A LOCATION-ROUTING PROBLEM FOR WASTE OIL COLLECTION

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A LOCATION-ROUTING PROBLEM FOR WASTE OIL COLLECTION

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To my love

ABSTRACT

This thesis is motivated by a real-world waste cooking oil collection system. Specifically, we focus on a biodiesel production company, which regularly collects waste cooking oil from different sources such as fast food restaurants, luxury restaurants, and cafes via a number of vehicles. The collected waste cooking oil is the main raw material in the company's production system. In addition to the current regular customers, the company wants to collect waste oil from the households. The company is interested in designing a collection system, in which people will bring their waste cooking oil to a set of community centers (such as schools, mosques, etc.). The company wants to determine the locations of these community centers so that people can access them easily. We define a location routing problem, which determines the locations of the community centers, the number of oil bins to place at each community center, and the vehicle routes to collect bins from the community centers every week. We present a mixed integer programming model for this location-routing problem, which minimizes operational and logistical costs. Since the size of the real-world problem instance does not allow us to obtain good solutions by using commercial optimization software, we focus on developing an efficient Simulated Annealing heuristic to solve the problem. We perform numerical analysis to evaluate the performance of our solution method.

Keywords : Waste Oil Collection, Location-Routing Problem, Metaheuristics.

ÖZETÇE

Bu tez bitkisel atık yağlardan biyodizel üreten bir firmanın operasyonlarına odaklanmaktadır. Bu firma bitkisel atık yağları kendi üretim sistemlerinde hammadde olarak kullanmaktadır. Bitkisel atık yağlar firmanın maliyetlerinin büyük bir bölümünü oluşturmaktadır. Firma kafe, restoran, otel gibi farklı noktalardan düzenli olarak atık yağ toplamaktadır. Firma bu düzenli müşterilerinin yanı sıra müşteri ağına evde bitksel yağ tüketen bireysel müşterilerini de ekleyerek, toplanan atık yağ miktarını artırmak istemektedir. Firma bireysel müşterilerinin evlerini ziyaret etmek yerine cami, okul ve belediye binası gibi toplama noktaları belirlemek ve bireysel müşterilerin bu noktalara atık yağlarını getirmesini hedeflemektedir. Bu bağlamda firmanın toplama noktalarının seçimi, seçilen toplama noktalarına kaç tane yağ bidonu konulacağı ve toplama noktalarından bidonların her hafta hangi rotalar ile toplanacağı kararlarını vermesi gerekmektedir. Bu problemi çözmek için bir karışık tam sayılı doğrusal programlama modeli geliştirilmiştir. Geliştirilen model, firma tarafından verilen gerçek veriler üzerinde uygulanmıştır. Gerçek hayat problem örnekleri, boyutları büyük olduğu için optimizasyon yazılımları kullanarak çözmek zordur. Bu yüzden ele alınan problemi çözmek için etkili bir Tavlama Benzetimi algoritması geliştirilmiştir. Geliştirilen sezgisel yöntemin performansı bilgisayısal analizler yapılarak değerlendirilmiştir.

Anahtar kelimeler : Atık Yağ Toplama Problemleri, Lokasyon-Rotalama Problemi, Sezgisel Yöntemler.

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CHAPTER I

INTRODUCTION

In recent years, reverse logistics have received increasing attention in the literature because of the increasing environmental concerns as well as its economical advantages. One of the most important issues for the companies, which use recycled materials as raw materials in their manufacturing process, is collecting these materials from different source points efficiently. This process constitutes a large portion of companies' total costs. These materials have also a negative effect on the environment. One of these materials is waste cooking oil. Waste cooking oil generates 25 % of water pollution in Turkey [1]. When one liter of waste cooking oil is mixed with clean water, it pollutes one million liters of drinking water [3]. The companies that produce biodiesel use waste cooking oil as a raw material in their manufacturing system to decrease the total costs because it is cheaper than virgin cooking oil [2]. Furthermore, waste cooking oil can be used to produce different kinds of products such as biodiesel, soap and so on. Each year, 108 million tons of waste vegetable oil is produced all over the world, but only 6 million tons are used in biodiesel production [3]. The remaining uncollected waste cooking oil causes serious problems on people's health and environment. According to Ministry of Environment and Forestry in Turkey, 350 thousand tons of waste cooking oil should be collected, but even 1% of total amount can not be collected currently by the licensed collectors [3].

This study is motivated by a real-world waste cooking oil collection system. We focus on a biodiesel production company, which has the highest waste cooking oil collection service in Turkey. According to Turkish law about collection of waste cooking oils, it is obligatory for the restaurants, cafes, hotels to give their waste cooking oil to any recovery companies. 80% of the waste cooking oil in Turkey is collected by this company that has the biggest market share. The company collects the accumulated waste cooking oil from a set of regular customers such as fast food restaurants, luxury restaurants, cafes, hotels, etc. The company distributes a certain number of bins to the regular customers to collect the waste cooking oil. The number of bins distributed to regular customers depends on the oil consumption of the customers. The company has an agreement with each of their regular customers to collect waste cooking oil in a certain day. The company already has a certain plan to collect waste cooking oil from its regular customers. The company can satisfy the raw material needs with waste cooking oil or by purchasing virgin oil. As virgin oil is more costly than waste cooking oil, the company gives significant importance on the collection of waste cooking oil from different sources.

The company wants to increase the number of customers in its oil collection network by focusing on the individual customers (households) which are called "source points" in this study. Currently, it is not obligatory for the individuals to give waste cooking oil to any recovery companies by Turkish law. As collecting of waste cooking oil from people's houses is too costly for the company, the company wants to determine a set of community centers (such as schools, mosques, municipality building, etc.) where individual customers can bring their waste cooking oil. To implement such a system, the company should also decide the number of bins to place at the chosen community centers (CC) and the routes to collect waste cooking oil from the CCs, while minimizing the total cost of collection system. As the selected CCs may not have any incentives to be a part of such a system, the company considers to support the CCs financially.

Source points should have easy access to the CCs. We focus on finding a set of CCs, which ensure that each source point can access a community center by walking at most a maximum distance. We assume that the company's vehicles visit each CC once a week to collect the bins. We consider capacitated CCs, multiple capacitated vehicles and a single depot. We aim to determine the number of bins at each open CC and the oil collection rates to minimize the sum of the fixed and variable costs for community centers and the routing costs.

A mixed integer programming (MILP) formulation is presented to solve the proposed Location-Routing Problem for Waste Oil Collection (LRPWOC). Because of the exponential growth in the problem size, exact approaches for the similar problems (such as Location-Routing Problem [32]) can be used to solve small and medium size instances. The problem we propose is difficult to solve with exact methods when the problem size increases. Javid et al. [15] show that the heuristic method is effective for a wide variety of problem sizes and structures. Simulated Annealing (SA) has been applied to a number of combinatorial problems with fairly good results [36]. Therefore, we develop a SA algorithm to solve this problem because of the previous promising applications and ease of implementation for complex problems. Yu et al. [32] propose a Simulated Annealing algorithm for location-routing problem which can applied to other combinatorial problems that contain multiple levels of decision making.

The proposed heuristic method is decomposed into two parts as the constructive part and the improvement part. An initial solution for the LRPWOC is determined by greedy heuristic algorithms in a sequential manner for location, assignment and routing problems. We also have three phases (location, assignment and routing) in the improvement stage. SA is used to improve the initial solution in each phase by using neighborhood moves. We conduct computer experiments to evaluate the performance of our heuristic regarding to the computation time and the solution quality.

The planning horizon for this problem is long-term. Thus, we do not need to set a time limit to run the model but due to the exponential increase in the problem size, the problem can not be solved by using OPL/Cplex for the large size instances.

We face out-of-memory error in OPL/CPLEX when the problem size increases. We compare the results of the exact MIP solutions and SA solutions on a set of instances and observe that the solutions obtained through our metaheuristic algorithm are slightly better than the solutions obtained from OPL/Cplex within 30 minutes for large-sized problems.

CHAPTER II

LOCATION-ROUTING IN WASTE OIL COLLECTION

2.1 Problem Description

In this section, we describe the details of the Location-Routing for Waste Oil Collection problem addressed in this study. We are given a set of source points, a set of candidate CCs and a depot (the biodiesel production company). Each source point produces a fixed amount of waste cooking oil per week. There is a capacity limit on the total number of bins that can be placed at a CC because of space limitations. We assume that vehicles collect bins from CCs at the end of each week. Each vehicle has a fixed capacity and route duration limits. The company needs to support the selected CCs financially as the CCs may not have any other incentives to be a part of such a system. The company also needs to give bins to the CCs to collect the waste cooking oils. It creates bin cost for the company. There are transportation costs associate with collecting waste cooking oil from CCs.

The LRPWOC aims to determine the opened CCs, the number of bins distributed to each CC, and the assignment of source points to the CCs, and the routes to be followed by each vehicle to collect oil. Figure 1 shows the waste cooking collection network. A coverage distance, which shows the longest distance between a CC and given source point, is defined. The source points can be assigned to CCs which are within the coverage distance. The assumptions, decisions, constraints and the objective of the LRPWOC are presented below.

• Assumptions

− The amount of waste cooking oil at each source point is known.

