unit cost of production and storage of the production plant *p*, u_{pi}, in addition to the unit cost of the shipment from the production plant *p* and the warehouse *i*, $v_{pi} = u_p + i_b\left(d_{pi}\right)$. The term i_b represents the arrival unit cost per mile for each shipment, whereas d_{pi} represents the distance from the warehouse *i* to the production plant *p*.

The cost of relocation is significantly reliant on the volume of a standing warehouse at the selected location *j*, which is to be repositioned $\left(c_j\right)$ along with the distance $\left(d_{ji}\right)$ from its present (consolidated) position at the new location *i*. Although the fixed costs of moving the warehouse are autonomous to volume and distance, it is reliant on the onsite position *j* and *i*, $\left(rf_{ji}\right)$. Therefore, the repositioning costs for *j* to a new warehouse location, *i* is $r_{ji} = rf_{ji} + \left(rc_{ji} + \mathrm{r}_d\left(d_{ji}\right)\right)c_j$. The term rc_{ji} represents the cost of a unit of volume of transfer, however, r_d is the unit moving cost of a volume per distance far from the present location. This factor is accounted for on a *pro-rata* basis annually for the scope of planning with the intention of making r_{ji} the yearly cost. Lastly, the concomitant redeemable costs accrued from terminating the warehouse *i* comprises the fixed cost, f_i^m, the cost per volume, along with the proceeds from asset sales on an annual prorate basis for the scope of the plan, $f_i^s = f_i^m + ac_i$. Here the term, *a* denotes the costs saved per unit volume of the items despatched.

According to Leonard (2009), parametric optimisation is crucial to upholding the cost of statistical value where it is valid or parallel to the comparable historical data. To ensure success, it is crucial to have a detailed inquiry of associated datasets. In addition, the projected costs should be established to obtain the highest cost with the aim of designing an effective cost for the model parameters. Next, the model will be further developed using a computed relation ranging from a simple thumb rule to a complicated equation of regression. The study by Dysert (2008) highlighted the merits of appraising the parameters, as follows:

i) Effective: Saves time without complex methods,
ii) Objective: Totally based on the quantity,
iii) Reliable: Offers a reliable format or documentation for valuations,
iv) Flexible: Variety of models and applications are simply modified,
v) Defensible: Delivers significant numerical relations and standards for assessing additional developments.

However, Dysert (2008) highlighted some flaws in estimating the parameters. One notable example is that the process is inferior to the ensuing model, which can be ascribed to the program’s inability to execute good data. However, numerous variables could trigger the expenditures of the total input of cost and the production (output) of the warehouse to be identified. In the study by Richards (2010), a simple flowchart for the general distribution cost and a cost-tree for the warehouse are constructed as helpful guidelines.

2.3.3 Related Works on Warehouse Redesign Network

Despite the importance of redesigning and reshaping existing networks, there is limited information on the subject in the literature. The study by Melachrinoudis and Min (2000), recommended a multiple objective-based models for the repositioning of a unit facility. Hence, the bulk could be transported from the current location to the terminus facility. Nevertheless, the consideration that the total network capacity could be extended or reduced is neither abandoned nor ambiguous. Lastly, commercial based software was used to compute the ensuing mixed-integer linear program (MILP).

Melo et al. (2005) suggested an all-inclusive model for the subject area. Therefore, the tactical decisions for reform are unrestricted based on a level or facility. The size of the facilities can be relocated to some extent, as an integer or in a continuous manner, to an alternative location. Similarly, the increase or decrease of the total capacity of the network is possible. Another concern is the budget constraint on redesign choices for the property. However, the authors could not proffer a potential procedure to resolve the MILP model.

Melachrinoudis and Min (2007) presented a solution to a redesign problem for a warehouse network. The planned decisions for redesign comprise the phase-out, size allocation (or merging) of prevailing warehouses, and the establishment of novel locations. The decisions regarding the repositioning are deliberated on at the same time for several facilities. However, the limitation on the distance from the warehouse to the buyer is noteworthy. Therefore, decisions regarding redesign are required to prevent the interruption of the warehouses' capacity to satisfy the demands of the customer. One approach is to relocate the capacity through the phase-out of the warehouse or reduction of the total size of the network. However, the entire increase in capacity was not reflected. Furthermore, the single source condition is demonstrated without bearing in mind the uncertainty or multiple sourcing dynamics. Lastly, the MILP model was resolved by partly reducing the integer parametric allocations joined with the rounding techniques.

Anaraki et al. (2009) upgraded a network model for redesigning a warehouse. The study deliberated on the lead times for delivery and due dates for goods requested by customers along with factor or warehouse size. The decisions for redesign, as demonstrated by the study, are tactical and thereby necessitate considerable investment in capital. Furthermore, the choices considerably influence the activities of the operation and consequently the total cost per unit of the goods. Based on the explanations, the choices for redesigning networks are required to uphold the necessary optimality or near optimality throughout the lifetime of the supply chain. However, the parameters, including demand or cost of operation, cannot continue to be constant over extended periods.

Therefore, the ambiguity of the operational parameters is one of the inescapable parts of the project redesign process. Certainly, the application of tactical decisions that do not deliberate the indecisive expectations are prone to high risks. Subsequently, the study by Farhad and Hamid (2012) presented a stochastic program for redesigning a warehouse network under improbability.

2.4 Solution Methods for Solving Warehouse Location Problem

Facility location is an essential criterion in the supply chain and influences operational logistics. The location of the facility affects the cost of transportation and lead time required to increase the efficiency of satisfying the demands of customers (Santosa and Kresna, 2015). Numerous methods have been implemented to resolve the difficulties of warehouse location such as the linearization of Euclidean distance (You et al., 2019), simulated annealing (Budi and Kresna, 2015) and genetic algorithm (Gültekin, 2018).

The problem of warehouse location requires defining one (or multiple) sites as centres for assembling or dispensing various materials or goods. These locations are responsible for serving various customers distributed over a geographical region, at minimal total costs of transportation. The most common and extensively adopted method for resolving the warehouse location problem (WLP) is the algorithm called the weighted *k*-means. Nevertheless, the algorithm is not a widely considered method, since it continually traps the local optima. In addition, it is considered vulnerable to preliminary settings during application. The numeric instances of the study showed that the solutions deduced from the weighted *k*-means tend to digress from the optima by approximately 16.8% on average.

You et al. (2019) presented a novel approach for optimal programming for resolving a WLP based on mixed-integer linear programming (MILP). The approach used a commercial solver to resolve the problem without an initial solution optimally. For sizable datasets, the authors established the MILP-based dynamic, iterative partial optimisation (MILP-DIPO) approach. The technique functions by identifying and examining the near-optimum findings under a manageable time of computation. Conversely, Micale et al., (2019) proposed the collective ELECTRE TRI and TOPSIS based design method under an uncertain environment. The study was aimed at sufficiently addressing the indecision of the selection process. Hence, an intermission was suggested and added to the ELECTRE TRI and TOPSIS method. Therefore, the ELECTRE TRI is first utilized to assign goods to various levels on the shelf, while subsequently, the TOPSIS is used to regulate the best sites for storage on each level. In practice, the TOPSIS approach is an alternative to the policy of random assignment. The entire procedure was designed with the collaboration of a firm in Sicily that delivers logistic facilities in Italy.

Larco et al. (2017) suggested a novel storage allocation methodology based on MILP. The objective of this multi-objective method was to reduce the cycle time for organising orders that cause distress to staffs. Contrariwise, Ene and Öztürk (2012) deciphered the issue of class allocation storage using MILP and a genetic algorithm. Hence, the objective of the study was to reduce the commuting duration for the recovery and storage of goods in the car business. Likewise, Fumi et al. (2013) answered the problem of storing and allocating multiple products in a gift production firm. The study adopted a numeric scientific model and an enthusiastic policy to diminish the overall sites used by the firm. Ang et al. (2012) suggested the use of a robust model of optimisation to reduce the total costs of storage based on selected factors of demand. Lastly, Bodnar and Lysgaard (2014) established an algorithm based on vibrant programming to decrease the entire quantity of replacements in a firm.

A heuristic model comprising sequencing and location was implemented by Wutthisirisart et al. (2015). The model was suggested to reduce the travel distance of order preparation. Also, Guerriero et al. (2015) designed deployment heuristics to assign locations and reduce handling costs, considering product compatibility factors in multi-level warehouses. On the other hand, Boysen and Stephan (2013) introduced a location-allocation algorithm based on dynamic programming and two greedy heuristics to reduce the travel distance of order preparation. Lastly, Accorsi et al. (2012) established an efficient procedure based on hierarchical descent, which permits the combined use of consecutive stages for selecting and allocating storage

Pan et al. (2015) implemented an inherent algorithm that addresses the allocation of storage in a multi-collection pick-and-pass system. The objective of the algorithm was to control the suitable spaces for storing each product and equilibrate the capacity of respective zones selected by the firm. Conversely, Cruz-Domínguez and Santos-Mayorga (2016) suggested an artificial neural network and genetic algorithm-based system for the apportionment of storage. The combined ANN algorithm adapts precise responses with the aim of reducing the distance between primed orders. The study by Guerriero et al. (2013) established a model based on a narrow iteration-based search. The objective was to resolve the issues associated with assigning locations for storage based on multilevel and competent compatibility constraints. Besides, Kim and Smith (2012) deciphered the difficulties linked to allotting storage based on simulated annealing. The study was established based on interrelated interchange, which is typically required to reduce the processing duration for orders. Lastly, Chen et al. (2010) adopted the taboo based search approach with the aim of lessening the processing during an automatic system for storage.

The study of Antunes and Peeters (2001) was aimed at evaluating the capabilities of Simulated Annealing (SA) in dealing with complex, real-world, and multi-period location problems. The results showed that SA is a useful tool for solving these types of models. According to Righini (1995), the recent development of SA applied to Combinatorial Optimization (CO) is mean-field annealing (MFA). The MFA is a technique inspired by the analogy of the physical annealing process in systems of magnetic spin interaction. Hence, the MFA is a deterministic version of Simulated Annealing (SA).

Drezner et al., (2002) proposed five heuristic procedures for the solution of the multiple competitive facilities location problems. The authors performed extensive computational tests and concluded that a two-step heuristic procedure combining Simulated Annealing and an ascent algorithm provides the best solutions. In general, the annealing procedure provides better solutions for small problems when allowed to run longer than the Lagrangian method (Syam, 2002). Rajagopalan et al., (2007) suggested that Simulated Annealing gives excellent results with minimal computational effort (time) for particularly significant problems.

2.4.1 Simulation Method

Franzke et al. (2017) proposed the agent-based simulation approach. The objective of the study was to estimate the influence of assigning storage and routing on functional efficiency of physical processes for selecting orders. Besides, Gagliardi et al. (2014) recommended the adoption of isolated simulation-based events. The objective was to enhance the comparison between the distance journeyed based on diverse strategies for allocating storage in computerized settings. Lastly, Yang (2008) proposed the adoption of isolated simulations tools for appraising system performance. The proposed system was designed to account for diverse strategies for preparing and storing orders.

2.4.2 Policies and Rules Method

There are several pertinent researches on policies and rules methods. The most notable include the paper by Sharma and Shah (2015) whose study proposed a solution for assigning different classes and volumes for storage. Similarly, Meneghetti and Monti (2014), developed a novel strategy for energy-efficient storage. Notable authors, including Yu and de Koster (2013), have also modified archetypal allocation models for storage dedicated to the optimisation of various variables from processing travel time to sales policies on capacity. Conversely, the study by Zaerpour et al. (2013) examined the influence of processing time, classes, and rotation on the random strategies for allocating forms in warehouses. Xiao and Zheng (2010) examined the associated strategy for assigning storage in a high-volume block and aisle warehouse. The investigation was based on the evidence deduced from manufacturing zones. Similarly, Bindi et al. (2009) examined the associated plans for allocation by developing and testing diverse guidelines and methods for grouping. Lastly, Ho and Liu (2005) determined various guidelines and sites for linked storage in separate zones.

2.4.3 Multi-criteria Method

Fontana and Nepomuceno (2017), proposed a model for apportionment based on Electre III. The program was designed specifically to cater to the features of goods in a multiple layered warehouses. In addition, the objective was to improve the order preparation time and inventory control. Similarly, da Silva et al. (2015), proposed a methodology based on multiple criteria. The Smarter based technique permits the organisation and assignment of products in a decreasing manner in the warehouse. The objective is to determine the best or worst selections for locating the respective products.

2.4.4 Other solution trends and support tools

Pang and Chan (2017) adopted data mining principles to develop a novel algorithm for allocating storage. The proposed technique reveals the relationship amongst goods with the goal of limiting the distance covered during the storage and recovery of the goods. Choy et al. (2017) revealed developed an intelligent system based on the classification of radio frequency and fuzzy logic using the DSS program. Likewise, Hui et al. (2016) proposed a novel decision-making system based on cloud infrastructure and fuzzy logic. The objective of the system was to enhance the apportionment of sites in a food-packaging business. Lastly, Lam et al. (2009) established an intelligent system with the features of fuzzy rules and online analytical processing. The objective was to promote data accessibility and incorporate human information for addressing decisions of storage locations in a system.

2.5 Gap Analysis

In this section, the gap that exists in various literature for redesigning warehouse network problems earlier discussed is presented. Table 2.1 summarises the contributions of each of the previous studies and their shortcomings.

A number of previous researches were based on model developed by Melachrinoudis and Min (2007). The model was intended to minimize the overall operational cost by consolidating adjacent warehouses and increasing warehouses operational efficiency by adding constraint to minimize the time taken for customers to receive their orders. Even so, within some area this constraint is unfulfilled because of long delivery distance from the nearest warehouse to customer location. The objective function in this model does not include the associated cost with opening a new warehouse. Instead, the objective function covers the transportation cost from the warehouse to customer and from the warehouse to plant, consolidation cost if there is warehouse consolidation, and operational cost for running the warehouse.

Later research would use the said model with little changes, most of them listed in Table 2.1 did not consider the addition of new site. Previous research also used small size data while some implemented commercial software. The differences among the research are ranging from adding new constraint such as delivery date and times, using case studies as data source, and changing the objective function partly by considering the cost saving achievable if there is warehouse closure but no demand for opening new one. Melachrinoudis and Min (2007) introduced a model to assist a company from the United States of America to minimize operational cost and improve their service by declaring that customers in certain vicinity radius will receive their orders quicker. As in Table 2.1, other weakness identified in the previous study includes the non-ideal warehouse location, no additional warehouses, and no potential warehouse sites.

Table 2.1 Review on warehouse redesigning network problem

Reference	**Contribution**	**Limitation /remarks**
Melachrinoudis and Min (2007)	• Stated the need for redesigning a warehouse network.	• Focuses on relocation to existing facilities. • No detailed graphical presentation before or after redesigning the network.
Melo et al. (2005)	• Improved on previous studies by introducing a more comprehensive model.	• Failed to recommend any answer or procedure for the proposed MIP based model.
Melachrinoudis and Min (2007)	• Suggested a mathematical model for redesigning warehouse network, which considers the costs of consolidation, phase out and savings. • Increased the delivery time to improve quality service.	• Specified new sites but did not account for the cost of the additions. • The new site was at a non-strategic location. • Solved a case study with a small scale problem using the software.
Anaraki et al. (2009)	• Reported increased delivery constraints due to date and times.	• Only considered the consolidation cost and no potential site for a new warehouse.
Sridurongkatum (2010)	• Complete case studies with their fixed cost estimation, as there is no accurate data.	• The small problem scales. • No additional of a new warehouse. • Only considered the consolidation but not consolidation costs in the objective function.
Farhad and Hamid (2012)	• Introduced a stochastic programming approach to re-designing a warehouse network under uncertainty.	• Only considered consolidation costs but not the potential site for a new warehouse.

Based on the findings in Table 2.1, several steps are proposed to overcome the weaknesses. Therefore, Table 2.2 presents a detailed list of potential suggestions for improvement. First, the previous model did not suggest strategic location for new warehouse, so this study improves it by combining location and allocation criteria for proposing new strategically located warehouse taking into account customer and plant location. With that, objective function should include the related cost of new warehouse opening and not just the operational cost of existing warehouses.

Table 2.2 Knowledge gap in the study

	Weakness in previous study	**New Contribution / Remarks**
1.	The new proposed site is not strategic, which is far from the customer. Hence, this may be randomly suggested as reviewed by Melachrinoudis and Min (2007).	Suggests a model that considers the addition of a new warehouse with a more strategic location.
2.	All mathematical models show a new site calculation on only operating costs.	The objective function needs to account for additional new warehouse costs and not just the operational cost.
3.	The problems are mostly resolved with software due to the small size, except for the test problem by Farhad and Hamid, (2012).	Solve redesign warehouse network problems on a larger scale to see how models can solve larger network sizes using the heuristic method of SA.
4.	Most of the redesign factors account for delivery times, as suggested by Melo (2005), although more factors can be considered.	Considering new redesign factors such as introducing zone dependent fixed cost problem.

Other observed models only implemented a small data size that could be solved using certain commercial software. With the increase of data size, this method would prove challenging thus necessitate the use of heuristic method. This study proposes to use Simulated Annealing as the base metaheuristic method to solve the warehouse redesign network problem. The advantages include its flexibility and its ability to approach global optimal over other local search methods. Weakness identified within Simulated Annealing includes it lone search method for finding the best solution which would require longer time, even more with big data size. Therefore, multi start with dynamic stopping criteria is introduced in this study to overcome the said problem.

This multi start method will give more searching area for Simulated Annealing algorithm to find its best solution without being trapped in any local minima.

Some previous researches in warehouse network design only took into account the time of delivery while there is other factor that could be considered such as zone dependent fixed cost. This factor is seen as important because in the event of warehouse closure due to unseen circumstances, the customers need to be diverted to other nearby warehouses. With this event, adding capacity constraint criteria will avoid over capacity in the nearby warehouse. The model presented in this study will suggest improvement from the previous model with adding the zone dependent factor with capacity constraint. As such, the new strategic warehouse location will examine the cost for every zone and warehouse capacity.

The knowledge gap identified is focused on the development of the redesign warehouse network model by integrating zone dependent fixed cost and the addition of a new potential site of a warehouse at a strategic location.

2.6 Summary

In conclusion, this chapter has explained the concept of warehouse location problem and warehouse redesign network based on the content found in literature. The review on warehouse location, redesigning warehouse network and the solution methods that have been used to solve the warehouse location problem provides very useful and practical information that can be benefited when formulating and solving the model of this study.

The gaps leading towards building the research problems had been identified in the literature where in this study an improvement by combining location and allocation criteria for proposing new strategically located warehouse taking into account customer and plant location. With that, objective function should include the related cost of new warehouse opening and not just the operational cost of existing warehouses.

Lastly, advantages and disadvantages of using SA in this research topic had been clarified in the literature review section in order to lead on the development of new research methodology. The model presented in this study will suggest improvement from the previous model with adding the zone dependent factor with capacity constraint. As such, the new strategic warehouse location will examine the cost for every zone and warehouse capacity.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter discusses a method of solving a redesign warehouse network problem. The main steps of Simulated Annealing and its implementation to solve multiple facilities problems are further described in detail. The Transportation Problem method used for allocation of a customer to a warehouse and allocation of the warehouse to plant is discussed further in this chapter.

3.2 Research Framework

Figure 3.1 illustrates the workflow executed in order to complete this study. The beginning of research was to acquire three sets of warehouse network location. This location was obtained from the location allocation problem analysis in Khairuddin et al. (2007) which covered three data distribution types (uniform, cluster, and dense). In Khairuddin et al. (2007), the analysis of plant and warehouse location model was using the customer distribution data from Eilon et al. (1971). Afterward, based from the model developed by Melachrinoudis and Min (2007) a redesign of existing network distribution was done to determine the most suitable parameter for Simulated Annealing model.

In the Simulated Annealing model, the first analysis performed was in selecting the most fitting cooling schedule for the obtained distribution data. Comparison was done in three types of cooling schedule: linear, logarithmic, and geometric. After picking the most appropriate cooling schedule, initial temperature needed to be fixed due to fact that the number of data and types of distribution were different. To estimate the initial temperature, a couple of approaches by Yaghini (2010) were implemented.

Lastly, study was done to ascertain the best stopping criterion either using static or dynamic method. Since Simulated Annealing is well known as implementing random search method, a technique called Multi-start Simulated Annealing was introduced to allow the model to find the best solution while not being trapped in the local minimum, other than to function as other population-based heuristic. This will be further discussed in Chapter 4.

After deciding the deemed suitable Simulated Annealing parameter, this parameter is adopted to find the solution of the warehouse network redesign problem by improving the earlier model from Melachrinoudis and Min (2007). Three redesign methods implemented were consolidation, closure, and addition of new sites. Specific method that was improved in this study is addition of new warehouse where the location is suggested strategically based on model in the prior location allocation study. The details of this method is discussed in Chapter 5.

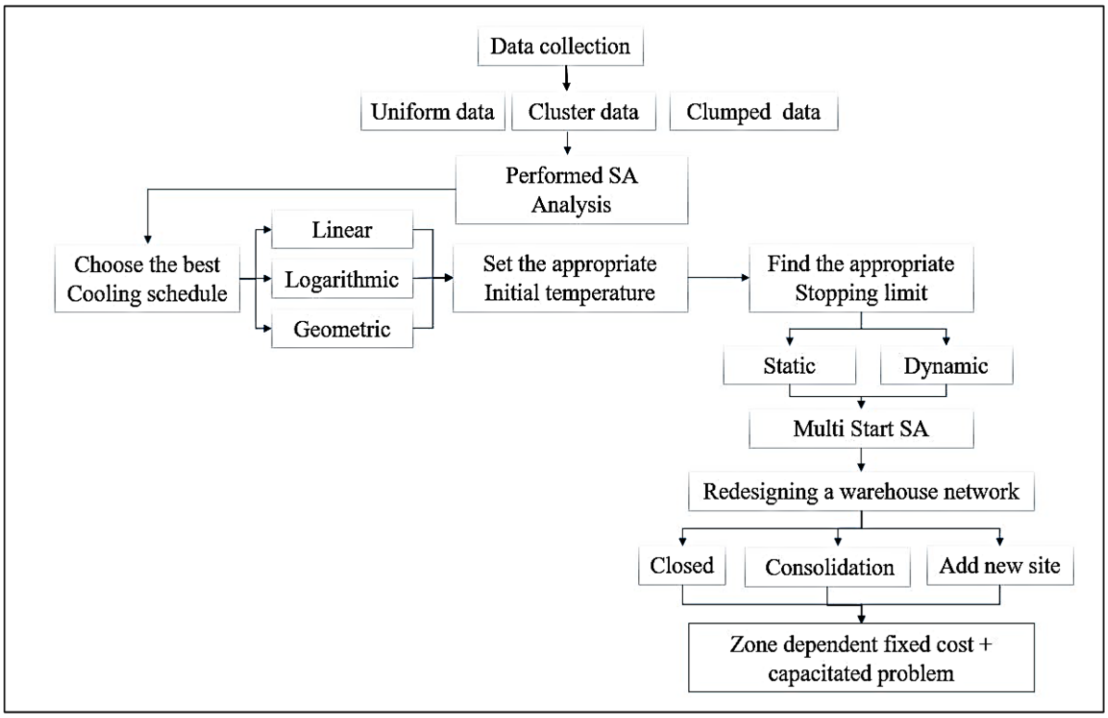

Figure 3.1 Research framework

Another factor not considered in other previous studies of warehouse redesign is zone dependent fixed cost. Therefore, this factor is included here by dividing the network area in certain zones with different cost. So, the selection of warehouses that would be opened, closed, or consolidated is determined by the zones fixed cost. Usually, the warehouse with the lowest zone cost and higher number of customers is more likely to be opened. Henceforth, the network capacity needs to be fixed for each warehouse for more realistic model, given the actual constraint. The details are in Chapter 6.

3.3 Methods for Solving Location Problem

Most location problems are recognised as NP-complete combinatorial optimisation problems that have been stimulated with several robust, precise, or approximate solution methodologies (Tijink, 2017). Typically, the algorithms used to solve these types of problems are generally combinatorial. According to the basic strategies, such problems may be classified as decomposition, enumeration or heuristics Mateus et al. (1991). The main difficulty in solving the problem arises from the non-convex nature of the objective function Cooper (1964). As such, it generally contains a large number of local minima. Due to the complex shape of the objective function, the problem falls within the realm of global optimisation. Several heuristic methods have been proposed to solve these problems.

Global search heuristics or meta-heuristics is a general solution method that provides both a general structure and strategic guideline for developing a specific method to fit a particular kind of problem. These methods can escape from local optimum by (i) hill-climbing techniques since non-improving moves are also accepted, (ii) introducing a new neighbourhood and (iii) allowing perturbation or infeasibility to guide the search. In (i), the allowance of uphill moves provides the ability to escape from the local minimum. Unlike in the steepest descent, there is no mechanism to move out of the local minimum.

Some techniques use random sampling and increase the neighbourhood size to avoid becoming trapped in the local optimum, but these are not always entirely satisfactory (Drezner, 2004). In (ii), once a local minimum is found, another procedure (descent) such as multi-level heuristics or a larger neighbourhood such as the Variable

Neighbourhood Search can be used. This is because local optimality is linked to a neighbourhood or a procedure. In (iii), the perturbations of the solution permit diversification of the search and hence escape from the local minima. Some examples of global search methods include; Tabu Search, Simulated Annealing, and Genetic Algorithms. In this study, Simulated Annealing will be used as the solution technique for determining the best location for the facility. Therefore, further discussion of the method will be detailed in the next section.

3.4 Simulated Annealing

Simulated Annealing is widely used because it enables the search process to escape from a local optimum. It is similar to a hill-climbing or gradient search with a few modifications (Seshadri, 1995). In the gradient-based search, the search direction is dependent on the gradient and hence, the function to be optimised should be continuous. However, Simulated Annealing does not require the function to be smooth and continuous, since it is not based on the gradient of the function. Consequently, the basic concepts of the Simulated Annealing will be further examined in the next subsections.

