OPTIMIZATION OF A SUPPLY CHAIN NETWORK FOR BIOENERGY PRODUCTION FROM FOOD WASTE

BY

MENGYE CHEN

THESIS

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Adviser:

Professor Hayri Önal

ABSTRACT

Food waste has potential to be recycled and converted to energy and other valuable products. In China, the food waste is partially collected and processed by illegal organizations to produce ‘gutter oil’, which is a serious public health and safety issue. Therefore, the city government plans to develop a central management system where the food waste from large number of restaurants and food vendors will be collected, pre-processed at existing facilities, and then converted into bioenergy and other usable products at a central treatment facility whose location is to be determined. A mixed integer linear programming (MILP) approach is present in this thesis to determine an optimal supply chain and processing network. We first develop a p-median model and determine an optimal grouping of the waste sources in multiple clusters where each cluster is served by a single preprocessing facility. This is considered as a proxy to the aggregate cost of delivering food waste to intermediate and final processing locations. The true minimum delivery cost is then determined by routing the delivery vehicles optimally within each cluster where the waste at all sources is collected by multiple delivery vehicles. This approach is a heuristic procedure. The difference between exact optimum and heuristic solution is about 12 percent. The empirical application of the MILP model is presented with a real data set involving a large number of food waste sources in City of Shenzhen, China, and evaluate the economic viability of the centralized collection and precession system. The results show that such system is profitable and environmentally beneficial.

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Table of Contents

List of Figures

List of Tables

CHAPTER 1. INTRODUCTION

1.1. Research problem

Food waste[1] is becoming a global resource use issue nowadays. Including United Kingdom, European Union, USA and developing countries in Asia, most counties are facing this challenge. In UK, about 30% of the food purchased in the market ends up as food waste every year, which was approximately 6.7 million tons of total waste (WRAP, 2010) from all consumption activities. The total amount of waste for EU has been estimated as 89.3 million tons in 2006 (European Commission, 2010). In USA, 36.4 million tons of food waste was generated in 2012, of which only 1.7 million tons was recovered and the rest was treated as landfill, which made up the largest share, 21.1 percent of the total domestic solid waste in landfills (EPA, 2014). Since the food waste is generally comprised by organic materials that can be easily degraded by microorganisms, it has the potential of being converted to methane under anaerobic conditions. The EPA indicates that landfill is the number one human-related methane emission source in USA, which is about 20 percent of the total methane emission. A life cycle analysis (LCA) study for food waste in Europe shows that every ton of food waste contributes 1.9 tons of CO_2 to the total greenhouse gas (GHG) emission (European Commission, 2010). In a developing country like China, the food waste causes other serious problems besides environmental concerns. The food waste takes precious land space in China and

[1] Food waste is "Composed of raw or cooked food materials and includes food loss before, during or after meal preparation in the household, as well as discarded in the process of manufacturing, distribution, retail and food service activities. It comprises materials such as vegetable peelings, meat trimmings and spoiled or excess ingredients or prepared food as well as bones, carcasses and organs" (European Commission, 2010).

turns those sites into less valuable landfill sites. Due to the lack of legal and political enforcements, some illegal groups use the food waste to produce the "gutter oil" and sell it back to the food service industry and gain large amounts of profits from this illegal recycled cooking oil. This raises a serious public health and safety issue. Modern technology and science allows us to transfer organic waste into more usable and valuable products (STSC, 2014). For example, organic waste can be transformed to lower value products such as heat, power and fuel, or higher value products such as pharmaceuticals, bio-material and aviation fuel. Science and Technology Select Committee (STSC) of UK reported in 2014 that there would be roughly £100 billion market in UK for waste-converted products. About £60 billion transportation biofuel could be generated from waste alone. The goal of this thesis is to analyze the economic viability of converting food waste to lower value products (biogas and biodiesel) in a centralized treatment facility in a metropolitan area in China and determine the optimal supply chain management for collection, transportation, and processing of food waste into fuels.

The thesis uses a dataset including restaurants of all size in the city of Shenzhen, China. Until now, household food waste and industrial food processing waste are not considered as potential sources. While it is highly difficult to enforce household recycling, it is relatively easier to apply standard regulation to the food service industry in Shenzhen to collect the food waste. In this thesis, I restrict the scope of the analysis to restaurant food waste only ignoring the household food waste and industrial food manufacturing waste. This narrow scope leads to less variety on the composition of food waste.

Shenzhen is located in the south coast of China. The city has roughly 10.5 million people and 1,952.8 square kilometers of area. The urban area is about 411.8 square kilometers. As the 6th biggest city in mainland China, the population density is very high in Shenzhen. The urban area has an average of 8,600 people per square kilometers while the population density in the suburbs is 5,100 people per square kilometers. The food services industry in Shenzhen is stimulated by the large population. According to an incomplete statistical survey reported as a private report (Xu, 2012), there was proximately 50,000 restaurants in Shenzhen producing over 2,500 tons of food waste every day (solid food waste). Currently, there is no standard procedure to treat food waste alone. It is considered as domestic solid waste and sent to landfill sites. Since the food waste treatment is not regulated, illegal groups in the city collect food waste from restaurants, then use simple, primitive, non-hygienic methods to separate oil out of the waste and sell the recycled oil back to food service businesses. This is called the “gutter oil” which comprises about 10 percent of the total cooking oil sold in the market. The “gutter oil” is a common problem in some other parts of China as well and considered as a serious public health issue, since the oil separation methods seriously violate the sanitary regulations. Involving about 90 percent profit margin, this type of illegal operation has been appealing to the informal sector especially in large metropolitan area. The city authorities believe that the “gutter oil” operation may be financially empowering mobs and outlaws, which could potentially cause other public safety issues.

Having the above concerns, the city government of Shenzhen is seeking for feasible solutions to the food waste utilization and is currently in the process of planning a centrally managed system where food waste can be collected and processed in a safe and economically efficient way. A sound operational analysis of a profitable, regulated and environmental friendly business operation may increase the public confidence for local authorities to regulate and enforce a centralized food waste treatment system.

To address the issues above a mathematical programming model is developed in this thesis and solved using the data from Shenzhen. The model partitions the food waste sources scattered throughout the Shenzhen metropolitan area into an optimal number of service areas where each area is assigned to a pretreatment station which sorts the food waste, separates the organic and other solid waste from the collected waste, and transfers those to a final processing facility that converts the organic waste to fertilizer, biofuel, and bioenergy. The model determines the boundaries of all service areas optimally together with the entire supply chain network, namely the size and location of pretreatment and final processing facilities and assignment of individual service areas to those processing facilities.

1.2. Literature review

The bioenergy and biorefinery is a very broad topic. The related literature defines the supply chain network as: harvest, storage, and transportation of feedstocks (usually biomass), biorefinery location and size, pipeline/ delivery and terminals/ clients that may use the end product(s) (Iakovou et al., 2010; Papapostolou et al., 2011; Xie 2014). This leads to a multi-stage transshipment problem which is typically formulated as a mixed integer linear programming (MILP) model that can be solved using commercial optimization software (see, for example, Chen and Önal, 2014). Xie (2014) presents a review of optimal supply chain management studies in bioenergy production. Unlike energy crops, waste wood material or other common bioenergy feedstocks, the food waste supply chain problem is basically a local waste management and logistics problem[2]. The common approach for evaluating waste to energy potential did not consider the transshipment aspect of the problem (Münster et al., 2011; Mavrotas et al., 2013). Instead, previous studies assumed the transshipment cost as a constant part of the total operational cost regardless of the size of the operation. An industrial operational analysis study by Mohammadshirazi (2014) did not consider transportation at all. Another study by Lu (2014) assumed that all the available biomass was accessible for the biorefinery facility disregarding the cost of transportation. This thesis addresses the issue of transshipment in bioenergy from food waste considering restaurant food waste as the only feedstock source. In spirit

[2] Moreover, food waste supply does not have seasonal fluctuations as other bioenergy feedstock, such as energy crop, and is produced locally.

it is somewhat similar to a recent study by Ng et al. (2014). However, the focus of that study was on municipal solid waste and the possibility of different waste-to-energy (WTE) conversion methods. The modeling methodology used in the present study is fundamentally different from the multiple objective optimization methodology used by Ng et al. who introduced a fuzzy parameter to represent the satisfaction level when considering different objectives. The MILP methodology was used in two previous studies by Dondo and Cerdá (2014) and Cóccola et al. (2013) who studied cross-dock distribution system and multi-echelon supply chain system, respectively.

1.3. Data sources

The data set used in the mathematical programing model is obtained mainly from Baidu API services, a search engine web site in China. The geographic data set includes the name, address and longitude/latitude information for 12,450 restaurants and 121 municipal solid waste (MSW) collection hubs[3] in Shenzhen. Since Google cannot be fully accessed in mainland China, Baidu.com is more commonly used and has more comprehensive information about regional/spatial aspects in China. Baidu API service allows users to access and download the geographical data from its Baidu Map geo-database by a user-defined Java script. However, Baidu API services have constraints on free license users' accessibility to the database, so the location data did not include every restaurant in the city of Shenzhen. I assumed that the location data included the bigger restaurants in the

[3] MSW is usually concentrated in MSW hubs and then shipped to landfill sites

city, since the internet search engine has the convention to list more popular results on the top of the search results. The location data of five industrial parks in Shenzhen is obtained with the same method and used for modeling future facility site selections. If a centralized treatment facility is to be built in near future, it is assumed that it would be built in one of those five industrial parks.

The capital cost of the centralized treatment facility is partially calculated by using the EPA Food Waste Biogas Economic Model (FWBE), which was created by the EPA region 9, in 2010. The model is modified for the specific purposes of this study in consultations with professional engineers in Baxter & Woodman Inc. and Greeley and Hanson LLC. The price information for equipment is collected from commercial venders. Random sampling method is used to assign food waste data to individual restaurants. The details of the data processing will be explained in Essay One.

1.4. Contributions

There is a strong motivation among policy makers to enforce restaurant owners to hand over their waste to a centrally managed waste treatment system, in order to stop the recycling operations of illegal organizations and take advantage of a ‘free’ resource for producing bioenergy and other value products at the expense of transportation and processing costs. The present study is an effort to provide insight to the city government in a big metropolitan area about the possibility of solving the food waste problem in an economically efficient way, namely by designing an optimal supply chain network for converting waste-to-energy and other value products. The study also provides a methodological framework that can be applied to similar problems in large cities considering WTE is an option.

The major scholarly contribution of the thesis are:

1. The development of a mathematical modeling framework for optimizing local food waste collection and processing into energy and other value products in a metropolitan area: Unlike most standard transshipment problems, here we address the problem of delivering small amounts of waste from numerous sources to a relatively large number of processing location(s). A generalized biomass to bioenergy supply chain model such as the ones used by Chen and Önal (2014) and Xie (2011) would not apply to the problem at hand. Rather, in the case of waste collection a vehicle routing model is needed to minimize the cost of pick-ups and moving from one source to another rather than delivering the feedstock directly from sources to processors. The present thesis addresses the routing aspect of the problem using a two-stage modeling methodology where a mixed integer linear programming (MILP) model is developed for each stage.
2. A different approach to address the computation resource limitations: Even a moderate size multi-stage transshipment problem can be difficult to solve using MILP and may require a large amount of memory. For instance, in a previous study by Xie (2014), it is reported that a problem with 74 biomass sources, 7 storage hubs and 29 facility sites was solvable in 1 hour. Chen and Önal (2014) considered a much larger model which also involved multi-year

dynamics. Because of computational difficulties, they had to use a two-stage backward recursive procedure using MILP to find only an approximately optimal solution because the size of their problem was too big to handle by commercial solvers. The problems solved in those studies are very small compared to the problem addressed here. More importantly, the modeling methods used in this study are fundamentally different from the methods used in the above studies.

3. Incorporating vehicle routing in the bioenergy supply chain study: Food waste is produced locally but dispersed across a fairly large area (city). Collecting and transporting food waste is fundamentally different from harvesting and shipping biomass as bioenergy feedstocks, since typically a waste delivery truck cannot take a full load at one location and deliver it directly to a processing facility. Usually, a restaurant produces a small amount (e.g. about 35 kg of dry waste in the present study) of food waste daily, which is much smaller than one truckload. Therefore, each truck needs to stop at multiple sources to pick up their waste until it reaches its capacity, then takes the load to processing stations, and performs many round trips until completing the entire delivery. Therefore, the food waste problem is essentially a Vehicle Routing Problem (VRP). The VRP is one of the most extensively studied problem in the transportation literatures. However, it has not been applied to bioenergy supply chain studies, most of which focused on biomass (energy crops, crop residues and corn) transportation from fairly

large aggregate supply areas (in some US studies counties were considered as the smallest spatial units, e.g. Kang et al, 2009; Melo et al. 2009; Huang et al. 2010; Parker 2011), where large amounts of deliveries were assumed to be done directly between supply points and processing facilities without routing. Due to the scope and scale of the problem, the food waste transshipment problem has a different problem setting. A previous study by Cóccola et al. (2013) constructed a three echelon supply chain network including manufacture, warehouse and customers. Their MILP model minimized the total transportation cost and transportation time as alternative objective functions. The food waste supply chain problem, includes restaurants, pretreatment stations and a central treatment facility as nodes, which is also a three echelon network. However, Cóccola's study used a very small supply chain network, which had only 20 nodes (2 manufactures, 2 warehouses and 16 customers. In the present study, there are over 12 thousands network nodes, which causes a major challenge because of the limited computational capacity. Another previous study by Önal et al. (1996) addressed a somewhat similar problem, using MILP and dynamic programming methods, but they considered a two-echelon supply chain including only 30 warehouses and 40 clients. Due to the size of the problem addressed here the formulations used in those studies would be computational challenging since the MILP models would be extremely difficult to solve, if not impossible. For these reasons, a hybrid heuristic-optimization approach is developed here in a two-stage solution procedure. First, the entire network is divided into several smaller two-echelon supply chain networks. In the second stage, each of those smaller networks is optimized by solving a relatively small VRP formulation. This approach finds a sub-optimal solution which is considered as a proxy to the true optimal solution. The details of this methodology, solution accuracy, and computational aspects will be elaborated in the subsequent chapters of this thesis.

1.5. Outline of the thesis

The thesis has five chapters. The second and the third chapters contain two essays. The first essay, Essay One presents a set partition model which produces the baseline solution that is used as input for the model developed in a second model that addresses the routing problem. Essay One describes the mathematical model, a MILP, used in the first step of the two-step solutions procedure, and presents empirical results of an application of the model using the Shenzhen data. The second essay, Essay Two presents a MILP for routing the delivery vehicles, which is the second step of the solution procedure, and presents empirical results of the model applied to the Shenzhen food waste data and restaurant waste collection problem. Chapter 4 presents a discussion of the model robustness and a sensitivity analysis varying the values of some key model parameters and data for which reliable estimates are not currently available. Chapter 5 presents a summary and discusses the limitations of the approach used in this thesis. Every chapter has the related figures included in the text body and the tables listed at its last section.

CHAPTER 2. ESSAY ONE:

OPTIMIZING FOOD WASTE TRANSSHIPMENT AND SERVICE AREA COVERAGE

2.1. Introduction

There are over 50,000 restaurants in city of Shenzhen, China, estimated to be producing over 2,500 tons of solid food waste (SFW)[4] every day. Yet, there has not been any specified food waste treatment regulations or standards in the city. The food waste has been considered as part of municipal solid waste (MSW) and treated as landfill. At landfill sites, food waste can be decomposed by microorganisms under anaerobic condition and converted to greenhouse gases (GHG) such as methane and carbon dioxide (WRAP, 2008). The GHG impact of untreated food waste was estimated to be 1.9 tons CO_2-e per ton of waste (European Commission, 2010), which means that food waste in Shenzhen might be contributing as much as 4,750 tons of CO_2-e GHG emission every day, which is equivalent to the GHG emission of 339,951 vehicles[5]. Treating food waste as landfill also consumes land space and reduces the value of usable land. City of Shenzhen is the 6th largest city in mainland China. The city has 10.46 million people and the population density is about 8,600 per km^2. The land space is very limited, so saving landfill space is a strong incentive to regulate food waste treatment. Another equally important incentive is the "gutter

[4] Food waste contains solid food, oil and water, we define all insoluble matters as solid food waste (SFW) and all soluble matters plus liquid phase waste including alcohol and water bases solutions as liquid food waste (LFW)
[5] EPA estimated a typical passenger vehicle emits 5.1 tons of CO_2 every year. (EPA, 2011)

oil"[6] problem in China. Various illegal groups collect the food waste from restaurants and separate the oil content by very simple and unregulated methods under poor hygienic conditions. The gutter oil is then sold in the food market as a low price cooking oil alternative. This poses a very serious health problem, because the gutter oil is believed to contain certain pathogens, toxic compounds and carcinogens, such as Polycyclic Aromatic Hydrocarbon (PAHs). Unfortunately, gutter oil comprised about 10% of the cooking oil market in mainland China in 2012. This regulatory loophole increases the public health risk. Besides, authorities also believe that the local underworld is financially empowered from the gutter oil business, due to its high profit margin which may cause other social problems.

Science and technology have allowed us to convert certain types of waste into useful and valuable products (STSC, 2014). Anaerobic digestion (AD)[7] is a mature technology to produce biogas from organic solid waste, which has been studied since 1930s (Lusk, 1998). A previous literature demonstrated that AD was the most cost-effective biological process to treat solid organic waste[8], since AD has high energy recovery and limited environmental impact (Mata-Alvarez et al., 2000). The recovered biogas from AD can be further converted to electric power and heat, or be purified and compressed into transportation fuel or as an alternative for natural gas. Biodiesel is a mono-alkyl ester of long chain fatty acid from bioenergy feedstock

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[6] Illicit cooking oil reprocessed from waste oil collected from restaurant fryers, sewer drains and grease traps. The reprocessing is very rudimentary.

[7] AD is a natural process in which microorganisms break down organic matter, in the absence of oxygen, into biogas (a mixture of 60-70% of methane [CH_4] and 30-40% of carbon dioxide [CO2]) and digestate (a nitrogen-rich residue, which can be used as fertilizer). (STSC, 2014)

[8] Normally, it is organic-biodegradable-waste with moisture content between 85-90%. (Mata-Alvarez, 2000)

(Mohammadshirazi et al., 2014). It is a good biodegradable drop-in fuel[9] that can be an alternative for the petroleum-based diesel and it is better in term of sulfur content, flash point and aromatic content. The conventional (first generation) biodiesel feedstocks are agricultural products, more specifically, oil crops such as soybean and palm. Commercial biodiesel is an expensive fuel, due to high prices of eatable oils, and has economic implications by raising the food prices if produced at large scale. However, this may not be the case for waste oil from food waste, which is much a cheaper source that can be collected at the cost of transportation and processing only. When the tipping fee is charged for waste recycling and the environmental impacts are considered, waste oil even has a negative cost. Biodiesel production from oil is a mature technology. It was first practiced as early as 1853 and has been well studied since 1937[10]. A previous study by Mohammadshirazi et al. (2014) indicates that the total cost of producing biodiesel from waste cooking oil was less than half of its total revenue, and 54 percent of the cost was due to the collection and transshipment of waste oil to processing facilities.

Both biogas and biodiesel production form food waste have potential to solve the food waste problem and eliminate the health risks caused by recycling oil from repeated use. Like other bioenergy feedstocks, the challenge is the transportation and logistics cost (Ekşioğlu et al., 2009). This is because bioenergy feedstocks have lower bulk energy density compared to fossil fuels and their supplies are

[9] Drop-in fuels are biofuels that meet the existing diesel, gasoline, and jet fuel quality specification and be ready to "drop-in" to existing infrastructure by being chemically indistinguishable from petroleum derived fuels. (DOE)
[10] History of biodiesel: http://www.odec.ca/projects/2007/ardi7m2/history_biodiesels.html

geographically dispersed. From the industrial operation perspective, minimizing the transportation and logistics cost is the primary focus (Xie et al., 2014). Many studies addressed the problem of minimizing cost and environmental impact of biomass transportation. Xie et al. 2014 studied the issue using a multi-period model of cellulosic bioenergy supply chain. Their model emphasized the different mode of transportation. This is an important issue because the cellulosic biomass is a bulky material and usually the supply points are highly dispersed in space. Tong et al, (2014) looked at the possibility of using existing petroleum refinery facilities for distributing advanced biomass converted drop-in fuel[11]. Ekşioğlu et al. (2009) studied the supply chain of corn and corn stover for potential cellulosic ethanol production. They used a multi-stage transshipment model to analyze the dynamic of biomass collection supply chain and operation of biorefineries considering the seasonal variations in bioenergy feedstocks supply, and facility site selections. None of the previous studies in the bioenergy supply chain literature has considered the food waste as the feedstock. While most of the studies presented in the supply chain literature ignored the industrial operation costs, which is a reasonable omission since there is a lack of the industrial scale information of cellulosic or drop-in biofuel production. Bioenergy economic evaluation studies ignored the operational issues related to the supply chain (Münster and Meibom, 2010, 2011; Lu et al, 2014; Ng et al, 2014).

[11] "Drop-in biofuels are the hydrocarbon fuels substantially similar to gasoline, diesel or jet fuel. These fuels can be made of variety of biomass feedstocks including crop residues, woody biomass, dedicated energy crops and algae." (US Department of Energy)

The food waste as a bioenergy feedstock has some peculiarities compared to traditional bioenergy feedstocks such as corn and cellulosic biomass (energy grasses, corn stover, and wheat straw): First, generally, food waste supply is not seasonal, rather the waste is produced at steady levels and every day. Second, the food waste supply is not as dispersed in space as energy crops or corn production, it is usually generated within the boundaries of cities and metropolitan areas, where the distances between supply points, thus the distance to an existing or potential processing facility, is generally very short. Third, unlike the biomass transportation that can be done by use of different means (barges, tail, truck, etc.), the main mode of food waste transportation is trucking. Fourth, food waste can be treated using mature technologies which have been studied extensively over years, therefore it is easier to obtain operational costs data to model the industrial operation aspects of the issue.

The AD process and biodiesel production from food waste require a centralized facility which would require large capital investment (Mata-Alvarez et al., 2000). However, once installed, such facilities can operate for a long time. There is no study that measured the positive social impacts of food waste treatment, in particular termination of the waste oil used as gutter oil and resulting reduction in public health risks. Therefore, here we consider only the economic benefits from the end products after waste treatment and cost of collecting and processing the food waste for bioenergy and other products. Despite this simplification, determining the economically efficient operations and supply chain network is a computationally difficult problem. This study is an effort to look into the profitability of such operations through optimizing the transshipment of food waste. Designing an optimal supply chain and evaluation of industrial operations may provide useful insight to investors, businesses and local government officials and increase their confidence on WTE businesses and willingness to implement appropriate policies and regulations to facilitate the food waste collection and processing. Such policies may include food waste collection mandates, subsidies to cooperating restaurant owners, or waste collection authorizations provided to business entities.

