A LOCATION AND ROUTING-WITH-PROFIT PROBLEM IN GLASS RECYCLING

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ABSTRACT

A LOCATION AND ROUTING-WITH-PROFIT PROBLEM IN GLASS RECYCLING

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In this study, our aim is to determine the locations of bottle banks used in collecting recycled glass. The collection of recycled glass is done by a fleet of vehicles that visit some predetermined collection points, like restaurants and hospitals. The location of bottle banks depends on the closeness of the banks to the population zones where the recycled class is generated, and to the closeness of the banks to the predetermined collection points. A mathematical model, which combines the maximal covering problem in the presence of partial coverage and vehicle routing problem with profits, is presented. Heuristic procedures are proposed for the solution of the problem. Computational results based on generated test problems are provided. We also discuss a case study, where bottle banks are located in Yenimahalle, a district of Ankara.

Keywords: Location-routing, recycling, TSP with profits, maximal covering problem in the presence of partial coverage

ÖZ

CAM GERİ DÖNÜŞÜMÜNDE KAR AMAÇLI YERLEŞİM VE ROTALAMA PROBLEMİ

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Bu çalışmada amacımız geri dönüşebilen camların toplanmasında kullanılan kumbaraların konumlarına karar vermektir. Geri dönüşebilen camların toplanması restoran ve hastane gibi bazı daha önceden belirlenmiş toplama noktalarından özel araçlar aracılığı ile yapılmaktadır. Kumbaraların konumu, cam atıklarının oluştuğu yerleşim bölgelerine ve daha önceden belirlenmiş toplama noktalarına olan uzaklığına bağlıdır. Kısmi kapsama varlığında maksimum kapsama problemini ve kar amaçlı araç rotalama problemini birleştiren matematiksel bir model sunulmuştur. Problemin çözümü için sezgisel yöntemler önerilmiştir. Oluşturulan test problemlerine dayalı sayısal sonuçlar verilmiştir. Ayrıca, Ankara'nın ilçesi Yenimahalle'de kumbaraların konumlandırılması bir vaka problemi olarak çözülmüştür.

Anahtar Kelimeler: yerleşim-rotalama, geri dönüşüm, kar amaçlı GSP, Kısmi kapsama varlığında maksimum kapsama problemi

To my family, thank you for everything

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INTRODUCTION

1.1. Problem definition

Recycling is one of the vital issues concerning the future of the environment. Resources of the world are not unlimited but people do generally ignore this situation while spending generously. Technological improvements, globalized movements of the world, economical worries of the countries prevent the implementation of the studies of sustainable development. Sustainable development leads to improvement in technology and economical issues while preserving the environment. In sustainable development optimum usage of resources should be supported with reuse, recycling and treatment activities.

The recycling process starts with the owner of the waste material who should separate the useful fraction so that it can be collected separately from the rest of the solid waste. Many of the components of waste can be used as a recycling material, the most important materials being paper, steel, aluminum, plastic, glass, and yard waste. There are important obstacles in the recycling process such as low value of returned material, uncertainty of supply, legal restrictions, means of collecting waste, and uncertain markets (Vesilind, 2002). Legal restrictions should be arranged clearly and conveniently in order to overcome the difficulties on recycling process. The most important thing to be considered by lawmakers is to provide the environment for the education of the residents. People should be informed about the environmental sensitivity and encouraged to be a part of the environmental processes. Also, other conditions should be considered, like locations of the collection sites should be near enough to encourage people to leave their wastes.

Recycling helps the environment by reducing the energy needed to produce new resources is protected against air, land, and water pollution by recycling. For example, emissions of CO_2, the main gas associated with global warming, are reduced by involvement of the recycled materials into the production phase.

Recycling conserves the landscape and main resources of the world. Including the recycled materials to the production phase instead of just calling them "waste" saves thousands of tons of primary raw materials each year. This action also reduces the need of landfill extending the life of increasingly scarce landfill sites and conserves the environment. Therefore, recycling has multiplier effect for the countries' economy by cutting waste disposal costs including transportation, employment, and land filling operations.

products. For instance, for glass, the energy needed to melt recycled glass is 30% less than that needed to melt raw materials used to make new containers (Web1). Reducing energy consumption and controlling raw materials usage, environmental Recycling, repairing, refurbishing, remanufacturing are types of product recovery systems that have gained considerable importance as a sustainable development issue. Environmental and economical issues are the reasons for product recovery becoming popular among industrial facilities.

Reverse logistics involves the logistic activities of the recovery of products that are no longer required by the consumer to products used again in the markets after remanufacturing, repairing, refurbishing, and/or recycling. The most significant part of these reverse activities is the physical collection of the products recovered. There are several papers on the reverse logistics network design problem (Jayaraman et al., 2003; Fleishmann et al.,2000, Aras, 2008; Krikke et al., 1999). Also, there are case studies that address the recycling framework in reverse logistic network design problems.

Fleischmann et al. (2000) explained the general characteristics of reverse logistic networks by identifying their general properties, providing a comparison of such networks with other networks, and providing a classification for such networks. There are five specific stages that could be required in such networks: Collection, inspection/separation, re-processing, disposal, and re-distribution. Storage and transportation stages may appear between each of the above stages.

From a topological view, reverse logistics networks can be divided into three parts: disposer market, recovery facilities, and re-use market. These parts may include several source and demand points. Reverse logistics network is the distribution of the recovered products between these points as depicted in Figure 1 (Fleishmann, 2000). Figure 1 demonstrates the whole structure of the distribution system on both forward and reverse channels. This is a general structure of the distribution system and it can be modified according to the situations and cases. The box in Figure 1 represents the part that is going to be considered in this study.

Differences of the traditional production-distribution networks from the product recovery networks are:

- Supply part is highly uncertain in product recovery networks.
- Interaction between collection and re-distribution is more important in product recovery networks.

The structure of the disposer and re-use markets is significant to define the model as a closed or open loop. Closed loop systems are such systems where the disposer and re-use markets coincide. and In open loop systems, the markets are different. Thus, remanufacturing in product recovery systems is a closed loop system where all activities are carried out by original producers. However, recycling is an example for open loop systems since this operation is generally implemented by the third parties (Langevin, 2005).

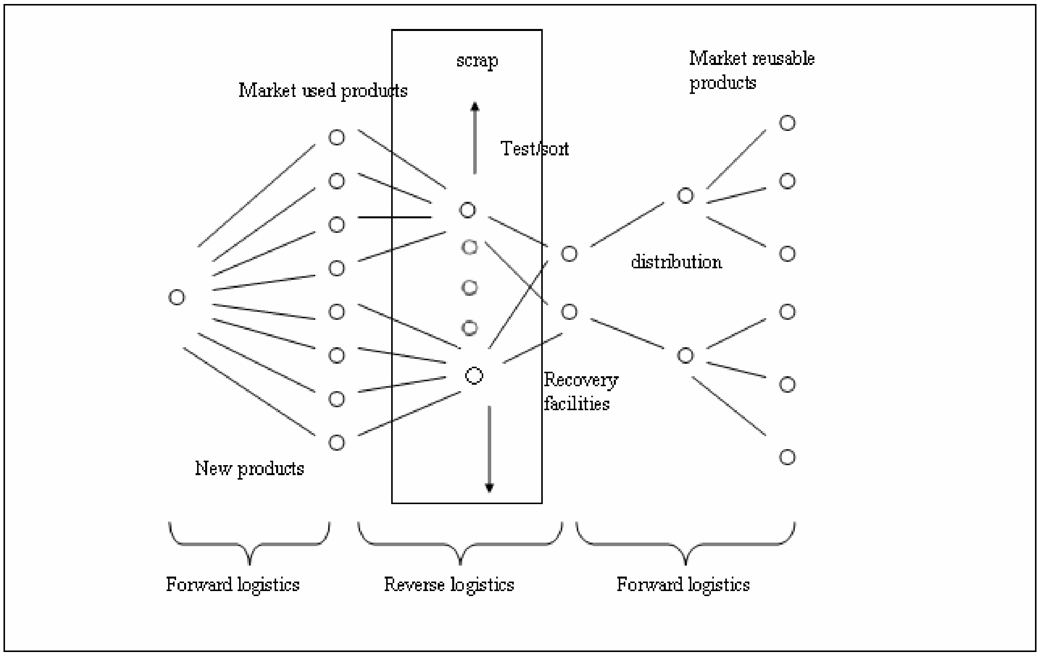

Figure 1. Reverse logistics network structure

The reverse logistics networks are classified according to the degree of centralization, number of levels, links with other networks, and open vs. closed loop structure. It is stated that there are three reverse logistics network types which are; bulk recycling network, assembly product remanufacturing network, and re-usable item network.

Distribution term in traditional logistics system is converted into the term “collection” in reverse distribution channels. Collection systems are highly significant at recycling operations. There are two common collection methods implemented by the collection companies: combined and multi-material (BIO, 2005). Combined refers to collecting all the recyclable materials together and as the name refers multi-material collection is to collect separately in terms of their material types. There are various studies conducted by environmental agencies EPA (Web 2), comparing the two systems according to their efficiency, total cost, and environmental impact. It is observed that efficiencies of the combined and multi-material collection systems are the same according to the quality of the material. When gross costs were evaluated in terms of investment costs, operation and variable costs, sorting and transportation costs; total cost is lower in the multi-material collection system. At last, comparing the adverse environmental impact, the combined system has worse performance than the multi-material system. As a conclusion, for the set of hypotheses considered, the multi-material collection system presents better environmental and cost-efficiency performance than the combined system (BIO, 2005).

There are three types of recycling pick up systems. Drop-off centers are sites set up for the consumers to leave materials for recycling. They serve as convenient central pick-up locations for processors or recyclers. Another system is buy-back centers, which pay consumers for recyclable materials. Many people recycle aluminum cans, plastic and glass pop bottles at buy-back centers. Also there are waste companies, which buy recyclables from offices, businesses, institutions, schools, and industries. These companies may be subcontracted by the local government to provide curbside collection to private homes.

1.2.Objectives of the thesis

The objective of this study is to design an efficient collection system for a recyclable material, glass. The reason of selecting glass is related with the properties of glass. Glass is 100% recyclable, without any loss in quality, no matter how many times it is recycled. After re-melting and forming, containers are as pure and clean as those made from raw materials (Web 1). Also, the optimum recycling rate of the glass is satisfactory enough with the rate between 40 % and 72 %. (BIO, 2005). Also glass can be collected easily with the use of bottle banks, which is a type of a drop-off center, (minimum density: 1 bottle bank per 1000

inhabitants) (Web 3). However, without loss of generality, the designed system could be applied for collecting other recyclable materials, like plastics, metal, etc.
The designed system would be applied, as a case study, to recycling of glass in Yenimahalle, which is a district of Ankara. Thus we first examined the recycling of glass in Turkey and in Ankara. Up-to-date information about recycling processes in Turkey is obtained from the Ministry of Environment and Forestry. Since 1992, the Ministry of Environment and Forestry encourages people to return recyclable materials and support this action with related laws and regulations. According to studies done to set these regulations, registered recyclable materials produced from 1992 to 2004 in Turkey are 3.615.794 tons and the amount of collected recyclable material totals 1.220.228 tons. The recycling collection system in Turkey is a combined system due to its easiness. (Web 4)

The ministry has observed that the most efficient way of collecting glass in Turkey is by bottle banks. It should be remembered that the ideal collection system is the multi-material collection system; however applying this system in the near future is not possible in Turkey. The first step of the transition is to educate the residents. This education process needs extensive effort. As changing the collection system in the near future is not possible, improving the current system seems to be more efficient and suitable.

Thus, glass recycling is performed via the bottle banks provided by ÇEVKO, which is a non-governmental organization established to arrange recycling activities. ÇEVKO has worked with the Ministry of Environment and Forestry and located the bottle banks considering the properties of the areas in terms of population and closeness to the industry. Recently ÇEVKO handed over the possession of the bottle banks to a collecting company in Ankara. The glass collected with the given number of bottle banks, cannot provide satisfactory revenues for the collecting company to compensate for their expenses. For this reason, the Ministry of Environment and Forestry decided to support the collection companies in Turkey by giving an additional incentive per ton of recyclable materials. The company wants to determine new locations for the bottle banks, considering the changes in the population of the residential areas. The company also has some customers, with whom it has made contracts to collect glass on a regular basis. We will refer to these customers as contracted (collection) points in the thesis.

Such a definition of the problem is similar to the problems defined in the reverse logistic network design literature. Most literature on reverse logistics define the problem as a multi-echelon capacitated facility location problem as in papers of Barros et al. (1998), Ammons et al. (1996), Jayaraman et al. (2003) and Min et al. (2006). In our study, we consider a single-echelon facility location problem that determines the location of bottle banks, which will be used by the residents living in different population zones (Figure 2).

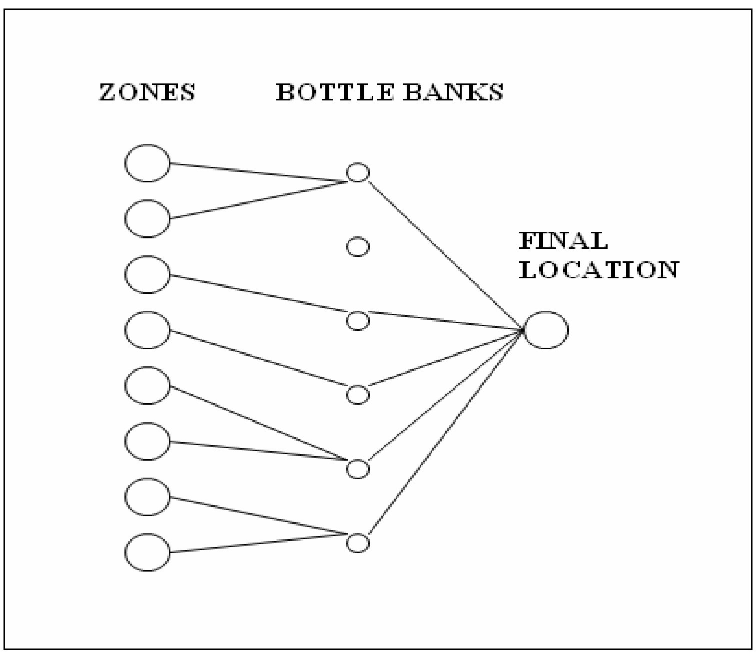

Figure 2. Bottle bank location network structure

The amount of waste generated in a population zone can be forecasted considering the relevant parameters like the population in the zone, and the characteristics of the residents living in the zone. Then the problem reduces to determining the location of the bottle banks and the assignment of zones to the bottle banks.

Moreover, instead of defining the problem as a single-echelon bottle bank location problem, we looked from a different view considering the company in question. As the revenue from the recycled glass is not high, locating a bottle bank to a site does not have a fixed cost, and there are some contracted collection points who should be visited on a regular basis, we considered the problem as a type of location-routing problem. In this problem, the determination of locations of the bottle banks will be done while considering the routing of vehicles that serve the contracted collection points.

We assume that the company has a fixed number, P, of bottle banks, and there are a number of potential sites to locate these P banks. There are two main factors that affect the desirability of locating a bottle bank in a given potential site: closeness of the site to the routes that serve the contracted points and the amount of waste that can be collected in a potential site. It is required that the vehicles will be routed to serve all of the contracted customers and the sites where the bottle banks are located. Since not all potential points are to be served by a vehicle, this problem can be seen as a modified vehicle routing problem with profits (VRP-P). Our formulation differs from (VRP-P) in the sense that all contracted customers must be included in the routes, whereas only P of the total potential sites will be included in the routes.

The recycled glass that can be collected by a bottle bank at a potential site, however, is related with the proximity of the bottle banks to the residences of the droppers. The people will return bottles to a bottle bank if it is convenient for them. Defined as such, the problem can be seen as maximal coverage location problem (MCLP) in the sense that a potential site will cover a population zone, if the proximity to the nearest bank is convenient. Moreover we can include partial coverage as well, and consider the problem as a MCLP in the presence of partial coverage (MCLP-P).

Considering the two aspects, the problem of determination of the location of bottle banks is done by a special type of the location-routing problem which is a combined vehicle routing problem with profits, VRP-P and MCLP in the presence of partial coverage, MCLP-P.

In the case study, data is provided via Geographical information systems (GIS) applications. GIS is used in this study as a tool to store, modify, and analyze the geographical data. GIS is extensively used in waste management studies throughout the world. Rapid improvements in the hardware and software for GIS have enhanced its potential to solve various types of engineering and management problems. Most of the developed countries are getting benefit from GIS tools for solid waste management.

1.3. Organization of the thesis

In Chapter 2 related literature review on reverse logistics, location-routing problems, vehicle routing problems, Travelling Salesman Problem (TSP) with profits and maximal covering location problems in the presence of partial coverage are given. Chapter 3 involves the definition and formulation of the problem. Developed solution procedures are explained in Chapter 4 and computational results of the solution procedures are given in Chapter 5. The case study is depicted in Chapter 6 and the last chapter is the conclusion chapter.

CHAPTER 2

LITERATURE REVIEW

This chapter is divided into seven sections. In each section, some of the research in the defined problems is highlighted. However, the discussion is restricted to the research on deterministic problems only. In the first section, research on reverse logistics network design in the most general sense is introduced. In the next two sections, research on location-routing problems in general, and in the context of waste management is discussed. In Section 4, research on vehicle routing problem, in Section 5 research on TSP with profits and in Section 6, research on MCP in the presence of partial coverage are discussed, and the formulations of these problems are provided. Section 7 pinpoints some of the research on GIS applications for logistic network design.

2.1. Reverse Logistics Network Design Problem

Fleischmann et al. (1997) reviewed the concept of quantitative models for reverse logistics and analyzed the related research under three main areas, distribution planning, inventory control, and production planning.

Fleischmann et al. (2001) surveyed research on reverse logistic network design, and developed some multi-echelon facility location models or modifications of these models in Fleishmann et al. (2002).

Min et al. (2006) considered the multi-echelon reverse logistics network design problem for product returns and formulated a single-objective, nonlinear, mixed-integer programming model that determines the optimal number and locations of collecting points as well as centralized return centers while considering the shipping costs, closeness of the collection points, and in-transit inventory. A genetic algorithm is developed to solve the problem.

Jayaraman et al. (2003) analyzed the situation of product recalls or returns as a reverse distribution activity that withdraws goods from customers. Customers will return the products to the collection centers, from where the products are sent to the refurbishing points. They developed the reverse distribution model as a two-echelon capacitated facility location problem with minimum and maximum numbers of collection and refurbishing facilities. Some heuristic solution procedures are used to solve the model.

