INCENTIVE-LOCATION PLANNING FOR WASTE-TO-ENERGY SYSTEM

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Declaration

I hereby declare that the thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

Gai Nian

Gai Nian

6 August 2016

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Contents

Summary

In this work, we address two major problems in Waste-to-Energy (WTE) System. One is the facility location problem of operating WTE plants. The other is the incentive policy that induces residents to participate in waste recycling.

In megacities, residential solid wastes are generated in huge quantities by the dense population, including food wastes, paper, plastics, and etc.

WTE system aims to collect sufficient qualified and profitable residential waste to generate energy and avoid emitting pollutants. We propose a framework to resolve which facilities should be opened periodically based on waste generation of its neighbour resident zones in the coming season.

Incentivation design is a challenging problem for which multiple contradictory factors exist in the system. On one side, the distances, the resident zones, and the incentive reservation levels, which also varies with different individuals, are supposed to be taken into account for the accurate formulation. On the other side, this formulation would increase the complexity of the overall model and make it hard to compute. So sample average approximation is adopted to make it computable.

A two-stage stochastic programming model is proposed to describe the incentive-location joint planning problem. Two scenarios are discussed: In the first scenario the waste collected from resident zones is profitable and abundant, and in the second one the residential waste is short and waste purchased from professional refuse processing station is available. We adopt some heuristic methods and parallel computing with Map-Reduce and to solve the problem in large scales which a single computer is incapable of, and provide an upper bound and lower bound generated by Lagragian relaxation to estimate the accuracy.

List of Tables

List of Figures

List of Symbols

For clarity of presentations, we define some generic notations here. Other notations specific to the context will be defined prior to the formulations. In this thesis, matrices and vectors are represented as upper and lower case boldface characters respectively. Sets are denoted in calligraphic notations.

Sets and parameters

i	index of WTE sites ($i = 1, \cdots, \mathcal{I}$)
j	index of resident zones ($j = 1, \cdots, \mathcal{J}$)
t	index of sample of residents ($t = 1, \cdots, T$)
l	index of scenarios generated (($l = 1, \cdots, L$)
h	transportation cost per unit distance traveled for per unit amount of waste
d_{ij}	travel distance between the WTE site i and the resident zone j
q	unit revenue of the waste from WTE process output (e.g. electricity generation)
f_i	cost of each WTE site i for per unit capacity
b_i	the fixed groundbreaking cost of ith facility
W	unit operating expense of a WTE facility
θ_j	the purity ratio (the proportion of usable waste) of the feedstock collected in zone j
c_D	the disposal and incineration cost for per unit impure feedstock
g_i	penalty cost of per unit excess capacity at site i
u	total amount of secondary feedstock
u_{il}	the amount of secondary feedstock allocated to the ith facility in scenario l
K	the capacity limit for each WTE facility
θ_j	the purity ratio (the proportion of usable waste) of waste collected from zone j
γ	the purity ratio (the proportion of usable waste) of secondary feedstock

l_i the transport cost for per unit secondary feedstock allocated to site i

$\hat{p}(r_j)$ the estimator of the portion of participators in recycling in resident zone j

z_{jt} an indicator of whether the tth resident of zone j is a participator in recycling

ξ_{jt} the reservation incentive level of the tth resident in zone j for unit amount of waste

η_{jl} the waste generation in resident zone j in the lth scenario

Uncertain parameters

$\tilde{\eta}_j$ uncertain waste generation in resident zone j, which is modeled as a random variable

$\tilde{\lambda}_i$ uncertain excess feedstock in plant i

$\tilde{u}_i$ uncertain amount of secondary feedstock allocated to the ith facility

Decision Variables

r_j incentive paid to the resident in resident zone j for unit amount of waste transported

ν_i capacity of each WTE site i

$$x_i = \begin{cases} 1 & \text{if falicity } i \text{ is opened} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ij} = \begin{cases} 1 & \text{resident zone } j \text{ is assigned to the facility at site } i \\ 0 & \text{otherwise} \end{cases}$$

Chapter 1

Introduction

In this thesis, we mainly focus on the location decision and policy making in waste management. Waste management is composed of all the activities concerned about refuse from the generation to the disposal. The relevant challenge of waste management in any modern highly-populated society nowadays encompasses the conflicts among the sharply increasing waste generation, shrinking landfill site capacity, and the related atmospheric and environmental pollution problems.

Rogner (Rogner et al.) believes that as to prevent from further global warming, greenhouse gas should be emitted 50 percent less of the amount in 1990 by 2050. And Mikac (Mikac et al., 1998) studies the highly-polluted land state in Zagreb, which contains 5 million tons of waste and points out the significant harm of landfill. The process of landfill inevitably releases emissions including gas like methane and poisonous residue that both contribute significantly to global warming and environmental pollution. Global population explosion requires much more efficient approaches to utilize limited non-renewable resources to avoid the possible crisis caused by meager resources. Also, in the research area of sustainable development, resource utilization is one of the most important topics. To make full use of resources, effective waste management systems are considered necessary (Brunner and Rechberger, 2015) .

Therefore, due to the urgency generated by decreasing landfill availability, and poisonous material contamination from incineration, waste recycling programme has been regarded as an intermediary step in waste management. With the main purpose to reduce the environmental pollution and achieve sustainable development of the environment, waste recycling can save energy, highly utilize resources and reduce the heavy load of landfills (Seik, 1997; Rondinelli and Berry, 2000; Ekins et al., 2003; Tınmaz and Demir, 2006; Tsai, 2008; Paleologos et al., 2016) .

Take an instance in Singapore, the amount of residential waste disposed has risen from 1,260 tonnes per day in 1970 to 8,280 tonnes per day in 2015 because of the rapid increasing population and prosperous economy. Before the late 1970s, the landfill is the main approach to deal with the waste disposed around the country. But after that, the decreasing land space made it critical to find another method for waste disposal.

Growing volumes of waste and soaring energy prices are making sustainable waste management a leading solution for a cleaner future. As one kind of source recovery activities, Waste-to-Energy (WTE) system is world-widely considered as an complementary municipal solid waste management method. Therefore the Singapore government preferred to adopt Waste-to-Energy system for its its highly efficiency to reduce the amount of waste. The precedent of IUT global Ltd. chose a framework with a centralized waste processing plant and public donated residential waste but did not sustain the maintenance (IUTgroup, 2008; TheStraitTimes, 2011). The low rate of public participation and high transportation cost around the city are the main factors to a successive of years of financial loss. Therefore other types of facility-location frameworks need to be introduced and a better policy to encourage residents' participation is necessary.

1.1 Waste-to-Energy System

Some advanced techniques of Waste-to-Energy (WTE), such as anaerobic digestion (AD), aerobic composting (AC), and gasification have contributed to the application of waste management systems all over the world (Wang et al., 2014). Its flexibility and sustainability enable the system especially applicable to the areas with dense population and thus low landfill capacity.

Nowadays, the waste is being generated at a high speed. The annual amount of residential waste in Denmark is more than 3.5 million tonnes. They prompt the waste recycling programme by sorting the waste into more than 20 types and more than that, some materials need to be recycled by the producer for reusing. Besides, the annual amount of industrial waste is more than 12 million (Bogh et al., 2014). So the waste recycling and reusing policy are critically necessary to make. Waste recycling is usually regarded as a legislation and some common models are built under the specific rules and assumptions. However, if the recycled materials can be utilized properly, the waste and CO2 emissions may be reduced significantly and it can also generate some new material resource. which is a basic foundation of waste-to-energy conversation.

WTE system in Singapore is started as a waste management, absorbing both business and residential waste. Reusable materials are sorted and made use of to save resources before incineration. Proper incineration technologies can reduce the waste volume greatly up to 10% and generate the heat and steam to help run the facilities and supply electricity power. Therefore this system can help Singapore to save the land and prolong the life span of landfills.

As mentioned, the energy generated in WTE system can be used in the form of electricity or heat so it may seem a profitable programme. However in practice, this system did not even achieve self-financing due to insufficient qualified waste. In Singapore, IUT Global Ltd has to stop running the WTE system due to the great loss in three years without enough qualified feedstock.

To this end, we propose to develop effective planning and scheduling strategies to optimize the performance of the system.

The topic of supply chain management has become an area of interest for many researchers who want to explore. Part of the models we propose are about the design of green energy supply chain network, in line with the research on biomass supply chain management.

The structure of this supply chain (Figure 1.1) is driven by the technology requirement for this product. And a premise of the problem is to determine the source of feedstock. To simplify the problem, we just focus on the waste generated in daily residential life, not taking the industrial waste into account. Considering about the failure precedent, it is clear that a desirable household recycling incentive policy need to be established in order to attain the recycling targets. But it is not easy to raise the residents' environmental awareness and make the recycling policy more effective. Also, the failure of precedent indicates the significant effect of feedstock shortage as it is the only foundation of profitability. Hence a complementary source need to be added in case of loss of the primary feedstock. Besides, complementary feedstock can work as a buffer

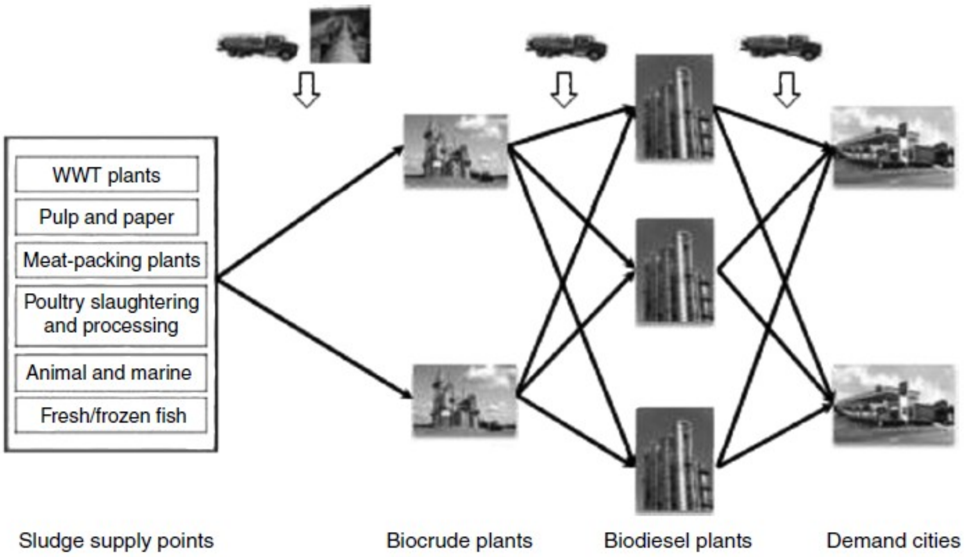

Figure 1.1: Biocrude Supply Chain Structure

of the system in dealing with the variance of primary feedstock. Therefore, importing qualified waste from large-scale professional waste-processing plant is proposed as an optional secondary feedstock.

1.2 Incentive Policy in Recycling Program

Recycling needs people's participation, and without it, the recycling cannot sustain. From the point of view, during the policy making, public's willing need to be fully taken account into. Underestimation of its importance may lead to the failure of the decision. Because without public's participation, there is no raw resource for the WTE system and thus the system will lose the ability to gain profit. People's awareness helps to raise the amount of waste and to improve the quality of the waste and thus makes the system sustainable. From this perspective, incentive policy designing plays a critical role in this recycling and processing program.

An effective incentivation policy should consider many factors, such as the local culture, people's behaviour and even the traffic conditions (Timlett and Williams, 2008). The first thing that need to make clear is the recycling pattern, which is how they recycle and why. Urgent as it is to launch recycling programs widely, many countries and areas have applied various recycling incentives to prompt public participation. For example, South Korea has gained remarkable progress and successful experience in recycling systems (Today, 2012, 2013) since it applied 'pay for improperly disposing of unclassified waste' policy. Also, it is also found in the recycling system of Hong Kong that small rewards have a positive relationship with the amount of sorted waste (Yau, 2010) . In addition, in the past 10 years, Singapore has also made remarkable progress on waste reduction and raising residents' environmental awareness on waste classification with many environmental campaigns (Times, 2015).

1.3 Location-Incentivation Joint Design

Traditionally, the optimization of configuration in waste management framework (i.e., facility location) and policy design of incentivation in recycling programme are proceeded sequentially: configuration optimization first, followed by incentivation policy making. However, such a sequential strategy does not fully account for the interaction between the configuration and incentivation optimization problems. And a simple example is introduced to demonstrate this interaction below.

Consider a simple supply chain model consisting of one larger resident zone A with 1000 residents and one smaller zone B with only 100 people. The objective of facility location is to maximize the total profit by minimizing the each person's path to the facility. And assume the price of waste in zone A is too high to be profitable while it is well profitable in zone B, then the objective of policy is to maximize the profit of waste we bought.

With sequential approaches, the location solution is to build the facility near zone A, while the policy chooses to buy all the waste in B. This solution is feasible but not necessarily optimal as the transportation cost from zone B to the facility may result in a great loss. Here the transportation cost for waste is the interaction, which is decided both by the facility location and incentivation policy. Now with the evolution of technology, the system design shifts focus from feasibility to optimality. In this aspect, although the sequential optimization is appealing for its simplicity, the simultaneous joint optimization is the better to apply.

Today's the WTE systems in mega cities are difficult to optimize: they are large, complex and comprised of numerous interconnected components rather than the simple example given above. To optimize such systems, one must accurately model not only their components, but also the potentially sophisticated interactions among those components. Moreover, even if accurate system models are obtained, their complexity often renders them mathematically and computationally intractable. So that it is also necessary to propose proper computational approaches.

As discussed in preceding sections, in this thesis we propose to build up a facility location framework embedded with incentive policy designing to balance the expense of WTE plants, the cost of feedstock, etc. with the final criterion of maximizing the system's overall revenue.

More specifically, that is how many of WTE plants should be opened and where they or it should be, and how the incentive should be decided.

To verify the feasibility and effectiveness of the proposed method, One-stage problem with the only source from resident zones is set up as benchmark. It would be a typical traditional design of supply chain network aiming to solve facility location and capacity. And the subproblem is to determine the incentive. Our core improved model is to allow for the secondary feedstock and its allocation.

In this paper, we let bold face lower case letters denote vectors, and bold face upper case letters denote matrices. Besides, a tilde sign $\tilde{}$ is used as an identification of random variables (for vectors or matrices denoted with a tilde sign like $\tilde{\boldsymbol{\xi}}$, every entry of which is a random variable). For any $x \in \Re$, we define $x^+ = \max\{x, 0\}, x^- = \max\{-x, 0\}$. For vectors vectors $\boldsymbol{x} \in \Re^m$, $\boldsymbol{x}^+$ and $\boldsymbol{x}^-$ are defined in a similar way.

The main contribution of this thesis is developing optimization models that aim to design cost-efficient supply chains for the operation of WTE system. We propose a two-stage stochastic programming model for siting the recycling plant locations, and incentivzation under uncertainty of residents' reservation incentives and waste volumes. To raise public environmental awareness, residents are paid some cash as incentive to keep a habit of sorting their waste initiatively. It is supposed to be a long-term goal to develop waste-to-energy sense and to encourage people to practice waste sorting. Despite of the lack of residential waste, the system can also purchase secondary feedstock as complement from professional waste plants. This strategy also helps to reduce the amount of waste proceeded with traditional landfill or burning way.

1.4 Outline of Thesis

The thesis consists of two major parts. The first (Chapter 3 and Chapter 4) and second (Chapter 5 and Chapter 6) parts respectively deal with the model formulation and the methodologies and the corresponding numerical results. Chapter 3 lays a model foundation with a basic framework for the WTE recycling system. After taking the secondary feedstock into account, Chapter 4 improves the model by providing a more complicated framework. Then Chapter 5 introduces the methodologies adopted in this thesis with the priority of different aspects like speed and accuracy. Chapter 6 shows some numerical results to validate the effectiveness of the methods adopted and compares their application range. In the final chapter, the conclusion is presented with areas for improvements and suggestions for future research.

Chapter 2

Literature Review

In this chapter there are two main parts. Section 2.1 introduces related literature, focusing on the Waste-to-Energy system and the policy design in some recycling programs. Section 2.2 presents an overview of methodologies adopted in this research.

2.1 Research Problem Related Literature

The related topics in this research is the Waste-to-Energy system background and incentivation policy making for the recycling programme.

2.1.1 Waste-to-Energy

Municipal waste management is seen as one of the public services to provide people an environmental and economical way to deal with their household waste.

However, due to the increasing population, the municipal solid waste management has to tackle with some problems including the conflicts among growing waste generation, limited landfill capability, and the CO2 emission impact. As one of the most widespread and commercially viable Waste-to-Energy (WTE) technology, anaerobic digesters (AD) produce methane from the biomass as a green and renewable bio-energy source from the organic wastes. This methane gas mixture has a high calorific value which can be converted to electricity or burnt to release heat energy. Besides, as one final product of the digester, the solid sludge produced can be re-used as agricultural fertilizers or as input for the gasification units. The economically feasible AD implementation enables the profitability of a well-designed WTE system.

The literature on modelling of waste management system (Gottinger, 1988; MacDonald, 1996; Berger et al., 1999; Tanskanen, 2000; Morrissey and Browne, 2004) presents a comprehensive brief of some common models. Initial waste management models are based on Municipal Solid Waste management (MSW) and developed to deal with specific topics like waste transport problems. Due to the development system approach and the wider application of waste management, MSW models then began to take into consideration some environmental and system factors. However, most of the models focused on economical problems, especially the problems on minimizing the cost. Only a few considered the relationships of the variables within the systems. Nevertheless, the shortcomings of the early models include not considering the recycling part, limited alternatives solutions, and so on. From early 2000s, researchers began to consider the environmental and social aspects as well. Thus the waste management models targeted on all the waste streams to be managed and considered more available options.

Currently, some of the models are related to waste transport problems, discussing how to lower the transport expense adopting different vehicle options and scheduling strategies. Johansson (Johansson, 2006) integrates the cost of transport into the overall system expense and proposed a model optimizing the waste collection under dynamic scheduling and routing strategies. Macharis (Macharis et al., 2012) points out that the barge transport is more environmental friendly as it emitted less CO2 than truck and train. Palak (Palak et al., 2014) analyses how the CO2 emission policy influence the transport decision in a biofuel waste management system. Inghels (Inghels et al., 2016) examine the feasibility of replacing the traditional truck transport with barge and multimodal truck.