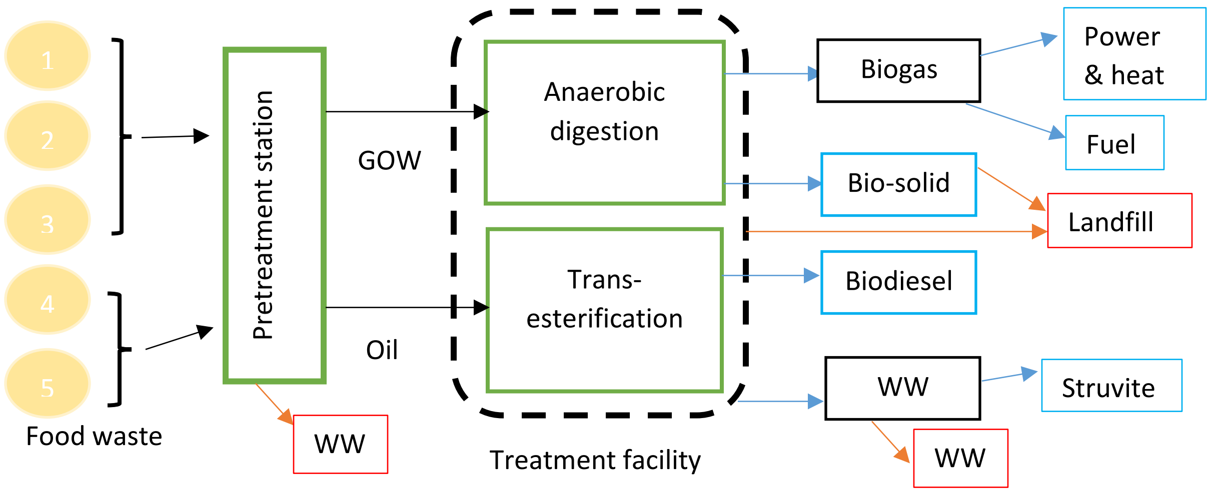
2.2. Methodology

2.2.1. Problem description

As stated earlier, the supply chain of food waste to energy (WTE) operation is different from that of conventional bioenergy production. Figure 2.1 demonstrates the envisioned supply chain and production process structure of food waste treatment for bioenergy. In this system, the food waste is collected from individual restaurants where typically the waste production by a single source would not be enough to make a full truckload. Therefore, one truck may need to visit several, in some cases many restaurants until reaching its full delivery capacity and delivering its load to a pretreatment station. At the pretreatment station, the food waste is drained, degreased, grinded, and compacted into the granular organic waste (GOW), and the waste oil is recovered from drained wastewater by oil-water separation. After the pretreatment, the GOW and waste oil are separately delivered to a centralized food waste treatment facility and the wastewater from pre-processing is discharged into the sewer pipeline. In the treatment facility, the GOW is treated by the AD process and converted to biogas, water and biosolids. The excessive water from the AD process is further treated to extract the struvite[12], and then discharged into the sewer pipeline. The waste oil is treated by the transesterification process and converted to biodiesel. Biodiesel can be sold directly on-site or sold to local fuel distributor who deliver the product by their own vehicles. Biogas can be purified and used to generate electric power and heat or used as transportation fuel after compressing. According to the US Department of Energy (DOE), when biogas is further treated to meet the natural gas pipeline specification (by increasing its methane content and decreasing contaminants), it can be distributed through the existing natural gas pipeline system. After all, some non-biodegradable solid and unsold biosolids are sent to the landfill.

[12] Struvite is a crystalline fertilizer that contains Mg, NH_4 and P. It forms under alkaline condition usually in nutrient rich environment such as wastewater and anaerobic digestion effluent. (Rahman et al., 2014)

Figure 2.1 Supply chain structure of food waste treatment for bioenergy



A well designed supply chain and management plan may significantly reduce the transshipment costs and maximize the overall profitability of the system. Designing the optimal supply chain means: a) identify the number, location and capacity of pretreatment stations needed to process the collected food waste; b) identify the location of a centralized food waste treatment facility; c) identify the coverage (area) of food waste collection; d) identify the groups of restaurants providing food waste to each pretreatment facility; e) the amounts supplied by each pretreatment facility to the central facility; and f) determine the amount of different value products and bioenergy produced. The total waste generated in the entire area and the total amount of waste shipped from waste sources to processing facilities determine the amount of waste that should be directed to landfills (if any). The supply chain structure and optimum management plan interacts with each other since the locations of pretreatment stations determine the transshipment cost of the operation, which in turn impacts the food waste collection coverage area and the amount of collection.

To accomplish the above objectives, a mixed integer linear programming (MILP) model is developed. A mathematical representation of the model is described below.

2.2.2. Model specification

The mixed integer programming model is consistent with the supply chain structure shown in Figure 2.1. The objective of the model includes three components: daily revenue, daily operational cost and annual fixed cost. It is assumed that the capital cost for building the facilities and the cost of purchasing equipment is paid in annual payments over years at a specified interest rate. Other important assumptions include: a) the general annual operational cost (such as power utility bills, salaries, office supplies, etc.) is constant and independent of the operational cost related to food waste handling and transshipment; b) all shipments occur within the city boundaries and delivery times do not pose a limitation; c) there are enough trucks to deliver the collected food waste; d) the city traffic will not be affected (traffic jams, rush hours, etc.). We use a 1-1 ratio the waste oil to biodiesel conversion (Ma and Hanna, 1999), and consider the struvite as a value product which forms a small fraction of the total GOW feeding into the plant[13]

The model presented below groups a large number of waste sources and a 'central site' in each cluster and the distances between cluster centers and pretreatment facilities which serve their assigned clusters is minimized. This

[13] Struvite is a valuable final product from the AD process, yet, its production is highly volatile but small. Therefore the assumption of a small fraction can reduce its volatility effecting to the overall model.

problem is known as the p-median or p-region problem in the mathematical modeling literature (See, for example Duque et al, 2011). Grouping the waste sources in this leads to compact collection area and is likely to make the waste collection less costly, but it may not necessarily lead to an optimal supply chain network where the total collection and delivery costs is minimized simultaneously while considering the optimal routing of delivery vehicles. Therefore, the clustering solution should be considered as a proxy to the true optimal coverage solution. In the clustering model, the load at each source is assumed to be delivered to a cluster center, where both the cluster center and assignment of waste sources to cluster are determined by the model. When determining the optimal clustering, the distances between individual sources in a cluster and the cluster center multiplied by the unit transportation cost are used as surrogates for the delivery costs. This assumes that all loads are delivered directly to the cluster center, therefore, almost all such deliveries will be partial loads. On the other hand, the deliveries made between a selected pretreatment station and the final processing facility are assumed to be done in full truckloads whose trip numbers is determined by the total waste collected from all sources in the cluster(s) assigned to that pretreatment station. The total cost associated with these deliveries is determined by the distances driven between the two facilities multiplied by the unit delivery cost. As mentioned above, a given delivery truck may need to visit multiple waste sources (restaurants) to fill up and deliver the load to a pretreatment station. This is essentially a vehicle routing problem, which is not explicitly modeled here to reduce the computational complexity problem. The vehicle routing will be studied Essay Two.

In the mathematical model, we use the following notation:

Parameters:

i, l	Food waste source locations
j	Potential pretreatment station locations
k	Potential central treatment facility site locations
p_g	Price of biogas, \$/1000 ft^3
p_e	Price of electricity, \$/KWH
p_s	Price of biosolids, \$/ton
p_{ds}	Price of biodiesel, \$/gal
p_{str}	Price of struvite, \$/ton
p_{tip}	Price of tipping fee for each ton of food waste collected from source, \$/ton
en	Energy content of biogas, KWH/ ft^3
ef	Energy to power conversion efficiency
de_{ds}	Density of biodiesel, tons/gal
de_s	Density of organic solid waste, tons/yd^3
cov_{str}	Struvite conversion factor, ton of struvite from GOW
c_t	The cost of a full load trip, \$/km
c_p	Unit transportation cost during the source packing stage, \$/ton/km
c_{dis}	Solid waste disposal cost, \$/yd^3
c_{CAP}	Capital cost of the facility except some major equipment costs listed below, \$
$c_{O\&M}$	Operation and Maintenance (O&M) cost except transshipment cost, \$
c_{eng}	Cost of a biogas-electricity generator plus installation and related site building, \$
c_{com}	Cost of a biogas compressor plus installation and related site building, \$
c_{pre}	Cost of building a pretreatment station, \$
$d_{i,j}$	Distances from sources i to pretreatment j stations, km
$d_{j,k}$	Distances from pretreatment stations j to central facility k, km
$d_{i,l}$	Distances between waste sources, km
s_i	The amount of food waste daily supply from source i, tons
wc_{be}	Water content (free liquid) of food waste before pretreatment

wc_{af}	Water content of GOW (after pretreatment)
pc_j	Handling capacity of pretreatment station j, tons
oil	Waste oil content in food waste before pretreatment
$loss$	Percentage of oil not being separated during pretreatment
tra	Percentage of oil wicked with GOW
fc_k	Central facility k GOW handling capacity, tons
foc_k	Central facility k waste oil handling capacity, tons
org	Organic content of GOW
sr	Percentage of organic solid reduction due to AD process
cov_{og}	Organic matter to biogas conversion factor, one ton of organic to ft^3 of biogas.
$cond$	Percentage of gas reduction due to biogas conditioning (purification)
ec	Biogas-electric power generator capacity, KWH/day
bc	Biogas compressor capacity, ft^3/day
$load$	Full truck load, tons

Variables

$BIOG_c$	Biogas output as fuel or blend with natural gas supply, ft^3
$BIOG_e$	Biogas output as feedstock for electricity generation, ft^3
$BIOS_k$	Amount of biosolids produced, tons
$W_{i,j}$	Amount of food waste shipped from sources (i) to pretreatment stations (j), tons
$W_{j,k}$	Amount of GOW shipped from pretreatment stations (j) to central treatment facility (k), tons
$O_{j,k}$	Amount of waste oil shipped from pretreatment stations (j) to central treatment facility (k), tons
R	Daily revenue, $
DC	Daily operational cost, $
AC	Annual fixed cost, $
LF_k	Non-biodegradable portion of food waste, tons
NC_i	Amount of food waste that is not collected at i, tons
CL_i	Amount of food waste of each sources group at i, tons
$SO_{j,k}$	Amount of waste oil wicked in GOW, tons
GAS_k	Total amount of biogas produced during AD process, ft^3

Integer variable

$WT_{i,j}$	Numbers of daily trips made to ship food waste from i to j
$WT_{j,k}$	Numbers of daily trips made to ship GOW from j to k
$OT_{j,k}$	Numbers of annual trips made to ship waste oil from j to k

N_{eng} Numbers of biogas-electric power generator required for the plant

N_{com} Numbers of biogas compressor required for the plant

N_{pre_j} Numbers of pretreatment stations needed to be built at location j

Binary variable

$P_{i,l}$ It equals to 1, when waste source l groups with source i

F_k It equals to 1, when the location k is selected to build the facility

The complete algebraic model is presented below. All variables except binary variables and integer variables are defined as non-negative real-valued variables. For convenience, upper case symbols are used for endogenous model variables while lower case symbols denote scalars and parameters used in the algebraic model.

$$\text{MAXIMIZE}(R - DC) * 365 - AC \tag{1}$$

Where:

$$\begin{aligned} R = {} & BIOG_c * p_g + BIOG_e * En * Ef * p_e + \left(\sum_k BIOS_k\right) * p_s + \left(\sum_j \sum_k \frac{O_{j,k}}{de_{ds}}\right) * p_{ds} \\ & + \left(\sum_j \sum_k W_{j,k}\right) * cov_{str} * p_{str} + \left(\sum_i \sum_j W_{i,j}\right) * p_{tip} \end{aligned} \tag{2}$$

$$\begin{aligned} DC = {} & c_t * \left(\sum_i \sum_j WT_{i,j} * d_{i,j} + \sum_j \sum_k WT_{j,k} * d_{j,k}\right) + c_p * \sum_i \sum_l d_{i,l} * s_i * P_{i,l} \\ & + c_{dis} * \frac{(\sum_k LF_k + \sum_i NC_i)}{de_s} \end{aligned} \tag{3}$$

$$\begin{aligned} AC = {} & c_t * \sum_j \sum_k OT_{j,k} * d_{j,k} + c_{CAP} + c_{O\&M} + N_{eng} * c_{eng} + N_{com} * c_{com} + \sum_j N_{pre_j} \\ & * c_{pre} \end{aligned} \tag{4}$$

The objective function (1), involving the terms defined in Equations (2-4), represents the total revenue, R, which is maximized subject to the constraints that will follow. In the model, it is assumed that all the biofuel and biosolids produced in the central treatment plant can be sold at the ongoing market prices. This is a realistic assumption given that the demand for transportation fuels and energy is high enough to utilize the entire fuel/energy produced by this system. Also, the amount of biosolids that can be produced by the WTE system is small compared to their total supply, therefore the WTE system would not have a significant effect on biosolids prices. The model also assumes that the solid waste disposal is done by a third party at a flat rate for service; for simplicity, the distance between uncollected waste sources and landfill site(s) is not considered in the model.

The model constrains are described below

$$\sum_{l} s_i * P_{i,l} = CL_i \; \forall \; i \tag{5}$$

$$\sum_{i} CL_i \leq \sum_{i} s_i \tag{6}$$

$$\sum_{i} P_{i,l} = 1 \; \forall \; l \tag{7}$$

$$\sum_{j} W_{i,j} + NC_i = CL_i \; \forall \; i \tag{8}$$

$$W_{i,j} = WT_{i,j} * load \; \forall \; i,j \tag{9}$$

$$\sum_{l} P_{i,l} \leq m * P_{i,i} \tag{10}$$

Constraints (5-9) combined with constraint (10) to ensure that each waste source, *l*, is grouped with other sources to form a cluster centered at some source *i*. Equation (5) aggregates the amounts of waste at all sources grouped in cluster center at *i*. Since cluster assignments are determined endogenously, the total waste in cluster i is defined as a variable. Constraint (7) ensures that every waste source can be packed at most in one cluster. Constrain (10) ensures that only the sources gathering their own waste could serve as cluster centers and can receive food waste from other sources. In this case, up to m sources, where m is an arbitrarily specified large number, can be assigned to the cluster centered at i. Otherwise, no such assignment can be done. Constrain (6) ensures that after packing, the variable was still contained within given data range. Some extremely dispersed waste sources may not be collected for processing, if not collected, the waste at those sources will be directed to landfill (NC_i), as stated by constrain (8). Constraint (9) relates the waste amount shipped to pretreatment facility (in full loads) and the outgoing delivery trips from that facility to the conversion facility.

$$\left(\sum_i W_{i,j}\right) * (1 - wc_{be}) \leq pc_j * N_{pre_j} \ \forall j \tag{11}$$

$$\left(\sum_i W_{i,j}\right) * (1 - wc_{be}) * oil * (1 - loss) = \sum_k O_{j,k} \ \forall j \tag{12}$$

$$\left(\sum_i W_{i,j}\right) * (1 - wc_{be}) * oil * loss * tra = \sum_k SO_{j,k} \ \forall j \tag{13}$$

$$\sum_i W_{i,j} * (1 - oil) * \frac{(1 - wc_{be})}{(1 - wc_{af})} = \sum_k W_{j,k} \ \forall j \tag{14}$$

Constraints (11-14) model the transshipment at the second layer of the supply chain structure. Constraint (11) ensures that food waste shipped to station j cannot exceed its handling capacity. Constraints (12-14) describe the oil, water and solid separations during the pretreatment phase. The main function of pretreatment stations is to remove the excessive water, reduce the weight and volume of the food waste (14) and separate waste oil (12). Note that, the waste oil that is wicked by GOW is not included in Equation (14), thus the shipping of wicked oil is omitted. Equation (15) describe the AD process and organic matter to biogas conversion. Therefore, only a small percentage of oil can be hold in GOW. Otherwise, if the held oil adds up to a large amount of GOW shipment, the transshipment cost would be impacted. This assumption holds when the pretreatment station has a high efficiency in oil/solid separation, which is a matter of cost[14].

$$\left(\sum_j W_{j,k} * \left(1 - wc_{af}\right) * org * sr * cov_{og} * cond\right) + \sum_j SO_{j,k} * cov_{og} * cond = GAS_k \ \forall\, k \tag{15}$$

$$\sum_j W_{j,k} * \left(1 - wc_{af}\right) * org * (1 - sr) = BIOS_k \ \forall\, k \tag{16}$$

$$\sum_k F_k = 1 \tag{17}$$

$$\sum_j \left(W_{j,k} + SO_{j,k}\right) \leq F_k * fc_k \ \forall\, k \tag{18}$$

$$\sum_j O_{j,k} \leq F_k * foc_k \ \forall\, k \tag{19}$$

$$\sum_j W_{j,k} * \left(1 - wc_{af}\right) * (1 - org) = LF_k \ \forall\, k \tag{20}$$

Constraints (15-20) describe the third layer of the supply chain and the AD process. The AD process is simplified by use of a constant conversion factor in Equation (15). A more comprehensive kinetic model for the AD can be found in a previous study by Pavlostathis (2011). Note that, the wicked oil was omitted in transshipment phase, yet, it is considered as a feedstock for the AD process.

[14] Better oil and solid separation requires more water usage to wash off oil and better quality standard of the equipment.

Constraints (15) and (16) represent the biogas and biosolids production from the AD. Biogas usually requires to be purified before use, the term $cond$ was used as the gas purification factor along with the organic to biogas conversion factor (cov_{og}). The AD processes cannot convert all the organic matter to biogas, so a solid reduction factor (sr) is used to determine the amount of solid converted during the AD process. Constraint (17) ensures that there can be only one central treatment facility built in the city. Constraints (18) and (19) ensure that the incoming feedstocks (GOW and oil) cannot exceed the handling capacity of the plant. Equation (20) represents the inorganic portion of food waste that is separated by the system at the end.

$$\sum_{k} GAS_k = BIOG_c + BIOG_e \tag{21}$$

$$\frac{BIOG_e * cov_e}{ec} * 1.2 \leq N_{eng} \tag{22}$$

$$\frac{BIOG_c}{bc} * 1.2 \leq N_{com} \tag{23}$$

$$W_{j,k} = WT_{j,k} * load \tag{24}$$

$$365 * O_{j,k} = OT_{j,k} * load \tag{25}$$

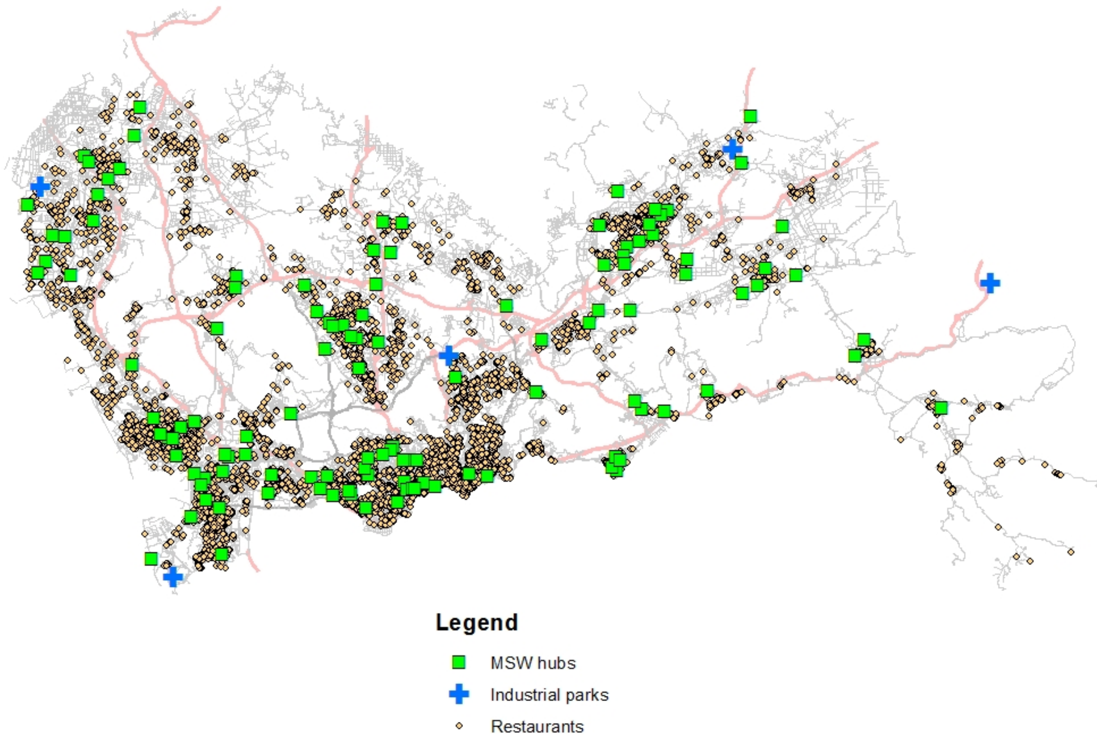
Constraint (21) is an accounting equation for the usages of biogas. We consider two alternative uses of biogas, namely biogas sold as bio-fuel or biogas sold for power generation. Constraints (22) and (23) calculate the number of equipment related to different biogas uses, namely biogas electric power generators and biogas compressors, respectively. A 20 percent safety factor is used, which is an engineering convention to select a higher capacity equipment to minimize the risk caused by the volatility of product flow. Constraints (24) and (25) ensure that shipment of GOW and waste oil are integers (representing the numbers of truckloads). Note that since the oil content is generally a small portion of the food waste, the amount of waste oil may not reach a full truckload within a day. Therefore, in constraint (25), the total number of shipping trips for entire year is calculated instead of daily trips. If the annual waste oil shipping trips ($O_{j,k}$) is less than 365, it means that the waste oil stays overnights in some pretreatment stations before shipping to the central treatment facility.

2.2.3. Case study

The model is implemented using the restaurant waste and location data and existing and potential facility locations in the city of Shenzhen, China. Before presenting the model results, we first present the steps of processing the raw data to generate the actual input data used in the empirical application.

We obtained the location of 12,450 restaurants and 121 municipal solid waste (MSW) hubs in Shenzhen, through Baidu API services. The data set included the name, address and longitude/latitude information for all data points. We assumed that restaurants as food waste sources and future pretreatment stations would be built on the existing MSW hubs. We selected five industrial parks as possible plant locations for central food waste treatment facility. Figure 2.2 displays the raw data map.

Figure 2.2 Map view of raw data



There is no comprehensive data set about the food waste production in China. Most of the statistics for food waste use random-draw methods rather than the actual food waste data for individual restaurants. In the data set used here, we know where the restaurants are, but we do not know their size; therefore the amount of food waste generated by each restaurant is unavailable. As a proxy, we used a random sampling procedure to generate a representative data base. We used the statistical results of a previous reports by Xu (2012) to form a triangular distribution for waste generation by an average (representative) source, which is then used to randomly generate an artificial food waste data for all sources. The

Matlab code can be found in Appendix A. The parameters used for the triangular distribution are listed in Table 2.1 in Section 2.5. The artificial food waste data could potentially impact the accuracy of model results. Therefore, a sensitivity analysis is carried out to address this problem in Chapter 4. According to the random sampling, each of the 12,450 restaurant produces between 3kg to 197kg of food waste every day with the average of 68.01kg and total of 846.74 tons per day. The random sampling yielded more food waste than the reported amount in Xu, (2012). Our samples are bigger and more well-known restaurants, so this difference is considered acceptable. Due to the limitations on Baidu API database access, we modeled the only one fourth of the restaurant population (50,000 in total), which contributes to one third of the daily food waste production in Shenzhen (2,000 to 3,000 tons per day in total).

To reduce the computational requirements (processing time and memory), the restaurant location data set was aggregated. We first ranked restaurants based on their distribution density weight in their 500m radius. The weight considered the amount of food waste produced at the source, the average direct distance[15] between the sources and the number of sources (see Equation 27). Then, starting from the restaurant with the highest weight, we summed the food waste amounts of all restaurants within 500m radius without double counting. After aggregation, the data size reduced from 12,450 to 946. The aggregated data set was used in the model as food waste sources. The ranking procedure is explained as follows:

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[15] Direct distance is the linear distance between two points without considering the actual street travel distance, the data is generated from longitude/latitude information.

$$w_n = wa_n * m/\overline{d_{n,n}} \;\; \forall\, d_{n,n} \leq 500m \tag{26}$$

Where w_n is the distribution density weight, n is the node, wa_n is the amount of food waste from node n, m is the number of nodes within 500m radius and $d_{n,n'}$ is the direct distances between each node. The number of nodes divides by the average direct distance between nodes yields a value representing the density of sources at node n. Then multiplying the value with the food waste amount yields the density weight. If the source has a high value weight, it means the source produce a large amount of food waste while there are many sources close to it. The Matlab code can be found in Appendix A.

Table 2.2 lists the input parameters used in the model. We put an effort to obtain actual data from China, so that the model could be more representative for the local problem. However, some price data could be obtained only from US references. There were two reasons: first, some products do not have market prices in China, such as landfill costs, prices of biosolids and struvite process, etc.; second, we could not obtain reliable figures for some of the data from Chinese sources. The US prices are usually lower than the Chinese prices for biodiesel and natural gas, therefore, we the assumed that the facility would sell the final products at lower prices to enter the market. There is no standard market price for biogas; even in the US biogas is usually converted to heat and power as end products. We used the natural gas price as a proxy for biogas prices due to the potential of biogas to be blended with natural gas. Most of the parameter related to food waste processing were conservative estimates based on the equipment specification sheet and engineering conventions. For example, the biogas purification usually reduces the flow volume of gas by 25-40 percent, which is assumed as 40 percent reduction here. The struvite production rate is determined by the phosphorous content of the food waste, which was a missing information. We use a very small conservative estimate since the struvite production rate is usually small (Westerman et al, 2009).