3.4.1 Introduction to Simulated Annealing

In the early 1980s, Kirkpatrick et al. (1983) introduced the statistical mechanics techniques generally applied to condensed matter physics to bear on the problem of combinatory optimisation. Statistical mechanics is a body of methods used to analyse the general properties of large numbers of atoms found in samples of liquid or solid matter. One of the interesting questions addressed by this field is “what happens when a sample is melted and then cooled?” Will the material solidify, and if it does, will it form a crystalline solid or a glass? This solidification process is called annealing and involves slowly lowering the temperature and then holding the temperature near the freezing point for a long time. Typically, the process gives the atom adequate opportunity to align at low energy configurations. However, if the system is cooled too quickly, little or no alignment occurs, and the result may be a crystal with many defects or glass with no crystalline and locally optimal structures. These are the basic ideas of Simulated Annealing introduced by Kirkpatrick et al., (1983).

A good annealing process is essential for producing high-quality crystals. In a mathematical problem, the crystal represents the solution, whereas the cooling strategy is the search technique. The search for low energy configurations is equivalent to the search for an optimal solution and the temperature is the control parameter. At each evaluation of a neighbouring solution during the search, it is vital to select a move that improves the solution. However, the moves that increase the cost of the solution are also accepted based on a probability function.

3.4.2 Simulated Annealing Procedure

Before the development of the mathematical model, the following fundamental postulations were made by marginally adapting the earlier methods of Khairuddin et al., (2007). The summary of a fundamental empirical Simulated Annealing approach for solving combinatorial optimisation concerns is presented next:

1. Select the empirical parameter settings to create a preliminary solution and its fee. This is described as the existing solution.
2. Acquire an adjacent solution to the existing solution through a localised exploration method.
3. Determine the cost of the adjacent solution and relate it to the present solution.
    a. If the cost is more favourable, it is recognised as the existing solution.
    b. If it is not cost-effective, then it is recognised as the existing solution with some likelihood. Alternatively, the existing solution is maintained.
    c. Revise the counters and constraints and then replicate stages 2 to 4 pending when the suitable ending standard is achieved.

In particular, every repetition of the Simulated Annealing exploration technique migrates from its existing trial result to an immediate neighbour in the localised region of this result. Hence, the value of F(x) is the objective function for the existing trial result, whereas F (x') is the objective function of the current entrant in the subsequent trial result. Lastly, the term T_k measures the propensity to receive the existing candidate. This is based on the next trial solution, provided the entrant does not enhance the existing trial result. The rationale for choosing the immediate neighbour is hinged on the selection rule.

3.4.2.1 Move Selection Rule

From the direct neighbours of the actual test result, randomly choose one as the present entrant for the subsequent test result. If the aim is to maximise the objective function, the user can assent or discard the entrant as the ensuing test result according to the following criteria: If $F(x')\geq F(x)$, always agree to this candidate. However, when $F(x')$ is less than $F(x)$, select the option with the defined likelihood: Prob{acceptance}=e^{δ}. Hence, the term $\delta = (F(x')-F(x))/T_k$. However, if the aim is to minimise the objective, the terms $F(x')$ and $F(x)$ can be inverted in the outlined equations. If the selected entrant is forbidden, recreate the procedure with a fresh arbitrarily designated direct neighbour of the actual test result. In the absence of any immediate neighbours, the algorithm must be shutdown. However, if the considered existing entrant is superior to the actual test result, it must be approved as the resulting test result. However, if inferior, the likelihood of approval is contingent on the measure of how bad it is (or the magnitude of T).

Conversely, the rule of move selection typically approves a phase that is just somewhat downhill but never a sharp downward phase. Beginning with a comparatively high T value (as typically observed during Simulated Annealing) dramatically enhances the likelihood of approval. Typically, this facilitates continuous examination in a nearly arbitrary pattern. Similarly, slowly reducing the T value during the search (as typically observed during Simulated Annealing) increasingly lowers the likelihood of approval, which highlights that climbing is mostly upward. Therefore, over time, the selection of T values affects the measure of uncertainty in the procedure that permits the downward phase.

The typical technique of deploying the move selection rule to ascertain the likelihood of approval of a specific downward phase is through the random assessment of numbers from 0 to 1. These random numbers are assumed to be random interpretations of an identical distribution from 0 to 1. Numerous techniques have been proposed for creating such random numbers. Assuming a random number is less than Prob{acceptance}, a downward phase will be approved or else rejected.

The justification for adopting the specific equation of Prob{acceptance} outlined by the move selection rule during Simulated Annealing is due to its resemblance to the process of physical annealing. Initially, the procedure entails the extreme temperature melting of metal or glass, and gradual cooling pending when the substance attains a stable state of low energy with the anticipated physical characteristics. Typically, the atomic energy level in the substance, at any specified temperature *T* during the procedure, fluctuates although this tends to decline. The mathematical model of how the energy levels vary postulates that random variations occur but that only selective enhancements are recognised. Specifically, the likelihood of an increase is acceptable once the temperature *T* is similar to the form Prob{acceptance} based on the rule of move selection for Simulated Annealing.

Similar to the process of physical annealing, an essential consideration during the design of an algorithm to resolve optimisation problems during Simulated Annealing is to select and use a suitable temperature schedule. Due to the physical annealing example, the term *T* in the Simulated Annealing algorithm is defined as temperature. The schedule in question must define an original and somewhat high *T* value along with other gradually decreased values. Likewise, the number of iterations (moves) must be defined for each value of *T*. The choice of the outlined variables to resolve the problem under deliberation is a critical dynamic when considering the effectiveness of the algorithmic. However, initial testing could be accepted to guide the choice of parameters used in the algorithm.

3.4.3 Illustration of the Simulated Annealing Algorithm in Pseudo-Code for a Minimisation problem

The pseudo-code of the implemented Simulated Annealing algorithm is shown in Figure 3.2. In the pseudo-code the basic procedure to execute the routine is to evaluate the objective function on the random points in the vicinity of the current best point area. If the new evaluated point value using the objective function is smaller than the best current value, then the new value is accepted and updated as the new best point. If the evaluated point gives higher value than the best current value then the new value is selectively accepted or rejected, meaning the acceptance is based on the probability density function of Boltszman-Gibbs distribution function.

```
Pick an opening solution x;
Pick an opening temperature T_k > 0;
Choose temperature alteration counter k = 0;
Repeat
Set repetition counter = n (number of iterations to be performed at each
temperature)
Repeat
Choose a solution x' in N(x), a neighbour of x;
Calculate δ = F(x')-F(x);
If δ < 0 then x = x'
else if random (0,1) < exp(-δ/ T_k) then x = x';
If F(x') < F(x) then set x̂ = x and T̂ = T_k
Else keep x̂
n = n+1;
until n = N(k);
k = k+1;
T_k = cooling function (T_k, k), T_k ≤ T_{k-1}
Up until the stopping criterion is satisfied.
```

Figure 3.2 Pseudo-code of SA

If the probability density function gives a value higher than assigned random number, then the trial point is accepted as the best point solution even though the calculated value is higher than the best current value. In finding the probability density function, temperature parameter is used where the temperature becomes the targeted value in the cost optimization function. In the beginning, bigger targeted temperature is selected. Then in the trial process the temperature is reduced according to the pre-defined cooling schedule and the optimization process stops when the set stopping criteria is achieved. The probability of acceptance decreases to zero when the temperature is reduced. Therefore, in the early process this method may resolve to accepting a worse design while in the final process the worse design is almost always be rejected. This strategy is to avoid the solution from being trapped in local minimum point.

3.4.4 Factors affecting the Annealing Process Efficiency

Several factors that should be considered in the annealing process are:

a) Annealing Schedule

The cooling schedule is the heart of Simulated Annealing, which explains why most of the optimisation is conducted in the middle stages of the cooling schedule. First, a reasonable initial temperature must be selected. Next, the cooling rate (α) is set between 0 and 1. Note that a fast cooling schedule is similar to the greedy algorithm, whereas a prolonged cooling schedule will require considerable computation. Therefore it is essential to select the appropriate cooling rate so that the global optima can be reached at a minimum amount of computation. In the Simulated Annealing algorithm, the temperature is gradually decreased, such that:

$$T_i > 0, \forall_i \tag{3.1}$$

and

$$\lim_{h \to \infty} T_i = 0 \tag{3.2}$$

There is always a compromise between the quality of the solutions obtained and the speed of the cooling schedule. If the temperature is decreased slowly, better solutions are obtained but with more significant computation time. The temperature T can be updated in different ways (Talbi, 2009) as the following:

- Linear: In the trivial linear schedule, the temperature T is updated as follows:

$$T = T - \beta \tag{3.3}$$

  where β is a specified constant value.

- Geometric: in the geometric schedule, the temperature is updated using the formula:

$$T = \alpha T \tag{3.4}$$

  Where $\alpha \in \left]0,1\right[$. It is the most popular cooling function. Experience has shown that α should be between 0.5 and 0.99.

- Logarithmic: the following formula is used:

$$T_i = \frac{T_0}{\log(i)} \tag{3.5}$$

  This schedule is too slow to be applied in practice but has the property of the convergence proof to the global optimum.

- Adaptive: most of the cooling schedules are static in the sense that the cooling schedule is defined completely priori. In this case, the cooling schedule is blind to the characteristics of the search landscapes. In an adaptive cooling schedule, the decreasing rate is dynamic and depends on some information obtained during the search. A dynamic cooling schedule may be used where a small number of iterations are performed at high temperatures and a large number of iterations at low temperature.

b) Stopping Criteria

There are two types of stopping criteria, i.e. static and dynamic. Static stopping criteria is the type of stop command where the setting has been created at the beginning of the search. For example, the number of iterations can be one of the stopping criteria or reaching a final temperature T_f. This is the most popular stopping criteria, but this temperature must be low (Talbi, 2009). Hence, a sufficiently large iteration is set so that the algorithm has a widened search space. To improve the solution, a dynamic stopping criterion that considers the objective values can be used. For example, stop is executed when there is no improvement in the cost after 50 successive iterations or when it has found the same best solution 10 times. Selecting the correct stopping criteria is vital for an extended period, so that the algorithm can proceed to the local minimum and ideally the global minimum of the cost function (Vigeh, 2011).

c) Initial Temperature

It is common to start the Simulated Annealing from a random configuration. Hence, it might be better to start from a configuration that is a local minima. For example, a configuration obtained from a greedy algorithm search. Starting from a local minima with initial high temperature will provide an opportunity to escape from the local minima and attain a better solution, possibly a global minimum. However, if it is too high, it will search for nothing, but a random search occurs as the temperature declines.

Furthermore, most of the random configurations are accepted because the probability of acceptance is high. However, if it is too low, it is much like a greedy algorithm that prevents the escape of a local optima. There are a few strategies to deal with these parameters:

- Accept all: The starting temperature is set high enough to accept all neighbours during the initial phase of the algorithm. Ben-Ameur, (2004) states the main drawback of this strategy is its high computational cost.
- Acceptance deviation: The starting temperature is computed by $k\sigma$ using preliminary experimentations, where σ represents the standard deviations of the difference between values of the objective functions and $k = -3/\ln(p)$ with the acceptance probability of p, which is higher than 3σ.
- Acceptance ratio: the starting temperature is defined to make the acceptance ratio of solutions higher than a predetermined value a_0

$$T_0 = \frac{\Delta^+}{\ln\left(m_1\left(a_0 - 1\right)/m_2 + a_0\right)} \tag{3.6}$$

where m_1 and m_2 are the numbers of solutions to be decreased and increased in preliminary experiments, respectively, and Δ^+ is the average of the objective function values increased (Ben-Ameur, 2004). For instance, the initial temperature should be primed in a manner that the acceptance rate is in the interval of 40% to 50%. Boltzmann distribution acceptance ratio: The simplest way is to make sure that the first probability acceptance is nearly 1.

3.5 Transportation Problem (TP)

Once the set of open facilities has been selected, the resulting problem reduces to the usual Transportation Problem (TP). Consequently, the problem can be solved optimally in polynomial time. Typically, a network can be adapted to represent the general problem as illustrated in Figure 3.3.

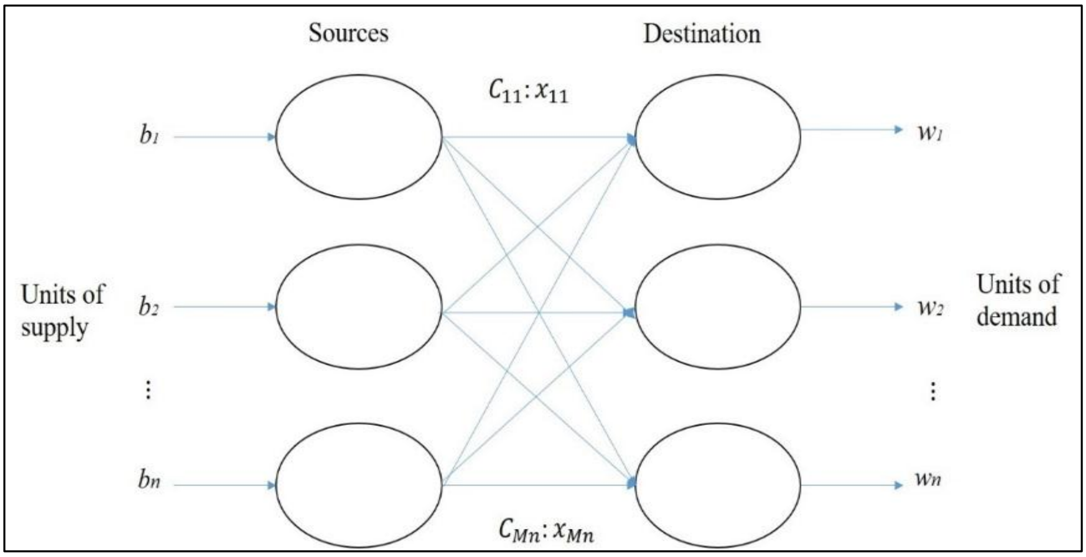

Figure 3.3 Network representation of a Transportation Problem (Zainuddin, 2004)

As observed, there are M sources and n destinations, each represented by a node. The arcs represent the routes between the sources and the destination. The amount of supply at source i is b_i and the demand at the destination j is w_j. The objective of the model is to determine the unknowns x_{ij}, which is the amount shipped that will minimise the total transportation cost while filling all the supply and demand restrictions.

3.5.1 Mathematical Formulation of a Transportation Problem (TP)

Given

j = index for warehouse $(j = 1, 2, \ldots, n)$

k = index for customer $(k = 1, 2, \ldots, q)$

c_{kj} = cost of the shipment from existing warehouse *j* to customer *k*

x_{jk} = volume of products shipped from warehouse *j* to customer *k*,

s_j = supply available at warehouse *j* as a fraction of total customer demand

d_k = customer's demand

The mathematical formulation is as follows:

Minimize $\sum_{i \in I} \sum_{j \in J} c_{ij} x_{ij}$ (3.7)

Subject to

$$\sum_{j \in J} x_{jk} \le s_j \quad (j = 1, 2, \ldots, n) \tag{3.8}$$

$$\sum_{j \in J} x_{jk} \le d_k \quad k = 1, 2, \ldots, q \tag{3.9}$$

$$x_{jk} \ge 0 \quad \forall j \in J, \forall k \in K \tag{3.10}$$

Equation (3.7) is the objective function that is to minimise the total transportation cost. The constraint (Equation 3.8) ensures that supply is not violated, whereas constraint (Equation 3.9) ensures that demand is satisfied. Furthermore, the constraint (Equation 3.10) allows demand to be satisfied not necessarily from more than one open facility. Note that once selected, each configuration must be feasible. In other words, the overall capacity of all facilities must be sufficiently large to accommodate all customers, i.e. $\sum_{j \in J} s_j \ge \sum_{k \in K} d_k \, (*)$. Therefore, any configurations that violate (*) can be discarded from the investigation. The problem is balanced if $\sum_{j \in J} s_j = \sum_{k \in K} d_k$ with all

$s_j > 0$ and $d_k > 0$. The aim is to prepare a minimal cost shipment plan from facilities to customers such that all customers' demands are met without exceeding the supply available at any facility.

3.5.2 Methods for Solving Transportation Problem (TP)

The TP is commonly solved by; (i) Finding an initial basic feasible solution and (ii) Generating an optimal feasible solution.

Several rules are used to obtain the initial feasible solution. Examples include; the Vogel's Approximation Method (VAM), row minimum cost method, column minimum-cost method and the north-west corner method. Among these, the VAM typically provides a better initial solution. However, according to Zainuddin (2004), the computational time required for VAM is rather excessive. Furthermore, the VAM is ineffective if zero cost is used in an origin row or destination column. For a selected unbalanced Transportation Problem, the total opportunity cost method (TOM), outperformed the VAM (Kirca and Satir, 2017). The advantage is that the total opportunity cost is found for each cell by considering both the supply and the demand factors, whereas in VAM the 'penalty cost' is determined on a row or column basis alone. Another advantage is that a new penalty cost must be calculated after each allocation during VAM, whereas the total opportunity cost is calculated only once.

In generating the optimal feasible solution, a few techniques can be used, such as the method of multipliers, modified distribution method (MODI) or the stepping stone method (SSM). There is a selected software that can be used to solve TP such as Excel Solver, TORA and QM. However, for this study, a programming code will be written to solve the TP using Microsoft Visual C++. Since VAM provides an ideal starting solution for TP as described in the literature, the method will be adopted to find the initial basic feasible solution. Lastly, the method of multipliers will then be used to generate an optimal solution.

3.5.2.1 Vogel's Approximation Method (VAM)

The VAM is an improved version of the least cost method that generally produces better starting solutions (Reinfeld and Vogel, 1958). This research study will apply the Vogel's method with minor modification (Gani et al., 2014). The given procedure of VAM is depicted in Figure 3.4.

The flow chart of the primary solution method adopted in this study for redesigning a warehouse network problem is shown in Figure 3.5. Figure 3.5 gives the process overview of the redesigning warehouse network procedures. The neighbourhood solution is obtained using Simulated Annealing method where the warehouse that need to be opened is selected and then Transportation Problem method is applied to allocate customers to warehouse as well as to allocate the warehouse to the nearest plant. The objective function is evaluated and compared to previous iterated value. If the new value is better than the previous value then the new value is updated as the best current solution but if the new value is worse, then the process is repeated in the new neighbourhood using Simulated Annealing method. The process continues until the set stopping criteria is triggered.

If another redesigning factor is considered, such as having to change the original network due to a change to the customer distribution, the existing warehouse will no longer be available. However, when the factor of natural disasters or warfare paralyses an area for long or unpredictable periods, then the existing model needs to be changed and set zone dependent fixed cost in customising the existing network. The next subsection describes the algorithm used in this study to improve the above model to meet the needs of modifying the network warehouse network.

3.6 Zone Dependent Fixed Cost

The redesign factor due to natural disasters or wars that prevent the use of warehouses for long or unworkable periods has been described by (Brimberg and Salhi, 2005). The study considered the dependent fixed cost zone, which can also be

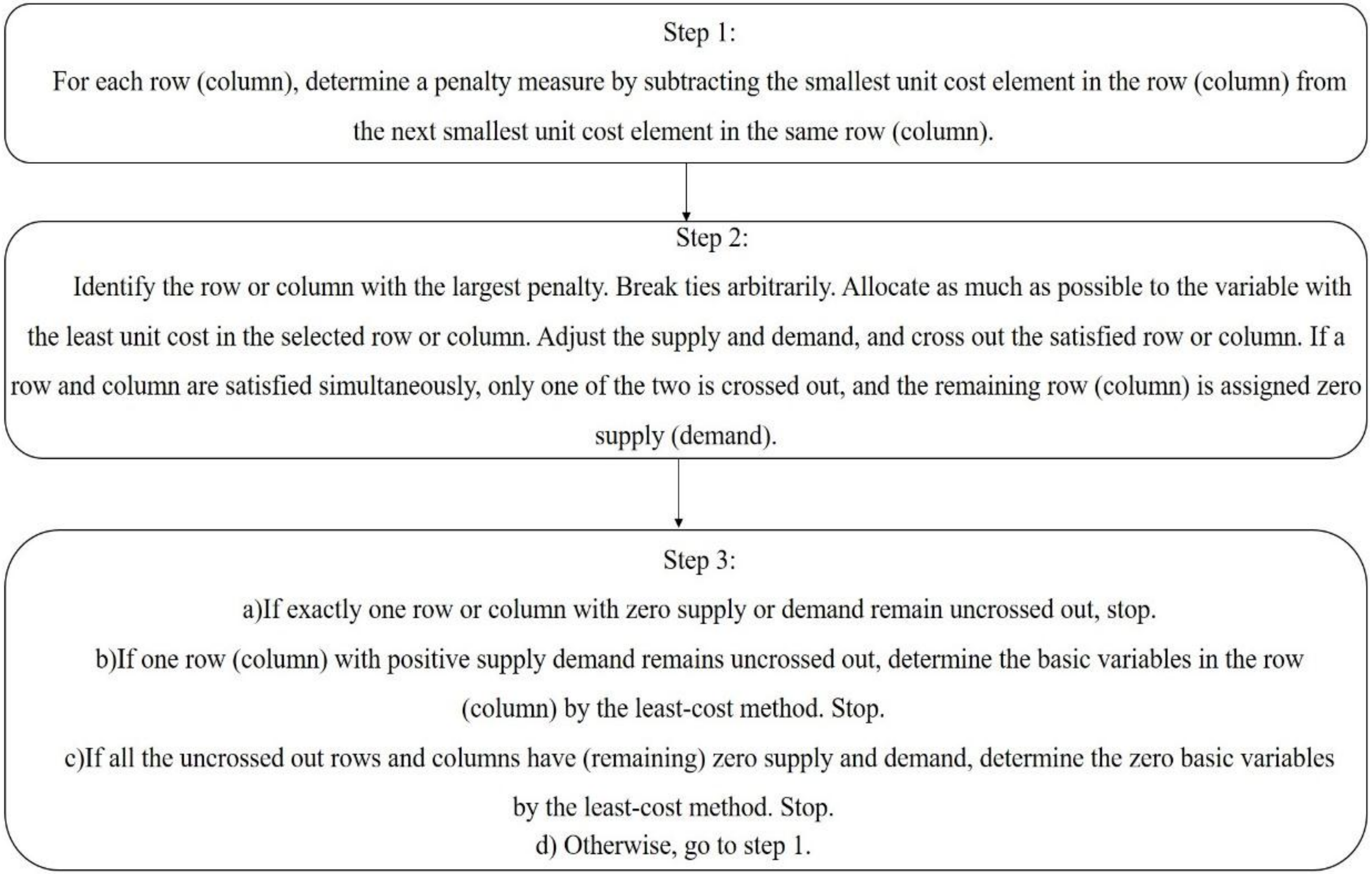

Figure 3.4 Flow procedure of VAM adapted from Gani et al., (2014)

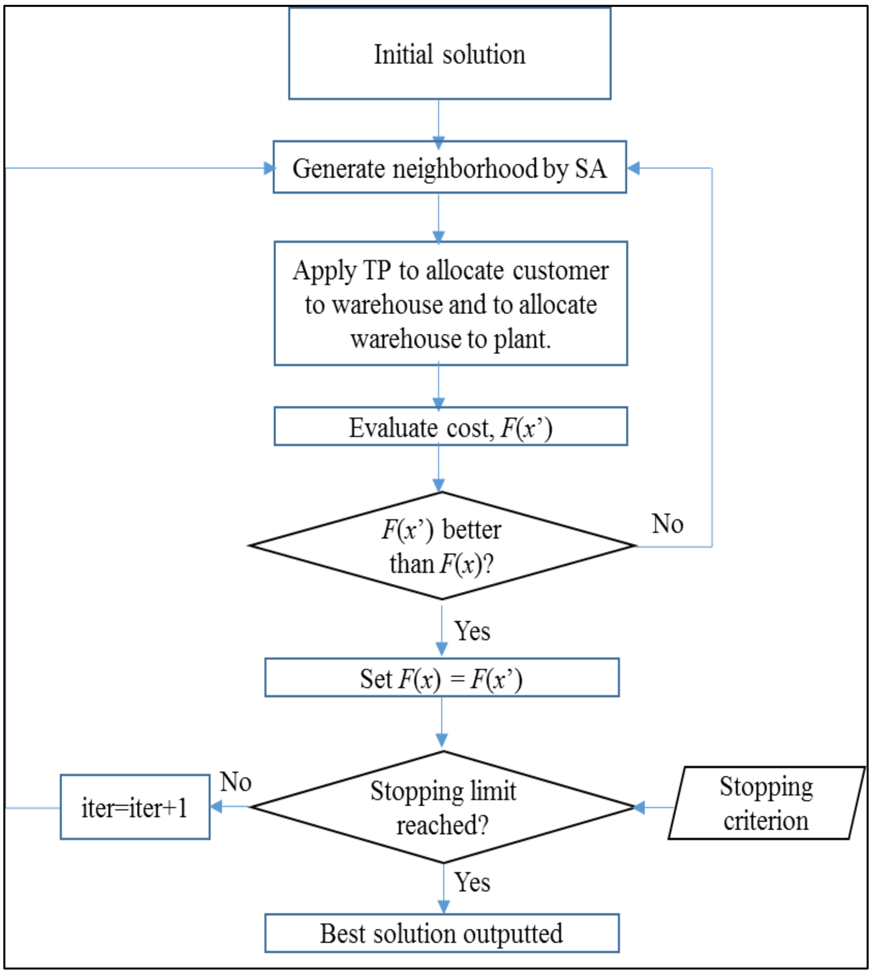

Figure 3.5 Outline of the solution of warehouse redesigning network problem

adapted in the present study. The model suggests that the study space is set to a particular zone dependent fixed cost. Therefore, areas or warehouses affected by a natural disaster and no longer suitable for use will be placed in the high zone cost, so that the model avoids selecting the warehouse involved from operating.

