A MULTI-PHASE MATHEURISTIC ALGORITHM FOR THE DISTRIBUTION NETWORK DESIGN PROBLEM OF A SPARE-PARTS SUPPLY CHAIN

by
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ABSTRACT

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After-sales services provide companies both financial and competitive advantages. However, operating distribution networks of after-sales service logistics systems are more challenging than traditional supply chain networks. Thus, establishing a cost-efficient network is an arduous task. It requires making critical decisions at both strategic and tactical levels. Facility location decisions are considered as strategic whereas the tactical level decisions include vehicle size, transshipment amount, service level and last-mile routes. We study a multi-period multi-commodity spare-parts distribution network design problem. We propose a mixed integer linear programming problem formulation of the problem. To solve this combinatorial optimization problem in a reasonable time, a three-phase matheuristic involving variations of the original problem formulation is developed. We share and discuss our findings from a computational study.

ÖZET

BİR YEDEK PARÇA TEDARİK ZİNCİRİNİN DAĞITIM AĞI TASARIM PROBLEMİNİ ÇÖZMEK İÇİN ÇOK FAZLI MATSEZGİSEL BİR ALGORİTMA

SEMİH BOZ

ENDÜSTRİ MÜHENDİSLİĞİ YÜKSEK LİSANS TEZİ, EYLÜL 2020

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Anahtar Kelimeler: çok periyot, ağ tasarımı, tesis yerleşimi, rotalama, satış sonrası hizmet

Satış sonrası hizmetler, firmalara hem finansal hem de rekabetçi avantajlar sağlamaktadır. Fakat, satış sonrası hizmetleri için kullanılan lojistik sistemlerindeki dağıtım ağlarını işletmek bilinen geleneksel tedarik zinciri ağlarına göre çok daha zorludur. Bu durum maliyet açısından verimli bir dağıtım ağı oluşturmayı zorlaştırır. Maliyet açısından verimli bir dağıtım ağı, stratejik ve taktik seviyede çok kritik kararlara bağlıdır. Tesislerin yer seçimi stratejik kararlardan iken, nakliye miktarları, araç büyüklükleri, hizmet seviyeleri ve rotalar taktiksel kararları oluşturmaktadır. Bu amaçla, çok periyotlu çok ürünlü yedek parça dağıtım ağı tasarımı problemini çalışıyoruz ve problemin karma tam sayılı doğrusal programlama problem gösterimini öneriyoruz. Bu kombinatoryel en iyileme problemini makul bir zamanda çözebilmek için problem gösteriminin çeşitli versiyonlarını barındıran 3 fazlı bir mat-sezgisel bir geliştiriyoruz. Bilgisayısal çalışmamızın sonuçlarını paylaşıyor ve tartışıyoruz.

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LIST OF ABBREVIATIONS

DC Distribution Center 6

VRP Vehicle Routing Problem 3

1. INTRODUCTION

After-sales service logistics systems provide end product users with service parts, maintenance and repair services (Cohen, Zheng & Agrawal, 1997). Generally, the profit margin for initial sale products is around 10% while after-sales service products can yield a profit margin up to 30% (Murthy, Solem & Roren, 2004). After-sales services also bring competitive advantages besides its financial benefits (Cohen, Agrawal & Agrawal, 2006)

Even though the after-sales services have lots of benefits, they also bring challenges that make it harder to establish a cost efficient distribution network configuration. We address this issue in this thesis. The arrangement of the network we work on is as follows: A single distribution center which is responsible of procurement of the parts is employed. The parts are first moved from the distribution center to the regional depots and then shipped to the service points. Transportation operations are performed by inbound (from distribution center to regional depots) and outbound (from regional depots to the service points) trucks. Our aim is to minimize the total cost while making both strategic and tactical level decisions. Strategic level decisions are the depot location assignments and the tactical level decisions include transshipment amounts, truck size, service level and routing decisions. In this sense, a connection can be drawn between the problems known as location routing problems and the spare parts distribution network design problem (Ercan, 2019).

The system we try to optimize constitutes a multi-period multi-commodity multi-level network design problem. We develop a mixed integer linear programming formulation where the objective function is minimizing the total cost. The contributions of this study are as follows:

- We present a multi-period multi-commodity multi-level spare parts distribution network design problem.
- In order to solve the problem, we build a mixed integer linear programming model incorporating the facility location decisions, inbound and outbound transportation mode decisions, outbound vehicle routing and service level de-

cisions.

- We develop a heuristic method to this large scale combinatorial optimization problem.

The organization of this thesis is as follows: Chapter 2 contains the literature review. In Chapter 3, the problem is stressed in details and the corresponding mathematical model is presented. Chapter 4 expatiates the heuristic solution method that we developed. In Chapter 5, we present and discuss the results obtained from our experiments. Lastly, we provide the conclusions of the work in Chapter 6.

2. LITERATURE REVIEW

After-sales service distribution network problems can include routing decisions, location decisions for distribution centers and depots, truck size decisions, inventory decisions, staff decisions, shift decisions and service level decisions as they are practised in the literature. Our problem of interest is involved with location, routing, truck size and service level decisions. We begin reviewing the works done in the most sub problem.

The vehicle routing problems (VRP) are extensively studied in the past. Laporte & Osman (1995) present a summary of the works done regarding multi drop truck load. Toth & Vigo (1998) develop an exact solution method for deterministic cases. Due to high complexity of the problem, various heuristic procedures are proposed (Laporte, Gendreau, Potvin & Semet, 2000). Integrating the location decisions, location routing problems are stressed firstly by Laporte (1988). He proposes deterministic formulations of the problem. Following, heuristic solution methods are proposed to solve deterministic VRP cases by Chien (1993), Tuzun & Burke (1999), Barreto, Ferreira, Paixao & Santos (2007); Prins, Prodhon, Ruiz, Soriano & Wolfler Calvo (2007).

Harks, Konig, Matuschke, Richter & Schulz (2016) study a supply chain network design problem where transportation tariff and inventory decisions are made. The mathematical model that they present deals with a multi-commodity, multi-period, capacitated logistics problem. They investigate tariff selection subproblem for different transportation cost structures. Although the procedures they suggest may not necessarily find the optimal solution, they still yield good bounds for mixed integer programming model.