− Each source point is served by only one CC.

– The capacity in terms of the maximum number of bins at each candidate CC is known.

– We assume that when a CC is visited, all of the accumulated oil is collected; i.e., partial collection is not permitted.

– We assume that the vehicles are identical and capacity of vehicles in terms of bins are known.

• Decisions

– Location decisions address which CC should be opened.

– Allocation decisions address the number of bins to place at each CC.

– Assignment decisions are for determining which source points should be assigned to which opened CC.

– Routing decisions adddress constructing oil collection routes of vehicles.

• Constraints

The following constraints must hold:

– The number of bins at each CC must not exceed the capacity of CC.

– Each CC must be served by one vehicle.

– Route duration must not exceed the working hours of the vehicles.

– Vehicles' total loads in terms of bins must not exceed the capacity of the vehicles.

• Objective

The aim is to minimize the total costs including fixed openning cost of a community center, bin cost at each open community center and transportation cost.

2.2 Mathematical Model Formulation

The proposed model is formulated as a mixed integer programming model with an objective that minimizes the total cost. The following indices, parameters, and decision variables are used in the mathematical model.

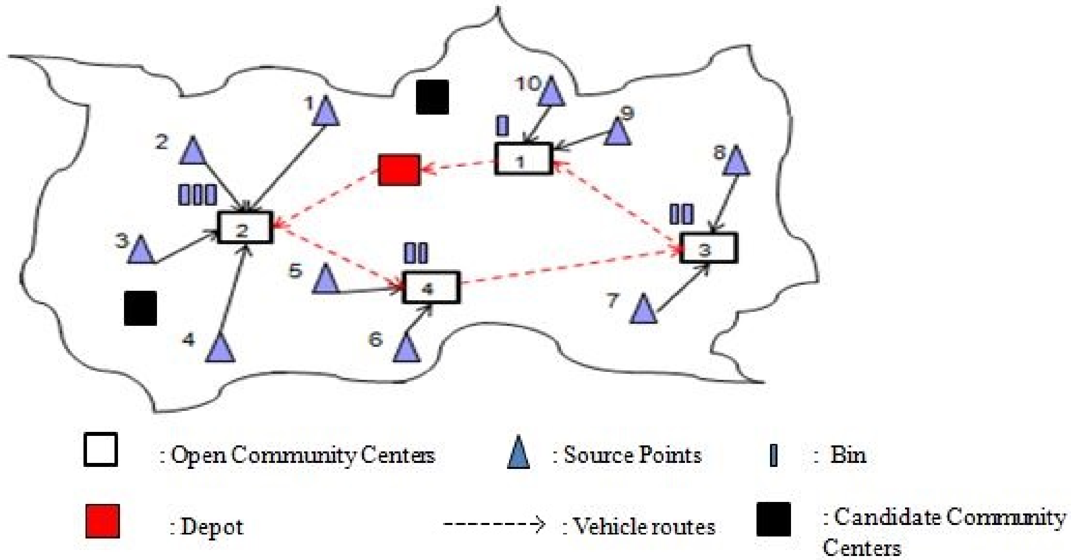


Figure 1: An illustration of the waste oil collection network

Notation

G : set of candidate CCs ; $i \in G$.

I : the number of candidate CCs.

H : set of source points ; $j \in H$.

K : set of vehicles; $k \in K$.

G' : $\{G \cup \{0\}\}$ the nodes in the network including the depot.

Parameters

τ : target coverage distance

N_j : $\{i \in G | d_{ij} \leq \tau\}$ the set of CCs that can cover node $j \in H$.

B_i : maximum number of bins that can be located at CC $i \in G$.

C : the capacity of a bin (liters).

λ_j : average weekly amount of waste oil produced by source point $j \in H$ (liters).

F_i the weekly cost of establishing and operating CC $i \in G$.

b_i : the weekly cost of placing a bin at CC $i \in G$.

d'_{im} : the distance from node $i \in G'$ to node $m \in G'$.

Q_k : the capacity of vehicle $k \in K$ (number of bins).

α : the travelling cost per unit distance (TL/km).

$Time_{im}$: the travelling time from node $i \in G'$ to node $m \in G'$.

T_k : the total travelling time for each vehicle $k \in K$.

M : a big number.

Decision Variables

X_i : 1, if CC $i \in G$ is opened; 0, otherwise.

Y_i : the number of bins placed at open CC $i \in G$.

Z_{ij} : 1, if source point $j \in H$ is assigned to CC $i \in G$;

0, otherwise.

V_{imk} : 1, if vehicle $k \in K$ goes from node $i \in G'$ to node $m \in G'$; 0, otherwise.

t_{imk} : : the number of bins placed at open CC $m \in G$ if the vehicle $k \in K$ goes from CC $i \in G'$ to CC $m \in G'$.

U_i : auxiliary variables for subtour elimination constraints.

Next, we present the mathematical model for the LRPWOC :

$$Min \sum_{i\in G'} \sum_{m\in G'} \sum_{k\in K} V_{imk} d'_{im} \alpha + \sum_{i\in G} X_i F_i + \sum_{i\in G} Y_i b_i \tag{1}$$

$$\sum_{j\in H} Z_{ij} \lambda_j \leq Y_i C \qquad \forall i \in G \tag{2}$$

$$Y_i \leq B_i X_i \qquad \forall i \in G \tag{3}$$

$$Z_{ij} \leq X_i \qquad \forall i \in G, j \in N_j \tag{4}$$

$$\sum_{i\in N_j} Z_{ij} = 1 \qquad \forall j \in H \tag{5}$$

$$\sum_{i\in G'} \sum_{m\in G} V_{imk} Y_m \leq Q_k \qquad \forall k \in K \tag{6}$$

$$\sum_{i\in G'} V_{ipk} - \sum_{m\in G'} V_{pmk} = 0 \qquad \forall k \in K, p \in G' \tag{7}$$

$$\sum_{m\in G} V_{0mk} \leq 1 \qquad \forall k \in K \tag{8}$$

$$\sum_{k\in K} \sum_{m\in G'} V_{imk} - X_i = 0 \qquad \forall i \in G \tag{9}$$

$$\sum_{i\in G'} \sum_{k\in K} V_{imk} - X_m = 0 \qquad \forall m \in G \tag{10}$$

$$\sum_{i\in G'} \sum_{m\in G} V_{imk} Time_{im} \leq T_k \qquad \forall k \in K \tag{11}$$

$$U_i - U_m + I \sum_{k\in K} V_{imk} \leq I - 1 \qquad \forall i \in G, m \in G \tag{12}$$

$$X_i \in \{0, 1\} \qquad \forall i \in G \tag{13}$$

$$Z_{ij} \in \{0, 1\} \qquad \forall i \in G, j \in H \tag{14}$$

$$Y_i \ integer \qquad \forall i \in G \tag{15}$$

$$V_{imk} \in \{0, 1\} \qquad \forall i \in G', m \in G', k \in K \tag{16}$$

$$U_i \geq 0 \qquad \forall i \in G \tag{17}$$

The objective function (1) minimizes weekly total cost. Constraints (2) specify that the total demand assigned to a CC must be less than or equal to the total bin capacity at that CC. Constraints (3) satisfy that the number of bins placed at each CC must be less than or equal to the maximum number of bins allowed at CCs. Constraints (4) specify that a source point can be assigned to a CC only if that CC is opened. Constraints (5) ensure that each source point should be assigned to only one CC. Constraints (6) satisfy that vehicle capacity constraint is not exceeded for any of the vehicles. Constraints (7) are route continuity constraints. Constraints (8) ensure that each vehicle is routed from a depot. Constraints (9) and (10) ensure that a vehicle is routed from a CC if and only if that CC is opened. Constraints (11) satisfy the maximum time limit for each vehicle. Subtours are eliminated by constraints (12). Constraints (13), (14), (16) are used to define binary variables. Constraints (15) define the integer variables. Constraints (17) define the continuous variables.

Note that constraints (6) are nonlinear in the model above, since the number of bins at a CC is not determined beforehand. If a CC is included in a given route, the load of vehicle assigned to that route will be determined after the number of bins are also determined. These constraints can be linearized by introducing a new integer variable t_{imk} instead of $V_{imk} * Y_m$ and by replacing constraints (6) by the following set of constraints:

$$t_{imk} \leq MV_{imk} \qquad \forall i \in G', m \in G, k \in K, \quad i \neq m \tag{18}$$

$$t_{imk} \leq Y_m \qquad \forall i \in G', m \in G, k \in K, \quad i \neq m \tag{19}$$

$$Y_m + MV_{imk} \leq t_{imk} + M \qquad \forall i \in G', m \in G, k \in K, \quad i \neq m \tag{20}$$

$$\sum_{i \in G'} \sum_{m \in G} t_{imk} \leq Q_k \qquad \forall k \in K \tag{21}$$

$$t_{imk} \ integer \qquad \forall i \in G', m \in G, k \in K, \quad i \neq m \tag{22}$$

The LRPWOC is similar to the LRPs. In this study, the LRPWOC includes some additional decisions. LRPs are generally solved by using heuristic methods as these problems are difficult to solve. LRPWOC is also difficult to solve with large size instances. One way to solve large instances efficiently is by using heuristics which have some benefits such as getting good solutions in reasonable time and dealing with larger problems [23]. In this thesis, a Simulated Annealing algorithm is developed to solve the LRPWOC because of previous promising applications and its ease to implement for complex problems.