3.6.1 Algorithm for Zone Dependent Fixed Cost

This algorithm by Abdullah et al. (2008) is used to determine a location X of a new facility (M=1) in order to:

Minimize $\sum_{i=1}^{M}\sum_{j=1}^{n}x_{ij}d\left(X_i,a_j\right)+\sum_{i=1}^{M}f\left(X_i\right)$ (3.11)

Subject to

$$\sum_{i=1}^{M}x_{ij}=w_j \quad \left(j=1,\dots,n\right) \tag{3.12}$$

$$x_{ij}\ge 0,\ \forall i=1,\dots,M;\ j=1,\dots,n \tag{3.13}$$

Where $d\left(X_i,a_j\right)$ represent distance between facility i and customer j and $f\left(X_i\right)$ represents the fixed cost for facility *i*. Equation (3.11) denotes the objective function which is the total cost, Equation (3.12) guarantees that the demand of every customer is satisfied and Equation (3.13) refers nonnegativity of the decision variables.

The distance between the customer points to the facility point $d\left(X_i,a_j\right)$ is calculated using rectangular distance. Below is the procedure to solve the zone-dependent single facility location problem:

Step 1: Solve the single-facility minimum problem to obtain the term X_M^* .

If X_M^* belongs to a zone with the smallest fixed cost, stop $\left(X^*=X_M^*\right)$;

else set the current solution $\left(X_c=X_M^*\right)$, *LIST* = { }, *r* = index of the zone containing X_M^* $\left(\text{set } r=K+1,\ \text{if } X_M^*\notin\bigcup_{k=1}^{K}P_k\right)$, and proceed to Step 2.

Step 2: {Process candidate polygons}

For each $P_k, k=r$, do the following:

If $f_k<f\left(X_M^*\right)$, determine the visible boundary, $E_k^{'}\subset E_k$, and store $E_k^{'}$ in *LIST*.

Step 3: {Solve candidate polygons}

Repeat for each $E_k^{'}\in LIST$ until *LIST* = { }:

Use a one-dimensional interval bisection search to find X_k^* (or show by comparing fixed costs of adjoining zones that $E_k^{'}$ can be eliminated).

If $w\left(X_k^*\right)+f_k<Z\left(X_c\right)$, set $X_c=X_k^*$. Set $LIST=LIST-E_k^{'}$

3.6.2 Numerical Example

The algorithm is demonstrated by solving the example shown in Figure 3.6. Here a 10×10 square is divided into 12 zones, $P_1,\ldots,P_{12}$ all rectangular. There are a total of 11 demand points $\left(A_j\right)$ with coordinates as given in the Figure 3.6. The customers are assumed to be homogeneous so that the weights may all be taken as one $\left(w_j = 1,\ j = 1,\ldots,11\right)$. The fixed cost $\left(f_k\right)$ to locate a facility in zone *k* is the value shown by the red number in that zone.

In Step 1 of the algorithm, the median point is readily found to be the unique point $X_M^* = \left(6,4\right)$, with $Z\left(X_M^*\right) = \left(8+5+3+4+4+5+5+6+5+4+7\right)\times 1 + 40 = 96$. Since X_M^* is on the boundary of P_8 and P_9 , it can be assigned to P_9 with the lower fixed cost and proceed to Step 2. The candidate zones for relocation $\left(f_k < 40\right)$ are identified as $P_1,P_2,P_3,P_4,P_5,P_6,P_{10},P_{12}$ the remaining zones P_7,P_8,P_{11} are deleted, and the visible edges set $E_k^{'}, k = 1,\ldots,6,10,12$ are determined. At this stage, P_3 can be deleted since its visible edges $\left(E_3^{'} = \left[\left(8,6\right),\left(10,6\right)\right] \cup \left[\left(8,6\right),\left(8,10\right)\right]\right)$ all belong to adjacent zones with lower fixed costs; similarly for P_4. Furthermore, since P_5 cast the shadow over the entire visible boundary of P_4, it can be eliminated irrespective of the fixed cost at P_6. After storing all the relevant edge sets in *LIST*, the procedure can proceed to step 3.

Since the problem falls under the rectangular distance and zones, its' X_k^* may be determined analytically (Brimberg and Salhi, 2005). Examining the zones in the order of proximity to X_M^* , the candidate's solutions are; $X_2^* = \left(6,6\right)\left(Z\left(X_2^*\right) = 90\right)$, $X_{10}^* = \left(8,4\right)\left(Z\left(X_{10}^*\right) = 74\right)$, and $X_{12}^* = \left(6,2\right)\left(Z\left(X_{12}^*\right) = 97\right)$. Since X_{10}^* has the lowest cost, therefore the current solution is updated to X_{10}^*. Next, examine

$X_5^* = (5,5)\left(Z\left(X_5^*\right) = 73\right)$ and $X_1^* = (5,8)\left(Z\left(X_1^*\right) = 81\right)$; the current solution changes to X_5^*. Finally, $X_6^* = (2,4)\left(Z\left(X_6^*\right) = 76\right)$ it provides no further improvement, so that the last retained solution, $X_c = (5,5)$ is optimal.

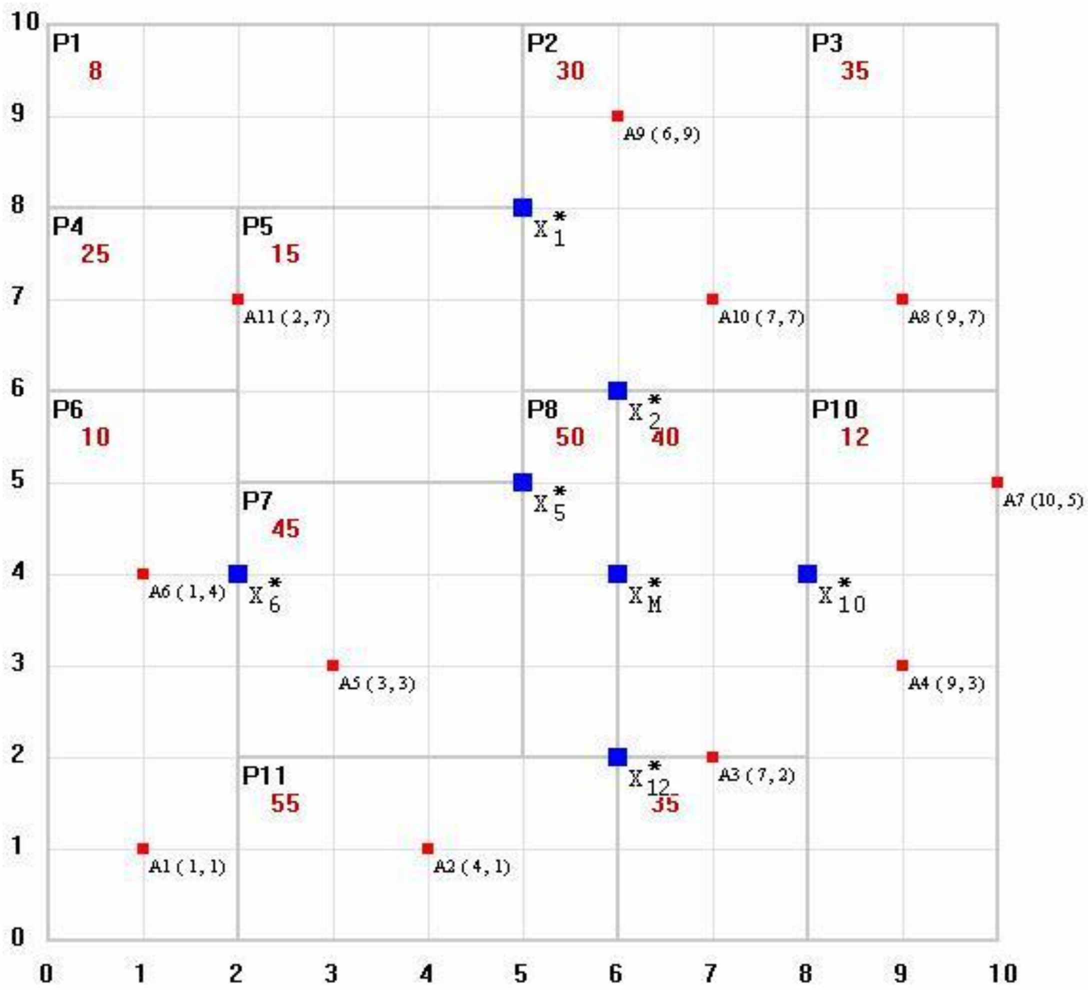

Figure 3.6 Numerical example for solving the zone dependent fixed cost problem

3.7 Summary

This chapter has discussed the solution method for Simulated Annealing. The main steps of Simulated Annealing and the factors that affect the efficiency of the annealing process are also presented. This chapter also reviews the related works on Simulated Annealing location problems. Likewise, this chapter discussed the TP methods that will be used to solve customer allocation problems to the warehouse and the warehouse allocation to plants. As the factor zone is considered in this redesign study, a brief explanation has been discussed regarding zone dependent fixed cost. The next chapter will discuss the best Simulated Annealing parameter for solving the problems of redesigning warehouse networks such as the appropriate initial temperature, best cooling strategies, and best stopping criterion.

CHAPTER 4

RESULT ON THE EFFICIENCY OF THE SIMULATED ANNEALING APPROACH

4.1 Introduction

This chapter presents the implementation of the Simulated Annealing (SA) technique used to address a redesign warehouse network location problem. This is one of the attempts to enable the solution to escape from the local optimum. An investigation on a few elements of this meta-heuristic was also carried out in this chapter. Lastly, the proposed SA implementation was evaluated using the test problems from the literature (Eilon et al. 1971) as described in Chapter 3.

4.2 Warehouse Network Re-design Problem Description

This analysis was performed for three layers of the network, otherwise known as the three echelon analysis, which comprises the customer to the warehouse and the warehouse to the customer networks (Figure 4.1). The type of warehouse considered is a private warehouse that stores only one type of item. The redesigned study was carried out on three different types of network data types, namely; Data type 1 – uniform, Data type 2 – cluster, and Datatype 3 – compact. For the first network 1, which was named Dataset 1 has 2 plants, 10 warehouses, and 50 customers. The second network, also known as Dataset 2, has 2 plants, 10 warehouses, and 654 customers. Lastly, the third network for Dataset 3 has 2 plants, 10 warehouses, and 1060 customers. For this analysis, the initial solution used consisted of 10 randomly assigned warehouse locations, which was used as the warehouse location for all three sets of studies. Two plant locations were also randomly assigned and used as the plant location for all the data sets in the study. Table 4.1 provides details for all three data sets used in this chapter. Three different types of distribution data were taken from the

Eilon (1971) and considered as customer locations. then the facility location allocation model by Khairuddin et al. (2007) used to obtain the warehouse location network to be used as initial solution for the study of warehouse network redesign problem using some new constraints.

Table 4.1 Location of the Plants, Warehouses and Customers for Data 1, 2 and 3

Items	Data 1	Data 2	Data 3
Plant	P1 (111, 111.1) P2 (666, 888.8)	P1 (111, 111.1) P2 (666, 888.8)	P1 (111, 111.1) P2 (666, 888.8)
Warehouse	W1 (133, 889) W2 (189, 77) W3 (927, 149) W4 (946, 936) W5 (920, 869) W6 (743, 161) W7 (608, 134) W8 (557, 460) W9 (670, 277) W10 (899, 245)	W1 (133, 889) W2 (189, 77) W3 (927, 149) W4 (946, 936) W5 (920, 869) W6 (743, 161) W7 (608, 134) W8 (557, 460) W9 (670, 277) W10 (899, 245)	W1 (133, 889) W2 (189, 77) W3 (927, 149) W4 (946, 936) W5 (920, 869) W6 (743, 161) W7 (608, 134) W8 (557, 460) W9 (670, 277) W10 (899, 245)
Number of customers	50	654	1060

This study also assumes that the warehouse is uncapacitated, which can supply as many customers as possible, but the customer can only accept goods from one warehouse. The plant is assumed to have the equal capacity, i.e. the number of warehouses served is the same for both except the number of warehouses it needs to serve is odd. Therefore, the term capacity in this study refers to the capacity of the number of customers to be served by a warehouse and the capacity of the number of warehouses served by a plant. The problem being studied is also discrete, which means that the neighbouring point is the facility point only.

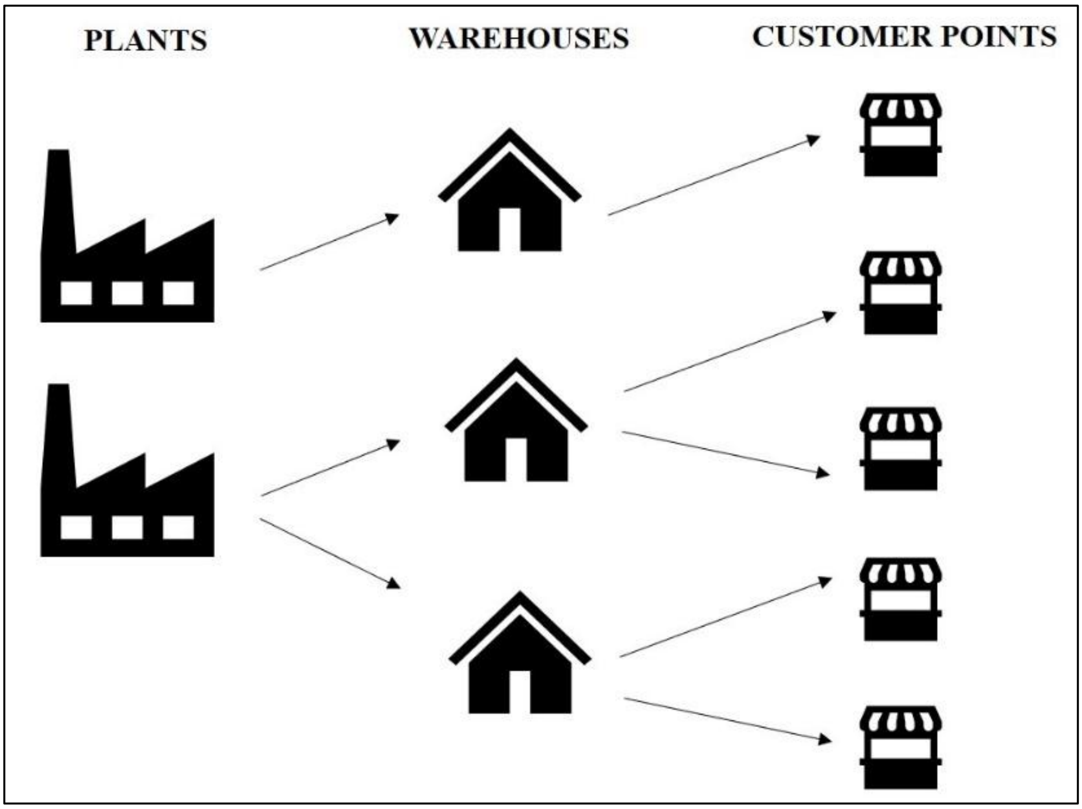

Figure 4.1 Possible configuration of a three echelons network

4.3 Basic Simulated Annealing Implementations

As discussed earlier, the success of SA depends on the parameter values. In the following subsections, a basic implementation of SA is presented in detail. This consists of the way the initial solution is generated, the moves, cooling schedule, and the stopping criteria used in this study. The number of warehouses investigated in this study is $W = 10$, the number of customers is 50, 654, and 1060, as given by the test problem, see Eilon et al. (1971). However, the number of plants that will be considered is $P = 2$ with equal capacity. Figure 4.2 (a-c) shows the warehouse, customer, and plant positions for Data 1, 2, and 3, respectively.

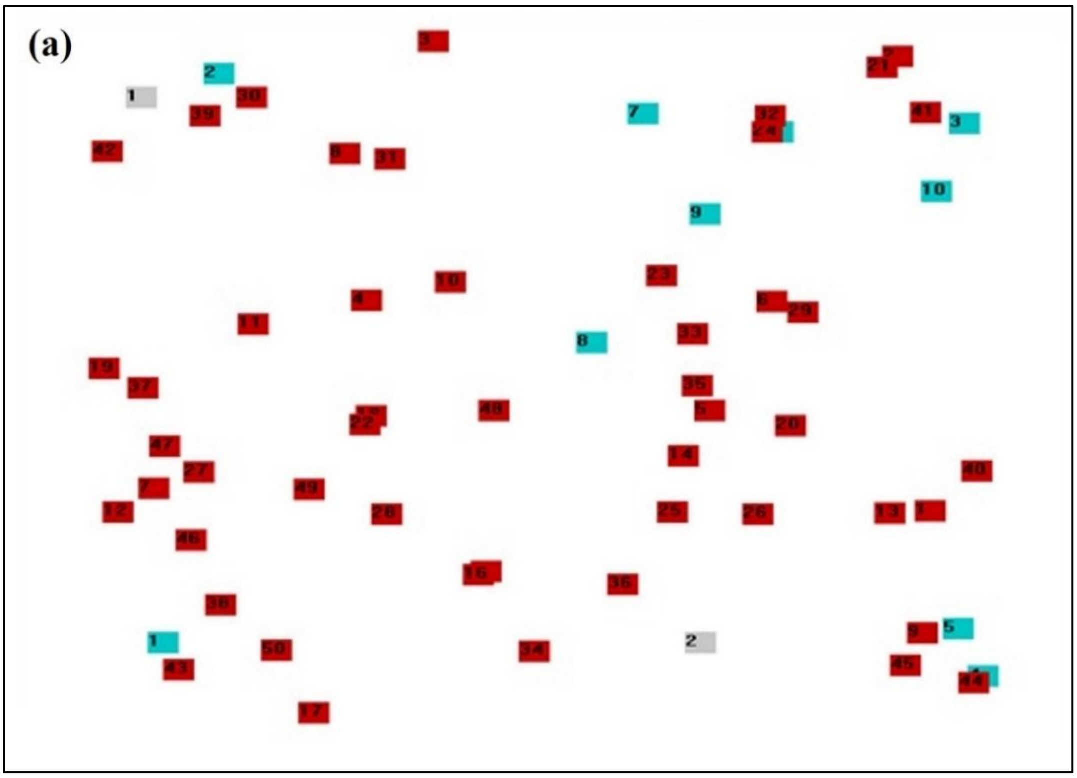

Figure 4.2a Customer location for Data 1

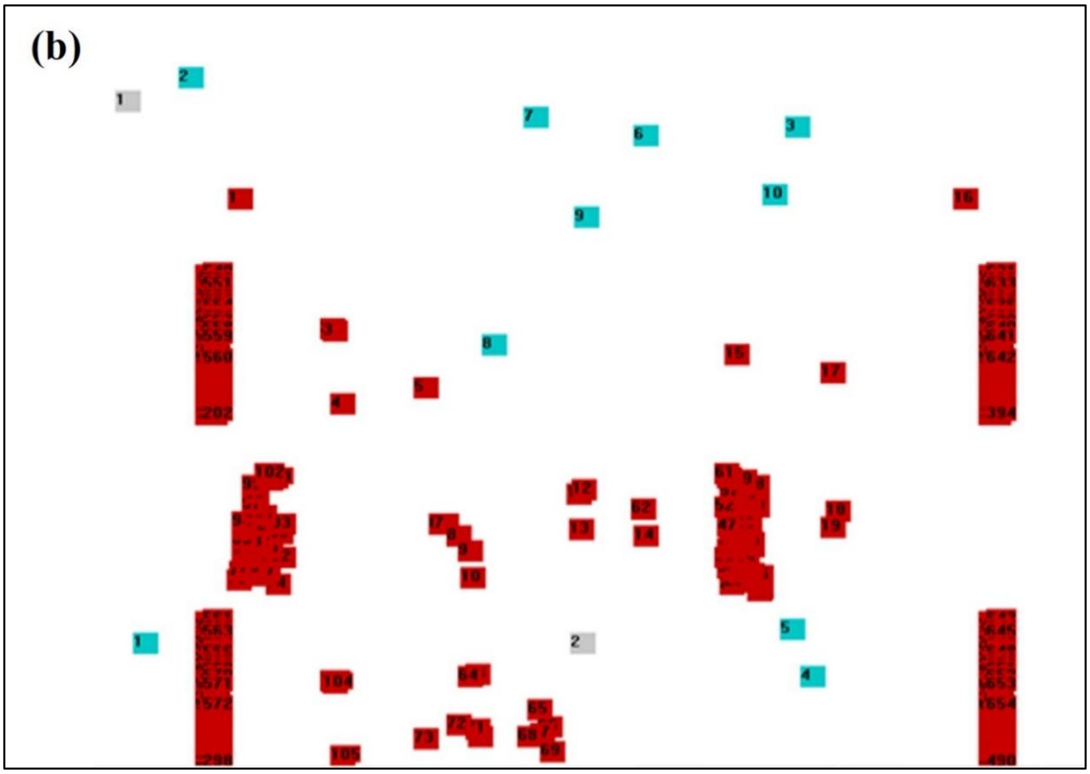

Figure 4.2b Customer location for Data 2

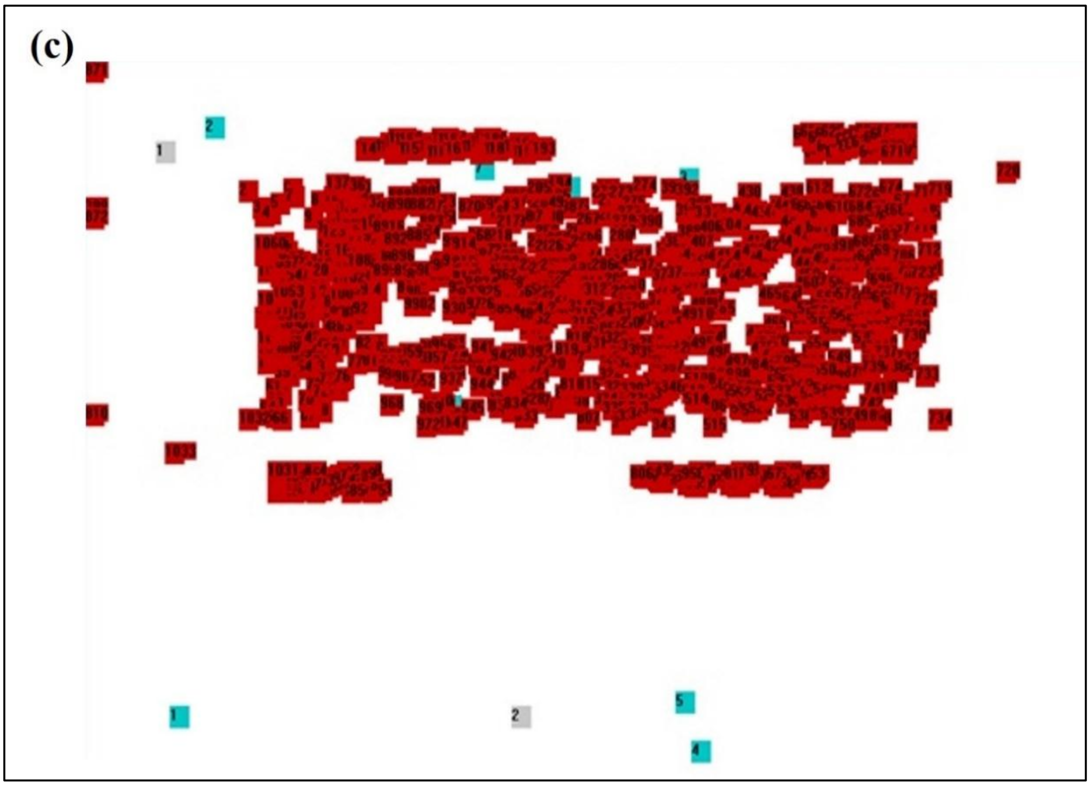

Figure 4.2c Customer location for Data 3

4.3.1 Initial solution

The objective of this study is to redesign an existing network to meet the current economic needs. The study takes into account three (3) echelons. For the warehouse assignment to the customer, the warehouses are randomly assigned to the nearest customer. The TP will be applied again to this new assignment to obtain a new allocation for the selected warehouse to an appropriate plant. Lastly, the cost is evaluated and taken as the initial cost.

4.3.2 Moves

A move is a translation of a current configuration to a neighbouring one. A neighbouring configuration can be defined by changing the location of some facilities. In this study, the neighbouring fixed points of the facility are defined as the fixed point that lies within a certain radius from the facilities taken to be $r_i = {}^{d(i,j)}\!/_{2}$ where

$d(i, j)$ is the distance between facility *i* and its furthest allocated customer. If there are more than one neighbouring points, then it moves the facility randomly to one of the points. However, if there are no neighbouring points, then the current facility will be kept at its current location. A simple example of M=3 and n=10 is shown in Figure 4.2a.

The algorithm for this move is outlined as follows:

Algorithm 4.1
Step 1: Set the existing network that needs redesign as the initial solution
Step 2: Apply TP to the customer to find the new allocation for the uncapacitated problem to the warehouse.
Step 3: Solve the TP using the selected warehouse from Step 2 to determine the new corresponding allocation for the capacitated problem to plant.
Step 4: Repeat steps 2 and 3 until there is no more improvement.
Step 5: End

Let *X1* and *X2* be the current facility location; the furthest allocated customer of facility *X1* is a_4. So $r_1 = d(a_4, X1)/2$, where $d(a_4, X1)$ is a distance from customer a_4 to warehouse 1 and the radius is obtained from the facility, as shown in Figure 4.3. It can be seen that we only have one neighbouring point of *X1*, so it moves the facility to that neighbouring point, *X3*. The furthest allocated customer of facility *X2* is b_3. Then $r_2 = d(b_3, X2)/2$. As can be seen from Figure 4.3a, there is no neighbouring point. So *X2* will be kept at its current location. Therefore, the new locations of the facility are; *X3* and *X2*. The allocation of the warehouse to the nearest plant will only be done after the selection of the operational warehouse is completed.