The capital costs are calculated by using a part of the Food Waste for Biogas Economic (FWBE) model. All the equipment prices and specifications are listed in Table 2.3. The construction quotes were provided by engineers in the environmental consulting industry (Table 2.4). We note that some major equipment units are 0 in Table 2.3, such as biogas electric power generators, biogas compressors and pretreatment processing equipment units. Those costs were separated out for the model to determine their quantities as model results. The annual operation and maintenance cost was assumed to be $5.4 million per year. All the up-front capital costs were treated as an annual payment to investors using a discount rate of 7.2% over 15 years.

The distance data were calculated by the ArcGIS origin-destination (OD) cost matrix analysis. The random sampling and data aggregation were done with a Matlab linear algorithm. The overall MILP model was run with General Algebraic Modeling System (GAMS) incorporating CPLEX 11.0.1. To reduce the number of binary variables needed when clustering the waste sources around endogenously determined cluster centers, the model considers only the pair of nodes where: a) the distances between waste sources are less than 15km, and b) distances between waste sources and pretreatment stations are less than 20km. This reduces the computation time enormously without loss of realism because in reality, distant sources would not be located in the same cluster or served by a remote pretreatment station. The MILP model is solved using GAMS/CPLEX assuming a relative optimality tolerance of 1 percent (i.e. optcr=0.01). The GAMS code can be found in Appendix A. The next section presents the model results in map forms generated by ArcGIS.

2.3. Results and discussion

The MILP model was solved using the CPLEX solver 11.0.1. The baseline problem had 43,838 equations, 273,774 single variables and 231,721 discrete variables[16], and it was solved in 1,979 seconds. This section reports the model results of the baseline study.

2.3.1. Baseline food waste collection results

The model yielded an optimal objective value to be $50,363 thousand, as the possible annual profit for the central food waste treatment facility. We broke down the financial results into revenues in Table 2.5 and costs in Table 2.6.

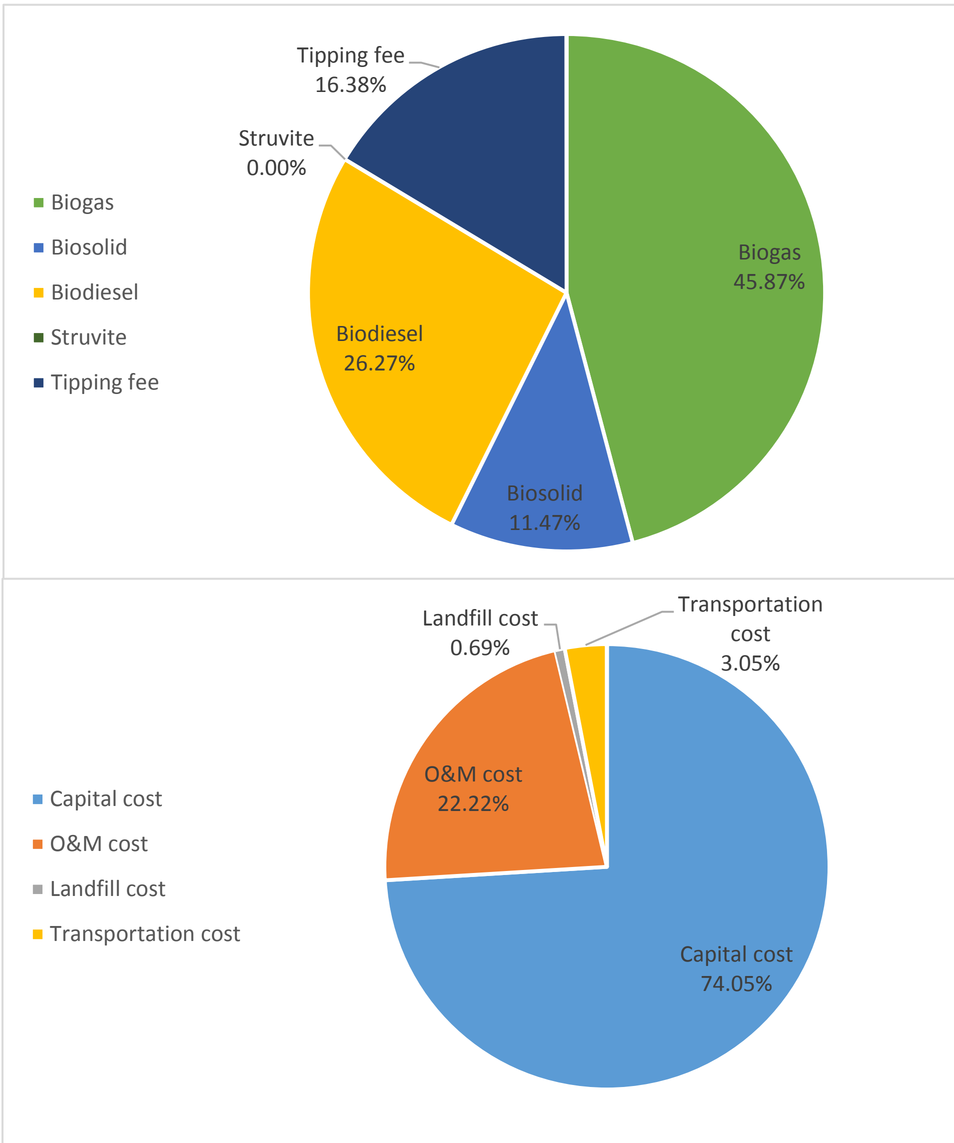
The total daily revenue is about $205 thousand, or $75 million a year. As shown in Figure 2.3, the biogas as fuel is the biggest revenue source followed by the biodiesel, which are 46 and 26 percent of the total revenue, respectively. The model did not select biogas for electric power generation. This is a reasonable finding, since with a 35 percent energy conversion efficiency the wasted 65 percent energy

[16] Discrete variables include binary variables and integer variables. (GAMs Users Guide)

cannot generate revenue for the plant combined with the costly biogas electricity generator (Table 2.6), which makes biogas electricity generation a very expensive alternative. However, in reality, most of the biogas producers choose to produce electric power instead, because the oil industry has not yet fully opened the door for distributing biogas using existing natural gas pipeline system and there is no related policy or regulation supporting the biogas industry (Underwood, 2013). The DOE believes that biogas purification technology is not fully developed and tested yet. Plus, business owners have concerns about the market demand. A possible alternative is using biogas as transportation fuel. Regular gasoline vehicles can be modified easily to use biogas as fuel, which would require an extra fuel tank to hold enough biogas for the vehicle to travel sufficiently long distances (since biogas has less energy density than gasoline[17]). We did not model the demand side explicitly, rather we assumed that all the biogas produced by the system will be sold at the price of natural gas.

[17] DOE Alternative Fuel Data Center: http://www.afdc.energy.gov/fuels/emerging_biogas.html

Figure 2.3 Revenue and cost



As shown in Figure 2.3, most of the cost is related to plant capital investment. The model suggests building 15 pretreatment stations, 45 biogas compressors to treat biogas and no biogas electricity generator. With these findings and using the information given in Table 2.3 and Table 2.4, the overall capital cost is estimated as \$162.3 million. Based on a 7.2% discount rate and 15 years of payback period, this leads to an annual payment to investors of $18 million and total annual cost of $24.3 million. The annual transshipment cost is about $665 thousand. Note, however, that the estimated transshipment cost ignores vehicle routing during the waste collection, thus it is likely to be a somewhat overestimation of the true delivery cost. This issue will be addressed in Chapter 3 by incorporating optimum routing of the delivery vehicles within each cluster obtained from the model used in this chapter.

Figure 2.4 Profitability with electricity generation

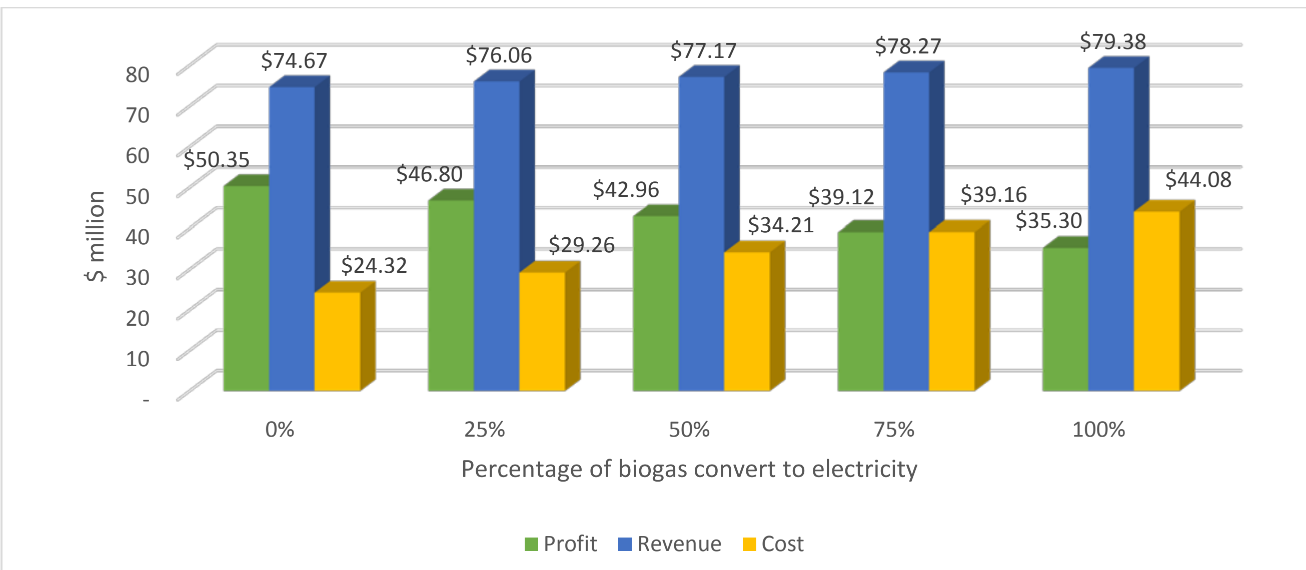


Figure 2.4 illustrates the change in revenue generation at different utilization rate of biogas in electricity generation. There is a clear trend that when the biogas usage for power generation is increased, the total revenue increases. However, the total cost also increases at a higher rate, therefore the profit decreases. This trend only holds when the price of biogas is the same as the market price of natural gas, which is $8 per a thousand ft^3. As mentioned earlier, biogas does not have a

standard market price. A simple calculation was done to find a biogas price that could make the biogas usages indifferent. The question was set as: at what price of biogas would the profit of using all of the biogas to generate electricity be equivalent to selling all of the biogas as fuel? The result is \$4.52 per thousand ft^3. When the biogas price is lower than the \$4.52 threshold, producing electricity with biogas would be preferred. This can be a financial planning indicator to determine how the plant would operate in the future. It should be noted that, the cost increase is caused mostly by equipment costs, which increases the capital cost. From an investor's perspective, higher capital cost could be a benefit. A higher priced equipment or higher capital cost could be equivalent to a higher value of permanent assets for the investors, which means possible higher asset earnings in the future or some positive impacts in the future stock market. Meanwhile, investors will have less risk for their investments, since biogas has higher market uncertainty compared to electricity. This explains why most of the biogas producers in the US prefer electricity generation. If the plant uses 100 percent of the biogas for power generation, the annual revenue becomes \$79 million, while the annual cost becomes \$44 million which gives an annual profit of \$35 million. The total overall capital investment becomes \$340 million.

The above results show that using food waste to generate bioenergy can be a profitable business operation. Due to its profitability, most of the food waste is collected in the model solution. The model estimates that 846.15 tons out of 846.74 tons of food waste would be collected, which is correspond to a 99.93 percent food waste recovery. We assumed a 6.3 percent of oil content in the food waste therefore, that is equivalent to 53.48 tons of waste oil recovered from restaurants every day instead of collection of the oil for recycling. About 43 tons of recovered waste oil is converted to biodiesel, about 4.3 tons is treated with GOW in AD process and 6.4 tons is washed out to sewer system during pretreatment. These results would provide valuable insight to investors and incentives to policy makers to develop a food waste collection and processing industry and generate safe renewable energy from a resource that is currently being used in environmentally and socially unsafe manners.

2.3.2. Optimal supply chain structure

The model selected the site called Shekou industrial park as the location for the central food waste treatment plant. The site is at the south end of Nanshan peninsula of Shenzhen. The industrial park sits next to the Shekou Port, which is one of two international ports in Shenzhen. The model also selected 15 municipal solid waste (MSW) hubs out of 121 as pretreatment station sites. 964 waste sources were grouped in 78 clusters. Every cluster has average 10.85 tons of solid food waste (SFW) collection, where the largest cluster has a total waste collection of 410.59 tons. Figure 2.5-2.8 display the optimal supply chain structure for different parts of the city. The downtown area is where most of the restaurants are located and majority of the food waste is produced. The model results suggest to locate pretreatment stations at the highest waste source population density areas (mostly downtown) or close to the central treatment facility, which is an intuitive result.

The central treatment facility is also selected to be close to downtown. The reason for having pretreatment stations in the system was to reduce the volume and weight of the collected food waste in order to reduce the transportation cost. However, the model prefers to transport raw food wastes long distances rather than transporting treated granular organic wastes (GOW). This is an unintuitive result since GOWs are more compacted and easier to transport. The reason for this is to optimize the capacity of pretreatment stations so that the investment costs can be reduced. This suggests that the capital cost of building pretreatment stations drives the optimal supply chain rather than the cost of the waste transshipment. A sensitivity analysis on truck numbers, purchasing cost and related impacts on the supply chain will be further discussed in Chapter 4.