In addition, some of MSW models are related facility location issues. Erkut (Erkut et al., 2008) presents a new multicriteria supply chain model to solve the facility location problem for waste management system at the regional level in North Greece. Sazvar (Sazvar et al., 2014b) proposes a replenishment policy under a centralized plant. Faghri (Faghri et al., 2002) proposes a geographic information system model to help make facility location decision considering various factors relating to environment, society and economy.

Of the mathematical models, many are focused on deterministic environments. For instance, Roni (Roni et al., 2014) designs the hub-and-spoke supply chain network using existing data as a deterministic problem and Niziolek (Niziolek et al., 2016) built a deterministic mixed-integer nonlinear model to optimize the liquid fuel production during the MSW process etc. However, the models under uncertain environment is usually more complex, as they are often related to some unpredictable parameters like the amount of demand. Jennings (Jennings and Suresh, 1986) takes the risk penalty as functions including uncertain parameters for optimization model and uses the risk rating techniques to solve the model. Escudero (Escudero et al., 1999) considers the demand, supply cost and price of product as uncertainties and propose a optimization model for multiperiod scheduling problem. Dempster (Dempster et al., 2000) focuses on a resource planning problem under the uncertain demand and prices of the product. The model proposed by Al-Othaman (Al-Othman et al., 2008) is developed as a multiperiod stochastic programming model for petroleum products under the uncertain prices and demand. Carneiro (Carneiro et al., 2010) regards the risk as uncertainty and present a two-stage stochastic model for oil supply chain. Khor (Khor et al., 2008) proposed a two-stage stochastic programming model for refinery under uncertain prices, demands and yields. Baetz and Neebe (Baetz and Neebe, 1994) built a mix integer programming model under dynamic environment. Everett (Everett and Modak, 1996) developed a multi-period model in multi-region. Sundberg (Sundberg et al., 1994) discussed a static non-linear programming model. And the summaries presents the model development of waste management over decades and points out the important developments of the modelling which are made in the research field of waste management in the past time.

In addition, at that time, the sustainability and integration have not been used in the waste management systems, that means the models built do not consider revenues. With the wide adoption of recycling programme, recent modelling has taken such factors into account (Chang and Wei, 1999; MacDonald, 1996; Ghose et al., 2006). And nowadays models are often built to adopt different waste management methods (Morrissey and Browne, 2004; Pan et al., 2015).

Nevertheless, there is limited literature addressing the expense for the recycling programme and the cost for the waste collected in waste management systems. And there is no existing model dealing with multi-stage feedstock. Our problem requires to combine these two goals together to co-design to optimize the system's performance.

2.1.2 Policy Design

Recent empirical researches have strongly revealed the positive impact of incentive mechanisms in waste recycling. For instance, the study of Yau (Yau, 2010) showed that in Hong Kong, the reward in monetary form can induce the people to deliver the waste and can greatly increase the household waste collected. In a study of using leisure voucher as an incentive for waste recycling collection in England, Harder (Harder and Woodard, 2007) proposed that most of the successful incentive schemes generally share three key characteristics: rewards based on individual household basis, the sufficient level of the incentive, and the ease of achieving these incentives. The research of Timlett and Williams (Timlett and Williams, 2009) discussed how the population transience influence the the participation rate in recycling programme in Portsmouth, which is a populated city with high rates of population flux and showed the relationship between the population dynamics and recycling participation rate. Incentive-driven recycling planning problems have been discussed in the literature mainly within the scope of reverse logistics for remanufacturing. Guide (Guide Jr et al., 2003) studied the impact of financial incentives (in the form of acquisition prices) on the remanufacturing industry which influence the quantity and quality of recyclables. The authors proposed a simple framework for determining the optimal acquisition prices that match the demand and supply to maximize the profitability of the remanufacturing firm, and provided an application example based on the cellular telephone industry. Wojanowski (Wojanowski et al., 2007) discussed a continuous modeling framework incorporating the deposit-refund policy in industrial firms collection, facility network design, and pricing decisions. This model targets to describe the relativity of customers' willing to buy and return some products with a stochastic model. The net value recoverable from a returned product is determined through parametric analysis as an important incentive for the company to offer deposit-refunds for free. The study also showed that it is not enough for the government to set a minimum deposit-refunds limit to raise the recycling participation portion when the products return value is low, and some complementary accessibility-based policies can be used.

Deposit-refund policy is commonly utilized in promoting the return of used products for remanufacturing, such as aluminium cans, glass bottles, batteries, and tires.

However, such financial incentive policy has not been used in waste recycling management as cost information related to the amount of waste collected. But the above literature provides a foundation to back up the relation between the amount of incentive and waste recycled.

2.2 Research Methodology Related Literature

In this research we mainly adopted two solution approaches, parallel computing with Map-reduced framework, Lagrangian relaxation and multi-stage optimization. Some of them are combined to improve the performance including speed and accuracy.

2.2.1 Parallel Computing and Map-reduced

Parallel computing is a method of having multiple small jobs to solve a large problem. In recent years it has been developed rapidly as the software and hardware in computer field have been upgraded fast. Nowadays it has emerged as an important technology in computing application. The past recent years have witnessed an ever-increasing acceptance and adopting of parallel processing, both for high-performance scientific computing and for more ”general-purpose” applications, was a result of the demand for higher performance, lower cost and sustained productivity. The acceptance has been facilitated by a major development, massively parallel processors (Geist, 1994).

Parallel computing has made a tremendous impact on a variety of areas ranging from computational simulations for scientific and engineering applications to commercial applications in data mining and transaction processing. The cost benefits of parallelism coupled with the performance requirements of applications present compelling arguments in favour of parallel computing (Grama, 2003).

Based on some studies by Chu et al. and Dean (Chu et al., 2007; Dean and Ghemawat, 2008), Map-reduced is a programming model and an associated implementation for processing and generating large data sets. Users specify a map function that processes a key/value pair to generate a set of intermediate key/value pairs, and a reduce function that merges all intermediate values associated with the same intermediate key. So one of its outstanding advantages is user-defined rules, allowing creating some unique functions to carry out. Also it is designed for multicore use, which is specialized for use over clusters that have unreliable communication.

2.2.2 Stochastic Programming Models in Waste Management

The basic mathematical models in (Huang et al., 2010) discuss the facility location and transport problems in supply chain framework under deterministic settings. And many optimization models under stochastic environment are proposed in (Grossmann and Guillén-Gosálbez, 2010; Chen and Fan, 2012) et al. They aim at dealing with different stochastic nature of biomass supply and cost, and study the multistage models to solve complicated problem. Furthermore, with the increasing publishment of GHG emossion policies, Marufuzzaman (Marufuzzaman et al., 2014a) discussed the performance of the biodiesel supply chain model with various constraints like carbon emission, carbon tax, carbon cap mechanisms. And they used real-life application in extensions of the classical economic lot-sizing (ELS) and economic order quantity (EOQ) models to get clear and insightful numerical results. The paper concluded with an summary of the impact of the biocrude supply chain design under different emission policies. And Md.S.Roni (Roni et al., 2014) proposed a supply chain network design model for biomass co-firing in coal-fired power plants due to practical problems that investment and processing costs necessary for production of biofuel are very high (Wallace et al., 2005). The paper used extensions of deterministic hub-and-spoken network design problem to model the biomass supply system and bender decomposition to solve the $NP-$ hard problem. Also, it applied real-life data to evaluate the feasibility of the model in practice.

Also motivated by the cost of carbon emission fee, M.Marufuzzaman et al. (Marufuzzaman et al., 2014b) investigated the biodiesel supply chain via waste water treatment under biomass supply and technology development uncertainties and develop the multi-cut L-shaped based algorithm to solve model. The model captured the tradeoff that exists between costs and emissions in the chain, and compared the formulation with different carbon emission considerations to the one without such constraints. However, Palak.G (Palak et al., 2014) suggested another perspective that analyzing the impact of such carbon mechanisms on supplier and mode selection decisions. The paper modified the extensions of classical EOQ models to evaluate different inventory replenishment decisions and showed some observation results on how the carbon mechanisms affect the decision variables like expenses, revenues, facility location, and emissions in the biomass supply chain models.

Sazvar.Z (Sazvar et al., 2014a) also worked on the EOQ models in a centralized supply chain aiming to balance the financial and environmental criteria by determining the transportation vehicles and inventory policy. In this paper, they linearized a scenario-based multi-stage stochastic optimization and use real data to demonstrate the feasibility and effectiveness. Rather than linearize the model, Oliveira.F (Oliveira et al., 2014) chose to use stochastic bender decomposition and present several approaches for enhancing the efficiency of the Benders cuts generated such as MagnantiWong cut generation and SheraliLunday alternative cut generation. In the computation section comparisons are made to prove the advancement of the algorithm.

2.3 Research Focus

It has never been addressed that the incentivation-location joint planning problem in supply chain network. In addition, no existing scheduling model can efficiently solve the two-stage scheduling problems in these plants. Thus in this research, we focus on joint design for incentive-location planning of WTE system.

Chapter 3

Incentive-Location Joint Planning: Basic Model

As is known, in recycling programme, incentive mechanism is referred to encourage people to classify their waste. And the configuration of waste management chain also has a great effect on the incentive policy making. However, limited literature exists for work involving embedding incentive policy design in a supply chain.

In this chapter, we begin with an establishment on the form of monetary incentive and then combine it into this WTE supply chain. Section 3.1 first introduces the background of incentive policy, then builds a model according to practical applications. Section 3.2 gives a detailed description on how location and incentive affect each other and what problems we should solve in this part. Then Section 3.3 propose a mathematical model aiming to resolve a general capacitated plant location problem embedded with incentive policy, and a special case in which the capacity constraint is relaxed is proposed for suburban districts. Section 3.4 provides a computational method for this joint planning model. And data test is carried out in Section 3.5 to demonstrate the validation of model and feasibility of method. At the end of this chapter, corresponding result analysis is discussed.

3.1 Incentive Policy in Recycling Program

The scarceness of land and exploding amount of waste generation enables strategic waste management be regarded as indispensable in megacities like Singapore, Shanghai and

Hong Kong etc. Recycling and reusing, as one of the major topics in the arena of waste management research, is adopted by more and more governments as an intermediary measure to manage waste disposal. With the primary aim to lessen environmental damage and achieve environmental sustainability, waste recycling can save energy, conserve resources, reduce emissions from incinerators and raise residents' environmental awareness (Seik, 1997; Rondinelli and Berry, 2000; Ekins et al., 2003; Tınmaz and Demir, 2006; Tsai, 2008). It is known, recycling and reusing from the household waste stream leads to reduced reliance on raw materials for the production of new goods and, at the same time, reduces the quantities of post consumer waste disposed of by undesirable means such as landfill. There is no doubt that effective management of household waste has major potential benefits to society. In addition to the social benefit, the manually-sorted residential waste usually has higher purity ratio thus is more profitable than those from waste collection plant. Therefore, household waste is often set as principle source of these recycling and reusing system(Shaw and Maynard, 2008).

Recycling from households has been promoted by firms and governments around the world as one of the most important practices for achieving sustainability. The residential waste,as primary feedstock, is the basis of all the functions. However, the success or failure of such a practice, relies heavily on the monetary incentive paid to the householders for material sorting and recycling (Chen and Liu, 2014). Although legislation on mandatory disposal is introduced in some countries, most governments and firms choose to use incentive to encourage more waste delivery. In the book named *The Logic of Collective Action*, Olson (2009) explained the failures of groups to work in their collective interest to achieve group benefits, with the insights drawn from the rational choice theory. The point depends on individuals self-interests or so-called rationality. Given that other people engage in a behaviour that is necessary to achieve a collective good, a rational individual seeking to maximize utility or wealth can free-ride their efforts while still gaining the benefits of their behaviour. This rational individual also reasons that if he or she acts to achieve the collective good, the others will free-rider his or her efforts. Therefore, he or she will not participate in the provision of the public good, and others will act in the same way. As a result, there will be no cooperation and no collective good is realized. In the failure case of IUT Global Ltd, what made the company suffer from loss-making situation for three years in succession is that less than 10% of food waste in

Singapore was being recycled under their quantity-based pricing policy. The companies in Hong Kong use daily goods as reward raised the domestic waste recycling rate from 10% in 2001 to 23% in 2007 (Yau, 2010), greatly improved the feedstock input of the system. Therefore an incentive plan should be developed as to support the feasibility of system. Thus in this section we will propose a mathematical programming model to help evaluate the appropriate incentivization plan.

3.1.1 Background

The success of incentive policy for recycling and reusing programme, in some previous literature, are measured with indicators like recycling ratio or residents' satisfaction. In our work, as this focuses on the engineering field, the performance evaluation criteria is the overall profit, thus the incentive is designed as monetary. This kind of measurement is also supported by many studies that have shown that monetary incentives and providing different types of recycling facilities matters (Hong et al., 1993; Jenkins et al., 2003; Jakus et al., 1996; Tiller et al., 1997; Reschovsky and Stone, 1994; Bruvoll et al., 2002; Fullerton and Kinnaman, 2002). But none of their cases involves the distance of recycling facility.

Moreover, some quantity-discount pricing policies, which means the more waste provided, the higher price offered, are not applicable to system due to low household waste generation level. Jean-Daniel M. Saphores suggest a positive correlation of the delivery distance and people's willingness to participate in the recycling. Higher transport cost is a result of longer path. So distance traveled is an important factor to take into account. Moreover, Jean-Daniel M. Saphores also points out that significant numbers of people are unwilling to sacrifice their time and energy to do sorting work for free (Saphores et al., 2006). They have reservation levels for the incentive, which varies with the individual. If the incentive minus transportation cost, also called net reward, is less than the reservation level, then it is most likely the resident would refuse to join the program. Hence with comprehensive considerations, the incentive in this WTE system should paid in monetary way and combine the household reservation levels and the distance for a delivery traveled.

3.1.2 Assumptions and Formulation on Policy design

Some basic assumptions in our policy-making work are given below:

(a) A sample of reservation incentive levels is assumed to be available for each resident zone. Hence we can use ξ_{jt} to indicate the reservation level of tth household in zone j.

(b) Each individual resident has a reservation incentive, and he or she will sort and deliver the waste to WTE facilities if the received incentive minus the transportation cost (to and from the WTE facility) achieves or exceeds the reservation incentive level.

If we refer r, d, h, ξ as incentive, delivery distance, unit transportation cost for unit waste, and reservation incentive level respectively, and denote z as an indicator whether this person would take the incentive and participate, then this assumption can be reflected as the mathematical form:

$$z = I_A(r) = \begin{cases} 1 & \text{if } r \in A \\ 0 & \text{if } r \notin A \end{cases}$$

$$A = \{r | r - dh - \xi \geq 0\} \tag{3.1}$$

where I_A is an indicator function defined as:

$$I_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{if } x \notin A \end{cases}$$

(c) Different incentive policies are applied to different resident zones. And residents in same zone will be taken as a whole to share the same distance information. That is, the incentive policy is only related to the difference of zones, not WTE sites or individuals. Thus we use r_j to replace r in assumption (b), for it only varies with different j.

Because the reservation incentive level is a random variable in this system for not all reservation data is available, it is necessary to introduce the sample estimation to denote the portion of the people participated. And hence the sample estimator $\hat{p}(r_j)$ is used to refer the portion participated in zone$j$ as follows:

$$\hat{p}(r_j) = \frac{1}{T} \sum_{t=1}^{T} z_{jt} \tag{3.2a}$$

$$z_{jt} = I_A(r_j), A = \{r_j | r_j - dh - \xi_{jt} \geq 0\}, \forall t \tag{3.2b}$$

where T is the amount of samples in zone j.

3.2 Problem Description

Facility location is a critical aspect of supply chain planning for a wide range of business systems. This is because it affects the overall cost, inventory price, and demand of the product. In this system discussed, facility location planning is to decide to open one or more capacitated WTE plants among multiple available sites which are limited by the physical environment. Although centralized plant is beneficial to capital expenditure,it may lead to the inconvenience of the waste delivery and high transportation cost, and then further result in the breakdown of WTE system. But for decentralized facilities, the higher rate of recycling may not be able to cover the heavy construction expense . Therefore it is necessary to propose an effective model to evaluate on which site to open a WTE plant.

The mathematical models we propose and our numerical analysis is focus on answering the following questions about the supply chain design and corresponding costs. These questions are to provided investors with a number of business rules to ensure the long-term success of their invention. The questions related to supply chain design are:

◦ Given the amount of waste available in each resident zone, which facility site and what plant capacity optimizes costs?

◦ Should a WTE plant locate centrally to receive all shipments from residential zones?

◦ How much should be offered to the participants in each residential zone?

The optimization model that we propose should maximize the total net profit of the system. The costs include investment, transportation, incentive and penalty cost, while the profit is the revenue by from WTE process output. Investment costs are the costs related to the location and capacity of WTE plants, input to the WTE processing, purchasing of waste. Transportation costs have only a variable component without fixed part depending on the distance traveled and quantity shipped (given in $S\$/km/kg$). Penalty cost is paid for excess waste, including overtime working cost for both workers and machines.

3.3 Formulation

3.3.1 Assumptions

There are some basic assumptions in the model building.

(a) All sorted waste from the same resident zone has the average purity ratio, denoted as θ_j. The purity ratio is a value between 0 to 1.

(b) The operating cost rates of per unit feedstock for all facilities are identical, denoted as W.

(c) Unit revenue of the waste from WTE process output (e.g. electricity generation) is donated as q. Thus $\theta_j q$ is unit gross revenue for per unit feedstock.

(d) The disposal and incineration cost for per unit impure feedstock is denoted as c_D. Thus $(1 - \theta_j)c_D$ is the disposal and incineration fee for per unit feedstock.

(e) The open-up cost for facility includes fixed groundbreaking expense, b_i and linearly dependent capacity expense, f_i.

(f) Given a set of open WTE facilities, the residents only consider the nearest open facility to travel to. So when given the open WTE facilities, the distance between resident zone and WTE facility is determined.

(g) WTE plants cannot transfer the excess waste to each other.

(h) r_j is the incentive offered for per unit feedstock for residents in zone j.