Figure 4.3(b) shows that each of the facilities of *X2* and *X3* is allocated to the nearest plant. Since the plants have an equal capacity of a number of the warehouse to be served, if there are odd numbers of the warehouse to be served, the furthest allocated warehouse will randomly be allocated to another plant.

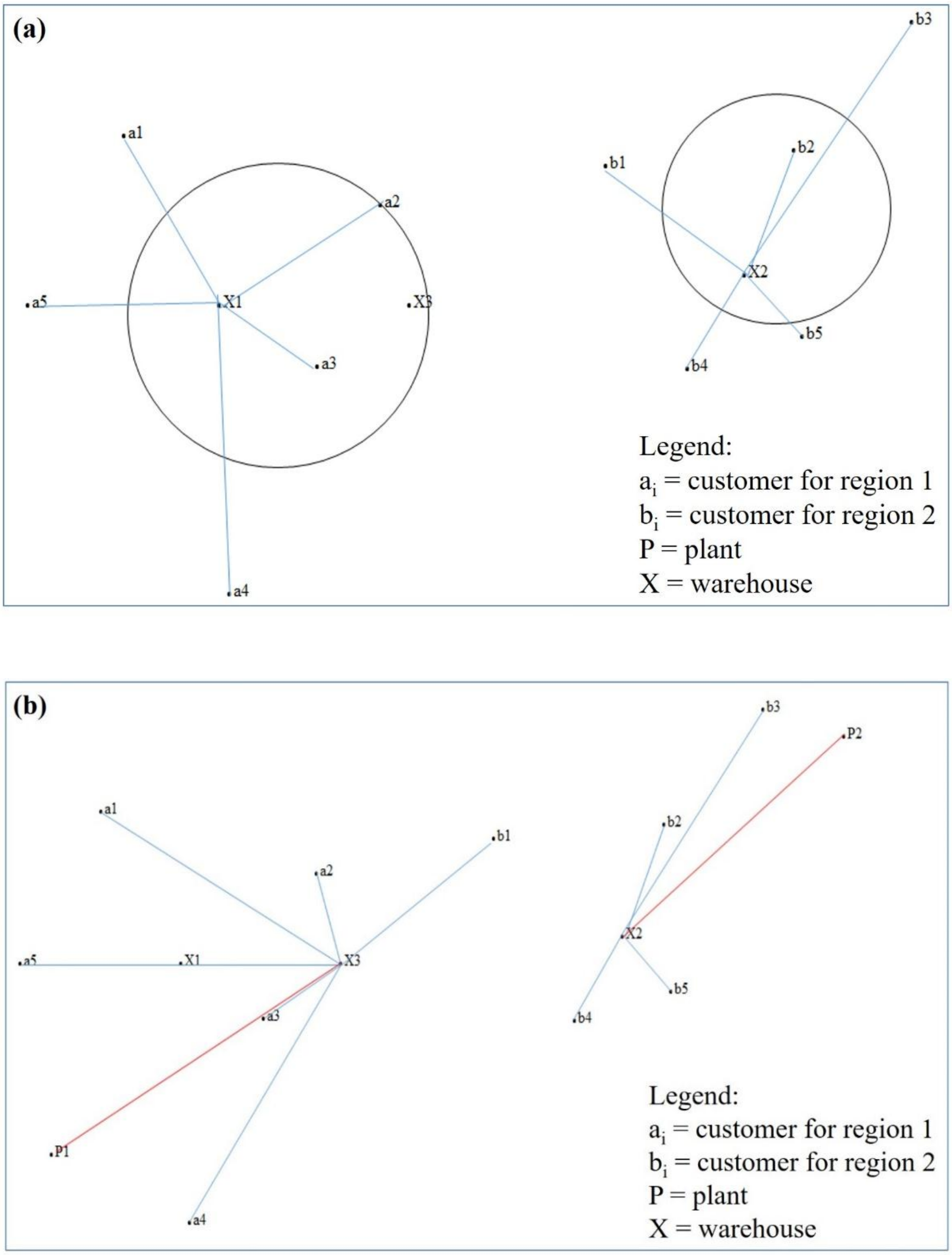

Figure 4.3 Illustration of (a) Facility Customer and (b) Facility Warehouse-Plant Location-Based Move

4.3.3 Cooling schedule

The cooling schedule is the heart of SA. The search starts by looking at the best cooling schemes to solve the warehouse redesigning network. For this purpose, the SA parameters are set up in Table 4.2.

Table 4.2 Simulated Annealing Parameters for Cooling Schedule Analysis

Simulated annealing parameters	
Initial temperature	10000
Cooling schedule	Geometric, linear, and logarithmic; cycle = 1.
Stopping limit	Temperature = 0.
Max iteration.	19000.

Table 4.3 compares the result of the three schemes across 30 runs, with the maximum iteration set at 19000. Maximum iteration at 19000 is considered in this study because the software used to perform the analysis is only compatible with this number of iterations and the maximum number of iterations obtained for all types of analysis never exceed this maximum number of iterations. While initial temperature is set to be that high based on Vigeh (2011). The average achievement for each scheme regardless of the time taken, is presented. As expected, the logarithmic scheme found the best solutions with the smallest standard deviation of average cost estimation. However, as discussed in the previous chapter, the logarithmic approach took a long time to reach the stopping criteria.

Therefore, based on the considerations made, namely; minimum average, small standard deviation, and reasonable running time, the geometric scheme offered the best performance within reasonable running time and cost estimation. This is in agreement with the previous study by Peprah et al., (2017), who observed that the geometric scheme produces faster cooling rates, which are suitable for the annealing process.

Based on results presented in Table 4.3 the geometric cooling schedule contributed better performance compared to the linear and logarithmic in the average running time. This behaviour is because the algorithm spends most of the time at lower temperatures ranges. Figures 4.4 (a - i) show the variation of cost (blue) and temperature (orange) against the iterations, i.e. the behaviour of the search algorithm for geometric, linear, and logarithmic cooling schedules respectively for all data set. From Figure 4.4, it can be seen that the geometric cooling function is consistent (Figure 4.4 a, d, and g). Furthermore, the cost values are in the small range for all Data sets

Table 4.3 Results of the Various Cooling Schedule

Results	Data Set 1			Data Set 2			Data Set 3		
	Geometric	Linear	Logarithmic	Geometric	Linear	Logarithmic	Geometric	Linear	Logarithmic
Average	11601.73	11884.68	11397.47	172290.33	172315.27	172063.00	212783.20	216850.67	212756.00
Standard Deviation	216.77	242.77	0.73	435.27	444.34	0.00	13.83	1425.12	0.00
Best Solution	11397.60	11397.60	11393.60	172063.00	172063.00	172063.00	212756.00	213461.00	212756.00
Average Running Time (Second)	6.14	4.38	73.92	9.94	4.82	455.60	13.82	4.97	645.07

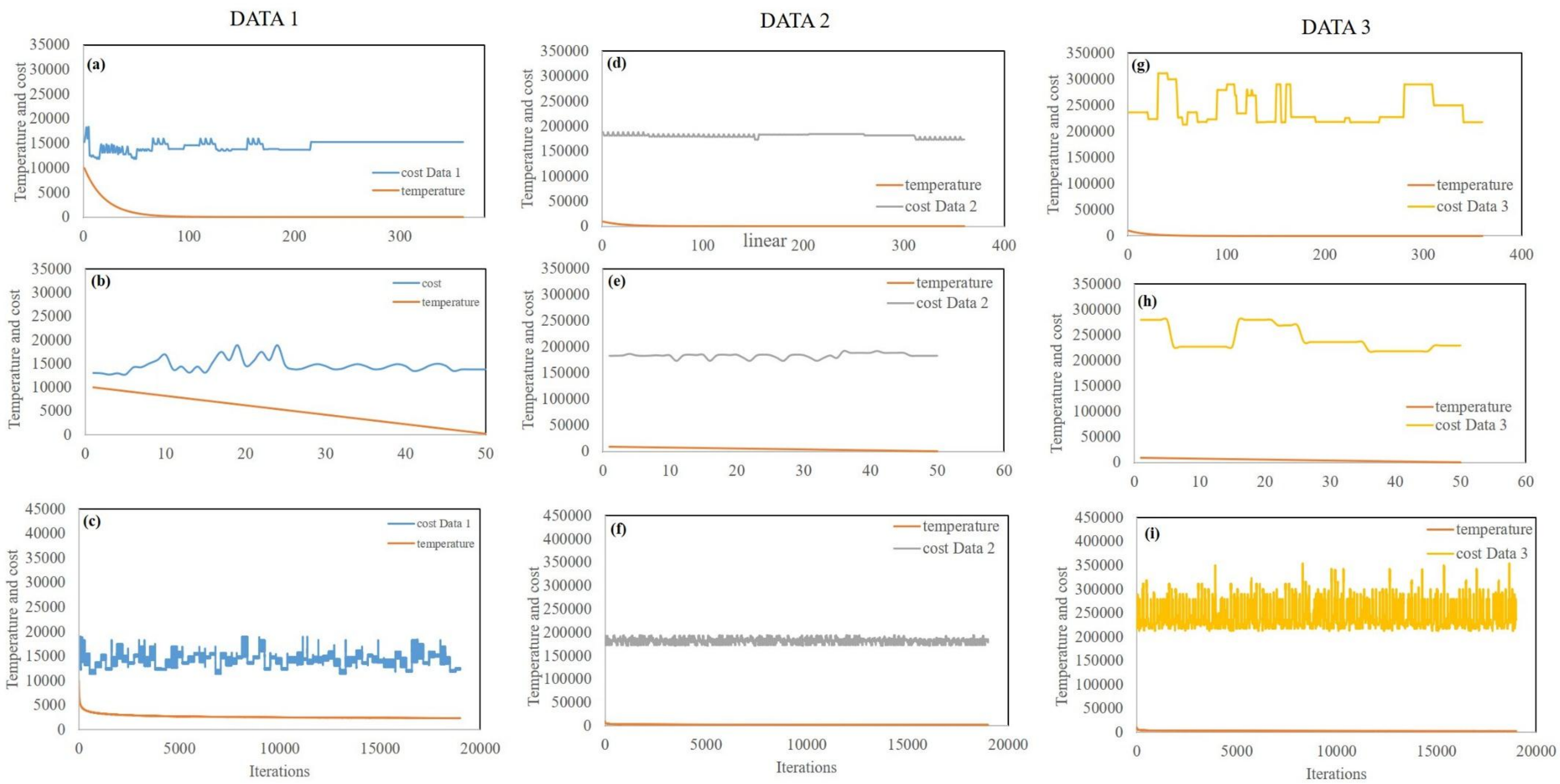

Figure 4.4 Variation of cost and temperature against the iteration of (a,d,g), (b,e,h) and (c,f,i) for geometric, linear and logarithmic

and eventually converge to a minimum value as the iteration increases. In contrast to the linear and logarithmic cooling function, it is noticeable that the graph cost fluctuations are quite high, especially for Data 1 and 3 (Figures 4.4 b, c, h and i).

As explained in the previous chapter, SA has both global and local search phases. In the geometric cooling schedule, the algorithm has more time to improvise on the obtained result, i.e. the algorithm spends more time in the local search phase. In a linear cooling schedule, the algorithm spends more time in the global search phase, while in the logarithmic cooling schedule, the algorithm works like a random search. Therefore, the cooling schedule should be appropriately adjusted to have the right mixture of both local and global search phases. Based on the best average of running time and reasonable standard deviation, the geometric cooling schedule is chosen for further investigation. The next subsection will discuss improvements on the cooling schedule.

4.3.3.1 Improvement of the geometric cooling function

The geometric cooling function was selected for this research because of its best performance. Hence, the analysis to increase the number of cycles used for each temperature was performed. Table 4.4 shows the parameters that have been set up for this analysis.

Table 4.4 SA Parameters for Geometric Cooling Function Analysis

Initial temperature	10000
Cooling schedule	Geometric, cycle=4
Stopping limit	Temperature = 0.
Max iteration.	19000.

The geometric cooling strategy was improved to provide a broader search with changes in temperature after four iterations. Table 4.5 shows the positive results of the improvements made because the average cost is better with a smaller standard deviation value. The increment in computational time is expected.

Table 4.5 Comparative Results of the Geometric Cooling Functions of K=1, K=4

Item	Geometric, K = 1			Geometric, K = 4		
	Data Set 1	Data Set 2	Data Set 3	Data Set 1	Data Set 2	Data Set 3
Average	11601.73	172290.33	212783.20	11522.08	172069.50	212788.07
Standard deviation	216.77	435.27	13.83	228.57	19.83	93.69
Best solution	11397.60	172063.00	212756.00	11397.60	172063.00	212756.00
Average running time	6.14	9.94	13.82	9.94	37.67	54.38

4.3.4 Variation of Probability Rate

The cooling rates of 0.3, 0.5, 0.9 and 0.95 will be tested at different temperatures to investigate the best value for solving the problems linked to the geometric cooling schedules in this study. From Tables 4.6 and 4.7, it is observed that $\alpha = 0.95$ gives the lowest average cost, and standard deviation and hence, this ratio will be adopted in other investigations.

Table 4.6 Computational Results of Various Probability Rate at $T_0 = 1000$

	$\alpha = 0.95$	$\alpha = 0.90$	$\alpha = 0.50$	$\alpha = 0.30$
Average	**12195.71**	12286.39	12478.71	12483.29
Standard deviation	**356.18**	458.36	463.82	454.86
Best solution	**11397.61**	11397.61	11397.61	11642.92

It can be seen from Tables 4.6 and Table 4.7, that when $\alpha = 0.95$, the average and the standard deviation has the minimum value and shows that this rate of probability value is consistent.

Table 4.7 Computational Results of Various Probability Rate at $T_0 = 10000$

	$\alpha = 0.95$	$\alpha = 0.90$	$\alpha = 0.80$	$\alpha = 0.50$	$\alpha = 0.30$
Average	**12042.86**	12164.86	12254.19	12250.76	12550.64
Standard deviation	**282.51**	431.52	466.01	416.63	541.46
Best solution	11522.26	**11397.61**	**11397.61**	11522.26	11619.35

4.3.5 Variation of Initial Temperature

As mentioned previously in Chapter 3, the appropriate initial temperature will provide an opportunity to escape from the local minima and attain a better solution. The comparison was made between the two initial temperatures for all three research data sets. Retaining the other parameters as in the previous subsection, SA parameters are set up, as shown in Table 4.8.

Table 4.8 SA Parameters for Variation of Initial Temperature Analysis

Simulated annealing parameters	
Initial temperature	Data 1: 8000, 30000 Data 2: 333000, 405000 Data 3: 1500000, 3331000
Cooling schedule	Geometric, cycle=4, $\alpha = 0.95$
Stopping limit	Temperature = 0.
Max iteration.	19000.

As observed in Table 4.8, two different approaches by Yaghini (2010) were used to estimate the initial temperature. All three sets of data used a different initial temperature due to the different number of customers and data type of distribution factor, as shown in Figure 4.2.

Figure 4.5 shows the variation of delta cost for Data 1, Data 2, and Data 3. The variation for Data 3 is considerable compared to the variation for Data 1 and Data 2.

This is because of the difference in cost on the accepted uphill move in the neighbourhood structure, as discussed in subsection 4.3.2. The different and much larger data distributions between each data set also play a role in why the initial temperature for each of these data sets is different. The variation of initial temperature causes changes in the amount of time the system spends in the local search and global search phases and also affects how quickly the temperature is reduced.

With the increase in initial temperature, the expectation is to find a solution with improved costs. With higher initial temperature, the algorithm rapidly moves into a different part of search space and chances of finding the solution with better costs are higher. However, the results in Table 4.9 show that the solutions for Data 1, Data 2 and Data 3 all performed differently. Furthermore, Data set 2 did not favour any of the initial temperatures (this may be because the data distribution is a cluster type). Data set 1 showed that lower initial temperatures are sufficient to find a good solution, whereas Data set 3 showed that higher initial temperatures provide a better average cost. This is due to the much larger customer data distribution and scattered warehouse locations.

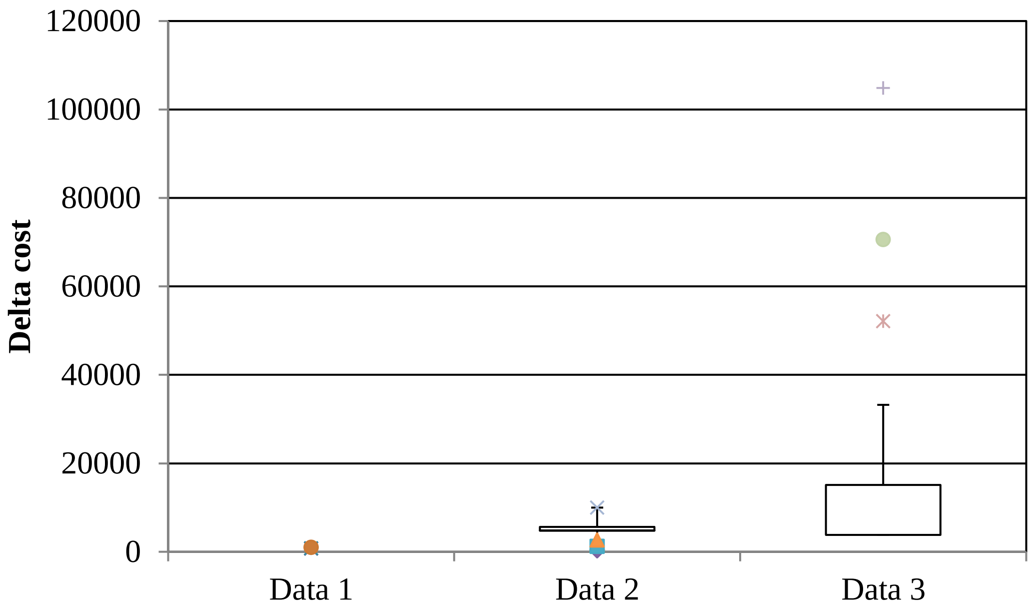

Figure 4.5 Variation of delta cost for Data 1, 2, and 3

Table 4.9 Computational Results of Various Initial Temperature

Data 1		Data 2		Data 3	
Initial temperature	Average cost	Initial temperature	Average cost	Initial temperature	Average cost
8000	11468.67	333000.00	172102.40	1500000.00	213163.60
30000	11532.01	405000.00	172102.40	3331000.00	212843.80

In conclusion, a larger initial temperature will be used for further study, i.e. Data 1 will use T_0 = 8000, Data 2 will use T_0 = 333000, and Data 3 will use T_0 = 3331000. The effect of this selection is the higher running time; the next section will discuss the method of upgrading to running time by controlling the stopping limit.

4.3.6 Variation of Stopping Limit

When placing a high initial temperature, the effect of the geometric cooling schedule is based on the number of iterations. This will increase as the algorithm stops at a temperature equal to zero, for example, for Data1 when T_0 = 8000, the algorithm will stop at iteration 1440 where the temperature is equal to zero. On the other hand if T_0 = 30000 the algorithm will reach zero at iteration 1540. This is an example of a static stopping criterion, so this study will improve this stopping limit by introducing a dynamic stopping limit. Retaining the other parameters as in the previous subsection, SA parameters are set up, as shown in Table 4.10. Hence, the algorithm will stop when the same number of best solutions occurs five (5) times or when the same solution for h times in successive iterations is found.

Table 4.10 SA Parameters for Variation of Stopping Criterion Analysis

Simulated annealing parameters	
Initial temperature	Data 1: 8000 Data 2: 333000 Data 3: 3331000
Cooling schedule	Geometric; cycle = 4.

Stopping limit	Static: Stop when temperature = 0 Dynamic: Stop when number of best solution equal to 5 or when there was no improvement in the cost after ***k*** successive iteration.
Max iteration.	19000.

Table 4.11 indicates a running time improvement if the dynamic stopping limit is used. Hence, the average running time for static stopping criterion is 28.80 seconds, whereas the dynamic stopping criterion is 14 or 15 seconds only. The average cost for static and limit is also not much different even as the expected average cost for static will be better compared to dynamic because the static has more space to search for a better solution due to its higher number of iterations. However, Table 4.11 also shows that the algorithm is still not consistent because the value of the standard deviation of the cost is still high. The next subsection will discuss a strategy to improve the results in term of the average and standard deviation of the cost.

Table 4.11 Computational Results of the Various Stopping Criterion

	Static	Dyamic *h* = 20	Dyamic *h* = 100
Average cost	11846.75	12069.99	12030.40
Standard deviation	488.79	557.38	365.15
Average running time	28.80	15.39	14.39
Best solution	11397.60	11397.60	11401.60

4.4 Multi start SA

SA is one population-based, so to improve the method so it can work as well as a population-based method, multi-start techniques are discussed in this section. Table 4.12 shows excellent results after this method is applied. The improved average cost and very low standard deviation suggest that this method is very consistent in finding the best solution to the study problem.

Table 4.12　　Computational Results of Various Multi-Start SA Analysis

		M = 1		M = 5		M = 10		M = 20	
		Objective value	Running Time	Objective value	Running Time	Objective value	Running Time	Objective value	Running Time
Data 1	avg	12030.40	14.39	11892.74	33.01	11793.23	73.49	11680.77	94.09
	sd	365.15	1.09	291.32	3.88	218.56	81.65	0.51	7.72
	best	11680.90	12.89	11397.60	28.18	11680.90	46.42	11678.90	81.94
Data 2	avg	173147.80	44.06	172535.80	79.86	172063.00	528.11	172063.00	569.47
	sd	1790.48	88.14	588.96	41.74	0.00	1273.93	0.00	117.64
	best	172063.00	5.47	172063.00	27.26	172063.00	124.96	172063.00	436.63
Data 3	avg	215879.30	45.17	212779.50	237.66	212756.00	475.94	212756.00	661.14
	sd	2967.28	89.33	128.71	43.43	0.00	76.42	0.00	106.31
	best	212756.00	6.05	212756.00	154.48	212756.00	319.53	212756.00	377.26

Table 4.12 shows that when M = 10 and M = 20, Data 2 and Data 3 retain the same minimum cost with a minimal standard deviation. However, the increase in the multi-start results in a decrease in the average and standard deviation values after SA, even though an increased running time is currently observed. Therefore, 10 multi-start for Data 2 and Data 3 is best suited for lower running time. This result overcomes the logarithmic results in Table 4.3 as this new approach is achieving results as well as lower running schedule. Surprisingly this result does not conform to Data 1, although it shows positive developments, this algorithm fails to find the best solution consistent with Data 2 and Data 3.

Figures 4.6 (a-c) below show that when multi-start numbers increase the average decreases. Figure 4.6a shows that the average cost decreased linearly with several multi-start. However, Figures 4.6(b) and 4.6(c) show that the average cost has exponentially decreased subject to several multi-start.