CHAPTER III

PREVIOUS WORK

In this chapter, we explain the literature related to our problem. We focus on literature on the location-routing problem (LRP), especially, the heuristic approaches developed to solve the LRP and studies that address waste collection.

3.1 Related Work in Oil Collection

Recently, reverse logistics and collection of recoverable products are widely studied problems in the literature (see Nuortio et al. [5]) because of health, environmental concerns, and cost impacts. Hemmelmayr et al. [6] focus on real-world study in waste collection. They take into consideration a collection system which includes the combination of a bin allocation and a vehicle routing problem. A Variable Neighborhood search metaheuristic method is proposed for the routing part with mixed integer linerar programming model and an exact method is proposed for the bin allocation part. Aksen et al. [7] present a selective inventory routing problem for waste vegetable oil collection. Two different mixed integer programming models are proposed in this paper. They also generate lower bounds with a partial linear relaxation approach. The performance of these two models are tested on real data. Ramos et al. [8] focus on a Multi-Depot Vehicle Routing Problem with mixed closed and open inter-depot routes. A waste cooking oil collection system is proposed by the multiple depots with an outsourced vehicle fleet and collection routes should be scheduled. To the best of our knowledge, location, routing, assignment and bin allocation decisions are not addressed all together in the literature.

3.2 *Related Work in LRP*

A LRP can be described as follows: given a set of potential depots and a set of customers with known demand, define the optimal locations of the depots with vehicle routes from chosen depots to the customers simultaneously while minimizing the total system costs [13]. Many studies, including, Perl et al. [4], Tuzun et al. [11], Prins et al. [14], Bouhafs et al. [17], Laporte et al. [19] and Chan et al. [20] proposed formulations and algorithms for the LRP and variants.

The LRP considers three main components of a logistic system, in a integrated way which are the facility location, assignment and vehicle routing. Generally, three index formulation is used to formulate the LRP (Perl and Daskin[10] ; Tuzun and Burke [11]). LRPs can be decomposed into three sub-problems (1) facility location (2) demand allocation and (3) vehicle routing [9]. There are many variants of LRPs such as LRP with limited number of vehicles, heterogeneous fleet types vehicles, capacitated routes and capacitated depots are worked in the literature [9]. The researchers assume either capacitated routes or capacitated depots, but both capacitated depots and routes are not considered (Laporte, Norbert, and Taillefer [18]). Stochastic location-routing problems are also studied in the literature (e.g., Laporte, Louveaux, and Mercure [19], Chan, Carter, and Burnes [20]). A Multi-Depot Location-Routing Problem is proposed by Liu et al. [21]. MDLRP combines vehicle routing and location decisions to define the depots' location and finds the set of vehicle schedules and routes. Inventory control decisions take into account vehicle routing and depot location. In most LRP models, the demands at visited nodes are known beforehand. Different from the previous models in the LRP literature, demands at the CCs in forming the routes are not known beforehand; that is, demands depend on the number of bins, which are decision variables themselves. Thus, it causes non-linearity in our model.

Because of complexity, LRP are difficult to solve in a reasonable time. LRP belongs to the class of NP-hard problems [4]. Exact algorithms are very restricted based on the problem size for LRPs. Because of the exponential growth in the problem size, exact approaches for the LRP have been limited to small and medium size. Due to the this reason, heuristics and metaheuristics are used to solve realistic sized LRP instances in recent studies. Solving the problems with metaheuristic approach also become more popular in various research areas. Many researchers concentrate on developing the heuristic algorithms for LRP such as Tabu Search (TS) [15], Simulated Annealing [32], Variable Neighbourhood Search (VNS), Ant Colony Optimization (ACO) [29] in the literature. SA is easy to implement and very flexible. It explores the large solution search space efficiently.

Several heuristic algorithms have been published for the LRP in the literature as shown in Table 1. Tuzun and Burke [11] use a two-phase approach to solve the LRP; they aim to integrate two levels of decision making (location and routing) in a computationally effcient manner. A TS is presented to determine the facilities to be used in the distribution in the location phase. For the given configuration, another TS is performed on routing part. A cooperative metaheuristic is proposed to solve the LRP with capacitated routes and depots [14]. The problem is decomposed into two stages. The location problem is solved in the first stage by aggregating the routes in the supercustomer. Lagrangean Relaxation method is performed on ssignment constraints to select the locations of the depots. A Granular Tabu Search algorithm is presented to improve the multi depot VRP solution obtained from the first stage. A Multiple Ant Colony Optimization algorithm is proposed to solve the LRP with capacitated depots and capacitated routes [29]. Capacitated location-routing problem is decomposed into facility location and multiple depot vehicle routing problem. A Bilevel Genetic Algorithm is proposed for a real life location routing problem [34]. A capacitated facility location problem is solved to build an initial population of solutions in the first stage of the algorithm. The followers problem requires the solution of a vehicle routing problem for each individual of the population. Wu et al. [9] propose an extended and more practical version of the LRPs by considering multiple fleet types, depots and the limited number of vehicles. They solve the problem in a sequential and iterative manner by using the simulated annealing algorithm. Metaheuristic approach is based on threshold on accepting and SA is developed to assist in making facility location, vehicle routing and loading decisions [33]. Vincent et al. [32] propose a SA heuristic to solve the LRP. They develop a SA heuristic with a special solution encoding scheme that combines the location-routing decisions to extend the search space. In this way, better solutions can be found.

Most recently, there are many studies in the literature which propose different hybrid heuristic approaches. The reason to select a hybridization of any heuristic methods is to simultaneously have the two powerful features of those heuristic algorithms. For example, Ahmadi Javid et al. [15] propose a hybrid heuristic combining TS and SA. Liu et al. [16] present a hybrid heuristic combining TS and SA by sharing the same tabu list which is used to develop the initial solution for each sub-problem separately and alternatively. Bouhafs et al. [17] propose a hybrid heuristic combining ACO & SA for a capaciated LRP. Marinakis et al. [30] propose a hybrid particle swarm optimization, combines a particle swarm optimization algorithm, the multiple phase neighborhood search-greedy randomized adaptive search procedure algorithm, the expanding neighborhood search strategy and a path relinking strategy.

Table 1: Metaheuristic applications for problems involving location and routing components

Author(s) (Years)	Problem	Solution Approach
Tuzun and Burke (1999)	LRP	Tabu Search
Wu,Low and Bai (2002)	LRP	Simulated Annealing
Lin, Chow, Chen (2002)	LRP & loading	Simulated Annealing
Liu and Lin (2005)	LRP and Inventory Problem	Hybrid heuristic combining Tabu Search & Simulated Annealing
Sambola, Diaz and Fernandeza (2005)	LRP	Tabu Search
Lin and Kwok (2006)	LRP	Tabu Search & Simulated Annealing
Caballero, Gonzalez, Guerrero, Molina, and Paralera (2007)	LRP	Tabu Search
Marinakis and Marinaki (2008)	LRP	Hybrid heuristic combining of Particle swarm & parth relinking
Javid and Azad (2010)	LRP& Inventory Decision	Hybrid heuristic combining Tabu Search & Simulated Annealing
Yu, Lin, Lee and Ting (2010)	LRP	Simulated Annealing
Hemmelmayr, Doerner, Hartl, and Vigo (2013)	Bin Allocation & VRP	VNS
Ting and Chen (2013)	LRP	Ant Colony Optimization

CHAPTER IV

SOLUTION APPROACH

In this section, we explain the SA algorithm developed for the LRPWOC. In subsection 4.1, we will explain main characteristics of a SA algorithm. In subsection 4.2, we will describe the SA heuristic proposed for the LRP-WOC.

4.1 Simulated Annealing

SA is a metaheuristic method for combinatorial optimization problems, which was introduced by Kirkpatrick et al. (1983). SA is a stochastic local search technique. SA algorithm starts with an initial solution, which is usually obtained by applying a constructive heuristic and conducts a search in the solution space by generating a candidate solution obtained from the neighbourhood of the current solution. At each iteration, if the candidate solution's objective function value is better than the current solution, then the current solution and the best solution are updated. If the candidate solution's objective function value is not better than the current solution, the current solution is replaced with the candidate solution with an acceptance probability. The probability of accepting a nonimproving solution is given by probability $p = e^{-\delta/T}$, where δ= $f(s)$-$f(s_0)$ and $f(s)$ is objective function value of the candidate solution, s; f(s_0) is the objective function value of current solution. T is the current temperature. Allowing nonimproving solutions with a probability helps the Simulated Annealing algorithm to avoid getting stuck at a local optima. The steps of the general Simulated Annealing algorithm we use are as follows [15] :

Step 1 : Initialization: setting cooling rule, initial temperature and stopping criterion.

Step 2 : Generate an initial feasible solution, and set the candidate solution and the best solution.

Step 3 : Generate a new candidate solution.