3.3.2 Modeling

If we refer y_{ij} as the accessibility of the delivery link from jth resident zone to ith potential site, then

$$y_{ij} = \begin{cases} 1 & \text{resident zone } j \text{ is assigned to the facility at site } i \\ 0 & \text{otherwise} \end{cases}$$

where $\sum_{i \in \mathcal{I}} y_{ij} = 1, \forall j$.

Then distance can be reformulated as $y_{ij} d_{ij}$, where d_{ij} is the distance from from jth resident zone to ith potential site.

In this way, the net profit for per unit primary feedstock should be the total revenues less operating and disposal costs, which we use $F_1(r_j)$ to express as follows:

$$F_1(r_j) = \theta_j q - r_j - (1-\theta_j)c_D - W \tag{3.3}$$

In this chapter, we only consider the waste collected from resident zone as the sole source, so decision variables are the opening status of WTE plant x_i (1 represents open and 0 otherwise), the capacity of each WTE plant ν_i, the amount of incentive for each zone r_j.

In the profit function (3.3), the primary feedstock purity ratio θ_j in each zone j by definition is the proportion of per unit waste collected that is eventually usable for WTE conversion,generating a revenue margin of $\theta_j q$ dollars. Also, for every unit waste collected, a fraction of $1-\theta_j$ will need to be disposed since they are unsuitable for WTE conversion, incurring a disposal cost of $(1-\theta_j)c_D$. The operating cost rate W, is unit operating expense of a WTE facility. In summary, the unit profit margin term $\theta_j q - r_j - (1-\theta_j)c_D - W$ in the above accounts for the revenue generation from pure feedstock $\theta_j q$ less the sum of incentive payout r_j, impurity disposal charges $(1-\theta_j)c_D$ and operating costs W.

On the condition of capacity constraint, there exist possibilities whether the amount of feedstock exceeds or fails to reach the capacity limit. As we focus on the residential waste, part of the waste is perishable and may contaminate the rest. Therefore excess waste cannot be stored to be used in next period and thus some cost will be charged as penalty. We have the expression λ_i for the amount of excess feedstock if η_j is referred as the waste generation of zone j:

$$\tilde{\lambda}_i = \left[\sum_{j \in \mathcal{J}(i)} y_{ij} \tilde{\eta}_j \hat{p}(r_j) - \nu_i \right]^+ \tag{3.4}$$

Where $\tilde{\eta}_j \hat{p}(r_j)$ represents the waste collected from zone j and thus $\sum_{j \in \mathcal{J}(i)} y_{ij} \tilde{\eta}_j \hat{p}(r_j)$ is the overall waste collected in facility site i.

The problem can then be formulated as the following stochastic optimization problem:

$$\max \ E_{\tilde{\eta},\tilde{\lambda}} \left[\sum_{j\in\mathcal{J}} \tilde{\eta}_j \hat{p}(r_j) F_1(r_j) - \sum_{i\in\mathcal{I}} g_i \tilde{\lambda}_i \right] - \sum_{i\in\mathcal{I}} (f_i \nu_i + b_i x_i) \tag{3.5a}$$

$$\text{s.t.} \ \ \tilde{\lambda}_i \geq \sum_{j\in\mathcal{J}} y_{ij} \tilde{\eta}_j \hat{p}(r_j) - \nu_i, \ \ \forall i \tag{3.5b}$$

$$\tilde{\lambda}_i \geq 0, \ \ \forall i \tag{3.5c}$$

$$K x_i \geq \nu_i \geq 0, \ \ \forall i \tag{3.5d}$$

$$\sum_{i\in\mathcal{I}} y_{ij} d_{ij} \leq x_i d_{ij}, \ \ \forall i, j \tag{3.5e}$$

$$\sum_{i\in\mathcal{I}} y_{ij} = 1, \ \ \forall j \tag{3.5f}$$

$$y_{ij} \leq x_i, \ \ \forall i, j \tag{3.5g}$$

$$x_i, y_{ij} \in \{0, 1\} \tag{3.5h}$$

$$\nu_i, r_j \geq 0 \tag{3.5i}$$

where g is the unit penalty cost, M is a suitable large number, and K is the capacity limit due to WTE facility's design.

Note that constraints (3.5b) and (3.5c) equals to expression (3.4) in a maximizing problem. Constraint (3.5d) restricts the 0 capacity with the premise of closed plant by setting $\nu_i = 0$ when $x_i = 0$. Constraint (3.5f) ensures for one zone there is only one facility to deliver and Constraint (3.5e) makes sure that zone j will choose the nearest opened facility to deliver by constraining $y_{ij} = 1$ when d_{ij} is least for all opened sites.

In the following we use the sample average approximation approach to obtain a mixed integer (non-linear) programming formulation of the above problem. L scenarios are simulated and the average of total profit in each scenario is taken to replace the original objective in the following form, :

$$\max \frac{1}{L} \sum_{l=1}^{L} \left\{ \sum_{j\in\mathcal{J}} \eta_{jl} \hat{p}(r_j) F_1(r_j) - \sum_{i\in\mathcal{I}} g_i \lambda_{il} \right\} - \sum_{i\in\mathcal{I}} (f_i \nu_i + b_i x_i) \tag{3.6a}$$

$$\text{s.t.} \ \ \lambda_{il} \geq \sum_{j\in\mathcal{J}} y_{ij} \eta_{jl} \hat{p}(r_j) - \nu_i, \ \ \forall i \tag{3.6b}$$

$$\lambda_{il} \geq 0, \ \ \forall i \tag{3.6c}$$

$$Kx_i \geq \nu_i \geq 0, \quad \forall i \tag{3.6d}$$

$$\sum_{i \in \mathcal{I}} y_{ij} d_{ij} \leq x_i d_{ij}, \quad \forall i, j \tag{3.6e}$$

$$\sum_{i \in \mathcal{I}} y_{ij} = 1, \quad \forall j \tag{3.6f}$$

$$y_{ij} \leq x_i, \quad \forall i, j \tag{3.6g}$$

$$x_i, y_{ij} \in \{0, 1\} \tag{3.6h}$$

$$\nu_i, r_j \geq 0 \tag{3.6i}$$

3.4 Solution Approach

3.4.1 General Case

However, Model 3.6 is still a non-linear MIP problem and to be solved more directly, it requires some alteration for the intractable part $\hat{p}(r_j)F_1(r_j)$ in the objective 3.6a. Note that $\hat{p}(r_j) = \frac{1}{T}\sum_{t=1}^{T} z_{jt}$ (3.2), we use auxiliary variables A_{jt} and B_{ijt} to help as:

$$Ajt = z_{jt}F_1(r_j) \tag{3.7}$$

$$Bijt = y_{ij}z_{jt} \tag{3.8}$$

Thus a MILP problem is formulated in the following way:

$$\max \frac{1}{L}\sum_{l=1}^{L}\left\{\frac{1}{T}\sum_{t=1}^{T}\sum_{j\in\mathcal{J}}\eta_{jl}A_{jt} - \sum_{i\in\mathcal{I}} g_i\lambda_{il}\right\} - \sum_{i\in\mathcal{I}}(f_i\nu_i + b_i x_i) \tag{3.9a}$$

$$\text{s.t.} \quad Kx_i \geq \nu_i \geq 0 \tag{3.9b}$$

$$\sum_{i \in \mathcal{I}} y_{ij} d_{ij} \leq x_i d_{ij} \tag{3.9c}$$

$$\sum_{i \in \mathcal{I}} y_{ij} = 1 \tag{3.9d}$$

$$M(1 - z_{jt}) + r_j - \sum_{i \in \mathcal{I}} y_{ij} d_{ij} h - \xi_{jt} \geq 0 \tag{3.9e}$$

$$Mz_{jt} \geq r_j - \sum_{i \in \mathcal{I}} y_{ij} d_{ij} h - \xi_{jt} \tag{3.9f}$$

$$-Mz_{jt} \leq A_{jt} \leq Mz_{jt} \tag{3.9g}$$

$$F_1(r_j) - (1 - z_{jt})M \leq A_{jt} \leq F_1(r_j) + (1 - z_{jt})M \tag{3.9h}$$

$$\lambda_{il} \geq \frac{1}{T}\sum_{t=1}^{T}\sum_{j\in\mathcal{J}} \eta_{jl}B_{ijt} - \nu_i \tag{3.9i}$$

$$\lambda_{il} \geq 0 \tag{3.9j}$$

$$B_{ijt} \leq z_{jt} \tag{3.9k}$$

$$B_{ijt} \leq y_{ij} \tag{3.9l}$$

$$B_{ijt} \geq y_{ij} + z_{jt} - 1 \tag{3.9m}$$

$$y_{ij} \leq x_i \tag{3.9n}$$

$$x_i, y_{ij}, z_{jt} \in \{0, 1\} \tag{3.9o}$$

$$\nu_i, r_j \geq 0 \tag{3.9p}$$

Now solving directly in CPLEX is applicable to the general case.

3.4.2 Uncapacitated Case

In the special case where capacity constraints of the recycling faciltiy are relaxed, a simpler solution approach is available. When the facility site is in remote and district with scarce population, it is assumed the capacity limit constraints are not considered. Correspondingly, the fixed cost b would increase by including the cost of uncapacitated facilities. The operating cost rate W, as stated, includes energy, material and labor overheads, and can also include an item to account for the annualized plant capacity payments. In this way, the model can be further simplified as:

$$\max \frac{1}{L}\sum_{l=1}^{L}\left\{\sum_{j\in\mathcal{J}} \eta_{jl}\hat{p}(r_j)F_1(r_j)\right\} - \sum_{i\in\mathcal{I}} b_i x_i \tag{3.10a}$$

$$\sum_{i\in\mathcal{I}} y_{ij}d_{ij} \leq x_i d_{ij}, \quad \forall i, j \tag{3.10b}$$

$$\sum_{i\in\mathcal{I}} y_{ij} = 1, \quad \forall j \tag{3.10c}$$

$$y_{ij} \leq x_i, \quad \forall i, j \tag{3.10d}$$

$$x_i, y_{ij} \in \{0, 1\} \tag{3.10e}$$

$$r_j \geq 0 \tag{3.10f}$$

First of all we need to transform $\sum_{j\in\mathcal{J}} \eta_{jl}\hat{p}(r_j)F_1(r_j)$ to $\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} y_{ij}\eta_{jl}\hat{p}(r_j)F_1(r_j)$ as $\sum_{i\in\mathcal{I}} y_{ij} = 1$. Thus the objective can be reformulated as follows:

$$\max \frac{1}{L}\sum_{l=1}^{L}\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} y_{ij}\eta_{jl}\hat{p}(r_j)F_1(r_j) - \sum_{i\in\mathcal{I}} b_i x_i \tag{3.11}$$

It is straightforward that the model can be decomposed for i in the following way.

$$\max \sum_{i\in\mathcal{I}} \left\{ \frac{1}{L}\sum_{l=1}^{L}\sum_{j\in\mathcal{J}} y_{ij}\eta_{jl}\hat{p}(r_j)F_1(r_j) - b_i x_i \right\} \tag{3.12}$$

Noted that the original objective can be seen as the sum of sub-objectives for each i. If the value of the x_i is given in each computation, in other words, it is known which plants would be opened, the value of y_{ij} would be fixed by constraints (3.5e)(3.5f) and each decomposed model has only one decision variables r_j.

Then, for each i, the subproblem is shown as follows:

$$G_i(r_j) = \max_{r_j} \frac{1}{L}\sum_{l=1}^{L}\sum_{j\in\mathcal{J}} y_{ij}\eta_{jl}\hat{p}(r_j)F_1(r_j) - b_i x_i \tag{3.13a}$$

$$r_j \geq 0 \tag{3.13b}$$

Based on our assumptions, the incentive reservation level is accessible from survey data or other ways. So before further computation, we first arrange the incentive reservation level ξ_{jt} with same j in ascending order $\{\xi_{j1}, \xi_{j2}, ..., \xi_{jT}\}$. It is not hard to see that for any residential zone j, when $r_j \in [\xi_{jt} + \sum_{i\in\mathcal{I}} y_{ij}d_{ij}h, \xi_{j(t+1)}\sum_{i\in\mathcal{I}} y_{ij}d_{ij}h)$, the value of $\hat{p}(r_j) = t/T$ remains same and $F_1(r_j)$ is negative linearly dependent with r_j. So if we increase $r_j \in [\xi_{jt} + \sum_{i\in\mathcal{I}} y_{ij}d_{ij}h, \xi_{j(t+1)}\sum_{i\in\mathcal{I}} y_{ij}d_{ij}h)$, the objective will decrease correspondingly. Given it is a maximum problem, r_j tends to choose the value of $\xi_{jt} + \sum_{i\in\mathcal{I}} y_{ij}d_{ij}h$ when $r_j \in [\xi_{jt} + \sum_{i\in\mathcal{I}} y_{ij}d_{ij}h, \xi_{j(t+1)}\sum_{i\in\mathcal{I}} y_{ij}d_{ij}h)$. Thus we could convert the continuous r_j into finite discrete values.

In this way, the optimal r_j can be picked out by obtaining the maximum value of $\hat{p}(r_j)F_1(r_j)$ via substituting r_j with different $\xi_{jt} + \sum_{i\in\mathcal{I}} y_{ij}d_{ij}h$. Add all the final profits of subproblems under one combination of x_i, and we can test all the combination of all x_i then get the optimal solution.

The flowchart of the steps is also displayed in Figure 3.1:

3.5 Data Experiment

3.5.1 Example Setting

After modeling, some numerical studies need to be carried out to demonstrate the solution method and evaluate the computational performance. As a typical magecity troubled with a rapidly growing amount of household waste, Shanghai has invested a lot on waste management system to develop a fitting and economic framework for its multiple districts. Therefore we take Shenjialou, a district of Shanghai for case instance to test the applicability of the model. In the map of Shenjialou District, 3.2 , there are mainly 5 residential zones and the historical values of parameters according to (TheStraitTimes, 2011; ZeroWasteSingapore, 2015)) are given as follows:

Table 3.1: The data setting for model parameters in Shenjialou District

Parameter	Value
$\mathcal{I}$, potential site numbers	2
$\mathcal{J}$, residential zone numbers	5
W, operating cost for processing per unit waste	0.013 SGD/Kg
c_D, unit disposal fee for the impure wastes	0.077 SGD/Kg
q, revenue for per unit pure waste	0.0985 SGD/Kg
h, unit transportation cost	0.003 SGD/(Kg * Km)
b, the fixed cost of each opened WTE facility	200 SGD
θ_j, the purity ratio of each resident zone	0.9

• The average of quarterly waste generation for each resident zone, $\tilde{\eta}_j$ is about 5000KG.

• The distance (Km) between each resident zone and WTE potential site is measured in table 3.2:

Table 3.2: Distances between every WTE site and every residential zone, d_{ij}

	Z1	Z2	Z3	Z4	Z5
S1	0.34	0.66	0.19	0.48	0.63
S2	0.76	0.98	0.54	0.38	0.20

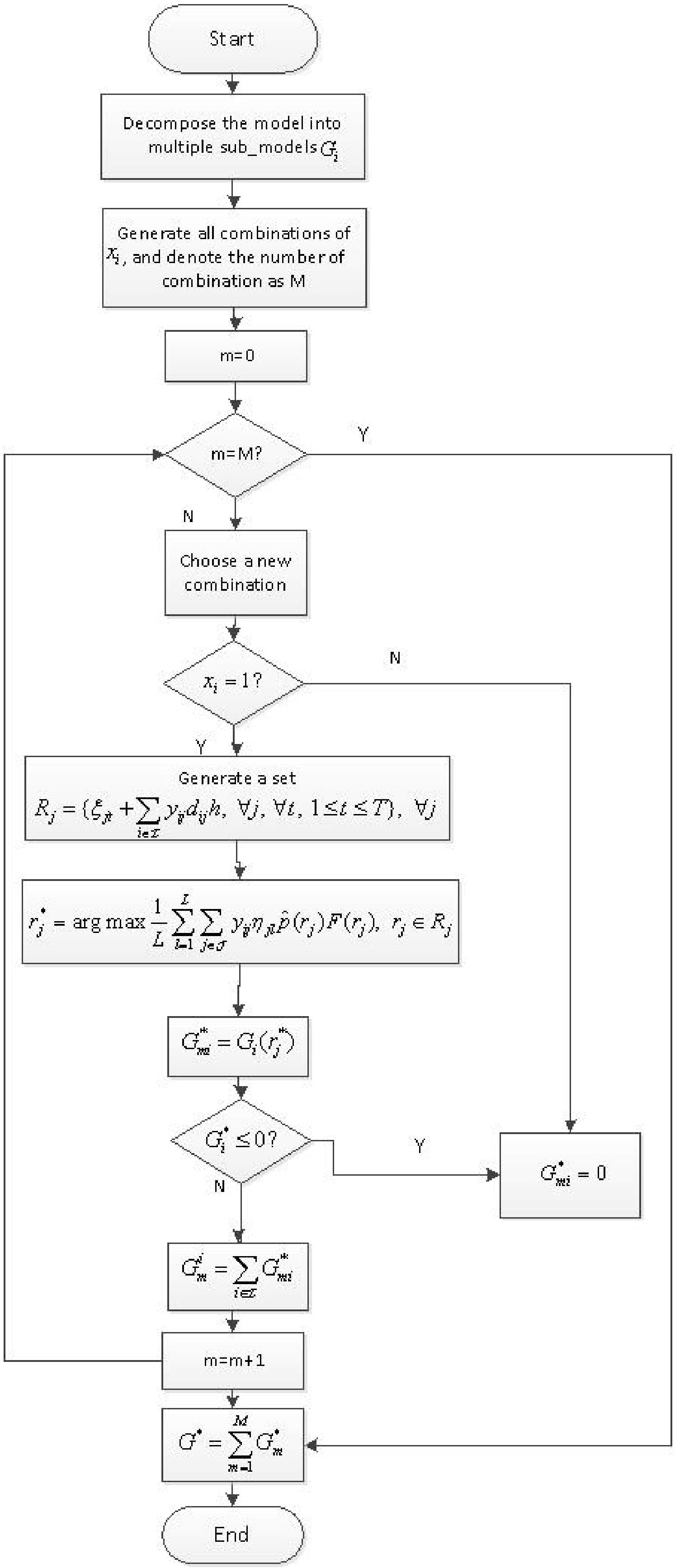

Figure 3.1: Flowchart of computational method for uncapacitated model

Figure 3.2: Distribution of zones and sites in Shenjialou District

- Samples of reservation incentive level in each zone are referred in table 3.3 :

Table 3.3: Samples of reservation incentive level in each zone, ξ_j

zone j	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5
1	0	0	0.2	0.3	1
2	0	0.2	0.25	0.25	0.5
3	0.01	0.01	0.03	0.05	0.5
4	0	0.2	0.2	0.5	0.8
5	0.1	0.1	0.15	0.3	2

3.5.2 Simulation Result

Following the steps in last section, we get the optimal solution step by step as follows:

1) Display all combinations of x_i in table 3.4:

Table 3.4: All scenarios of opened site x_i distribution

Scenario	x_1	x_2	Notation
1	1	0	S1 is open and S2 is closed.
2	1	1	Both S1 and S2 are open.
3	0	1	S2 is open and S1 is closed.
3	0	0	Both S1 and S2 are closed.