Krikke et al.(1998) present a business case study carried out at OceÂ, a copier manufacturer in The Netherlands. The study is about installing a remanufacturing process for copy machines including three stages as disassembly, preparation, and reassembly. They formulated a MILP-model for a multi-echelon reverse logistic network design for durable consumer products.

Spengler et al. (1997) developed a MILP-model for the recycling of industrial by-products in the German steel industry. Steel production releases a vast amount of residuals and this amount of waste should be recycled in order to avoid negative environmental impacts. Processing costs are significant so the companies should decide on the technologies used for recycling. Thus, it has to be determined which recycling processes or process chains have to be installed at which locations at what capacity level. The proposed model used for optimizing several scenarios, is a modified multi-echelon warehouse location model with piecewise linear cost functions.

Barros et al.(1998) reported a case study of designing a logistics network for recycling sand both obtained free from demolition waste and from reconstruction of old buildings in the Netherlands. Environmental legislations obligate the firms to give the waste for recycling purposes. They formulated the problem as two-echelon capacitated facility location problem that takes into consideration the transportation, processing and fixed costs. The solution of the problem was achieved via iterative rounding of LP-relaxations strengthened by valid inequalities (identifying lower and upper bound procedures).

Louwers et al. (1999) modelled the design of a recycling network for carpet waste which has high disposal volumes in Europe. Recycling carpet waste is required for both environmental issues and potential of valuable material resources. They modelled the carpet recycling problem as a continuous location-allocation model that determines the locations of regional pre-processing centers and allocation of customers to these centers while taking purchasing costs, transportation costs, storage costs, pre-processing costs, and waste disposal costs into consideration. They solved some real application cases using a heuristic approach that they have developed.

Realff et al. (2002) report on a case study on the design of a carpet recycling network in the USA. In the study uncertainty between selected scenarios were represented by formulating an MILP facility location model with several scenarios.

Different from the general applications of facility location problems, Aras and Aksen (2008) present a study of locating collection centers of a company to collect used products from customers, while taking into consideration incentive related returns. They formulated a mixed-integer nonlinear facility location-allocation model to maximize the profit from the returns. They state that, there are two motivations for product holders to return a product, the incentive offered to each quality of products, and closeness of the collection centers. The locations of the collection centers and optimal incentive values for each type of product are determined. A nested heuristic method is proposed to solve the problem.

Another collection network design under deposit-refund study is represented by Wojanowski et al. (2007). As the amount of returned products is insufficient, collection firms compensate for their expenses by deposit-refunds. The authors proposed a continuous framework to design a facility network. Deposit-refund is fixed in the model and the aim is to determine the sales price maximizing the companies' profit with fixed deposit.

2.2. Location-routing problems

In many distribution systems, the location of the distribution facilities and the routing of the vehicles from these facilities are interdependent. Although this interdependence has been recognized, attempts to integrate these two decisions have been limited. The location-routing problem (LRP), which combines the facility location and the vehicle routing decisions, is NP-hard. Due to the problem complexity, solution methods are limited to heuristics solution methods.

Nagy and Salhi (2007) analyzed the situation of dealing with location-routing problems simultaneously to have better results in a long planning horizon. The significant studies over this issue started with Salhi and Rand (1989) proposing a location, allocation and routing procedure that considers the stages simultaneously.

Nagy and Salhi (2007) have a detailed study on location-routing problems and developed a classification scheme including the structure, planning period, type of objective function, route structure, solution space, and the solution methods. Stochastic and dynamic solution methods are detailed extensively in the study.

There are several studies on heuristic solution methods for location-routing problems. Perl and Daskin (1985) proposed an IP model modification of the warehouse location-routing problem. The heuristic solution method of the model includes three stages; vehicle dispatch, location-allocation, and multiple dispatch routing allocation problems. The method is initially tested with small-sized problems and a large-scale case study is implemented.

“Hamiltonian p-median problem” is proposed by Branco and Coelho (1990) that uses the p-median and the travelling salesman problems. To apply this method, first clustering is implemented to partition data into p sets, and at each set a Hamiltonian tour is generated.

Min (1996) proposed a three phase clustering-based heuristic procedure to solve small scale problems. Phases start with capacitated clustering and continue by solving the p-median problem. At the last step the routing in each cluster are determined by the TSP solution method of Little et al. (1963).

Barreto et al.(2006) consider a discrete LRP with two levels: a set of potential capacitated distribution centres (DC) and a set of ordered customers with capacitated vehicles. Also, the problem deals with a homogeneous fleet of vehicles, carrying a single product. Several hierarchical and non-hierarchical clustering techniques with several proximity functions are integrated in a sequential heuristic algorithm to solve the model. Different clustering techniques, linkage methods are applied and compared in the study. Four phases are proposed for the model including, clustering, determining routes by TSP, improving routes, and assigning DC’s to routes.

Su (1998), Tüzün and Burke (1999), and Wu et al. (2002) proposed solution methods with meta-heuristic approaches such as genetic algorithm, tabu-search methods, and simulated annealing, respectively, to LRP.

2.3. Location-routing problems in solid waste management

Nagy and Salhi (2007) classify the solid waste management problems as transportation-location problems. Hazardous waste management problems are the most studied problems among solid waste problems.

Gottinger (1988) proposed a network flow model for regional solid waste management that minimizes a single objective function of the total costs of transportation, processing, and construction. Some models aim to maximize the average separation distance; some maximize the minimum separation distance, and others minimize the number of people within some critical distance or impact radius.

ReVelle et al.(1991) dealt with a problem to determine the location of disposal sites, allocation of types of wastes to particular disposal sites, and defining routes. As the problem is a hazardous waste management type problem, the objective is to decrease the transportation cost, while also decreasing the risk of hazardous wastes. The shortest paths for routing, a zero-one mathematical program for site selection, and the weighting method of multi objective programming is used to solve the problem.

Giannikos (1998) proposed a multi-objective model for locating disposal or treatment facilities and transporting hazardous waste. Population centers are considered in this study as hazardous waste generator points. A goal programming model to solve the problem is developed with four objectives. They are related to total operating cost, total perceived risk, distribution of risks among population centres, and the fair usage of disposal centres. There is a real life application where the model is implemented.

Ayanoğlu (2007) considered the location-routing problem for the solid waste management system. He formulated the problem as a location-routing problem with two facility layers, and solved the problem by applying an iterative clustering based heuristic.

2.4. Vehicle routing problems

Vehicle routing problem (VRP) is one of the most challenging combinatorial optimization problems for designing the optimal set of routes to serve a given set of customers with a fleet of vehicles. Also, “VRP in a broad sense is a generic name given to a whole class of problems in which a set of routes for a fleet of vehicles based at one or several depots must be determined for a number of geographically dispersed cities or customers" (Toth and Vigo, 2002).

Vehicle Routing Problem (VRP) represents a general term for an entire class of problems and it is defined on a graph $G = (V, A)$, where $V = \{v_0, v_1, \ldots, v_n\}$ is a set of vertices (or nodes) and the set of arcs is defined as $A = \{ (v_i, v_j) : i,j \in \{0, \ldots, n\}, v_i,v_j \in V\}$ between the vertices. A nonnegative cost, c_{ij}, is associated with each arc $(i,j) \in A$ and denotes the cost of traveling from vertex i to vertex j. There can be one or more vehicles starting from the depot (v_0), visiting all spatially distributed users ($v_1,\ldots, v_n$) and returning to the depot after having satisfied the demand of each customer (Toth and Vigo, 2002).

There are several different subclasses of the general VRP:

- Capacitated VRP (CVRP) is the simplest and most surveyed subclass of the VRP problems. The vehicles are identical and the vehicles load capacity defines the capacity restriction of the problem.
- The Distance-Constrained VRP (DCVRP) differs from the CVRP that each route has a limited length (or time) instead of considering capacity constraint.
- The VRP with Time Windows (VRPTW) represents that each customer i is served within the time interval $[a_i, b_i]$, called a *time window*.
- The VRP with Backhauls (VRPB) is the extension of the VRP in which the customer set $V\backslash\{ v_0\}$ is partitioned into two subsets where the first one contains customers serviced with a defined amount of products and the second subset includes customers where a given amount of inbound products must be picked up.

- The VRP with Pickup and Delivery (VRPPD) considers the type of problems in which the vehicles deliver or pickup the commodities at each customer (Toth and Vigo, 2002).

2.4.1. Capacitated vehicle routing problem and its mathematical formulation

When the capacity of a vehicle is considered in the vehicle routing problem, the problem is considered as a capacitated vehicle routing problem (CVRP). The integer formulation of the asymmetric CVRP (Toth and Vigo, 2001) is given below. The objective is to minimize the total cost while satisfying demands and considering the capacity limit of the vehicles.

The mathematical representation:

$$\text{(CVRP) Min z} = \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{m} c_{ij}x_{ijk} \qquad (2.4.1.1)$$

subject to;

$$\sum_{k=1}^{m} y_{0,k} = m \qquad (2.4.1.2)$$

$$\sum_{k=1}^{m} y_{ik} = 1 \qquad i = 1,.....n\,, \qquad (2.4.1.3)$$

$$\sum_{i=1}^{n} q_i y_{ik} \leq C \qquad k = 1,.....m\,, \qquad (2.4.1.4)$$

$$\sum_{j=1}^{n} x_{ijk} = \sum_{j=1}^{n} x_{jik} = y_{ik} \qquad i = 1,.....n\,, k = 1,.....m\,, \qquad (2.4.1.5)$$

$$\sum_{i\in S}\sum_{j\in S} x_{ijk} \leq |S| - 1 \qquad S \subset \{1,.....,n\}, |S| \geq 2, k = 1,....m, \qquad (2.4.1.6)$$

$$x_{ijk} \in \{0,1\} \qquad \forall i, j, k, i \neq j, \qquad (2.4.1.7)$$

$$y_{ik} \in \{0,1\} \qquad \forall i, k \qquad (2.4.1.8)$$

where the parameters defined in the formulation are: m representing the number of vehicles, C is the capacity of a vehicle, c_{ij} is the traveling cost from node i to node j, and q_i is the positive demand of customer i. Also, decision variables are x_{ijk}, which is 1 if vehicle k travels from node i to node j, and y_{ik}, which is the binary decision variable indicating the satisfaction of demand of node i by vehicle k.

Equation (2.4.1.2) is the objective function that minimizes the total cost or distance travelled. Constraint (2.4.1.3) sets the number of vehicles leaving the depot. Constraint (2.4.1.3) ensures that exactly one vehicle visits each customer. Constraint (2.4.1.4) is the capacity restriction for each vehicle. Constraints (2.4.1.5) and (2.4.1.6) are sub-tour elimination constraints. Constraints (2.4.1.7) and (2.4.1.8) are binary decision variables.

2.4.2. Heuristic solution procedures of VRP

The CVRP is one of the most widely studied versions of VRP problems since the early sixties and many new heuristic and exact approaches were developed in the last years. Laporte (1992) is a good reference for detailed information about exact algorithms of VRP. Heuristic methods can tackle with many practical applications where the number of customers can go above hundreds. (Toth and Vigo, 2002).

The heuristic approaches can be classified as, constructive heuristics, decomposition heuristics, improvement heuristics and meta-heuristics.

2.4.2.1 Constructive Heuristics

The Clarke and Wright savings algorithm (Clarke and Wright, 1964) is one of the most widely known heuristics for the VRP. The algorithm is:

1. Compute savings $s_{ij} = c_{i0} + c_{0j} - c_{ij}$ for $i, j \in \{1,......,n\}$
2. Sort savings in the non-increasing order.
3. Go through the saving list in the non-increasing order. If saving s_{ij} corresponds to a feasible merging, perform it by deleting arcs $(i,0)$ and $(0,j)$, and introducing arc (i,j).

Several enhancements of the savings algorithm were studied for years (Laporte et al., 2006). Also in his paper Laporte et al. (2006) improve the solution with 3-opt exchanges and obtain an average of 6.71% above the best known solution. Computation time is a drawback for the Clark and Wright algorithm as all the savings in the algorithm should be calculated and saved. Several studies and modifications were made in order to improve the algorithm. Desrochers and Verhoog (1989) and Altinkemer and Gavish (1991) modified the standard algorithm into matching based savings algorithms.

2.4.2.2 Decomposition Heuristics

Cluster-first, route-second algorithms first partition data into clusters and then determine a route in each cluster as the name implies. There are several types of cluster-first, route-second algorithms. In this study, most popular ones are explained in order to give brief information about the algorithms.

One of the cluster-first, route-second algorithm is the sweep algorithm, solving the problem in a planar surface. The algorithm is first proposed by Wren and Holliday (1972) and popularized by Gillet and Miller (1974). Cluster generation is done by rotating a ray centered at the depot. Then a vehicle route is obtained considering the capacity and route length constraint. Sweep algorithm is better than Clarke and Wright savings heuristics in terms of accuracy and speed, however it is inflexible and its planar structure limits its applicability (Cordeau et al, 2002).

The most common cluster-first route-second algorithm is Fisher and Jaikumar's algorithm that uses the generalized assignment problem (GAP) (Laporte et al., 2000). Solving GAP is NP-hard, hence it is usually solved by Lagrangian relaxation. According to Cordeau et al. (2002), the algorithm is not simple to program and its speed is determined by the choice of the seed and the implementation of the algorithm. Bramel and Simchi-Levi (1995) proposed a method in Fisher and Jaikumar algorithm which determines seeds by capacity location problem. Some of the algorithms are tested and compared by Cordeau et al. (2002).

Min (1996) considers a three-phase sequential heuristic solution procedure by grouping customers by a hierarchical method. The initial phase starts with aggregation of customers into capacitated clusters based on spatial proximity. Min et al. (1992) first use Ward's minimum variance method is used to generate clusters.

Srivastava (1993) determines the desired number of clusters by using minimum spanning trees. Then clusters are improved with respect to distance savings by exchanging customers from their initial clusters.

A recent study of Barreto et al. (2007) compares several clustering techniques to solve the CVRP. A sequential heuristic is applied, but different from Min (1996), routes are determined before locations of the terminals are defined.

Route-first and cluster-second type algorithms are the opposite of a cluster-first route-second algorithms. First a giant TSP tour is constructed disregarding side constraints and this route is separated into feasible vehicle routes. Beasley (1983) proposed that the second-phase of the problem is a standard shortest path on an acyclic graph.

Clustering analysis is used to aggregate the number of customers spatially to increase the efficiency. Then location of terminals is determined and resources are allocated to terminals. The last step is to generate routes. Thus, the complexity of the problems decreases and better solutions are obtained.

2.4.2.2.1 Clustering analysis

After detailing the studies of these methods, it is better to explain about the clustering. The classification of objects into different groups sharing the same characteristics is termed as clustering. Clustering is a common technique for data mining, image analysis, biology and machine learning. Techniques which search for separating data in to convenient groups or clusters are termed as clustering analysis (Everitt, 1974).
Ball (1971) listed seven possible uses of cluster analysis techniques:

- Finding a true typology,
- Model fitting,
- Prediction based on groups,
- Hypothesis testing,
- Data exploration,
- Hypothesis generating,
- Data reduction.

Cluster analysis techniques roughly classified into five types as follows (Everitt, 1974):

1. Hierarchical techniques: The classes themselves are classified into groups, the process being repeated iteratively resulting forming a tree structure.
2. Optimization-partitioning techniques: The classes are formed by optimizing using clustering criteria which form a partition of the set of entities.
3. Density or mode-seeking techniques: The clusters are formed considering the dense concentration of entities.
4. Clumping techniques: In this technique, overlapping of classes or clumps are allowed.
5. Other methods not falling into the other categories.

2.4.2.3 Improvement heuristics

Improvement heuristics is the next step after the construction stage that can be applied on each route or on several routes at a time. Lin (1965) generated a λ-opt exchange mechanism in which the procedure stops in $O(n^{\lambda})$ time when no further improvement is possible. Another exchange mechanism was proposed by Or (1976) that is implemented by exchanging 3, 2, or 1 consecutive vertices. 4-opt exchanges are further proposed by Renaud (1976) modifying the algorithm proposed by Or (1976).

2.4.2.4. Meta-heuristic methods applied to VRP problems

Meta-heuristics lead to a search of the solution space, allowing inferior and infeasible moves, to seek good solutions. This type of solutions approaches have been improved in the last fifteen years, bringing efficiency and simplicity to VRP. Tabu Search (TS) is the most commonly used meta-heuristic method applied to

VRP. Other search processes are simulated and deterministic annealing, genetic search, ant systems, and neural networks. Modifications and improvements are done on these algorithms to yield better solution methods. Many papers are presented including reviews and applications of various meta-heuristic methods applied to the VRP. Colorni, Maniezzo, and Dorigo (1991, 1996) studied on ant colony systems; Gendreau et al. (1997), Hertz et al.(1997), and Osman (1993) developed tabu search algorithms. Sources like Osman and Laporte (1996), and Osman and Kelly (1996) can be helpful for more detailed information about meta-heuristic methods applied to VRP.

2.5. Traveling Salesman Problems with Profits

TSP and VRP are the two most widely studied combinatorial optimization problems. There are numbers of extensions of TSP but the main constraint of the algorithm is to visit customers from a depot. Every customer has to be serviced but there is no value assigned to visiting a customer. However, in some problems customers are selected according to the profit gained by choosing them and generally when a single vehicle is involved, the problem is the TSP with profits, TSP-P. There are many applications of TSP-P. TSP-P has two opposite objectives, one is supporting to collect profits and the other is limiting the travel costs. Two of the objectives can be combined in the objective function or one of the objectives can be constrained with a specified bound value. TSP-P can be encountered in three types of problems depending on the objectives (Feillet, 2003):

Both objectives are addressed in the objective function; finding a circuit minimizing travel costs minus collected profit. This problem is defined as the profitable tour problem by Dell'Amico et al. (1995).

The travel cost objective is stated as a constraint while the profit objective remains in the objective function. This kind of problems is defined as the orienteering problem, (OP) (Chao et al., 1996).

The profit objective is stated as a constraint while the travel costs objective remains in the objective function. This kind of problem is prize-collecting TSP problems (Dell'Amico et al., 1998).