Step 4 : Compare the current solution with the candidate solution. If the candidate solution is better than the current solution, then update the current solution and the best solution. Otherwise, accept the candidate solution with probability of $p = e^{-\delta/T}$

Step 5 : Check the stopping criterion. If the stopping criterion is satisfied, the algorithm is stopped. Otherwise, update the parameters and continue to search with updated parameters and go to Step 3.

Step 6 : Return the best solution.

SA has a great promise to solve difficult combinatorial optimization problems such as the Location-Routing Problem [11]. It allows non-improving moves to avoid getting stuck at a local optimum. However, this metaheuristic does not keep previously visited solution in memory, so it may cause cycling, which is one of its drawbacks. Moreover, the quality of the solution may depend on the algorithm, but there is no certain criteria for setting the parameters of the SA algorithm.

Cooling schedule for SA consists of cooling rule, initial temperature, the number of feasible solutions and stopping criterion. There are many cooling rules which are used in the literature such as geometric, adaptive and linear. We explain the SA heuristic developed for the LRPWOC in the following subsection.

4.2 Simulated Annealing Algorithm for the LRPWOC

In this subsection, the SA algorithm developed for the LRPWOC will be explained. As shown in Figure 2, our SA algorithm consists of two stages : a constructive stage and an improvement stage. If the candidate solution evaluated is a better solution, then candidate solution is accepted. If not, it is only accepted with a probability that is determined by the quality of the candidate solution and the current temperature. Current and best solutions are updated once the candidate solution is accepted. The temperature is also updated regarding to the cooling rule. If stopping criterion is satisfied, then algorithm is stopped; otherwise, a new iteration proceeds. We initialize the parameters of the algorithm as follows. First, we set the initial temperature, T_0, which is determined by calculating the acceptance probability of the nonimproving solutions of the algorithm. We calculate the average increase (δ) in the objective over a predetermined number of iterations. An initial temperature is calculated by using $p_0 = e^{-\delta/T_0}$, where p_0 shows the acceptence probability. There are various cooling schedules applied in Simulated Annealing algorithm in the literature such as adaptive, geometric and linear. We apply linear cooling rule in this study. Epoch length is the number of iterations at each temperature. Our SA algorithm runs one iteration at each temperature. We set the stopping criterion based on temperature which is zero.

The proposed Simulated Annealing algorithm is coded by using Java programming language.

4.2.1 Generating an Initial Solution

The problem is decomposed into three sub-problems : (1) location problem, (2) assignment problem, and (3) vehicle routing problem. These sub problems are solved by greedy heuristic algorithms in a sequential manner. Firstly, we generate a feasible location solution and then given the location solution, we generate the assignment solution. Finally, we determine a routing plan using the solutions obtained from the location-allocation stages. In Figure 2, the flowchart of the initial feasible solution is presented. Next, we explain the details of the greedy heuristic methods used to generate initial location, assignment and routing solutions.

a. Generate a feasible location solution

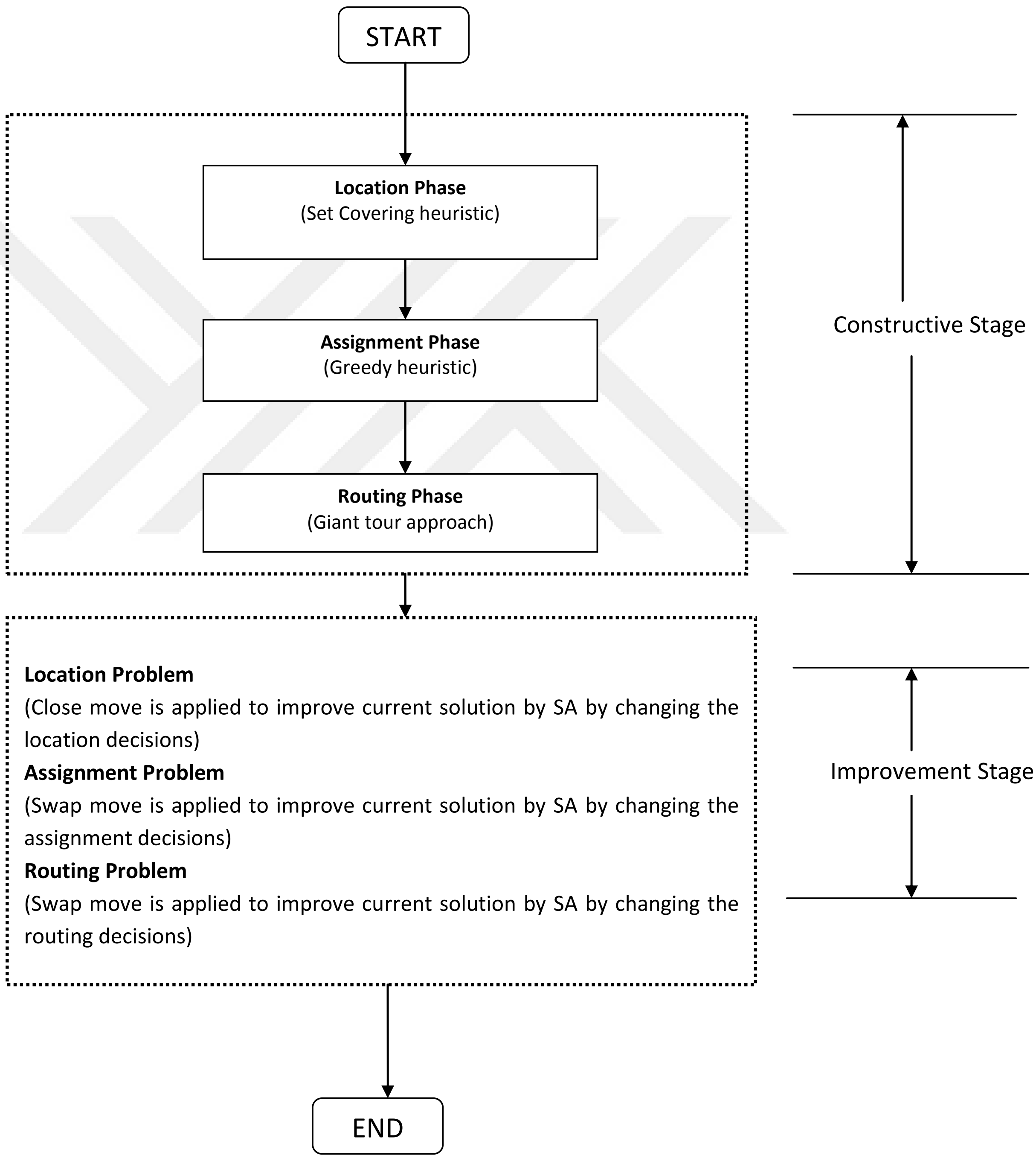


Figure 2: Flow chart of proposed heuristic method for LRPWOC

$$
\begin{array}{cc}
 & \text{Number of Community Centers} \\
\text{Number of Source Points} & \begin{bmatrix}
1 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 & 0 \\
1 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 \\
1 & 1 & 1 & 1 & 0 \\
1 & 0 & 0 & 1 & 0 \\
0 & 1 & 1 & 0 & 1
\end{bmatrix} \\
 & \begin{matrix} 6 & 4 & 5 & 3 & 3 \end{matrix} \Rightarrow \text{The number of source points covered by each community center} \\
\text{Capacity of each community center} \Leftarrow & \begin{matrix} 4 & 3 & 5 & 1 & 4 \end{matrix}
\end{array}
$$

Figure 3: An example coverage matrix

We consider the location problem as a set covering problem. A greedy location heuristic approach is developed and applied to set covering problem to find initial feasible CCs, which cover all source points (while respecting the capacity of the CCs). Firstly, the heuristic approach selects three CCs which cover the most source points. Then, it selects a CC which has the highest capacity among those three CCs as shown in Figure 3. The heuristic inserts the new CC in the location plan which cover the most source points. The process continues until all source points are covered once.

b. Generate a feasible assignment solution

In this stage, the initial location solution obtained in the first stage is used as an input to assign source points to CCs. When a CC is opened in the previous stage, the demand of source points which are covered by open CCs are sorted by descending order. Then, each source point starting from the highest demand is assigned to an open CC while respecting capacity and coverage distance restrictions. Each source point is assigned to exactly one open CC. The process continues until all source points are assigned once.

c. Generate a feasible routing solution

In the stage, we generate the feasible routes using the inputs obtained from the

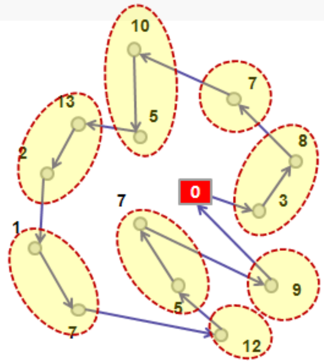


Figure 4: An example giant tour

location-allocation phases. The Giant tour approach is applied as shown in Figure 4. This heuristic approach starts to build a route by choosing the closest node to the depot. Next, the heuristic algorithm adds a node based on the closeness to the last inserted node into the route. The algorithm stops when all nodes are assigned to the route once. The route obtained using the giant tour approach is divided into different routes with respect to vehicle capacity feasibility and vehicle time feasibility. Each vehicle has only one route in a day. If the capacity of vehicle or total duration of the vehicle is not enough to serve a CC, then we create a new route with a new vehicle. Each route starts from the depot and returns to the depot at the end of the day.