Despite the fact that after-sales service logistics systems have some similarities with the traditional supply chain networks, they bring some extra challenges that make it harder to handle. After-sales services include large number and variety of parts (Cohen, Zheng-Yu-Sheng & Wang, 1999). They utilize multiple classes of service (Cohen et al., 1999). The geographical distribution of customers and the need of immediate response to the customers with unpredictable and intermittent demand are the other factors that cause operational difficulties within the system (Cohen et al., 1999); (Huiskonen, 2001); (Boylan & Syntetos, 2010).

There are also studies whose scope is broader in terms of the number of elements to be decided. Persson & Saccani (2009) develop a simulation model which calculates the transportation cost over different scenarios on demand. Suppliers and spare parts allocation decisions are made for a new second warehouse of which location is known. Wu, Hsu & Huang (2011) develop a mathematical model for a single period spare parts network design problem which includes depot location decisions, transportation mode decisions and staffing decisions. The study embraces a provision of metaheuristic solution methods. The study of Landrieux & Vandaele (2012) combines facility location and spare parts inventory management problems by minimizing the total cost. Recently, Altekin, Aylı & Şahin (2017) provide a cost minimizing mathematical model for a single period multi echelon spare part logistics network design problem of a household appliances manufacturer in Turkey. A mixed integer programming formulation which determines the facility locations and transportation modes along with the allocation of demand points to the facilities is proposed. This study also constitutes a base for our study. Klibi (2010) study a stochastic multi-period location transportation problem. They propose a hierarchical heuristic solution integrating a tabu search procedure. Their objective is to maximize the profit. The model involves the determination of facility locations, transportation modes and vehicle routing. Albareda-Sambola, Fernández & Nickel (2012) present a mathematical model for a multi period location-routing problem where the demand is known in advance. They aim to minimize the total cost while deciding on the facility locations, transportation and the routing schemes. An approximation method is also provided. A stochastic multi period inventory-routing problem is studied by Abdul Rahim, Zhong, Aghezzaf & Aouam (2014). They propose an approximation model using Lagrangian relaxation. They consider a system where the total cost consists of inventory cost and transportation-related costs. Employing a single facility, transportation configuration and routing settings are to be decided. Recently, Mohamed, Klibi & Vanderbeck (2020) study a two-level distribution network with stochastic multi period demand. Both distribution center and regional depot locations are to be decided along with the inbound and outbound transportation arrangement and routing mechanism. A two-stage stochastic programming formulation is proposed and solved by using Benders decomposition

The differences between our study and some other related studies are shown below.

	Persson & Saccani (2009)	Wu et al. (2011)	Landrieux & Vandaele (2012)	Altekin et al. (2017)	Klibi et al (2010)	Our Study
Problem	ASND	ASND	ASND	ASND	PDND	ASND
Number of Periods	Single	Single	Single	Single	Multi	Multi
Objective Function	MTC	MTC	MTC	MTC	MTP	MTC
Multi Commodity	X		X	X		X
Installed Base Products			X			
Transportation Cost	Linear	Constant	Linear	Linear	Staircase	Staircase
Inbound Logistics Cost	X	X	X			X
Outbound Logistics Cost	X	X	X	X	X	X
Facility Location Decisions			X	X	X	X
Flow Decisions	X		X	X	X	X
Transportation Mode Decisions	X	X	X	X		
Inventory Decisions		X				
Staffing Decisions		X				
Vehicle Decisions					X	X
Routing Decisions					X	X
Different Service Levels						X
Uncertainty					X	

Figure 2.1 The comparison of related studies.
ASND: After-Sales Network Design
PDND: Production Distribution Network Design.
MTC: Minimize Total Cost
MTP: Maximize Total Profit.

3. PROBLEM DEFINITION

We study a spare parts distribution network consisting of three types of facilities which are a distribution center (DC), regional depots and service points. Outsourced parts that are generally supplied by an external supplier are stored at the DC. Then, they are sent from the DC to service points through the regional depots. In our system, we employ a single DC. Inbound trucks are responsible for the direct shipment of the parts from the DC to the regional depots whereas outbound trucks carry the parts from the depots to the service points following routes that visit and serve several service points. We study a multi-period and multi-commodity setting. The setting is in the sense that service points have different demands in different periods depending on the length of the planning horizon.. A period can stand for a day or a three days or a week.

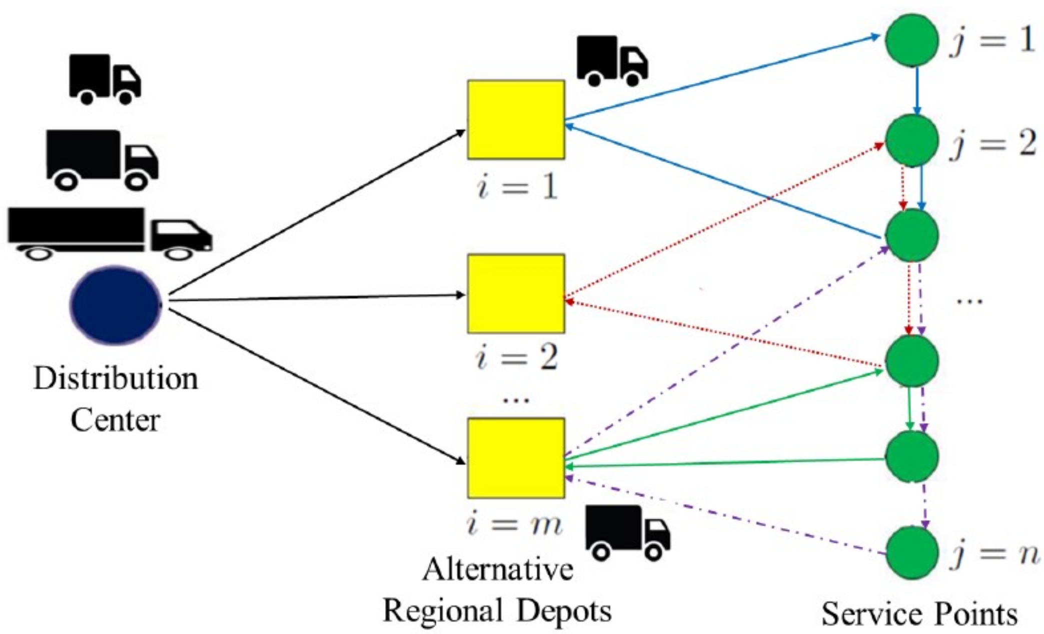

Figure 3.1 The main structure of the spare parts distribution network

We determine the location and the number of the regional depots to open among candidate locations, truck load and truck size for both inbound and outbound transportation and routes of the outbound trucks. Our aim is to find the transportation and distribution scheme with the least cost. The main cost terms are fixed opening costs of the regional depots and fixed operation costs of trucks. The cost function for the trucks has a staircase structure with respect to their capacity. It means that cost of operating a truck is a fixed parameter that varies with the changing sizes of the trucks.