The structure of the problems is summarized by Feillet et al. (2005) as follows:

(TSP-P) Min $\sum_{v_i, v_j \in A} c_{ij} x_{ij} - \sum_{v_i \in V} p_i y_i$

Subject to;

$$\sum_{v_j \in V - \{v_i\}} x_{ij} = y_i \quad (v_i \in V), \tag{2.5.1}$$

$$\sum_{v_i \in V - \{vj\}} x_{ij} = y_j \quad (v_j \in V), \tag{2.5.2}$$

Sub-tour elimination constraints, (2.5.3)

$$y_1 = 1, \tag{2.5.4}$$

$$x_{ij} \in \{0,1\} \quad ((v_i, v_j) \in A), \tag{2.5.5}$$

$$y_i \in \{0,1\} \quad (v_i \in V), \tag{2.5.6}$$

There are two binary variables, one binary variable is x_{ij}, which is 1 if the arc is used in the solution, and the other binary variable is y_i for $v_i \in V$, and is equal to 1 if the corresponding vertex is visited. p_i is the parameter gained by visiting vertex *i*. TSP-P all share the same constraints from (2.5.1) to (2.5.6), where constraints (2.5.1) and (2.5.2) are assignment constraints, constraints (2.5.3) eliminate sub-tours. The whole formulation represents profitable tour problem. Other problem types have some modifications:

For the orienteering problem (OP); the formulation differs in the objective function and there is one more additional constraint to the given constraints (2.5.1) to (2.5.6).

$$\text{Maximize} \sum_{v_i \in V} p_i y_i$$

Subject to,

(2.5.1) to (2.5.6),

$\sum_{(v_i, v_j) \in A} c_{ij} x_{ij} \leq c_{\max}$ as a knapsack constraint. ($c_{\max}$ is the maximum limit defined for the total travel cost)

For the prize collecting TSP, the formulation is modified as in OP.

$$\text{Minimize} \quad \sum_{v_i, v_j \in A} c_{ij} x_{ij}$$

Subject to,

(2.5.1) to (2.5.6),

$\sum_{v_i \in V} p_i y_i \geq p_{\min}$ as a covering constraint. ($p_{\min}$ is the minimum limit defined for the total prize)

2.5.1. Exact Solution Approaches for TSP-P

The exact solution approaches for TSP-P are branch and bound solution procedures that are adjusted from TSP solutions. Procedure are related with relaxing the sub-tour elimination constraints and solve the remaining assignment problem efficiently (Gendreau et al., 2005). This approach was modified by

Fischetti and Toth (1988) who preferred to compute the bound with Lagrangian relaxation of the resource constraints. The assignment-related bound and solution procedure can be applied to both symmetric and asymmetric TSP, but it is not as efficient as the solution procedure relaxing constraints enforcing a single successor for each customer.

Lagrangian decomposition approach is proposed by Göthe-Lundgren et al. (1995) in which the resource constraints are duplicated and inserted within the sub-tour elimination constraints. Laporte and Martello (1990) proposed the knapsack bound for the orienteering problem. The other exact solution approach is the additive approach studied by Fischetti and Toth (1988), in which bounds are found sequentially and solution is improved iteratively.

2.5.2. Classical Heuristic Solution procedures for TSP-P

It is important to note that the visit of every customer is not compulsory in TSP-P as in classical TSPs. However, the best result of one objective can be the worst result of the other objective. Hence, the purpose of the heuristic solutions is to balance the two objectives in the objective function. There are four kinds of route improvements:

- Adding a vertex to the route
- Deleting a vertex from the route
- Resequencing the route
- Replacing a vertex of the route with a vertex outside the route.

Combinations of these operations are the sources of many heuristics. However, all these heuristics should be implemented carefully to avoid difficulties like cycling, and local optima (Gendreau et al., 2005).

Dell'Amico et al. (1998) developed two heuristics for the prize collecting TSP. First the procedure starts with Lagrangian relaxation of the knapsack constraint and the solution is improved by two iterative phases. The second heuristic is Lagrangian heuristic that is applies the extension and collapse procedures during the computation of the lower bound. Tsiligirides (1984) proposed a solution approach based on the sweep algorithm. In the study, two methods were used and compared: stochastic and deterministic. Chao et al. (1996) developed a partitioning based solution approach. The improvement is done among the several feasible routes to find the best route. Two local search procedures are applied; two-point exchange procedure and one-point movement procedure. The difference of this procedure is that it does not only deal with a single route but tries to get the best solution among the feasible routes.

The extensions of TS, deterministic annealing, genetic algorithm, and neural network approach as meta-heuristic procedures are used to solve and improve the solutions of TSP-P.

2.5.2.1. Orienteering problem

Chao et al. (1996) developed a heuristic for the orienteering problem that is able to produce near optimal solutions with short computational times. The heuristic consists of two basic steps: initialization and improvement. Initialization starts with constructing an ellipse including the starting and the ending cities as foci and time limit $T_{\max}$ as the maximum distance limit that is the length of the major axis. After generating several solutions with greedy method, improvement step enables the system to find a feasible path decreasing the total cost and increasing the total score. Improvement step consists of two-point exchange with record to record improvement, one point movement and 2-opt procedure. The heuristic ends with re-initialization and reaching the near optimum solution.

2.6. Maximal covering problems with the presence of partial coverage

The maximal covering location problem (MCLP) was firstly developed to determine the locations that maximize the total demand serviced by the facilities within a maximal service distance (Chung, 1986). Chung et al. (1986) present the maximal covering location problem adding a capacity constraint and define the modified algorithm as the capacitated maximal covering location problem (CMCLP). In maximal covering problems, a demand point within a critical distance of the located facility is covered, whereas it is not covered if it is not within the critical distance. Karasakal and Karasakal (2004) formulate MCLP with partial coverage, MCLP-P, where an intermediate coverage level is defined as partial coverage.

The formulation of the problem is as follows:

$$\text{(MCLP-P) Max } \sum_{i \in I} \sum_{j \in M_i} C_{ij} x_{ij} \qquad (2.6.1)$$

Subject to

$$\sum_{j \in J} y_j = P, \qquad (2.6.2)$$

$$x_{ij} \le y_j \qquad \forall i \in I, j \in M_i, \qquad (2.6.3)$$

$$\sum_{j \in M_i} x_{ij} \le 1 \qquad \forall i \in I, \qquad (2.6.4)$$

$$y_j \in \{0,1\} \qquad \forall j \in J, \qquad (2.6.5)$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in I, j \in M_i, \qquad (2.6.6)$$

where P is the number of facilities to be located, I is the index set of all demand points, J is the index set of all potential facility sites, M_i is the set of facility sites that can cover the demand point i partially or fully, S is the minimum critical distance, T is the maximum critical distance, D_{ij} is the distance between the facility site j and demand point i, C_{ij} is the level of coverage of demand point i by facility site j, y_j is the binary variable of facility sited and x_{ij} is the binary variable representing the demand points' coverage by facility sites either fully or partially.

C_{ij} is defined according to the distance limits S and T. C_{ij} becomes 1 if the demand point is in the limit of minimum critical distance and 0 if the point is outside the distance T. If the demand point is between the distance limits S and T, a partial coverage function is considered to determine the level of coverage. Different coverage functions can be as given in Figure 3 (Karasakal and Karasakal, 2004).

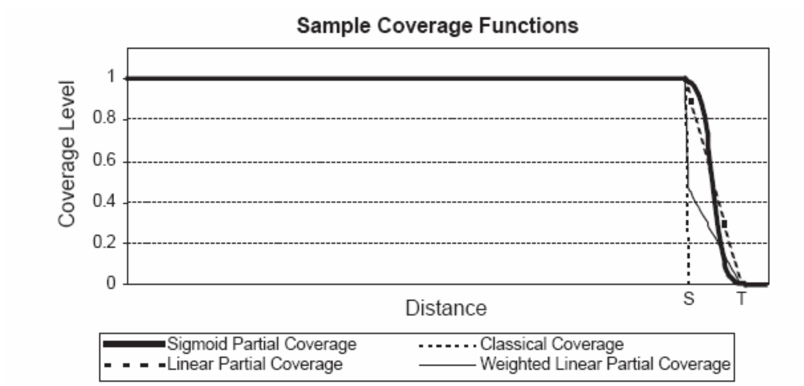

Figure 3. Sample coverage functions (Karasakal and Karasakal, 2004)

The objective function maximizes the coverage level of the demand points, first constraint limits the number of facilities to be sited to P. Constraint (2.6.3) ensures the allocation of x_{ij} to the facilities. The next constraint represents that a demand point is covered by at most one facility. Constraints (2.6.5) and (2.6.6) are the binary restrictions.

The solution procedure proposed in this paper is the Lagrangian relaxation where Constraints (2.6.4) are relaxed.

2.7. GIS applications for logistic network design

GIS is extensively used as a tool in logistic network design problems. Also, solid waste management problems are solved in GIS environment in order to get benefit from technology in environmental problems. There are several papers using GIS for vehicle routing and gathering data for the problem.

Repoussis et al. (2000) proposed a decision support system for the management of waste lube oils recycling. The system consists of three phases: reverse MRP phase that includes waste collection planning and determine collection points to be serviced by finding the quantity of the oil recycled. The second stage is vehicle routing stage that is achieved by GIS applications. The problem is defined as a heterogeneous fixed fleet vehicle routing problem. The service time of the vehicle is assumed to be dynamic according to the level of waste in the depots. The last stage is waste monitoring stage which provides real time information with the use of GPS. The location of the vehicles, the amount of waste collected and storage level can be detected with an online database.

Ni-Bin Chang (1997) made a study that develops a multi-objective, mixed-integer programming model for collection vehicle routing and scheduling for solid waste management systems within a GIS environment. Taiwan is used as a study area where the integration of the mathematical programming model and the GIS were applied. In the study GIS is used as a decision maker to analyze many waste collection alternatives before selecting a final operational scenario. Such a system also has potential application in many other environmental planning and management problems.

CHAPTER 3

DEFINITION AND MATHEMATICAL FORMULATION OF THE PROBLEM

3.1. Problem Definition

This study is a location-routing problem for locating *P* bottle banks in a recycling system. Returned glass is collected via bottle banks and the locations of the bottle banks are to be determined. The collecting company wants to increase its profit by collecting higher amounts of glass. There are two different types of collection points of returned glass. The first type is the contracted points where the amount of returnable material is high. These places can be suppliers like restaurants and hospitals where the amount of returnable glass per day is estimated based on the capacity and the serving area of the organization. The other type of collection point is the bottle bank. There are alternative sites at which the bottle banks can be located. These sites are determined based on the population zones. A population zone is a polygon area including the crowded and settled residential areas. The estimated amount of returned glass that can accumulate in a bottle bank is determined based on the population; socio-economic situation of the residents of the zones allocated to that bottle bank and is also varied as the distance between the zone centers and alternative site changes. The problem is to find the locations of the bottle banks, the allocation of population zones to the bottle banks and the routing of collecting vehicles so that the profit of the firm is maximized.

3.2. Mathematical formulation of the problem

Assumptions of the model:

- Travel cost per distance for all collection vehicles are the same.
- There is no fixed cost of locating a bottle bank.

- The bottle banks are assumed to be uncapacitated. This assumption is based on the observation that people leave the bottles near the bottle banks if they find the bank full.
- Collection vehicles are homogeneous and uncapacitated.
- People are assumed to be homogenous in terms of their willingness to return glass.

Under these assumptions, the mathematical formulation of the model is given below:

Parameters:

- Locations of contracted suppliers
- Alternative sites for bottle banks
- Centers of population zones.

Decisions:

- Locations for bottle banks
- Collection routes of collection vehicles

Definition of sets:

$N = \{1,\ldots\ldots\ldots,n,\ldots\ldots\ldots\ldots,|N|\}$ Set of population zones.

$G = \{1,\ldots\ldots\ldots,g,\ldots\ldots\ldots\ldots,|G|\}$ Set of alternative collection points.

L_n Set of alternative collection points that can either fully or partially cover zone n

$M = \{ |G|+1,\ldots\ldots\ldots\ldots,|G|+|M| \}$ Set of contracted collection points.

$K = \{\ 1,\ldots\ldots\ldots\ldots,k,\ldots\ldots\ldots\ldots,\ |K|\}$ Set of vehicles.

$H = \{G\}\mathrm{U}\{M\} = \{1,\ldots\ldots\ldots\ldots,i,j,\ldots\ldots\ldots\ldots,\ |G|+|M|\}$ Set of all collection points.

Definition of parameters:

c_{ij}: unit cost of distance traveled between nodes i and j ($\forall i, j \in H$).

d_{ij}: distance between node i and node j. ($\forall i, j \in H$).

q_{person}: daily amount (kg) of recyclable glass that a person can leave.

q_i : amount (kg) of recyclable glass to be picked up daily from contracted collection point i. ($\forall i \in M$)

h_n: number of people in the population zone n ($\forall n \in N$) .

R: revenue of 1 kg of glass recycled.

k_{ng}: coverage level defining the rate of returning glass in population zone n to an alternative site g, $0 \leq k_{ng} \leq 1$ ($\forall n \in N, \forall g \in G$) .

W_{ng}: coverage coefficient denoting the total revenue obtained when alternative site g provides coverage to population zone n.

$W_{ng} = k_{ng} h_n q_{person} R \qquad \forall n \in N, \forall g \in G)$

D: capacity of a vehicle (D being a large number since vehicles are assumed to be uncapacitated.)

P: number of bottle banks to be located.

t: maximum total distance of a tour of a vehicle.

The coverage level k_{ng} can be determined by using a coverage function as in Karasakal and Karasakal, (2004). Hence a population zone n is fully covered by alternative site g if the distance between them is less than S, and is partially covered by alternative site g if the distance between them is greater than S but less than T.

Coverage level provided by alternative site g to a population zone n, defined as the parameter k_{ng}, for $n \in N$, $g \in G$, is given by

$$k_{ng} = \begin{cases} 1 & \text{if } d_{ng} \leq \mathrm{S} \\ f(d_{ng}) & \text{if } \mathrm{S} < d_{ng} \leq \mathrm{T}, \\ 0 & \text{otherwise} \end{cases}$$

Variables:

$$X_{\mathrm{ijk}} = \begin{cases} 1 \text{ if vehicle } k \text{ goes from node } i \text{ to node } j\ (\forall i, j \in H),(\forall k \in K). \\ 0 \text{ otherwise} \end{cases}$$

$$Y_{\mathrm{g}} = \begin{cases} 1 \text{ if a bottle bank is located at alternative site } g\ (\forall g \in I). \\ 0 \text{ otherwise} \end{cases}$$

$$Z_{\mathrm{ng}} = \begin{cases} 1 \text{ if population zone n is fully or partially covered by bottle bank g} \\ \quad (\forall g \in L_n),(\forall n \in N). \\ 0 \text{ otherwise} \end{cases}$$

U_{i} = load of vehicle after visiting node i (for sub-tour elimination constraint) $(\forall i \in H)$.

Mathematical formulation of the model:

(VRP-P+MCLP-P)

$$\text{Min z} = \sum_{i \in H} \sum_{j \in H} \sum_{k \in K} c_{ij} d_{ij} X_{ijk} - \left(\sum_{n \in N} \sum_{g \in L_n} W_{ng} Z_{ng} \right)$$

subject to

$$\sum_{i\in H}\sum_{k\in K} X_{igk} \le 1 \qquad \forall g \in H \qquad (3.1)$$

$$\sum_{i\in H} X_{ijk} - \sum_{j\in H} X_{jik} = 0 \qquad \forall k \in K, \forall j \in H \qquad (3.2)$$

$$U_{\mathrm{i}}\text{-}U_{\mathrm{j}} + D\sum_{k\in K} X_{ijk} \le D - q_i \qquad \forall i \in M, \forall j \in H \quad i \ne j \qquad (3.3a)$$

$$U_{\mathrm{i}}\text{-}U_{\mathrm{j}} + D\sum_{k\in K} X_{ijk} \le D - \sum_{n\in N} W_{ni} Z_{ni} \qquad \forall i \in G, \forall j \in H \quad i \ne j \qquad (3.3b)$$

$$\sum_{i\in H}\sum_{k\in K} X_{gik} \ge Y_g \qquad \forall g \in G \qquad (3.4)$$

$$Z_{\mathrm{ng}} \le Y_{\mathrm{g}} \qquad \forall g \in Ln, n \in N \qquad (3.5)$$

$$\sum_{g\in Ln} Z_{ng} \le 1 \qquad \forall n \in N \qquad (3.6)$$

$$\sum_{g\in G} Y_g = P \qquad (3.7)$$

$$\sum_{i\in H}\sum_{j\in H} X_{ijk} d_{ij} \le t \qquad \forall k \in K \qquad (3.8)$$

$$X_{ijk} \in \{0,1\} \qquad \forall i, j \in H \ i \ne j, \forall k \in K \qquad (3.9)$$

$$Y_g \in \{0,1\} \qquad \forall g \in G \qquad (3.10)$$

$$Z_{ng} \in \{0,1\} \qquad \forall g \in L_n, \forall n \in N \qquad (3.11)$$

$$U_i \ge 0 \qquad \forall i \in H \qquad (3.12)$$

Explanation of the model

Objective function maximizes the profit, i.e. minimizes the traveling costs of collection vehicles minus the total revenue earned from the materials to be collected.

Constraints (3.1) ensure that each collection point is visited by at most one vehicle. Constraints (3.2) ensure route continuity. Constraints (3.3a) and (3.3b) eliminate sub tours. Constraints (3.4) ensure that if a bottle bank is located at alternative site g, then a vehicle should include it in its route. Constraints (3.5) ensure that population zones can be covered by a site if a bottle bank has been located at that site. Constraints (3.6) states that a population zone will be covered entirely or partially by at most one bottle bank. Constraints (3.7) ensure that bottle banks are located at P sites. Constraints (3.8) ensure that the vehicle collect returned materials in a specified time limit. Constraints (3.9)-(3.11) are the integrality constraints, and constraints (3.12) are the non-negativity constraints.

There may be some modifications of the assumptions of the model. For example, daily amount of returned material symbolized by q_{person} can be specific for each zone. Thus, the symbol becomes $q_{person,n}$ and the values can be determined based on the socio-economic situation of the population zone. The assumption behind this argument is that more educated people may be willing to participate in environmental issues more than those that have lower education level.