We can quickly see to the conclusion under $x_1 = x_2 = 0$ that the profit is 0. So this trivial scenario would not go through the following steps.

2) Take the scenario of $x_1 = 1, x_2 = 0$ for example:

According to constraint (3.5e)(3.5f), the value of y_{ij} can be got correspondingly.

Table 3.5: y_{ij} at $x_1 = 1, x_2 = 0$

No	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
$i=1$	1	1	1	0	0
$i=2$	0	0	0	1	1

Table 3.6: $\xi_{jt} + \sum_{i\in\mathcal{I}} y_{ij} d_{ij} h$ at $x_1 = 1, x_2 = 0$

zone j	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5
1	0.00102	0.00102	0.20102	0.30102	1.00264
2	0.00198	0.20198	0.25198	0.25198	0.50159
3	0.01057	0.01057	0.03057	0.05057	0.50003
4	0.00144	0.20144	0.20144	0.50144	0.80117
5	0.10189	0.10189	0.15189	0.30189	2.00273

Substitute r_j with all ξ_{jt} in the above table, and the corresponding result of $\hat{p}(r_j)F_1(r_j)$ is:

Table 3.7: The Optimal Value of $\hat{p}(r_j)F_1(r_j)$ under Given ξ_{jt}

zone j	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5
1	0.013386	0.026772	-0.079842	-0.186456	-0.93307
2	0.013194	-0.053612	-0.110418	-0.147224	-0.43403
3	0.011476	0.022952	0.022428	0.013904	-0.43262
4	0.013302	-0.053396	-0.080094	-0.346792	-0.73349
5	-0.006788	-0.013576	-0.050364	-0.187152	-1.93394

Therefore, the optimal solution is:

$r_1 = 0.00102,$

$r_2 = 0.00198,$

$r_3 = 0.01057,$

$r_4 = 0.00144,$

$r_5 = 0,$

The profit is $181.1SGD$.

3) In the same way, the optimal value under the other scenarios mentioned in 1) can be calculated:

Scenario 2, $-19.6SGD$

Scenario 3, $175.82SGD$

Scenario 4, 0

That means, the optimal solution in this case is to open $S1$.

3.5.3 Sensitivity analysis

a) We change the amount of residential zones from 1 to 5 to see how the profit is affected. There are 31 possible scenarios of residential zones including 5 of 1 residential zone, 10 of 2 zones, 10 of 3 zones, 5 of 4 zones and 1 of 5 zones. We denote OZ_{j^*} as the scenario in which the j^* residential zones are in the system. And the trend of the profit in each scenario of different zones is shown in Figure 3.3.

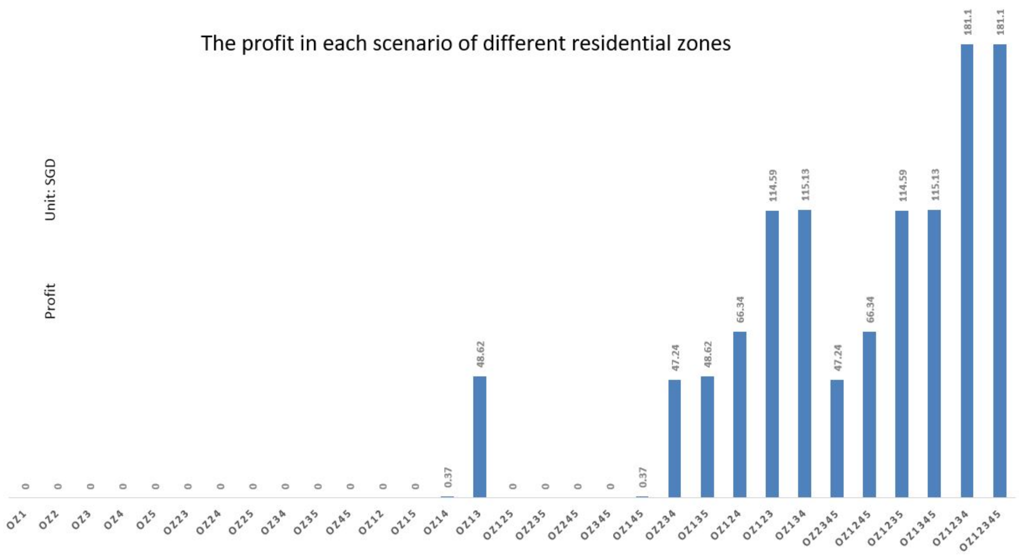

Figure 3.3: The trend of the profit in each scenario of different zones

From this figure, it is clear that none of the single zone scenarios is profitable, thus we can tell it is unsustainable to equip each zones with a plant in this environment. But when the amount of residential zones increases to 2, there are possibilities to make revenue. OZ13 and OZ14 are profitable, partially indicating the distance affects a lot, while OZ 34 is non-profitable, showing that the reservation incentive also makes an influence. And as the amount of residential zones increases, there is a marked improvement on the possibilities of profitability.

b) We change the fixed cost of the plant to see how the profit is affected. The trend of the profit to different fixed cost is shown in Figure 3.4.

Though the slope of the top of each profit bar seems steady, the profit to 0 fixed cost is a little special. Actually, when there is no fixed cost, the system tends to open 2 plants

Figure 3.4: The trend of the profit to different fixed cost

rather than only S1 in other scenarios in which the fixed cost is larger. It indicates that , despite of the fixed cost, or when the fixed cost is relatively little, S2 is profitable. If the residential zones that transported their waste to S2 has a larger population, there is a possibility that opening both two plants maximizes the system's profit.

3.6 Summary

In this chapter, an incentive-location joint model is proposed to embed the incentive policy making into a classical facility location problem. In the environment with uncertain parameters, a stochastic programming model is proposed to maximize the overall profit, which can be re-formulated into MILP by converting the continuous variable into discrete values with its monotonicity in intervals. Additionally, a special case without capacity limit constraints is discussed as some mecacities prefer to set the WTE potential sites in suburbs for the consideration of noise. And the solution approach is presented showing how the solution process is simplified. In the end, taking an area in Shanghai as the environmental background, a numerical case is showed in detail to demonstrate the solution process and the result also proves model's effectiveness.

Chapter 4

Incentive-Location Joint Planning with Secondary Feedstock

In this chapter, we propose a two-stage incentive-location joint planning model to be more resistant to environmental variability and thus better fit realistic situations. Section 4.1 gives a general description to introduce the new features of this model. Section 4.2 presents explanations of the additional assumptions and notations for further application. Then in section 4.3 mathematical formulation is presented.

4.1 Problem Description

In chapter 3, we built the model with the residential waste as the sole feedstock, and it is proved effective on some environment of small scale and little variability. However, such a system may not be sustainable economically if feedstock collected from resident zones is insufficient to achieve a healthy capacity utilization. In that case, the model in chapter 3 would suffer the consequence of waste shortage because there is no any buffer. IUT global's failure also reveals there is a huge risk to rely entirely on the waste collected for the factors influencing the waste generation are,to some degree, uncontrollable. So it is necessary to absorb waste from other sources as a secondary feedstock owing to its stable price and steadily constant resource. Some successful cases in Seoul (Lee and Paik, 2011) and Taiwan (Lu et al., 2006) also prove the contribution of secondary feedstock to system's maintenance .

In this chapter, we consider, in our joint location and incentive model, the option of purchasing and processing secondary feedstock.Generally, secondary feedstock can be implemented via two methods. One is bio-fuel, which can be used in the WTE to generate power which is sold to the grid. This is much more expensive to purchase due to government or state taxations and limitations, and is only regarded as a back-up to improve plant utilization. Another is to purchase low grade bio-waste which is cheap but can only recover limited energy due to poor feedstock purity, which can be purchased abundantly from professional waste-processing plants. In both cases, profit margin from secondary feedstock is very low. Hence, the WTE operator's primary revenue stream should still be soliciting feedstock from resident's if possible, and only using secondary feedstock as a back-up.

4.2 Assumptions and Notations

In addition to the assumptions in Chapter 3, more reasonable assumptions are generated for further application we may develop:

(a) We note that secondary feedstock ordering can take place either before or after actual waste based on the practical situations. However, the problem structure would be shown to be greatly simplified in the latter case, which is ordering secondary feedstock after the waste actually generated. Hence in this model we only consider the more general and difficult situation, the former case.

(b) Allocating the secondary feedstock to the individual plants is performed in the second stage, after the waste generation η_j is given. We refer u_i to the secondary feedstock allocated to the facility in site i.

(c) No transportation of waste between WTE plants is available as the system does not own vehicle fleet. Transshipment of feedstock from site to site also constitutes high costs and negative environmental impacts that cannot be justified by the operator or authorities.

And the following is the extra notations we may use in models.

Parameters

γ the purity ratio (the proportion of usable waste) of secondary feedstock

p price of per unit secondary feedstock

l_i the transportation cost for per unit secondary feedstock allocated to site i

Variables

u total amount of secondary feedstock

u_i amount of secondary feedstock allocated to ith facility

4.3 Two-stage Model Formulation

Before we start the detailed description of the two-stage model, the two stages are need to be introduced and explained first for further construction. The first stage of the framework design is the overall planning stage, aiming to determine all the parameters before environment parameters are known. Then in the second stage some decisions related to environment parameters are to make for further optimizaiton.

4.3.1 Formulations of Net Profit Function for the Secondary Feedstock

In the first stage, three decisions to be made are the capacity of each WTE plant k_i, the amount of incentive for each zone r_j, and the quantity of secondary feedstock u. These decisions will be made before the waste generations are known.

According to Expression (3.3), the net profit function referred to as F_2 for the secondary feedstock follows the same:

$$F_2 = \gamma q - p - (1 - \gamma) c_D - W \tag{4.1}$$

4.3.2 Formulations of Excess Waste

After the first stage, the volume of waste generation in resident zones and price of secondary feedstock will be known. Now in this second stage, the secondary feedstock should be allocated to each WTE plant to avoid waste and to maximize the profit. The amount of secondary waste transported to the ith facility is defined as u_i. Since it is determined after waste generation is known, u_i is related to the uncertainty η_j. Thus the respective transportation cost for each site is $u_i l_i$ and thereby expression λ_i for the amount of excess feedstock is updated as:

$$\tilde{\lambda}_i = \left[\sum_{j \in \mathcal{J}(i)} \tilde{\eta}_j \hat{p}_j(r_j) + \tilde{u}_i - \nu_i \right]^+ \tag{4.2}$$

4.3.3 Model Formulations

Accordingly, The joint location-incentive planning problem with two source feedstock can be formulated like basic model as the follows:

$$\max_{\boldsymbol{\nu}, u, \boldsymbol{y}, \boldsymbol{x}} -\sum_{i \in \mathcal{I}} (\boldsymbol{f'\nu} + \boldsymbol{b'x}) + E_{\tilde{\boldsymbol{\eta}}, \tilde{\boldsymbol{\lambda}}, \tilde{\boldsymbol{u}}} \left[Q\left(\boldsymbol{\nu}, u, \boldsymbol{y}, \boldsymbol{x}, \tilde{\boldsymbol{\eta}}, \tilde{\boldsymbol{\lambda}}, \tilde{\boldsymbol{u}} \right) \right] \tag{4.3a}$$

$$\text{s.t.} \;\; Kx_i \geq \nu_i \geq 0, \forall i \tag{4.3b}$$

$$\sum_{j \in \mathcal{J}} y_{ij} = 1, \forall i \tag{4.3c}$$

$$\sum_{i \in \mathcal{I}} y_{ij} d_{ij} \leq x_i d_{ij}, \forall i, j \tag{4.3d}$$

$$y_{ij} \leq x_i, \forall i, j \tag{4.3e}$$

$$x_i, y_{ij} \in \{0, 1\}, \forall i, j \tag{4.3f}$$

$$\boldsymbol{\nu}, u, \boldsymbol{u}, \boldsymbol{r} \geq 0 \tag{4.3g}$$

where

$$Q\left(\boldsymbol{\nu}, u, \boldsymbol{y}, \boldsymbol{x}, \tilde{\boldsymbol{\eta}}, \tilde{\boldsymbol{\lambda}}, \tilde{\boldsymbol{u}} \right) = \max_{u_i} \sum_{j \in \mathcal{J}} \tilde{\eta}_j \hat{p}_j(r_j) F_1(r_j) - \sum_{i \in \mathcal{I}} \tilde{u}_i l_i + uF_2 - \sum_{i \in \mathcal{I}} g_i \tilde{\lambda}_i \tag{4.4}$$

$$\tilde{\lambda}_i \geq \sum_{j \in \mathcal{J}} y_{ij} \tilde{\eta}_j \hat{p}(r_j) + \tilde{u}_i - \nu_i, \;\; \forall i \tag{4.5a}$$

$$\sum_{i \in \mathcal{I}} \tilde{u}_i = u \tag{4.5b}$$

$$\tilde{u}_i, \tilde{\lambda}_i \geq 0 \tag{4.5c}$$

Note that constraint (4.3a) restricts the 0 capacity with the premise of closed plant by setting $\nu_i = 0$ when $x_i = 0$. Constraint (4.3c) ensures for one zone there is only one facility to deliver and constraint (4.3d) makes sure that zone j will choose the nearest opened facility to deliver by constraining $y_{ij} = 1$ when d_{ij} is least for all opened sites and Besides, constraints (4.5a) and (4.5c) equal to expression (4.2) in a maximizing problem.

Multistage stochastic problem is acknowledged as difficulty to construct a general approach to solve. So the first step of is to bring in some method to reform it into the deterministic equivalent problem.

Sample estimator method is applied to make l as the index of scenarios for waste generation:

l index of scenarios for waste generation ($l = 1, \cdots, L$)

Then, under the assumption that we have L simulated scenarios, the waste generation for zone j in scenario l, the data of which is accessible and deterministic, can be referred as $\eta_{jl},\ 0 \le l \le L$. And correspondingly, the variables related in second stage are also changed, as they are supposed to be decided after the amount of waste generation is determined, like $\tilde{u}_i$ into u_{il} and $\tilde{\lambda}_i$ into λ_{il}. Therefore the objective of the model is thereby to maximize the summation of all the profit in each scenario by assigning values to variables. And thence we get the following deterministic programming model and name it as OM:

$$\max_{\nu_i, u, y_{ij}, x_i, z_{jt}} \quad -\sum_{i \in \mathcal{I}} (f_i \nu_i + b_i x_i) + E_{\tilde{\eta}_j, \tilde{\lambda}_i, \tilde{u}_i} \left[Q\left(\nu_i, u, y_{ij}, x_i, \tilde{\eta}_j, \tilde{\lambda}_i, \tilde{u}_i, z_{jt} \right) \right] \tag{4.6a}$$

$$M(1 - z_{jt}) + r_j - \sum_{i \in \mathcal{I}} y_{ij} d_{ij} h - \xi_{jt} \ge 0,\ \forall j, t \tag{4.6b}$$

$$z_{jt} \in \{0, 1\},\ \forall j, t \tag{4.6c}$$

$$\text{s.t.}\ \ K x_i \ge \nu_i \ge 0, \forall i \tag{4.6d}$$

$$\sum_{j \in \mathcal{J}} y_{ij} = 1, \forall i \tag{4.6e}$$

$$\sum_{i \in \mathcal{I}} y_{ij} d_{ij} \le x_i d_{ij}, \forall i, j \tag{4.6f}$$

$$y_{ij} \le x_i, \forall i, j \tag{4.6g}$$

$$x_i, y_{ij} \in \{0, 1\}, \forall i, j \tag{4.6h}$$

$$\boldsymbol{\nu}, u, \boldsymbol{u}, \boldsymbol{r} \ge 0 \tag{4.6i}$$

where

$$Q\left(\boldsymbol{\nu}, u, \boldsymbol{y}, \boldsymbol{x}, \tilde{\boldsymbol{\eta}}, \tilde{\boldsymbol{\lambda}}, \tilde{\boldsymbol{u}}, z_{jt}\right) = \max_{u_i} \sum_{j\in\mathcal{J}} \tilde{\eta}_j \left(\frac{1}{T}\sum_{t=1}^{T} z_{jt}\right) F_1(r_j) - \sum_{i\in\mathcal{I}} \tilde{u}_i l_i + uF_2 - \sum_{i\in\mathcal{I}} g_i \tilde{\lambda}_i \tag{4.7}$$

$$\tilde{\lambda}_i \geq \sum_{j\in\mathcal{J}} y_{ij}\tilde{\eta}_j \left(\frac{1}{T}\sum_{t=1}^{T} z_{jt}\right) + \tilde{u}_i - \nu_i, \ \ \forall i \tag{4.8a}$$

$$\tilde{\lambda}_i \geq 0, \ \forall i \tag{4.8b}$$

$$\sum_{i\in\mathcal{I}} \tilde{u}_i = u \tag{4.8c}$$

$$\tilde{u}_i \geq 0, \forall i \tag{4.8d}$$

where constraints (4.8a) and (4.8b) are equivalent to what the excess waste function (4.2) demonstrates in specific scenario. And constraints (4.6b) and (4.6c) reflect that as an indicator variable, z_{jt}=0 if the tth resident in zone j is not willing to contribute, which is confined by $r_j - \sum_{i\in\mathcal{I}} y_{ij} d_{ij} h - \xi_{jt} < 0$. And since the objective is a maximizing function with the signs of all z_{jt} are positive, z_{jt} in constraint (4.6b) tend to choose 1 instead of 0 when $r_j - \sum_{i\in\mathcal{I}} y_{ij} d_{ij} h - \xi_{jt} \geq 0$.