To solve this problem, we develop a mathematical model in the form of a mixed integer programming problem formulation. Therefore, we need to establish some assumptions as follows:

- The length of the planning horizon in terms of demand information is too short considering the useful life of the facilities. Therefore, location decisions are not period dependent.
- There is no lead time in transportation and procurement; transportation activity in a period satisfies the demand of that period.
- The periods are considered in a cyclic manner. To accommodate continuity, we treat the system in a way the time goes back to the initial period such that the first period's demand will be observed after the last period.
- Inventory related costs are neglected in regional depots and there is no capacity constraint for the inventory.
- A service point can be served by several regional depots.
- We can only use routes that are predetermined. So, the routing decision is simply selecting some routes from a finite set.
- There is no transshipment between the regional depots.
- The demand of a service point for a commodity in a period is known only at the beginning of that period. That hinders us from making a prudential shipment. However, a portion of back-ordering is allowed as long as some certain service level is satisfied for that period's demand.

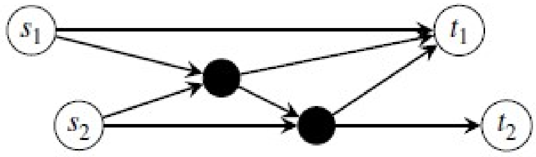

Figure 3.2 The single period problem network structure

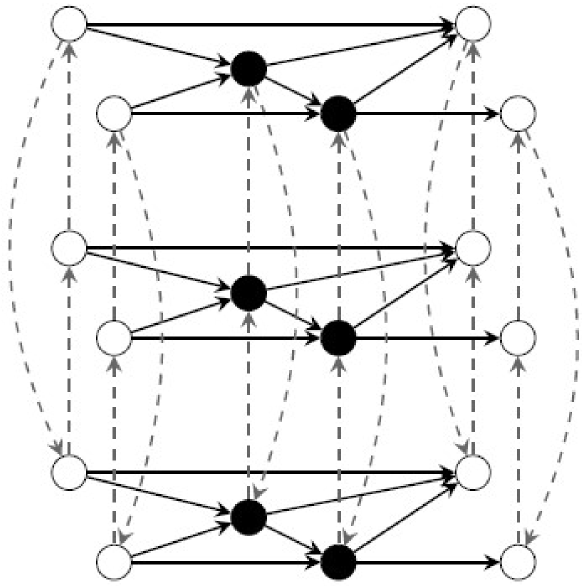

Figure 3.3 The multi period problem network structure

3.1 A Mathematical Model

In order to develop a mathematical model for the problem as a mixed integer programming problem formulation, we use the following notation.

Indices and Sets

$i \in I$: Alternative depot locations
$j \in J$: Service points
$p \in P$: Part families
$t \in T$: Time periods
$r \in R$: All the routes from potential depot locations to service points
R_i: Set of routes that are assigned to depot i

R_j: Set of routes that contains service point j
J_r: Set of service points covered in route r
I_j: Set of depots that can serve service point j
K_i: Set of volume breaks ($0 < Q_{i1} < Q_{i2} < . . .$) in transportation cost function from DC to depot i
$k \in K'_r$: Set of volume breaks ($0 < Q_{r1} < Q_{r2} < . . .$) in transportation cost function for route r

Parameters

D_{jpt}: Demand of service point j for part p for period t
f_i: Fixed cost of opening a depot at location i
Q_{rkt}: Capacity of the outbound truck type k using route r in period t
Q'_{iks}: Capacity of the inbound truck type k going to depot i in period s
c_{rkt}: Cost of carrying Q_{rkt} or less weight for period t using route r
c'_{iks}: Cost of carrying Q'_{iks} or less weight in period s from the depot i
L: Amount of late delivery allowance periods

Decision variables:

X_{jprstu}: Amount of part p delivered to service point j through route r in period u which was transferred to the corresponding depot in period t for the demand in period s where $s \leq t \leq u$

$$Y_i = \begin{cases} 1, & \text{if a depot is opened at location } i \\ 0, & \text{otherwise} \end{cases}$$

$$V_{rkt} = \begin{cases} 1, & \text{if the truck size } k \text{ on the route } r \text{ for the period } t \text{ is used} \\ 0, & \text{otherwise} \end{cases}$$

$$W_{iks} = \begin{cases} 1, & \text{if truck size } k \text{ utilized from DC to depot } i \text{ in period } s \\ 0, & \text{otherwise} \end{cases}$$

$$
\begin{aligned}
&(3.1) && \text{minimize} && \sum_{i\in I} f_i Y_i + \sum_{r\in R}\sum_{k\in K_r}\sum_{t\in T} V_{rkt} c_{rkt} + \sum_{i\in I}\sum_{k\in K_i}\sum_{s\in T} c'_{iks} W_{iks} && \\
&(3.2) && \text{s.t.} && \sum_{r\in R_j}\sum_{s\le t\le u} X_{jprstu} = D_{jpt} && \forall (j,p,s)\in (J,P,T)\\
&(3.3) && && \sum_{s\le t\le u}\sum_{j\in J_r}\sum_{p\in P} X_{jprstu} \le \sum_{k\in K_r} Q_{rks} V_{rku} && \forall r\in R, \forall u\in T\\
&(3.4) && && \sum_{s\le t\le u}\sum_{r\in R_i}\sum_{j\in J_r}\sum_{p\in P} X_{jprstu} \le \sum_{k\in K'_i} Q'_{iks} W_{ikt} && \forall i\in I, \forall t\in T\\
&(3.5) && && \sum_{k\in K_r} V_{rku} \le Y_i && \forall (i,r,u)\in (I,R_i,T)\\
&(3.6) && && \sum_{k\in K'_i} W_{ikt} \le Y_i && \forall i\in I, \forall t\in T\\
&(3.7) && && \sum_{r\in R_j}\sum_{u=s}^{s+l}\sum_{t=s}^{u} X_{jprstu} \ge \alpha_{pl} D_{jpt} && \forall (j,p,s)\in (J,P,T), l=0,1,..,L-1\\
&(3.8) && && Y_i \in \{0,1\} && \forall i\in I\\
&(3.9) && && W_{iks} \in \{0,1\} && \forall (i,k,s)\in (I,K_i,T)\\
&(3.10) && && V_{rkt} \in \{0,1\} && \forall (r,k,t)\in (R,K_r,T)\\
&(3.11) && && X_{jprstu} \ge 0 && \forall (j,p,r,s,t,u)\in (J,P,R,T,T,T)
\end{aligned}
$$

The objective function (3.1) minimizes the total cost that arises from depot opening, outbound and inbound truck operations. Constraint (3.2) ensures the demand is satisfied with on time or late deliveries. Constraint (3.3) and Constraint (3.4) are to determine the size of the outbound and inbound trucks respectively. Constraints (3.5) and (3.6) connect depot location decisions with outbound and inbound truck selection respectively. Constraint (3.7) ensures that the demand is satisfied at least at the minimum service level. Constraints (3.8), (3.9), (3.10) and (3.11) define the nature of decision variables. A pre-defined route set is given. We enlarged this set by adding routes that only serve a single service point. We added these routes for each and every service point.