3.3. Definition of the model with related literature

The model proposed in this study is a combined MCLP-P and VRP-P; maximal coverage location problem with partial coverage and vehicle routing problem with profits. People in the population zones can get incentives while leaving glass material to the collection sites. The other possibility is that people leave recyclable materials voluntarily being sensitive to the environment. Whatever the reason is, the location of the collection site is the most important issue to encourage people. People do not admit to walk for a long distance to leave the materials. Hence, the best locations should be determined by considering these distances. Currently, in the model, it is assumed that all people in the population zone are going to leave materials for a defined distance and some people is going to leave materials if the distance is between the minimum critical distance and the maximum critical distance. Thus, this part of the problem is MCLP-P where the formulation is:

MCLP-P

Max $\sum_{n\in N} \sum_{g\in Ln} W_{ng} Z_{ng}$

Subject to,

$Z_{ng} \leq Y_g \qquad \forall g \in L_n, n \in N$

$\sum_{g\in Ln} Z_{ng} \leq 1 \qquad \forall n \in N$

$\sum_{g\in G} Y_g = P$

$Y_g \in \{0,1\} \qquad \forall g \in G$

$Z_{ng} \in \{0,1\} \qquad \forall g \in Ln, \forall n \in N$

The second part of the model is a modification of VRP-P.

Min $\sum_{i\in H} \sum_{j\in H} \sum_{k\in K} c_{ij} d_{ij} X_{ijk}$

Subject to

$\sum_{i\in H} \sum_{k\in K} X_{igk} \leq 1 \qquad \forall g \in H$

$\sum_{i\in H} X_{ijk} - \sum_{j\in H} X_{jik} = 0 \qquad \forall k \in K, \forall j \in H$

$U_i - U_j + D \sum_{k\in K} X_{ijk} \leq D - q_i \qquad \forall i \in M, \forall j \in H \quad i \neq j$

$$U_i - U_j + D\sum_{k\in K} X_{ijk} \le D - \sum_{n\in N} w_{ni} z_{ni} \qquad \forall i \in G, \forall j \in H \quad i \neq j$$

$$X_{ijk} \in \{0,1\} \qquad \forall i, j \in H \;\; i \neq j\,, \forall k \in K$$

$$U_g \ge 0 \qquad \forall g \in G$$

The combined model is NP-hard since it is a combination of two NP-hard problems. Hence, heuristic solutions are preferred to get near optimal results. Suggested solution methods are presented in the next chapter.

CHAPTER 4

SOLUTION METHODS

We propose three heuristic solutions procedures for the problem. The first two are based on one of the classical heuristics for location-routing problems; the cluster-first, route-second algorithm. The third solution method is based on the solution procedure for the orienteering problem. All solution procedures are modified considering the nature of the problem under consideration.

4.1. The Solution Procedures based on Cluster-First Route-Second Approach

As discussed in the literature review section, cluster-first, route-second methods are used to solve the location-routing problems efficiently. As the name implies this type of solution method is basically separating data of point coordinates into clusters and determines a vehicle route on each cluster.

The heuristic, named CFRS-Ins-1 (Cluster-first route-second-Insertion-1), is as follows:

CFRS-Ins-1 Procedure

Phase1. Construct clusters according to the spatial proximity.

Input: Coordinates of contracted supply points

Number of vehicles: K

Output: K number of clusters

Centroids of clusters and the contracted points in each cluster.

Phase 2. Determine routes for each vehicle.

Input: K number of clusters and contracted points in each cluster

Output: K number of routes visiting the contracted points.

Phase 3.

- Define I_g = set of population zones that are partially or entirely covered by site g for all $g \in G$,

  J = set of alternative sites where a bottle bank is located, initially $J = \emptyset$,

  P = number of bottle banks to locate.
- Determine for each alternative site g, $g \in G$, the closest contracted supply point in any of the routes, and determine the insertion cost of point g into this route. Call this insertion cost as $ins_g \;\; g \in G$. The procedure of calculating ins_g is as follows:
- Determine all population zones that are partially or entirely covered by the alternative site g, for all $g \in G$. Also calculate the total coverage weight of site g (the revenue from site g), cov_g, where $cov_g = \sum_{n \in I_g} W_{ng}$ for all $g \in G$.
- Calculate the profit from site g, p_g, as $p_g = cov_g - ins_g$ for all $g \in G$.
- Apply the modified covering algorithm of Francis et al. (1992) (detailed in appendix B) as

WHILE $|J| \neq P$ DO

(1) p_v = Maximum $\{ p_g \,|\, g \notin J \}$

(2) $J \leftarrow J \cup \{v\}$

(3) $I_g \leftarrow I_g \setminus I_v$ for all $g \in G \setminus \{v\}$, and update p_g for all $g \in G \setminus \{v\}$.

ENDWHILE

Phase 4. Improve routes

Input: Generated routes

Output: Improved routes

CFRS-Ins-1 is a sequential procedure and each profitable bottle bank is inserted to the route of a vehicle with “revenue and cost trade-off” concept.

The first phase is the clustering part, in which K-means clustering method is performed. The K-means clustering method is a non-hierarchical clustering approach where data are divided into K groups. User is flexible to decide on the number K. The aim of this technique is to create K number of clusters so that the within group sum of squares are minimized. As iterating all the possible observations is enormous, the algorithm finds a local optimum. To reach the optima, algorithm is repeated several times and the best positioning K centers are found, and data is partitioned into K number of clusters (Levine, 2002).

Then the next phase is to generate routes for each vehicle in each cluster by solving TSP problems.

After routes are generated, alternative points are inserted into routes by considering revenue-cost trade-off in order to insert the most profitable points for the problem. This is phase 3. When the number of opened bottle banks reaches *P*, the insertion phase stops.

At the last phase, Phase 4, solution is improved with 2-opt solution procedure to develop new routes. The flowchart of CFRS-Ins-1 procedure is presented in Figure 4.

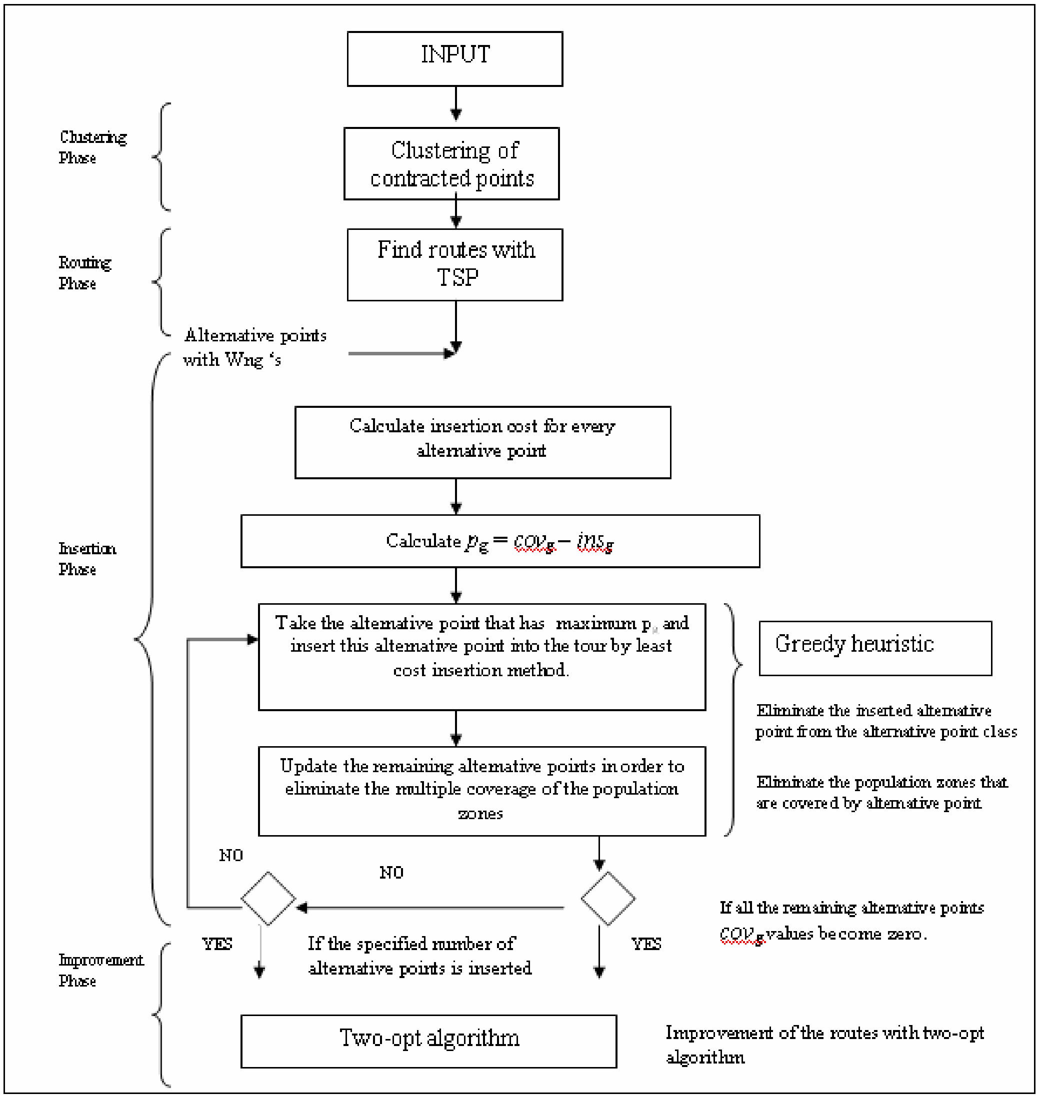

Figure 4. Flowchart of CFRS-Ins-1 Procedure

CFRS-Ins-2, on the other hand, uses only the "revenue" concept in inserting a bottle bank to the tours visiting the contracted points. Thus, phase 3 of CFRS-Ins-1 is changed in CFRS-Ins-2 as follows:

CFRS-Ins-2 Procedure

Phase 3.

- Define

  I_g = set of population zones that are partially or entirely covered by site g for

  all $g \in G$,

  J = set of alternative sites where a bottle bank is located, initially $J = \emptyset$,

  P = number of bottle banks to locate.

- Determine all population zones that are partially or entirely covered by the alternative site g, for all $g \in G$. Also calculate the total coverage weight of site g (the revenue from site g), cov_g, where $cov_g = \sum_{n \in I_g} W_{ng}$ for all $g \in G$.

- Apply the modified covering algorithm of Francis et al. (1992) (detailed in appendix B) as

WHILE | J | $\neq P$ DO

(1) Cov_v = Maximum { Cov_g | $g \notin J$ }

(2) $J \leftarrow J \cup \{v\}$

(3) $I_g \leftarrow I_g \setminus I_v$ for all $g \in G \setminus \{v\}$, and update Cov_g for all $g \in G \setminus \{v\}$.

ENDWHILE

4.2. The Solution Procedure based on the Orienteering Approach

The second heuristic procedure we propose is based on the heuristic proposed by Chao et al. (1996) for the orienteering problem (OP). This procedure is named as

O-LPR, the abbreviation for **O**rienteering procedure **i**n **L**ocation-**R**outing problem. The steps of the original procedure of Chao et al. given in Figure 5 is detailed in Appendix A.

```
Step 1. Initialization
        Perform initialization
        Set record = team score of the initial solution
        Set p
        Set deviation = p%*record
Step 2. Improvement
        For k=1,2,..........K
                For i = 1,2,.........I
                Perform two-point exchange
                Perform one point  movement
                Perform 2-opt
                If there is no movement, end Loop I
                If a better new solution is gained, then
                   Set record = score of the best solution
                   Set deviation = p%*record
                End Loop I
                Perform reinitialization
            End Loop K
Step 3. Reset if p is reached, and redo Step 2 once more
```

Figure 5. Heuristic proposed for OP by Chao et al.(1996)

O-LPR applies the procedure of Chao et al.(1996) after calculating the revenue that can be obtained from each of the alternative sites $g \in G$. When the routes are determined by the procedure of Chao et al.(1996), the last step includes the correction step, where overlaps of the coverages are removed, and the contracted points not included in the routes are forced into the routes. The details of O-LPR Procedure are as follows:

O-LPR Procedure

Phase1. Clustering Phase.

Construct clusters according to the spatial proximity.

Input: Coordinates of contracted supply points

Number of vehicles: K

Output: K number of clusters

Centroids of clusters and the contracted points in each cluster.

Phase 2. Preparation Phase

Determine the coverage weight (revenue) of alternative collection site g, for

all $g \in G$,

$Cov_g = \sum_{n \in N} W_{ng} = revenue_g$

Revenue from each contracted point are defined as

$revenue_i = q_i \times R$ for all $i \in M$.

Determine the first and the last points for the route. To solve the OP the first and the last point in the route should be defined. These points are determined by the routes generated by the CFRS-Ins-1 Procedure.

Phase 3. Orienteering Phase

Apply the heuristic proposed for OP by Chao et al.(1996).

Phase 4. Insertion Phase

Updating is applied to eliminate multiple coverage situations. As it is not possible to interfere with the algorithm during the orienteering process, the updating procedure is applied in the last phase. In the procedure for each population zone, maximum coverage value is saved and others are deleted. Hence, the maximum revenue is obtained from the alternative points. Contracted points that remains outside of the routes are inserted into the routes in this phase.

Phase 5. Improvement Phase

Input: Generated routes

Output: Improved routes

Flowchart of the O-LPR is shown below in Figure 6:

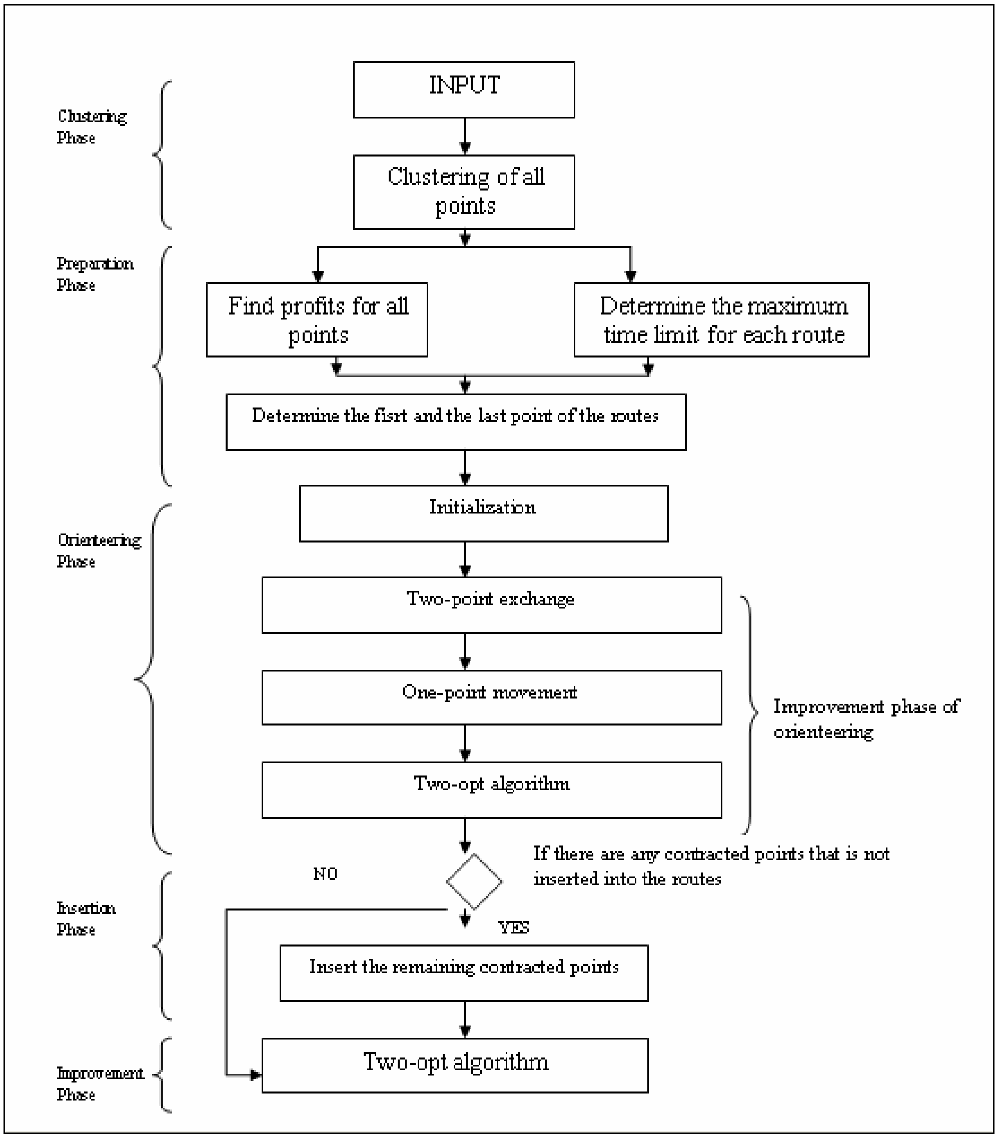

Figure 6. Flowchart of the O-LPR procedure

CHAPTER 5

COMPUTATIONAL RESULTS

In this chapter computational results are presented in order to analyze the performance of the solution approaches proposed for the problem. At the beginning, problem instances and parameters used in the experimental runs are explained. Then the results of the three heuristic procedures are compared with the optimal results for the small sized problems. Also, for large problem instances the results of heuristic solution approaches are compared and evaluated.

5.1. Explanation of test problem instances

Some of the problem data used in the computational experiments are randomly generated. The coordinates of the

- centers of population zones,
- the contracted collection points
- alternative sites for bottle banks

are generated from a uniform distribution in the interval [0,100]. The distances between each point are calculated using the Euclidean distance resulting with a symmetric distance matrix. Even though the procedures developed in the previous section allows several vehicles to be used in the collection process, for simplicity, we restrict our experiments with a single collecting vehicle.

Some of the parameters of the model are estimated using the real estimates related with transportation and glass usage. The details of these estimates are given as follows:

Collection vehicle traveling cost:

This cost, defined as the parameter c_{ij}, includes fuel consumption and other requirements of a vehicle. It is estimated as 0.5 YTL per unit distance traveled.

Amount of glass returned by a person daily:

This amount, defined as the parameter q_{person}, is determined as 0.025 kg daily. This parameter is found by the data taken from the paper published by European Commission (Web 5). This data is prepared for Turkey in 2001 and the average amount of waste generated per person per day is reported as 0.5 kg. At average nearly 20% of these wastes are recycled, meaning that the recyclable material gained per person is 0.1 kg. At last the ratio of the amount of glass among the recyclable materials is 25%. All these data indicates that the amount of glass returned daily per person is 0.025 kg.