Figure 2.5 Downtown Shenzhen supply chain map

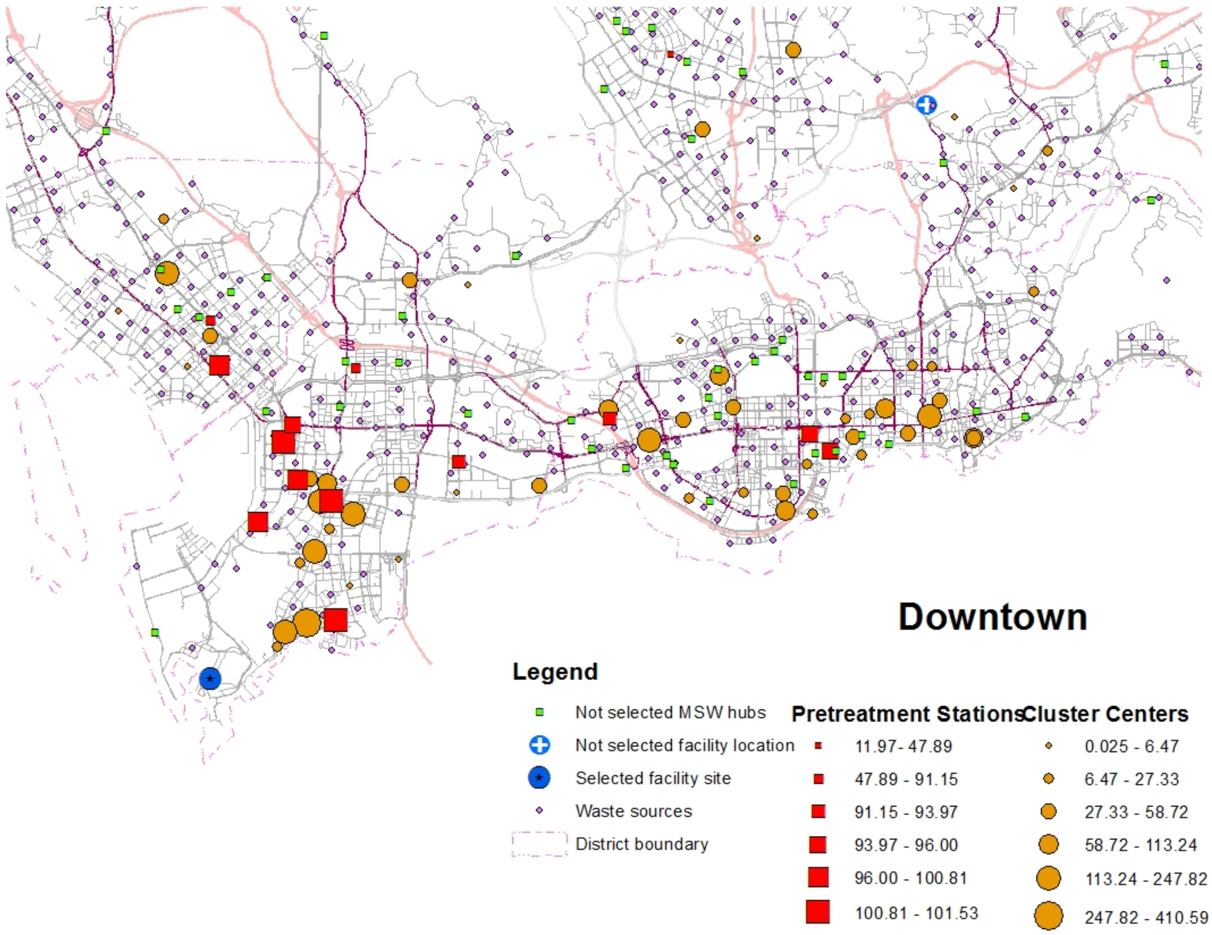


Figure 2.6 Northwest Shenzhen supply chain map

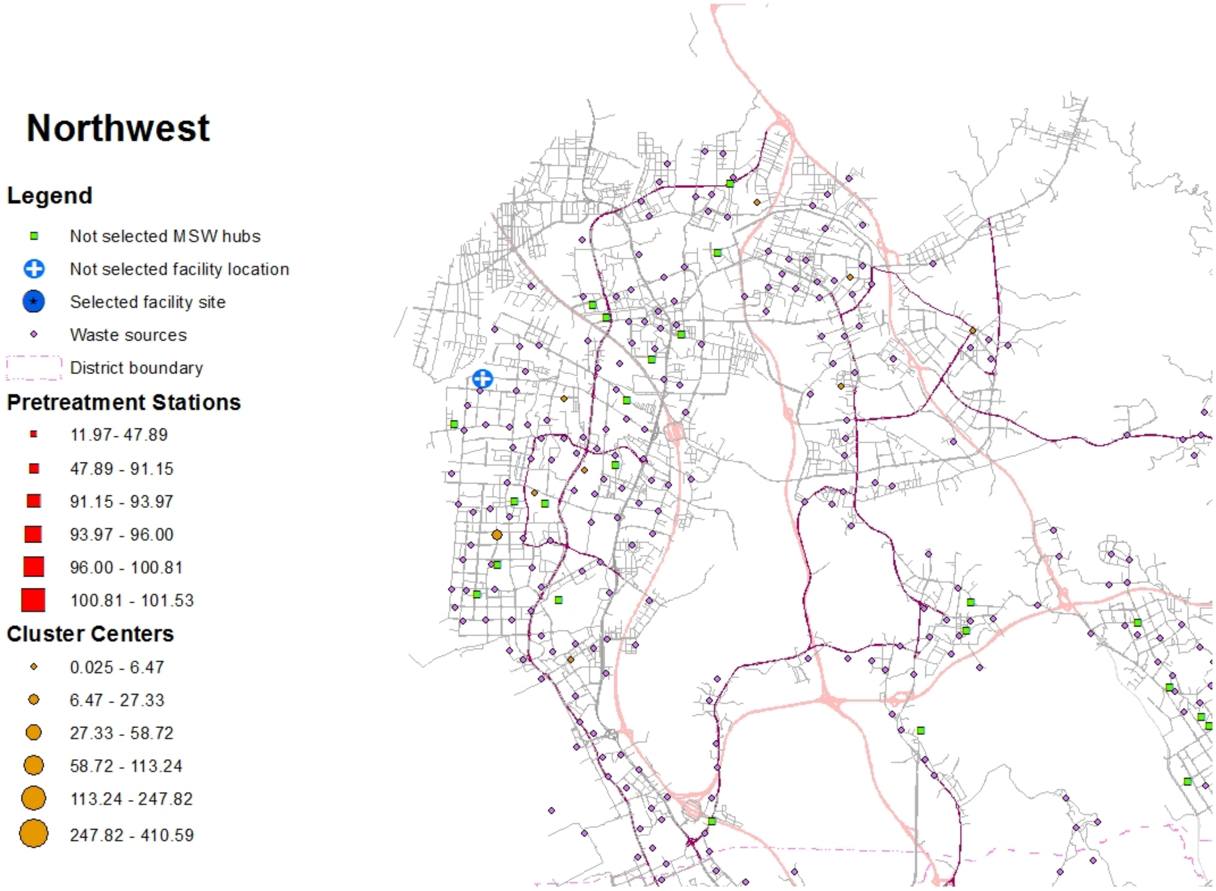


Figure 2.7 North Shenzhen supply chain map

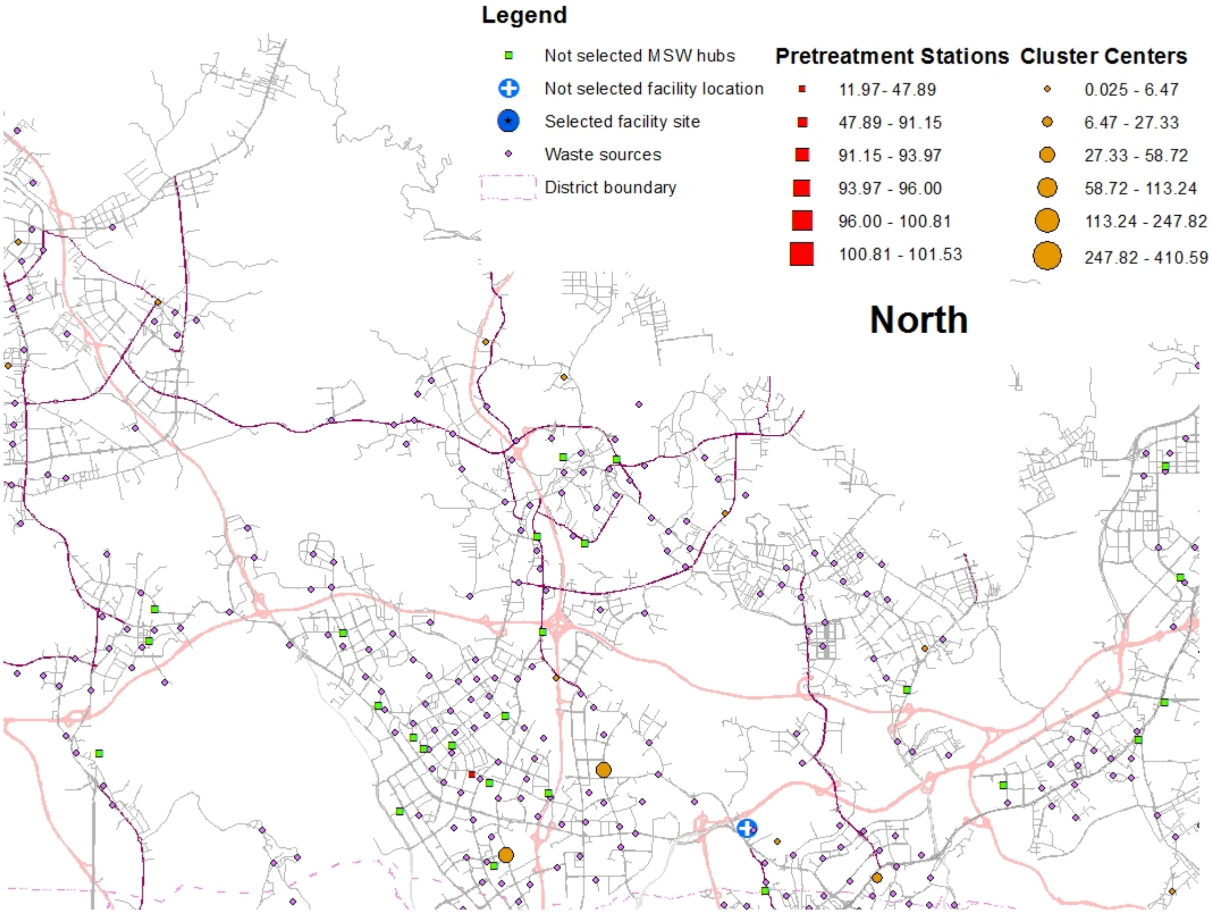
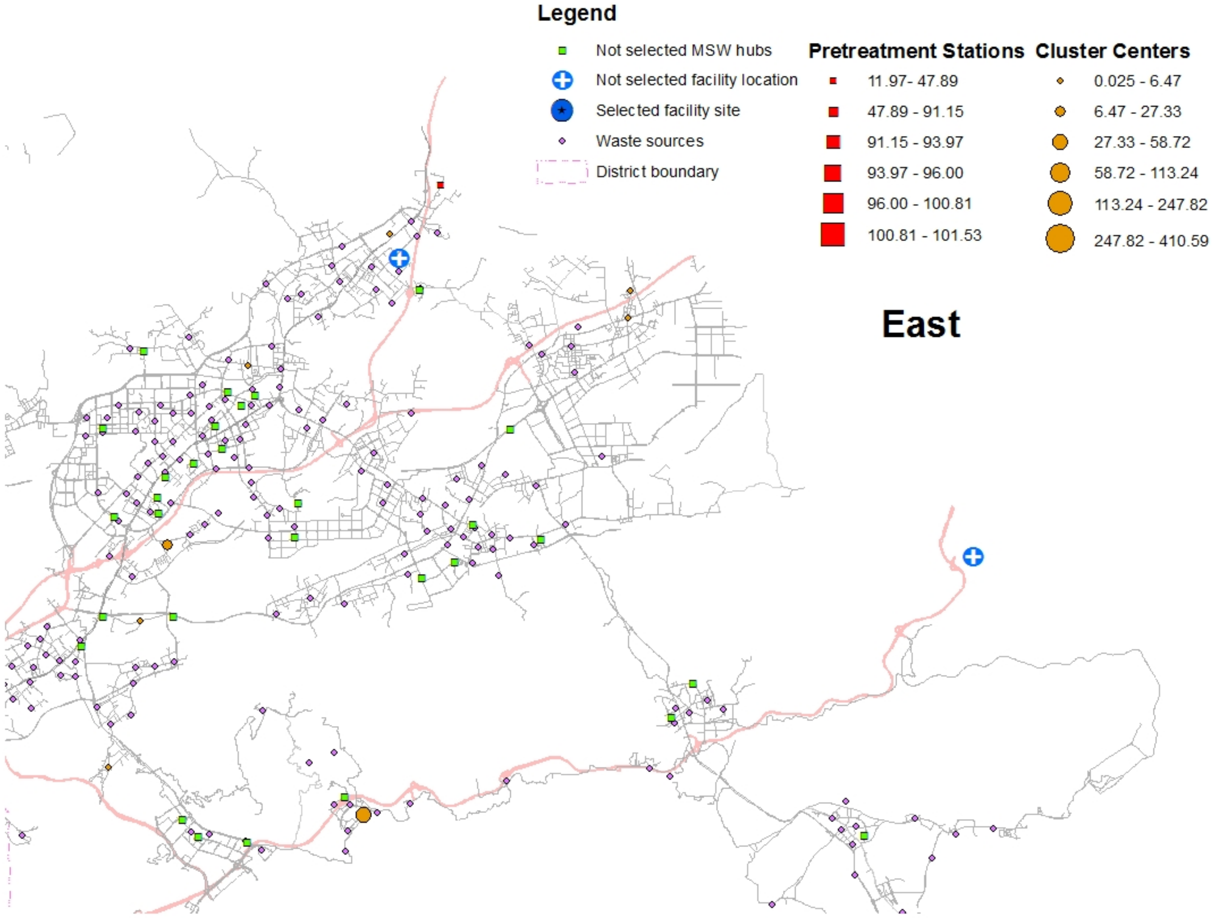


Figure 2.8 East Shenzhen supply chain map



In Figures 2.5-2.8, the sizes of the pretreatment stations and cluster centers are shown by the sizes of the circles the larger the circle, the more the GOW produced. For the cluster centers, the size of the square is used to show the amount of the raw food waste collected. Since the model maximized the capacity of pretreatment stations, all stations have similar sizes (Table 2.7) except one station. The cluster sizes vary across clusters. The downtown area has more clusters compared to suburbs (Figures 2.5 and 2.6), and the clusters are generally larger than the clusters in suburbs.

Figure 2.9 Pretreatment station service areas

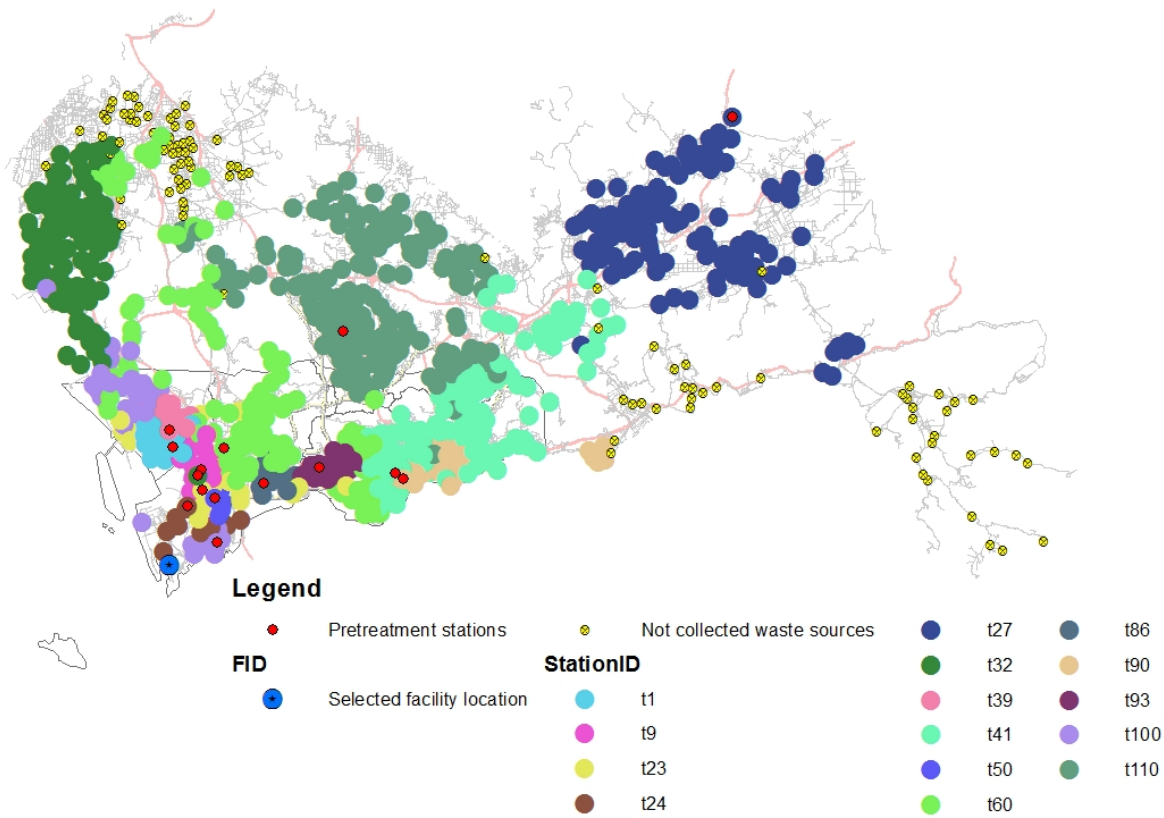


Figure 2.9 illustrates the food waste collection coverage of each selected pretreatment stations and the waste sources that are not included in the service area (i.e. the sources send their waste to landfills). Pretreatment stations located at sites t27, t32, t41, t60 and t110 need to cover large areas in the north part of the city. The service areas are much smaller in the downtown area than suburbs, since downtown has more waste produced in a small area. Some service areas overlap with other areas, especially in downtown and the area that is close to the central treatment facility. The collection begins with the pretreatment stations sitting at the center of a high source population density area and then some pretreatment

stations pick up the rest. Table 2.7 indicates that station t27 has the smallest waste collected, which is consistent with the information in Figure 2.9 where t27 service area has the largest number of sources from which waste is not collected (sent to landfills). Most those waste sources are located near the boundaries of service areas or the furthest from the pretreatment stations. However, some station service areas have many sources that are close to the station but the waste is not collected from those sources. An example is the source at the south end of t27 territory and some of those uncovered source at the north part of t60 territory. Most likely this is caused by the 1 percent optimality tolerance used when solving the MILP model. If the model could be solved to the exact optimum (which could take substantially more processing time), such close waste sources should be collected too. As mentioned in Section 2.3.1, the food waste recovery is 99.93 percent, therefore, those sources have small amounts of waste and may be assigned to the nearest preprocessing facility without a significant change in cost and revenue calculations.

Table 2.8 shows the waste source assignments for each pretreatment stations and the amount of raw food waste processed by individual facilities. Comparing Table 2.7 and 2.8, shows that the raw food waste collection is not as evenly divided as the GOW production. This is due to the cross shipping, which means that some food waste is delivered to multiple pretreatment stations from the same cluster, which is not restricted in the model set up. The details of crossing shipping logistics can be found in the GAMs reports in Appendix B.

2.4. Conclusions

This study presents an effort to design an optimal supply chain for a non-traditional bioenergy feedstock, namely food waste, that may contribute to the solution of renewable energy generation and GHG mitigation goals as well as to solve the health risk problem that is currently associated with the recycling of some waste materials particularly in the form of cooking oil. A spatial explicit MILP model is developed to determine the optimal grouping of waste sources in compact clusters, location of food waste treatment facilities (both intermediate and final), the waste collection coverage areas and supply chain network, and possible profitability of a hypothetical food waste treatment and renewable energy generation system. The case study for the City of Shenzhen demonstrates that such a system may be economically viable and collecting food waste as bioenergy feedstock can be a profitable business practice. The specific empirical findings show that Shenzhen could make $50 million of profit annually, by using the biogas produced by the hypothesized system as a renewable substitute natural gas.

2.5. Tables

Table 2.1 Statistics for food waste production in China

Mean*, kg/d	Min*, kg/d	Max*, kg/d	Water** content	Oil** content	Organic** content
35	3	200	74.75%	6.32%	98.70%

* All food waste data are in bulk weight, without free liquid

** Average percentages

Table 2.2 Parameters

Parameter	Value	Unit	Source
p_g	8	$/10³ ft³	US EIA[18]
p_e	0.08	$/KWH	Xu, 2012
p_s	120	$/ton	Farmers Weekly[19]
p_{de}	4.28	$/gallon	US DOE[20]
p_{str}	300	$/ton	Westerman et al, 2009
p_{tip}	10	$/ton	Xu, 2012
En	0.322671	KWH/ft³	Internal source*
Ef	35	%	FWBE[21]
$density_{de}$	0.9	ton/m³	
$density_s$	1,450	ton/yard³	
Cov_{str}	0.000015		Assumption
c_{trip}	0.81	$/km	Xu,2012
c_{pack}	0.075	$/km/ton	Gob et al, 2010
c_{dis}	24.68	$/yard³	Internal source*
wc_{be}	74.75	%	Xu, 2012
wc_{af}	40	%	JWC[22] SWM-11
$PreC_j$	96	ton/day	JWC[23] SWM-11
oil	6.32	%	Xu, 2012
$loss$	20	%	Assumption
$trap$	40	%	Assumption
FaC_k	2500	ton/day	Assumption

[18] US Energy Information Administration (EIA): http://www.eia.gov/dnav/ng/ng_pri_sum_dcu_nus_m.htm
[19] http://www.fwi.co.uk/articles/19/06/2010/121897/digesting-biosolid-pricing.htm
[20] US Department of Energy (DOE): http://www.afdc.energy.gov/fuels/prices.html
[21] EPA Food Waste Biogas Economic Model
[22] Based on the JWC Environmental company product brochure
[23] Based on the JWC Environmental company product brochure

Table 2.2 cont'd

$FaoC_k$	250	ton/day	Assumption
org	98.7	%	Xu, 2012
sr	75	%	Assumption
Cov_{og}	33,075	ft^3/ton	Internal source*
$cond$	60	%	Assumption
$EngC$	103,200	KWH/day	Caterpillar[24] CG-260
$ComC$	317,832	ft^3/day	CSH[25]
$load$	12	ton	Assumption

*Data were obtained from engineer consultant

Table 2.3 Central facility equipment pricing specification

Major costs	Cost per unit ($/unit)	Units Needed	Total cost ($)
50' Truck weighing scales	$32,700	2	65,400.00
Foundation for scales inclu. Const.	$20,000	2	40,000.00
Print Kiosk (for weight records)	$4,000	2	8,000.00
Software capable of running reports	$10,000	1	10,000.00
PC computer	$2,000	10	20,000.00
Card Scanner	$5,000	15	75,000.00
Odor Control System	$85,000	8	680,000.00
Front-End Loader	$118,000	7	826,000.00
Pre-processing equipment	$87,000	0	-
Metering Pumps	$40,000	15	600,000.00
Pumps	$90,000	65	5,850,000.00
Buffer tank ($/ft3)	$9	10,000	90,000.00
Mixers	$40,000	14	560,000.00
Gas collection equipment	$75,000	14	1,050,000.00
H2S Scrubber Tank	$5,000	14	70,000.00
H2S scrubber media (Sulfa Treat)	$5,760	14	80,640.00
Solids drying area ($/ft2) concrete slab	$30	2,000	60,000.00
Monitoring equipment (SCADA)	$100,000	20	2,000,000.00
Pearl system	$1,000,000	2	2,000,000.00

[24] Based on the Caterpillar company product brochure
[25] Based on the CSH company product brochure

Table 2.3 cont'd

Gas engine	$3,000,000	0	-
Dewatering	$120,000	5	600,000.00
Biogas compressor	$60,000	0	-
CHP system	$500,000	0	-
Software Program Design	$100,000	1	100,000.00
New Water Service	$110	1	110.00
BioSmart Ct-3 for biodiesel	$335,919.5	1	335,919.50
Digester vessel ($/gallon)	$2.00	14,000,000	28,000,000.00
Total		$43,121,069.50	

Table 2.4 Quote for plant construction

Costs	**Factors to equipment cost**	**Cost ($)**
Installation	0.35	15,092,374.33
Piping	0.16	6,899,371.12
Electrical	0.2	8,624,213.90
Instrumentation	0.1	4,312,106.95
Buildings	0.4	17,248,427.80
Plant service	0.08	3,449,685.56
Site improvement	0.15	6,468,160.43
Mobile & demobile	0.2	8,624,213.90
Sub Total		$113,839,623.48
Contingency	0.15	17,075,943.52
Engineering and management	0.15	17,075,943.52
Total		$147,991,510.52

Table 2.5 Baseline results: daily revenue

Final products	Biogas as fuel	Biogas to power	Biosolids	Biodiesel	Struvite	Tipping fee
Revenue	$93,836.24	$0	$23,471.16	$53,748.11	$5.99	$33,511.04
Quantity	11,729,530 ft^3	-	195.593 tons	43.785 tons	19.95kg	3,350.10tons

Table 2.6 Baseline results: annul cost

Name	Unit value	Quantity	Cost
Capital cost	$16,500,000	1	$16,500,000
O&M cost	$5,400,000	1	$5,400,000
Biogas electric generator cost	$1,300,000	0	$0
Biogas compressor	$23,000	45	$1,035,000
Pretreatment station	$33,000	17	$462,000
Landfill cost	$24.68/yard^3	13.50 ton/day	$167,743.60
Transshipment cost			$740,272.45

Table 2.7 Daily GOW and waste oil production of pretreatment stations

Station ID	GOW, tons	Waste oil, tons
t1	100.607	3.258
t9	95.007	3.077
t23	100.527	3.255
t24	100.815	3.265
t27	11.972	0.388
t32	101.526	3.288
t39	89.673	2.904
t41	96	3.109
t50	101.526	3.288
t60	91.146	2.952
t86	93.971	3.043
t90	96	3.109
t93	92.945	3.01
t100	101.526	3.288
t110	47.889	1.551

Table 2.8 Waste sources assignments to pretreatment stations

Station ID	Total food waste, tons	SFW, tons	Source assignments
t1	77.44075	19.55379	a56,a58,a113,a135,a157,a174,a181,a253,a312,a313,a350,a362,a419,a470,a485,a583,a722,a744,a753
t9	105.1737	26.55635	a33,a39,a40,a92,a121,a141,a148,a220,a228,a245,a246,a271,a303,a348,a409,a479,a492,a615,a812,a925
t23	207.3624	52.359	a19,a26,a31,a32,a45,a71,a80,a89,a112,a125,a128,a138,a156,a167,a193,a226,a270,a302,a316,a437,a439,a510,a532,a534,a725,a769
t24	53.66182	13.54961	a61,a81,a86,a122,a260,a384,a395,a454,a547,a632,a674,a803
t27	189.2961	47.79727	a105,a124,a126,a137,a150,a164,a168,a177,a202,a215,a229,a232,a233,a241,a256,a263,a264,a284,a289,a297,a298,a311,a315,a319,a323,a327,a328,a333,a355,a356,a373,a379,a382,a401,a406,a408,a412,a424,a427,a430,a435,a442,a447,a451,a464,a475,a489,a500,a512,a523,a539,a554,a559,a562,a564,a570,a572,a581,a590,a602,a614,a617,a626,a634,a639,a642,a646,a648,a649,a660,a663,a668,a672,a678,a681,a685,a687,a692,a697,a703,a704,a705,a709,a714,a715,a716,a717,a726,a740,a746,a748,a757,a759,a775,a786,a795,a802,a805,a809,a810,a814,a816,a818,a844,a846,a847,a850,a855,a859,a864,a865,a869,a872,a876,a877,a883,a887,a888,a894,a895,a911,a940
t32	117.0133	29.54587	a115,a129,a186,a247,a254,a274,a276,a282,a300,a317,a329,a360,a363,a369,a378,a383,a386,a389,a393,a414,a420,a422,a426,a432,a436,a449,a450,a455,a466,a467,a469,a477,a480,a486,a488,a493,a494,a525,a526,a528,a538,a552,a558,a561,a579,a582,a589,a593,a608,a619,a620,a623,a625,a633,a637,a640,a647,a650,a652,a654,a657,a659,a676,a683,a684,a688,a689,a693,a694,a696,a699,a701,a702,a706,a719,a723,a724,a731,a734,a741,a773,a774,a781,a784,a793,a817,a823,a829,a833,a837,a842,a862,a882,a902,a905,a909,a910,a932,a933
t39	78.28428	19.76678	a35,a85,a88,a94,a146,a203,a217,a273,a301,a324,a353,a374,a453,a474,a580,a610

Table 2.8 cont'd

t41	965.093	243.686	a2,a4,a5,a6,a7,a8,a10,a14,a15,a17,a21,a34,a38,a41,a42,a47,a48,a53,a65,a73,a76,a87,a90,a93,a95,a97,a98,a100,a102,a104,a108,a109,a110,a111,a120,a127,a136,a140,a142,a145,a149,a153,a155,a162,a163,a170,a175,a178,a179,a184,a188,a194,a198,a200,a219,a230,a231,a234,a238,a250,a252,a259,a261,a267,a272,a287,a288,a290,a292,a293,a296,a307,a309,a314,a320,a338,a342,a343,a349,a361,a364,a372,a387,a397,a405,a415,a417,a423,a425,a433,a440,a446,a456,a465,a481,a496,a499,a505,a507,a518,a520,a543,a568,a573,a594,a601,a603,a609,a616,a622,a624,a627,a636,a638,a643,a661,a720,a728,a739,a747,a756,a764,a789,a792,a798,a801,a819,a838,a840,a851,a852,a868,a878,a880,a886,a897,a901,a912
t50	69.0699	17.44015	a3,a72,a365,a567
t60	419.4829	105.9194	a13,a25,a37,a44,a51,a60,a62,a64,a67,a68,a75,a82,a91,a96,a107,a123,a130,a132,a134,a143,a147,a152,a159,a169,a176,a180,a182,a196,a201,a204,a205,a209,a213,a218,a221,a225,a236,a240,a251,a257,a277,a285,a286,a330,a344,a351,a357,a358,a359,a368,a376,a388,a398,a404,a407,a434,a443,a458,a462,a491,a495,a501,a502,a513,a515,a519,a521,a535,a540,a542,a548,a550,a557,a574,a577,a578,a597,a606,a621,a628,a641,a651,a655,a662,a665,a667,a675,a691,a707,a712,a732,a737,a742,a749,a750,a752,a754,a760,a768,a771,a787,a788,a794,a799,a800,a806,a811,a825,a826,a858,a863,a874,a875,a898,a900,a903,a907,a913,a929
t86	87.92123	22.20011	a43,a57,a59,a66,a79,a101,a195,a214,a255,a278,a399,a444,a653,a791
t90	292.3347	73.81451	a9,a11,a16,a20,a22,a24,a27,a29,a36,a50,a55,a63,a70,a74,a99,a116,a154,a197,a210,a243,a244,a262,a279,a334,a403,a459,a595
t93	125.2377	31.62251	a1,a23,a28,a46,a54,a78,a131,a133,a189,a208,a223,a275,a294,a347,a402,a658,a710,a820
t100	133.2659	33.64964	a18,a30,a77,a83,a114,a151,a166,a185,a192,a216,a248,a265,a268,a299,a304,a306,a322,a413,a441,a452,a457,a471,a545,a551,a585,a604,a644,a645,a666,a673,a695,a700,a713,a761,a765,a783,a828,a841,a881

Table 2.8 cont'd

t110	307.1641	77.55894	a12,a49,a52,a84,a117,a118,a119,a139,a144,a160,a165,a172,a183,a187,a206,a207,a211,a212,a222,a224,a227,a235,a249,a258,a266,a269,a280,a281,a283,a295,a308,a310,a318,a326,a332,a335,a337,a339,a340,a341,a345,a346,a352,a354,a367,a370,a371,a375,a377,a380,a381,a385,a390,a391,a392,a394,a396,a400,a410,a411,a431,a445,a448,a460,a463,a472,a473,a476,a478,a482,a483,a484,a487,a497,a498,a504,a506,a508,a509,a514,a516,a517,a524,a527,a529,a531,a533,a536,a537,a541,a544,a546,a549,a553,a555,a556,a560,a563,a566,a571,a575,a576,a586,a588,a596,a598,a600,a605,a607,a611,a612,a613,a629,a630,a631,a635,a664,a669,a670,a671,a679,a690,a698,a708,a718,a721,a727,a730,a733,a743,a751,a758,a766,a772,a776,a778,a779,a780,a790,a796,a815,a821,a827,a831,a832,a834,a843,a848,a854,a856,a860,a867,a870,a873,a879,a884,a885,a889,a892,a893,a896,a899,a904,a906,a915,a917,a921,a926,a927,a930,a931,a935,a936,a939,a941,a943
Not collected	125.6127	31.7172	a69,a103,a106,a158,a161,a171,a173,a190,a191,a199,a237,a239,a242,a291,a305,a321,a325,a331,a336,a366,a416,a418,a421,a428,a429,a438,a461,a468,a490,a503,a511,a522,a530,a565,a569,a584,a587,a591,a592,a599,a618,a656,a677,a680,a682,a686,a711,a729,a735,a736,a738,a745,a755,a762,a763,a767,a770,a777,a782,a785,a797,a804,a807,a808,a813,a822,a824,a830,a835,a836,a839,a845,a849,a853,a857,a861,a866,a871,a890,a891,a908,a914,a916,a918,a919,a920,a922,a923,a924,a928,a934,a937,a938,a942,a944,a945,a946

CHAPTER 3. ESSAY TWO

OPTIMAL VEHICLE ROUTING FOR FOOD WASTE COLLECTION

3.1. Introduction

The Vehicle routing problem (VRP) is an extensively studied topic (Bodin et al, 1983; Christofides et al, 1981; Desrocher et al, 1990; Golden and Assad, 1988; Laporte, 1992). There are numerous studies in the literature which addressed the VRP problem in different contexts. The well-known Traveling Salesmen Problem (TSP, Miller et al, 1960; Lawler et al, 1985) is a basic VRP. The TSP formulation has been extended to more complex multi-depot VRP, multi echelon VRPs, VRP with uncertainties, and more recently to green VRP, which considers the environmental impacts of routing.