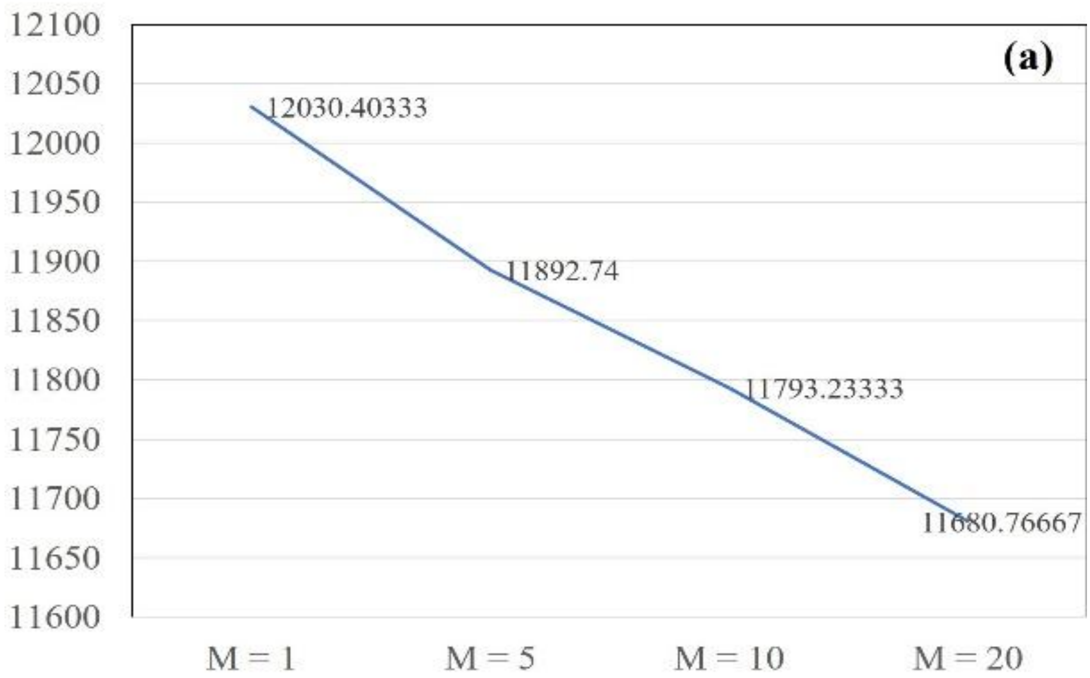

Figure 4.6a Decreasing trends for Data 1 average

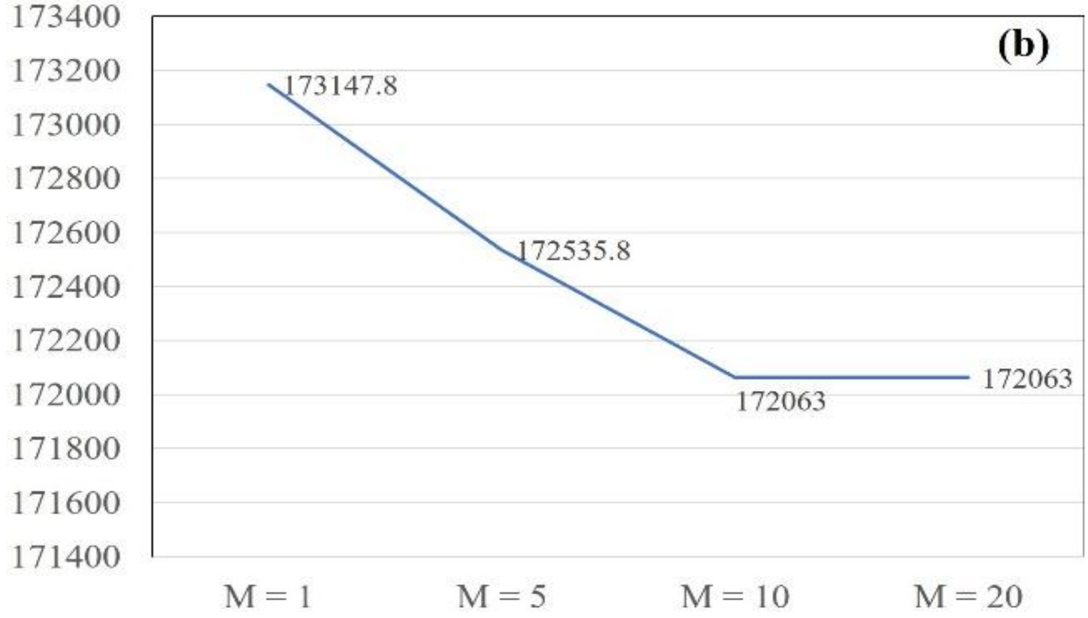

Figure 4.6b Decreasing trends for Data 2 average

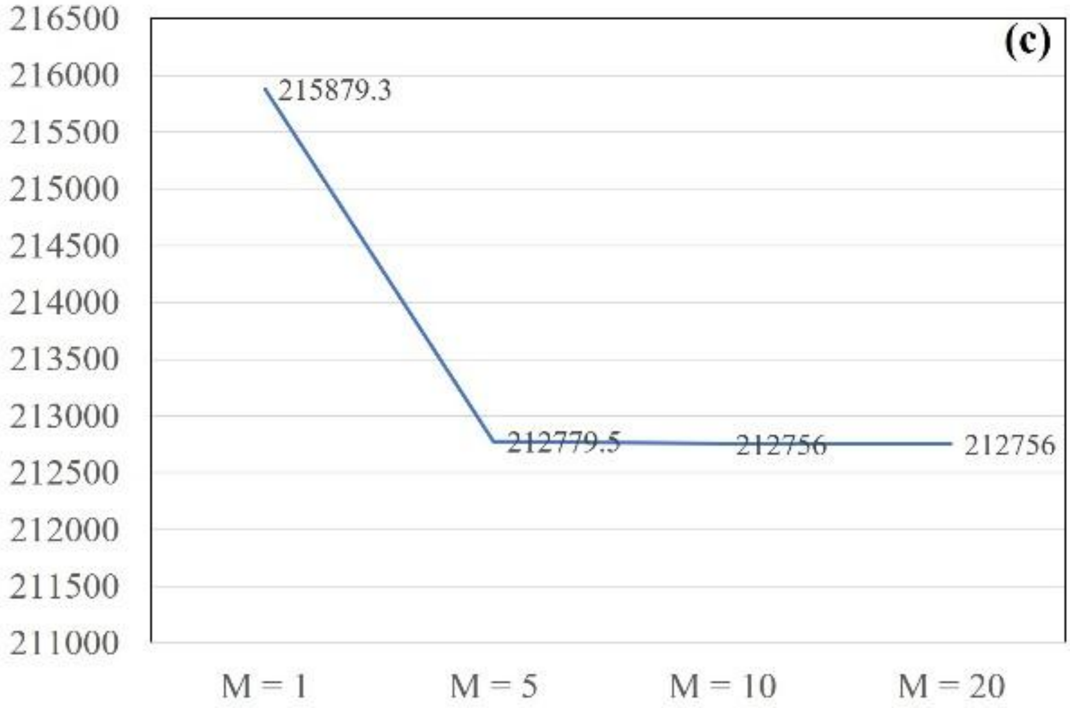

Figure 4.6c Decreasing trends for Data 3 average

Figure 4.7 shows a straightforward running time with the number of multi-start. As observed, the standard deviation is inversely proportional to the number of multi-starts. Therefore, M = 10 is adopted for further investigations in this study.

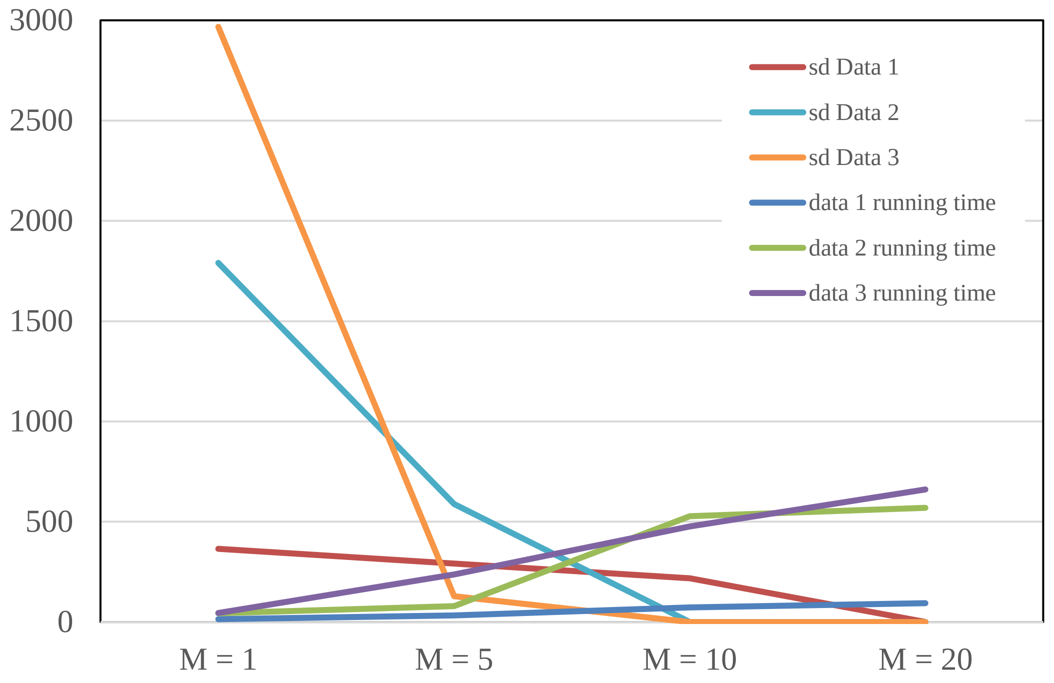

Figure 4.7 Running time and standard deviation for Data 1, 2 and 3

4.4 Summary

In this chapter, the best parametric setup for SA was studied. The parameters studied to produce the best SA algorithm are cooling schedule, probability ratio in geometric schemes, initial temperature, and stopping limit. The geometric cooling schedule $\alpha = 0.95$ was selected as the best cooling schemes based on its optimal performance in running time and minimum average cost. Some computational results of the geometric, linear, and logarithmic cooling schedule using 50, 654 and 1060 fixed point test problems from the literature are also given. The best initial temperature was found to be different for each of the data set because of the difference in the best and worst solution found for each data set and the distribution for each of the data set. Data 1 used T_0 = 8000, Data 2 used T_0 = 333000 and Data 3 used T_0 = 3331000. The SA model was also improved by using the dynamic stopping limit, although this approach gave inconsistent values of average cost and standard deviation. However, these were improved by introducing multi-start SA. Some computational results of this approach using the same test problem were also given. Consequently, a total of 10 multi-start

SA were selected for the algorithm to be used for the study in the next chapter. A comprehensive set of result are also presented in Appendix A, B, and C.

Therefore, Chapter five (5) will discuss redesigning a warehouse network by using all the appropriately selected parameters for this type of study.

CHAPTER 5

RESULTS OF THE MATHEMATICAL MODELS FOR THE WAREHOUSE REDESIGN PROBLEM

5.1 Introduction

The redesign of a warehouse network is currently a big step considering the global economic state of affairs. The factors leading to the redesign of a warehouse network are due to the need for improvements of the existing services for customer satisfaction. There are several other factors such as changes in geographical and placement structures resulting from migration or natural disasters, among others. Therefore, this scenario changes the customer distribution. The typical steps taken in literature Melachrinoudis and Min (2007) are to shut down the operation of a facility that is perceived as unnecessary based on the factors mentioned previously. The merger of two or more facilities is also an effort to optimise costs because it can save costs such as maintenance and utility costs of operating a warehouse. Lastly, redesigning a warehouse network adds new facilities to address the constraints that occur during factory operations.

5.1.1 Consolidation

Consolidation is the process of redesigning a network often performed by some companies. The process is accomplished by combining two or more nearby warehouse operations to serve customers. It could be seen as saving the operational or fixed costs imposed on a warehouse. However, it can result in increasing the cost of delivery. Therefore, reasonable considerations are required so that the process can enhance the optimisation of warehouse operating costs.

5.1.2 Elimination

The method of elimination is performed by closing the operation of a warehouse completely. This method is occasionally combined with the consolidation method. If only the closing method is completed, it can lead to savings in the warehouse operating costs, which positively impacts the company long-term.

5.1.3 Addition of a New Site

The last step is the addition of new facilities in a secluded area, as described in the literature. This measure results in cost-saving and inventory costs, but the opposite effect results in additional fixed and operating costs.

5.2 Data Collection

This subsection explains the input data needed for the MILP model and the techniques for collecting and aggregating all the data. The customer data point is used from the previous chapter, and the location of the customer and plant are selected based on the last research on location-allocation study. All the data needed include:

1. Location of the customers, warehouses, and manufacturing plants.
2. Distance between all manufacturing plants and the warehouses, between all warehouses and all customer points and distances between the warehouses.
3. Demands of each customer.
4. Transportation costs
5. Fixed and variable costs of the warehouses.
6. The capacity of the warehouse.

5.2.1 Customer Locations

In this chapter, the customer points used are similar to the previous chapter, where there are three (3) sets of data. Data 1 includes 50 customer points, Data 2 includes 654 customer points, and Data 3 includes 1060 customer points.

5.2.2 Manufacturing Plant and Warehouse Location

The two (2) manufacturing plants and the ten (10) warehouses in the present study are based on the solution from a previous study by Khairuddin et al. (2007). Nevertheless, in this chapter, potential warehouses were added to examine their impact of the network redesign study.

5.2.3 Distance Data

The distance between all manufacturing plants and all warehouses, between all warehouses and customer points along with the distances between the warehouses, must be computed as a basis for the calculation of the transportation costs.

5.2.4 Demands of Each Customer

In this study, it is assumed that all customers have similar demands which is equal to one.

5.2.5 Transportation Costs

The transportation cost from all manufacturing plants to all warehouses and from all the warehouses to all customer points are the products of distance and transportation rate.

5.2.6 Warehouse Fixed and Variable Costs

The warehouse fixed cost is in the unit of unit cost per year, whereas the warehouse variable cost is in unit cost per ton. Based on the model developed in Section 2.3.4, following table shows the assumptions made in this study for the warehouse input parameters.

Table 5.1 Parameter Setup for Redesigning A Warehouse Network Study

Input parameter for the warehouse		
Parameter	Index	Value
Fixed cost	f_i^m	200000
Unit capacity cost	f_i^c	1.5/cwt
Saving from warehouse closure	f_j^s	500000
Saving from recovering a capacity unit	a	1.2/cwt
Outbound shipping cost	osh	0.04/cwt km
Inbound shipping cost	ish	0.02/cwt km
Warehusing cost per unit of throughput volume	vw_i	1/cwt
Fixed portion of relocation cost	rf_{ji}	100000
Relocation cost per unit capacity	rc_{ji}	1/cwt
Cost of moving a unit of capacity one mile away from the current location	rcd	0.005/cwt km

*1cwt = 100 lbs.

5.2.7 Manufacturing Plant and Warehouse Capacity

The manufacturing plant and warehouse capacity are the maximum capacity of the manufacturing plant and warehouse, respectively. In other words, this is the maximum volume of products that can pass through the manufacturing plant and the warehouse annually.

5.3 Model Development

The best possible allocation of warehouse and customer was determined using a mixed-integer linear programming (MILP) model. Subsequently, the proposed MILP model was used to optimise the network redesign problem in this study. The MILP model addresses the following issues:

1. Which warehouses should be retained or closed so that the redesigned distribution network minimises the company's total distribution cost while meeting the demands of customers?
2. Which destination or provinces are to be served by the consolidated warehouses?
3. Which potentially open warehouses can minimise the costs of distribution?

Before developing the MILP model, the following assumptions will be considered:

1. The warehouses are company-owned (or private).
2. When a warehouse is consolidated into another warehouse, its total capacity is relocated to the nearest warehouse.
3. The restructuring plan covers a planning horizon within which no substantial changes are incurred in customer demands and the transportation infrastructure.
4. For a baseline study, it is assumed that a manufacturing plant has an equal capacity to serve warehouses, and there is an incapacitated allocation for any warehouses to serve the customer.

5.3.1 Objective Function

As discussed in Chapter 2, the objective function of the model by Melachrinoudis and Min (2007) is to minimise the total supply chain cost. This cost consists of production, transportation, warehousing and relocation costs. Typically, this approach maximises the cost-saving resulting from the closure or consolidation of redundant warehouses. However, this chapter also discusses the effect of cost savings annually derived from operating costs for the operational warehouse by Sridurongkatum (2010). Generally, these costs include specific utility, transport, and fixed cost since the cost of savings is long term due to the closure or sale of the company's assets. The objective function is as follows:

$$\text{Min} \sum_{p \in P} \sum_{i \in A} v_{pi} y_{pi} + \sum_{i \in A} \sum_{k \in C(i)} s_{ik} x_{ik} + \sum_{i \in A} f_i^c \sum_{j \in E} c_j z_{ji} + \sum_{i \in E} f_i^m z_{ii} \qquad (5.1)$$

Equation (5.1) represents the objective function, which is to minimise total product distribution cost, a set of constraints must be included in the MILP model. Therefore, a total of four constraints are included in the model, which reflect the following:

1. The inbound volume of all products to a warehouse must not exceed the capacity of the warehouse.
2. The inbound volume of a product to all warehouses from a plant must be equal to the production volume of the plant.
3. The outbound volume of a product from the warehouses to a destination province must equal the product demand for that destination or province.
4. The outbound volume of a product from warehouses must be equal to the inbound volume of the product to that warehouse.

The above constraints include the formulation models discussed in Chapter 2 in Subsection 2.3.4. However, the above constraints are for the baseline study specific to this thesis study, whereas other constraints which are also considered in this chapter are as follows:

$$\sum_{i \in A} x_{ik} \leq c_p \quad \forall p \in P, \tag{5.2}$$

where the constraint (5.2) ensures that the total volume of products shipped to customers does not exceed the throughput capacity of the warehouse it serves.

5.3.2 Scenarios

The model was run with both the existing situation and with other scenarios to see the sensitivity of warehouse selection due to the variability of warehouse fixed cost and appropriate location of the warehouse. Consideration of the percentage in the scenarios were based on the study by Vigeh (2011). The scenarios are:

Scenario 1: Baseline

In this scenario, the model is run by setting the capacity of each warehouse at 100%. This is to allow space at each warehouse to be at the appropriate level for convenient warehouse operation. The model agreed to use 100% of maximum warehouse capacity as a baseline of the model.

Scenario 2: Lower warehouse operating cost by 5% for a warehouse that was not selected in the Baseline scenario.

This scenario examines whether the warehouses that were not selected by the model in the Baseline scenario will be selected if their operating cost were decreased by 5%. In other words, this is to determine the extent of reduction in the operating cost that will make the warehouse eligible, i.e. higher or lower than 5%.

Scenario 3: Raise warehouse operating cost by 5% for a warehouse that was selected in the Baseline scenario.

This scenario examines whether the warehouses that were selected by the model in the Baseline scenario will be selected again if their operating cost is increased by 5%. In other words, this is to determine the level of increase in the operating cost that will make the warehouse ineligible, i.e. higher or lower than 5%.

Scenario 4: Increase the number of potential sites (two new warehouses)
Scenario 5: Increase the number of potential sites (five new warehouses)
Scenario 6: Increase the number of potential sites (10 new warehouses)
Scenario 7: Increase the number of potential sites (15 new warehouses)

The objective of these four scenarios is to determine the sensitivity of the warehouse selection due to the distance of the new potential warehouse. The increase in several potential site warehouse was based on offering more warehouses closer to the customer. It can be seen from these scenarios that if the model neglects the nearer options offered, the warehouses eventually selected are considered as located in the right locations. Hence, the expansion of their capacities should be considered to store more products, which can reduce the total costs of transportation.

Furthermore, an experiment was conducted to determine the optimal locations and number of warehouses using the model. In the experiment, the number of potentially closer warehouses varied from two, five, 10 and 15 new warehouses. This was to enable the model to shift more loads through warehouses in favourable locations and pull loads away from warehouses in less favourable locations. In order to experiment, the operating cost of each warehouse was kept constant to avoid a situation whereby the model selects heavy load from a warehouse with lower operating costs.

Consequently, a test problem with different dimensions in the original network (comprising manufacturing facilities, warehouses, and customers) was generated. Table 5.2 shows the number of facilities in each test problem. Each set of problems has different warehouse coordinates, although the customer coordinates similar for each dataset. Hence, row 1-2 is a test problem for Data 1; row 3-4 is a test problem for Data 2 and row 5-6 is a test problem for Data 3, and the results are listed in the next table.

Table 5.2 Number of Facilities in Each Test Problem

Test problem	Data	Manufacturing facilities	Warehouse	Customer
A	1	2	10	50
B		2	15	50
C	2	2	10	654
D		2	15	654
E	3	2	10	1060
F		2	15	1060

5.3.3 Optimization Results

This section analyses the results of running the model in the seven scenarios outlined in section 5.3.2. The reasons for using (or not) the selected warehouses in each scenario is explained. Besides, the total distribution cost of the existing distribution network and the network costs suggested by the model are compared. The results for running the seven scenarios are presented in Appendix D.

5.3.3.1 Scenario 1: Baseline

This experiment was made up of three different types of data, and each Dataset was grouped into two sets of problems, as shown in Appendix D. The analysis of each test problem is as follows:

i) Data 1

For problem set A, only one warehouse (warehouse. 10) is closed. This is because it is located rather far away from the customer. Initially, set problem B has more warehouses; the redesign effect is more noticeable when the model proposes to close six of the 15 existing warehouses. The warehouse opened for both sets of problems are the warehouse that is closest to the customer.

ii) Data 2

Set problem C indicates no warehouse closure. This is because the initial number of warehouses opened was just 10 to serve 654 customers. However, different effects were observed for the more significant number of warehouses, namely problem set D. For this case; there are two warehouses closed, namely warehouse 13 and 15. Hence, the model proposes 12 sufficient warehouses for 654 customers to streamline the operating and transportation costs.

iii) Data 3

Problem set E shows two warehouses closed, namely; warehouses 7 and 10. This is different from the problem set C for Data 2, although there is more data for Data 3, the model suggests only eight warehouses to serve 1060 customers. This is because the transportation cost is lower for eight than 10 operating warehouses. Although warehouses 8 and 14 were recommended to close for problem sets F. Data 3 shows conflicting results with Data 2 due to the increasing number of customers with dense data distribution, which makes the model overestimate the operating and transportation costs.

5.3.3.2 Scenario 2: Lower warehouse operating cost by 5%

The results obtained from the previous section are considered for this scenario. This scenario considered deduction of 5 % of warehouse operating cost for a warehouse that was not selected in the Baseline scenario. The analysis of each test problem is as follows:

i) Data 1

Both sets of problems A and B yield the same results as the baseline scenario. This shows that the model selection is consistent because it is not affected by small changes.

ii) Data 2

This experiment was not performed on the problem set C because no changes were made to the original network. This is because the number of warehouses available was either small for many customers, or it already has a good initial solution. The results obtained from this experiment for problem set D are similar to the baseline. This shows that the model selection is consistent because it is not affected by small changes.

iii) Data 3

The same result is shown by the two sets of problems E and F, with no change to the suggested network with the baseline scenario. This shows that the model was still consistent for more massive data sets despite the 5% reduction in operating costs.

5.3.3.3 Scenario 3: Raise warehouse operating cost by 5%.

The results obtained from section 5.3.3.1 are considered for this scenario. This scenario considered increase 5 % of warehouse operating cost for a warehouse that was not selected in the Baseline scenario. The results obtained from this experiment were similar to the others in the previous subsection for all problem sets. This is because the model is not affected by the small change in the 5% increase in operating costs to the unelected warehouse.

5.3.3.4 Scenario 4: Increase the number of potential sites (2 new warehouses)

This experiment was only for problem sets A, C, and E. Compared to the baseline scenario, two new warehouses were added to the original warehouse network to examine the model’s capacity to select a more appropriate warehouse location. The analysis of each test problem is as follows:

i) Data 1

For problem set A, a new warehouse was opened, which was warehouse 11. However, the model's proposal to close two old warehouses and warehouses 12 were not considered. This was because warehouse 11 is strategically closer to the customer compared to warehouses 3 and 10.

ii) Data 2

Problem set C shows the closure of 2 warehouses, i.e. 1 and 9. While two new warehouses were opened namely; warehouses 11 and 12. These two new warehouse locations are closer to the customer due to lower overall costs.

iii) Data 3

For this case, two new warehouses were opened, while warehouse 5 was closed. This shows that this new warehouse position is more appropriate or better in reducing transportation costs.

5.3.3.5 Scenario 5: Increase the number of potential sites (5 new warehouses)

This experiment was performed for problem sets A, C, and E. Compared to the baseline scenario, five new warehouses were added to the original warehouse network to determine if the model can select a better warehouse location. The analysis of each test problem is as follows:

i) Data 1

The optimisation result of this scenario was not different from the above scenario. From the five new warehouses added only warehouse 11 was opened, whereas two original warehouses (3 and 10) were closed. This indicated that the locations of the three additional warehouses are less appropriate than the original warehouse.

ii) Data 2

Contrary to the previous result, after the offering of five new warehouses, two of the original warehouses (1 and 5) were closed. While, from the 12 operating warehouses, four are new. The locations of the four new warehouses are closer to the customer, as the overall cost was lower than before.

iii) Data 3

The addition of three new locations, including the previous scenario, showed no changes to the proposed network in the previous subsection except warehouse 7, which was suggested for closure instead of warehouse 5. This shows that the three new locations were located far away and less suited to the existing customer networks.

5.3.3.6 Scenario 6: Increase the number of potential sites (10 new warehouses)

This experiment is only for the problem sets A, C, and E. Compared to the baseline scenario, 10 new warehouses were added to the original warehouse network to examine whether the model can select a better warehouse location. The analysis of each test problem is as follows:

i) Data 1

The optimisation result of this scenario was similar to the other two previous scenarios. Despite the five potential sites offered, the model did not propose to open a new warehouse even for unfavourable locations.

ii) Data 2

For this scenario, the number of warehouses used is 16, including five new warehouses. However, only warehouse 5 from existing network remained closed compared to the previous scenario. This neglected warehouse is farther than that selected warehouse.

iii) Data 3

There was an increase in the number of 16 operating warehouses. However, the overall cost decreased significantly from 1267300 to 1082580. The model strategically positioned the warehouse to be more operational and incorporates the operations of the old (closed) warehouse located near the new warehouse nearby.

5.3.3.7 Scenario 7: Increase the number of potential sites (15 new warehouses)

This experiment is only for problem sets A, C, and E. Compared to the baseline scenario, 15 new warehouses were added to the original warehouse network to determine if the model can select an appropriate warehouse location. The analysis of each test problem is as follows:

i) Data 1

Surprisingly, in this scenario, the model suggested reducing the transportation cost by accepting to open a newer site. Compared to the previous scenario, warehouses 3 and 10 were still dropped by the model, while warehouse 12 was selected yet again. So in this scenario, 12 warehouses are used. Refer to Appendix D, which shows the lowest transportation cost found in Scenario 7.

ii) Data 2

In this scenario, the model selected 20 warehouses. Warehouse 1 from the existing network was suggested for closure, while 11 new warehouses were selected to be open. Although the number of warehouses is double the original, the overall cost in this type of data is much lower as the transportation cost factor plays the leading role in this type of data. This is in agreement with Sridurongkatum (2010), which stated that if the model is successful in minimising the distribution cost, the overall cost will be reduced.

iii) Data 3

For this scenario, the model suggested to close two old warehouses from the existing network and opened seven new warehouses. Hence, the increase in the number of warehouses with a better position on the customer's network will generally reduce the total cost of distribution (Eshetu and Jinfessa, 2019).

From the optimisation results of the above scenarios, it was observed that some warehouses were selected by the model in every scenario whereas others were not. Furthermore, some warehouses are sensitive to the change in the new potential location of the warehouse. Therefore, the warehouses can be ranked by eligibility into three categories, as shown in Table 5.3.

The data shows which warehouse is preferred by the model. The findings imply that the warehouses are located at the appropriate locations. Hence, it presents guidelines about which warehouse a company should focus more attention. Similarly, Data 1 shows that numerous facilities are not needed to meet the demands of a small number of customers. As shown in Table 5.3, although 15 potential sites were proposed for the new warehouse, the model only recommended opening 9 new warehouses. Data 2 and Data 3 suggested more customers, so more warehouses were proposed to operate, as shown in Table 5.3, where the number of new warehouses never selected by the model is small.

5.4 Comparison between Existing Networks with Model Suggestion.

From the previous section, it can be seen that the model suggested different new distribution networks for Data 1, Data 2, and Data 3 except for Data 2 for the test problem C from the existing network. This section compares the characteristics of the existing networks to the suggested networks for all set problem except test problem C. The comparison between the total distribution cost of existing networks and the suggested networks by cost element is shown in Figures 5.1 to Figures 5.6.