Revenue gained from collected material:

This value, defined as the parameter R, is approximated after the interview with the collection firm in Ankara. People working in the collection firm informed us that the revenue gained from 1 ton of recycled glass is 100 YTL. Hence, revenue gained from 1 kg of recycled glass is 0.1 YTL.

The number of people in each population zone:

The number of people in each population zone, defined as the parameter h_n, for $n \in N$, is generated from a uniform distribution in the interval [400,800]. The population in each zone is assumed to be homogenous in terms of their willingness to return bottles.

Coverage level

Coverage level provided by alternative site g to a population zone n, defined as the parameter k_{ng}, for $n \in N$, $g \in G$, is given by

$$k_{ng} = \begin{cases} 1 & \text{if } d_{ng} \le \mathrm{S} \\ f(d_{ng}) & \text{if } \mathrm{S} < d_{ng} \le \mathrm{T}, \\ 0 & \text{otherwise} \end{cases}$$

where $f(d_{ng}) = 1 - \dfrac{d_{ng} - S}{T - S}$ for $\mathrm{S} < d_{ng} \le \mathrm{T}$.

Thus, a linear partial coverage function is assumed.

S and T values are set to 30 and 40 unit distances, respectively, for the instances where the number of population zones is less than 25; and to 25 and 35, respectively, for the instances where the number of population zones is higher than 25.

Amount of recyclable material to be picked up from a contracted point:

Amount of recyclable material (kg.) to be picked up from a contracted point, defined as the parameter $q_{i,}$ $\mathrm{i} \in \mathrm{M}$, is generated uniformly in the range [100,200].

For determining the parameters that define the size of the generated problems, the following notation is made use of. Let

$\delta = |N|$, be the number of population zones,

$\gamma = |M|$, be the number of contracted collection points, and

$\varphi = |G|$, be the number of alternative location sites for bottle banks.

While fixing δ, the number of population zones, γ, φ and P are determined by using predetermined percentages. The percentages used are:

$\frac{\gamma}{\delta}$ is taken as 1.0, $\frac{\varphi}{\delta}$ is taken as 0.5 and 1.0 and P is selected as a value not exceeding 0.5φ.

All heuristic procedures are coded in C++ and run on a Dell Inspiron 16400 with an Intel(R) Core(TM)2 1.83GHz processor. The tours of the vehicles are determined by utilizing the Concorde TSP solver (Applegate et al., 2006). The model (VRP-P+MCLP-P) is solved to optimality with GAMS\CPLEX 10.0.

5.2. Analysis of the solution methods

5.2.1. A Toy Example

A small example is used here to show the results of the heuristic procedures and a comparison is made with the optimal solution. Visualization is performed by MS Excel. There are 12 contracted points. Centers for 12 population zones are generated. Alternative points coincide with these centers. 3 bottle banks are to be located. In Figure 7 all the points are displayed.

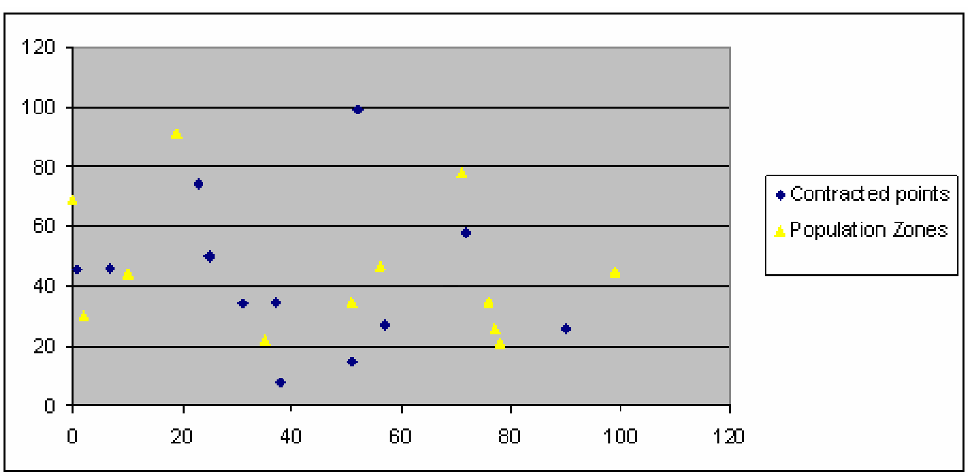

Figure 7 . Contracted points and population zones

Two parameters are defined for coverage of the population zones by alternative points. These values are determined as 15 and 25 units. After generating data, all solutions are visulized by drawing routes as given in Figure 8,9,10,11. Arcs in Figure 8,9,10,11 repesents the opened bottle banks among population zone centers.

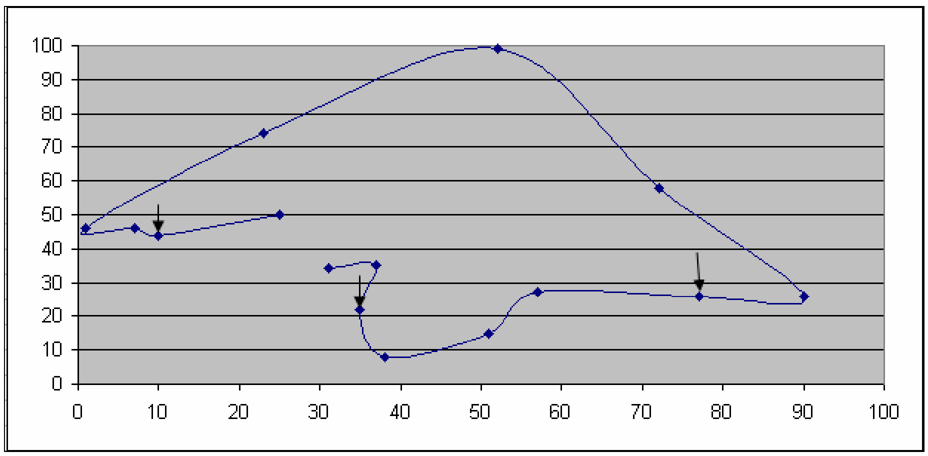

Figure 8. Route obtained by CFRS-Ins-1 Procedure

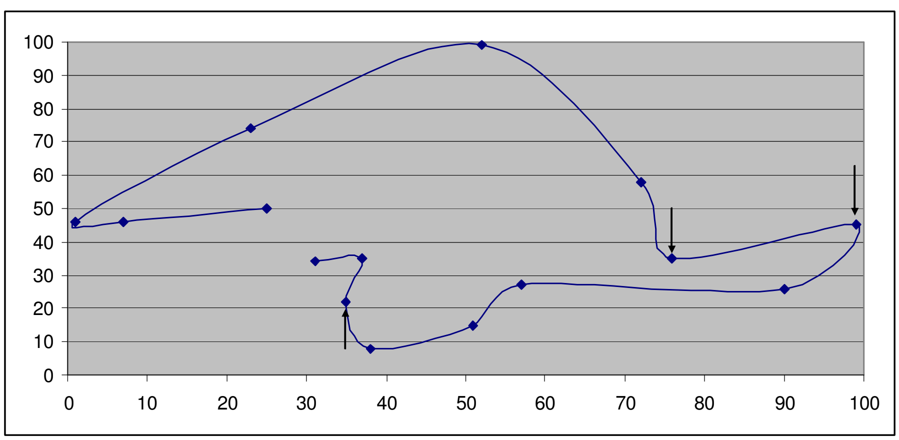

Figure 9. Route obtained by CFRS-Ins-2 Procedure

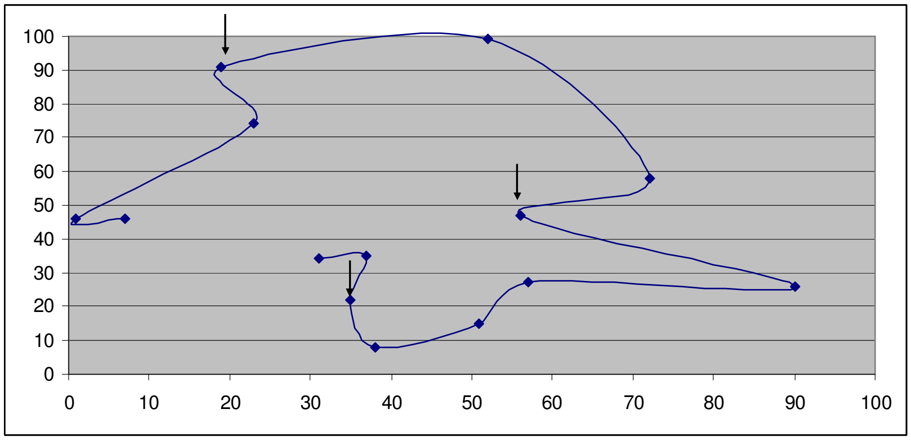

Figure 10. Route obtained by O-LPR procedure

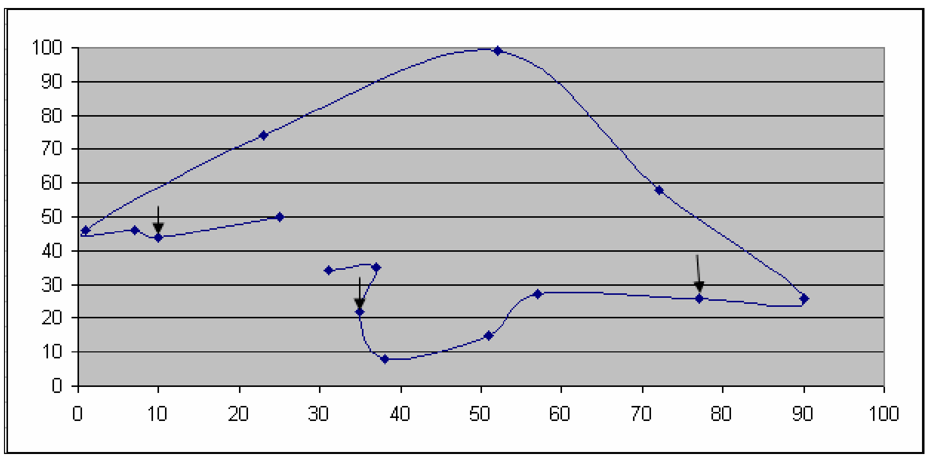

Figure 11. Route obtained by optimal solution

According to the results given in Table 1, CFRS-Ins-1 finds the optimal solution whereas CFRS-Ins-2 prefers to choose the alternative site having more revenue, resulting with a higher total cost. In this example O-LPR solution procedure has the worse performance in terms of total cost.

Table 1. Comparison of the solution methods for the toy example

	Travel cost	Revenue from alternative points	Total cost	CPU time (sec)
Optimal	138,4	7,5	130,9	0.1
CFRS-Ins-1 Procedure	138,4	7,5	130,9	<0.5
CFRS-Ins-2 Procedure	154,2	9,5	144,7	<0.5
O-LPR Procedure	152,9	5,5	147,4	<0.5

5.2.2. Results for small sized problems

The size of the problems depend on the number of population zones. The larger δ is, the higher the CPU times are. Different combinations of the ratios and parameters are analyzed and compared with the optimal values. Three different combinations are considered as:

- Combination 1: γ/δ is set to 1
- Combination 2: $\gamma/\delta > 1$
- Combination 3: Alternative points coincide with the centers of the population zones.

For each data set 5 instances are generated. The results are explained in the following sections.

Combination 1 where γ/δ is set to 1

This combination in this study refers to the combination of the number of the features as proposed and explained above. Ratios are determined as:

- $\gamma/\delta = 1$
- $\varphi/\delta \cong 0.5$

- $P/\varphi < 0.5$,

and δ is set as 20,25, and 30. In Table 2 the comparison of the performance of the three heuristic procedures; CFRS-Ins-1, CFRS-Ins-2, and O-LPR is provided. The performance is defined as the average percentage deviation of the objective function values of the heuristic procedures from the optimal objective function values. The averages are obtained from 5 instances. The detailed results of each instance is provided in Appendix C, in Tables C1,C2, and C3. In Tables C1,C2, and C3 the travel cost, revenue from alternative points, revenue from contracted points, % deviation of these results from the optimal are listed for each instance and procedure seperately.

Table 2.Avg. % deviation from optimal for solution methods in combination 1.

Data Set $\lvert N\rvert$-$\lvert M\rvert$-$\lvert G\rvert$	CFRS-Ins-1	CFRS-Ins-2	O-LPR
20-20-8	3,7	6,3	14,3
25-25-10	1,8	3,5	19,5
25-25-14	2,6	4,6	18
30-30-12	2,4	5,3	14,7
30-30-16	1,6	6,3	16,8

It is important to mention that the results are all problem specific. The distribution of the points in data sets effects the solutions obtained. However, solution methods differ in performance. CFRS-Ins-1 performs better than the other methods in terms of % deviation from the optimal. Results are meaningful as CFRS-Ins-1 considers both travel cost and revenue from alternative points while inserting alternative points. In the problems solved, CFRS-Ins-1 deviates a maximum of 5% from the optimal in travel cost, while CFRS-Ins-2 deviates 13% and O-LPR deviates 45%. For revenue from alternative points, the performance of CFRS-Ins-2 is better. CFRS-Ins-2 deviates a maximum of 11%, while CFRS-Ins-1 deviates 22% and O-LPR deviates 45% in the problems solved. As observed from the results, O-LPR method is not very suitable for our model.

Computation times of the heuristic solution methods are smaller than 1 second and this is very little when compared with the optimal computation time. Computation time for the optimal solution increases with the increase in the number of points in the problem as expected.

Combination 2 where $\gamma/\delta > 1$

This situation is analyzed in order to see the performance of the heuristic procedures when γ/δ is bigger than 1. In these analyses δ is set as 40 and 45. The number of contracted points are determined with respect to the number of population zones. Results of the solution methods given in Table 3 are averages of 5 instances. The detailed results of each instance is provided in Tables D1,D2, and D3 in Appendix D.

Table 3.Avg. % deviation from optimal for solution methods in Combination 2

Data Set $\|N\|$-$\|M\|$-$\|G\|$	CFRS-Ins-1 Procedure	CFRS-Ins-2 Procedure	O-LPR Procedure
40-25-10	3,8	9	17,1
40-25-12	4,4	9,3	21,5
40-25-14	5,0	11,1	18,6
45-30-12	5,9	7,4	15,3
45-30-15	4,8	9,1	13,6

Results indicate that % deviation from optimal are higher compared to the results when the ratio of γ/δ is 1. The difference is due to increase in the number of bottle banks opened. In the problems solved, CFRS-Ins-1 deviates a maximum of 8% from the optimal in travel cost, while CFRS-Ins-2 deviates 16% and O-LPR deviates 15%. For revenue from alternative points, the performance of CFRS-Ins-2 is better. CFRS-Ins-2 deviates a maximum of 13%, while CFRS-Ins-1 deviates 25% and O-LPR deviates 33% in the problems solved.

Combination 3 where alternative points coincide with the centers of the population zones

In this combination the population zones are at the same time alternative points. This combination is selected to eliminate the non-covarege of highly populated population zones .This is because of the random generation of the alternative points. The toy example is a good indicator for this situation. The averages are given in Table 4 and details can be seen in Tables E1,E2, and E3 in Appendix E. The results are very satisfactory for CFRS-Ins-1 procedure. Also, CFRS-Ins-2 procedure perform well in this combination and the results are compatible with the expected solutions. In this part, O-LPR procedure performs worse compared to other combinations.

Table 4.Avg. % deviation from optimal for solution methods in Combination 3

Data Set $\|N\|$-$\|M\|$	CFRS-Ins-1 Procedure	CFRS-Ins-2 Procedure	O-LPR Procedure
20-20	3,5	8,7	19,6
25-25	4,6	10,8	24,4
30-30	3,3	8,0	19,7

In the problems solved, CFRS-Ins-1 deviates a maximum of 6% from the optimal in travel cost, while CFRS-Ins-2 deviates 14% and O-LPR deviates 25%. For revenue from alternative points, the performance of CFRS-Ins-1 is also better than CFRS-Ins-2. CFRS-Ins-1 deviates a maximum of 22%, while CFRS-Ins-2 deviates 33% and O-LPR deviates 40% in the problems solved.

5.3.2. Experimental runs with large sized problems

For large sized problems the number of population zones is chosen as 50, 100, and 200. For 100 and 200 contracted point's combination, problems are solved with clustering approach, having 2 clusters.

Table 5. Avg. % deviation from optimal for solution methods for large-sized problems

Data Set $\|N\|$-$\|M\|$	CFRS-Ins-1 Procedure
50-50	5,5
100-100	2,5
200-200	2,8

After analyzing the results of runs, it is searched that travel costs of CFRS-Ins-1 are less than CFRS-Ins-2 as expected. Although there are not significant differences between the two methods in terms of total cost, CFRS-Ins-1 is better in all the problems solved. The average % deviation from the best known solutions (CFRS-Ins-1) is given in Table 5. Details of the results are given in Tables F1 in Appendix F.

CHAPTER 6

THE CASE STUDY

6.1. Definition of the problem

Collecting materials separately in recycling process always increases collection efficiency as noticed in the introduction section. However, the current situation in Turkey is different such that the materials are collected together by private collection vehicles. The only exception is the bottle banks located for collecting glass materials. To make collecting glass by bottle banks profitable, the location and the number of the bottle banks should be appropriate with respect to the properties of the location.

Ministry of Forestry and Environment associated with ÇEVKO intent to locate bottle banks in order to return more amount of glass into process. As mentioned before, collection of glass materials is awarded to private collection firms. However, as the amount of recycled glass from the region is not always adequate, firms are encouraged by the Ministry of Forestry and Environment via incentives. Although the profit gained from collection is not satisfactory, collection firms do not have any plans about increasing their profit. Thus, the aim of this study is to find the exact locations of bottle banks to increase the total profit of a firm.

Study area in this thesis is selected as the part of Yenimahalle district in Ankara which is the capital city of Turkey (Figure 12). The area covers Konutkent, Koru, Çayyolu, Ümit, and Buketkent districts. The area is one of the most popular places to reside and for social activities in Ankara. There are lots of restaurants and cafes in the area and also the residential settlement is structured.