However, the problem formulation (3.1)-(3.11) turns out to be very large to solve in a reasonable time even with the smallest data set. Therefore, we develop heuristic methods to solve the problem approximately in reasonable time.

4. A HEURISTIC SOLUTION METHOD

Since this problem is not solvable in reasonable time, we aim to find good feasible solutions heuristically. Our idea relies on identifying a feasible solution from a restricted solution space first and then try improving this solution by getting rid of the restrictions on the solution.

We propose a 3-phase algorithm. The goal of the first phase is to find an initial feasible solution to the problem by dealing with a restricted problem. In this phase, we take into account a single period problem for each period in the problem. We also enforce that each service point is served by only a single truck to restrict the problem further. We refer to this as "single-sourcing".

In the second phase, the solution found in the first phase is aggregated into a multiple period solution. The second phase reoptimizes the facility locations by considering the multiple single-period solutions.

The third phase is an iterative process that takes the result of the second phase and tries to modify it with slight improvements towards the original problem. The mechanism of the algorithm can be summarized as follows.

Phase 1:

Step 1.1) For each period, solve a single period problem with single sourcing constraints individually.

Step 1.2) Make up a restricted multi-period problem instance where selected routes and opened depots comprise the set of possible routes and candidate depots.

Phase 2:

Step 2.1) Solve the restricted multi-period problem formed in Phase 1.

Step 2.2) Declare the solution as an initial solution for Phase 3.

Phase 3:

Step 3.1) For each depot, perform local route set expansion and solve the expanded multi-period problem.

Step 3.2) Take the solution with the best local improvement as an initial solution for the next iteration.

Step 3.3) Reiterate this procedure until there is no improvement.

4.1 Phase 1: Single Period Single Sourcing Problem

In phase 1, we solve a single period problem for each period, i.e. we only take into account a period's demand and all transportation operations in that period. Late deliveries are neither allowed nor possible. We adopt a single-sourcing constraint as the restrictive ingredient to the model which allows a service point to be served by only one route. Consequently, a service point can be served by only one depot as each route is emerging from a specific depot. The corresponding integer programming formulation requires additional parameters as follows:

D_{jp}:	Demand of service point j for part p (in terms of weight)
c'_{ik}:	Cost of carrying Q'_{ik} or less weight to the depot i
c_r:	Cost of using route r

In addition to facility location decision variable Y_i, we define

$$W_{ik} = \begin{cases} 1, & \text{if transportation option } k \text{ is utilized from DC to depot } i \\ 0, & \text{otherwise} \end{cases}$$

$$Z_r = \begin{cases} 1, & \text{if the route } r \text{ is used} \\ 0, & \text{otherwise} \end{cases}$$

Accordingly, the problem formulation becomes:

$$\text{minimize} \quad \sum_{i \in I} f_i Y_i + \sum_{r \in R} Z_r c_r + \sum_{i \in I} \sum_{k \in K_i} c_{ik} W_{ik} \tag{4.1}$$

$$\text{s.t.} \quad \sum_{k \in K_i} Q_{ik} W_{ik} - \sum_{r \in R_i} D_r Z_r \geq 0, \qquad \forall i \in I \tag{4.2}$$

$$-\sum_{k \in K_i} W_{ik} + Y_i \geq 0, \qquad \forall i \in I \tag{4.3}$$

$$\sum_{r \in R_j} Z_r = 1, \qquad \forall j \in J \tag{4.4}$$

$$Y_i \in \{0,1\} \qquad \forall i \in I, \tag{4.5}$$

$$W_{ik} \in \{0,1\} \qquad \forall (i,k) \in (I, K_i) \tag{4.6}$$

$$Z_r \in \{0,1\} \qquad \forall r \in R \tag{4.7}$$

Similarly structured to the multi period problem formulation, the objective function (4.1) minimizes the total cost that arises from depot opening, outbound and inbound truck operations. Constraint (4.2) determines inbound truck size that can cover the demand. The constraint (4.3) controls the depot location decisions. Constraint (4.4) enforces single sourcing meaning that a service point can be served one and only one route. Constraints (4.5), (4.6) and (4.7) determine the nature of decision variables.

4.2 Phase 2: A Feasible Multi-Period Solution On Facility Locations

A reoptimization on facility locations using the original multi-period formulation based on the results of Phase 1 takes place during this phase. Selected routes and opened depots from Phase 1 comprise the set of candidate routes and candidate depots. Given the restricted route set and depot set, we solve a multi-period problem. As a result, we expect to end up with a better solution than previously obtained because the restrictions in the initial solution are no more in effect. Firstly, the solution obtained with the aggregation of the solutions of multiple single-period solutions enforces service levels to be 100 percent. In other words, the demand for a single period is fully satisfied in that period. However, the formulation used in Phase 2 allows this demand to be partially satisfied in the first period when it is received and the rest can be supplied via back-ordering. This gives a flexibility to adjust both inbound and outbound truckloads so that their utilization is higher. Therefore, it can result in operating less number of trucks decreasing the total cost. Secondly, the single-sourcing constraint is removed. It means that multiple trucks riding different routes can serve the same service point. It allows a demand of a service point to be shared between the serving trucks in any ratio. Thus, the more combinations of demand packing we have, the more the combinatorial flexibility is reached. Consequently, the better use of truck capacities can reflect as a lower cost. Thirdly, as the single period problem formulation focuses on a single period requirements, a facility which is opened for a period may be inert for other periods but this is ignored during the aggregation of solutions of single period problems. Hence, multi-period problem formulation could better handle this issue by not opening unnecessary depots. In this way, the total cost could be decreased.