Table 5.3 Warehouse Categories by Model Preference

Categories			Always selected	Location sensitive		Never been selected
Criteria			Been selected in all scenarios.	Not been selected in 2 or 5 new warehouse scenarios.	Not been selected in 10 or 15 new warehouse scenarios.	Not been selected in all scenarios
Data 1	Test problem a	Existing warehouse	1,2,4,5,6,7,8,9	3	-	10
		New warehouse	-	12	-	13,14,15,16,17,18, 19,20,21,23,24,25
	Test problem b	Existing warehouse	1,2,3,5,6,7,9,13,15	-	-	4,8,10,11,12,14
		New warehouse	-	-	-	-
Data 2	Test problem c	Existing warehouse	2,3,4,6,7,8,9,10	9	-	1,5
		New warehouse	11	12,13	13, 14	24,25
	Test problem d	Existing warehouse	2,3,4,6,7,8	5,9		1
		New warehouse	-	11,12		24,25
Data 3	Test problem e	Existing warehouse	1,2,3,4	5,6,7,8,9,10		-
		New warehouse	11,12	13,14,15	16	20,25
	Test problem f	Existing warehouse	1,2,3,4,5,6,7,8,9,11, 12,13,15	-	-	14
		New warehouse	-	-	-	-

Based on Figures 5.1, Figures 5.2 and Figures 5.3, these savings stem from the total of savings from three components the costs of inbound transportation, outbound transportation, and operations. The inbound transportation cost of the suggested networks shows a slight decrease in each test problem.

The second element of the total distribution cost is the outbound transportation cost. Most of the savings accrue from this component of the distribution cost. The savings are due to moving the product from manufacturing plants and storage at warehouses, which are closer to the customer. Consequently, storing the product at warehouses close to the customer minimises the outbound distance and transportation costs Sridurongkatum (2010). The third element of the total distribution cost is the operating cost. The fixed and variable costs of the warehouse were combined in computing the operating cost. For the test problems A and E, there is a decrease in the operating cost as there are two warehouses that are proposed to close for the two test problems. For other test problems, there is an increase in operating cost as the model proposes more warehouses to be opened to serving customers. However, due to the strategic position of the new warehouse and closer to the customer opening more warehouse does not increase the total cost of distribution.

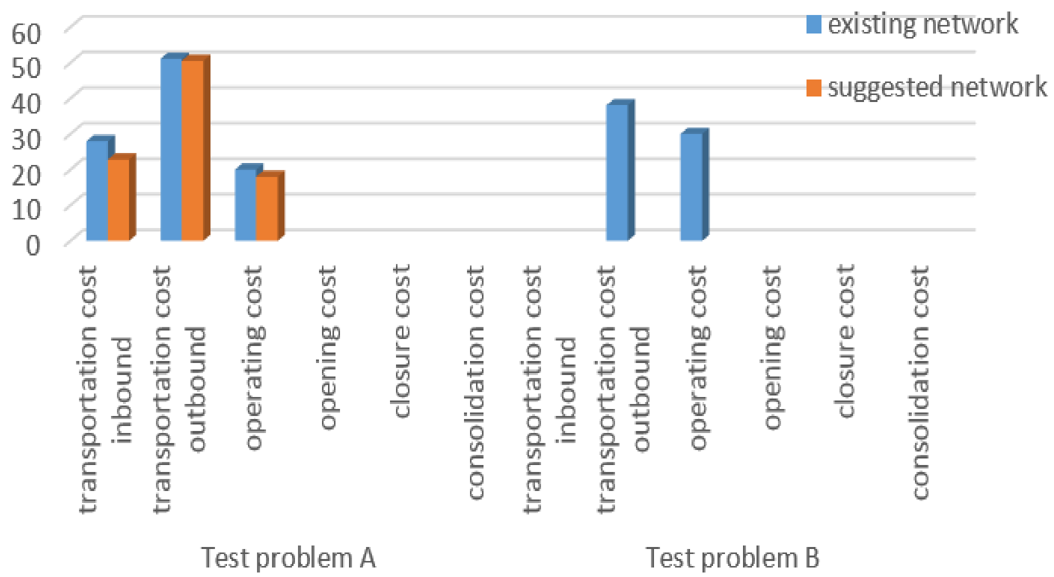

Figure 5.1 Comparison of total distribution cost of existing and suggested networks for Test Problem A and B

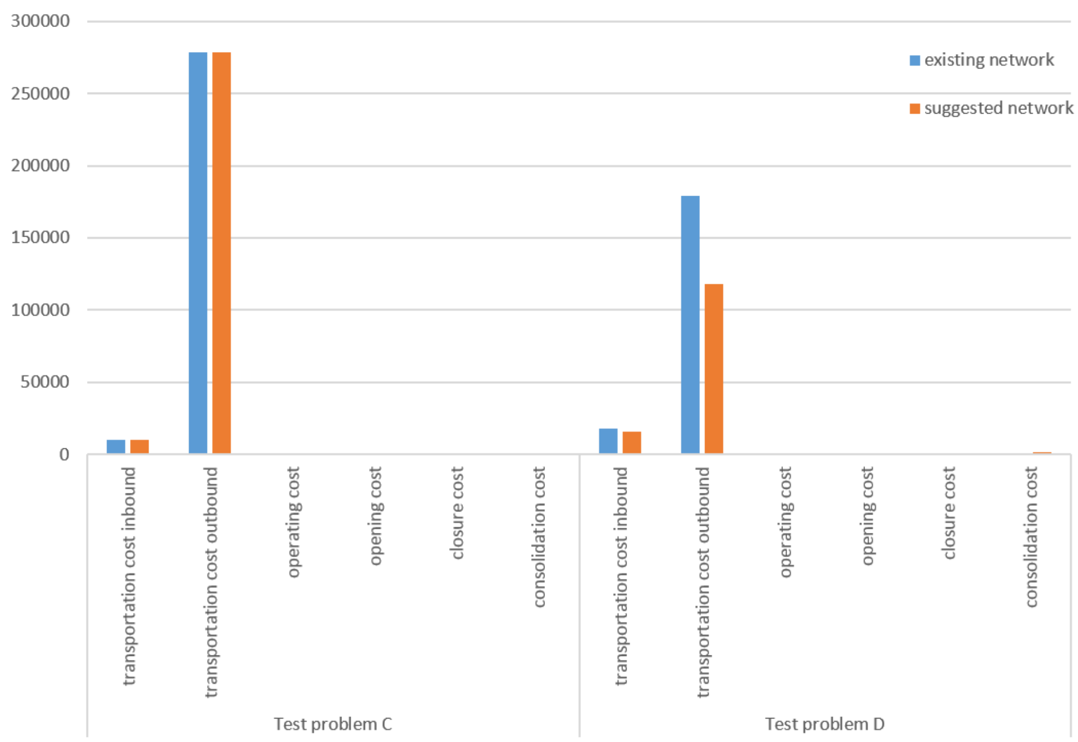

Figure 5.2 Comparison of total distribution cost of existing and suggested networks for Test Problem C and D

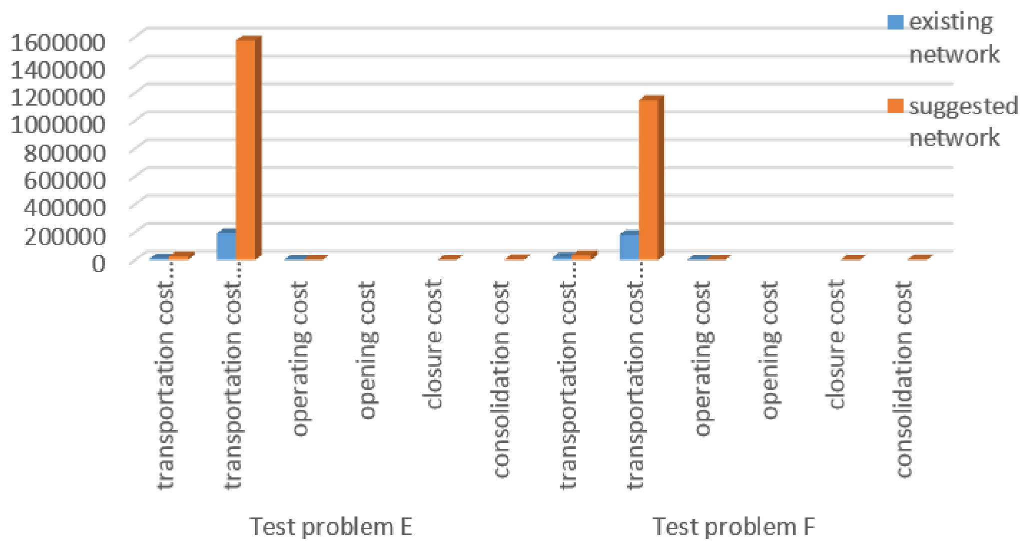

Figure 5.3 Comparison of total distribution cost of existing and suggested networks for Test Problem E and F

By carefully examining the results from the scenarios of offering more potential sites, significant improvements in terms of cost savings and utilised number of warehouses can be observed. Figures 5.4 until 5.6 compare the existing distribution networks and the model results for all increasing warehouse potential site scenarios.

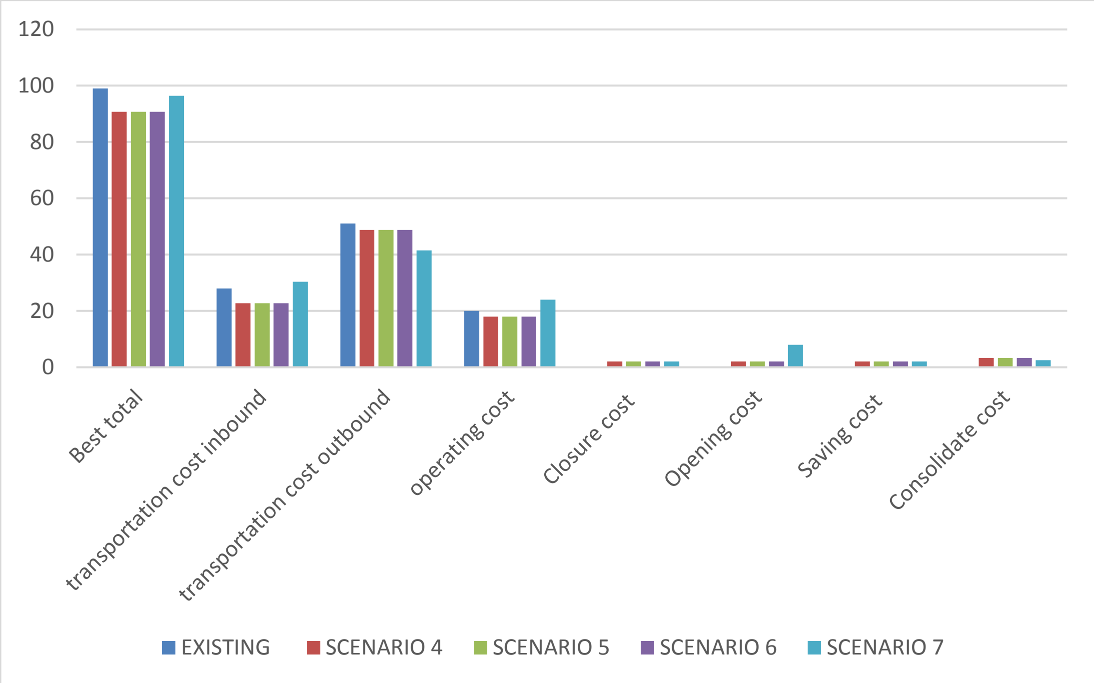

Figure 5.4 Comparison between the existing network and the model results of increasing more potential site scenarios for Data 1

As observed in Figures 5.4 until Figures 5.6, if a potential site is provided closer to the customer, the cost-saving will increase dramatically. Cost improvement mainly occurs by reducing the number of outbound transportation links from the warehouse to customers, thus making a significant reduction in outbound transportation costs. Figure 5.4 shows the minimum cost for Data 1 in Scenario 4.

Although additional warehouses were offered in Scenario 5 to Scenario 7, the model found only nine warehouses were optimally operational, two of which are two new warehouses offered in Scenario 4.

Figure 5.5 shows a slightly different result, as newer warehouses are offered, the model has more opportunities to find an optimum network location for network distribution. In Figure 5.5, the optimum cost of Data 2 was observed in Scenario 7. A similar observation was found in Figure 5.6, which is the minimum cost for Data 3 in Scenario 7.

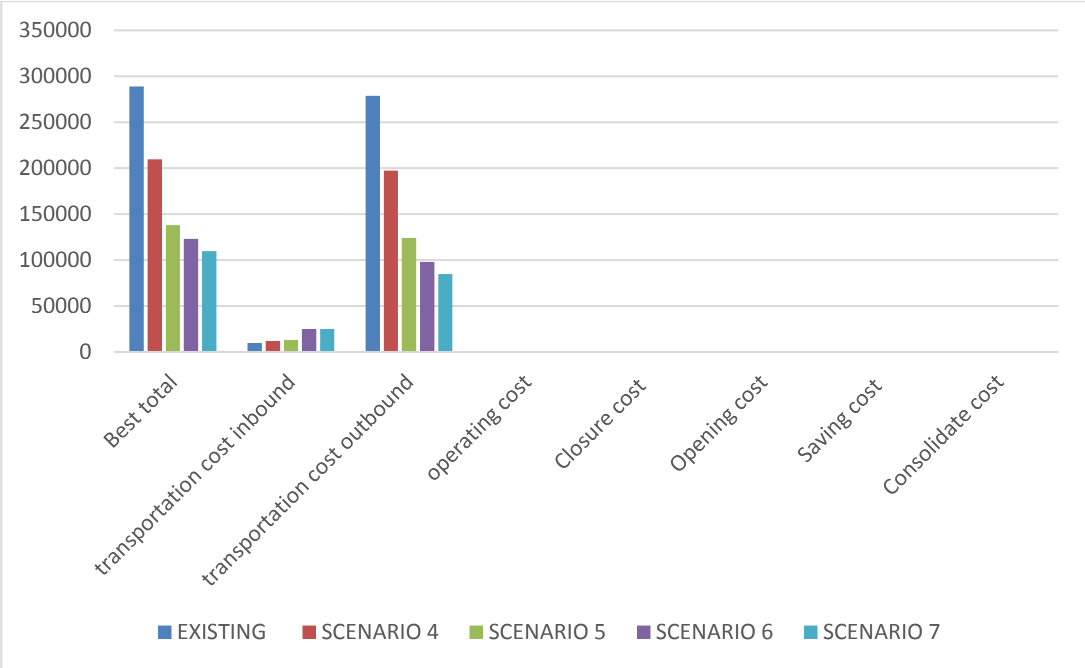

Figure 5.5 Comparison between the existing network and the model results of increasing more potential site scenarios for Data 2

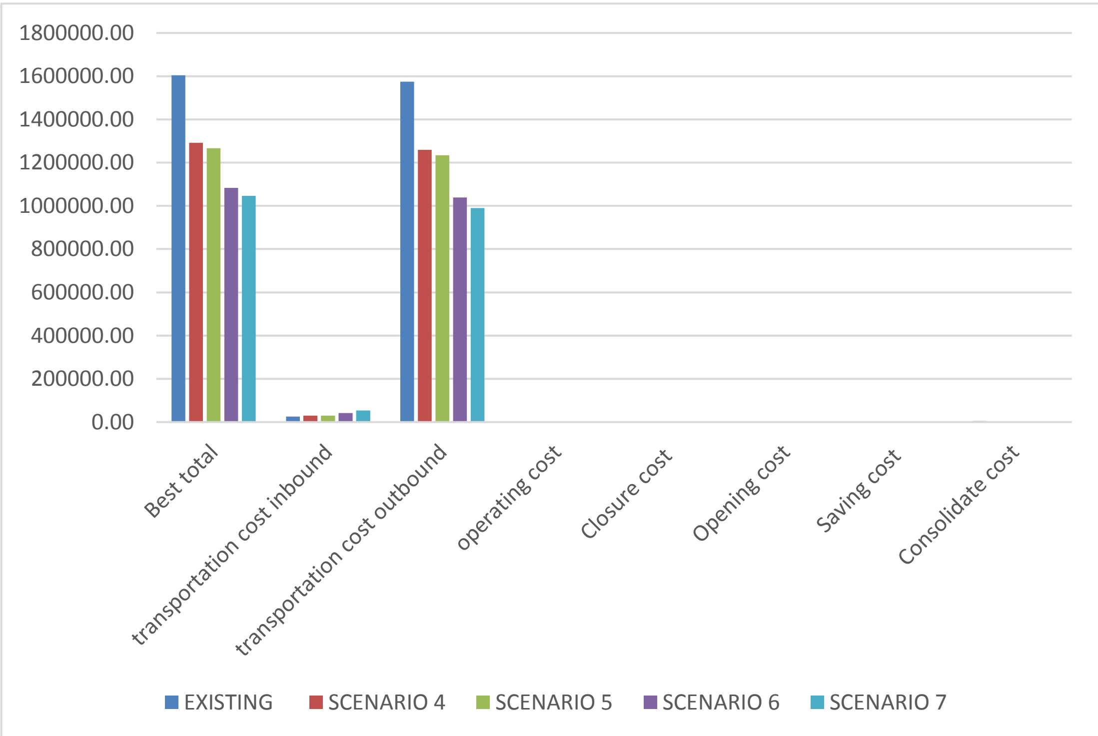

Figure 5.6 Comparison between the existing network and the model results of increasing more potential site scenarios for Data 3

5.5 Summary

This chapter analyzed the objective of the study on how to develop the solution procedure for solving the warehouse redesign model with consolidation, elimination and addition of new site. The analysis was performed on the same customer data set as in Chapter 4. However the location and allocation of warehouse to customer and manufacturing plant to warehouse were derived from the Location Allocation (LA) study by Khairuddin et al. (2007) and being considered as existing network. Location suggested for the new warehouse were derived from the same method. Therefore, the new warehouse proposed in this study is strategically located.

The analysis made in this chapter shows that redesign can be done by combining the operations of two or more warehouses or by closing the warehouse nearby. However, the total distance to the customer may be higher than others. Besides, the study model also shows that if there is a new warehouse that is nearer to the customer, the opening of the new warehouse is proposed by the combination of the merger, the opening of the new warehouse, and operating cost to be offset by the cost of transportation. For example, in case of 10% percent increase of warehouse, the fixed cost will also increase depending on the number of new facilities.

Data 1 shows that numerous facilities were not needed to meet the demands of a small number of customers. The model only recommended opening nine new warehouses. Data 2 and Data 3 suggested more customers, so more warehouses were proposed to operate, where the number of new warehouses never selected by the model was small.

The analysis in this chapter shows that all three types of data have differences in redesigning the Warehouse network. Most important is the improvement made in this study compared to the previous study is that new warehouse placements are not randomly placed but using the allocation location model by Khairuddin *et al*. (2007). Since the proposed new warehouse is in a strategic location, taking into account the position of the customer and plant with the warehouse, then a more optimal cost can be obtained as a result of this study.

Through this chapter, the model has proposed a better network for each type of data distribution discussed by considering several redesign methods and constraints as discussed by Melachrinoudis and Min (2007). However, there are other factors that can be taken into account as discussed in Chapter 2, namely zone dependent fixed cost. The best results obtained from this chapter will be used for analysis in the next chapter. The next chapter will consider other factors for redesigning a warehouse network that has not yet been undertaken, which is to increase the zoning cost to specific areas of the existing network.

CHAPTER 6

RESULTS CONCERNING THE NEED FOR ZONE-DEPENDENT FIXED COST AND CAPACITATED WAREHOUSE

6.1 Introduction

This chapter presents a zone dependent fixed cost implementation to address the redesigning problems of warehouse network location. This is one of the factors that must be considered when redesigning a warehouse network location problem. Furthermore, a capacitated location problem is also examined in this chapter to compensate for the result obtained after the zone dependent fixed factor is included in the study model. The proposed zone dependent fixed cost model implementation is evaluated using the same literature test problems, as described in the previous chapter.

6.2 Problem Description

According to Simon et al. (2011), factors such as war, natural disasters among others, require the introduction of zone dependent fixed cost into the redesign of warehouse network studies. During natural disasters, the entire affected area is completely closed down or the residents relocated to other neighbourhoods. Therefore, the zone dependent fixed cost is introduced in the objective function as given in Equation 6.1. This objective is an extension of the objective function given in Equation 2.20.

$$\begin{aligned}\text{Min} \sum_{p\in P}\sum_{i\in A} v_{pi} y_{pi} + \sum_{i\in A}\sum_{k\in C(i)} s_{ik} x_{ik} + \sum_{p\in P}\sum_{i\in A} r_{ji} z_{ji} + \sum_{i\in A} f_i^c \sum_{j\in E} c_j z_{ji} + \sum_{i\in E} f_i^m z_{ii} + \sum_{i\in N} f_i^m w_i \\ + \sum_{j=1}^{A}\sum_{r\subset R}\sum_{d\in D_r}\left(F_{rd}\cdot S_{jrd}\right) - \sum_{j\in E}\left[f_j^s \left(1 - \sum_{i\in A} z_{jk}\right) + f_i^m \sum_{\{i\in E, i\neq j\}} z_{ji}\right]\end{aligned} \tag{6.1}$$

The objective function Equation 6.1 reduces the total cost for the supply chain, which consists of manufacture, passage, storage and transfer and addition of zone dependent fixed cost. This occurs while exploiting the savings cost ensuing from the shutting or merging of empty warehouses or maximises the cost-saving resulting from the closure or consolidation of redundant warehouses. The constraints considered for this model are Constraints 2.21 until 2.30.

The research data used in this chapter is similar to the data used in the previous chapter. All the assumptions made in the previous chapter are also applicable to this chapter. The results obtained from the previous chapter are also used in this study, where the optimal number of the proposed warehouses operated are; 12, 23, and 25 for Data 1, Data 2 and Data 3, respectively. As this chapter discusses zone dependent fixed cost, the study areas for Data 1, Data 2, and Data 3 have been randomly divided into 12 different zone dependent fixed costs. Figures 6.1 until 6.3 show the zone fraction and cost per zone for Data 1, Data 2, and Data 3.