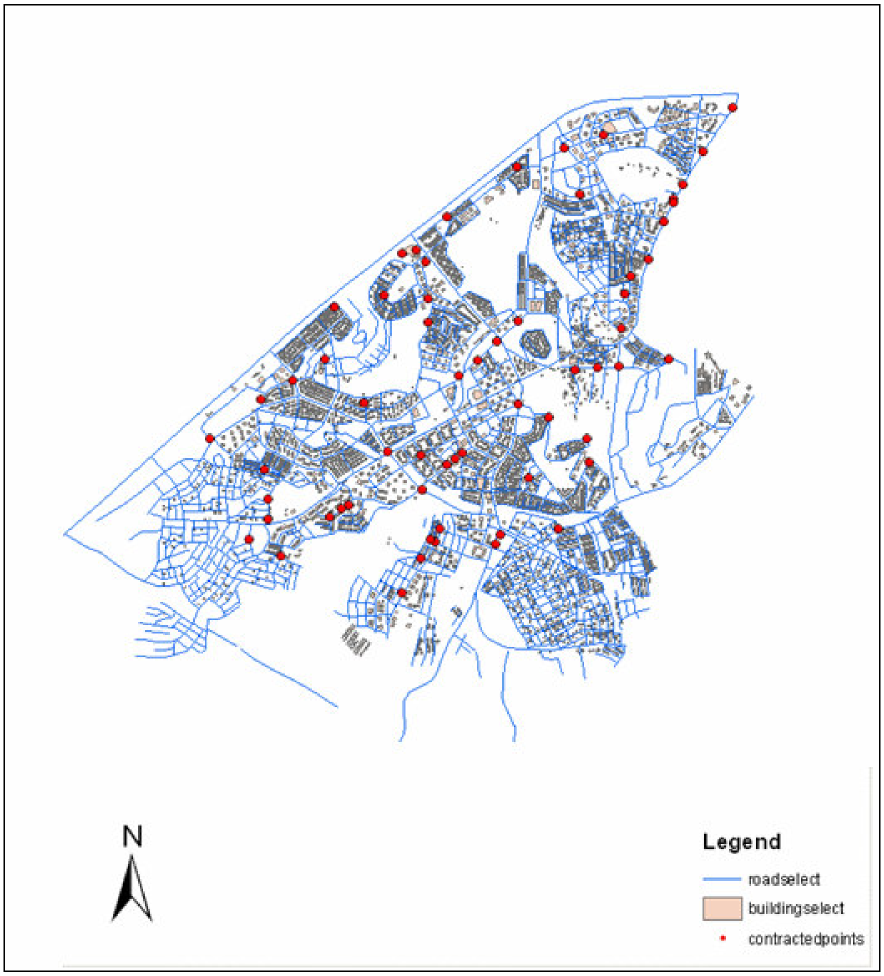

Figure 12. Contracted collection points in the study area

The most important reasons in choosing this area are; the areas structured settlement, socio-economic conditions of the residents being higher than the average of Ankara, and the availability of data in the GIS environment. Structured settlement is an advantage in the routing phase and the socio-economic situation of residents is significant assuming higher socio-economic conditions results in higher sensitivity to the environment.

6.2. Data generated for the case study

ArcGIS 9.1 is used to store, analyze and visualize the data. There are 60 contracted points in this area, most of them being bars and restaurants. The locations of the contracted points are shown in Figure 12. To determine the locations of the population zones in the area, the area is separated into 100 sub-locations (10*10 grids) by inserting grid layout to the area. Each grid is nearly 500*500 meters in size. Although there are 100 sub-locations, only 65 of these locations include residential areas (Figure 13).

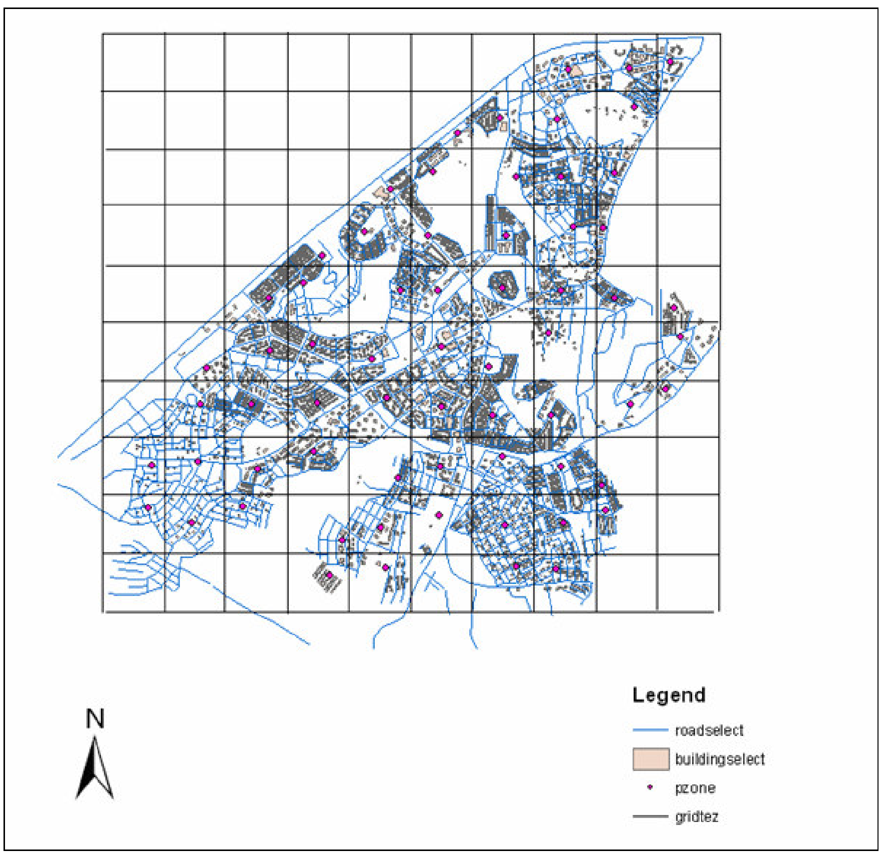

Figure 13. Population zone points and grid layout of the area

There are 65 population zones in the area to be served by alternative points. These areas have polygon type features but they should be converted into point type features to use at the calculations of the parameters. A point is inserted in each grid respecting the density of the buildings in the area as shown in Figure 13.

The reason to apply this procedure to find population zone points is to calculate the number of people living in each zone. To estimate the number, first the number of storey of each building is summed in the grid area. Then it is assumed that there are 2 blocks for each building and 4 people are living in each household. The formulation is given below:

*Population of the population zone x = Number of storey in the area x * 2 blocks * 4 people*

Each population number is assigned to the point representing the population zone. This information is used to calculate the amount of revenue obtained by each bottle bank (alternative points).

Alternative points are determined considering the population zone points. Alternative points are inserted regularly in the area. The distance between each alternative point is leaved at least 500 m. in order to locate bottle banks efficiently (Figure 14). 24 alternative points are defined in the area.

Parameters used in the study:

- Amount (kg) of returned glass picked up from each collection point is determined according to area its serves (100-200 kg/day).
- Amount (kg) of returned glass from each person (0.025 kg/day).
- Money gained from 1 kg of glass materials returned (0.1 TL).
- Travel cost is estimated as 2 YTL per km.

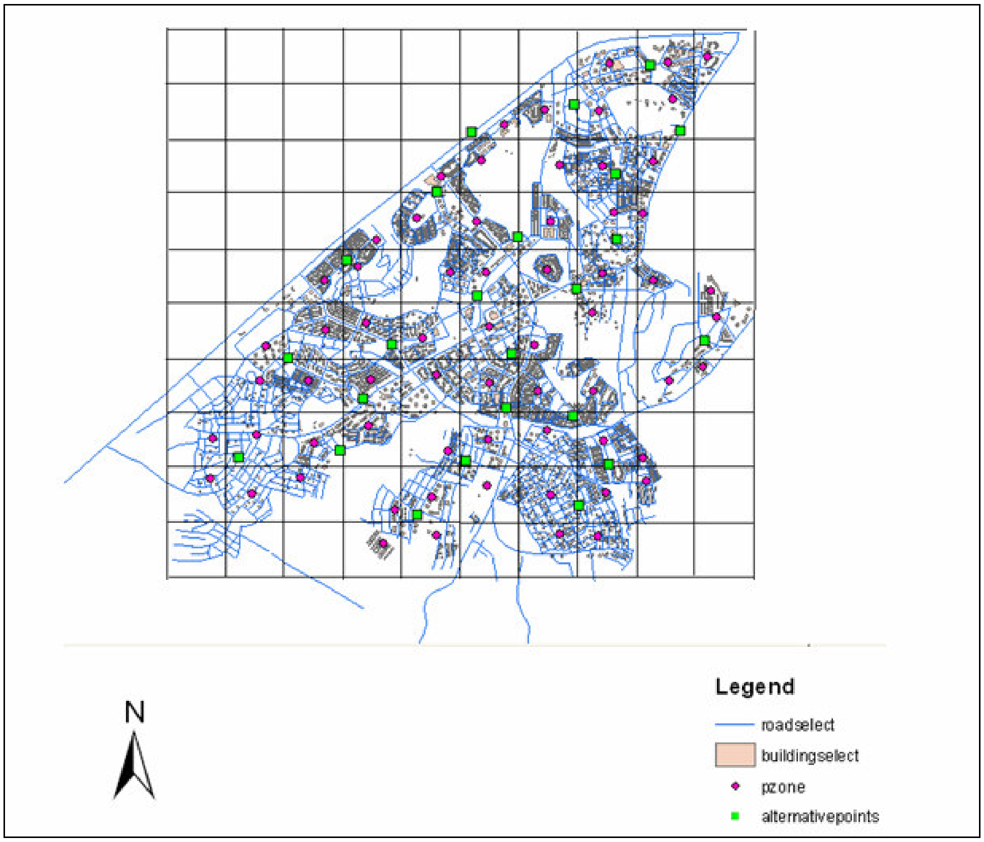

Figure 14. Alternative points located in the area

To solve the problem, the covering coefficient denoting the total revenue obtained when alternative site g provides coverage to population zone n should be known. The formulation of the W_{ng} value is:

$$W_{ng} = k_{ng} h_n q_{person} R$$

where;

q_{person}: 0.025 kg/day

h_n: is calculated in the population zone section.

R: 0.1 TL/kg

k_{ng}: function defining the rate of returning recyclable materials in population zone n to an alternative site g ($\forall n \in N, \forall g \in G$)).

Considering all these parameters W_{ng} values are estimated for each population zone-alternative point pair.

6.3. Solution of the case study

The number of each layer is indicated below:

- Population Zone: 65
- Contracted Points: 60
- Alternative Points: 24
- Bottle banks: 12

The case study is solved by CFRS-Ins-1 and CFRS-Ins-2 procedures. However, the results of two procedures are the same for this instance. The route for the vehicle, and the allocation of the population zones to the bottle banks are digitized on maps, and are shown in Figures 15 and 16, respectively.

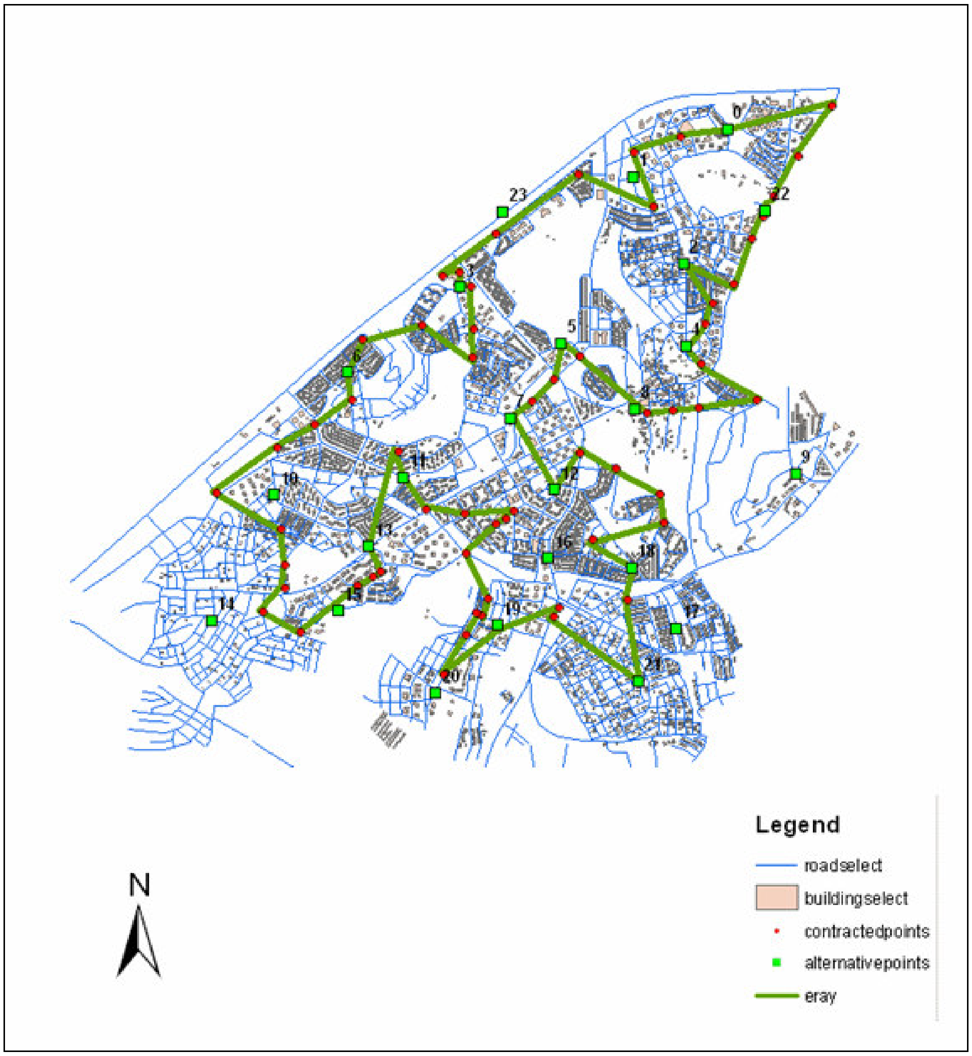

Figure 15. Route obtained by CFRS-Ins-1 procedure

As expected, located bottle banks cover densely populated areas. For example, south-west part of the area does not have much population and the procedures does not locate bottle banks in these places. Results of the solution method are given below:

- Total distance traveled: 22,98 km.
- Total travel cost: 22,98 * 2 YTL = 45,96 YTL
- Revenue from alternative points = 99,02 YTL
- Revenue from contracted points = 897 YTL
- Total profit = 950 YTL.

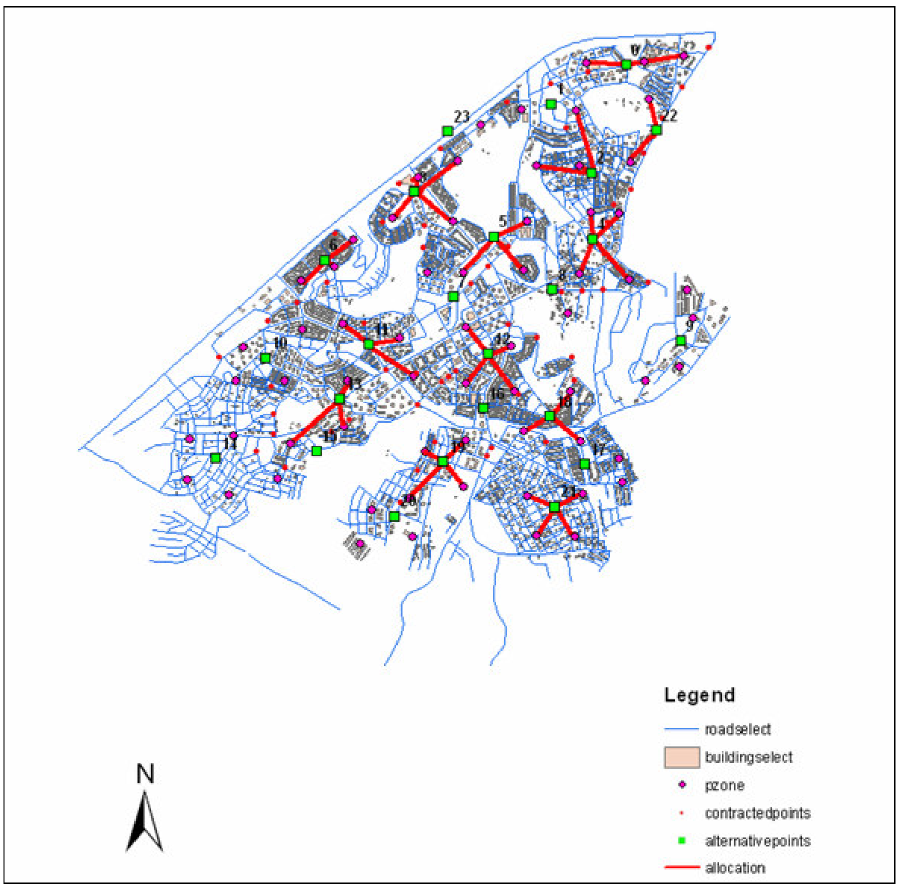

Figure 16. Allocation of the population zones to each alternative point

In order to analyze the solution with GIS applications, a kernel density analysis is implemented to the problem. Kernel density analysis is applied to the population property of population zones. Thus, the dark green areas in Figure 17 represents the areas having large population. It can be observed from Figure 17 that most of the alternative points are opened in dark shaded areas. However, all dark shaded population zones are covered by opened bottle banks.