After obtaining a solution for the multi-period model, the selected routes make up the route set for the next phase such that if $V_{rkt} = 1$, $\exists r \in R$ then $R' = R' \cup r$ where R' is the route set for the problem in Phase 3. Similarly, the opened depots will be added into the depot set for the next phase such that $Y_i = 1$, $\exists i \in I$ then $I' = I' \cup i$ where I' is the depot set for Phase 3.

4.3 Phase 3: Improvements Over The Route Selections

This phase provides an iterative local search procedure. By setting the solution obtained in Phase 2 as the parent solution, we produce multiple child problems and obtain their solutions out of the parent solution in each iteration. For a given solution, a child solution requires modifications of the solution associated with a particular facility represented by the child. The best child solution is set to be the parent solution of the next generation problems and solutions. This procedure continues until no child solution is better than its parent.

Given a parent solution, we perform local route set expansion for each selected depot representing the child solution in that solution separately. Let R' be the route set after Phase 2 and let R'_i be the route set of the child multi-period problem created by the local route set expansion using the routes that are emanating from depot i such that $R'_i = R' \cup R_i$. Having different child problems with different route sets and solving them, the solution with the best local improvement will be the parent solution for the next iteration. From this solution we redefine the set R' as follows:

$$R' = \{r \mid V_{rkt} = 1 \text{ ,} \exists r \in R \text{ ,} \exists k \in K'_r \text{ ,} \exists t \in T\}$$

Let F be the parent solution's objective function value and F_i be the the child solution's objective function value which is produced by the local route set expansion for depot i. We stop the procedure if $\min_i\{F_i\} = F \quad \forall i \in I'$.

The procedure of Phase 3 is as follows:

Let R' be the route set, I' be the depot set and F be the objective function value of the (initial) solution.

Step 1) **For** i in I';

$R'' = R' \cup R_i$

Solve multi-period problem by taking the route set as R''

$F_i =$ Objective function value

$R_i^s = \{\}$ (Selected routes)

For r, k, t in $R'' \times K_r' \times T$;

if $V_{rkt} = 1$

Append r to R_i^s

Step 2) **if** $\min_i\{F_i\} < F$ **then;**

$F = \min_i\{F_i\}$

$i^* = \arg\min_i\{F_i\}$

$R' = R_{i^*}^s$

Go to Step 1

else

Terminate!

5. COMPUTATIONAL RESULTS

5.1 Experiment Setup

We generated 3 different problem sizes to investigate how the scale of the problem affects the performance. They differ in terms of the number of service points, alternative depots, and routes contained. We created 10 data sets for instances of different sizes to compare the performance of the proposed models and algorithms. The instance sizes are as follows:

- 30 service points and 10 alternative regional depot locations (30SP)
- 50 service points and 15 alternative regional depot locations (50SP)
- 100 service points and 30 alternative regional depot locations (100SP)

Number of routes in 30SP datasets is ranging between 58 and 91, in 50SP datasets is between 150 and 213 and in 100SP datasets is ranging between 610 and 786. The route sets are generated by neighbor search and expanded neighbor search algorithms adopted from the study by Ercan (2019).

We used a 100x100 grid coordinate system with a single distribution center located at the center to generate the problem instances. The unit distance is one kilometer. For each instance, the location of service points are generated randomly and k-means algorithm is utilized to determine the location of alternative regional depots.

Transportation costs arise from both inbound and outbound operating trucks. Both type of trucks travel the Euclidean distance between any two points they visit. Inbound trucks transport the spare parts from DC to a single regional depot. Therefore, they do not follow a route or go to a combination of depots. However, outbound trucks deliver the spare parts to the service points following a route. So, their cost

Figure 5.1 The layout of the system for Instance 1 of 30SP data set

structure is also different. There is a fixed amount to be incurred per kilometer travelled for inbound trucks whereas the cost of outbound trucks does not depend on the distance travelled but it is a fixed operating cost for a truck for a period regardless of the length of its route. We employ trucks of 3 different sizes. The amount paid per unit distance increases as the size of the inbound trucks increases. In similar fashion, the fixed cost of an outbound truck also increases with respect to its size.

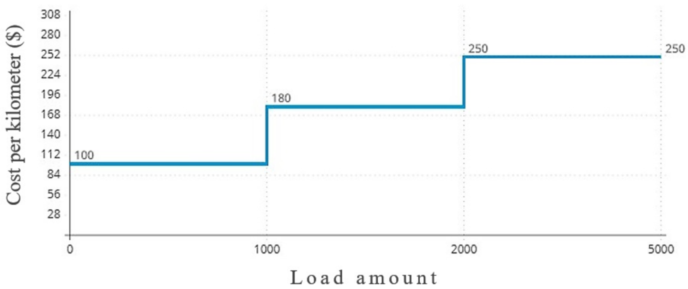

Figure 5.2 The cost function for inbound trucks.

As seen on the graph above, employing a bigger sized truck is better than multiple small sized ones due to economies of scale. Therefore, the model implicitly tries to use as fewer trucks as possible.

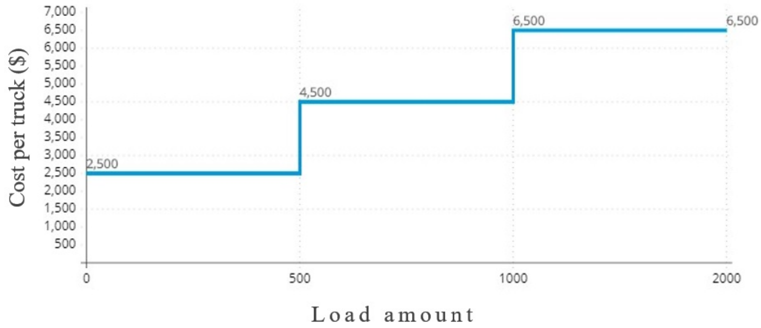

Figure 5.3 The cost function for outbound trucks.

The last cost term which is fixed opening costs of the regional depots varies between 12800 and 16600

In our problem setup, we have 3 periods and 3 commodities which are generated by the aggregation of 10 commodities to simplify the model and to be still able to work with a multi commodity problem. We allow for one period of late deliveries to the service points as long as the minimum service level is satisfied for the period when the demand is received. Different service levels for different commodities are adopted to create the heterogeneity that stems from the nature of having an environment with multi commodity.

5.2 Example Problem Results

In order to exhibit how the initial solution evolves into a better solution by the 3-Phase Algorithm and to analyze its cost breakdown we select Instance 2 of the 30SP data set.