4.4 Summary

In this chapter, to improve the performance of basic model of WTE system by modifying it to be more resistant to environmental variability and thus better fit realistic situations, secondary feedstock is implemented. So some additional explanations and notations are presented like the new introduced variable the amount of secondary feedstock, the quantity of secondary feedstock allocated etc.

Correspondingly, the entire model now includes a second stage in which there occurs secondary feedstock allocation besides determining more decisions at the first stage. This changes convert the model into a two-stage stochastic problem and the mathematical formulations are introduced to explain net profit function and excess waste denotion.

There are some estimations and simplifications adopted for computational tractability. Although it is still complicated to jointly design for incentive and location in a multi-stage problem under uncertain environment. However, this measure enhances the resistance to environmental variability and makes the system more stabilized. And the capacity utilization is also enhanced.

The measure of WTE system is not only a prompt for public waste classification but also a tempt to take all profitable waste into consideration, thus with the development of exploiting value of waste, it provides a potential to add waste from other sources instead.

Chapter 5

Solution Approaches

Although for a fixed incentive level, model 4.6 is in the format of a mixed integer linear programming (MILP) model, and can ideally be solved using commercially available mixed integer solvers such as CPLEX, in general it is still non-linear in structure and can pose computational difficulties when problem size scales up. Then in this chapter we propose three solution approaches based on model OM. The first one is large-scale mixed integer linear programming(MILP), the second is a parallel computing approach based on Map-Reduce method, and the third is Lagrangian relaxation approach. Each of them has its own advantage and shortcomings in order to apply in different cases.

5.1 Large-scale MILP

For a non linear problem with a part of multiplying two decision variables, a general idea is to linearize it as a MILP problem and call the CPLEX solver. So we solve the model by linearizing both the objective and constraints like what is processed in section 3.3.1.

Be noted the net profit function 3.3 is

$$F_1(r_j) = \theta_j q - r_j - (1 - \theta_j)c_D - W \tag{5.1}$$

And two auxiliary variables A_{jt} and B_{jt} are constructed that

$$A_{jt} = z_{jt} F(r_j) \tag{5.2}$$

$$B_{ijt} = y_{ij} z_{jt} \tag{5.3}$$

Correspondingly, by replacing the part of multiplying two decision variables, the whole model named $MILP$ can be reformulated as follows,

$$MILP: \quad \max \frac{1}{L} \sum_{l=1}^{L} \left\{ \frac{1}{T} \sum_{t=1}^{T} \sum_{j \in \mathcal{J}} \eta_{jl} A_{jt} - \sum_{i \in \mathcal{I}} u_{il} l_i + u F_2(p) - \sum_{i \in \mathcal{I}} g_i \lambda_{il} \right\} - \sum_{i \in \mathcal{I}} (f_i \nu_i + b_i x_i) \tag{5.4a}$$

$$\text{s.t. } K x_i \geq \nu_i \geq 0, \forall i \tag{5.4b}$$

$$\sum_{i \in \mathcal{I}} y_{ij} d_{ij} \leq M x_i d_{ij}, \forall i, j \tag{5.4c}$$

$$\sum_{i \in \mathcal{I}} y_{ij} = 1, \forall j \tag{5.4d}$$

$$M(1 - z_{jt}) + r_j - \sum_{i \in \mathcal{I}} y_{ij} d_{ij} h - \xi_{jt} \geq 0, \forall j, t \tag{5.4e}$$

$$-M z_{jt} \leq A_{jt} \leq M z_{jt}, \forall j, t \tag{5.4f}$$

$$F_1(r_j) - (1 - z_{jt}) M \leq A_{jt} \leq F_1(r_j) + (1 - z_{jt}) M, \forall j, t \tag{5.4g}$$

$$\lambda_{il} \geq \frac{1}{T} \sum_{t=1}^{T} \sum_{j \in \mathcal{J}} \eta_{jl} B_{ijt} + u_{il} - \nu_i, \forall i, l \tag{5.4h}$$

$$\lambda_{il} \geq 0, \forall i, l \tag{5.4i}$$

$$B_{ijt} \leq z_{jt}, \forall i, j, t \tag{5.4j}$$

$$B_{ijt} \leq y_{ij}, \forall i, j, t \tag{5.4k}$$

$$B_{ijt} \geq y_{ij} + z_{jt} - 1, \forall i, j, t \tag{5.4l}$$

$$\sum_{i \in \mathcal{I}} u_{il} = u, \forall l \tag{5.4m}$$

$$y_{ij} \leq x_i, \forall i, j \tag{5.4n}$$

$$x_i, y_{ij}, z_{jt} \in \{0, 1\} \tag{5.4o}$$

$$u, u_{il}, \nu_i, r_j \geq 0 \tag{5.4p}$$

$$\tag{5.4q}$$

To ensure the accuracy of $A_{jt} = z_{jt} F(r_j)$ (5.2)and $B_{ijt} = y_{ij} z_{jt}$ (5.3), some constraints are added in this model formulation. Be Noted that $F_1(r_j)$ has bounds $[-M, M]$

when M is a suitable large number. Based on constraints (5.4f) and (5.4g), if $z_{jt} = 0$ then A_{jt} has to be zero as well. And if $z_{jt} = 1$ then A_{jt} is forced to be $F_1(r_j)$. Also, constraints (5.4j) and (5.4k) ensure that B_{ijt} will be zero if either z_{jt} or y_{ij} is zero. The constraint (5.4l) will make sure that B_{ijt} will take value 1 if both binary variables y_{ij} and z_{jt} are set to 1. And the explanation of other constraints follows those stated in section 3.4.1 and section 4.3.3.

Now that it is a normal MILP model that can be solved by CPLEX.

However, although linearization into a MILP model is proposed as a solution approach to solve the two-stage problem directly, incapability of data processing in large scale prevents it from being a general solution for this model. Therefore in the following part we suggest two other methods for wider application.

5.2 Parallel Computing Solution Approach using Map-reduced Method

Now with the rapid development of network technologies, it is acknowledged that in the past recent years the parallel computing has been increasingly accepted and adopted both for computing theory and practical applications. It is applied to solve large problems which can be decomposed into a series of smaller ones that can be solved individually at the same time, especially for NPC(non-deterministic polynomial complete) problems. As the parallel processors are increasingly utilized and the distributed processing spreads wider, the parallel computing established its advantage as a high performance computing methodology for large volume numerical calculations. Instead of a possible failure from dealing with an entire large problem in a local processor, parallel computing can produce unequalled computational power in some cases by enabling multiple processors do similar tasks at one time so each processor only need to focus on one or several small jobs. The independent failure also enables the system fault tolerant in case of any failure of one of the components. The schematic diagrams of traditional serial computing and the parallel one are shown as Figure 5.1 and Figure 5.2 (Barney, 2015).

Map-reduced is an improved programming models for parallel processing and an associated implementation for processing and generating large data sets. The master

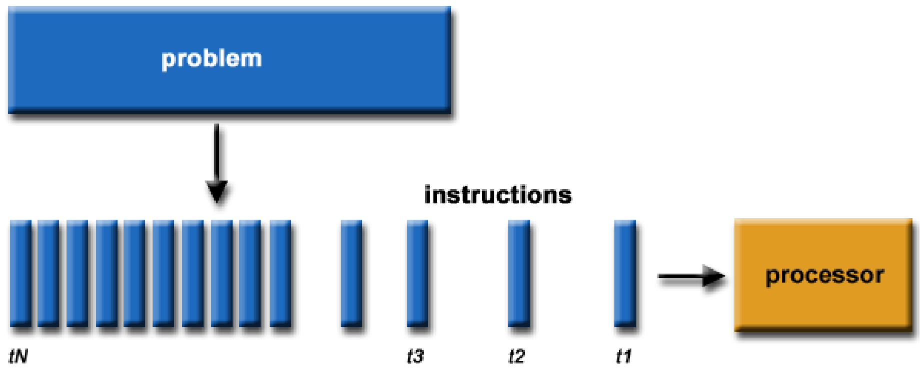

Figure 5.1: Traditional Series Computing Diagram

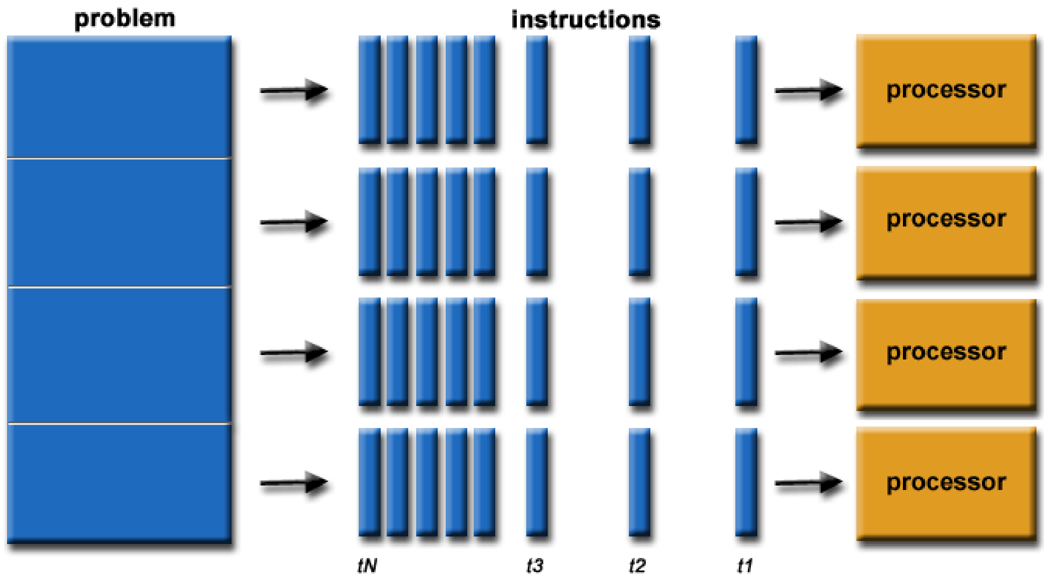

Figure 5.2: Parallel Computing Diagram

can collect the discrete results from each processor and do further process. And users specify a map function that processes a value pair to generate a set of intermediate value pairs, and a reduce function that merges all intermediate values associated with the same intermediate key. (Dean and Ghemawat, 2008)

This process requires a series of input value pairs and finally provides a series of output value pairs. And the Map-reduced library defines this computation process as two function which are Map and Reduce. Function Map is designed to take a value pair as input and produce a series of value pairs as intermediate output. Usually in this step, the master computer need to decompose the whole job into subproblems in some way and then assign the subproblems to the parallel clusters. And then, with the Map-reduced library, the master computer collects all the intermediate output from the clusters to pass the output to Function Reduce. After accepting these values, Function Reduce uses defined rules to generate a value pair as the final output. During this step, multiple rules can be added like sum up, choosing the maximum or minimum, picking out and reformation etc. So in this method, Function Map and Reduce are both specified by users, which enables a wide application of parallel, distributed algorithms. And the schematic diagram is displayed as Figure 5.3(Chu et al., 2007).

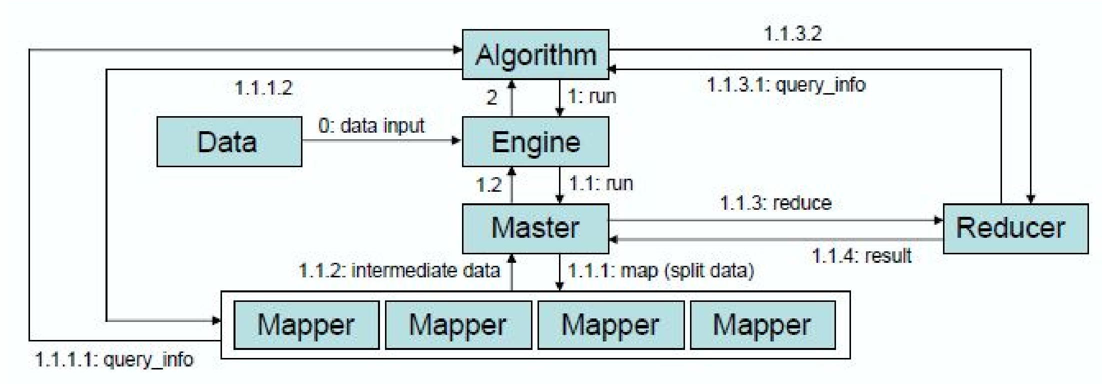

Figure 5.3: Map-reduced Framework Diagram

Take an example of a problem how many times the word *the* occurs most among a large collection of books to demonstrate how Map and Reduce functions work in the system. Usually the functions can be defined as the following pseudo-code 1 and 2.

Algorithm 1 Mapping Function

map(String InputKey, String InputValue):
//InputKey: book name
//InputValue: book contents
for each word *the* in InputValue:
EmitIntermediate(*the*, ”1”)

The Map function splits the books by their names into several parts and each mapper gets one part, which are some books. And for each mapper, its job is to search for word *the* and mark 1 when word *the* appears once.

Then the Reduce function receives all the keys, which are name of books, and the intermediate values, which are some ”1” as many as the occurrences of word *the*. As shown, the Reduce function we defined is to add up the occurrences of 1 and output.

Therefore we propose to convert the MILP in section 5.1 into a set of small problems taking advantage of some discrete variables by generating finite subproblems with less

Algorithm 2 Reducing Function

```
reduce(String OutputKey, Iterator IntermediateValues):
// OutputKey: a word
// OutputValues: a list of counts
intresult = 0;
for each 1 in IntermediateValues:
result += ParseInt(1);
Emit(AsString(result));
```

decision variables so that every subproblem can be solved independently with each single compute resource.

5.2.1 Implementation of Parallel Computing Solution

The most obvious discrete decision variable in model 5.4 is the binary variable $\boldsymbol{x}$, which is quite suitable for enumeration for its discrete and narrow range. Enumerating $\boldsymbol{x}$ will reduce the decision variable's dimension and thus lower the large problem's complexity by fixing the value of $\boldsymbol{x}$. Suppose there are 2 potential sites, enumerating $\boldsymbol{x}$ means 4 possible scenarios exist: $x_1 = 1, x_2 = 1$; $x_1 = 1, x_2 = 0$; $x_1 = 0, x_2 = 0$; $x_1 = 0, x_2 = 1$. If X is denoted as the set of combinations of all the possible values of x_i, here $X = \{\{x_1, x_2\} \,|\, \{x_1 = 1, x_2 = 1\}, \{x_1 = 1, x_2 = 0\}, \{x_1 = 0, x_2 = 0\}, \{x_1 = 0, x_2 = 1\}\}$ However, the size of each sub-problem can still be very large, and computational requirements are still quite high for a single processor that may cause failure. We therefore further partition the remaining decision variables to get a set of solvable tasks.

It is observed the incentive $\boldsymbol{r}$ is related to discrete parameters. So before the computation, arrange the incentive reservation level ξ_{jt} with same j in ascending order $\{\xi_{11}, \xi_{12}, ..., \xi_{1T}\}$,$\{\xi_{21}, \xi_{22}, ..., \xi_{2T}\}$,...,$\{\xi_{\mathcal{J}1}, \xi_{\mathcal{J}2}, ...\xi_{\mathcal{J}T}\}$, where T is the amount of incentive reservation levels of each zone.

And the only part in the objective related to r_j is $\sum_{j\in\mathcal{J}} \tilde{\eta}_j \hat{p}_j(r_j) F_1(r_j)$, and referring to the extracted core part is $\hat{p}_j(r_j)F_1(r_j) = \left(\frac{1}{T}\sum_{t=1}^{T} I\left\{r_j - \sum_{i\in\mathcal{I}} y_{ij} d_{ij} h - \xi_{jt} \geq 0\right\}\right)(\theta_j q - r_j - (1-\theta_j)c_D - W)$. Therefore it is reasonable to consider the original range of r_j, which is $[0, +\infty)$, as a series of smaller intervals that $[0, \xi_{j1} + \sum_{i\in\mathcal{I}} y_{ij} d_{ij} h)$, $[\xi_{j1} + \sum_{i\in\mathcal{I}} y_{ij} d_{ij} h, \xi_{j2} + \sum_{i\in\mathcal{I}} y_{ij} d_{ij} h)$, ..., $[\xi_{jT} + \sum_{i\in\mathcal{I}} y_{ij} d_{ij} h, +\infty)$.

Note that for any resident zone j, when $r_j \in [\xi_{jt}+\sum_{i\in\mathcal{I}} y_{ij}d_{ij}h, \xi_{j(t+1)} \sum_{i\in\mathcal{I}} y_{ij}d_{ij}h),\ t = 1, 2...T-1$, the value of $I\left\{r_j - \sum_{i\in\mathcal{I}} y_{ij}d_{ij}h - \xi_{jt} \geq 0\right\}$ remains same and it is apparent that $F_1(r_j)$ is negatively correlated with r_j. As it is a maximizing problem, r_j is supposed to tend to choose the value of $\xi_{jt} + \sum_{i\in\mathcal{I}} y_{ij}d_{ij}h$ when $r_j \in [\xi_{jt} + \sum_{i\in\mathcal{I}} y_{ij}d_{ij}h, \xi_{j(t+1)} \sum_{i\in\mathcal{I}} y_{ij}d_{ij}h)$, which enables the range of r_j now can be converted from a continuity into finite discrete values as $\left\{0, \xi_{jt} + \sum_{i\in\mathcal{I}} y_{ij}d_{ij}h | t = 1, 2, ..., T\right\}$. Now the dimensionality can be greatly lowered by enumerating the incentive variable $\boldsymbol{r}$.

Denote X as the set of combinations of all the possible values of x_i, and R as the combinations of all the possible values of r_j. Then the detailed steps are shown as follows:

Step 1. Display all combinations in X as the values to assign to $\{x_1, x_2...x_{\mathcal{I}}\}$;

Step 2. Display all combinations in R as the values to assign to $\{r_1, r_2...r_{\mathcal{J}}\}$;

Step 3. The subproblem under given $\boldsymbol{x}$ and $\boldsymbol{r}$ is an independent problem that can be referred as $g(\boldsymbol{x}, \boldsymbol{r})$. Thus the problems can be decomposed into multiple subproblems with different $\boldsymbol{x}$ and $\boldsymbol{r}$. So Map-reduced method is applied to process all these optimization subproblems to get optimal u, u_{il}, ν_i, and the maximum profit $g(\boldsymbol{x}, \boldsymbol{r})$;

Step 4. When all subproblems are done, collect and compare all the results from the computers and pick out the maximum profit and corresponding optimal solution .