4.2.2 Improvement Stage

The current solution is improved by applying different moves in the location, assignment and routing phases. The procedures applied to generate a new solution in the neighbourhood of the current solution are explained next.

a. Location phase

In this phase, the main target is to improve the current solution by modifying the number and location of CCs. As shown in Figure 5, for a given solution, this move is used to close randomly one of the opened CCs. All its source points are reassigned to the remaining opened CCs by selecting the closest one. Then, we remove closed CC from the existing route. If the remaining capacities of opened CCs are not enough

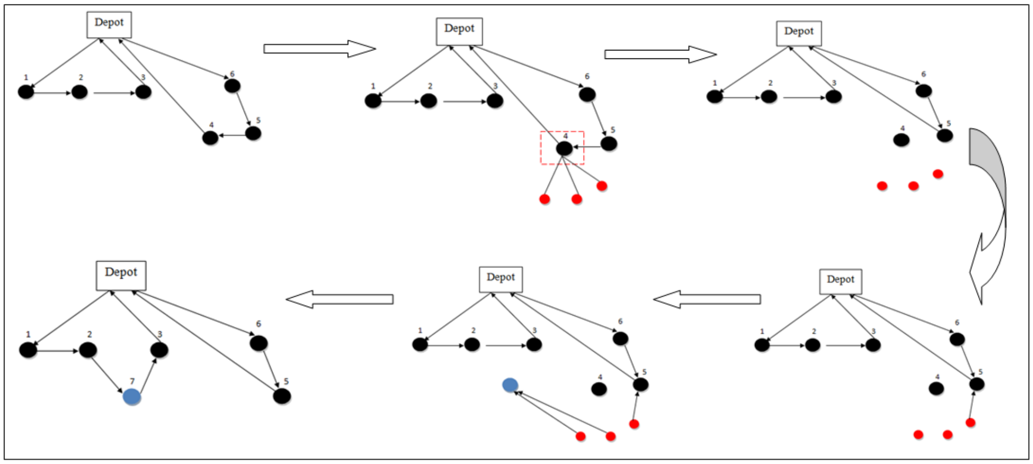
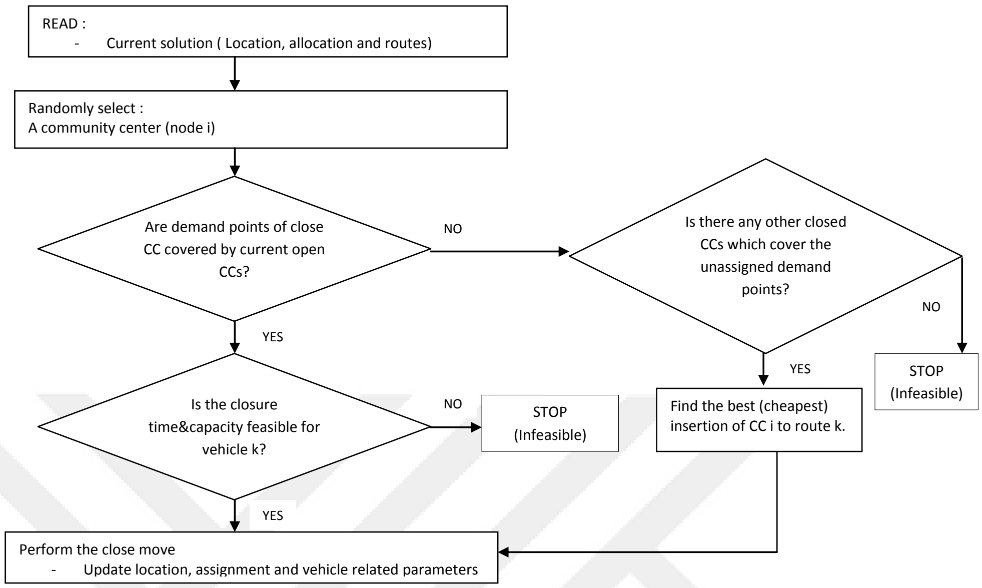


Figure 5: Illustration of a location move

to serve the source points of the closed CCs regarding to time limit for the routes, then we open new closed CCs which cover the remaining unassigned source points. Finally, we rebuild the routes by applying the cheapest insertion heuristic algorithm. The cheapest insertion heuristic selects a place to insert a node into a route in order to minimize the total cost of the routes. This move affects the costs related to the location of CCs, bins at CCs and routes. The process of the location move is shown in Figure 6.

Figure 6: Flowchart a location move



b. Assignment phase

In this phase, we first randomly select two CCs. After selecting two CCs, we randomly choose two demand points assigned to CCs as shown in Figure 7. Swap move generates a solution by exchanging the demand points of selected CCs. This move only changes the number bins at the affected CCs. The number of CCs and the sequence of routes are not affected by the move. If the solution obtained by applying swap move is feasible with respect to the capacity of the CC(s), capacity of vehicle and vehicle time, we perform the move and update the number of bins at the CC. Figure 8 shows the flowchart of the swap move.

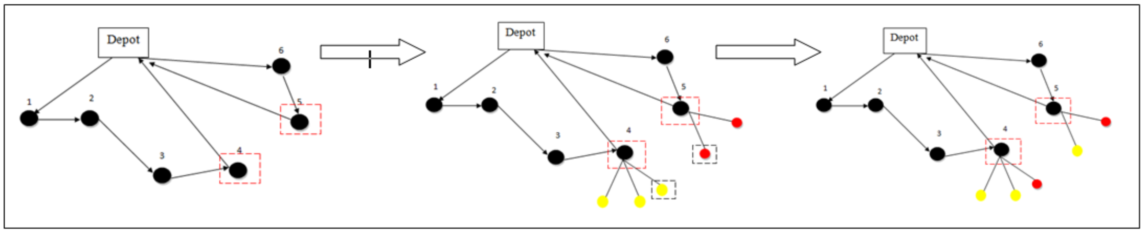
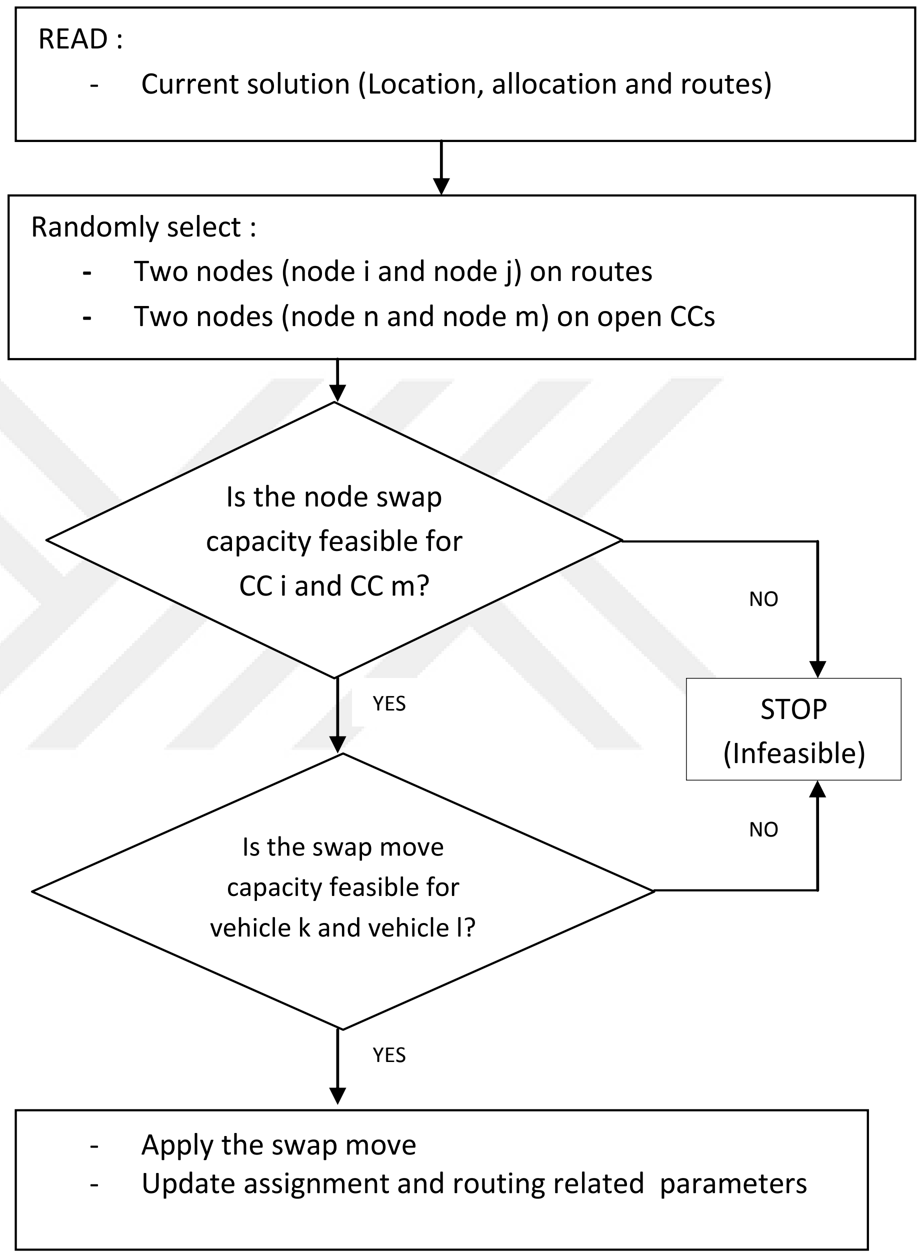


Figure 7: Illustration of an assignment move

c. Routing phase

In this phase, we first select randomly two community centers (node i and node j). Swap move generates a solution by exchanging the locations of selected CCs on routes as shown in Figure 9 and Figure 10. Swap move is performed if the resulting route(s) is (are) feasible for the affected vehicles with respect to the capacity of vehicles and duration of routes. Note that the nodes considered for exchanging can be on the same vehicle or different vehicles which needs to be considered in feasibility check. Since the move only changes the sequence of node visits on a route, the number of open CCs and bins are not affected by the move. This move only affects the transportation cost. The process of the swap move is shown in Figure 11.