First, the optimal value found by the commercial solver is 208765 which consists of location costs, inbound and outbound truck costs. The 3-Phase Algorithm is able to obtain the optimal solution quicker than the solver. The comparison table is presented below. The CPU times are in seconds.

3-Phase Algorithm						SOLVER		
Phase 1		Phase 2		Phase 3				
Objective	Time	Objective	Time	Objective	Time	Objective	Time	Gap
402030	0,3	216623	74,3	208765	29,3	208765	715	0,00%

Figure 5.4 The results of Instance 2 of 30SP.

The solution found in Phase 1 is quite loose as its objective function value is far from the optimal solution compared to other phases' result. Phase 2 is where the biggest improvement is observed and it is already able to find very good upper bound for a minimization problem. Phase 3 is the fine tuning phase that it tries to improve solution by small relaxations in every iteration and it finds the optimal solution for this instance. Next, we present how the components of the objective function changes within the phases.

	PHASE 1			PHASE 2			PHASE 3					
							ITERATION 1			ITERATION 2		
	1	2	3	1	2	3	1	2	3	1	2	3
Total Cost	121220,8	125900,3	154909,3	216622,7			212265,1			208765,1		
Outbound Transportation Cost	37500	39000	44500	32000	32500	30000	32000	32500	30000	30500	30500	30000
	R3 b3	R2 b3	R3 b2	R3 b1	R6 b1	R3 b1	R36 b2	R36 b2	R36 b1	R36 b1	R36 b1	R36 b1
	R6 b2	R4 b2	R21 b3	R6 b1	R9 b1	R6 b2	R6 b1	R30 b3	R30 b3	R6 b1	R38 b1	R30 b3
	R9 b2	R10 b2	R32 b2	R9 b1	R32 b2	R9 b2	R30 b3	R2 b1	R2 b1	R30 b3	R30 b3	R2 b1
	R30 b3	R31 b3	R34 b2	R30 b3	R34 b1	R30 b3	R2 b2	R34 b1	R34 b1	R2 b2	R2 b1	R34 b1
	R32 b3	R32 b2	R36 b2	R32 b2	R36 b2	R32 b2	R3 b1	R3 b1	R3 b1	R37 b1	R3 b1	R3 b1
	R34 b2	R39 b1	RR1 b1	R36 b2	R2 b2	R34 b1	R10 b2	R10 b1	R9 b2	R3 b1	R10 b1	R9 b2
	R36 b2	RR1 b1	RR2 b1	R2 b2	R4 b1	R36 b1	R9 b1	R9 b1	R32 b2	R10 b1	R9 b1	R32 b2
		RR2 b1	RR3 b1	R10 b2	R10 b1	R2 b1	R32 b2	R32 b2	R29 b2	R9 b1	R32 b2	R29 b2
		RR15 b1	RR8 b1		R31 b3			R29 b2		R32 b2	R29 b2	
		RR26 b1	RR10 b1									
			RR11 b1									
			RR12 b1									
			RR15 b1									

Figure 5.5 The outbound truck cost of phases of Instance 2.

Numbers on the column headings represent the period. Gap stands for the mixed-integer programming optimality gap. For Phase 1, each period's total cost is displayed since the Phase 1 consists of single period problem solutions for each period. The multi period solution's total cost is displayed for Phase 2 and Phase 3 problem solutions. In each column, there is the outbound transportation cost and the routes used in that period along with the truck sizes. $b1$ represents the truck with the smallest size and $b3$ represents the one with the largest truck. It can be seen that the number of routes used are decreased in Phase 2 compared to Phase 1. In addition, the number of large-sized trucks used is decreased while the total number of trucks used also reduced. That is reflected in the outbound transportation cost. We have 2 iterations in Phase 2. Each one has an improvement on the total cost even though the outbound transportation cost remains the same in iteration 1. The last iteration exhibits how the cost benefit is obtained. If we compare the list of routes used in period 1 of iteration 1 and iteration 2, the fact that the outbound transportation cost is decreased in iteration 2. This is achieved by simply replacing 2 middle-sized truck with 2 small-sized trucks despite using one more additional truck in total. A similar behaviour follows in period 2.

The truck utilization also provides good insights about the performance of the system. We examine the unused spaces of the trucks rather than the percentage utilization. The total truck capacity scrapped in Phase 1 is 9582.9. This number dramatically decreases in Phase 2 to 1954.2. Iteration 1 of Phase 3, however, provides no improvement as the set of trucks used is the same with that of Phase 2. The number of trucks used in full capacity increases in iteration 2 of Phase 3. The total unused truck capacity in iteration 1 is almost halved in iteration 2 and turns out to be 954.2.

PHASE1						PHASE 2						PHASE 3																	
												ITERATION 1						ITERATION 2											
1		2		3		1		2		3		1		2		3		1		2		3							
R3	990,7	R2	604,8	R3	179,5	R3	0,0	R6	0,0	R3	0,0	R3	0,0	R2	0,0	R2	0,0	R36	0,0	R36	0,0	R36	0,0						
R6	212,1	R4	418,2	R21	501,6	R6	0,0	R9	15,8	R6	0,0	R32	0,0	R3	0,0	R34	0,0	R6	0,0	R2	0,0	R2	0,0						
R9	344,8	R10	310,8	R32	25,4	R9	113,1	R32	206,1	R9	155,2	R6	0,0	R9	0,0	R3	0,0	R30	0,0	R3	0,0	R34	0,0						
R30	0,0	R31	355,1	R34	428,3	R30	21,3	R34	86,6	R30	93,1	R2	2,1	R10	33,7	R32	0,0	R2	0,0	R10	0,0	R3	0,0						
R32	909,6	R32	281,1	R36	424,1	R32	0,0	R36	435,8	R32	10,0	R9	71,4	R30	113,6	R36	30,2	R37	0,0	R9	3,9	R32	25,4						
R34	304,2	R39	250,2	RR1	383,5	R36	9,5	R2	0,0	R34	20,3	R30	127,5	R34	176,5	R29	37,6	R3	0,0	R38	18,7	R29	37,6						
R36	64,1	RR1	400,7	RR2	211,3	R2	0,0	R4	0,0	R36	30,2	R36	141,4	R32	216,1	R30	55,8	R10	0,0	R32	75,6	R30	108,0						
		RR2	238,9	RR3	98,2	R10	298,8	R10	137,6	R2	0,0	R10	333,2	R29	217,6	R9	93,6	R9	10,3	R30	188,9	R9	153,0						
		RR15	370,0	RR8	98,7			R31	320,9					R36	303,9			R32	115,2	R29	217,6								
		RR26	237,1	RR10	155,4																								
				RR11	228,7																								
				RR12	242,8																								
				RR15	313,1																								

Figure 5.6 The unused outbound truck spaces.