To make it more clear in a mathematical form, the pseudo-code can be described as Algorithm 3.

Algorithm 3 Pseudo-code for Implementation of Parallel Computing Solution

Input: $\boldsymbol{d}, \boldsymbol{xi}$
Output: $X_0, MR(X_0)$

```
Xset = {x_1, x_2, ..., x_{2^I} | x_nt = x_1, x_2, ..., x_I | x_i = 0or1, i ∈ I, nt ∈ 1, 2, ..., 2^I}
for nt = 1 : 2^I do
    solve y according to x_nt based on constraints (5.4c), (5.4d), and (5.4n)
    Rset = {r_1, r_2, ..., r_{(T+1)^J} |
    r_mt = {r_1, r_2, ..., r_J | r_j ∈ {0, ξ_jt + Σ_{i∈I} y_ij d_ij h | t = 1, 2, ..., T}, j ∈ J}, mt ∈ 1, 2, ..., (T+1)^J}
    for mt = 1 : (T+1)^J do
        Solve the model MILP(x_nt, r_mt) to get solution as xs_{nt,mt}
    end
end
Find the maximum value among all MILP(x_nt, r_mt, xs_{nt,mt}), ∀nt, mt as final profit
    MR(X_0) and correspondingly its solution as X_0
```

This enumeration applied with Map-reduced method is applicable if there are a large number of parallel processors available. But in practice can still be inefficient for very large scale problems, or when computing resources are limited. Hence it is necessary that sometimes we sacrifice a little accuracy to exchange for better speed. Therefore, in the next part, we propose a heuristic solution approach, based on the Map-reduce framework.

5.2.2 Small Map: Parallel Computing Using a Heuristic Method

In this part we suggest small maps as a heuristic method to solve this problem. Small map method is after the step X is generated and a combination is picked. Under that premise that $\boldsymbol{x}$, y_{ij} can be calculated so it is known which resident zones are allocated to which facility. So based on given $\boldsymbol{x}$ and $\boldsymbol{y}$, we manually divide the whole map into small maps which contains only 1 opened facility and the corresponding resident zones. Subproblems are thereby generated and in each subproblem there is only one distince i that makes $x_i = 1$, which enables the working of MILP by CPLEX solver.The procedures are displayed as follows:

Step 1. Choose a combination in X as the value to assign to $\{x_1, x_2 ... x_{|\mathcal{I}|}\}$, then y_{ij} is calculated correspondingly;

Step 2. Based on the value of y_{ij} and x_i, small maps which contains only one opened facility and resident zones allocated to this facility are divided from the original full map;

Step 3. According to the description of the small map, a subproblem can be regarded in the form of MILP where there is only one i making $x_i = 1$. So by CPLEX solver we can obtain the values of r_j, ν_i, u_i and the profit in each small map.

Step 4. Sum up all the profit as the total profit under this $\boldsymbol{x}$, which is defined as $g(\boldsymbol{x})$;

Step 5. Choose a new combination in X and return to step 2 until all combinations have been tried or excluded.

Step 6. When all parts are done, compare all $g(\boldsymbol{x})$ and pick out the maximal and the corresponding solution. Set $u = \sum_{i \in \mathcal{I}} u_i$.

Here we need to address that this method produces a lower bound on the original objective function, which is the expected profit, essentially due to the resolution of the secondary feedstock constraints. In this constraint, the summation of u_{il} for i is supposed to be after the scenario l is given but here we exchange their sequences to save time.

This will place harder restriction on the allocation of secondary feedstock by setting two constraints $u_i = u_{il},\ \forall i$ and $\sum_i u_i = u$ instead of $u = \sum_{i \in \mathcal{I}} u_{il},\ \forall l$. So the result of this method actually is a feasible solution instead of necessarily optimal. The pseudo-code can be described as Algorithm 4.

Algorithm 4 Pseudo-code for Small Maps

Input: $\boldsymbol{d}, \boldsymbol{xi}$
Output: $X_0, SM(X_0)$
$Xset = \{\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_{2^I} | \boldsymbol{x}_{nt} = x_1, x_2, ..., x_I | x_i = 0or\ 1, i \in \mathcal{I}, nt \in 1, 2, ..., 2^I\}$
for $nt = 1 : 2^I$ **do**
    get the values of $\boldsymbol{y}$ according to $\boldsymbol{x}_{nt}$ based on constraints (5.4c), (5.4d), and (5.4n) and denote it as $\boldsymbol{y}_{nt}$
    for $i = 1 : I$ **do**
        if $x_i = 1$ **then**
            $\boldsymbol{J}_i = \{j' | y_{ij'} = 1andy_{ij'} \in \boldsymbol{y}_{nt}\}$
            Solve the model $MILP$ under the premise that $x_i = 1, j \in \boldsymbol{J}_i, y_{ij} = 1$ to get solution as $xs_{i,nt}$ and the value of objective as $pf_{i,nt}$
        end
        $i = i + 1$
    end
    Calculate $pf_nt = \sum_i pf_{i,nt}$
end
Find the maximum value among all pf_nt as final profit $SM(X_0)$ and correspondingly its solution as X_0

This small maps method lower the dimensions of the system by decomposition and heuristic and thus can greatly speed up the computation process. However the characteristic of heuristic implies that some loss of optimality will need to be accepted.

5.3 Lagrangian Relaxation Solution Approach

The application of Lagrangian relaxation has been widely adopted in optimizing problems. (Mulvey and Crowder, 1979) proposed to use Lagrangian relaxation to do cluster analysis for this optimization algorithm is an effective solution technique for homogeneous clustering problem and also a good approach to providing tight lower bounds for evaluating the quality of solutions generated by other methods. (Muckstadt and Koenig, 1977) applied a Lagrangian relaxation combined with a branch-and-bound algorithm to decompose the problem into single generator problems and a sub-gradient method is used to select the Lagrange multipliers that maximize the lower bound produced by the relaxation. It proves the technique is capable of solving large problems to within acceptable error tolerances. That is why this method is adopted to solve the model of large scale.

The key point of Lagrangian relaxation is to choose a proper constraint to relax in order to reduce the difficulty and computation time. So in this model, we try to relax the constraint (5.5e) $\lambda_{il} \geq \sum_{j\in\mathcal{J}} y_{ij}\eta_{jl}\left(\frac{1}{T}\sum_{t=1}^{T} z_{jt}\right) + u_{il} - \nu_i,\ \forall l, i$, into the objective. Then the model named LRM is converted to:

$$LRM: \quad \max \frac{1}{L}\sum_{l=1}^{L}\left\{\sum_{j\in\mathcal{J}}\eta_{jl}\left(\frac{1}{T}\sum_{t=1}^{T} z_{jt}\right)F_1(r_j) - \sum_{i\in\mathcal{I}} u_{il}l_i + uF_2 - \sum_{i\in\mathcal{I}} g_i\lambda_{il}\right\} - \sum_{i\in\mathcal{I}}(f_i\nu_i + b_ix_i) \tag{5.5a}$$

$$+\sum_{l=1}^{L}\sum_{i\in\mathcal{I}}\mu_{il}(\lambda_{il} - \sum_{j\in\mathcal{J}} y_{ij}\eta_{jl}\left(\frac{1}{T}\sum_{t=1}^{T} z_{jt}\right) - u_{il} + \nu_i) \tag{5.5b}$$

$$\text{s.t.}\ \ M(1 - z_{jt}) + r_j - \sum_{i\in\mathcal{I}} y_{ij}d_{ij}h - \xi_{jt} \geq 0 \tag{5.5c}$$

$$\sum_{i\in\mathcal{I}} u_{il} = u, \forall l \tag{5.5d}$$

$$Mx_i \geq \nu_i \geq 0, \forall i \tag{5.5e}$$

$$\sum_{i\in\mathcal{I}} y_{ij}d_{ij} \leq Mx_id_{ij}, \forall i, j \tag{5.5f}$$

$$\sum_{i\in\mathcal{I}} y_{ij} = 1, \forall j \tag{5.5g}$$

$$y_{ij} \leq x_i, \forall i, j \tag{5.5h}$$

$$x_i, y_{ij}, z_{jt} \in \{0, 1\}\ \forall i, j, t \tag{5.5i}$$

$$\lambda_{il}, u, u_{il}, \nu_i, r_j \geq 0, \forall i, j, l \tag{5.5j}$$

where $\boldsymbol{\mu}$ is the Lagrangian multiplier.

Using the subgradient method as the computational solution for LRM model, and the pseudo-code can be generated as Algorithm 5.

where π is the scalar that satisfies $0 < \pi < 2$, ϵ is the approximation error, and LB and UB represent the lower bound and upper bound respectively. Be noted that ϵ is dependent on the scale of the system's input which, in small-scale problem ϵ could be set a little smaller to get more accurate result but in larger-scale cases, ϵ should be a little larger to balance speed and accuracy. The original values of LB and UB can be determined by

Algorithm 5 Subgradient Method for LRM

Input: $\mu, \pi, LB, UB, \epsilon$

Output: X

while $UB - LB <= \epsilon$ **do**

  solve $LRM(\mu)$

  get optimal solution X and corresponding $\lambda_{il}, y_{ij}, z_{jt}, u_{il}, \nu_i$

  replace UB with $LRM(\mu, X)$

  if $\lambda_{il} \geq \sum_{j \in \mathcal{J}} y_{ij} \eta_{jl} \left(\frac{1}{T} \sum_{t=1}^{T} z_{jt} \right) + u_{il} - \nu_i$ *and* $OM(X) > LB$ **then**

    replace LB with $OM(X)$

  end

  $sz = \pi(UB - LB)/||\lambda_{il} - \sum_{j \in \mathcal{J}} y_{ij} \eta_{jl} \left(\frac{1}{T} \sum_{t=1}^{T} z_{jt} \right) + u_{il} - \nu_i||^2$

  $\mu = \mu + sz * (\lambda_{il} - \sum_{j \in \mathcal{J}} y_{ij} \eta_{jl} \left(\frac{1}{T} \sum_{t=1}^{T} z_{jt} \right) + u_{il} - \nu_i)$

end

the minimum observed profit and the maximum observed profit of the system. And μ is required to be positive.

Although in general the Lagrangian relaxation cannot achieve the optimal solution for the system planning problem, it can be used to generate an upper bound, and a lower bound, on the optimal solution. That means, in addition to a feasible solution, which usually is the lower bound, we can also get the maximum error rate to evaluate this solution.

5.3.1 Lagrangian relaxation combined with Map-reduced method

In section 5.2, we have discussed the application of Map-reduced method. And in this part, noted that each iteration is still a MILP problem that can be decomposed, we propose to combine Lagrangian relation with Map-reduced and name it LR-MR for short. The decomposition is similar to the approach in setion 5.2.1 in which enumerate the values of $x_i, \ \forall i$ first and then distribute to paralleled clusters to save time. Also using the subgradient method as the computational solution for this LR-MR method, and the pseudo-code can be generated as Algorithm 6, where the parameters follows the explanation and values in section 5.3.

This method improves Lagrangian relaxation with Map-reduced method to get a better speed by decomposing each iteration into subproblems to solve in a parallel way.

Algorithm 6 Lagrangian relaxation combined with Map-reduced method

Input: $\mu, \pi, LB, UB, \epsilon$

Output: X

$Xset = \left\{\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_{2^I} | \boldsymbol{x}_{nt} = x_1, x_2, ..., x_I | x_i = 0 or 1, i \in \mathcal{I}, nt \in 1, 2, ..., 2^I\right\}$

while $UB - LB <= \epsilon$ **do**

  decompose $LRM(\mu)$ into multiple subproblems $LRM(\mu, \boldsymbol{x}_1)$, $LRM(\mu, \boldsymbol{x}_2)$,...,$LRM(\mu, \boldsymbol{x}_{2^I})$

  use Map-reduced method to map these subproblems to solve;

  collect all the results to get optimal solution X and corresponding $\lambda_{il}, y_{ij}, z_{jt}, u_{il}, \nu_i$

  replace UB with $LRM(\mu, X)$

  if $\lambda_{il} \geq \sum_{j \in \mathcal{J}} y_{ij} \eta_{jl} \left(\frac{1}{T} \sum_{t=1}^{T} z_{jt}\right) + u_{il} - \nu_i$ *and* $OM(X) > LB$ **then**

    replace LB with $OM(X)$

  end

  $sz = \pi(UB - LB)/||\lambda_{il} - \sum_{j \in \mathcal{J}} y_{ij} \eta_{jl} \left(\frac{1}{T} \sum_{t=1}^{T} z_{jt}\right) + u_{il} - \nu_i||^2$

  $\mu = \mu + sz * (\lambda_{il} - \sum_{j \in \mathcal{J}} y_{ij} \eta_{jl} \left(\frac{1}{T} \sum_{t=1}^{T} z_{jt}\right) + u_{il} - \nu_i)$

end

5.4 Summary

In this chapter of methodology, three solution approaches are introduced for computationally solving the non-liner two-stage stochastic programming model 4.6. Each of the solution has its unique main application range and can provides different types of solutions, enabling the system widely applicable.

As a most general linearization method, MILP can present the most accurately optimal solution as it fully describes all the constraints without relaxation or restriction. However, with the increase of data scale, it is hardly practicable without a super computer as the data need to be processed get burgeoning massive at the same time.

Then the parallel computing method, with the idea of 'breaking an entirety into a group of small pieces' forms up a series of individual subproblems and allocated to multiple independent processors. Allocating the tasks and collecting the results also lead to some time delay so its computational time performance will not be shortened proportionally. Based on this thought, a small change on constraints will also reduce the complexity of subproblems on slight sacrifice of accuracy. But it provides no measurement for error rate of this solution.

However, Lagrangian relaxation can measure the error rate by offering an upper bound and a lower bound of the solutions. And making the same change to the model can also speed up the solution process.

Chapter 6

Numerical Experiment

In this chapter, we first perform a series of numerical studies to assess the computational performance and draw comparisons between the three solution approaches proposed in chapter 5. And then we provide a a large scale case study to further illustrate the application of our model in the realistic deployment situations. Furthermore, sensitivity analysis of different parameters is conducted to develop a understanding of how the input variables influence the performance of system.

6.1 Data Setting

For the computational studies in this chapter, the period is set as one year as the base time unit. And all the cost and revenue parameters for this model are listed below. The WTE data are based on an actual Anaerobic Digestion (AD) plant that operated in Singapore (IUT Global Ltd, Singapores largest food waste recycling company (TheStraitTimes, 2011; ZeroWasteSingapore, 2015)):

(1)The variable operating cost for processing per unit waste is $W = 0.0259SGD/Kg$.

(2)The unit disposal fee for the impure wastes paid to the incinerator is $c_D = 0.077SGD/Kg$ waste.

(3)The revenue is composed of the sales of electricity generated ($0.24KWH/Kg$ waste (net power generated during the processing)) and compost produced ($0.675Kg$ compost/Kg waste). The computed revenue rate q is $0.0985SGD/Kg$ waste.

(4)The unit transportation cost is assumed to be $h = 0.02SGD$ per Kg and per Km.

(5)The building cost of per unit capacity is assumed to be $f = 0.01 SGD/Kg$ and the annualized fixed cost of each opened WTE facility b is $20000SGD$.

(6)The penalty cost paid for excess waste is $g_i = 0.1SGD/Kg$ including the labor fee and extra machine depreciation.

All codes are developed by MATLAB, and integer and linear programming models are solved using the CPLEX 12.5 solver. The computer used is equipped with I5 4590 core and 4G memory. The distributed computing toolbox is activated in MATLAB and allows the four processors works in parallel.

6.2 Comparison between the three computational approaches

In chapter 5, we proposed three solution approaches for the two-stage incentive-location joint planning in case of the purpose for different application. So in this section several numerical experiments are executed to compare the advantages and disadvantages among the three methods in section 4.4 to discuss the situations that each solution is better suitable for.

In this part, all purity ratio of primary feedstock θ_j are assumed to equal to 0.9 and γ of secondary feedstock to 0.8. Besides, all transportation cost of unit secondary feedstock l_i are assumed to have the same value 0.01 based on the price of transportation of trucks.

The total waste generated for each resident zone is generated randomly from interval [1000, 1500], and the distance (Km) between each resident zone and WTE potential site is generated randomly from interval [0, 1]. And assume the amount of scenarios is $L = 100$. And incentive reservation levels following a uniform distribution are generated randomly by simulation.

Table 6.1 provides a comprehensive comparison of the results calculated by each method.

Table 6.1: The performance for three solution approaches in cases with different scale data

	MILP		Small Maps		LRM					
Scale					Value		Time			Error Rate
	Value	Time	Value	Time	UB	LB	LR	LR-MR	LR-MR/LR	
I=3, J=6	16.272	6s	16.254	3s	16.393	16.098	0.15hr	0.45hr	3	0.85%
I=4, J=8	22.193	1min	22.069	10s	22.404	22.143	3hrs	3.7hrs	1.23	1.16%
I=3, J=10	33.584	2min	33.502	4s	34.053	32.525	2.5hrs	6.3hrs	2.52	1.62%
I=5, J=10	26.162	6min	26.099	13s	26.691	24.397	4hrs	3hr	0.75	2.22%
I=10, J=10	\	\	28.027	23min	30.125	24.365	5.2hrs	3.2hrs	0.62	6.96%
I=10, J=15	\	\	41.552	40min	45.023	37.278	8hrs	4.8hrs	0.6	7.71%
I=10, J=20	\	\	52.482	1hr	57.164	50.429	12.4hrs	6.6hrs	0.53	8.19%
I=10,J=30	\	\	76.81	1.6hrs	84.406	75.119	16hrs	7.7hrs	0.48	8.99%

The aim of this table is mainly to present how theses approaches perform in aspect of accuracy and computational speed in the cases of different scales.