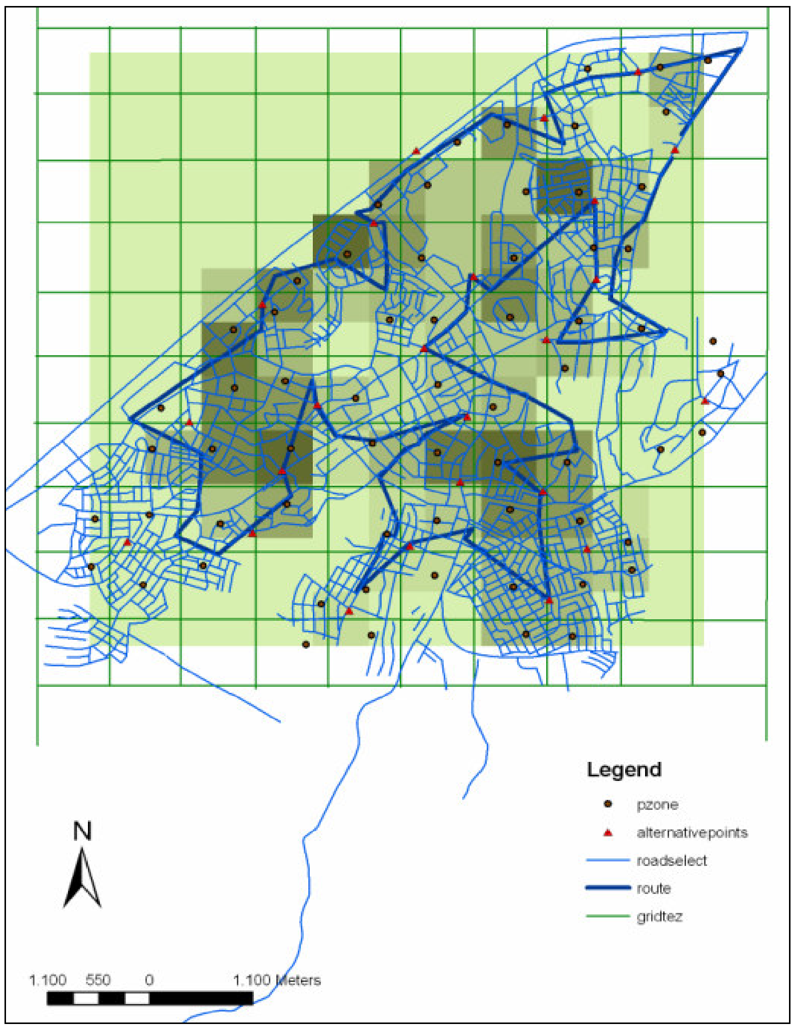

Figure 17. Kernel density estimation of the population zones

CHAPTER 7

CONCLUSION AND RECOMMENDATIONS

This study is related with the location-routing problem for determining the location of bottle banks in glass recycling. The defined problem is a combination of two problems; VRP-P, the vehicle routing problem with profits, and MCLP-P, maximal coverage location problem in the presence of partial coverage. Three types of heuristic procedures are proposed for this model: CFRS-Ins-1, CFRS-Ins-2, and O-LPR. First two methods are cluster-first route-second methods differing in the insertion procedures and the last one is a procedure based on the orienteering algorithm of Chao et al. (1996). Experimental runs are performed and comparisons with the optimal results are made. Although the results obtained by cluster-first route-second procedures are not so different, CFRS-Ins-1 performs better. After the analysis it is observed that the orienteering algorithm is not suitable for the model proposed.

A case study is applied by using GIS data and applications. Euclidean distance is used as a spatial proximity although using road network is more meaningful. However, as the structures of the algorithms are not compatible with the road network, all analysis are done via Euclidean distance.

The aim of this study is to locate alternative collection points to the area in order to increase the profit while decreasing the distribution costs. This approach can be beneficial for the government, the collection firms, and the non-governmental organizations related to environmental issues. The government and the non-governmental organizations aim to locate bottle banks to return more amounts of glass materials to the recycling process. This is awarded to private collection firms intend to get more profit in the collection phase. Hence, the aim of this study is compatible with the aims of the stake holders in this issue.

Future studies for this thesis include developing different solution methods. Meta-heuristic solution methods can be applied and the results can be compared. Data used in this study is deterministic however, stochastic data can be used and different solution methods can be developed. The modification of the parameters is possible like the willingness of the people living in the area. It is assumed as homogenous in this study, whereas the heterogeneity of the willingness of people can be meaningful to analyze. In this study, all computational experiments are performed with generated data. However, TSP problems in literature can be adjusted to our problem and analyzed.

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APPENDIX A

ORIENTEERING PROBLEM HEURISTIC SOLUTION

Heuristic solution for orienteering problem proposed by Chao et al. (1996):

Initialization

Let there are n cities inside the ellipse including the first and the last city. For all cities from 1 to n-1, the sum of distance between cities i and the first and the last city (d_i) is smaller than T_{max} not to violate the time limit. Paths are constructed from point 0 to n using greedy method in with respect to cheapest insertion cost ignoring its score. L solutions are constructed, where L= min (10, N). N refers to number of points in the ellipse. First path is constructed by finding the l-th largest d(i), and forming a path with the first, the l-th largest, and the last point. Other points are inserted into the path by greedy method concerning the distance. The insertion continues until the T_{max} is violated. Remaining points in the ellipse are included in other paths with greedy method either until the time limitation is violated. The procedure continues until all the points are on a path. Among these paths, the path with the largest total score is selected as the solution path with its score. Among all the L solutions, the path having the highest total score is chosen as the inital solution denoting the $path_{op.}$ All the remaining paths in the solution hence become $path_{nop}$.

Two-point exchange

The first step of the improvement phase is two-point exchange. The selected solution in the initialization step is used for improvement. By keeping all the paths feasible, point i is moved from a $path_{nop}$ and inserted into $path_{op}$, and point j is moved from $path_{op}$ and inserted into $path_{nop.}$ All the insertions are made in the cheapest way by inserting point i between two points in $path_{op}$ hence the increase in distance is minimized. Also, point *j* is inserted into a path where the cost of insertion is least and feasible. If there is no feasible path for point *j*, a new path is created. This exchange can lead $path_{op}$ to be one of path_{nop} and hence one of $path_{nop}$ has the largest score.

The feasibility of the path can be checked by the following expression:

$$L(\text{p}) - (c_{\text{j,fj}} + c_{\text{pj,j}} - c_{\text{pj,fj}}) + \min_{\text{k in path p, k}\neq 1,\text{j}} \{c_{\text{i,k}} + c_{\text{i,pk}} - c_{\text{k,pk}}\},$$

Where L(p) refers to the lenght of path p, p_{j} is the point precedes point *j* on path p, f_{j} is the point that follows point *j* on path p, and p_{k} is the point that precedes point *k* on path p after point *j* has been removed from the path. When point *i* is inserted into path p and point *j* is removed from path p feasibility of the path is checked by the expression. If the solution is less than or equal to T_{max}, the path is feasible. In the expression $(c_{\text{j,fj}} + c_{\text{pj,j}} - c_{\text{pj,fj}})$ is the savings by removing point *j*, and $\min_{\text{k in path p, k}\neq 1,\text{j}} \{c_{\text{i,k}} + c_{\text{i,pk}} - c_{\text{k,pk}}\}$ is the cost payed for inserting point *i* into path p.

For each point in $path_{op}$ when the candidate exchange yields a better total score the exchange is performed immediately. If there are no candidate exchange for a point that increases the total score, then the exchanges decreasing the total score by an acceptable amount is considered. Yet there are no exchanges preserving the acceptable decrease, the point remains in the current position and other points are continued to be exchanged. The score of the best solution is kept as *record* and the allowable decrease is called the *deviation*. This approach is named as record-to-record improvement and is due to Dueck(1990). In Figure 6 the two-point exchange algorithm is given.

Step 1. Set the route with the highest score as a starting route = $route_{op}$, and remaining routes as $route_{nop}$.

Step 2. Set the $point_{best\text{-}exchange}$= 0, and $record_{two\text{-}point}$ = 0.

Step 3. For j = the first to the last point in $route_{op}$. (Loop A)

Step 4. For i = the first to the last point in the first to the last path in $route_{nop}$. (Loop B)

Step 5. If exchanging point i and j is feasible and the total score increases, do the exchange and go to Step 6, else go to Step 7.

Step 6. If the total score of $\mathrm{route}_{\mathrm{nop}}$ become higher than the total score of $\mathrm{route}_{\mathrm{op}}$,update $\mathrm{route}_{\mathrm{op}}$ and $\mathrm{route}_{\mathrm{nop}}$;record the value and go to Step 3, else go to Step 7.

Step 7. If total score value ≥ $record_{two\text{-}point}$; go to Step 8.

Step 8. Set the $point_{best\text{-}exchange}$= i, and $record_{two\text{-}point}$ = total score.

Step 9. If all points are evaluated end Loop B; go to Step 10 else go to Step 4.

Step 10. If $record_{two\text{-}point}$ ≥ 90% * record, than exchange point j with the $point_{best\text{-}exchange}$; Set the $point_{best\text{-}exchange}$= 0, and $record_{two\text{-}point}$ = 0.

One Point Movement

As the name implies, one point movement is moving one point at a time between paths in a greedy way. Point i is intended to be inserted in the first edge of path and than in the second edge and so on. The movement is done when the total score increases and the insertion is feasible. If there is no solution increases the total score than feasible movement is done that decreases the total score by the least amount. It should be noted that only one point is moved at a time, this can still change $path_{op}$. There is no restriction between the movements, thus a point between paths in $paths_{nop}$ can be moved.

The feasibility of the path can be checked by the following expression:

$$L(\mathrm{p}) - (c_{\mathrm{j,fj}} + c_{\mathrm{pj,j}} - c_{\mathrm{pj,fj}}) + \{c_{\mathrm{i,k}} + c_{\mathrm{i,pk}} - c_{\mathrm{k,pk}}\},$$

Where $L(\mathrm{p})$ refers to the lenght of path p, c refers to cost, p_{j} is the point precedes point j on path p, f_{j} is the point that follows point j on path p, and p_{k} is the point that precedes point k on path p after point j has been removed from the path. When point i is inserted into path p and point j is removed from path p feasibility of the path is checked by the expression. If the solution is less than or equal to T_{max}, the path is feasible. In the expression $(c_{\mathrm{j,fj}} + c_{\mathrm{pj,j}} - c_{\mathrm{pj,fj}})$ is the savings by removing point j, and $\{c_{\mathrm{i,k}} + c_{\mathrm{i,pk}} - c_{\mathrm{k,pk}}\}$is the cost payed for inserting point i into path p.

Step 1. Set the $point_{bes\text{-}tmovement}$= 0, and $record_{one\text{-}point\text{-}movement}$ = 0.

Step 2. For i = the first to the last point in the T_{max} ellipse *(say point i is in path q)*. (Loop K)

Step 3. For j = the first to the last point in the first to the last path (path p) in both $route_{op}$ and $route_{nop}$ ($p \neq q$). (Loop L)

Step 4. If inserting point i in front of j on path p is feasible and the total score increases, make the movement and go to Step 5, else go to Step 6.

Step 5. If the total score of $route_{nop}$ become higher than the total score of $route_{op}$,update $route_{op}$ and $route_{nop}$;record the value and go to Step 2, else go to Step 6.

Step 6. If total score value ≥ $record_{one\text{-}point\text{-}movement}$; go to Step 7.

Step 7. Set the $point_{bes\text{-}tmovement}$ = j, and $record_{one\text{-}point\text{-}movement}$ = total score.

Step 8. If all points are evaluated end Loop L; go to Step 9 else go to Step 4.

Step 9. If $record_{one\text{-}point\text{-}movement} \geq 90\%$ * record, than insert point i in front of point j with the $point_{bes\text{-}tmovement}$; Set the $point_{best\text{-}exchange}$= 0, and $record_{two\text{-}point}$ = 0.

Step 10. If all points are evaluated end Loop A.

2-opt procedure

2-opt procedure is implemented in order to shorten the length of $path_{op}$ (Lin, 1965). If the sum of distance between point *i* and point *i+1*, point *j* and point *j+1* is higher than the sum of distance between point *i* and point *j*, point *i+1* and point *j+1*; then the sequence of the cities can be change to improve the route cost. In the procedure sequence of points can be changed according to the expression:

Max{d(i, i+1) + d(j, j+1) - d(i, j) + d(i+1, j+1)}, for i = 1,....,number of points in the path.

Step 1. Set the $best_{2\text{-opt}} = 0$, $best_i = 0$, $best_j = 0$,

Step 2. For i = the first to the last city in path p. (Loop A)

Step 3. For j = the first to the last city in path p, $i \neq j$. (Loop B)

Step 4. Calculate d(i, i+1) + d(j, j+1) - d(i, j) + d(i+1, j+1)

Step 5. Set $best_{2\text{-opt}}$ = d(i, i+1) + d(j, j+1) - d(i, j) + d(i+1, j+1) and $best_i = i$, $best_j = j$, if the calculated value d(i, i+1) + d(j, j+1) - d(i, j) + d(i+1, j+1) $\geq best_{2\text{-opt}}$.

Step 6. If all point are evaluated as j, end Loop B, then go to Step 7, else go to Step 3.

Step 7. If all point are evaluated as i, end Loop A, then go to Step 8, else go to Step 2.

Step 8. If $best_{2\text{-opt}} > 0$, then change the sequence by $best_i = i$, $best_j = j$.

In order to find a route that has a larger total score, k cities are removed from *$path_{op}$* that is chosen by the smallest ratio of:

$$P_i/cost_i,$$

Where P_i is the profit associated with point i, and cost i is the current insertion cost of point i, between point $i-1$ and $i+1$. Removed k points are inserted into $paths_{nop}$ by the first feasible insertion rule. As the iteration number increases, the value of k increases meaning removing more points from *$path_{op}$*.

APPENDIX B

A GREEDY HEURISTIC FOR SET COVERING

Given the formulation of set covering problem:

(SCP) Minimize $z = \sum_{j=1}^{p} c_j x_j$

Subject to

$$\sum_{j=1}^{p} a_{ij} x_j \geq 1, \qquad i \in I$$
$$x_j \in \{0,1\}, \qquad j \in J$$

The algorithm starts with taking all c_j's = 1 and all x_j's = 0, proceeds with selecting one x_j to make nonzero. The algorithm stops when all constraints are satisfied.

Notation used in the greedy algorithm:

I_j = set of vertices that can be covered by a center at location *j*.
k_j = the number of not yet covered rows that can be covered by x_j.

$f(c_j, k_j) = \dfrac{c_j}{k_j}$, a measure of reward for selecting x_j.

The greedy algorithm is:

WHILE | I | $\neq P$ DO

(1) $f(c_{v,}\ k_v) = \text{Minimum}\ \{\ f(c_{j,}\ k_j)\ |\ j \notin\ J\ \}$

(2) $J \leftarrow J \cup \{v\}$

(3) $\mathrm{I} \leftarrow I \setminus (I_v \cap I)$

ENDWHILE

APPENDIX C

Details of the computational comparison of γ/δ taken as 1

Table C1. Comparison of CFRS-Ins-1 solution with the optimal solution and the % deviation from optimal.

	Optimal				CFRS-Ins-1				% Deviation from Optimal		
|*N*|-|*M*|-|*G*|- #*	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Total
20-20-8-1	195	30,7	267	25	197,6	27	267	<1	1,3	12,1	6,1
20-20-8-2	207,5	25,5	297	26	209	22,6	297	<1	0,7	11,4	3,8
20-20-8-3	196,8	32,5	345	33	194,6	28	345	<1	-1,1	13,8	1,3
20-20-8-4	209	23,5	298	9	222,7	25	298	<1	6,6	-6,4	10,8
20-20-8-5	193,8	25,5	299	29	206	27	299	<1	6,3	-5,9	8,2
25-25-10-1	206,9	32,7	362	96	211,1	31,8	362	<1	2,0	2,8	1,0
25-25-10-2	212	27,3	360	512	212	26	360	<1	0,0	4,8	1,3
25-25-10-3	213	34,4	365	102	212,3	31,8	365	<1	-0,3	7,6	9,2
25-25-10-4	218,5	31,1	377	646	218,9	28,7	377	<1	0,2	7,7	0,5
25-25-10-5	231,5	32,3	335	6420	228,7	25	335	<1	-1,2	22,6	1,7
25-25-14-1	207,4	32,2	376	42	208,2	30,4	376	<1	0,4	5,6	1,3
25-25-14-2	231,5	30,5	358	1737	244,5	29	358	<1	5,6	4,9	9,2
25-25-14-3	202,5	32,6	403	664	200	29	403	<1	-1,2	11,0	0,5
25-25-14-4	193,8	31,9	389	211	193,6	29,5	389	<1	-0,1	7,5	1,0
25-25-14-5	212,5	28,6	388	2327	215,8	30	388	<1	1,6	-4,9	0,9

#* indicates the instance numbers

Table C1. Comparison of CFRS-Ins-1 solution with the optimal solution and the % deviation from optimal (cont'd).

	Optimal				CFRS-Ins-1				% Deviation from Optimal		
|*N*|-|*M*|-|*G*|- #*	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Total
30-30-12-1	248,9	37,8	483	952	251,5	35,8	483	<1	1,0	5,3	1,7
30-30-12-2	242	30	500	916	246,6	27,2	500	<1	1,9	9,3	2,6
30-30-12-3	238,3	38	499	1205	240,3	30,4	499	<1	0,8	20,0	3,2
30-30-12-4	223,5	36,6	434	6744	227	36,6	434	<1	1,6	0,0	1,4
30-30-12-5	240,1	41,4	430	148	245,6	39,4	430	<1	2,3	4,8	3,2
30-30-16-1	252,5	41,6	486	1853	249,6	36	486	<1	-1,1	13,5	1,0
30-30-16-2	239,1	39,2	497	1456	242	34	497	<1	1,2	13,3	2,7
30-30-16-3	302,6	38,4	501	1989	307	37	501	<1	1,5	3,6	2,4
30-30-16-4	229,5	38,5	440	3122	227,5	33,5	440	<1	-0,9	13,0	1,2
30-30-16-5	234,6	41	462	18123	229,5	34,5	462	<1	-2,2	15,9	0,5

#* indicates the instance numbers

Table C2. Comparison of CFRS-Ins-2 solution with the optimal solution and the % deviation from optimal.