	Phase 1	Phase 2	Phase 3	
			Iteration 1	Iteration 2
b1	50,33%	93,27%	86,95%	98,32%
b2	72,79%	88,85%	88,28%	88,28%
b3	71,98%	92,74%	100,00%	100,00%

Figure 5.7 The average percentage outbound truck utilizations of each truck size.

By the table above, we can observe the increasing behaviour of the truck utilization for further phases. Especially, the improvement in Phase 2 from Phase 1 is steep.

Figure 5.8 has a similar structure to Figure 5.5. In each column, the destination of the inbound trucks (a depot) and its size are displayed. $b1$ represents the truck with the smallest size and $b3$ represents the one with the largest truck. This table also shows the information of open depots for each period. While Phase 1 solution suggests to open depot #4, the Phase 2 solution denies it. An immediate benefit observed in Phase 2 is that the depot #4 is closed. Iteration 1 of Phase 3 gains cost advantage by replacing a middle sized truck with a small sized one for both

	PHASE 1			PHASE 2			PHASE 3					
							ITERATION 1			ITERATION 2		
	1	2	3	1	2	3	1	2	3	1	2	3
Total Cost	121220,8	125900,3	154909,3	216622,7			212265,1			208765,1		
Inbound Transportation Cost	25010,75	28190,26	41099,28	21691,96	20028,81	21691,96	21691,96	18681,55	18681,55	21691,96	18681,55	18681,55
	W1 b2	W1 b3	W1 b3	W1 b2	W1 b2	W1 b2	W1 b2	W1 b1	W1 b1	W1 b2	W1 b1	W1 b1
	W2 b1	W2 b2	W2 b1	W2 b1	W2 b1	W2 b1	W2 b1	W2 b1	W2 b1	W2 b1	W2 b1	W2 b1
	W5 b3	W5 b3	W4 b3	W5 b3	W5 b2	W5 b3	W5 b3	W5 b3	W5 b3	W5 b3	W5 b3	W5 b3
	W6 b2	W6 b1	W5 b3	W6 b1	W6 b1	W6 b1	W6 b1	W6 b1	W6 b1	W6 b1	W6 b1	W6 b1
			W6 b3									

Figure 5.8 The inbound truck cost of phases of Instance 2.

period 2 and 3.

5.3 Results Summary

The experiments we conduct are for the comparison of the performance of the commercial solver and the 3-Phase Algorithm for 30SP data sets. The performance is measured by both the solution time and the objective function value of the solution. During the experiments, we utilized GUROBI 7.5.2 on PYTHON 3.6 using an Intel Xeon CPU E5-2640 processor with 2.60 GHz speed, 16 GB RAM and 64-bit Windows 7 operating system.

We experimented on data sets with different sizes as previously mentioned. For 50SP and 100SP data sets, we calculated both long run and short run performances since the optimal solution cannot be obtained.

The summary of the experiments are presented in the tables below. The time figures are in seconds.

For 30 SP data sets, we put 4 hours time limit for both the commercial solver and 3-Phase Algorithm. As seen in the table below, in none of the instances, 3-Phase Algorithm is terminated by the time limit. However, the solver fails to find the optimal solution in 5 of the instances. Given that, 3-Phase Algorithm is able to find

30 SP	3-Phase Algorithm						SOLVER		
	Phase 1		Phase 2		Phase 3				
	Low Bound	Time	Objective	Time	Objective	Time	Objective	Time	Gap
Instance 01	343279	0,3	216109	100,5	208007	3372,3	192469	14403	1,10%
Instance 02	402030	0,3	216623	74,3	208765	29,3	208765	715	0,00%
Instance 03	495375	0,3	277358	1,7	263891	499,4	257691	12158	0,00%
Instance 04	317479	0,8	185460	5,2	179506	195,3	175607	14403	5,49%
Instance 05	379898	0,3	224229	100,4	214224	7114,7	194238	13545	0,00%
Instance 06	406798	0,5	245632	18,6	215702	1154,6	214779	14402	1,39%
Instance 07	445871	0,5	256728	100,6	218001	6923,1	207382	11519	0,00%
Instance 08	373755	0,5	222059	100,5	205561	8466,8	196425	14402	1,04%
Instance 09	395492	0,4	237953	52,4	223652	404,8	216551	14402	1,04%
Instance 10	426412	0,5	247026	2,4	228657	429,4	205147	4029	0,00%

Figure 5.9 The results of 30SP data set.

the optimal solution in only instance 2. Although the 3-Phase Algorithm cannot yield better solutions than the solver, the algorithm's solutions can be considered as good enough and it finds those solutions quicker than the solver.

50 SP	3-Phase Algorithm						SOLVER		
	Phase 1		Phase 2		Phase 3				
	Objective	Time	Objective	Time	Objective	Time	Objective	Time	Gap
Instance 01	536624	1,0	303590	48,8	280557	29795,4	251052	28800	5,66%
Instance 02	534967	0,5	326982	764,8	305168	28247,0	259059	28800	3,84%
Instance 03	626450	0,6	361252	162,9	330740	29139,1	294336	28800	6,13%
Instance 04	576675	0,8	327923	2431,1	297971	26447,3	270999	28800	10,61%
Instance 05	647120	1,3	375431	3601,1	334873	26176,0	283471	28800	6,88%
Instance 06	529419	1,7	311470	27,2	276567	29948,3	261460	28800	9,37%
Instance 07	593917	1,2	331005	43,8	302456	15747,6	305391	28808	6,93%
Instance 08	648921	1,8	377251	607,4	326953	29984,2	329953	28806	8,77%
Instance 09	600488	1,0	331762	26,9	313039	30177,5	305908	28808	7,41%
Instance 10	569818	0,8	351880	145,6	321074	29035,7	323841	28808	11,69%

Figure 5.10 The results of 50SP data set in 8 hours.

For 50SP and beyond data sets, we enforced 8 hours time limit to both solver and the algorithm long runs. The 3-Phase Algorithm yields better solutions in Instances 7, 8 and 10 in 8-hour runs. We should also note that the run taken on Instance 7 terminated before the time limit is exceeded. We allocated 1 hour to Phase 2 but the total run time of the algorithm is 8 hours.