Compare the cases where $I = 3, J = 10$ and $I = 5, J = 10$ respectively under the same column, MILP, it can be seen that the speed of MILP decreases with the number of potential sites I as the former takes $2min$ and the latter takes $6min$. Similarly, compare the cases where $I = 3, J = 6$ and $I = 3, J = 10$ still under the column MILP, the time difference between $6s$ and $2min$ shows an increase in number of zones J also slows down the method significantly. Also, the computation time of the three cases where $I = 3, J = 6$, $I = 4, J = 8$, and $I = 3, J = 10$ respectively are $6s$,$1min$ and $2min$ correspondingly, indicating the influence of the increase of I on the computational time is also significant. In short, the computational time of MILP are not only related with the amount of zones J but influenced more by the number of potential sites I. So when the dimension of the case is above $I = 10, J = 30$, this method is incapable of solving this problem, causing the machine to stall.

In the column of Parallel computing using the Small Maps heuristic, we compare all the time in the similar way but the conclusion is different with that of MILP. The amount of I, rather than J, has more effects on the computational time. In addition, the computation by Map-reduced method is the fastest that can be completed within several minutes in small-scale cases and 2hrs in large-scale ones. In other words, the speed of Parallel computing method with Small Maps heuristic is quite desirable. In addition, in spite of reducing the time considerably, this method does not scarifies the accuracy much. In the four cases displayed, the error rates of the results by Map-reduced are all within 5% that can be ignored.

And in the column of Lagrangian relaxation method (LRM), the computational time is far more than that of MILP and Map-reduced by reason of numerous iterations. However, since the main part of LRM is the amount of iterations which is not directly related with the amount of I and J, so the increase of I and J does not result in exponential growth of computational time. Thus in large-scale cases, the computation time can still remains acceptable compared to the small-scale cases. When combined with Map-reduced method, the speed of LRM is enhanced rapidly in medium-scale and large-scale cases rather than small-scale. That is caused by the procedure of Map-reduced that first use *map* function to distribute all the jobs to clusters and then use *reduce* function to collect all the results to proceed for the final output. So when an individual iteration can be done fast enough, the main part in computational time of the LR-MR is spent on the distribution and collection. But when the scale get larger that one subproblem takes long, LR-MR can make notable progress on shorten the computational time. And the larger scale the case is, the more significant is the computational savings. Hence the LR-MR method is regarded especially applicable to large-scale cases. Moreover, the LRM provides an upper bound and lower bound for evaluation, so that the maximum error rate can be obtained. Although the error rates get lager with the increase of case's scale, in these five cases, the maximum error rates are all acceptable and within 10% even in large-scale cases, which proves the effectiveness of our methods.

To make it more clear, we choose the case of $I = 3, J = 6$ and $I = 5, J = 10$ to discuss in detail in table 6.2. When the case of $I = 5, J = 10$ applied with LRM, the case can get a stable value gap within 4 hours. And the amount of iterations are about 4400. Using the 'tic toc' function we got that the time for environment configuration is nearly zero, only around 0.03 second. But one iteration averagely need 3.3 seconds to run over including the 0.3 second of replacement of lagrangian multiplier μ. While for LR-MR case, it takes 2.8 seconds including 0.08 second for all configuration and generation of the mapping set.

Table 6.2: Add caption

	Time for per iteration		Amount of iterations
	LR	LR-MR	
I=3,J=6	0.8s	1.7s	7000
I=5,J=10	3.3s	2.8s	4400

So it can be sees that the time spent on data preparation is quite limited and can be ignored but the distribution and taking-back process is not negligible. The distribution and taking-back process is the key factor to explain why LR-MR underperforms for cases of small scales but is better in those of large scales. No matter in large or small problems, the time of such process does not vary much. So in small cases, this process account for too much comparing to the short time, while in large cases, it is insignificant.

In this table it is clear to see with the development of data scale, the increasing of computational time is rapid. MILP can provide an accurate result but just for cases of limited scales. Map-reduced method is the fastest for its cooperation with multiple parallel computers. Its shortage is lacking a criterion to evaluate its optimality gap solved by a heuristic way. And Lagrangian relaxation supplement this criterion with a range of the optimal solution, so the maximum possible error rate can be thus evaluated. And as a feasible solution, the result served by map-reduced can also be regarded as a lower bound. However, with multiple iterations, the disadvantage for the Lagrangian relaxation is requiring much more time to get a stable interval. Therefore there three methods is suitable to different occasions with different requirements.

6.3 Case Study

As another representative megacity, the waste management is a vital issue in Singapore for it directly affects or even decides the sustainable development of the small island. Hence in this case study, we consider the city status of Singapore as the test bed and focus on a highly populated residential district in the west of Singapore, Clementi town. Close to 83% of the Singapore population resides in state-owned high rise flats (Housing and Development Board). The district is partitioned into 30 resident zones, each consisting of several high-rise residential blocks, and 10 potential WTE facility sites are considered. The figure below illustrates the map information obtained from the Housing and Development Board (HDB) Singapore. ((PropertyGuru, 2015))

The waste generation in each scenario is randomly generated using a normal distribution. The mean of residential waste generated in each zone, which is listed in the table below, is estimated by multiplying the amount of per-capita household waste generation in Singapore by the average population of each resident zones. And the standard variance is assumed empirically $0.1ton$. The capacity limit of the WTE facility follows the size of IUT global, which is 30000 tons per year.

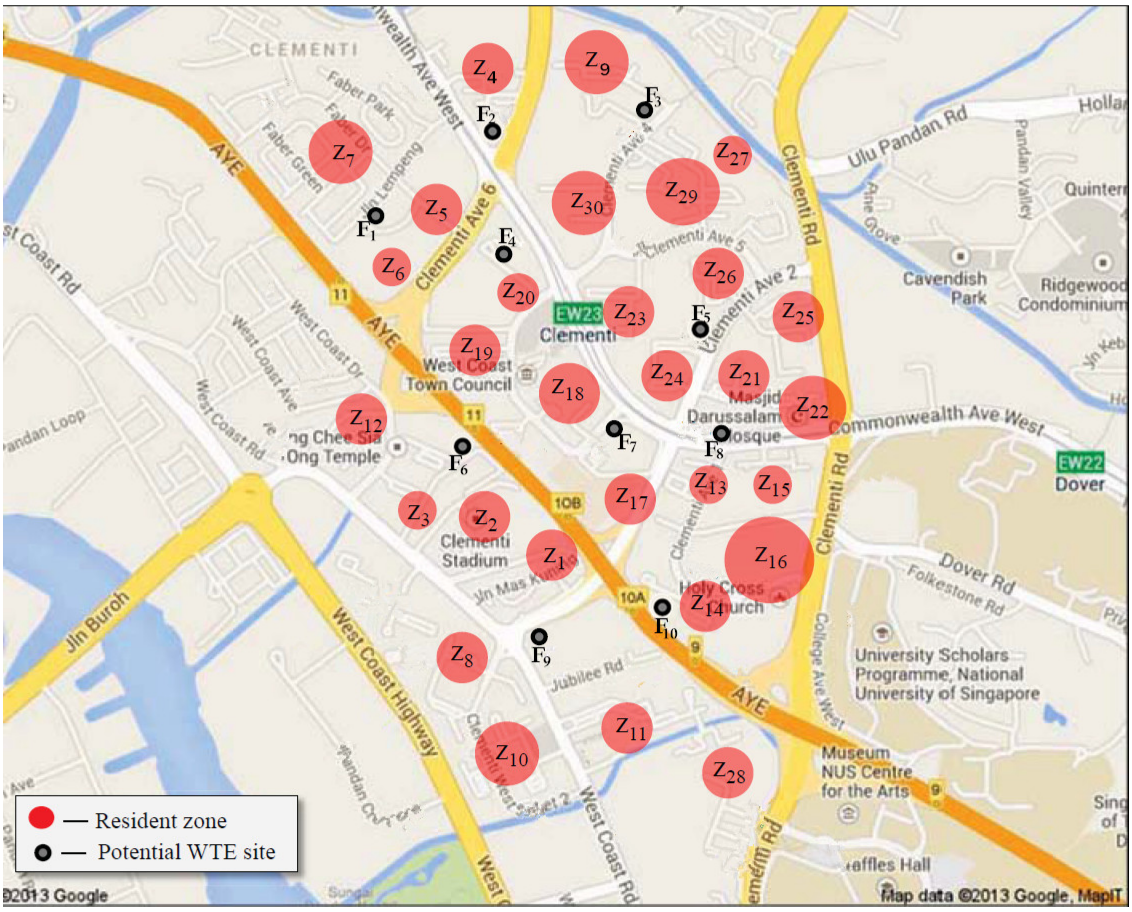

Figure 6.1: Distribution of 30 resident zones and 10 potential WTE sites in Clementi town,where F_i for $i = 1, 2, 10$ are the indicators of potential facility sites and Z_j for $j = 1, 2, , 30$ are the indicators for resident zones

Table 6.3: The means of waste generations in 30 resident zones Unit: $100 tons$ per year

1	2	3	4	5	6	7	8	9	10
1.53	1.53	0.76	1.53	0.76	2.3	1.53	2.3	1.53	1.53

11	12	13	14	15	16	17	18	19	20
0.76	1.53	0.76	3.83	1.53	2.3	1.53	0.76	1.53	2.3

21	22	23	24	25	26	27	28	29	30
1.53	1.53	1.53	1.53	0.76	1.53	3.06	2.3	2.3	1.53

The distance from each resident zone to each potential WTE site is measured on Google Map and the data are listed in the Appendix.

With MATLAB with CPLEX solver we get the result as follows:

The overall profit is 538230 SGD with all 4 potential sites opened.

Table 6.4: The incentive price of each resident zone   Unit: $SGDperton$

1	2	3	4	5	6	7	8	9	10
22.72	24.32	20.66	24.13	23.86	27.65	22.56	23.86	24.12	23.09

The incentive price are listed in the table 6.4.

11	12	13	14	15	16	17	18	19	20
21.73	21.36	22.35	23.73	22.26	21.82	20.11	20.35	21.94	23.11

21	22	23	24	25	26	27	28	29	30
23.88	22.43	24.53	20.16	23.97	20.56	22.94	22.35	26.89	27.26

And based on the result it is clear that all the opened sites only absorb the residential waste as the price of secondary feedstock is too high to make profit. And the assignment of resident zones to opened facilities are displayed in figure 6.2.

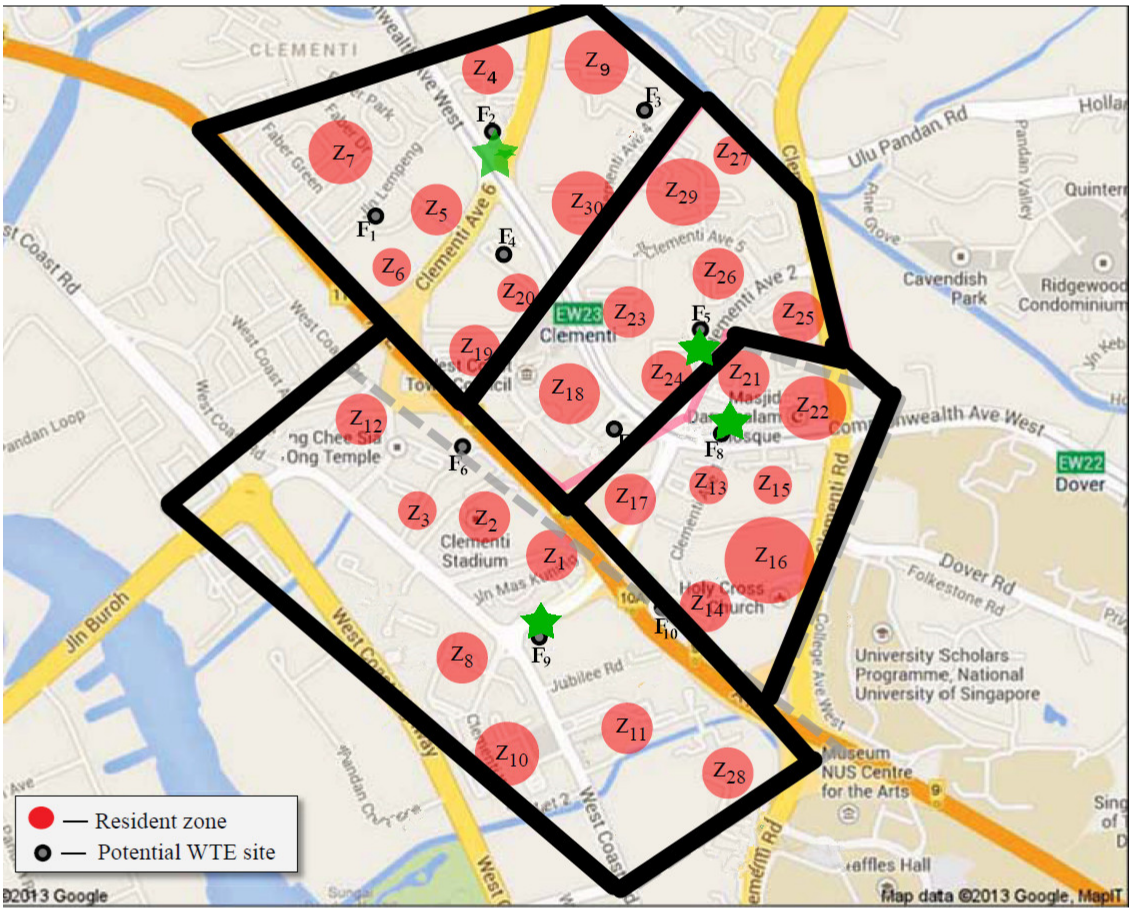

Figure 6.2: The solution of opened facility and its assigned resident zones

It is straightforward that the whole map are divided into four areas according to opened sites which is indicated with a star and its assigned zones. And the specific data are shown in table 6.5.

Table 6.5: The assignment of resident zones and capacity

Site	Zone	Capacity	Unit: $Tons$ per year
7	4,5,6,10,15,16,17,18,21,22,28,29,30		11580
8	11,13,19,20,23,24,25,27		6985.7
9	1,2,3,7,8		4689.4
10	9,12,14,26		5072.2

The capacities of each facility are 11580, 6985.7, 4689.4, and 5072.2 tons, added up to 28327.3 tons while the IUT global set their facility centralized and the capacity around 90000 tons, far more the amount it can collect. Too much idle capacity is also a negative factors to its maintainability.

6.4 Sensitivity Analysis

In this section we change the values of several variables and make the sensitivity analysis to evaluate how the optimal solution varies with the each variable.

6.4.1 Capacity Limit of Recycling Facilities

Here the capacity limit is changed. In the following the capacity of each site and the amount of feedstock of each source are displayed in table 6.6.

Table 6.6: The capacity of each site and the amount of feedstock of each source

Capacity limit	Capacity of each site	Primary feedstock	Secondary feedstock
0	0	0	0
300000	0	0	0
600000	0	0	0
900000	900000	9000000	0
1200000	900000	11726916.32	273083.6773
1500000	900000	14419858.79	580141.2108
1800000	900000	16758788.59	1241211.406
2100000	900000	20442283.43	557716.5674
2400000	900000	23932672.31	67327.69479
2700000	900000	26146243.45	853756.5478
3000000	900000	28747895.25	1252104.747

In this table the first three rows implies when the capacity limit is under 600000 Kg, the system tends to close all plants for it is nonprofitable. Also, we notice the individual's capacity is same to the capacity limit from 900000, which reveals two facts that the fixed cost for opening facility is considerable and thus cannot be overlooked, and the feedstock is profitable enough that the capacity tends to reach the limit. In addition we notice the primary feedstock is also increasing which means the capacity limit is also a factor to incentive. And this trend also indicate the primary feedstock is still a prime source of the system for its profitable characteristic, otherwise the system would tend to absorb all secondary feedstock instead.

And the trend of profit is also shown in figure 6.3.

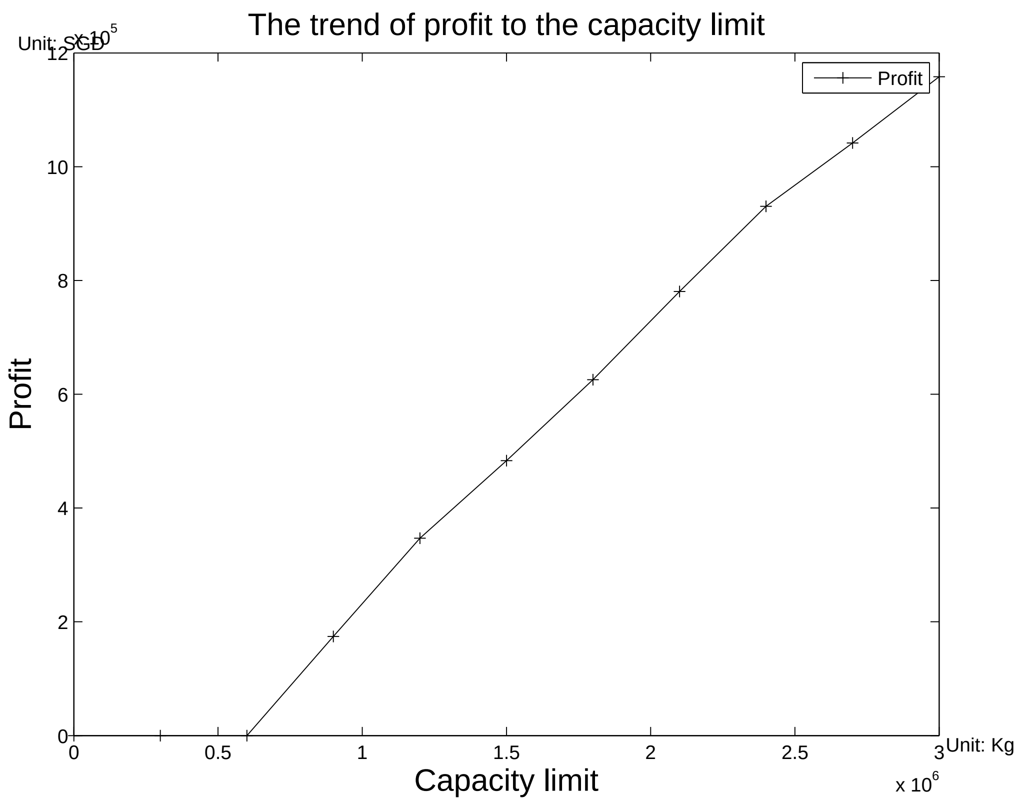

Figure 6.3: Profit to the capacity limit

In this figure it is not hard to see that although the slope is generally linearly but not consistent all the time. When others are fixed, generally the more the primary feedstock is taken in, the faster the profit is obtained.