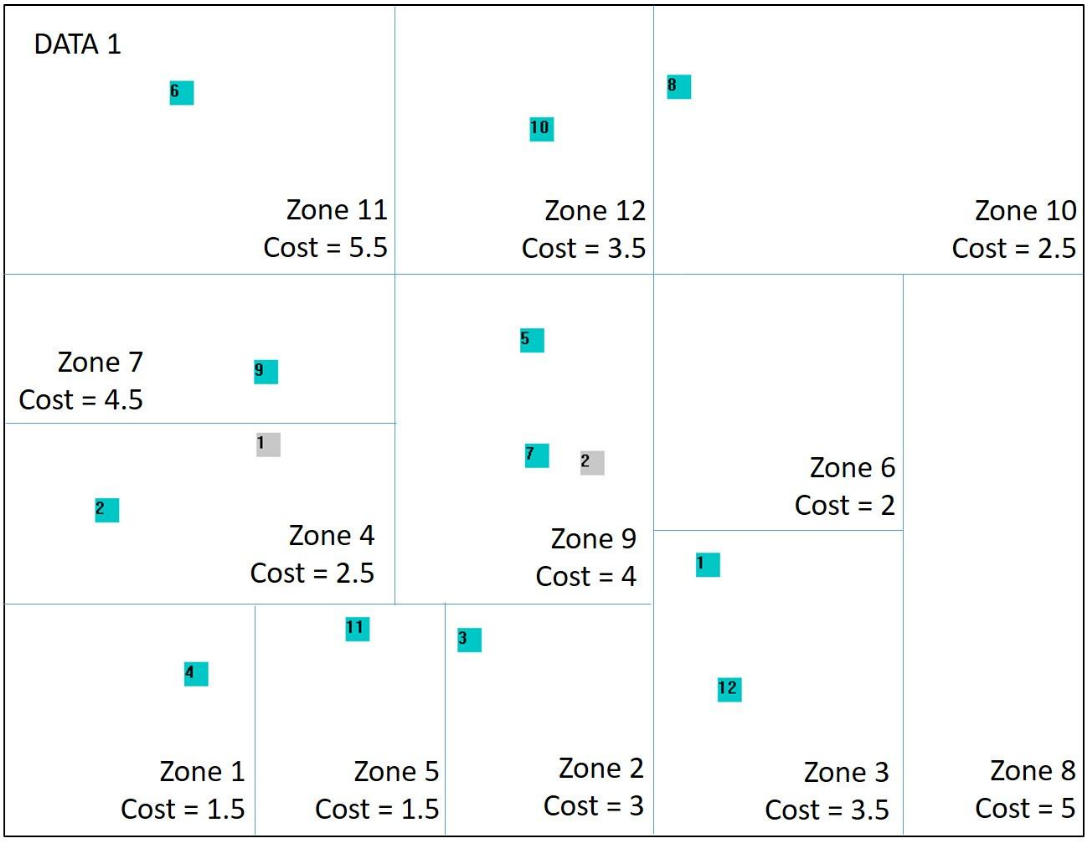

Figure 6.1 Zone distribution for Data 1

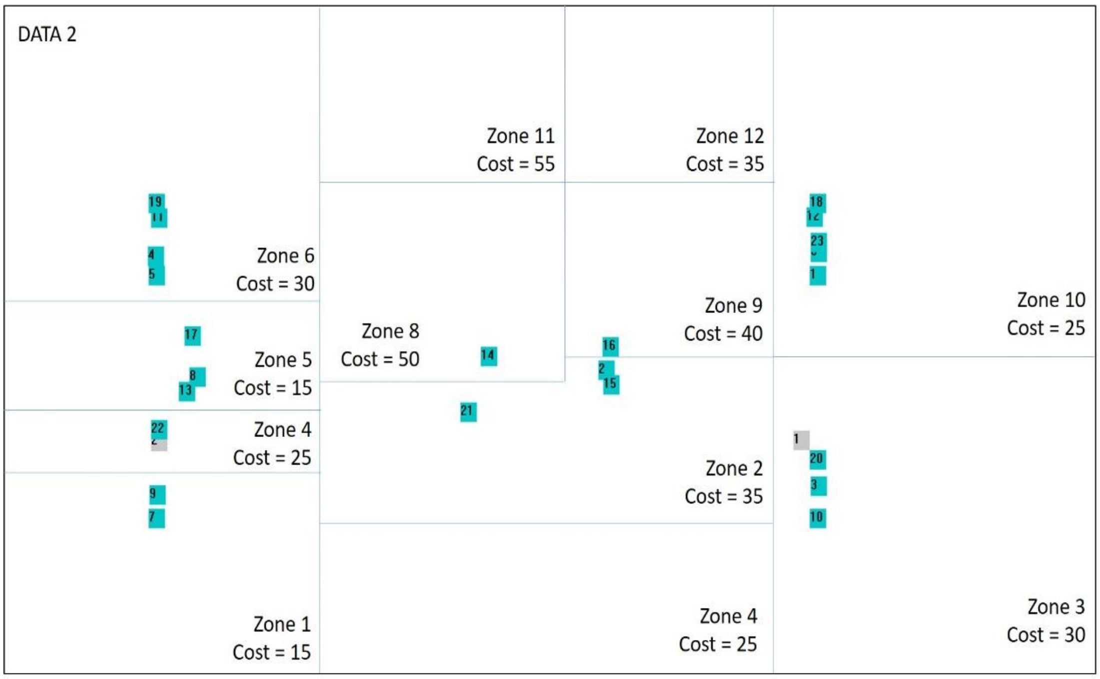

Figure 6.2 Zone distribution for Data 2

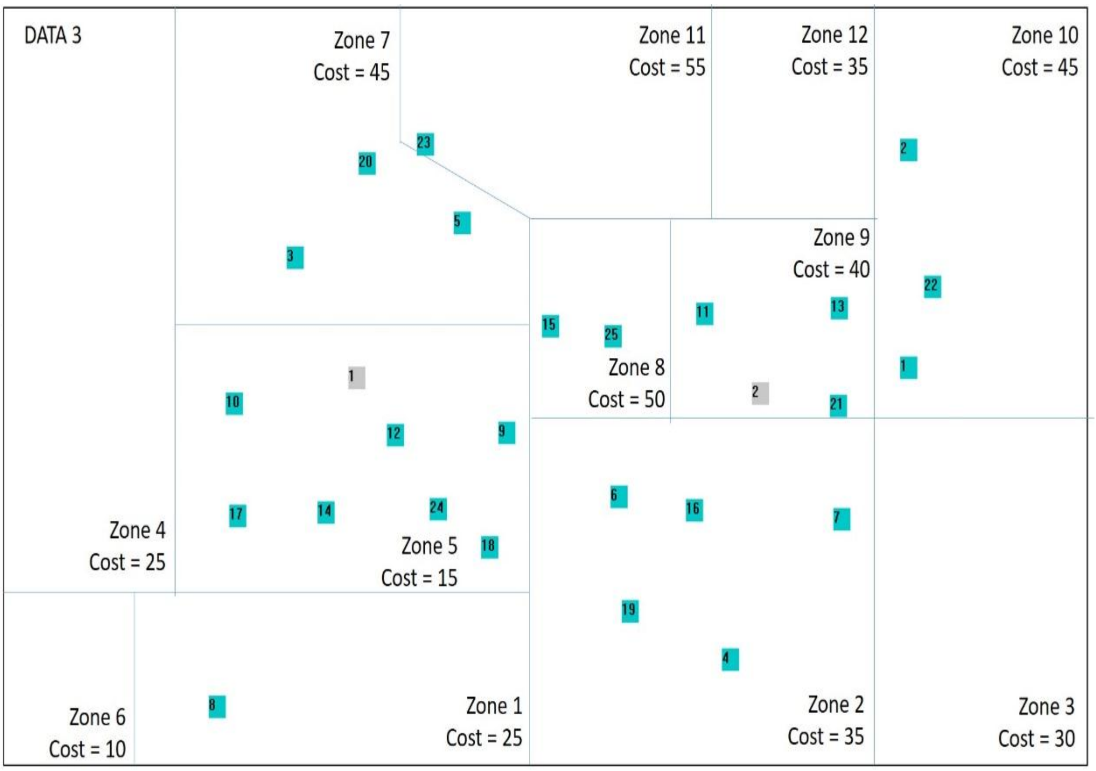

Figure 6.3 Zone distribution for Data 3

6.3 Scenarios

The model was run with the addition of zone dependent fixed cost, as shown in section 6.2, with other scenarios to examine the sensitivity of warehouse selection. The selected scenarios are:

Scenario 1: Baseline

In this scenario, the model is run by introducing the zone dependent fixed cost, as shown in Figure 6.1 until 6.3. The model agreed to use 100% of maximum warehouse capacity as a baseline for the model.

Scenario 2: Lower zone dependent cost by 5% for a warehouse that was not selected in the Baseline scenario.

This scenario examines whether the warehouses that were not selected by the model in the Baseline scenario will be selected if the zone dependent fixed cost is decreased by 5%. In other words, this is to examine how much the reduction in the zone dependent fixed cost will make the warehouse eligible, i.e. higher or lower than 5%.

Scenario 3: Raise the zone dependent cost by 5% for a warehouse that was selected in the Baseline scenario.

This scenario examines whether the warehouses that were selected by the model in the Baseline scenario will be reselected if the zone dependent fixed cost is increased by 5%. In other words, this is to examine how much the increase in the zone dependent fixed cost will make the warehouse ineligible; higher or lower than 5%.

Scenario 4: Add one extreme zone dependent fixed cost.

For the experiments performed in the baseline scenario, the differences between the zone dependent fixed costs were not significantly different from each other for all the data sets. Therefore, this scenario was proposed to examine a more significant effect.

For example, when a high value is randomly assigned to any zone that has been broken down into the study area for Data 1, Data 2, and Data 3.

Scenario 5: Add two extreme zone dependent fixed costs.

This scenario adds another extreme zone to the study area for Data 1, Data 2, and Data 3. Appendix E provides details of the cost changes between these scenarios.

6.3.1 Optimization Results

This section analyses the results of running the model in the five scenarios mentioned in the previous section. The results from running the five scenarios are shown in Table 6.1. The analysis of the optimisation results for each scenario is presented in subsection 6.3.2.

6.3.2 Analysis of the Optimization Results

The results obtained from this experiment were processed from Scenario 1 to Scenario 3, as shown in Table 6.1. The results show that Data 1 and Data 2 are consistent due to the small changes in Scenario 2 and Scenario 3, which did not affect the results obtained from the baseline scenario. This is because Data 1 has a small amount of data, whereas Data 2 has a different type of data distribution. However, the results for Data 3 are different because, after the small changes in Scenario 2 and Scenario 3, the results obtained are different from the baseline study. This is expected because the size of Data 3 is enormous, and the cost difference between each zone is not very different.

In Scenarios 4 and Scenario 5, when one or two zones are set with an enormous zone dependent fixed cost value, there was an increase in cost distribution or objective

Table 6.1 Optimization Results

Data	Criteria	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Data 1	Number of used warehouse	7	7	7	8	6
	Number of closed warehouse	5	5	5	4	6
	Objective value	117.9919	117.7852	119.2852	119.8961	130.5283
Data 2	Number of used warehouse	16	16	16	16	11
	Number of closed warehouse	7	7	7	7	12
	Objective value	116628.7370	116346.0467	117220.4396	198708.9675	435523
Data 3	Number of used warehouse	20	18	19	12	13
	Number of closed warehouse	5	7	6	13	12
	Objective value	1020212.4014	1039849.4624	1032730.3621	1369436.0858	1480680

value to the Data 1, Data 2, and Data 3. In Scenario 4, Data 1 shows an increase in the number of operational warehouses. Therefore, there was an increase in operating costs. However, Data 2 shows no changes in the number of warehouses operating and Data 3 shows the number of proposed operating warehouses to be only 12 warehouses. So for Data 2 and Data 3, the addition of the objective value could be due to the increased consolidation cost. This was because the model avoids opening or allowing the warehouse in the zone to operate, and its operation was merged into the warehouse located in the nearby zone. Appendix F shows the details of the inbound transportation cost and the number of customers served by the open warehouse in Scenario 4 and Scenario 5.

Based on Appendix F, it can be seen that when a zone with extreme value is introduced, the model avoids opening a warehouse within that zone. For example, in Data 1, Zone 5 had the highest zone dependent cost value. Hence the model recommended the closure of a warehouse in that zone. However, for Data 2, Zone 1 had the highest cost dependent zones, and the model recommended the closure of warehouses 5 and 7 within the zone. Warehouse 22, located in Zone 4 and adjacent to Zone 1, had the highest inbound transportation costs along with the highest number of customers (146) to serve. This is because the warehouse operation was merged with a warehouse in a nearby zone. Refer to Figure 6.1 to Figure 6.3 for reference to the position of the extreme zone and the zone next to it.

Similarly, the study model recommended the closure of all the warehouses in Zone 5, derived from Data 3. Consequently, the warehouses within the immediate zone received an increase in inbound transportation costs and the need to serve more customers compared to others. This represents an unrealistic decision if required, to solve the real problem. Although the model initially assumed that each warehouse was incapacitated to serve any number of customers, the current scenario is unrealistic. Therefore, the next section will consider the addition of a capacity constraint to the warehouse, as described in Equation 5.2.

6.4 Solving the Capacity Problem

For this study, each warehouse was assigned a specific capacity taking into account the average warehouse provided and the number of customers available per data set. For example, in Data set 1, the 50 customers were distributed into the 12 warehouses provided, so each warehouse had an average supply of five (5) customers. As the model recommended the closure of the warehouse in the critical zone, the warehouse capacity in the immediate zone will be three (3) times higher than the previous average. Meanwhile, the capacity of the other warehouse was randomly assigned. Similar calculations were made for all the data sets, and Table 6.4 shows the capacity assigned to each warehouse for data 1, 2, and 3. The algorithms that describe this analysis are as follows:

Algorithm 6.1

Step 1: The results in Scenario 4 above are used as an initial solution.

Step 2: Calculate the average number of customers served by each warehouse, set the average as standard capacity.

Step 3: Identify the zone closest to the critical zone, which is the highest cost zone.

Step 4: Set the capacity three times higher than the warehouse in Step 3 and standard capacity to another warehouse.

Step 5: Use TP to allocate customers to the appropriate warehouses.

Step 6: Apply TP to allocate the selected warehouse from Step 5 to the plant and calculate its corresponding cost using equations (6.1).

Step 7: Repeat Step 5 and 6 until the stopping limit.

Table 6.2 Normal Capacity Per Warehouse for Data 1, Data 2 and Data 3

Warehouse	Data 1	Data 2	Data 3
1	12	28	130
2	12	50	130
3	12	109	130
4	12	50	130
5	4	50	130
6	12	28	130
7	4	28	130
8	12	50	130
9	12	28	42
10	12	109	42
11	4	50	42
12	12	28	42
13	-	50	42
14	-	50	42
15	-	50	130
16	-	109	130
17	-	50	42
18	-	28	42
19	-	50	130
20	-	109	130
21	-	50	42
22	-	109	130
23	-	28	100
24	-	-	42
25	-	-	130

6.4.1 Computational Result on Capacitated Problem

In this section, the analysis results for redesigning a warehouse network problem with capacitated zone dependent fixed cost will be discussed. Appendix G shows the results obtained after assigning a specific capacity to each warehouse. The table below shows the results after setting two scenarios for this problem. Scenario 6 assigns the capacity to the warehouse as specified in Table 6.4. Meanwhile, Scenario 7 adds two times higher capacity than the first scenario to a warehouse located in a zone near the critical zone.

The capacity warehouse for Scenario 6 is lower than Scenario 7. Appendix G shows that when a warehouse has a small capacity, the number of warehouses that need to be opened will increase. This is because more warehouses are needed to serve all customers. Data 1 shows six warehouses need to be opened for Scenario 6 while seven warehouses were opened for Scenario 7. Whilst, Data 2 shows that twelve warehouses are opened for Scenario 6 and only nine warehouses are opened for Scenario 7. Whereas for data 3, the number of open warehouses for Scenario 6 is eleven and twelve for Scenario 7.

From Figure 6.4a, Figure 6.4b and Figure 6.4c it can be seen that the warehouse closest to the critical zone has a much larger number of customers than any other warehouse. Figure 6.4a shows that Warehouse 3 and Warehouse 10 were having a relatively high number of customers compared to the others as these two warehouses are located closest to the critical zones. Meanwhile, Figure 6.4b of Data 2 shows that Warehouse 16 and Warehouse 22 have the highest number of customers to be served as these two warehouses are also located closest to the critical zone.

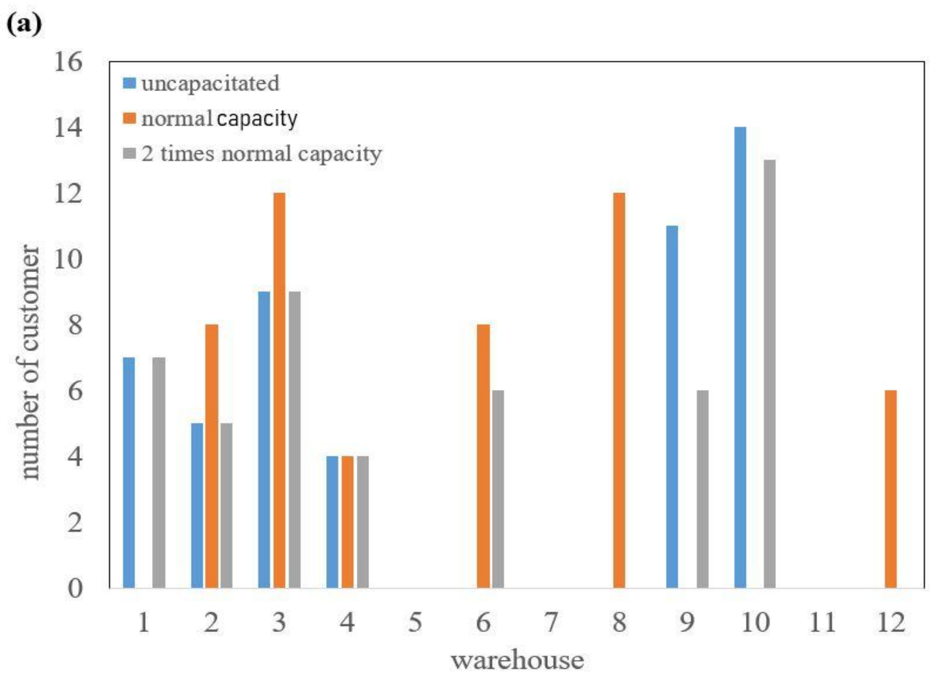

Figure 6.4a Comparison of customer served by each warehouse for uncapacitated, normal capacity and 2 times normal capacity scenarios in Data 1

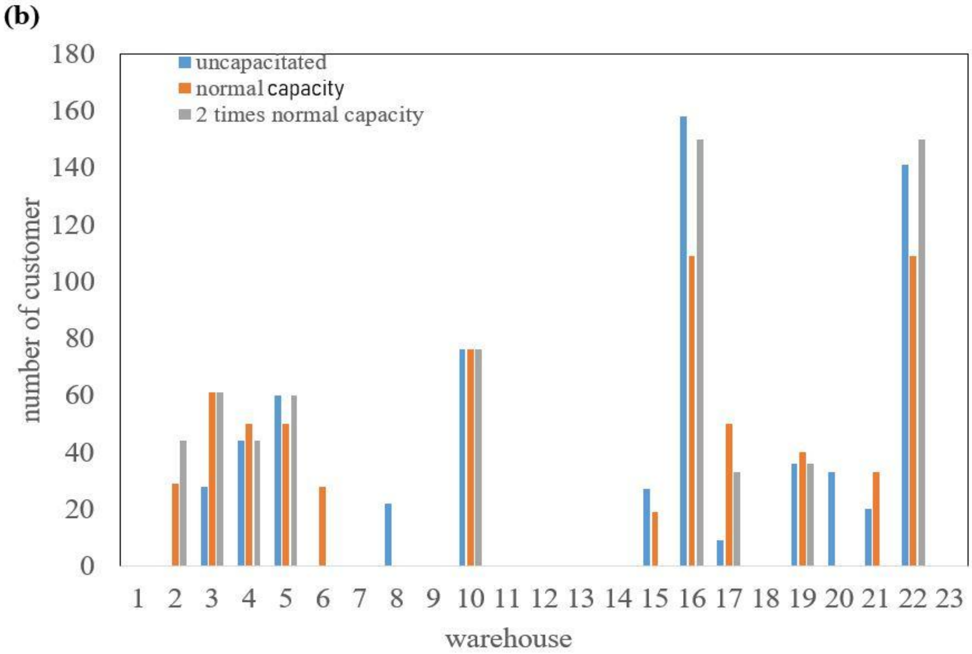

Figure 6.4b Comparison of customer served by each warehouse for uncapacitated, normal capacity and 2 times normal capacity scenarios in Data 2

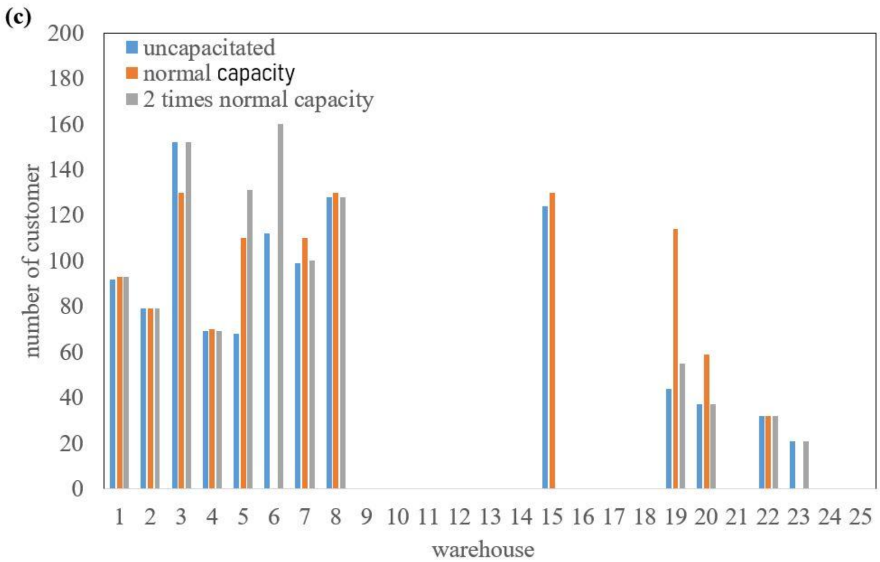

Figure 6.4c Comparison of customer served by each warehouse for uncapacitated, normal capacity and 2 times normal capacity scenarios in Data 3

Whereas for Data 3, (Figure 6.4c) suggested that warehouse 3, 5, 15, 6, 19 and 7 was the most inconsistent to be serve because of all the warehouses mentioned this is a warehouse that is closest to the highest cost zone. This indicates that when the redesign of a network needs to be done on a dependent zone, factor such as an instance of disaster, the research model needs to provide a high capacity for the warehouse close to that critical zone.

Table 6.3 shows the total cost distribution between Scenario 5, 6 and 7 for all set of data. It shows that when capacity was higher, as the total distribution cost became lower. This result was confirmed by a study conducted by Sudorongkatum (2010) on the effect of capacity on transportation cost. Scenario 5 shows the lowest total cost distribution value for all data sets because there is no defined capacity for all warehouses. Whilst, in Scenario 6, total distribution cost was the highest because in this scenario every warehouse had a low capacity.

Table 6.3 Comparison of Total Distribution Cost for Scenario 5, 6 and 7

Data	Scenario 5	Scenario 6	Scenario 7
Data 1	130.53	139.56	130.53
Data 2	435523.00	468987.00	460200.00
Data 3	1480680.00	1621640.00	1603230.00

6.5 Summary

This chapter analyzed the effects of adding zone dependent fixed cost in a model redesigning a warehouse network problem. When zone dependent fixed cost was introduced as one of the factors for redesign, this cost was included in the objective function calculation. The effect of introducing zone dependent fixed cost to the three research data was that the model will avoid opening any warehouse located in a high value zone known as the critical zone because the objective of the study was to find the most optimum or minimum cost. When this happened, Data 2 and Data 3 showed alarming results as warehouses near the critical zone had to provide supply to very high numbers of customers. This suggests that the effect is practically unrealistic as it may exceed the capabilities of a warehouse even though this study is an uncapacitated location problem.

To solve this problem, capacitated zone dependent fixed cost was introduced. The capacity here is defined as the capacity of a warehouse in providing supply to a certain number of customers. When this capacity constraint is added to the study model, it revealed different effects on the three types of data studied.

Data 1 had small number of customers and has a uniform distribution type. Thus, adding one or two critical zones does not show a significant change in the total distribution cost.

Distribution of Data 2 cluster type showed different effects when two critical zones were introduced. The significant change in the total distribution cost was due to the increased in inbound transportation cost as the warehouse distance is far from the customer group within this critical zone.

The dense distribution of Data 3 and the number of customers which were many times larger than the rest of the data sets showed no significant effect on the change in total distribution cost as the warehouse position is not far between the defined zones. So when a zone is closed, the customer's distance from the warehouse to the nearest zone is not far apart.

However, this depends on the critical zone of each study because what was specified in this study was a random selection. When zone dependent fixed cost is introduced the model requires more search space because new constraints have been introduced with difference value of zone dependent fixed, multi start SA method provides more search space in obtaining optimal results.

CHAPTER 7

CONCLUSION AND RECOMMENDATIONS

7.1 Conclusion

This chapter concludes all the findings from this research and also gives an outline of some research avenues which are worthwhile investigating in the future. The first part of this work, Chapter 1, is the introduction of the study including the problem statements, objectives of the study, scopes of the study, significance of the study and outline of the thesis.

Chapter 2 dealt with the literature review concerning the concept of warehouse location problem and warehouse redesign network. The review on warehouse location, redesigning the warehouse network and the solution methods that have been used to solve the warehouse location problem provides us very useful and practical information to this study.

Chapter 3 discussed the solution method for Simulated Annealing (SA). The main steps of SA and the factors that affect the efficiency of the annealing process were also presented. It also reviewed the related works on SA location problems. Likewise, Chapter 3 also discussed the TP methods that was used to solve customer allocation problems to the warehouse and the warehouse allocation to plants. As the factor zone was considered in this redesign study, a brief explanation had been discussed regarding zone dependent fixed cost in Chapter 3.

An investigation on the best parameter for Simulated Annealing was carried out in Chapter 4 where the best parametric setup for SA was studied. The parameters studied to produce the best SA algorithm were cooling schedule, probability ratio in geometric schemes, initial temperature, and stopping limit. The geometric cooling schedule $\alpha = 0.95$ was selected as the best cooling scheme based on its optimal performance in running time and minimum average cost. Some computational results of the geometric, linear, and logarithmic cooling schedule using 50, 654 and 1060 fixed point test problems from the literature were also given. The best initial temperature was found to be different for each of the data set because of the difference in the best and worst solution found for each data set and the distribution for each of the data set. Data 1 used T_0 = 8000, Data 2 used T_0 = 333000 and Data 3 used T_0 = 3331000. The SA model was also improved by using the dynamic stopping limit, although this approach gave inconsistent values of average cost and standard deviation. However, these were improved by introducing multi-start SA. Some computational results of this approach using the same test problem were also given. Consequently, a total of 10 multi-start SA were selected for the algorithm to be used for the study in Chapter 5.

Chapter 5 analyzed the objective of the study on how to develop the solution procedure for solving the warehouse redesign model with consolidation, elimination and addition of new site. The analysis was performed on the same customer data set as in Chapter 4. However the location and allocation of warehouse to customer and manufacturing plant to warehouse were derived from the Location-allocation (LA) study by Khairuddin et al., 2007 and being considered as existing network. Location suggested for the new warehouse were derived from the same method. Therefore, the new warehouse proposed in this study was strategically located.

Besides that, the analysis made in Chapter 5 showed that redesign can be done by combining the operations of two or more warehouses or by closing the warehouse nearby. However, the total distance to the customer may be higher than others. Besides, the study model also shows that if there is a new warehouse that is closer to the customer, the opening of the new warehouse is proposed by the combination of the merger, the opening of the new warehouse, and operating cost to be offset by the cost of transportation. Data 1 shows that numerous facilities were not needed to meet the demands of a small number of customers. The model only recommended opening nine new warehouses. Data 2 and Data 3 suggested more customers, so more warehouses were proposed to operate, where the number of new warehouses never selected by the model was small. The best results obtained from this chapter will be then used for analysis in Chapter 6.

Chapter 6 analyzed the effects of adding zone dependent fixed cost in a model redesigning a warehouse network problem. When zone dependent fixed cost was introduced as one of the factors for redesign, this cost was included in the objective function calculation. The effect of introducing zone dependent fixed cost to the three research data was that the model will avoid opening any warehouse located in a high value zone known as the critical zone because the objective of the study was to find the most optimum or minimum cost. When this happened, Data set 2 and Data 3 showed alarming results as warehouses near the critical zone had to provide supply to very high numbers of customers. This suggested that the effect is practically unrealistic as it may exceed the capabilities of a warehouse even though this study is an uncapacitated location problem.