50 SP	3-Phase Algorithm						SOLVER		
	Phase 1		Phase 2		Phase 3				
	Objective	Time	Objective	Time	Objective	Time	Objective	Time	Gap
Instance 01	536624	1,1	303590	46,7	290301	1762,9	290330	1806	15,36%
Instance 02	534967	0,6	327482	601,0	310849	1237,2	313810	1806	14,29%
Instance 03	626450	0,7	361252	175,1	343298	1761,6	329734	1807	12,43%
Instance 04	576675	1,0	329423	601,1	301227	1374,6	315369	1808	17,35%
Instance 05	647120	1,1	375672	601,0	347680	1209,4	365108	1806	21,13%
Instance 06	529419	1,6	311470	25,2	290927	1952,0	289335	1807	14,28%
Instance 07	593917	1,2	331005	42,6	311247	1418,7	307391	1807	11,38%
Instance 08	648921	1,6	377251	579,5	354668	1187,2	337430	1805	15,14%
Instance 09	600488	0,9	331762	26,8	316958	1863,0	309908	1807	12,12%
Instance 10	569818	0,8	351880	147,6	330887	1696,4	329756	1805	17,63%

Figure 5.11 The results of 50SP data set in 30 minutes.

By the results of short run experiments where the time limit is 30 minutes, we can observe that in Instances 1, 2, 4 and 5 the 3-Phase Algorithm performs better than the solver. Moreover, the algorithm still produces good solutions compared to the solver in the other instances.

100 SP	3-Phase Algorithm						SOLVER		
	Phase 1		Phase 2		Phase 3				
	Objective	Time	Objective	Time	Objective	Time	Objective	Time	Gap
Instance 01	1039604	24,7	589333	7202,2	569181	22309,9	556927	28845	19,61%
Instance 02	1063204	15,5	622096	7201,9	578440	22004,4	529373	28854	15,45%
Instance 03	997333	8,9	572310	7145,1	554199	21735,2	488211	28843	12,38%
Instance 04	1001299	26,3	539610	2244,6	514110	27485,7	535463	28854	18,92%
Instance 05	1016546	14,5	576994	7202,7	522374	22089,2	484582	28848	11,46%
Instance 06	1072369	25,2	610958	7202,3	580356	22116,0	586308	28848	21,22%
Instance 07	1055097	13,5	593851	7202,5	567554	22898,5	578763	28838	17,63%
Instance 08	986822	16,0	552562	7202,3	524902	21686,9	492538	28843	10,79%
Instance 09	970073	19,1	579383	402,3	551628	29768,3	524300	28847	13,56%
Instance 10	1024594	44,2	599218	7202,2	574447	22625,1	492338	28845	10,86%

Figure 5.12 The results of 100SP data set in 8 hours.

In experiments with 100SP data set, we imposed a 8-hour limit where 2 hours are devoted to Phase 2. In 3 of the 10 instances the 3-Phase Algorithm finds better

100 SP	3-Phase Algorithm						SOLVER		
	Phase 1		Phase 2		Phase 3				
	Objective	Time	Objective	Time	Objective	Time	Objective	Time	Gap
Instance 01	1039604	21,8	597333	102,0	565181	1735,3	573927	1846	25,65%
Instance 02	1063204	13,8	642516	101,8	573705	1731,0	590324	1845	28,57%
Instance 03	997333	8,6	596171	101,9	528680	1724,8	552552	1842	24,87%
Instance 04	1001299	25,0	539610	101,9	517610	1738,6	611952	1849	31,91%
Instance 05	1016546	13,4	661600	102,3	583233	1877,2	519702	1843	20,46%
Instance 06	1072369	22,9	706859	102,2	614533	1743,7	626039	1846	29,12%
Instance 07	1055097	13,7	602991	102,5	563941	1730,2	603675	1839	24,36%
Instance 08	986822	15,2	589024	102,3	529967	1728,0	521538	1840	18,14%
Instance 09	970073	18,3	579383	101,6	548437	1731,6	572951	1845	23,64%
Instance 10	1024594	40,6	614656	102,1	584841	1756,2	570731	1848	26,27%

Figure 5.13 The results of 100SP data set in 30 minutes.

solutions than the solver. If we compare the short run results in which the total time limit is 30 minutes and at most 10 minutes are allocated to Phase 2, the performance of the algorithm outweighs the solver's. In 7 of the 10 instances, the solver cannot produce superior solutions than that of the proposed algorithm.

6. CONCLUSION

In this study, we present a mathematical model for multi period spare parts distribution network design problem. The model includes facility location decision, inbound and outbound truckload with the truck size decision, routing decision for outbound trucks and service level decision. A total cost minimizing mixed integer linear programming formulation is proposed. Since, the problem is a large scale combinatorial optimization problem, the commercial solver struggles to find the optimal solution for small data sets and fails to find the optimal solution in a reasonable time as the problem size increases. Therefore, we proposed a heuristic method to deal with the problem. Because the scale of the problem creates challenges, the idea behind this heuristic method is to restrict the problem so as to find a feasible initial solution and seek for improvements from that solution. The proposed algorithm is comprised of 3 phases that the algorithm is named after. The first phase of 3-Phase Algorithm solves a single period problem with single sourcing constraint. A multi period solution is built upon the single period problem solutions. This solution undergoes a reoptimization phase. After that, the third phase tries to improve this solution by relaxing the problem with local route set expansion iteratively.

We test the algorithm on 3 different data sets having 10 instances each. The first one has 30 service points, 10 candidate regional depot locations and routes .The second one has 50 service points, 15 candidate regional depot locations and routes. The last one has 100 service points, 30 candidate regional depot locations and routes. The 3-Phase Algorithm seems to be slightly overtaken by the solver solutions in smaller cases. However, the algorithm is strong in producing good solutions for bigger cases in short time against the solver.

One weakness of the algorithm can be that it spends a lot of time solving a problem during Phase 3 when the average number of routes serving to a service point is high. Basically, when this statistics is higher, the number of possible deliveries gets higher and this situation makes it harder to find the optimal one. Thus, spending more time for an iteration results in completion of less number of iterations. Therefore, the potential improvement margin may not be achieved in desired time.

We can suggest to work on this system with a seasonality effect on demand as a future work. One can also consider incorporating distribution center location decisions into this study. In addition, including an inventory cost term to the objective function can be possible without defining any additional decision variables. So, we can suggest this extension, as well.

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