In many supply chain systems, the allocation and routing of vehicles are essential elements (Golden et al. 1977). In the previous chapter, the total transshipment cost was optimized without consideration of the routing of waste collection and delivery vehicles. Since the total cost of deliveries is significant, which is about 12 percent of the total operational cost (O&M cost and transshipment cost), ignoring the routing would overestimate the total cost. In this essay a second MILP model is developed to obtain a more accurate estimation of the food waste collection cost by routing the vehicles in each service area. Ideally the transshipment cost should be determined by routing the delivery vehicles operating in the entire are, but this problem would be too large and too difficult to solve using commercial optimization software. Instead the analysis is restricted here to optimal routing of vehicles operating within the area served by each pretreatment station. The individual service areas were determined by the clustering (p-regions) model presented in Essay One. While consideration of the vehicle routing may reduce the delivery costs substantially, compared to the cost estimated by the clustering analysis, still some overestimation may occur due to the restriction of the routing analysis to on sub-region (service area) at a time rather than considering the entire area of operation simultaneously. Therefore, the piecemeal approach used here is essentially heuristic. To investigate the solution accuracy (sub-optimality) of this approach we apply the clustering model to one service area assuming that the restaurants in that area are the only food waste sources. This step generates an optimal sub-clustering of the area. We solve the VRP for each of those sub-clusters and compare the total cost of the respective optimum solutions with the cost of vehicle routing solution for the service area (original cluster). If the difference between the two is within a tolerable range, this would be an indication of the adequacy of the hybrid heuristic-optimization procedure used here. This is done for several service areas to test for robustness of the model and independence of the findings from the data set used.

The analysis presented in Essay One used a model which configured 'compact' service area where the food waste from all sources in each area is collected and delivered to an endogenously determined cluster center in such a way that the collected food waste would not travel too long distances. This approach assumes that trucks ship the collected food waste from waste sources to the cluster center directly. Trucks then pick up the waste from each cluster center to a pretreatment station determined by the model. In the actual operations there will be no such cluster center that serves as a collection hub. Defining a center for each cluster is just for modeling purposes, namely to group waste sources around a central site so that the sources in the cluster will be in close proximity to the center, thus to other sources in that cluster. According to the GAMS output (see Appendix B), in the optimal solution most of the cluster centers receive more waste than one full truckload and transship the treated waste to the final processing plant in full or almost full truckloads. In reality, each truck would leave its assigned pretreatment station, visit a source in the first stop of its trip, pick up the waste, then visit a second, third, etc. source and pick up their loads in subsequent legs of the trip, and when the load is near its full capacity or all the loads are picked up it would return to the pretreatment station to unload.

Unfortunately, solving the problem described above considering all 946 waste sources simultaneously is a computationally challenging problem. It is highly unlikely (if not impossible) to solve such a large-scale problem to an exact optimum using existing optimization software, especially on a personal computer with limited memory. In this chapter, we partition the problem in to smaller routing problems and develop a MILP model to solve each of those problems separately. As partitioned waste sources, we used the service area determined by the p-region model developed in Essay One and solve the optimal routing for each pretreatment station service area individually. Since the service areas determined in the first station are ‘compact’, routing the vehicles within each area is expected to be close to the true optimal routing solution that could be obtained by consideration of all sources simultaneously.

3.2. The vehicle routing problem

The vehicle routing problem (VRP) is an extensively studied topic in the transportation science literature. The problem was introduced as early as 1959 (Lin et al, 2014). Most of the VRP models are based on the TSP formulation (Bellmore and Nemhauser, 1968, Golden et al, 1977). The TSP formulation has been extended later to more complex multi-depot, multi echelon VRPs. Recent VRP studies emphasis on environmental impacts of transportation networks and the optimal routing of vehivles to reduce emission from burning transportation fuels. This requires more complex model formulations as in Lin et al. (2014). Tajik et al. (2014) consider uncertainties in the pick-up and delivery conditions, environmental costs of CO_2 emission, and the vehicle speed impact on GHG emissions. Dondo and Jaime (2014) studied the cross docking aspect of the delivery and pick up problem. Aksen and Altinkemer (2007) studied on a multi-function depot, which not only sells goods through internet but also has a store for walk-in customers. The authors modeled the impacts of walk-in customers on store inventory and the delivery of goods to online customers. Ramos et al. (2013) looked into a logistics problem with the same perspective considered in the present study. They developed a model to design a waste oil collection logistic system, which is a combination of the reverse logistic problem and multi-depot VRP. Cóccola et al (2013) introduced a more complicated multi-vehicle time window constrained pickup and delivery model to design a multi-echelon supply and distribution system. The extended VRP studies have a common characteristic, namely they are generally very abstract and input datasets are very small. This is mainly due to the limitation on computational resources. For example, Ramos et al. (2013) reported that their model took 8 hours to solve a VRP that had 2 depots and 100 demand points achieving a 5.7 percent optimality tolerance. Önal et al. (1996) also reported that a MILP formulation of the VRP problem could be solved within two hours of computation time when less than 15 nodes and two delivery vehicles were considered, but larger problems could not be solved within two hours on a personal computer. Therefore, instead of using MILP, they used a dynamic programming procedure. The computational experience with the two approach showed that the latter approach is extremely efficient in the problems they studied. However, the dynamic programming approach also suffers from the 'curse of dimensionality' and may fail to solve large-scale routing problems like the one considered.

3.3. Methodology

3.3.1. A MILP formulation of the routing problem

The model developed here aims to minimize the vehicle travel cost associated with the total distance traveled by all vehicles. The vehicles are assumed to have a uniform delivery capacity and the delivery schedule for each vehicle is assumed to start from the pretreatment station and ends at the same station with full load of food waste.

This model is a variant of the VRP model developed by Önal et al (1996). Before presenting the mathematical formulation for VRP, we introduce the notation.

Parameters:

i, l	Food waste sources, pickup demand nodes
t	Trips made to collect waste from all sources
s	Individual steps to complete a trip
$d_{o,l}$ or $d_{l,o}$	Distances between waste sources to the pretreatment station, km
$d_{i,l}$	Distances between pairs of waste sources, km
c_{ve}	Transportation cost for vehicle to travel with full load, \$/km
c_{la}	Landfill disposal cost, \$/yard^3
c_{ex}	Shipping cost for extra loads of food waste when the source has more than one load of waste, \$
w_l	Amount of food waste from each source, tons
cap_t	Load capacity for each pickup trip, tons
de	Density of organic waste, tons/yard^3
wa	Water content of food waste, %

Binary Variables:

$X_{t,s,l}$	Location variable: equals to 1 if the vehicle arrives at source l at the end of the step s at trip t
$Y_{t,s,i,l}$	Travel arc variable: equals to 1 if the vehicle travels from source i to source l at step s of trip t
$Z_{t,s,i}$	Return variable: equals to 1 if at trip t, step s, the vehicle has no more loading space and needs to return from source i to the pretreatment station

Positive Variable:

L_l	Amount of food waste that goes to landfill, tons

In terms of above notations, the MILP model is presented below:

$$\min \ cost_{ve} * \sum_{t} \left(\sum_{l} d_{o,l} * X_{t,1,l} + \sum_{s>1} \sum_{i} \sum_{l} d_{i,l} * Y_{t,s,i,l} + \sum_{m} \sum_{l} 1.1 * d_{l,o} * Z_{t,s,l} \right) + \sum_{l} c_{la} * \frac{L_l}{de} + c_{ex} \tag{27}$$

Subject to:

$$\sum_{l} X_{t,s,l} \leq 1 \ \forall \ t, s \tag{28}$$

$$X_{t,s,i} \geq \sum_{l} Y_{t,s+1,i,l} \ \ \forall \ t, s, i \tag{29}$$

$$X_{t,s,l} = \sum_{i} Y_{t,s,i,l} \ \ \forall \ t, s > 1, l \tag{30}$$

$$\sum_{t} w_l * X_{t,1,l} + \sum_{t} \sum_{s>1} \sum_{i} w_l * Y_{t,s,i,l} + L_l = w_l \ \forall \ l \tag{31}$$

$$\sum_{s} \sum_{l} w_l X_{t,s,l} \leq C_t \ \ \forall \ t \tag{32}$$

$$Z_{t,s,i} = X_{t,s,i} - \sum_{l} Y_{t,s+1,i,l} \ \ \forall \ t, s, i \tag{33}$$

$$Y_{t,s,i,l} = 0 \ \forall \ t, s, i = l \tag{34}$$

$$\sum_{t} \sum_{s} X_{t,s,l} \leq 1 \ \forall \ l \tag{35}$$

The objective represents the total transportation cost, including all pickup trips and the possible landfill cost if a waste is not picked, which is minimized. The total cost is a linear function of the traveled distances. The cost of a full load return trip is higher (by 10 percent) than the cost of an empty trip for the same distance (departure from the pretreatment station). Since the restaurant data set was aggregated from 12,450 to 946 sources, some aggregated waste sources had more than a full truckload of food waste. Therefore, a truck needs to pick up the first full load, deliver to the pretreatment station location and pick up another full load if necessary, until there is less than one truckload left at the source. We calculate the costs of such trips up front rather than incorporating in the optimization model.

Constraint (28) ensures that a truck cannot visit more than one waste source at any step of any trip. Equations (29) and (30) ensure the continuity of the steps of each trip, namely if a truck is at a particular waste source, then it has to leave that waste source in the subsequent step. Conversely, if a trip is made from source i to source l, then the vehicle will be at source l in the subsequent step of its trip. Equation (31) implies that the entire food waste at all sources has to be picked up. Equation (32) is the vehicle capacity constraint, namely a truck cannot pick up more than its food waste capacity. The return variables are determined by Equation (33) by subtracting Y at step s+1 from X at step s. Equation (34) states that a vehicle cannot travel from a waste source to itself at any step. Finally, Equation (35) ensures that vehicle can be at most in one location at any step of its trip.

3.3.2. Case study

The case study is an extension of Essay One. The location, distance and food waste data were the same as the data used previously. The waste source assignment results (see the service area in Table 2.8) are used as the model inputs here. We assume that there are enough trucks to transport the entire food waste. The trip parameter (t) is estimated by dividing the total amount of food waste at all sources within the collection area by the truck loading capacity. The step parameter (s) is estimated by dividing the truck loading capacity by the average food waste amount of all sources within the collection area multiply by 2. Table 3.1 lists the parameters used in the model. A complete GAMS code is given in Appendix A. To reduce the computational difficulty, only those waste sources that are no more than 2 km apart or 1-1.3 km apart for larger service areas, are included when defining the Y variables, which means that if a vehicle is at source *i*, the next source in its trip cannot be more than 2 km away. This reduces the number of Y variables substantially, thus the overall size and computational complexity of MILP model.

To test the degree of possible sub-optimality of the approach used here, after solving the routing problem for one service area in to sub-clusters using again the p-region model introduced in Essay One. We then solve the VRP model for each of those sub clusters and add their total costs. A comparison of this cost with the cost of the routing model where all sources are considered simultaneously would indicate the degree of sub-optimality. Repeating this for several sub-clusters would indicate the robustness of the approach and data independence of the conclusions from the analysis.

3.4. Results and discussion

3.4.1. VRP model results for entire service area

In order to optimize the food waste collection routes, the MILP model was implemented in GAMS and solved by CPLEX 11.0.1. Fifteen VRP instances are considered including 15 pretreatment stations and 849 waste sources assigned to those stations.

Table 3.2 reports the results from the application of the VRP model. The first column is the station ID, followed by the number of waste sources assigned to that station. The third column shows whether this data set is solvable within the given computation time. With the input data is large, GAMS often consumes all the available computer memory before an optimal solution is found. The results are presented in the following columns: the time (in seconds) needed to find the solution; the optimality tolerance (gap) when the solutions is found or memory limit is reached; the trips needed to pick up and deliver food waste from sources to pretreatment station; the route sequence for each trip; and the total transshipment cost.

A clear observation from Table 3.1 is that it is more difficult to solve the VRPs when a large data input is involved. Usually, MIP solvers find an optimal solutions relatively early in the process, but a large number of iterations (branch and bound) are needed to confirm that the solution is optimal or cannot be improved upon. This occurs more often as the model size increases. A practical approach in such cases is to relax the optimality tolerance. Some instances with very large number of waste sources could not be solved within given computation time (resource limit). In some instances, the gaps are too big to be accepted as a reasonable sub-optimality. Therefore, the total transshipment cost for the entire system could not be determined, due to some missing model solutions. However, we can make a comparison of the costs on a case (service area) basis, namely the optimal transshipment cost associated with each cluster in the p-region solution and the corresponding cost when vehicle routing is incorporated.

Figures 3.1 and 3.2 display several vehicle routing sequences for some sample pretreatment stations. The stations were assigned between 4 to 20 waste sources. The arrows show the direction of routing sequences. Note that, the extras trips for sources having more food waste than a full truckload are not presented in Figures 3.1 and 3.2. However, the transshipment costs include the extra cost for those trips.

Figure 3.1 Food waste collection routes for sample pretreatment stations

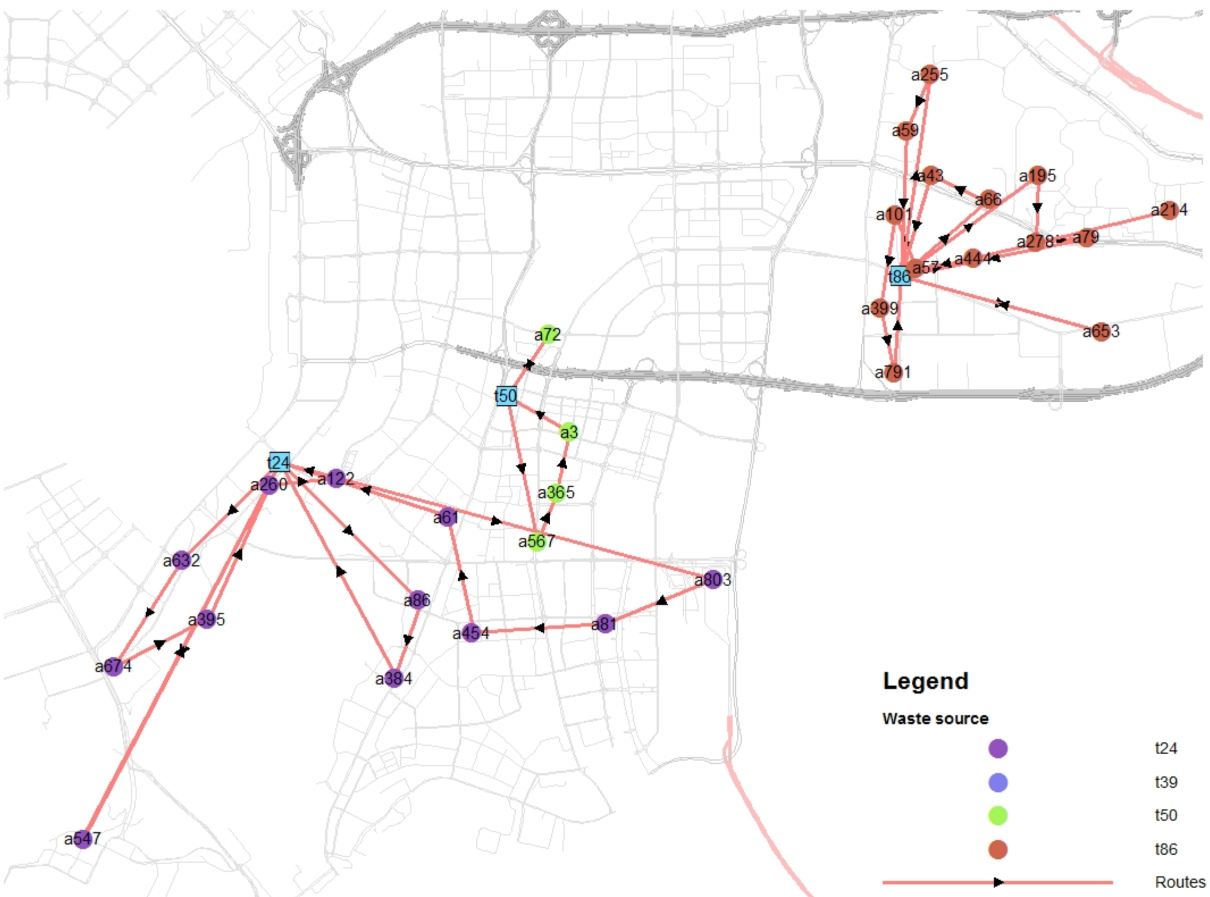
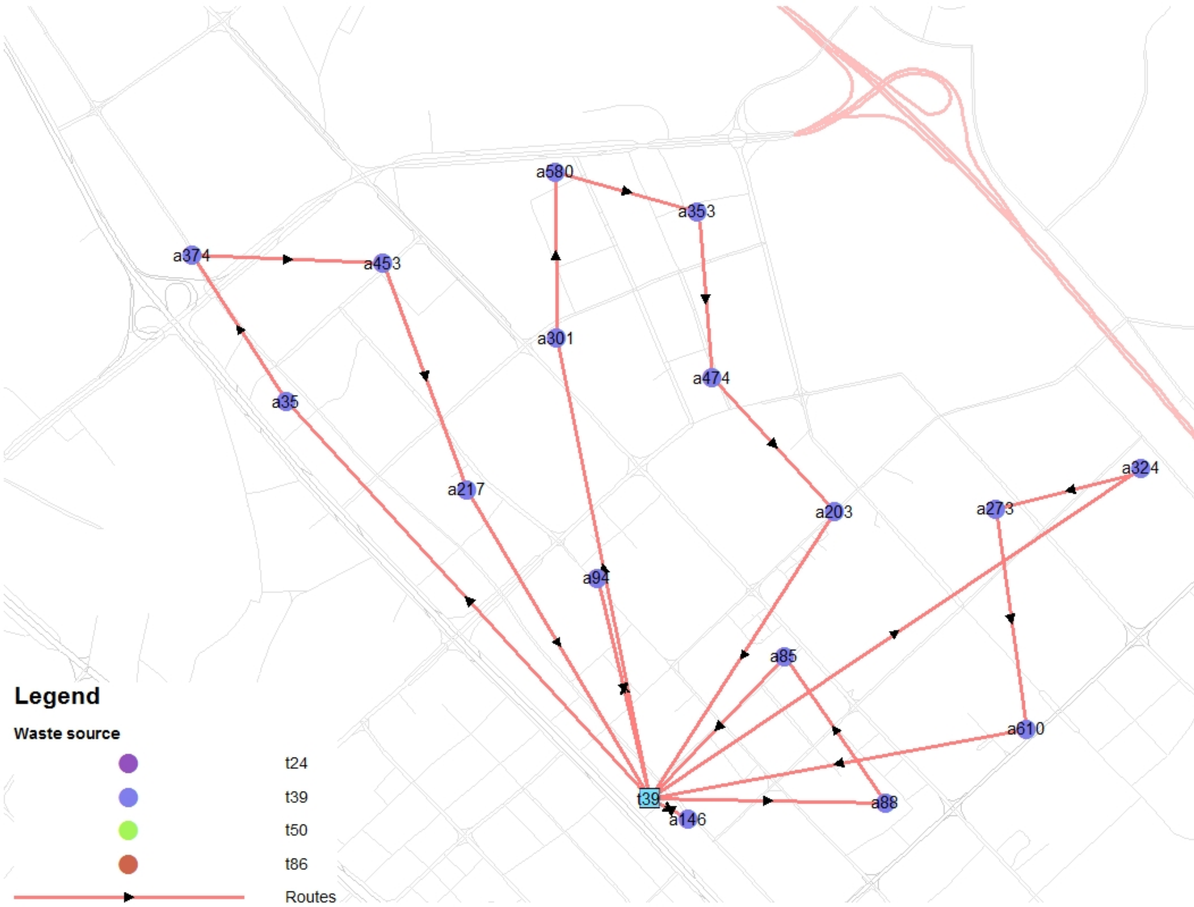


Figure 3.2 Selective food waste collection routes for sample pretreatment stations



3.4.2. Sub-clustering and accuracy of the heuristic VRP approach

In this section we consider a few pretreatment stations to test the accuracy or the degree of sub-optimality of the approach used here, where a service area is partitioned into sub-areas using the p-region model and optimal routing of deliveries is determined for each area separately vis-à-vis the true optimum solution of the VRP model when all waste sources in the area are considered simultaneously. The straight VRP model yields the optimal routes and the costs presented in section 3.3.1. The results obtained by using the two-step heuristic approach are listed in Table 3.3. Comparing Table 3.3 and Table 3.2 show that, the optimal routing within sub-clusters and in the entire cluster are not identical, as can be expected. In general, the costs are higher in the case of heuristic approach, about 12 percent, except in one case (the cluster at t86). This may be considered as a somewhat large degree of sub-optimality, but it may be an acceptable tolerance especially when working with a big dataset. After all, the heuristic approach can provide an approximately optimal solution in terms of the total cost (with perhaps 12 percent deviation from the true cost), but this may be considered an acceptable deviation since the alternative is no solution.

3.5. Conclusions

This essay presents a model to solve a large-scale complex vehicle routing problem for food waste collection by use of a two-stage hybrid heuristic optimization approach. In the first stage of this approach, the waste sources are grouped in to service areas, each served by a single pretreatment station, by using a p-region model. In the second stage the VRP for each pretreatment station service area is solved individually. This may be a practical approach in similar large scale problems. However, despite the compact grouping of waste sources in the first stage and optimization of vehicle routing in the second stage, some sub-optimality may occur due to handling each service area separately instead of considering all sources simultaneously. The test results show that the sub-optimality can be as large as 12 percent.

3.6. Tables

Table 3.1 Constance data input for VRP MILP model

Notations	Value
$cost_{ve}$	0.81 \$/km
$cost_{la}$	24.68 \$/yard^3
C_t	12 tons
$Water$	74.75%
De	0.725 tons/ yard^3

Table 3.2 Optimal vehicle routing analysis results

Station	Sources#	Solvable?	CPU time, s	Gap	Trip #	Routes	Cost, $
t1	19	Y	60	5%	8	I. a135 II. a485-a313 III. a722-a58 IV. a157-a470-a181 V. a312-a362-a583-a744-a253-a753 VI. a56-a350 VII. a419-a113	31.67
t9	20	Y	90	5%	8	I. a228 II. a246-a492-a245-a92-a121-a303 III. a615 IV. a812 V. a348-a148-a39-a141 VI. a479-a40 VII. a271 VIII. a33-a220-a409	52.75
t23	26	N	-	-	-	-	-
t24	12	Y	71	1%	4	I. a86-a384 II. a547 III. a803-a81-a454-a61 IV. a632-a674-a395-a260-a122	35.42

Table 3.2 cont'd

t27	122	N	-	-	-	-	-
t32	99	N	-	-	-	-	-
t39	16	Y	873	5%	6	I.a301-a580-a353-a474-a203 II.a324-a273-a610 III.a94 IV.a146 V.a88-a85 VI.a35-a374-a453-a217	25.55
t41	138	N	-	-	-	-	-
t50	4	Y	0.13	0%	2	I.a567-a365-a3 II.a72	12.32
t60	119	N	-	-	-	-	-
t86	14	Y	13	0%	6	I. a195-a278-a79 II. a214 III. a444-a57-a101-a399-a791 IV. a653 V. a255-a59 VI. a66-a43	38.90
t90	27	N	-	-	-	-	-
t93	18	Y	85	5%	8	I. a820-a23 II. a223 III. a28-a275 IV. a133 V. a78 VI. a710-a658-a1-a208-a294-a189 VII. a46-a54 VIII. a131-a347	70.01
t100	39	N	-	-	-	-	-
t110	176	N	-	-	-	-	-

Table 3.3 Heuristic VRP approach for selected service areas

Cluster center	Waste sources	Sub routing cost, $	VPR routing cost, $
t24			
a86	a86	3.84	
a122	a61,a122	8.99	
a260	a260,a395,a454,a674	9.80	
a632	a81,a384,a547,a632,a803	15.56	
Total		**38.19**	**35.42**
t86			
a57	a57,a101,a399,a444,a791	4.74	
a66	a66	3.70	
a278	a278,a43,a59,a195,a214,a255,a278,a653	18.51	
Total		**26.95**	**38.90**
t39			
a85	a85,a88,a203	5.90	
a94	a94	1.82	
a146	a146,a217,a273	4.81	
a610	a35,a301,a324,a353,a374,a453,a474,a580,a610	16.70	
Total		**29.23**	**25.55**
t1			
a58	a58,a135,a181,a350,a470	6.94	
a722	a56,a113,a157,a174,a253,a312,a313, a362,a419,a485,a583,a722,a744,a753	29.51	
Total		**36.45**	**31.67**

CHAPTER 4. SENSITIVITY ANALYSIS, DISCUSSION AND CONCLUDING REMARKS

4.1. Overview

The two essays presented in this thesis, introduce a hybrid heuristic optimization approach to solve a real world supply chain problem. As discussed earlier, it is more likely that the model may not produce an exact optimum, yet the 'optimal' solutions may be satisfactory and can offer good solutions to the problem. Based on the empirical results of the model for a relatively small-scale problem derived from the same data set, we found that the sub-optimality (in this particular application) can be as much as 12 percent with respect to the true optimum solution. Ideally, the optimal solution to the waste collection and processing problem should be obtained from a multi-depot VRP considering all 946 waste sources and 15 pretreatment stations. However, due to the limited computational sources (in particular computer memory) and limited capacity of the optimization solver (GAMS/CPLEX, although CPLEX is the most widely used and very efficient MILP solver), it is impossible to solve the resulting VRP for 946 nodes. A heuristic approach can be a practical option for a real world problem like this.