To solve this problem, capacitated zone dependent fixed cost was introduced. The capacity here was defined as the capacity of a warehouse in providing supply to a certain number of customers. When this capacity constraint is added to the study model, it revealed different effects on the three types of data studied. Data 1 had small number of customers and has a uniform distribution type. Thus, adding one or two critical zones does not show a significant change in the total distribution cost. Meanwhile, distribution of Data 2 cluster type showed different effects when two critical zones were introduced. The significant change in the total distribution cost was due to the increased in inbound transportation cost as the warehouse distance is far from the customer group within this critical zone. Finally, the dense distribution of Data 3 and the number of customers which were many times larger than the rest of the data sets showed no significant effect on the change in total distribution cost as the warehouse position is not far between the defined zones. So when a zone is closed, the customer's distance from the warehouse to the nearest zone is not far apart. Nevertheless, this depends on the critical zone of each study because what was specified in this study was a random selection.

7.2 Recommendations for future works

There are several recommendations for future research such as:

i) Extension of the heuristics

- Change the move in SA procedure, especially when introducing the zone dependent fixed cost, for example, move the selected facility point to the point with the largest cost among the points in the neighbourhood, to avoid being trapped in the local optimum solution.
- Develop a more intensive and deterministic way for the facility based move where more possibilities are explored. For example, the number of facilities that are moved may depend on the current iteration. One way is that initially all facilities will be allowed to be changed, then the number will be reduced until only a few or one facility will be changed at a time.

ii) Locate the new facilities with any location allocation (LA) method. For example combining the study of location allocation and this study, whenever any warehouse with a large number of customer to be supplied use the LA method to identify the best location for a new warehouse to open.

7.3 Summary

This chapter summarizes the entire chapter in this thesis and also provides suggestions to improve this study for the future. The first section of the chapter provides a summary for each chapter in this thesis. While the second section discusses suggestions for improvements that can be taken for future study. All objectives in this thesis had been accomplished accordingly

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APPENDIX

APPENDIX A: ANALYSIS ON COOLING SCHEDULE

	DATA SET 1			DATA SET 2			DATA SET 3			GEOMETRIC K=4		
	geometric	linear	logarithmic	geometric	linear	logarithmic	geometric	linear	logarithmic	DATA SET 1	DATA SET 2	DATA SET 3
	obj value			obj value			obj value			obj value		
	11872.7	12682.7	11397.6	173245	173245	172063	212756	218367	212756	12332.7	172063	213276
	11872.7	11872.7	11397.6	173245	173245	172063	212790	218477	212756	12104.3	172063	212756
	11949.7	11872.7	11397.6	173245	173321	172063	212790	218477	212756	12104.3	172063	212756
	11872.7	11949.7	11397.6	173245	173321	172063	212790	217257	212756	11397.6	172128	212756
	11949.7	11949.7	11397.6	173245	173321	172063	212790	217356	212756	11474.6	172063	212790
	11949.7	11949.7	11397.6	172063	172063	172063	212790	217356	212756	11474.6	172063	212790
	11949.7	11949.7	11397.6	172063	172128	172063	212756	217356	212756	11397.6	172063	212756
	11949.7	11949.7	11397.6	172063	172128	172063	212756	217356	212756	11474.6	172063	212790
	11949.7	11949.7	11397.6	172128	172128	172063	212790	217356	212756	11474.6	172063	212756
	11397.6	11949.7	11397.6	172128	172128	172063	212756	217356	212756	11474.6	172063	212790
	11474.6	11949.7	11397.6	172128	172128	172063	212790	217356	212756	11474.6	172063	212790
	11474.6	11949.7	11397.6	172128	172128	172063	212790	217257	212756	11474.6	172063	212756
	11474.6	11949.7	11397.6	172063	172128	172063	212790	217356	212756	11474.6	172063	212790
	11474.6	11949.7	11397.6	172063	172128	172063	212790	217356	212756	11474.6	172063	212790
	11474.6	11949.7	11397.6	172063	172128	172063	212790	217257	212756	11474.6	172063	212790
	11474.6	11949.7	11397.6	172063	172128	172063	212790	217257	212756	11474.6	172063	212756
	11397.6	11949.7	11397.6	172128	172128	172063	212790	217257	212756	11474.6	172063	212756
	11474.6	11949.7	11397.6	172128	172128	172063	212790	217356	212756	11397.6	172063	212756
	11474.6	11949.7	11393.6	172128	172063	172063	212756	217356	212756	11397.6	172128	212756
	11474.6	11949.7	11397.6	172128	172128	172063	212790	217356	212756	11474.6	172063	212790
	11474.6	11949.7	11397.6	172128	172128	172063	212790	217257	212756	11397.6	172128	212756
	11474.6	11949.7	11397.6	172063	172128	172063	212790	217356	212756	11474.6	172063	212756
	11474.6	11949.7	11397.6	172063	172128	172063	212790	217257	212756	11474.6	172063	212756
	11474.6	11949.7	11397.6	172128	172063	172063	212790	217356	212756	11397.6	172063	212756
	11474.6	11949.7	11397.6	172128	172128	172063	212790	217356	212756	11474.6	172063	212790
	11397.6	11397.6	11397.6	172128	172128	172063	212756	213866	212756	11474.6	172063	212756
	11474.6	11397.6	11397.6	172128	172128	172063	212790	213911	212756	11397.6	172063	212790
	11474.6	11474.6	11397.6	172128	172128	172063	212790	213911	212756	11397.6	172063	212790
	11474.6	11474.6	11397.6	172063	172128	172063	212790	213911	212756	11474.6	172063	212790
	11474.6	11474.6	11397.6	172063	172128	172063	212790	213461	212756	11397.6	172063	212756
average	11601.73	11884.68333	11397.46667	172290.3333	172315.2667	172063	212783.2	216850.7	212756	11522.08333	172069.5	212788.0667
standard deviation	216.7707181	242.7657337	0.730296743	435.2706913	444.341274	0	13.832495	1425.124	0	228.5713336	19.83335748	93.69426926
best solution	11397.6	11397.6	11393.6	172063	172063	172063	212756	213461	212756	11397.6	172063	212756
average running time	6.140933333	4.379166667	73.91733333	9.935266667	4.823133333	455.6033333	13.821767	4.965	645.073333	9.938266667	37.66733333	54.38

APPENDIX B: ANALYSIS ON MULTISTART

	M=1				M=10						M=20					
	DATA 2		DATA 3		DATA 1		DATA 2		DATA 3		DATA 1		DATA 2		DATA 3	
	0bje value	running tin	0bje value	running tin	0bje value	running tin	0bje value	running tin	0bje value	running tin	0bje value	running tin	0bje value	running tin	0bje value	running tim
	172063	47.908	212756	75.869	11680.9	35.457	172063	91.935	212756	192.703	11680.9	83.701	172063	513.889	212756	623.043
	173245	504.639	212756	504.639	12510.5	38.608	172063	135.214	212756	295.679	11680.9	95.618	172063	493.317	212756	504.639
	173245	8.35	217257	25.099	12104.3	32.732	172063	86.221	212756	215.668	11680.9	87.057	172063	553.867	212756	604.57
	173245	23.416	217257	36.004	11680.9	31.637	173245	45.876	212756	216.872	11680.9	91.005	172063	602.28	212756	710.526
	173245	12.666	217847	17.921	11680.9	32.21	173245	31.634	212756	231.877	11680.9	87.734	172063	553.558	212756	565.852
	173245	14.112	217257	32.28	12100.3	28.373	173245	42.595	212756	283.212	11680.9	89.302	172063	504.559	212756	731.623
	173245	30.049	217257	26.499	11680.9	35.333	172063	78.729	212756	242.128	11678.9	89.08	172063	566.14	212756	472.274
	172063	51.06	212756	61.555	11680.9	31.57	172063	134.694	212756	334.871	11680.9	87.426	172063	463.957	212756	665.64
	173245	30.738	217257	32.547	12104.3	32.607	172063	122.306	212756	197.941	11680.9	86.73	172063	436.634	212756	747.372
	173245	21.958	217257	31.399	11680.9	29.356	172063	78.217	212756	275.982	11680.9	84.255	172063	442.72	212756	645.768
	172063	26.943	217257	26.242	12104.3	28.181	172063	57.107	212756	169.437	11680.9	92.252	172063	577.878	212756	733.515
	173245	36.194	212756	16.233	11397.6	29.476	173245	41.851	212756	222.29	11680.9	82.083	172063	566.315	212756	772.095
	173245	20.971	212756	73.46	11680.9	31.313	173245	35.534	212756	230.676	11680.9	111.959	172063	589.476	212756	377.263
	172063	53.36	212756	11.816	12104.3	30.29	173245	27.259	212756	242.586	11680.9	102.668	172063	607.623	212756	737.449
	173245	21.222	212756	73.829	11680.9	32.899	172063	76.502	212756	179.707	11680.9	104.601	172063	551.319	212756	732.548
	173245	20.091	217257	32.289	12104.3	30.76	172063	100.384	212756	223.493	11680.9	102.2	172063	588.547	212756	722.658
	172063	54.456	212756	73.891	11680.9	32.147	173245	37.089	212756	237.296	11680.9	106.73	172063	677.129	212756	676.631
	173245	32.535	212756	35.384	11680.9	48.599	172063	45.816	212756	250.446	11678.9	99.645	172063	542.569	212756	601.624
	173245	18.213	213866	14.389	12104.3	34.748	173245	42.499	212756	274.388	11680.9	96.947	172063	982.381	212756	686.453
	172063	59.359	217257	17.696	11680.9	33.235	173245	55.056	212756	226.128	11680.9	96.463	172063	910.646	212756	802.038
	173245	20.023	217847	9.682	11680.9	34.633	172063	117.136	212756	227.687	11680.9	101.403	172063	603.357	212756	763.188
	172063	24.004	217257	15.651	11680.9	32.501	172063	55.274	212756	277.649	11680.9	100.093	172063	584.413	212756	653.203
	172063	23.059	217257	11.201	12430.2	33.738	172063	155.091	212756	183.428	11680.9	100.193	172063	531.104	212756	813.808
	173245	19.155	217257	11.858	12104.3	30.795	172063	108.757	212756	279.174	11680.9	93.668	172063	587.751	212756	609.958
	172063	31.242	217847	8.238	11680.9	34.837	173245	49.584	213461	199.669	11680.9	94.085	172063	592.003	212756	815.187
	173245	20.771	217257	20.813	11680.9	33.793	173245	30.127	212756	287.192	11680.9	98.433	172063	553.399	212756	560.311
	173245	20.104	212756	24.742	12510.5	30.998	172063	130.373	212756	281.633	11680.9	97.03	172063	506.272	212756	600.333
	182149	5.47	217257	16.374	11680.9	38.286	173245	74.678	212756	294.13	11680.9	90.336	172063	485.989	212756	504.344
	173245	20.607	213461	11.54	12104.3	30.591	172063	154.089	212756	154.475	11680.9	88.006	172063	457.466	212756	697.893
	172063	49.115	226353	6.05	12104.3	30.591	172063	154.089	212756	201.437	11680.9	81.939	172063	457.466	212756	702.353
average	173147.8	44.05967	215879.3	45.173	11892.74	33.0098	172535.8	79.8572	212779.5	237.6618	11680.77	94.08807	172063	569.4675	212756	661.1386
standard d	1790.483	88.13062	2967.283	89.3258	291.3228	3.878659	588.9585	41.74433	128.7148	43.43457	0.507416	7.717602	0	117.6446	0	106.3085
best soluti	172063	5.47	212756	6.05	11397.6	28.181	172063	27.259	212756	154.475	11678.9	81.939	172063	436.634	212756	377.263

APPENDIX C ANALYSIS ON DYNAMIC STOPPING CRITERIA

	dynamic k=20		dynamic k=100	
	obj value	times taken	obj value	times taken
	11680.9	56.468	11680.9	828.648
	12430.2	57.083	11680.9	70.351
	12104.3	57.281	11401.6	64.524
	11680.9	59.48	12104.3	63.123
	12104.3	58.474	11680.9	64.824
	12510.5	59.115	11680.9	70.855
	11680.9	60.342	11680.9	71.151
	11680.9	61.074	11680.9	68.166
	11680.9	62.612	11680.9	85.01
	11680.9	61.249	11680.9	114.215
	12104.3	61.134	11680.9	99.509
	11680.9	60.657	12104.3	23159.1
	12104.3	61.379	11680.9	77.152
	11680.9	62.369	11680.9	70.98
	11397.6	62.671	11680.9	72.498
	12104.3	59.807	11680.9	71.878
	11680.9	63.81	11680.9	107.047
	11680.9	57.571	11680.9	98.571
	11680.9	63.136	11678.9	102.818
	11680.9	58.495	11680.9	96.676
	11680.9	90.603	11680.9	99.959
	11680.9	78.222	11680.9	66.832
	12510.5	73.158	11680.9	65.879
	11680.9	67.716	11680.9	64.824
	11680.9	65.334	11680.9	67.001
	11680.9	65.005	11680.9	63.729
	12104.3	63.975	11680.9	67.331
	11680.9	79.863	11680.9	69.233
	11680.9	62.934	11680.9	69.067
	11680.9	91.76	11680.9	70.331
average	11836.42	64.75923333	11699.75	872.0427333
standard d	285.7653	9.084323567	121.1849	4211.610051
best soluti	11397.6	56.468	11401.6	63.123

APPENDIX D Optimization Results

Test problem	Criteria	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
A	Number of used warehouse	9	9	9	9	9	9	12
	Warehouse closed	10	10	10	3, 10, 12	3, 10, 12, 13, 14, 15	3, 10, 12, 13, 14, 15, 16, 17, 18, 19, 20	3, 10, 13, 14, 15, 16, 18, 19, 20, 21, 23, 24, 25
	Objective value	91.3736	91.2736	91.4736	89.4971	89.4971	89.4971	95.8318
B	Number of used warehouse	9	9	9				
	Warehouse closed	4, 8, 10, 11, 12, 14	4, 8, 10, 11, 12, 14	4, 8, 10, 11, 12, 14				
	Objective value	92.7662	92.6662	92.8662				
C	Number of used warehouse	10	10	10	10	12	16	20
	Warehouse closed	0	0	0	1,9	1, 5, 12	5, 12, 13, 20	1, 11, 14, 24, 25
	Objective value	288,848	-	-	209,738	138,013	123,337	109,811

APPENDIX D Optimization Results

Test problem	Criteria	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
D	Number of used warehouse							
	Warehouse closed							
	Objective value							
E	Number of used warehouse	8	8	8	11	11	16	19
	Warehouse closed	7, 10	7, 10	7, 10	5	7, 13, 14, 15	6, 15, 17, 20	9,10, 14, 16, 20, 25
	Objective value	1,604,380			1,291,260	1,267,300	1,082,580	1,046,570
F	Number of used warehouse	13	13	13				
	Warehouse closed	8, 14	8, 14	8, 14				
	Objective value	1,184,290	1,184,090	1,184,790				

APPENDIX E Zone Dependent Fixed Cost for Each Scenario for Data 1, Data 2 and Data 3

Data	Zone	Cost		
		Baseline	Scenario 4	Scenario 5
Data 1	1	1.5	1.5	1.5
	2	3	3	3
	3	3.5	3.5	3.5
	4	2.5	2.5	2.5
	5	1.5	150000	150000
	6	2	2	2
	7	4.5	4.5	4.5
	8	5	5	5
	9	4	4	150000
	10	2.5	2.5	2.5
	11	5.5	5.5	5.5
	12	3.5	3.5	3.5
Data 2	1	15	150000	150000
	2	35	35	35
	3	30	30	30
	4	25	25	25
	5	15	15	15
	6	30	30	30
	7	45	45	45
	8	50	50	50
	9	40	40	40
	10	25	25	150000
	11	55	55	55
	12	35	35	35
Data 3	1	25	25	25
	2	35	35	35
	3	30	30	30
	4	25	25	25
	5	15	150000	150000
	6	10	10	10
	7	45	45	45
	8	50	50	50
	9	40	40	150000
	10	45	45	45
	11	55	55	55
	12	35	35	35

APPENDIX F Inbound Transportation Cost and Several Customers for Each Warehouse

Data	Zone area	Warehouse	Scenario 4			Scenario 5		
			Zone cost	Inbound transportation cost	Number of customer per warehouse	Zone cost	Inbound transportation cost	Number of customer per warehouse
1	1	4	1.5	4.93826	4	1.5	4.93826	4
	2	3	3	8.86433	7	3	14.4238	9
	3	1	3.5	6.88453	6	3.5	8.78729	7
		12		-	-		-	-
	4	2	2.5	4.10656	5	2.5	4.10656	5
	5	11	150000	-	-	150000	-	-
	6	-	2			2		
	7	9	4.5	5.16138	5	4.5	24.3465	11
	8	-	5			5		
	9	5	4	9.39719	9	150000	-	-
		7		-	-		-	-
	10	8	2.5	9.59717	8	2.5	-	-
	11	6	5.5	5.82371	6	5.5	-	-
	12	10	3.5	-	-	3.5	25.8329	14
2	1	7	150000	-	-	150000	-	-
		9		-	-		-	-
	2	2	35	12323.3	46	35	6691.95	31

APPENDIX F Inbound Transportation Cost and Several Customers for Each Warehouse

Data	Zone area	Warehouse	Scenario 4			Scenario 5		
			Zone cost	Inbound transportation cost	Number of customer per warehouse	Zone cost	Inbound transportation cost	Number of customer per warehouse
2	2	15	35	-	-	35	-	-
		21		18,414.00	20		18,414.00	20
	3	3	30	3,137.67	28	30	3,137.67	28
		10		5,755.72	76		5,755.72	76
		20		4,888.73	33		4,888.73	33
	4	22	25	99,953.6	148	25	99,953.6	148
	5	8	15	-	-	15	-	-
		13		-	-		-	-
		17		8,798.54	24		8,798.54	24
	6	4	30	2,071.21	40	30	-	-
		5		3,600.61	60		10,573.2	98
		11		2,865.04	18		8,521.87	42
		19		2,433.56	22		-	-
	7	-	45			45		
	8	14	50	-	-	50	-	-
	9	16	40	-	-	40	2,905.9	15
	10	1	25	4,059.98	64	150,000	-	-

APPENDIX F Inbound Transportation Cost and Several Customers for Each Warehouse

Data	Zone area	Warehouse	Scenario 4			Scenario 5		
			Zone cost	Inbound transportation cost	Number of customer per warehouse	Zone cost	Inbound transportation cost	Number of customer per warehouse
2	10	6	25	4,562.69	43	150,000	-	-
		12		-	-		-	-
		18		4,186.41	32		-	-
		23					41,418.9	139
	11	-	55			55		
	12	-	35			35		
3	1	8	25	215,318	128	25	65,488.8	74
	2	4	35	79,148.5	70	35	79,113.5	69
		6		105,216	80		56,799.8	59
		7		120,242	101		110,368	92
		16		-	-		-	-
		19		48,193.7	44		34,597.5	38
	3	-	30			30		
	4	-	25			25		
	5	9	150,000	-	-	150,000	-	-
		10		-	-		142,787	118
		12		-	-		-	-

APPENDIX F Inbound Transportation Cost and Several Customers for Each Warehouse

Data	Zone area	Warehouse	Scenario 4			Scenario 5		
			Zone cost	Inbound transportation cost	Number of customer per warehouse	Zone cost	Inbound transportation cost	Number of customer per warehouse
3	5	14	150,000	-	-	150,000	-	-
		17		-	-		-	-
		18		-	-		116,808	86
		24		-	-		-	-
	6	-	10			10		
	7	3	45	306,946	174	45	92,524.1	83
		5		-	-		77,607.6	63
		20		-	-		-	-
	8	15	50	208,029	139	50	58,296	62
		25		-	-		122,628	78
	9	11	40	65,041.3	69	150000	-	-
		13		43,543.5	54		-	-
		21		-	-		-	-
	10	1	45	-	-	45	109,524	104
		2		40,645	64		94,768.2	92
		22		62,500.7	62		-	-
	11	23	55	82,749.6	72	55	29,624	40
	12	-	35			35		

APPENDIX G Inbound Transportation Cost and the Number of Customers Per Warehouse for Capacitated Zone Dependent Fixed Cost

Data	Zone area	Warehouse	Scenario 6		Scenario 7	
			Capacity	Number of customer per warehouse	Capacity	Number of customer per warehouse
1	1	4	12	4	15	4
	2	3	12	12	15	9
	3	1	12	0	15	7
		12	12	6	15	0
	4	2	12	8	15	5
	5	11	5	0	5	0
	6					
	7	9	12	0	15	6
	8					
	9	5	5	0	5	0
		7	5	0	5	0
	10	8	12	12	15	0
	11	6	12	8	15	6
	12	10	12	0	15	13
2	1	7	28	0	28	0
		9	28	0	28	0
	2	2	50	29	50	0
		15	50	19	50	0
		21	50	33	50	0
	3	3	109	61	120	61
		10	109	76	120	76
		20	109	0	120	0
	4	22	109	109	120	166
	5	8	50	0	50	0
		13	50	0	50	0
		17	50	50	50	0
	6	4	50	50	50	44
		5	50	50	50	68
		11	50	0	50	0
		19	50	40	50	36
	7					

APPENDIX G Inbound Transportation Cost and the Number of Customers Per Warehouse for Capacitated Zone Dependent Fixed Cost

Data	Zone area	Warehouse	Scenario 6 Capacity	Scenario 6 Number of customer per warehouse	Scenario 7 Capacity	Scenario 7 Number of customer per warehouse
2	8	14	50	0	50	19
	9	16	109	109	120	184
	10	1	28	0	28	0
		6	28	28	28	0
		12	28	0	28	0
		18	28	0	28	0
		23	28	0	28	0
	11					
	12					
3	1	8	130	130	160	128
	2	4	130	70	160	69
		6	130	0	160	160
		7	130	110	160	100
		16	130	0	160	0
		19	130	45	160	55
	3					
	4					
	5	9	42	0	42	0
		10	42	0	42	0
		12	42	0	42	0
		14	42	0	42	0
		17	42	0	42	0
		18	42	0	42	0
		24	42	0	42	0
	6					
	7	3	130	130	160	152
		5	130	110	160	131
		20	130	130	160	37
	8	15	130	120	160	0
		25	130	0	160	0
	9	11	42	0	42	0

APPENDIX G Inbound Transportation Cost and the Number of Customers Per Warehouse for Capacitated Zone Dependent Fixed Cost

Data	Zone area	Warehouse	Scenario 6		Scenario 7	
			Capacity	Number of customer per warehouse	Capacity	Number of customer per warehouse
3	9	13	42	0	42	0
		21	42	0	42	0
	10	1	130	93	160	93
		2	130	79	160	79
		22	130	32	160	32
	11	23	100	41	100	21
	12					

APPENDIX H: List of Publications

H1: Research Article (Published) Journal of Physics: Conference Series (2017)

ICoAIMS 2017 IOP Publishing
IOP Conf. Series: Journal of Physics: Conf. Series **890** (2017) 012109 doi:10.1088/1742-6596/890/1/012109

A simulated annealing approach for redesigning a warehouse network problem

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Abstract. Now a day, several companies consider downsizing their distribution networks in ways that involve consolidation or phase-out of some of their current warehousing facilities due to the increasing competition, mounting cost pressure and taking advantage on the economies of scale. Consequently, the changes on economic situation after a certain period of time require an adjustment on the network model in order to get the optimal cost under the current economic conditions. This paper aimed to develop a mixed-integer linear programming model for a two-echelon warehouse network redesign problem with capacitated plant and uncapacitated warehouses. The main contribution of this study is considering capacity constraint for existing warehouses. A Simulated Annealing algorithm is proposed to tackle with the proposed model. The numerical solution showed the model and method of solution proposed was practical.

1. Introduction

A warehouse is a building for storing of personal properties or goods and chattels. Warehouses are usually being used by manufacturers, wholesalers including the importers and exporters, transport businesses, and government society's i.e customs. Warehouses usually situated in industrial areas of cities, towns or villages as a bulky ordinary building where it composed an important part in the overall supply chain process. Besides, the overall supply chain process, logistics, environmental sustainability and information technology (IT) are further progressing the functions of the warehouses due to the ongoing globalization process.

The business landscape and the way of doing it has recently transformed by the globalization and development of the business scene. As stated by [5], supply chain management controls material flow among suppliers, plants, warehouses and customers efficiently such that the total cost in the supply chain can be minimized. Traditionally, planning, purchasing, manufacturing, distribution, and marketing organizations along the supply chain have operated independently, but now it is a strategy through which integration can be achieved [4]. A major number of recent researches in this area have been well established within operations research. The concurrent optimization of different functions

 1

H2: Publication (Proceeding): 1st International Conferences on Applied & Industrial Mathematics and Statistics 2017. 8th-10th August 2017 at Vistana Kuantan City Centre, Pahang Malaysia.

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H3: Publication (Proceeding): 2nd International Conferences on Applied & Industrial Mathematics and Statistics 2019. 23rd -25th July 2019 at Zenith Kuantan, Pahang Malaysia.

A Comparison of Simulated Annealing Cooling Strategies for Redesigning a Warehouse Network Problem

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Abstract. Simulated annealing (SA) is considered a valuable stochastic technique for resolving difficulties associated with comprehensive multidimensional optimisation, which guarantees optimal global convergence. This study explores the use of SA to address the challenges of redesigning warehouse networks and relates the effectiveness of three (3) diverse SA cooling schedules, namely; the basic geometric, logarithmic, and linear. The broad computational findings performed and described in the study indicate that the geometric cooling schedule generates consistent, superior quality, and timely solutions compared to the other schemes.

Keywords: Simulated Annealing, Redesigning Network problems, Cooling Schedules

H4: Publication (Proceeding): Statistics and Operational Research International 2013. 3rd -5th December 2013 at Riverside Majestic Hotel, Kuching Sarawak, Malaysia.

WAREHOUSE LOCATION: A REVIEW

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Abstract: Warehouse location problem have been studied for many years. Based on location allocation problem, Many researchers have produced a variety of models to solve the specific warehouse location problems. To provide support in modeling problem characteristic and in suggesting applicable algorithm, this paper reviews the relevant literature. Particular focus is put on redesigning a warehouse location problem.

Keywords: warehouse location problem; redesigning