	Optimal				CFRS-Ins-2				% Deviation from Optimal		
|*N*|-|*M*|-|*G*|- #*	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Total
20-20-8-1	195	30,7	267	25	202	28,6	267	<1	3,6	6,8	8,9
20-20-8-2	207,5	25,5	297	26	211	26,3	297	<1	1,7	-3,1	2,3
20-20-8-3	196,8	32,5	345	33	197,6	31	345	<1	0,4	4,6	1,3
20-20-8-4	209	23,5	298	9	222,7	25	298	<1	6,6	-6,4	10,8
20-20-8-5	193,8	25,5	299	29	206	27	299	<1	6,3	-5,9	8,2
25-25-10-1	206,9	32,7	362	96	213,9	32,6	362	<1	3,4	0,3	3,8
25-25-10-2	212	27,3	360	512	216,5	28,6	360	<1	2,1	-4,8	1,8
25-25-10-3	213	34,4	365	102	212,3	31,8	365	<1	-0,3	7,6	1,0
25-25-10-4	218,5	31,1	377	646	225	31	377	<1	3,0	0,3	3,5
25-25-10-5	231,5	32,3	335	6420	239,2	29,8	335	<1	3,3	7,7	7,5
25-25-14-1	207,4	32,2	376	42	209	31	376	<1	0,8	3,7	1,4
25-25-14-2	231,5	30,5	358	1737	249,7	30	358	<1	7,9	1,6	11,9
25-25-14-3	202,5	32,6	403	664	203	30	403	<1	0,2	8,0	1,3
25-25-14-4	193,8	31,9	389	211	208,5	30,5	389	<1	7,6	4,4	7,1
25-25-14-5	212,5	28,6	388	2327	219	32	388	<1	3,1	-11,9	1,5

#* indicates the instance numbers

Table C2. Comparison of CFR-Ins-2 solution with the optimal solution and the % deviation from optimal (cont'd)

	Optimal				CFRS-Ins-2				% Deviation from Optimal		
|*N*|-|*M*|-|*G*|	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Total
30-30-12-1	248,9	37,8	483	952	266	38,8	483	<1	6,9	-2,6	5,9
30-30-12-2	242	30	500	916	261,1	34,3	500	<1	7,9	-14,3	5,1
30-30-12-3	238,3	38	499	1205	269,8	40,5	499	<1	13,2	-6,6	9,7
30-30-12-4	223,5	36,6	434	6744	227	36,6	434	<1	1,6	0,0	1,4
30-30-12-5	240,1	41,4	430	148	251	41,6	430	<1	4,5	-0,5	4,6
30-30-16-1	252,5	41,6	486	1853	266,6	41	486	<1	5,6	1,4	5,3
30-30-16-2	239,1	39,2	497	1456	252,4	40,3	497	<1	5,6	-2,8	4,1
30-30-16-3	302,6	38,4	501	1989	317	37,3	501	<1	4,8	2,9	6,5
30-30-16-4	229,5	38,5	440	3122	249	37,7	440	<1	8,5	2,1	8,2
30-30-16-5	234,6	41	462	18123	249,5	36,4	462	<1	6,4	11,2	7,3

#* indicates the instance numbers

Table C3. Comparison of O-LRP solution with the optimal solution and the % deviation from optimal

	Optimal				O-LPR				% Deviation from Optimal		
|*N*|-|*M*|-|*G*|-#*	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Total
20-20-8-1	195	30,7	267	25	201	26	267	<1	3,1	15,3	10,4
20-20-8-2	207,5	25,5	297	26	219	19	297	<1	5,5	25,5	15,7
20-20-8-3	196,8	32,5	345	33	213,7	18	345	<1	8,6	44,6	17,4
20-20-8-4	209	23,5	298	9	234	22	298	<1	12,0	6,4	23,6
20-20-8-5	193,8	25,5	299	29	201	27	299	<1	3,7	-5,9	4,4
25-25-10-1	206,9	32,7	362	96	248,5	29	362	<1	20,1	11,3	24,1
25-25-10-2	212	27,3	360	512	215	19,5	360	<1	1,4	28,6	6,2
25-25-10-3	213	34,4	365	102	240	24,6	365	<1	12,7	28,5	19,7
25-25-10-4	218,5	31,1	377	646	265,7	28,9	377	<1	21,6	7,1	26,1
25-25-10-5	231,5	32,3	335	6420	255	26,7	335	<1	10,2	17,3	21,4
25-25-14-1	207,4	32,2	376	42	242	24,9	376	<1	16,7	22,7	20,9
25-25-14-2	231,5	30,5	358	1737	260,5	28	358	<1	12,5	8,2	20,1
25-25-14-3	202,5	32,6	403	664	250,9	27	403	<1	23,9	17,2	23,2
25-25-14-4	193,8	31,9	389	211	217	24,5	389	<1	12,0	23,2	13,5
25-25-14-5	212,5	28,6	388	2327	236	27	388	<1	11,1	5,6	12,3

#* indicates the instance numbers

Table C3. Comparison of O-LRP solution with the optimal solution and the % deviation from optimal (cont'd)

	Optimal				O-LPR				% Deviation from Optimal		
|*N*|-|*M*|-|*G*|-#*	Travel Cost	Revenue from Alternative Points	Revenue from Contracte d Points	CPU	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Total
30-30-12-1	248,9	37,8	483	952	284,5	30,8	483	<1	14,3	18,5	15,7
30-30-12-2	242	30	500	916	264	33	500	<1	9,1	-10,0	6,6
30-30-12-3	238,3	38	499	1205	274	28,5	499	<1	15,0	25,0	15,1
30-30-12-4	223,5	36,6	434	6744	260	30,5	434	<1	16,3	16,7	17,2
30-30-12-5	240,1	41,4	430	148	271	29	430	<1	12,9	30,0	18,7
30-30-16-1	252,5	41,6	486	1853	298	29	486	<1	18,0	30,3	21,1
30-30-16-2	239,1	39,2	497	1456	263	32	497	<1	10,0	18,4	10,5
30-30-16-3	302,6	38,4	501	1989	329	25	501	<1	8,7	34,9	16,8
30-30-16-4	229,5	38,5	440	3122	265	30	440	<1	15,5	22,1	17,7
30-30-16-5	234,6	41	462	18123	270	28	462	<1	15,1	31,7	18,0

#* indicates the instance numbers

APPENDIX D

Details of the computational comparison of γ/δ is bigger than 1

Table D1. Comparison of CFRS-Ins-1 solution with the optimal solution and the % deviation from optimal

	Optimal				CFRS-Ins-1				% Deviation from Optimal		
|*N*|-|*M*|-|*G*|- #	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Total
40-25-10-1	206,5	38	366	5	208,4	34	366	<1	0,9	10,5	3,0
40-25-10-2	214,6	41	368	28	217,2	38	368	<1	1,2	7,3	2,9
40-25-10-3	209,5	39	367	45	202,6	32	367	<1	-3,3	17,9	0,1
40-25-10-4	200,2	36	359	11	205,4	31	359	<1	2,6	13,9	5,2
40-25-10-5	202,5	34	353	9	212	29	353	<1	4,7	14,7	7,9
40-25-12-1	222,1	49,6	370	11	225	46	370	<1	1,3	7,3	3,3
40-25-12-2	215,8	45,2	376	1586	214,6	42	376	<1	-0,6	7,1	1,0
40-25-12-3	218,1	46	372	39	222,6	44	372	<1	2,1	4,3	3,3
40-25-12-4	220,8	51	359	41	228,4	41	359	<1	3,4	19,6	9,3
40-25-12-5	222,6	46	361	2001	225,2	39	361	<1	1,2	15,2	5,2
40-25-14-1	215,9	48,3	351	206	219,5	44	351	<1	1,7	8,9	4,3
40-25-14-2	221,4	48,2	376	239	222	46	376	<1	0,3	4,6	1,4
40-25-14-3	224,9	51	372	397	234	48	372	<1	4,0	5,9	6,1
40-25-14-4	213,5	46	359	3400	216	41	359	<1	1,2	10,9	3,9
40-25-14-5	209,5	46	361	188	222	40	361	<1	6,0	13,0	9,4
45-30-12-1	224,1	56,9	444	5212	235,6	54	444	<1	5,1	5,1	5,2
45-30-12-2	229,6	58,3	456	356	238	48	456	<1	3,7	17,7	6,6
45-30-12-3	237,8	59	420	6721	242	44	420	<1	1,8	25,4	8,0
45-30-12-4	231,6	58	470	4320	234	56	470	<1	1,0	3,4	1,5
45-30-12-5	235,9	61	481	4561	254	54	481	<1	7,7	11,5	8,2

Table D2. Comparison of CFRS-Ins-2 solution with the optimal solution and the % deviation from optimal

	Optimal				CFRS-Ins-2				% Deviation from Optimal		
$\|N\|$-$\|M\|$-$\|G\|$-#	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Total
40-25-10-1	206,5	38	366	5	230	41	366	<1	11,4	-7,9	10,4
40-25-10-2	214,6	41	368	28	231	42	368	<1	7,6	-2,4	7,9
40-25-10-3	209,5	39	367	45	222,7	34	367	<1	6,3	12,8	9,3
40-25-10-4	200,2	36	359	11	212,6	34	359	<1	6,2	5,6	7,4
40-25-10-5	202,5	34	353	9	218,6	32	353	<1	8,0	5,9	9,8
40-25-12-1	222,1	49,6	370	11	235	46	370	<1	5,8	7,3	8,4
40-25-12-2	215,8	45,2	376	1586	230	44	376	<1	6,6	2,7	7,5
40-25-12-3	218,1	46	372	39	236	45	372	<1	8,2	2,2	9,5
40-25-12-4	220,8	51	359	41	239	44	359	<1	8,2	13,7	13,3
40-25-12-5	222,6	46	361	2001	232	41	361	<1	4,2	10,9	7,8
40-25-14-1	215,9	48,3	351	206	251	44	351	<1	16,3	8,9	21,5
40-25-14-2	221,4	48,2	376	239	232	46	376	<1	4,8	4,6	6,3
40-25-14-3	224,9	51	372	397	234	48	372	<1	4,0	5,9	6,1
40-25-14-4	213,5	46	359	3400	229	43	359	<1	7,3	6,5	9,7
40-25-14-5	209,5	46	361	188	228	41	361	<1	8,8	10,9	11,9
45-30-12-1	224,1	56,9	444	5212	235,6	54	444	<1	5,1	5,1	5,2
45-30-12-2	229,6	58,3	456	356	254	52	456	<1	10,6	10,8	10,8
45-30-12-3	237,8	59	420	6721	254	54	420	<1	6,8	8,5	8,8
45-30-12-4	231,6	58	470	4320	238	56	470	<1	2,8	3,4	2,8
45-30-12-5	235,9	61	481	4561	262	58	481	<1	11,1	4,9	9,5

Table D3. Comparison of O-LRP solution with the optimal solution and the % deviation from optimal

	Optimal				O-LPR				% Deviation from Optimal		
|N|-|M|-|G|-#	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Total
40-25-10-1	206,5	38	366	5	232,5	33	366	<1	12,6	13,2	15,7
40-25-10-2	214,6	41	368	28	234	32	368	<1	9,0	22,0	14,6
40-25-10-3	209,5	39	367	45	241	28	367	<1	15,0	28,2	21,6
40-25-10-4	200,2	36	359	11	228,4	26	359	<1	14,1	27,8	19,6
40-25-10-5	202,5	34	353	9	218,6	24	353	<1	8,0	29,4	14,1
40-25-12-1	222,1	49,6	370	11	260	38	370	<1	17,1	23,4	25,1
40-25-12-2	215,8	45,2	376	1586	234	32	376	<1	8,4	29,2	15,3
40-25-12-3	218,1	46	372	39	251	32	372	<1	15,1	30,4	23,5
40-25-12-4	220,8	51	359	41	252	34	359	<1	14,1	33,3	25,5
40-25-12-5	222,6	46	361	2001	242	32	361	<1	8,7	30,4	18,1
40-25-14-1	215,9	48,3	351	206	239	41	351	<1	10,7	15,1	16,6
40-25-14-2	221,4	48,2	376	239	249	38	376	<1	12,5	21,2	18,6
40-25-14-3	224,9	51	372	397	254	34	372	<1	12,9	33,3	23,3
40-25-14-4	213,5	46	359	3400	230	32	359	<1	7,7	30,4	15,9
40-25-14-5	209,5	46	361	188	234	34	361	<1	11,7	26,1	18,5
45-30-12-1	224,1	56,9	444	5212	244,5	42	444	<1	9,1	26,2	12,8
45-30-12-2	229,6	58,3	456	356	264	39	456	<1	15,0	33,1	18,9
45-30-12-3	237,8	59	420	6721	262	42	420	<1	10,2	28,8	17,1
45-30-12-4	231,6	58	470	4320	260	48	470	<1	12,3	17,2	13,0
45-30-12-5	235,9	61	481	4561	264	44	481	<1	11,9	27,9	14,7

APPENDIX E

Details of the computational comparison where population zones coincide with alternative points

Table E1. Comparison of CFRS-Ins-1 solution with the optimal solution and the % deviation from optimal

	Optimal				CFRS-Ins-1				% Deviation from Optimal		
|N|-|M|- #	Travel Cost	Revenue from Alternative Points	Revenue from Contract ed Points	CPU	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Total
20-20-1	188	31	302	25	186,4	28,6	302	<1	-0,9	7,7	0,6
20-20-2	187,7	27	311	26	191,4	26,3	311	<1	2,0	2,6	2,9
20-20-3	177	22	321	33	182	20	321	<1	2,8	9,1	4,2
20-20-4	198	24	330	96	203	22	330	<1	2,5	8,3	4,5
20-20-5	171,5	32,3	303	512	176,7	28,6	303	<1	3,0	11,5	5,4
25-25-1	210,5	32,1	371	1029	216,3	29,2	371	<1	2,8	9,0	4,5
25-25-2	215,5	24,9	362	538	223,3	24,4	362	<1	3,6	2,0	4,8
25-25-3	222,3	21,8	384	1737	225	23,1	384	<1	1,2	-6,0	0,8
25-25-4	205,3	30	376	5421	214	28,4	376	<1	4,2	5,3	5,1
25-25-5	203,7	28	389	8674	214,4	22	389	<1	5,3	21,4	7,8
30-30-1	240,5	34	471	12609	242,6	31,4	471	<1	0,9	7,6	1,8
30-30-2	232,3	38,1	449	14520	236,3	36,41	449	<1	1,7	4,4	2,2
30-30-3	242	35	436	12982	246	30	436	<1	1,7	14,3	3,9
30-30-4	241	39,8	457	9876	246,5	35,4	457	<1	2,3	11,1	3,9
30-30-5	239,5	36,5	487	1989	252,6	36,8	487	<1	5,5	-0,8	4,5

Table E2. Comparison of CFRS-Ins-2 solution with the optimal solution and the % deviation from optimal

	Optimal				CFRS-Ins-2				% Deviation from Optimal		
|*N*|-|*M*|- #	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Total
20-20-1	188	31	302	25	200,1	32	302	<1	6,4	-3,2	7,7
20-20-2	187,7	27	311	26	202	29	311	<1	7,6	-7,4	8,2
20-20-3	177	22	321	33	191	26	321	<1	7,9	-18,2	6,0
20-20-4	198	24	330	96	220	27	330	<1	11,1	-12,5	12,2
20-20-5	171,5	32,3	303	512	190	35	303	<1	10,8	-8,4	9,6
25-25-1	210,5	32,1	371	1029	232	33	371	<1	10,2	-2,8	10,7
25-25-2	215,5	24,9	362	538	244,5	32	362	<1	13,5	-28,5	12,8
25-25-3	222,3	21,8	384	1737	246,5	29	384	<1	10,9	-33,0	9,3
25-25-4	205,3	30	376	5421	233	33	376	<1	13,5	-10,0	12,3
25-25-5	203,7	28	389	8674	227	32	389	<1	11,4	-14,3	9,0
30-30-1	240,5	34	471	12609	274,1	37,5	471	<1	14,0	-10,3	11,4
30-30-2	232,3	38,1	449	14520	243,8	38	449	<1	5,0	0,3	4,6
30-30-3	242	35	436	12982	258,9	34	436	<1	7,0	2,9	7,8
30-30-4	241	39,8	457	9876	262,5	39,4	457	<1	8,9	1,0	8,6
30-30-5	239,5	36,5	487	1989	261	36,8	487	<1	9,0	-0,8	7,5

Table E3. Comparison of O-LRP solution with the optimal solution and the % deviation from optimal

	Optimal				O-LPR				% Deviation from Optimal		
|*N*|-|*M*|- #	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Revenue from Contracted Points	CPU	Travel Cost	Revenue from Alternative Points	Total
20-20-1	188	31	302	25	203,9	20	302	<1	8,5	35,5	18,6
20-20-2	187,7	27	311	26	214	20	311	<1	14,0	25,9	22,2
20-20-3	177	22	321	33	199	16	321	<1	12,4	27,3	16,9
20-20-4	198	24	330	96	225	19	330	<1	13,6	20,8	20,5
20-20-5	171,5	32,3	303	512	197	25	303	<1	14,9	22,6	20,0
25-25-1	210,5	32,1	371	1029	243	18	371	<1	15,4	43,9	24,2
25-25-2	215,5	24,9	362	538	249	20	362	<1	15,5	19,7	22,4
25-25-3	222,3	21,8	384	1737	259	18	384	<1	16,5	17,4	22,1
25-25-4	205,3	30	376	5421	257	22	376	<1	25,2	26,7	29,7
25-25-5	203,7	28	389	8674	247	21	389	<1	21,3	25,0	23,6
30-30-1	240,5	34	471	12609	294,5	21	471	<1	22,5	38,2	25,3
30-30-2	232,3	38,1	449	14520	266,5	25	449	<1	14,7	34,4	18,6
30-30-3	242	35	436	12982	272	27,5	436	<1	12,4	21,4	16,4
30-30-4	241	39,8	457	9876	284	24	457	<1	17,8	39,7	23,0
30-30-5	239,5	36,5	487	1989	273	26	487	<1	14,0	28,8	15,5

APPENDIX F

Details of the computational runs of large-sized instances

Table F1. Comparison of large-sized problems

	CFRS-Ins-1				CFRS-Ins-2			
Data set $\|N\|$-$\|M\|$-$\|G\|$ - #	Travel Cost	Revenue from Alternative Points	Total cost	CPU	Travel Cost	Revenue from Alternative Points	Total cost	CPU
50-50-25-1	627	62,2	564,8	<1	647	65	582	<1
50-50-25-2	565	58,5	506,5	<1	582	65	517	<1
50-50-25-3	600	61,1	538,9	<1	664	67	597	<1
50-50-25-4	584	58,6	525,4	<1	614,5	63	551,5	<1
50-50-25-5	602	62	540	<2	641	65	576	<1
100-100-40-1	843	128	715	<2	871	137	734	<2
100-100-40-2	770	125	645	<2	792	129	663	<2
100-100-40-3	803	129	674	<3	819	135	684	<2
100-100-40-4	771	126	645	<3	796	131	665	<2
100-100-40-5	818	131	687	<3	838	136	702	<2
200-200-80-1	1084	216	868	<3	1132	230	902	<3
200-200-80-2	1083	216	867	<3	1142	234	908	<3
200-200-80-3	1091	215	876	<3	1151	233	918	<3
200-200-80-4	1102	220	882	<3	1124	243	881	<3
200-200-80-5	1118	220	898	<3	1136	242	894	<3