Figure 8: Flowchart an assignment move



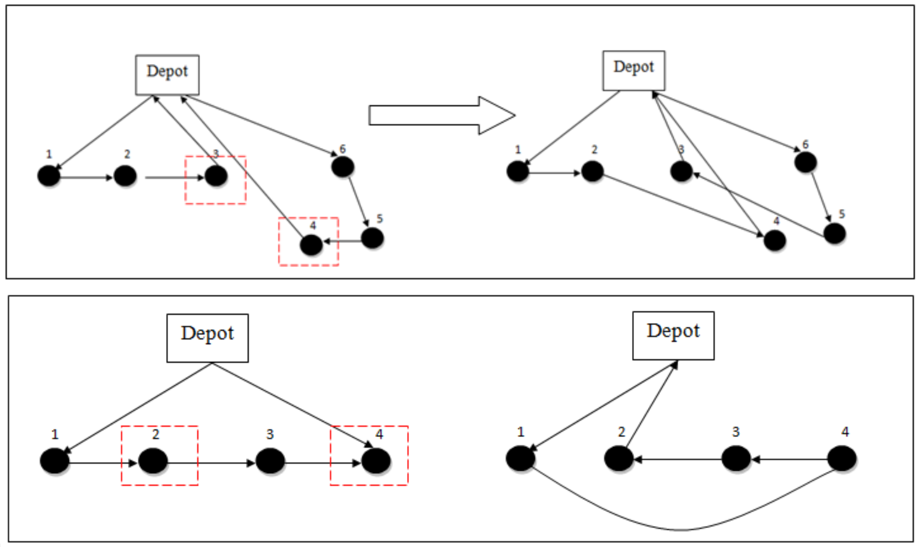


Figure 9: Illustration of two routing moves

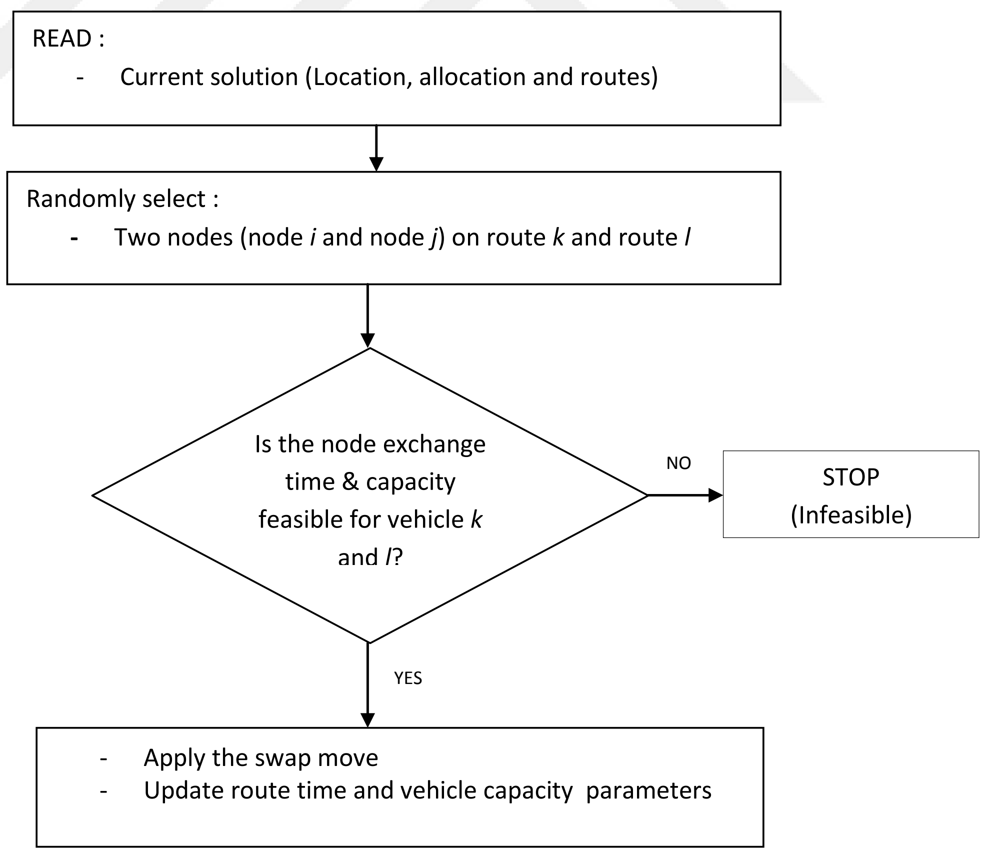


Figure 10: Flowchart of a routing Move

CHAPTER V

COMPUTATIONAL RESULTS

In this section, we present computational results performed to test the SA algorithm. First, we describe the problem instances used. Then, we present the solutions obtained by OPL/Cplex for each problem instance. Next, we explain the implementation details of the SA algorithm and present computational results. Finally, we present our observations related to the performance of the solution algorithm.

5.1 Numerical Analysis of the Simulated Annealing

In this section, we present numerical results performed to evaluate the performance of the SA heuristic. We describe test instances and present the solutions obtained by the exact approach, evaluate the solution quality of the SA and present our observations and insights about the solutions.

5.2 Hypothetical Problem Instances

We develop different number of source points and different number of CCs. We assume different number of vehicles for each problem instance. We assume that the available operating time for each vehicle is 8 hours per day. We generate demand locations and community centers' locations in each network randomly. We assume symmetric networks; that is, the transportation times and costs are assumed to be the same in each direction for each pair of nodes. For all of the instances, we assume that for a given network, vehicles have identical speeds (travel times) and costs. Vehicle capacities are set proportionally to the total demand in each problem instance. Demand, vehicle capacity, number of bins parameters are provided for each problem

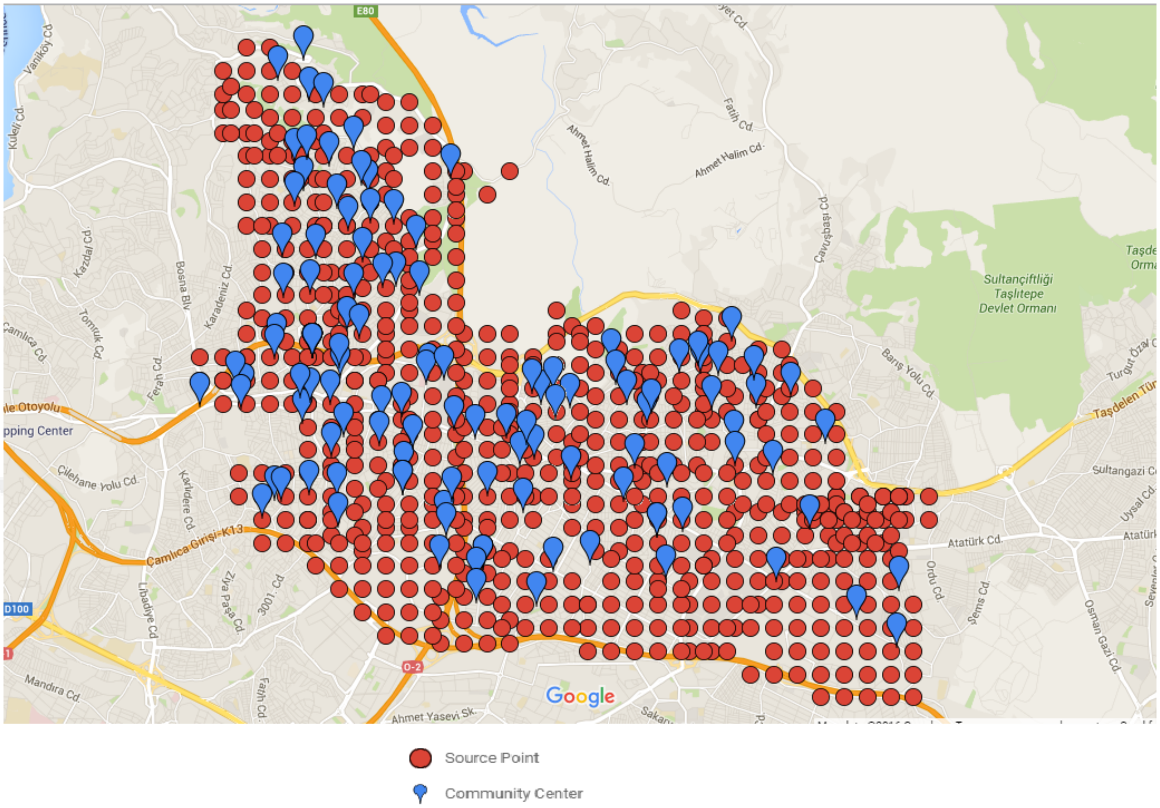


Figure 11: The locations of 668 source points and 123 CCs

instance in Table 2.