Other than the issue of sub-optimality there are few concerns related to the application presented in this study: 1) the artificial nature of the food waste input data which may not exactly match the actual data, 2) the capital costs and financing of processing equipment, 3) the land availability for building treatment facilities, and 4) the biogas utilization in real world market. This section, addresses the issues of imperfect data and presents a sensitivity analysis to investigate the impact of variation in the input data and test whether the model is robust and suitable for other datasets and explore whether the conclusions based on the empirical findings are still valid under moderate changes in the data.

The last, but not the least, important issue that needs to be discussed is the environmental impacts for food waste treatment system hypothesized in the modeling analysis. In this chapter, we address this issue and evaluate the environmental benefits that could be obtained by developing a food waste treatment system with a particular focus on the GHG emission impacts.

4.2. Sensitivity analysis

4.2.1. Cost of trucks

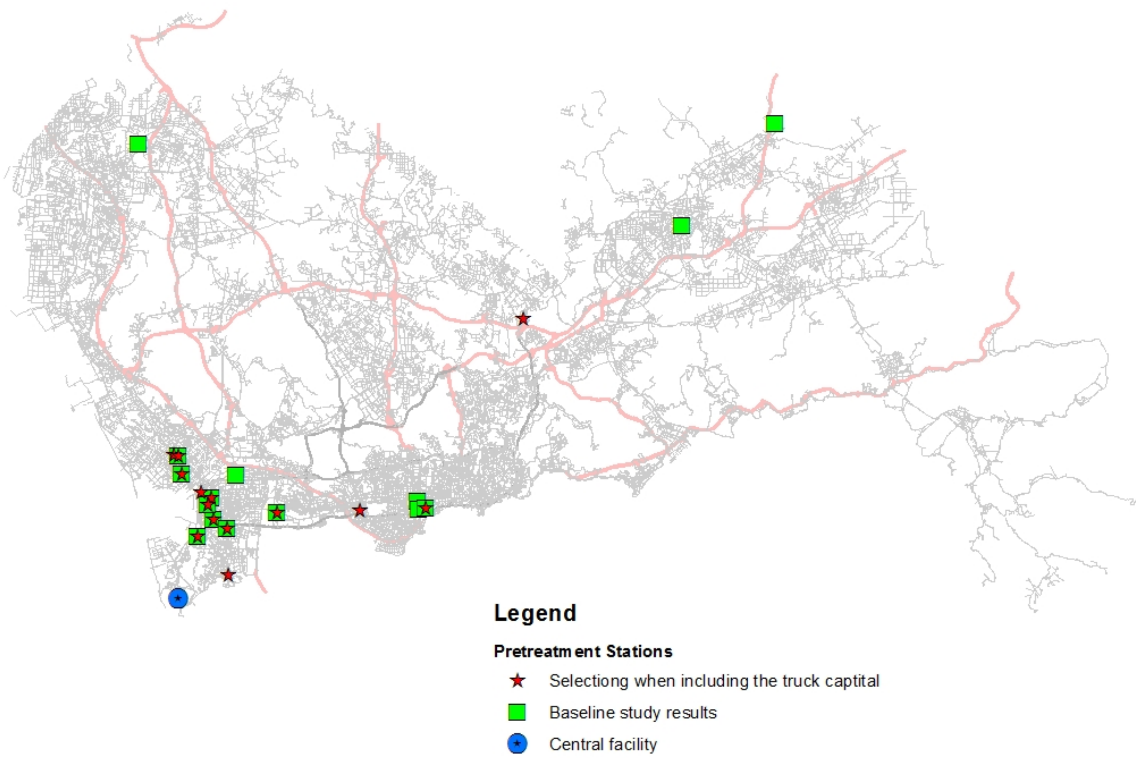
In the Essay One, the capital cost of trucks was not considered in the model and it was assumed that there would be as many trucks as needed to transport the food waste that the treatment facilities could process. In reality, purchasing trucks would be a significant part of the capital cost. Depending on the optimal amount of waste collection and the distances travelled, more waste collection trips may be needed or it may take longer times to complete the trips, therefore more deliver vehicles may be needed. That may translate into a higher cost of truck purchases. Assuming a 12 ton capacity for heavy duty delivery trucks, in China this costs approximately $40,000 per vehicle. With 5 years of financing at 6% annual interest rate, the annualized cost of a vehicle is $9,495. To find the number of trucks needed, a new variable is created in the model which is determined by the collective travel distance driven by all delivery vehicles to perform the food waste transportation. We assume that each truck operates over a 12 hour shift[26], the city average vehicle travelling speed is 20 km/hour and the contingency factor is 20 percent, which consider the case when some trucks are off duty due to mechanical issues. The number of trucks is obtained by dividing the collective travel distance by travelling speed which in turn is divided by the shift duration multiplied by contingency factor. The number of trucks needed is defined as integer variable which has to be equal or larger than the resulting figure. Cost minimization forces the integer variable to take the ceiling value of the figure.

After incorporating the truck cost information into the model and subtracting the total capital cost of delivery vehicles, the annual profit for the plant reduces from $50.36 to $50.34 million due to the cost of purchasing trucks. Simultaneously, the food waste collection decreases from 846.15 to 845.99 tons, which is 99.91% food waste recovery. In order to reduce the transportation related costs, in the optimal solution the model selects one less food waste pretreatment station. However, this requires the delivery vehicles to travel longer distances. According to the model results, the daily cumulative travelling distance is now 9,070 km, up from 7,965 km, and it requires 46 trucks operating 12 hours per day. The model has similar site selections as the baseline study. Location "f1" is selected as the best location for the future plant site, but only 14 pretreatment stations are selected now since the model decides to eliminate one pretreatment station and divert the saved cost to

[26] In China, truck drivers can have 8 hour day and night shifts schedule, but trucks can be used 24/7.

balance the spending of truck purchases. Figure 4.1 illustrates the differences on site selections between the two solutions with and without considering the capital cost of trucks. When the increased truck capital cost is considered, the model yields lower waste recovery and longer vehicle travel distances. As mentioned in Essay One, according to the model results transporting raw food waste from the sources to the pretreatment stations is preferred to transporting the processed GOW to the central treatment facility. This still holds when the truck capital cost is considered, and the selection pretreatment stations are again located close to the central facility. This result is based on the capital cost for pretreatment stations and the transportation related costs. It should be noted, however, that shipping raw food waste might cause the liquid food waste leakage and odor problems which are not taken into account in the optimization.

Figure 4.1 displays the site selections with and without consideration of the truck capital cost



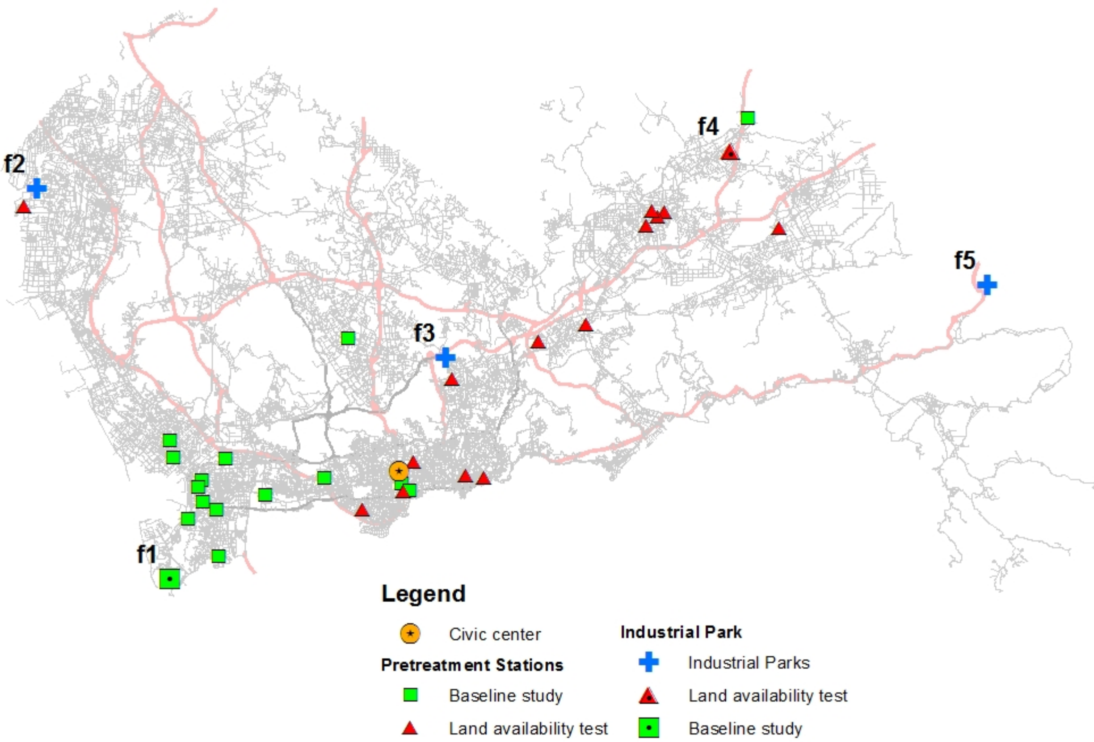
4.2.2. The land availability for siting treatment facilities

In the baseline solution, five industrial parks were considered as potential sites for building a central treatment facility in the city of Shenzhen. The crucial assumption in the analysis was that all sites would be available and they would cost the same. This is not the case in reality. Since the downtown area is more densely developed, due to the lack of available land and much higher land values, building a large treatment facility in that area would be substantially more expensive than building the facility in the suburbs. Moreover, constructions in the downtown area would cost more due to permits requirements, the road usage authorizations, public relations, traffic controls, etc. Converting these into economic costs ($) is not straightforward (or practically impossible) since some of these attributes have not been measured. To reflect the geographical differences and location preferences between the alternative potential sites, a set of site-specific weights is incorporated in the baseline model (Table 4.1). The weights for individual sites are subjectively assigned according to their distance to the civic center of Shenzhen and vary from 2 to 0.85, where a higher weight means a larger cost or lower preference (Figure 4.2). Location f4 is a special case, since the city of Shenzhen is planning to build a "low carbon district", which is located around that area. Therefore, an environment friendly facility that plans to build within the boundaries of a "low carbon district", may receive significant subsidies from the city government. Therefore, a relatively low weight is assigned to f4. On the other hand, location f1 is a fully developed harbor area of the city and its part of the special economic zone (SEZ) in China, therefore the land is very precious in that area. In the model, the highest weight is assigned to that location.

In the optimal solution the model selects location f4 for the central treatment plant. The annual profit increases up to $52.34 million, mainly due to the weight on the land availability. The food waste recovery also slightly increases from 99.93% in the baseline solution to 99.97%. The cumulative travelling distance increases from 7,965 km to 10,250 km. The reasons for this finding are two-fold: i) the pretreatment station selections are located mostly around the downtown area

(Figure 4.2), and ii) the central treatment facility location which is far from the downtown area.

Figure 4.2 Site selections in the baseline solution and under differential land weights



When the central plant selection was close to high density areas, such as f1 in the downtown area, the model prefers selecting pretreatment stations close to the plant and consequently there is more raw food waste shipping from the waste sources to the selected pretreatment facilities. However, when the selected central plant is far from downtown and close to suburbs, it is too costly to locate all the pretreatment stations close to the plant and ship a large amount of the raw food waste to those stations. The model shows that it would be optimal to locate some pretreatment stations in or nearby the downtown area, this is because the raw food waste is heavier and more costly to deliver than GOW.

4.2.3. Sensitivity analysis on food waste data

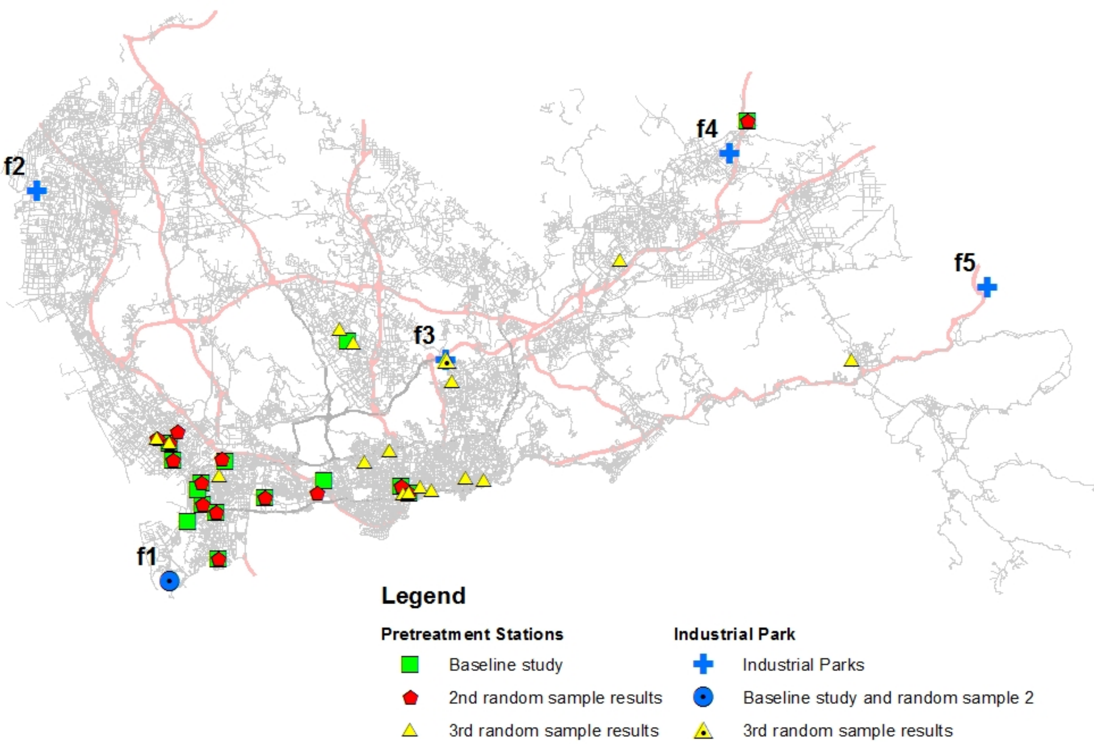
In this thesis study, due to the lack of actual data for the amount of waste produced by each restaurant, the food waste data is generated artificially by using a randomly sampling procedure. The data generation was done using a triangular distribution based on the estimated minimum, maximum, and most likely values of food waste produced by a single source. Since the waste data is artificial, the validity of the finding reported in Essay One and Essay Two can be questioned. To address this issue, we perform a test to evaluate the sensitivity of the model results to the data input. This is accomplished by using the same triangle distribution and doing multiple random sampling to generate alternative food waste data sets. We solve the model using each of those data sets and compare the model results. Table 4.2 lists the basic parameters for three randomly generated data sets. After the aggregation procedure (to reduce the number of sources from 12,450 to a reasonable number, see Essay One), the first random sample had 949 aggregate sources and the second random sample had 938 aggregate sources. Besides the number of aggregate sources, the amount of waste generated at each aggregate source and the locations of large aggregate sources (restaurants) are altered, which may have important effects on the location of processing facilities and the overall supply chain network.

The model yields slightly different results for different sets of data. Figure 4.3 compares the site selections obtained with each dataset. Table 4.3 presents a comparison of the selected model results, including the annual profit, the location selections for the central plant and pretreatment stations, the food waste recovery, the annual cost and cumulative travel distance. The biogas and biosolids production are proportional to the amount of SFW recovered, therefore they are not listed in the table.

The general observation is that different datasets have moderate impacts on the model results. From Table 4.2 and Table 4.3, we observe that the annual profit and the food waste recovery have a positive correlation with the total amount of food waste available. This is an expected result, because the profitability of food waste is high, thus, if there is more food waste available, the system can generate more revenue by recycling more. This results remains valid even when the waste generation is spatially more dispersed and more waste is delivered relatively longer distances. For example, the first dataset yields the highest annual cost, because trucks travel longer distances (as shown by the total distance traveled), yet the annual profit is still higher than the baseline case. This is an important finding and evidence about the economic potential of food waste recovery as bioenergy feedstock.

Both in the baseline solution and in the solution obtained with the first random sample, the model selects f1 for the location of the central treatment plant. However, the second random sample yields a different site selection, namely f3 (Figure 4.3). This is due the altered locations of large food waste producers. Note, however, that both f1 and f3 are close to downtown (coast line). In light of the precious sensitive analysis on site cost, if higher weights were assigned to the downtown facility sites, the selections could be different. The sensitivity exercise here shows that the density of the waste sources is an important parameter that may have serious impact on the model results. This implies that collecting a truly representative dataset is crucial for determining the best locations and carrying out a sound economic analysis of the food waste recovery and supply chain management.

Figure 4.3 Site selections in the sensitive analysis on food waste data



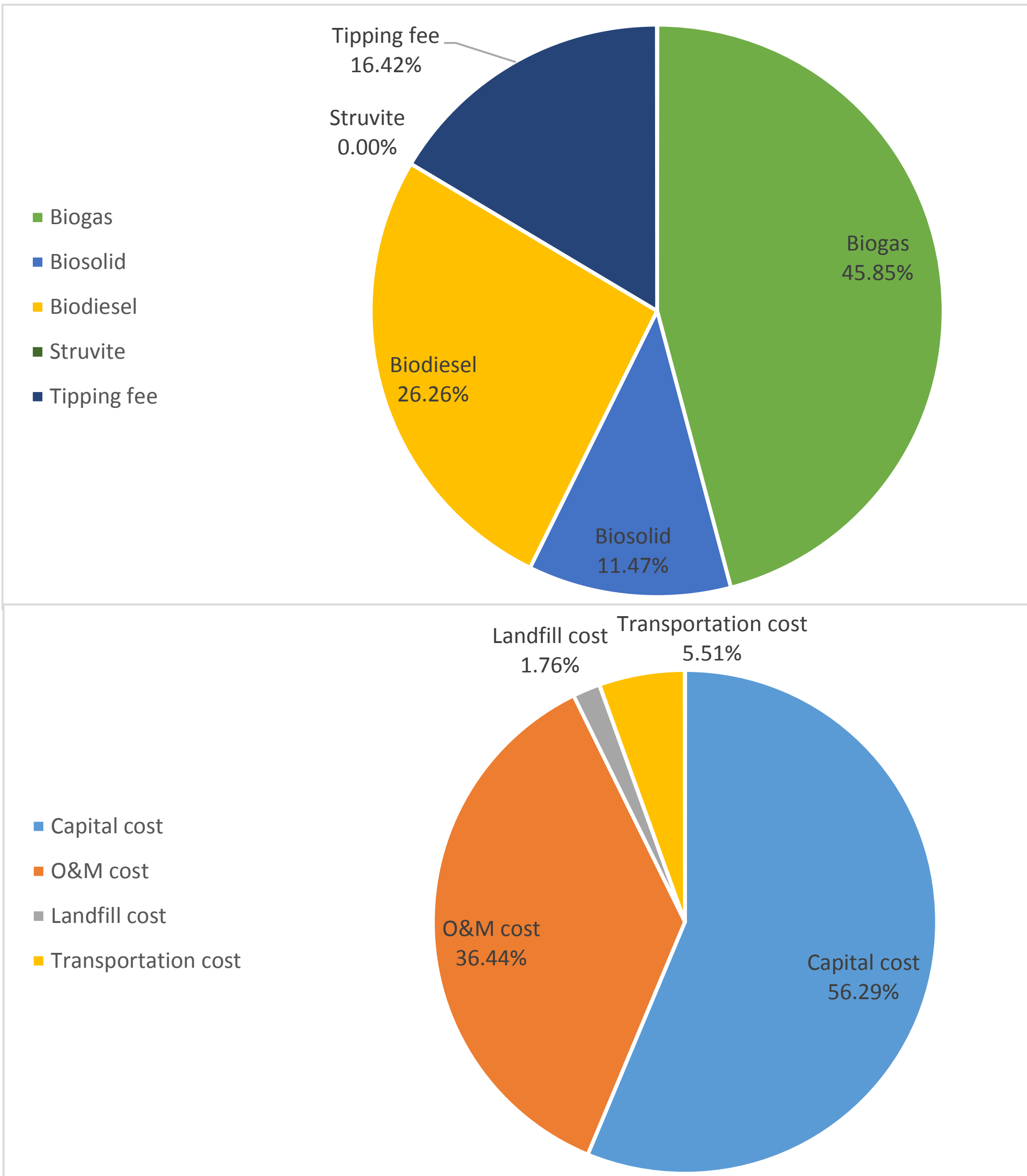
4.2.4. The plant capital cost

In the Essay One, the capital cost of the central treatment plant was assumed to be an annual payment to investors using a discount rate of 7.2% over 15 years. However, this financing offer might be different depending on the perspective of individual investor. Usually, the financial rate for a single project is varied and depended on various factors, such as the local policies, the international policies, the negotiation process, investors' confidence and even the reputation of the executives. To demonstrate the impact of capital cost to the supply chain network, a simple test is done by using a different financing offer, where the discount rate is 3% and the term is 30 years. With the new financial offer, the annual payment for the plant capital cost reduces from \$16.5 million to \$7.5 million. The payment for other equipment, such as biogas power generator, pretreatment station and biogas compressor also reduced over 50 percent.

As expected, the model yielded a much higher annual profit of \$59.54 million comparing to \$50.36 million in the baseline results, when the lower financing offer was implemented. Since the annual payment for building each pretreatment station is lower, the model selected 21 MSW hubs as future pretreatment station location instead of 15 locations in the baseline result. Consequently, the travelling distance for all trucks reduces to 6,800 km but the waste recovery decreases to 99.47%. The model selected the site f3 as the future central treatment facility. The composition of the annual revenue and cost is moderately impacted.

Figure 4.4 demonstrate the impact of implementing lower financing rate. Since let food waste is recovered, the total annual revenue decreases about $309 thousand to $74.4 million. The transportation cost increases its portion among all costs, mainly due to the decrease of annual payment for capital cost. Compared with the baseline results, the total annual cost decreases over $9.4 million. Under the low financing rate, the model selected 45 biogas compressor and 21 pretreatment stations, therefore the total capital investment becomes $163.5 million, which is $1.2 million more than the capital investment required for the baseline results, which is majorly contributed by the extra pretreatment stations. Having 21 pretreatment stations is more than the system needs to process the food waste. In average, the pretreatment stations run at 62% of total design capacity. In the baseline study, the pretreatment stations run at 93% of total design capacity. We can conclude that when a lower financing rate is implemented, the model is less optimal on the capacity maximization. Consequently, the effect of capital minimization is reduced, so the model yields a higher capital investment while some plant capacity is wasted. Therefore, it is necessary to add more constraints to prevent the pretreatment stations running at low level.

Figure 4.4 Revenue and cost when a lower financing rate is implemented



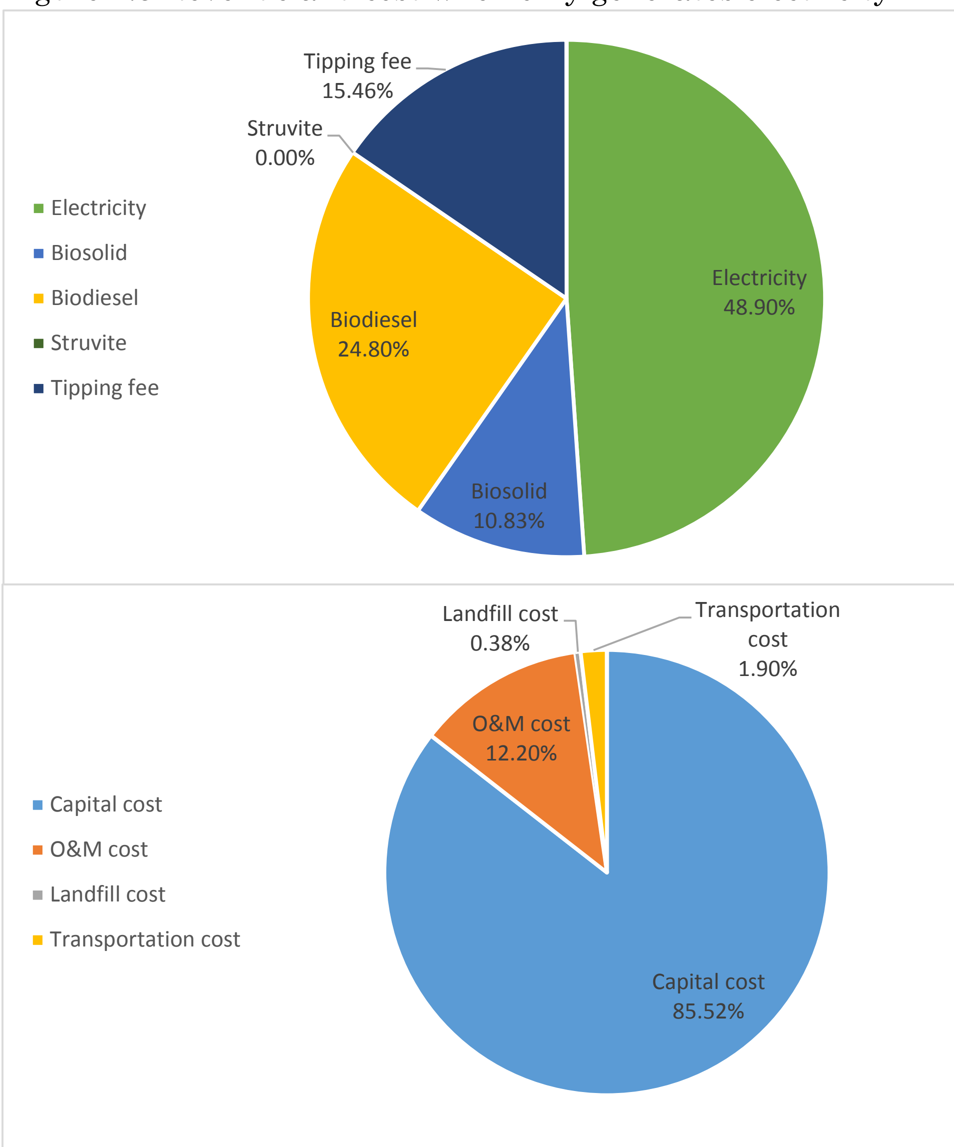
4.2.5. Energy products from biogas

In this thesis, we assume there are two possible output products for biogas: converting into electric power and as alternative natural gas. The baseline results indicate the alternative natural gas is the better option, which produces the optimal annual profit. However, most of the existing AD related WTE facilities produce electricity instead. Therefore, it is important to explore what the impact to the baseline results is when only producing electricity.

To perform this sensitivity analysis, we set the model to select electricity as the only biogas output product. The model solution shows a low annual profit of $34.9 million, since the annual payment for the biogas power generator is much higher than the biogas compressor, which are $1.3 million and $23 thousand, respectively. The model selects the same location f1 as the baseline results as the site for the central treatment facility. However, 17 pretreatment stations are selected which is two more stations than the baseline results. Consequently, the total travel distance decreased to 6,045 km per day. The hypothesis is that the annual payment for biogas power generator is so high, that the model needs to add more cost on pretreatment station to save money on the transportation cost. The food waste recovery increases to almost 100% to create more revenue.

Figure 4.5 shows that generating electricity can create more revenue. However, since the price of the biogas power generator is very high, the capital cost becomes an even bigger composition in all cost. The annual revenue increases from $74.7 million to $79.1, while the annual cost increases from $24.3 million to $44.3 million. The transportation cost does not change much but since the total cost increase, the cost of the transportation is lower percentage-wise. The observation is that producing electricity from biogas is more valuable than the alternative natural gas. The capital cost of the biogas power generator is the main consideration to determine what final product should choose. When the treatment plant receives small quantity of food waste, which only requires low capacity power generator, the capital can be substantially reduced. In this thesis, the selected sample biogas power generator can only manufactured in two companies in the world, which causes the price of certain machine is very high ($3.5 million without extra fees).

Figure 4.5 Revenue and cost when only generates electricity



4.2.6. An alternative business strategy

The previous discussion assumes that food waste is processed in a three-echelon system where the waste is collected and delivered to pretreatment stations from which it is transshipped to a final processing facility. There is an alternative business strategy proposed by a third party firm who is interested in the food waste-to-energy operation. The basic idea of the alternative strategy is to eliminate the pretreatment stations. Instead, a smaller and cheaper food waste processor will be installed at every food waste source pretreating the waste at the sources. The delivery crew will pick up the preprocessed food waste (GOW and waste oil) from the sources and deliver it to the central treatment facility. However, since the equipment is smaller and of commercial grade, the dewatering and oil separation efficiency is much lower than the larger industrial grade equipment. This alternative strategy is proposed by an equipment manufacturer, who wants to sell the lower grade food waste processors to restaurant owners. Therefore, if this plan is implemented the burden of pretreatment capital and operational cost would be diverted to the food service business, and the food waste treatment plant could gain a higher profit margin. In China, this proposal is practically feasible since the government has the power to enforce food service business owners to purchase the proposed food waste processors as part of the existing sanitary regulations. Even if the business owners may not embrace the idea, this may receive public support since this policy can be a practical and efficient way to deal with the gutter oil problem. This business strategy is a much simplified alternative to the baseline model. To investigate the impact of this alternative, we used the same dataset and run the model with the following changes: a) food waste is converted to GOW and waste oil at the sources, b) the cost for pretreatment stations is eliminated and c) the dewater and oil separation efficiency is lower than baseline case (Table 4.4). In this system, the problem becomes a standard transportation problem.

The model solution indicates that the alternative strategy would yield a higher annual profit compared to the baseline solution, which is \$52.43 million compared to \$50.36 million. The total saving by eliminating the pretreatment stations is \$462 thousand per year. Another source of saving is the increase of daily biogas production (11.89 million ft^3), because the oil content in GOW is higher when oil separation is done by a commercial processer. The extra biogas value is estimated as \$467.2 thousand per year. The remaining source of saving is due to be the reduced cost of the direct shipments of GOW from sources to the central facility. Because of the higher profitability, this alternative increases the food waste recovery to almost 100 percent.

This scheme diverts the pretreatment related costs to the food service industry, so the industry would face a big loss if such a regulation is enforced. The cost of such a restaurant size equipment is estimated as \$4,000[27], the total cost to the food service industry would be \$37.35 million for 12,450 restaurants. If the same financing rate used in Essay One is applied to this amount, the capital cost would be \$4.15 million per year excluding the related power consumption cost and

[27] Based on the pricing quote of Grease Guardian® from FM Environmental Ltd.

maintenance cost. Therefore, the alternative strategy is socially beneficial, but the economic burden is transferred to restaurant owners, while the food waste treatment facility owners would be the main beneficiaries.

4.3. Environmental impact

According to the EPA, the rotting organic waste (e.g. food waste) in landfills is a major source of methane emissions accounting for 20% of the total methane emissions in the US. A previous LCA study (European Commission, 2010) shows that every ton of food waste emits 1.9 tons of CO_2 equivalent GHG. Thus, using food waste to produce biogas and biodiesel would have a positive environmental impact by reducing the methane emissions to the atmosphere. On the other hand, collecting and delivering food waste to processing facilities requires vehicle pickup and delivery, which would consume fossil (liquid transportation) fuels and produce GHG, which would have a negative environmental impact. This section aims to explore the two effects and determine whether using food waste as energy source may have a positive or negative impact on the overall emission.

The baseline solution recycles 846.15 tons of SFW, which has GHG potential of 1,608 CO_2-e tons. A 2011 EPA study reports the CO_2 emission from gasoline is 8,887 grams per gallon. A regular 10 to 25-ton capacity truck has a fuel economy of 2.5 to 6 miles per gallon or 8.7 gallons per thousand tons per mile (CTA, 2013). In the baseline solution, the daily cumulative travel distance for food waste recovery was 7,964.76 km. Therefore, the total GHG emission from the food waste transportation is calculated as:

$$845.15\ ton * \frac{8.7\ gallon}{1000\ tons * 1\ mile} * \frac{1\ mile}{1.61\ km} * \frac{8887\ g\ of\ CO_2}{1\ gallon} * 7964.76km * \frac{1\ ton}{10^6 g}$$
$$\approx 323\ tons\ of\ CO_2$$

The EPA reported in 2002 that there was no unambiguous difference in CO_2 emissions between biodiesel and petroleous diesel. It was reported that biodiesel contains 5.69 pounds of CO_2 per gallon. The US EIA also reported that the CO_2 emission coefficient for biogas (as an alternative natural gas) is 53.1 kg of CO_2 per a thousand cubic of gas[28]. According to the baseline results, the daily biodiesel production is 42.79 tons and the daily biogas production is 11.73 million cubic feet. The GHG emission from the end products is:

$$42.79\ ton * \frac{1\ gallon}{0.003407\ ton} * \frac{5.69\ lb\ of\ CO_2}{1\ gallon} * \frac{0.00045\ ton}{1\ lb} + 11.73 * 10^6 ft^3$$
$$* \frac{53.1\ kg\ of\ CO_2}{1000\ ft^3} * \frac{1\ ton}{1000\ kg} \approx 655\ tons\ of\ CO_2$$

To recycle 846.15 tons of SFW, the supply chain network emits 323 tons of CO_2, the end products emit 655 tons of CO_2, and save 1,608 CO_2-e tons of GHG. A third party Chinese engineering firm estimated that a central treatment facility could potentially consume about 28,000 KWH electricity per day. On average, every KWH of electricity contributes $6.89551*10^{-4}$ tons of CO_2, according to the EPA[29]. Therefore, the plant's emission contribution is 19 tons of CO_2. Considering only the plant operation, then transshipment of food waste through the entire supply chain, and the consumption of end products, there would be a positive environmental

[28] EIA environment: http://www.eia.gov/environment/emissions/co2_vol_mass.cfm
[29] EPA clean energy reference: http://www.epa.gov/cleanenergy/energy-resources/refs.html

impact, namely 611 CO_2-e tons of GHG could be saved, which amounts to 223 thousand tons of CO_2-e per year. According to EPA estimations, the social cost of CO_2 in the year 2050 would be $26 per ton. Therefore, the economic value of the above emission reduction is $16.9 thousand per day, or $6 million per year. Another positive impact of recycling food waste is the reduction in landfill space and possible reductions in leaching of hazardous materials to groundwater. The 846.15 tons of recovered food waste has the potential to reduce the landfill cost by $29 thousand per day. Finally, a previous LCA study by Damgaard et al. (2011) indicated that €13.7 per tons of wet waste is required to avoid landfill leachate. Therefore, the total opportunity cost of avoided landfill is $45 thousand per day. Overall, the positive environmental impact of food waste recovery and use as bioenergy feedstock would have the value of $62 thousand per day or $23 million a year.

The social cost of 'gutter oil' is another major public health and safety issue related to food waste recycling in China. Unfortunately, there is no study on health related economic analysis of the gutter oil issue because this is a fairly recent and emerging social phenomenon in China. Future studies should address this issue and incorporate the economics benefits due to reduced health risks resulting from the use of food waste for bioenergy.

4.4. Tables

Table 4.1 Land availability weights

Site ID	f1	f2	f3	f4	f5
Distance to Civic Center, km	24.34427	41.58515	12.48796	39.83741	55.15347
Weight	2	1.1	1.5	0.85	1

Table 4.2 Three random sampling datasets

Unit, kg	Mean	Standard deviation	Upper bound	Lower bound	Median	Total
Baseline study	68.011	46.498	198.972	3.012	59.805	846,737.081
Random sample 1	68.483	46.157	197.163	3.007	60.965	852,616.432
Random sample 2	68.986	46.277	198.935	3.005	61.263	858,881.140

Table 4.3 Model results for three randomly generated datasets

	Baseline study	Random sample 1	Random sample 2
Annual profit	$50,363,163.33	$50,837,277.28	$51,411,871.74
Central plant selection	f1	f1	f3
Pretreatment station #	15	14	16
SFW recovered, tons	846.15	852.12	858.54
Biodiesel production (waste oil recovered), tons	42.77	43.08	43.41
Food waste recovery	99.93%	99.94%	99.96%
Annual cost	$24,305,016.04	$24,357,526.44	$24,350,401.32
Cumulative traveling distance, km	7,964.76	9,070.34	8,559.70

CHAPTER 5. CONCLUSIONS

This thesis presents a mathematical programming approach and practical solution methods to analyze the profitability, industrial operation and supply chain network design of a food waste treatment system to produce bioenergy. The core body of the thesis is a two-step hybrid heuristic optimization approach where the supply chain network and facility location problem and routing of delivery vehicles are formulated as mixed integer programs (MILP).

The methodology and results of the two MILP models developed here are presented in two essays. The first essay uses a spatially explicit MILP, namely a p-region model, to find the optimal grouping of waste sources, site selection for supply chain design and the waste sources assignments for pretreatment stations. The second essay solves the optimal routing of delivery vehicles operating in each of the regions determined by the p-region model. This leads to a large-scale complex vehicle routing problem (VRP), which is formulated and solved using a linear integer programming solve (GAMS/CPLEX). The two-step heuristic approach introduced here is considered as a viable option to solve large-scale VRPs in similar problem situation. Finally, because of the lack of reliable information in some parts of the input data, the thesis presents a sensitivity analysis considering different modeling assumptions and parameter specifications used in the baseline model to test the robustness of the modeling approaches and sensitivity of the conclusions to those parameter variations. Finally, the thesis presents an analysis of the environmental impact of recycling food waste for bioenergy production.

The empirical results of this modeling study suggest that recovering food waste as bioenergy feedstock can be a profitable business practice. Moreover, the study demonstrates that the recovery of food waste for bioenergy feedstock would have positive environmental impact, in terms of both GHG emissions and avoid landfill leaching, which would contribute significantly to global climate change and local groundwater quality.

The main limitation of the modeling approach presented in this study is the limited computational resources, in particular the memory limitation when working with personal computers and relatively large data sets. These problem can be overcome by aggregation of the waste sources (to reduce the problem size and computational complexity) and by reducing the optimality tolerance when solving the MILP problems. Both approaches have been used in this particular application and proven to be extremely helpful. The second major limitation is the lack of data that may be encountered in many other similar studies. These incomplete data may include several key model parameters, the food waste data, and environmental impact parameters. Several steps have been used to generate a representative data base for particular application presented here. We used random sampling method to generate the food waste data for individual food waste sources, which may or may not be truly representative. Our results show that the geographical distribution of the food waste could have important impact on the model results, in particular facility locations and delineation of the waste collection areas served individual treatment facilities. Therefore special emphasis and effort should be devoted to the collection and processing of input data before conducting an empirical analysis that may provide useful insight to actual decision makers (e.g. governments of metropolitan cities). Finally, while emission impact of food waste processing and emission/percolation impact of landfills have been studies and documented in some studies, there is no empirical study on the health effects, thus related social and economic costs, of reducing ‘gutter oil. This is an important research area particularly in the case of China food service industry.

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APPENDIX A

The triangular distribution Matlab code:

```
%Script by Dr.Mongkut Piantanakulchai
%To simulate the triangular distribution
%Return a vector of random variable
%The range of the value is between (a,b)
%The mode is c (most probable value)
%n is to tatal number of values generated
%Example of using
%X = trirnd(1,5,10,100000);
% this will generate 100000 random numbers between 1 and 10 (where most
probable
% value is 5)
% To visualize the result use the command
% hist(X,50);

function X=trirnd(a,c,b,n)
X=zeros(n,1);
for i=1:n
%Assume a<X<c
z=rand;
if sqrt(z*(b-a)*(c-a))+a<c
    X(i)=sqrt(z*(b-a)*(c-a))+a;
else
    X(i)=b-sqrt((1-z)*(b-a)*(b-c));
end
end %for
%hist(X,50); Remove this comment % to look at histogram of X
end %function


ranwaste=trirnd(3,3,200,12450)
```

The raw data aggregation Matlab code:

```
%ACE project Restaurant aggregation Jan 30th 2014 3rd edition

%Import longitude (X,third column)  and latitude (Y,second column) data set
re=importdata('Relocation2.csv');
%fourth column is waste in kg

%count rows
r=size(re,1);

%new matrix with weight
newrow=[];
wre=[];
%calculate the weight
for g=1:1:r
    dst=[];
    for f=1:1:r
```

```
distb=6371*acos(sin(degtorad(re(g,2)))*sin(degtorad(re(f,2)))+cos(degtorad(re
(g,2)))*cos(degtorad(re(f,2)))*cos(degtorad(re(f,3)-re(g,3))));
        if (g~=f && distb>=0 && distb<=0.5)
            dst=[dst;distb];
        end;
    end;
    if (sum(dst)==0)
        ds=1;
    else
        ds=mean(dst);
    end;
    if (size(dst,1)>=1)
        weight=(re(g,4)/ds)*size(dst,1);
    else
        weight=re(g,4)/ds;
    end;
    newrow=[re(g,:),weight,re(g,4)];
    wre=[wre;newrow];
end;

%sort new matrix
sre=sortrows(wre,-5);
%count rows for new matrix
c=size(sre,1);

%storage table
newre1=[];
ctable=[];
distm=[];
%calculate direct distance
for i=1:1:c
    midst=0;
    if (sre(i,6)~=1)
    for j=1:1:c

dista1=6371*acos(sin(degtorad(sre(i,2)))*sin(degtorad(sre(j,2)))+cos(degtorad
(sre(i,2)))*cos(degtorad(sre(j,2)))*cos(degtorad(sre(j,3)-sre(i,3))));
       if (i~=j && dista1>=0 && dista1<=0.5 && sre(j,6)~=1)
          w=sre(j,4);
       else
          w=0;
       end;
       midst=midst+w;
       if (i~=j && w~=0)
           sre(j,6)=1;
       end;
    end;
    distm=[distm;dista1];
    ctable=[sre(i,1),sre(i,2),sre(i,3),midst+sre(i,4),sre(i,5)];
    newre1=[newre1;ctable];
    end;
end;

%display total waste amount
totalw=sum(newre1,1);
```

The baseline model GAMS code:

```
OPTION reslim=100000;

OPTION optcr=0.01;

OPTION iterlim=100000;

OPTION limrow=0;

OPTION limcol=0;

OPTION solprint=off;


$offlisting


SET RE restaurant /a1*a946/
   MT prestreatment stations /t1*t121/
   FA treatment facility /f1*f5/
   GA biogas usage g1 is compressed biogas for fuel g2 is electricity /g1, g2/

ALIAS (RE,RERE);

PARAMETER dist1(RE,MT) distance from source to pretreatment stations km
/
$ondelim
$include C:\Users\mchen14\Downloads\ACE Project\REMT500mRR.csv
$offdelim
/
;
PARAMETER dist2(MT,FA) distance from pretreatment stations to final facility
/
$ondelim
$include C:\Users\mchen14\Downloads\ACE Project\MTFAR.csv
$offdelim
/
;
PARAMETER waste(RE) food waste dry weight in kg
```

```
/
$ondelim
$include C:\Users\mchen14\Downloads\ACE Project\wastekg500mR.csv
$offdelim
/
;
PARAMETER dist3(RE,RERE) distance between each source km
/
$ondelim
$include C:\Users\mchen14\Downloads\ACE Project\retore1.csv
$offdelim
/
;
PARAMETER gasout(GA) incomes from selling biogas in two ways g1- compressed dollar per thousand cuft g2- electricity dollar per KWH
        /g1 8, g2 0.08/;

SCALAR Moafter water content after pretreatment /0.4/
      Oill oil loss during pretreatment /0.2/
      Mobefore water content before pretratment /0.7475/
      Oilc oil content before pretreatment per dry food waste /0.0632/
      Orga organic content of food waste /0.987/
      Red organic reduction to biogas percentage /0.75/
      ToGas Organic coversion to biogas 1 ton of organic to cubic feet of gas /33075/
      Cond percentage of gas left after conditioning /0.6/
      Elec electric power conversion factor /0.35/
      Struv struvite conversion factor /0.000015/
      Energ energy production factors for biogas KWH per cubic feet /0.322671/
      Bdensity biodiesel density 0.9 ton per cu meter and 264.172 gal per cu meter so tons per gal is /0.003407/
      BSdens biosolid density 1450 lbs per cu yar in tons per cu yard is /0.725/

      Oiltos oil that stays in the solid food waste is 40% of oil loss/0.4/
```

Load solid waste truck load in tons /12/

Oprice biodiesel price dollar per gallon /4.28/

Sprice biosolid price dollar per ton /120/

Stprice struvite price dollar per ton /300/

Tipping tipping fee provided by city government dollar per ton /10/

Engcap electric engine production capacity 4300KW in a day unit of KWH /103200/

Comcap biogas compressor capacity is 375 cu meter per hour in cuft per day /317832/

Capco Capital cost without pretreatment gas engine and compressoras annual payment over 15 years assuming discount rate of 0.072 /16500000/

Tranco transportation cost dollar per ton per km /0.075/

Tripco truck trip cost dollar per km /0.81/

OMco OM cost regardless of transshipment /5400000/

Engco electric engine (3M USD) plus CHP (500K USD) plus installation cost as annual present value over 15 years assuming discount rate of 0.072 /1300000/

Comco biogas compressor cost (60K USD+installations) as annual present value over 15 years with rate of 0.072 /23000/

Disposal solid disposal cost dollar per cubuic yard /24.68/

Premco pretreatment equipment cost (90K+installations) as annual payment over 15 years with rate of 0.072 /33000/;

PARAMETER twaste(RE) total waste is food waste plus water and oil in tons;

twaste(RE)=(waste(RE)/(1-Mobefore))/1000;

PARAMETER precap(MT) pretreatment station handling max capacity ton per day;

precap(MT)=96;

PARAMETER facap(FA) facility capacity tons per day;

facap(FA)=2500;

PARAMETER faocap(FA) facility oil treatment capacity tons per day;

faocap(FA)=250;

scalar big /5/

VARIABLE MAXPROF maximizing annual profit of the plant

POSITIVE VARIABLE WRship(RE,MT) amount of total waste shipping from source to pretreatment station

WTship(MT,FA) amount of food waste shipping from pretreatment to central facility

OTship(MT,FA) amount of waste oil shipping from pretreatment to central facilit

Ncollect(RE) not collected waste

OilTrap(MT,FA) amount of oil trapped in solid food waste

LandF(FA) amount of waste going to landfill

BioG(FA) biogas production unit in cubic feet

BioSolid(FA) biosolid production in tons

BioGuse(GA) biogas usage in cubic feet

Scenter(RE) waste source centers for all clustors

TravD travel distance

BINARY VARIABLE FACI(FA) equal to 1 when this location is chosen to build the facility

PACK(RE,RERE) equal to 1 when RERE is packed into RE

INTEGER VARIABLE EXNUM(MT) number of pretreatment units needed for pretreatment stations

ENGNUM number of gas engine needed for the plant

COMNUM number of biogas compressor needed for the plant

ZT(RE,MT) number of truck trips from sources to pretreatment stations

ZF(MT,FA) number of solid waste truck trips from pretreatment stations to facility

ZO(MT,FA) number of annual oil truck trips from pretreatment station to facility;