5.3 *Real-World Problem Instances*

In this study, we focus on a region to collect waste oil of individual customers of the company. This region, Umraniye, is located in the Asian part of Istanbul. These region has 36 neighbourhoods and population of the region is 645,237. It has 123 potential CCs. We assume that individuals come from the center of clusters to bring waste oil to the CCs. To define centers of clusters for individuals, the region is divided by 4,527 grids. The size of the each grid is 300 square meters. The center of each grid is defined as a source point. As mentioned in Section 1, 350 thousand tons of waste cooking oil should be collected but even 1% of the total amount cannot be collected in Turkey. We assume that 1% of total amount will be collected by our company.

Table 2: Problem parameters

No	# of Source Points	# of CCs	Demand at each node	# of Vehicles	CC Capacity	Vehicle Capacity
1	10	5	$\geq$30 & $\leq$50	3	2,2,2,2,2	4
2	10	5	$\geq$30 & $\leq$50	3	2,3,1,1,3	4
3	10	5	$\geq$30 & $\leq$50	3	5,5,5,5,5	6
4	10	5	$\geq$30 & $\leq$50	3	1,2,3,3,1	4
5	10	5	$\geq$10 & $\leq$50	3	2,2,2,2,2	3
6	10	5	$\geq$10 & $\leq$50	1	1,1,1,1,1	5
7	10	5	$\geq$10 & $\leq$50	3	1,1,1,1,1	2
8	10	5	$\geq$50 & $\leq$100	2	4,4,4,4,4	8
9	10	5	$\geq$50 & $\leq$100	2	2,3,4,3,4	9
10	10	5	$\geq$50 & $\leq$100	2	5,5,5,5,5	10
11	20	5	$\geq$100 & $\leq$1000	2	90,70,86,78,71	200
12	20	5	$\geq$100 & $\leq$1000	3	90,70,86,78,71	300
13	20	5	$\geq$10 & $\leq$100	3	5,5,5,5,5	10
14	20	5	$\geq$10 & $\leq$100	2	5,5,5,5,5	25
15	20	5	$\geq$10 & $\leq$100	3	5,4,5,6,4	14
16	30	5	$\geq$100 & $\leq$1000	5	100	200
17	30	8	$\geq$100 & $\leq$1000	5	100	200
18	30	10	$\geq$100 & $\leq$1000	5	100	200
19	50	10	$\geq$100 & $\leq$1000	5	$\geq$68 & $\leq$100	500
20	150	36	$\geq$10 & $\leq$100	10	50...50	100
21	250	36	$\geq$10 & $\leq$100	10	50...50	200
22	250	60	$\geq$10 & $\leq$100	10	50...50	100
23	668	36	$\geq$0.01 & $\leq$18	10	5...5	50
24	400	123	$\geq$0.01 & $\leq$18	10	5...5	50
25	500	123	$\geq$0.01 & $\leq$18	10	5...5	50
26	668	123	$\geq$0.01 & $\leq$18	10	5...5	50

First, we calculate the waste cooking oil produced by a person considering Turkey population and above assumption (1% of total amount / Turkey population). We are given the population of each grid by the company. The amount of waste cooking oil at each source point depends on the population in each grid and the amount of waste oil collected by one person. The multiplication of the amount of waste oil produced by one person and the population in the grid gives us the total amount of waste oil at each source point. The depot of company is located in Gebze. Gebze is almost 50 km east of Istanbul on the northern shore of the Marmara Sea. The distances between depot and community centers is calculated using the Euclidean distance formula. We calculated the transportation cost multiplied by the unit transportation cost (0.6 TL/km) with these distances. We assume that the coverage distance is one kilometer. Moreover, we assume that each CC has five bins capacity to place bins.

We assume that travel costs among nodes are proportional to travel distance. Weekly cost for openning a new CC is assumed as 100 TL and weekly cost for each bin is assumed as 20 TL. The capacity of each bin is 50 liters.

We test the proposed model with two different real-world problem instances. First problem instance considers all potential CCs, which are 123 and covers all demand points in 1 kilometer, and 668 source points. Second one is 36 CCs, which are selected by company by considering the their regular customers and cover all customers in 3 kilometers, and 668 source points.

5.4 Optimal Solutions by OPL/Cplex

In this section, we examine results obtained for each problem instance. We use OPL and ILOG Cplex solver to solve the MIP model. The proposed mathematical model is implemented in a computer with 2.40 GHz CPU and 3GB RAM. Some preliminary computations are performed to observe the results of Cplex and determine an appropriate run length for further computations. According to the results, 10 and 20 source nodes and 5 CCs instances could be solved optimally in a few minutes. Less than 50 source points could be solved with small optimality gaps using OPL/Cplex. Cplex solutions obtained for each problem instance are provided in Table 3.
We present solutions in terms of lower bound and best integer values obtained for each problem within 30 minutes as we have out-of-memory error when the problem size increases. We also report the resulting optimality gap. The optimality gap

Table 3: Solutions obtained by Cplex in 30 minutes

No	# of demand nodes	# of CCs	Cplex solution (30 min.)		
			Best solution	Lower bound	Optimality gap (%)
1	10	5	710.2	710.2	0.0%
2			587.2	587.2	0.0%
3			383.59	383.59	0.0%
4			589.3	589.3	0.0%
5			283.59	283.59	0.0%
6			619.2	619.2	0.0%
7			645.6	645.6	0.0%
8			731.5	731.5	0.0%
9			831.8	831.8	0.0%
10			629.1	629.1	0.0%
11	20	5	4,859.8	4,859.8	0.0%
12			4.852	4.852	0.0%
13			954.19	954.19	0.0%
14			933.8	933.8	0.0%
15			944	944	0.0%
16	30	5	7.207	7.190	0.24%
17		8	7.307	7.287	0.27%
18		10	7.204	7.167	0.52%
19	50	10	11.928	11.863	0.54%
20	150	36	4.492	3.556	20.83%
21	250	36	6.099	5.888	3.45%
22	250	60	6.833	5.888	13.83%
23	668	36	2.261	1.805	20.17%
24	400	123	out-of-memory		
25	500	123	out-of-memory		
26	668	123	out-of-memory		

percentage is defined as : [(Best solution - Lower Bound) / Best solution]*100. Cplex solution performance degrades quickly with increasing problem size. In other words, our preliminary computations show that Cplex is unlikely to guarantee an optimal solution for large problem instances within reasonable times.

We provide detailed solutions for problem instances in Tables 6. The table shows the open CCs, routes and number of bins at the CC. In the next subsection, we compare the quality solutions obtained by the optimal solution approach with the SA solutions.

5.5 Simulated Annealing Paramaters

In this subsection, we will describe the implementation of the SA in detail and evaluate the performance of the metaheuristic. The SA heuristic is coded using Java. Parameter selection is important as it affects the quality of the computational results. Preliminary computations are run on some problem instances to define the cooling

Table 4: Comparison of SA heuristic and Cplex

No	# of demand nodes	# of CCs	Simulated Annealing with linear cooling rule Min. % gap	Ave. % gap	Max. % gap
1	10	5	0.0%	0.0%	0.0%
2			0.0%	0.0%	0.0%
3			0.0%	0.0%	0.0%
4			0.0%	0.0%	0.0%
5			0.0%	0.0%	0.0%
6			0.0%	0.0%	0.0%
7			0.0%	0.0%	0.0%
8			0.0%	0.0%	0.0%
9			0.0%	0.0%	0.0%
10			0.0%	0.0%	0.0%
11	20	5	0.0%	0.0%	0.0%
12			0.0%	0.0%	0.0%
13			0.0%	0.0%	0.0%
14			0.0%	0.0%	0.0%
15			0.0%	0.0%	0.0%
16	30	5	-0.07%	0.04%	0.21%
17		8	-0.15%	-0.08%	0.12%
18		10	0.08%	0.12%	0.22%
19	50	10	-0.13%	-0.08%	0.05%
20	150	36	-14.14%	-14.14%	-14.14%
21	250	36	-0.39%	-0.39%	-0.39%
22	250	60	-6.51%	-6.22%	-5.66%
23	668	36	-12.9%	-12.9%	-12.9%

Table 5: Solutions obtained by SA

No	# of demand nodes	# of CCs	Simulated Annealing with linear cooling rule Minimum	Average	Maximum
24	400	123	1,616.47	1,647.52	1,760.32
25	500	123	2,148.634	2,149.6	2,156.926
26	686	123	2,223.78	2,223.78	2,223.78

schedule components. Initial temperature is set by considering the acceptance probability of non improving solutions. We calculate the average increase in the objective function by considering the objective function values of the accepted non improving solutions. An initial temperature is calculated by using $p_0 = e^{-}\delta/T_0$, where p_0 shows the acceptence probability, δ shows the average increase in the objective function and T_0 represents the initial temperature. Acceptance probability $p_0 = 0.9$ is used in determining the initial temperature, which is T_0 =130. The epoch length is set to one. Linear cooling rule is applied during our preliminary computations; the current temperature is decreased by one in each iteration. A local search procedure is performed close and swap moves sequentially to improve the best solution. We set the stopping criterion based on the temperature. The algorithm is terminated when the current temperature reach out to zero.