EQUATION OBJ bojective functions maximizing profit

CHCENT(RE) choosing centers and amount of waste distribution

WSOURCE(RE) waste source constrain: amount of waste shipping out cannot be bigger than what restaurants have

CS constrain on sources

PWCAP(MT) pretreatment capacity constrain and extension indicators

SEPOIL(MT) waste oil source constrain: oil shipping from pretreatment is less than what restaurants provides

OILLOSS(MT) oil loss during pretreatment separation

DEWATER(MT) waste dewater constrain: solid waste shipping out is less than what comes in

LOCATION facility location constrain: there is only one location will be chosen for new facility

FACAPW(FA) facility handling capacity constrain

FACAPO(FA) facility capacity contrain for waste oil

BIOS(FA) biosolid constrain

BIOGE(FA) biogas production constrain

BIOGU biogas usages constrain

CALENG calculate the number of electric engine needed for the plant

CALCOM calculate the number of biogas compressor needed for the plant

DISPO(FA) solid waste generated from the plant

ASSIGN(RERE) assignment constrain for each source that can be only packed for once

CENTEREQ(RE) center and assignment constraint

TRUCK1(RE,MT) truck load constrain for shipping from sources to pretreatment stations

TRUCK2(MT,FA) truck load constrain for pretreatment site selections

TRUCKO(MT,FA) truck load constrain for waste oil transportation

TDIS total travel distance

;

```
OBJ..MAXPROF=e=365*(BioGuse("g1")*gasout("g1")/1000+BioGuse("g2")*Energ*Elec*gasout("g2")+
        sum(FA,BioSolid(FA))*Sprice+(sum((MT,FA),OTship(MT,FA))/Bdensity)*Oprice+
        sum((MT,FA),WTship(MT,FA))*Struv*Stprice+
        sum((RE,MT)$(dist1(RE,MT) le 20),WRship(RE,MT))*Tipping
        -Tripco*(sum((RE,MT)$(dist1(RE,MT) le
20),ZT(RE,MT)*dist1(RE,MT))+sum((MT,FA),ZF(MT,FA)*dist2(MT,FA)))
        -Tranco*sum((RE,RERE)$(dist3(RE,RERE) le
15),dist3(RE,RERE)*twaste(RE)*PACK(RE,RERE))
```

```
        -Disposal*(sum(FA,LandF(FA))+sum(RE,Ncollect(RE)))/BSdens)
        -Tripco*sum((MT,FA),ZO(MT,FA)*dist2(MT,FA))
        -Capco-OMco-ENGNUM*Engco-COMNUM*Comco
        -sum(MT,EXNUM(MT))*Premco
;
CHCENT(RE)..   sum(RERE$(dist3(RE,RERE) le 15),twaste(RE)*PACK(RE,RERE))=e=Scenter(RE);
CS..           sum(RE,Scenter(RE))=l=sum(RE,twaste(RE));


WSOURCE(RE)..  sum(MT$(dist1(RE,MT) le 20),WRship(RE,MT))+Ncollect(RE)=e=Scenter(RE);
PWCAP(MT)..    sum(RE$(dist1(RE,MT) le 20),WRship(RE,MT))*(1-
Mobefore)=l=precap(MT)*EXNUM(MT);


SEPOIL(MT)..   sum(RE$(dist1(RE,MT) le 20),WRship(RE,MT))*(1-Mobefore)*Oilc*(1-
Oill)=e=sum(FA,OTship(MT,FA));
OILLOSS(MT)..  sum(RE$(dist1(RE,MT) le 20),WRship(RE,MT))*(1-
Mobefore)*Oilc*Oill*Oiltos=e=sum(FA,OilTrap(MT,FA));
DEWATER(MT)..  sum(RE$(dist1(RE,MT) le 20),(WRship(RE,MT)*(1-Oilc)*(1-Mobefore))/(1-
Moafter))=e=sum(FA,WTship(MT,FA));


LOCATION..     sum(FA, FACI(FA))=e=1;
FACAPW(FA)..   sum(MT,WTship(MT,FA)+OilTrap(MT,FA))=l=FACI(FA)*facap(FA);
FACAPO(FA)..   sum(MT,OTship(MT,FA))=l=FACI(FA)*faocap(FA);
BIOS(FA)..     sum(MT,WTship(MT,FA))*(1-Moafter)*Orga*(1-Red)=e=BioSolid(FA);
BIOGE(FA)..    sum(MT,WTship(MT,FA)*(1-
Moafter)*Orga)*ToGas*Red*Cond+sum(MT,OilTrap(MT,FA))*ToGas*Cond=e=BioG(FA);
BIOGU..        sum(FA,BioG(FA))=e=sum(GA,BioGuse(GA));


CALENG..       BioGuse("g2")*Energ*Elec/Engcap*1.2=l=ENGNUM;
CALCOM..       BioGuse("g1")/Comcap*1.2=l=COMNUM;
DISPO(FA)..    sum(MT,WTship(MT,FA)*(1-Moafter)*(1-Orga))=e=LandF(FA);


ASSIGN(RERE).. sum(RE$(dist3(RE,RERE) le 15),PACK(RE,RERE))=e=1;
CENTEREQ(RE).. sum(RERE$(dist3(RE,RERE) le 15),PACK(RE,RERE))=l=big*PACK(RE,RE);
```

```
TRUCK1(RE,MT)$(dist1(RE,MT) le 20)..WRship(RE,MT)=l=Load*ZT(RE,MT);

TRUCK2(MT,FA)..WTship(MT,FA)=l=Load*ZF(MT,FA);

TRUCKO(MT,FA)..365*OTship(MT,FA)=l=Load*ZO(MT,FA);


TDIS..       TravD=e=sum((RE,MT)$(dist1(RE,MT) le
20),ZT(RE,MT)*dist1(RE,MT))+sum((MT,FA),ZF(MT,FA)*dist2(MT,FA))

                 +sum((MT,FA),ZO(MT,FA)*dist2(MT,FA))/365

                 +sum((RE,RERE)$(dist3(RE,RERE) le 15), dist3(RE,RERE)*PACK(RE,RERE));


MODEL FWTREAT /ALL/;


FWTREAT.workspace=8000;


SOLVE FWTREAT USING MIP MAXIMIZING MAXPROF;


DISPLAY WRship.L, WTship.L, OTship.L, Biosolid.L, BioG.L, BioGuse.L, FACI.L, EXNUM.L,
ENGNUM.L, COMNUM.L, Ncollect.L, Scenter.L, ZT.L,

      ZF.L, ZO.L, OilTrap.L, TravD.L;

*display serve.l;


parameter packl(RE,RERE);

       packl(RE,RERE)= pack.l(RE,RERE);


file soutopre /soutopre_4_22.txt/;

    soutopre.pc=5;

put soutopre;

loop((RE,MT),

    if(WRship.L(RE,MT) ne 0, put @3, RE.tl:6:0, @12, MT.tl:6:0, @20, WRship.L(RE,MT):8:4 /));


file packgroup/paking_4_22.txt/;

    packgroup.pc=5;

put packgroup;

loop((RE,RERE),
```

```
    if(PACK.L(RE,RERE) ne 0, put @3, RERE.tl:6:0, @12, RE.tl:6:0 /));


file npick/npick_4_22.txt/;
    npick.pc=5;
put npick;
loop(RE,
    if(Ncollect.L(RE) ne 0, put @3, RE.tl:6:0, @12, Ncollect.L(RE):8:4 /));


file center/clusters_4_22.txt/;
    center.pc=5;
put center;
loop (RE,
    if(Scenter.L(RE) ne 0, put @3, RE.tl:6:0, @12, Scenter.L(RE):8:4/));
```

The VRP model GAMS code:

```
OPTION reslim=1000000;
OPTION optcr=0.05;
OPTION iterlim=1000000;
OPTION limrow=0;
OPTION limcol=0;
OPTION solprint=off;

$offlisting

SET i(RE) sources for t1 /a56,a113,a157,a174,a253,a312,a313,a362,a419,a485,a583,a711,a744,a753/
   t trips /i1*i6/
   m steps /s1*s5/;

alias (i,j);
SCALAR cost /0.81/
     shifthour no truck can work beyound 8 hours /8/
     speed truck average speed km per hour /20/
```

```
liq liquid contend in food waste /0.7475/
disc disposal cost dollar per cu yard /24.68/
dens density of waste ton per cu yard /0.725/;

PARAMETER rload(t) truck load;
    rload(t)=12;

PARAMETER rwaste(j) waste subtact full load if truckload
    etcost(j) cost of an extra trip
    ew(j) waste carried by extra trip;

    loop (j, if (twaste(j)>36,
            rwaste(j)=twaste(j)-36;
            etcost(j)=3*2*cost*dist1(j,'t1');
            ew(j)=36;
        else if (twaste(j)>24,
              rwaste(j)=twaste(j)-24;
              etcost(j)=2*2*cost*dist1(j,'t1');
              ew(j)=24;
        else if (twaste(j)>12,
              rwaste(j)=twaste(j)-12;
              etcost(j)=1*2*cost*dist1(j,'t1');
              ew(j)=12;
        else rwaste(j)=twaste(j);
            etcost(j)=0;
            ew(j)=0; ))))
;

Display ew,rwaste;

VARIABLE TCOST;
```

```
POSITIVE VARIABLE rlandf(j) amount of waste goes to landfill
                  Ws(j) totoal waste pick up from sources;

BINARY VARIABLES X(t,m,j) equals to 1 if truck from pretreatment visit the source first
                  Y(t,m,i,j) equals to 1 if truck makes a trip
                  Z(t,m,j) equals to 1 if truck returns
;
INTEGER VARIABLES NUM number of truck driver needed
                  RETRIP number of trips to one single source;

EQUATION OBJ2 objective function to minimize cost
         pick1(t,m) pickup constrain every source is visited for once
         cont(t,m,j) continuity constrain
         ccon(t,m,i) continous
         sourC(j) source constrain where all waste need to be picked
         return(t,m,i) return constrain
         vcon(j) constrain for visiting all sources
         ycon(t,m,i,j) constrain for Y
         cap(t) truck load constrain that one truck cannot carry more than 12 tons
         tpick(j) total waste pick up
;

OBJ2..TCOST=e=cost*sum(t,(sum((m,j)$(ord(m) eq 1),dist1(j,'t1')*X(t,m,j))+
           sum((m,i,j)$(ord(m) gt 1 and dist3(i,j) le 2),dist3(i,j)*Y(t,m,i,j))+
           sum((m,j),1.1*dist1(j,'t1')*Z(t,m,j))))+sum(j,rlandf(j))*disc+sum(j,etcost(j));

pick1(t,m)..sum(j, X(t,m,j))=l=1;

cont(t,m,j)$(ord(m) gt 1).. X(t,m,j)=e=sum(i$(dist3(i,j) le 2),Y(t,m,i,j));

ccon(t,m,i)..sum(j$(dist3(i,j) le 2),Y(t,m+1,i,j))=l=X(t,m,i);
```

```
sourC(j)..sum((t,m)$(ord(m) eq 1), rwaste(j)*X(t,m,j))+sum((t,m,i)$(ord(m) gt 1 and dist3(i,j) le 1.5),
        rwaste(j)*Y(t,m,i,j))+rlandf(j)=e=rwaste(j);

return(t,m,i)..Z(t,m,i)=e=X(t,m,i)-sum(j$(dist3(i,j) le 2),Y(t,m+1,i,j));

vcon(j)..sum((t,m),X(t,m,j))=l=1;

ycon(t,m,i,j)$(ord(i) eq ord(j)and dist3(i,j) le 2)..Y(t,m,i,j)=e=0;

cap(t)..sum((m,j),rwaste(j)*X(t,m,j))=l=rload(t);

tpick(j)..Ws(j)=e=sum((t,m),rwaste(j)*X(t,m,j))+ew(j);

MODEL route /ALL/;
route.workspace=16000;

SOLVE route USING MIP MINIMIZING TCOST;

DISPLAY X.L,Y.L,Z.L,Ws.L,rlandf.L;
```

APPENDIX B

The baseline solution GAMS report:

```
GAMS Rev 227  x86/MS Windows                    05/04/14 05:19:24 Page 1
G e n e r a l   A l g e b r a i c   M o d e l i n g   S y s t e m
C o m p i l a t i o n


   1  OPTION reslim=100000;
   2  OPTION optcr=0.01;
   3  OPTION iterlim=100000;
   4  OPTION limrow=0;
   5  OPTION limcol=0;
   6  OPTION solprint=off;
   7
GAMS Rev 227  x86/MS Windows                    05/04/14 05:19:24 Page 2
G e n e r a l   A l g e b r a i c   M o d e l i n g   S y s t e m
Include File Summary


   SEQ   GLOBAL TYPE      PARENT   LOCAL  FILENAME

     1        1 INPUT          0       0  C:\Users\mchen14\Downloads\ACE Project
                                          \modelPack050314.gms
     2       20 INCLUDE        1      20  .C:\Users\mchen14\Downloads\ACE Projec
                                          t\REMT500mRR.csv
     3   114495 INCLUDE        1      29  .C:\Users\mchen14\Downloads\ACE Projec
                                          t\MTFAR.csv
     4   115110 INCLUDE        1      39  .C:\Users\mchen14\Downloads\ACE Projec
                                          t\wastekg500mR.csv
     5   116064 INCLUDE        1      47  .C:\Users\mchen14\Downloads\ACE Projec
                                          t\retore1.csv
```

COMPILATION TIME   =   0.905 SECONDS   27 Mb WIN227-227 May 8, 2008

GAMS Rev 227 x86/MS Windows   05/04/14 05:19:24 Page 3

G e n e r a l   A l g e b r a i c   M o d e l i n g   S y s t e m

Model Statistics   SOLVE FWTREAT Using MIP From line 1011148

MODEL STATISTICS

BLOCKS OF EQUATIONS   24   SINGLE EQUATIONS   43,838

BLOCKS OF VARIABLES   20   SINGLE VARIABLES   273,774

NON ZERO ELEMENTS   1,550,843   DISCRETE VARIABLES   231,721

GENERATION TIME   =   5.928 SECONDS   84 Mb WIN227-227 May 8, 2008

EXECUTION TIME   =   5.928 SECONDS   84 Mb WIN227-227 May 8, 2008

GAMS Rev 227 x86/MS Windows   05/04/14 05:19:24 Page 4

G e n e r a l   A l g e b r a i c   M o d e l i n g   S y s t e m

Solution Report   SOLVE FWTREAT Using MIP From line 1011148

S O L V E   S U M M A R Y

MODEL   FWTREAT   OBJECTIVE MAXPROF

TYPE   MIP   DIRECTION MAXIMIZE

SOLVER CPLEX   FROM LINE 1011148

**** SOLVER STATUS   1 NORMAL COMPLETION

**** MODEL STATUS   8 INTEGER SOLUTION

**** OBJECTIVE VALUE   50363163.3274

RESOURCE USAGE, LIMIT 1969.898 100000.000

ITERATION COUNT, LIMIT 507388 100000

ILOG CPLEX May 1, 2008 22.7.2 WIN 4792.4799 VIS x86/MS Windows

Cplex 11.0.1, GAMS Link 34

Cplex licensed for 1 use of lp and barrier.

Solution satisfies tolerances.

MIP Solution: 50363163.327458 (507377 iterations, 4129 nodes)

Final Solve: 50363163.327405 (11 iterations)

Best possible: 50857997.875349

Absolute gap: 494834.547891

Relative gap: 0.009825

**** REPORT SUMMARY : 0 NONOPT

0 INFEASIBLE

0 UNBOUNDED

GAMS Rev 227 x86/MS Windows 05/04/14 05:19:24 Page 5

G e n e r a l A l g e b r a i c M o d e l i n g S y s t e m

E x e c u t i o n

----1011150 VARIABLE WRship.L amount of total waste shipping from source to pre

treatment station

t1 t9 t23 t24 t27 t32

a19			48.000	150.752		
a26			206.763			
a33		56.577				
a39		163.525				247.065
a58	219.882					
a61				15.697		
a81				4.285		
a86				31.805		
a92		20.886				
a122				51.904		
a174	35.312					
a395				1.278		
a562					11.666	
a649					0.673	
a716					11.698	
a757					3.869	
a769			0.227			
a784						10.461
a895					2.461	

+	t39	t41	t50	t60	t86	t90
a3			247.825			
a5		21.773				46.186
a8		25.419				
a14		50.098				
a15		18.791				
a19			9.700			
a35	53.072					
a36						194.960
a41		36.701				
a43					113.246	

a57				92.142	
a62			35.977		
a79				32.974	
a85	149.746				
a92			24.000		
a94	23.290				
a102		54.265			
a110		16.794			
a123			23.196		
a147			32.753		
a159			35.230		
a180			11.556		
a184		11.517			
a188		4.560			
a218			6.476		
a240			58.723		
a279					2.362
a353	1.016				
a577			0.961		
a580	0.336				
a747		1.988			
a749			0.825		
a840		1.603			
a929			1.498		

+	t93	t100	t110
a23	34.116		
a28	102.013		
a30		168.141	
a46	23.286		
a52			87.474

a77		78.665	
a78	11.516		
a81		9.391	
a131	32.814		
a133	21.087		
a207			27.334
a208	10.929		
a354			2.325
a445			1.117
a700		1.328	
a780			0.879
a790			1.145
a899			1.055
a936			0.144

----1011150 VARIABLE WTship.L amount of food waste shipping from pretreatment t
o central facility

	f1
t1	100.607
t9	95.007
t23	100.527
t24	100.815
t27	11.972
t32	101.526
t39	89.673
t41	96.000
t50	101.526
t60	91.146
t86	93.971

t90	96.000
t93	92.945
t100	101.526
t110	47.889

----1011150 VARIABLE OTship.L amount of waste oil shipping from pretreatment to central facilit

	f1
t1	3.258
t9	3.077
t23	3.255
t24	3.265
t27	0.388
t32	3.288
t39	2.904
t41	3.109
t50	3.288
t60	2.952
t86	3.043
t90	3.109
t93	3.010
t100	3.288
t110	1.551

----1011150 VARIABLE BioSolid.L biosolid production in tons

f1 195.593

----1011150 VARIABLE BioG.L biogas production unit in cubic feet

f1 1.172953E+7

----1011150 VARIABLE BioGuse.L biogas usage in cubic feet

g1 1.172953E+7

----1011150 VARIABLE FACI.L equal to 1 when this location is chosen to build th
e facility

f1 1.000

----1011150 VARIABLE EXNUM.L number of pretreatment units needed for pretreatme
nt stations

```
t1   1.000,    t9   1.000,    t23  1.000,    t24  1.000,    t27  1.000
t32  1.000,    t39  1.000,    t41  1.000,    t50  1.000,    t60  1.000
t86  1.000,    t90  1.000,    t93  1.000,    t100 1.000,    t110 1.000
```

```
----1011150 VARIABLE ENGNUM.L          =        0.000  number of gas engine
                                                       needed for the plant
            VARIABLE COMNUM.L          =       45.000  number of biogas comp
                                                       ressor needed for the
                                                       plant
```

----1011150 VARIABLE Ncollect.L not collected waste

a5 0.093, a839 0.393, a866 0.133, a922 0.028, a934 0.078
a938 0.197, a942 0.025, a944 0.847, a945 0.357, a946 0.107

----1011150 VARIABLE Scenter.L waste source centers for all clustors

a3 247.825, a5 68.052, a8 25.419, a14 50.098, a15 18.791
a19 208.452, a23 34.116, a26 206.763, a28 102.013, a30 168.141
a33 56.577, a35 53.072, a36 194.960, a39 410.590, a41 36.701
a43 113.246, a46 23.286, a52 87.474, a57 92.142, a58 219.882
a61 15.697, a62 35.977, a77 78.665, a78 11.516, a79 32.974
a81 13.676, a85 149.746, a86 31.805, a92 44.886, a94 23.290
a102 54.265, a110 16.794, a122 51.904, a123 23.196, a131 32.814
a133 21.087, a147 32.753, a159 35.230, a174 35.312, a180 11.556
a184 11.517, a188 4.560, a207 27.334, a208 10.929, a218 6.476
a240 58.723, a279 2.362, a353 1.016, a354 2.325, a395 1.278
a445 1.117, a562 11.666, a577 0.961, a580 0.336, a649 0.673
a700 1.328, a716 11.698, a747 1.988, a749 0.825, a757 3.869
a769 0.227, a780 0.879, a784 10.461, a790 1.145, a839 0.393
a840 1.603, a866 0.133, a895 2.461, a899 1.055, a922 0.028
a929 1.498, a934 0.078, a936 0.144, a938 0.197, a942 0.025
a944 0.847, a945 0.357, a946 0.107

----1011150 VARIABLE ZT.L number of truck trips from sources to pretreatment st
ations

	t1	t9	t23	t24	t27	t32
a19			4.000	13.000		
a26			18.000			

a33		5.000				
a39		14.000				21.000
a58	19.000					
a61				2.000		
a81				1.000		
a86				3.000		
a92		2.000				
a122				5.000		
a174	3.000					
a395				1.000		
a562					1.000	
a649					1.000	
a716					1.000	
a757					1.000	
a769			1.000			
a784						1.000
a895					1.000	

+	t39	t41	t50	t60	t86	t90
a3			21.000			
a5		2.000				4.000
a8		3.000				
a14		5.000				
a15		2.000				
a19			1.000			
a35	5.000					
a36						17.000
a41		4.000				
a43					10.000	
a57					8.000	
a62				3.000		

a79				3.000	
a85	13.000				
a92			2.000		
a94	2.000				
a102		5.000			
a110		2.000			
a123			2.000		
a147			3.000		
a159			3.000		
a180			1.000		
a184		1.000			
a188		1.000			
a218			1.000		
a240			5.000		
a279					1.000
a353	1.000				
a577			1.000		
a580	1.000				
a747		1.000			
a749			1.000		
a840		1.000			
a929			1.000		

+	t93	t100	t110
a23	3.000		
a28	9.000		
a30		15.000	
a46	2.000		
a52			8.000
a77		7.000	
a78	1.000		

a81		1.000	
a131	3.000		
a133	2.000		
a207			3.000
a208	1.000		
a354			1.000
a445			1.000
a700		1.000	
a780			1.000
a790			1.000
a899			1.000
a936			1.000

----1011150 VARIABLE ZF.L number of solid waste truck trips from pretreatment s
tations to facility

	f1
t1	9.000
t9	8.000
t23	9.000
t24	9.000
t27	1.000
t32	9.000
t39	8.000
t41	8.000
t50	9.000
t60	8.000
t86	8.000
t90	8.000
t93	8.000

```
t100      9.000
t110      4.000


----1011150 VARIABLE ZO.L  number of annual oil truck trips from pretreatment st
                          ation to facility

             f1

t1      100.000
t9       94.000
t23     100.000
t24     100.000
t27      12.000
t32     100.000
t39      89.000
t41      95.000
t50     100.000
t60      90.000
t86      93.000
t90      95.000
t93      92.000
t100    100.000
t110     48.000


----1011150 VARIABLE OilTrap.L  amount of oil trapped in solid food waste

             f1

t1        0.326
t9        0.308
```

t23	0.326
t24	0.326
t27	0.039
t32	0.329
t39	0.290
t41	0.311
t50	0.329
t60	0.295
t86	0.304
t90	0.311
t93	0.301
t100	0.329
t110	0.155

----1011150 VARIABLE TravD.L = 7964.756 travel distance

**** REPORT FILE SUMMARY

soutopre C:\Users\mchen14\Downloads\ACE Project\soutopre_4_22.txt

packgroup C:\Users\mchen14\Downloads\ACE Project\paking_4_22.txt

npick C:\Users\mchen14\Downloads\ACE Project\npick_4_22.txt

center C:\Users\mchen14\Downloads\ACE Project\clusters_4_22.txt

EXECUTION TIME = 0.109 SECONDS 49 Mb WIN227-227 May 8, 2008

USER: Agricultural and Consumer Economics G080205:1456AP-WIN

University of Illinois, Urbana-Champaign DC6884

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**** FILE SUMMARY

Input   C:\Users\mchen14\Downloads\ACE Project\modelPack050314.gms

Output   C:\Users\mchen14\Downloads\ACE Project\modelPack050314.lst

Save   C:\Users\mchen14\Downloads\ACE Project\baseline.g0?