5.6 Simulated Annealing Results

In this section, we presents the results to evaluate the solution accuracy of the SA algorithm. Table 4 shows the percentage (%) gaps between the solutions found by Cplex in 30 minutes and those attained by the SA heuristic by applying linear cooling rule. Each value in the table is calculated as: 100 * (SA solution - Cplex solution) / Cplex solution). A negative percentage value in Table 4 shows that the solution found using SA was better than the solution found using Cplex. SA is run five times for each problem instance as SA is stochastic algorithm. Minimum, average and maximum absolute percentage (%) gaps attained over 5 SA runs are reported in the Table 4.

According to the the results on Table 3, the average percentage difference between Cplex solution and SA solutions range from -14.14% to 0.12%. The worst SA solution is within 0.22% of Cplex solutions. The running time of SA solutions range from one minute to one hour and 18 minutes.

In summary, the proposed SA heuristic performs better than Cplex solutions obtained in 30 minutes in general. The SA heuristic is likely to outperform the exact approach in terms of solution quality and solution times in realistic-size problem instances when there are many demand points and CCs.

Table 6: Solutions for the problem instances

# of Source points	# of CCs	Open CC	# of Vehicles	Bins at CC	Routes
10	5	0,1,2,3,4	3	2,2,2,2,2	0-4, 2-3, 1
10	5	0,1,3,4	3	2,3,0,1,3	3-4, 0, 1
10	5	1,3	3	0,4,0,5,0	1, 3
10	5	0,1,2,3	3	1,2,3,3,0	0-2, 1, 3
10	5	1,3	3	0,2,0,2,0	1, 3
10	5	0,1,2,3,4	1	1,1,1,1,1	0-1-2-3-4
10	5	0,1,2,3,4	3	1,1,1,1,1	3-2, 0-4, 1
10	5	0,1,3,4	2	4,4,0,4,3	4-0, 1-3
10	5	0,1,2,3,4	2	2,2,4,3,4	1-2-3, 4-0
10	5	0,1,3	2	5,5,0,5,0	3-0, 1
20	5	0,3,4	2	86,0,0,75,66	0-3, 4
20	5	0,3,4	3	86,0,0,75,66	4-0-3
20	5	0,1,2,3,4	3	5,4,2,5,5	0-1, 3-2, 4
20	5	0,1,2,3,4	2	4,4,3,5,5	3-1-0-2-4
20	5	0,1,2,3,4	3	4,4,5,5,3	0-2-4, 1-3
30	5	0,1,2,3	2	92,98,89,60	2-1, 3-0
30	8	0,1,2,3,4	2	42,70,79,51,97	0-3-4, 2-1
30	10	0,1,4,5	2	93,80,96,70	0-1, 4-5
50	10	0,2,3,4,6,8,9	2	88,84,78,64,52,98,98	3-2-6-9-4, 8-0
150	36	0,2,10,15,18	2	3,50,50,11,49	10-0-15, 2-18
250	36	0,2,12, 14,18,34	2	50,50,50 50,50,19	14-34-12-0, 2-18
250	60	0,4,14 16,18,20 35,33,40	4	30,50,49 50,28,50 7, 6,50	16-25-20-33 18,14-4 40
668	36	5,6,7 8,10,12,14 18,23,29	1	3,5,5 5,3,5,5 5,5,5	14-12-10-8-23 29-6-7 18-5
400	123	1,10,30,43 49,51,53,65 85,92,104	1	1,1,1,1 1,1,2,1 1,1,1,2	85-49-1-43 30-51-65-10 104 92-53
500	123	14,83,4,32 77,2,99,82 16,35,51,40 10,12,30,53,92	1	1,1,1,2 1,1,2,1 1,1,1,2 2,1,1,2,1	14-83-4-32 77-2-99-82 16-35-51-40 10-12-30-53-92
668	123	99,1,30,41 121,112,82 83,40,14,10 12,18,51 53,103,92	1	1,1,1,1 1,1,1 1,1,1,1 1,1,1 1,1,1	99-1-30-41 121-112-82 83-40-14-10 12-18-51 53-103-92

CHAPTER VI

CONCLUSION

In this thesis, we focus on a location-routing problem for waste oil collection. We develop a mathematical model that determines the open CCs, the number of bins distributed to each CC and assignment of source points to the CCs, and the routes to be followed by each vehicle to collect oil while minimizing total costs including the fixed cost of open CCs, the cost of bin at each CC and the transportation cost. There are four decision elements (facility location, assignment, allocation and vehicle routing) where the decisions made for one element affect the other. We present a heuristic method which is decomposed into two phases: constructive phase where the inital solution is created by using some greedy heuristic approches, and improvement phase where the solution is developed iteratively in three stages: location stage, assignment stage and routing stage. Simulated Annealing is used to develeop the current solution in each stage in the improvement phase. The proposed methaheuristic method is applied to real instances obtained from a biodiesel company in Turkey. The algorithm is also tested on hypothetical problem instances. We compared the proposed method with exact method which is implemented in OPL/Cplex. The result of the experimental analysis revealed that the developed metaheuristic method works well and solves the problems to optimality with small size problem instances. In the case of large number of source points, it finds the local optimum with an acceptable gap compared to the exact methods.

As future agenda, more effective heuristic algorithms can be developed to solve this problem. A tabu list can be used in the Simulated Annealing to avoid cycling and stuck in the local optima. A number of extensions are possible to the proposed location routing problem for waste oil collection. We only focus on individual customers in this study. The scope of the this study can be extended by considering the regular customers of the company. The proposed algorithm includes multiple level of decision making. Future research would also focus on the performance of the algorithm which can be tested by using different cooling schedules as geometric and adaptive.

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EDUCATION

M.S., Industrial Engineering, May 2016

Ozyegin University, Istanbul, Turkey

Thesis Title: Location-Routing Problem for Waste Oil Collection

B.S., Industrial Engineering, June 2012

Kadir Has University, Istanbul, Turkey

B.S., Computer Engineering, June 2012

Kadir Has University, Istanbul, Turkey

CONFERENCE PRESENTATIONS

Fahriye Karabak, Burcu Balcik: A Location-Routing Problem for Waste Oil Collection, Presented in: 20th Conference of the International Federation of Operation Research Societies (IFORS), Barcelona, Spain, July 2014.

Funda Samanlioglu, Yaprak Kucuk, Kubra Gunes , Fahriye Karabak: Location-Routing Decisions in an Earthquake Relief Network, Presented in 2013 Industrial and Systems Engineering Research Conference.

WORK EXPERIENCES

UPS TURKEY Istanbul, Turkey (12/2014 -)

Position : Building and Facilities Specialist, Department of Industrial Engineering

- Conduct yearly buildings and facilities planning cycle: projects building and facility requirements for mid- and long-term. Check alternative project development
- Conduct economic modeling of buildings and facilities project. Prepare and present the business case for buildings and facilities projects to senior management

OZYEGIN UNIVERSITY- Istanbul, Turkey (09/2012-10/2014)

Position: Teaching Assistant, Department of Industrial Engineering

- Computational Methods for IE (twice), Project Management, Engineering Economics (twice), Statistics, Operation Research II
- Was responsible for preparing course materials, exams, assignments, and quizzes and managing course projects.
- Provide assistance with grading quizzes, exams and assignments in a timely manner.
- Assisted in delivering recitation sessions.

- Take a leading role to coordinate other teaching assistants.

TURKISH STANDARDS INSTITUTION- Gebze/Kocaeli, Turkey (07/2012 08/2012)

Position: Intern, Data Processing Unit

- Worked as an intern technical maintenance specialist as a member of a team
- Supported the team about hardware problems
- Supported design of the website by using software such as Microsoft Expression and Visual Studio 2010.

TURKISH AEROSPACE INDUSTRIES- Ankara, Turkey (08/2011 10/2011)

Position: Intern, Production Planning and Control Department

- Used ERP systems planning and scheduling modules.
- Was responsible to track the production processes
- Performed routine daily tasks including data entry to ERP system and distributing the daily production schedule to the employees.

NET CIVATA- Istanbul, Turkey (09/2010 10/2010)

Position: Intern, Production Planning Department

- Observed and analyzed work flow in production planning to improve production processes.
- Performed routine daily tasks and participated in the department meetings.

TUBITAK UEKAE Gebze/Kocaeli, Turkey (08/2010 09/2010)

Position: Intern, Speech and Natural Processing Tech. Lab.

- Collaborated with a team to develop a language translate software program.

- Attended in a seminar program to learn about different research areas in the department.