6.4.2 Price of the secondary feedstock

In this part we set the price of secondary feedstock as variable to see how it influence the system's performance. And in the following table 6.7 displays the capacity of each site and the amount of feedstock of each source. Be noted that the amount of open sites remains 10 when the price of secondary feedstock changes due to the abundant profitable primary feedstock.

Table 6.7: The capacity of each site and the amount of feedstock of each source as a function of secondary feedstock price

price	capacity	primary feedstock	secondary feedstock
0	10000000	9569290	430709.8
0.005	10000000	9569779	430221.5
0.01	10000000	9612837	387162.8
0.015	10000000	9612837	387162.8
0.02	10000000	9613128	386871.7
0.025	10000000	9613128	386871.7
0.03	10000000	9613561	386438.9
0.035	9613561	9613561	0
0.04	9613561	9613561	0
0.045	9613561	9613561	0
0.05	9613561	9613561	0
0.055	9613561	9613561	0

In this table it is notable the secondary feedstock would stop being absorbed as the price gets higher to a limit. It tells the price between 0.03 0.035 SGD/kg of secondary feedstock would result in nonprofit of importing foreign waste and when it gets higher, the system tends to focus on the resident waste only and thus the capacity will be designed to reduce to only take in primary feedstock.

And the trend of profit is also shown in figure 6.4.

The profit in this figure declines steadily as the price gets higher before a limit between 0.03 0.035 SGD/Kg. It is understandable that the loss of profit is partly caused by the rise of the price paid. And figure 6.5 can show more details about how the price of secondary feedstock profit by affecting the amount of each feedstock.

Before the price reaches 0.03 SGD/Kg, the primary feedstock is slightly increased while the secondary is decreasing. In this period, the price has an effect on the amount of secondary feedstock and the incentive. Therefore these two can influence mutually to fill

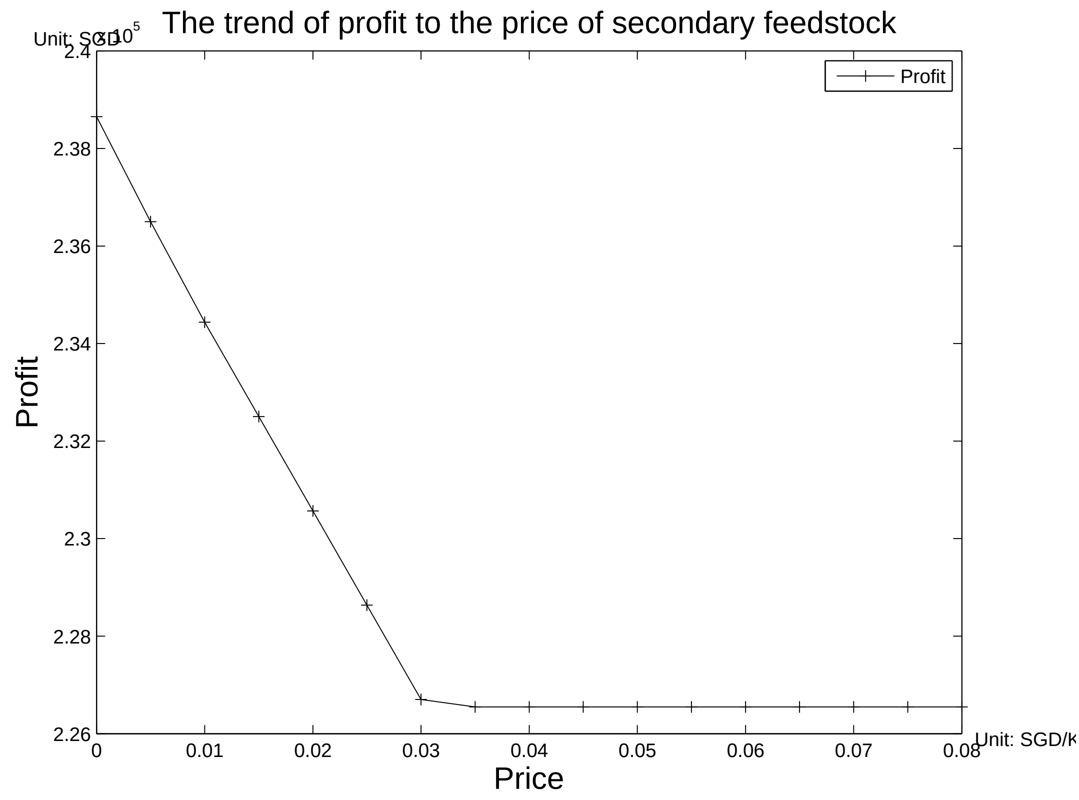

Figure 6.4: Profit to the price of the secondary feedstock

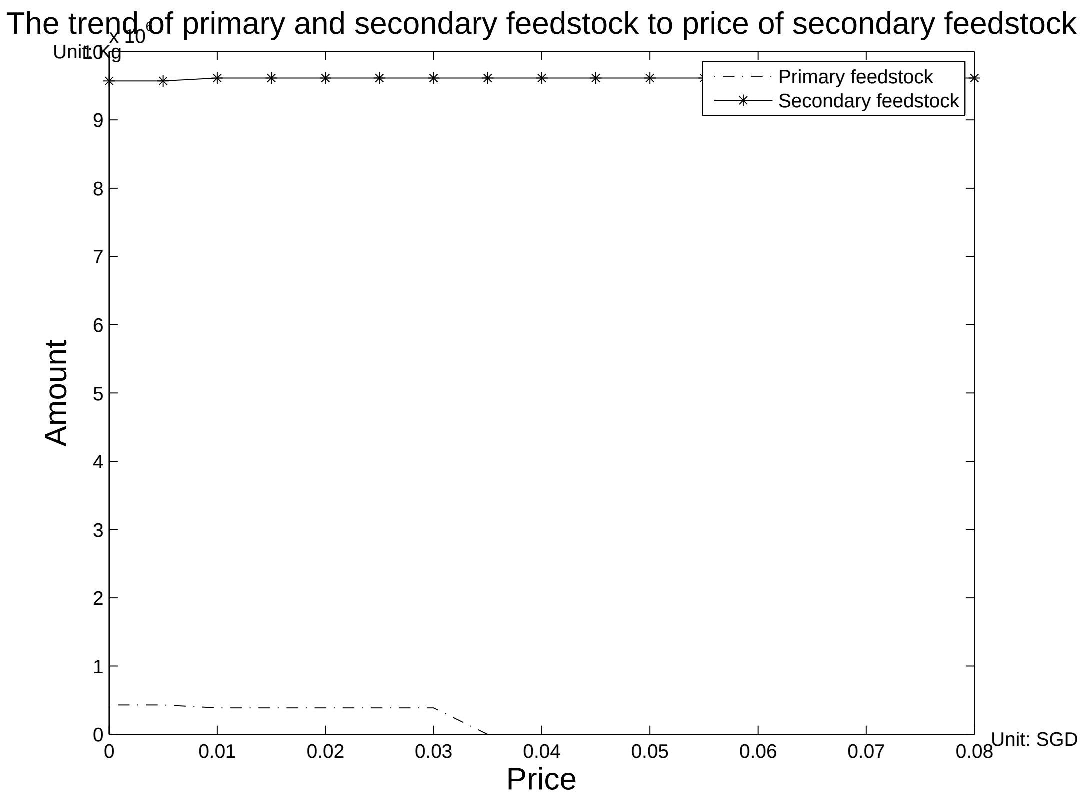

Figure 6.5: amount of feedstock to the price of the secondary feedstock

the capacity with profitable waste. When the price surpasses 0.035 SGD/Kg, the price will no longer affect the system's performance for it is a just characteristic of secondary feedstock which is totally out of the system. So the system will be unchanged however the price increases.

Combined the two figures above, it is a fact that both the portion and total amount of each feedstock are generally steady before price reaches 0.03SGD/Kg, so it is not the main factor resulting in the decline of the profit and the higher price paid for secondary feedstock is. However after price surpasses 0.035SGD/Kg, the profit is determined by the structure and amount of feedstock absorbed because the price is excluded by the system with secondary feedstock.

6.4.3 Purity ratios

In reality, feedstock purity ratio can drift from the assumed values. Here we integrated the profit to the two variable into one table so that we can compare the data both horizontally and vertically.

Table 6.8: The profit to θ and γ

$\theta\backslash\gamma$	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00
0.6	0	0	0	0	0	0	0	51250	139000
0.65	0	0	0	0	0	0	0	51250	139000
0.7	0	0	0	0	0	0	0	51250	139000
0.75	0	0	0	0	0	0	0	51250	139000
0.8	57642	57642	57642	58340	62111	65884	71598	80644	139000
0.85	141611	141611	141611	142309	146080	149853	153629	159346	168395
0.9	226547	226547	226547	227175	230569	233965	237598	241377	247096
0.95	312615	312615	312615	313243	316638	320034	323431	326832	330234
1	400125	400125	400125	400334	402706	406102	409500	412901	416303

And the 3D figure 6.6 is drawn to make it more clear.

Combining the table and figure we note that the profit value of the area where γ is below 0.9 and θ is below 0.75 remains 0. That means when the purity ratios of both feedstock are not high enough, the system tends not to open. And since 0.75 is remarkably less than 0.9, the requirement for purity ratio of primary feedstock is much lower. That is mainly because of the higher price we paid for secondary feedstock. In addition, the increase in the purity ratio of any feedstock can assure the maintenance of

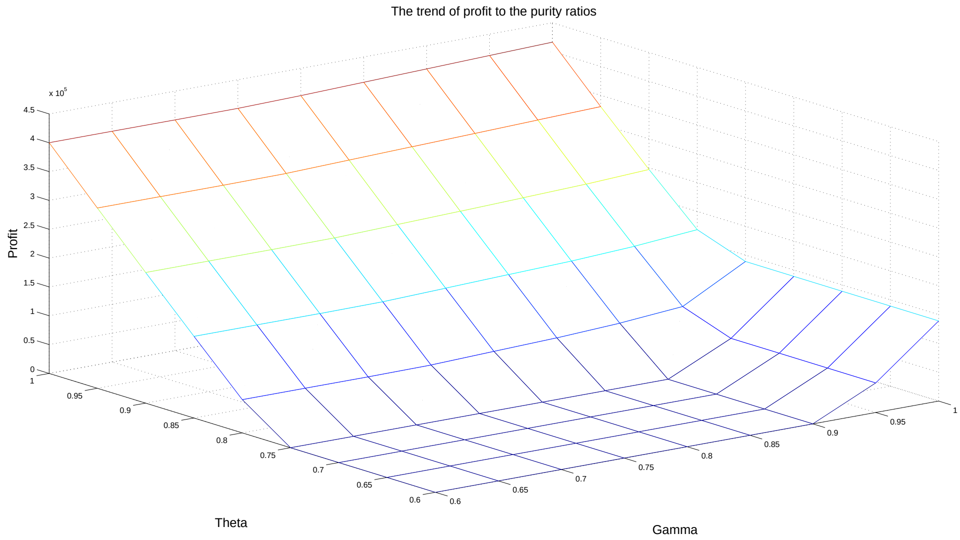

Figure 6.6: The trend of profit to the purity ratios

system, not necessarily for both feedstock, which implies that raising people's recycling awareness or the secondary feedstock of better quality can somehow enables WTE system running smoothly. Thus it is important to launch related campaign among residents and to carefully choose a supplier with fine waste. And also, it can be seen from the table both higher θ and γ contribute to the profit, but the rise of θ, the one of the primary feedstock, contributes more considerable.Considering that it takes more effort to raise the purity ratio from 0.95 to 1, the limitation, than that from 0.8 to 0.85, the system needs to lay more emphasis on how to raise the quality of residents' waste. In that case, it is vitally necessary to raise residents' awareness to sorting and recycling for the sustainable development of this WTE system.

Then, the figure 6.7 shows the trend of secondary feedstock to the purity ratios and the figure 6.8 is its contour plot for clear observation. These two figures help to understand how the purity ratios influence the amount of supplement, or in other word how much to buy if the secondary feedstock is of high quality.

Generally, the increase of the γ, the purity ratio of secondary feedstock helps the system absorb more secondary feedstock while the increase of θ, the purity ratio of primary feedstock is on the contrary. More specifically, when the residents' waste is of poor quality and the supplier's waste of remarkable high quality, the system tends to buy a lot of secondary waste. But as long as θ rises up, the system can stop relying too much

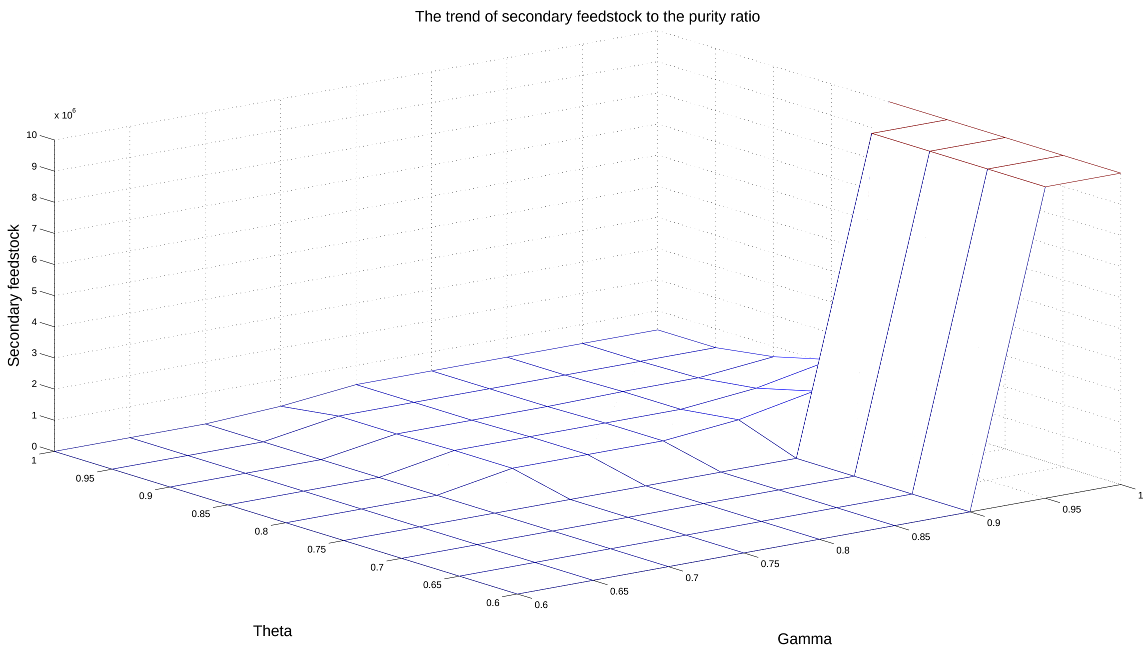

Figure 6.7: The trend of secondary feedstock to the purity ratios

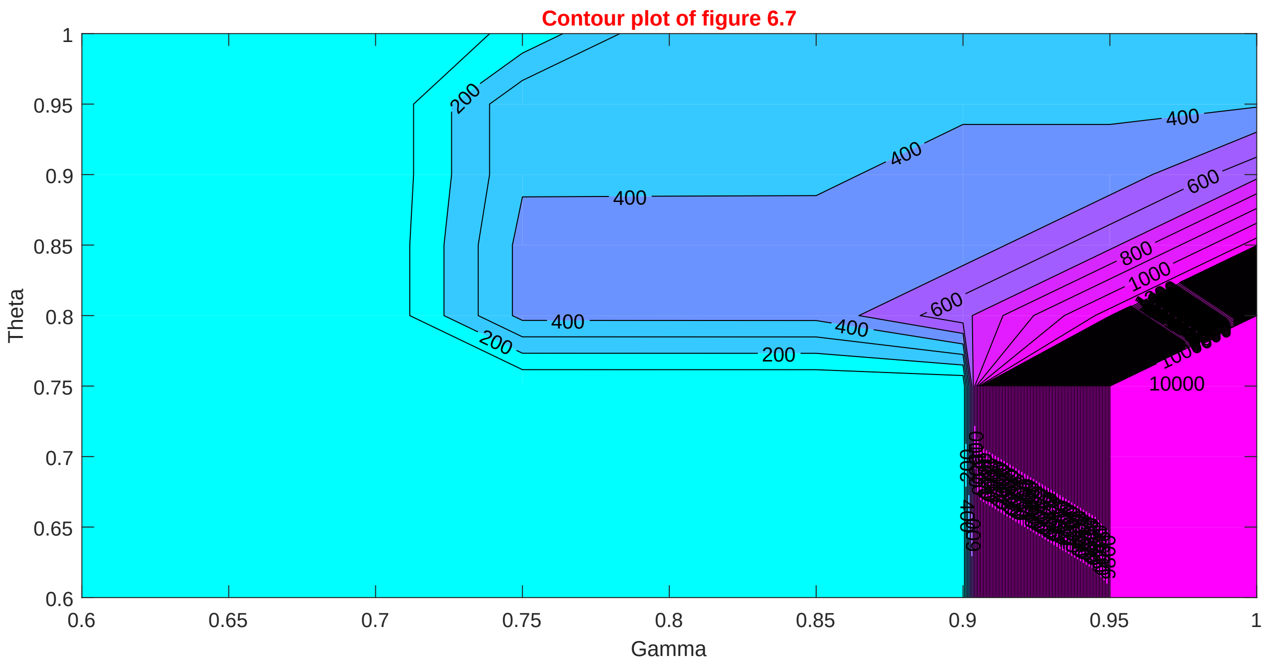

Figure 6.8: Contour plot of figure 6.7

on the foreign supplier, which development model is not healthy. As a result, tit can be seen that when θ is above 0.75, the increase of γ does not influence the system's decision significantly, which means system is stable when the foreign environment varies. In that case, enhancing the primary feedstock is not only a way to make more revenue but also and more importantly, a way to construct the system healthily.

6.4.4 Fixed cost for opened facility

In this part we set the fixed cost b as variable to see how it influence the system's performance.

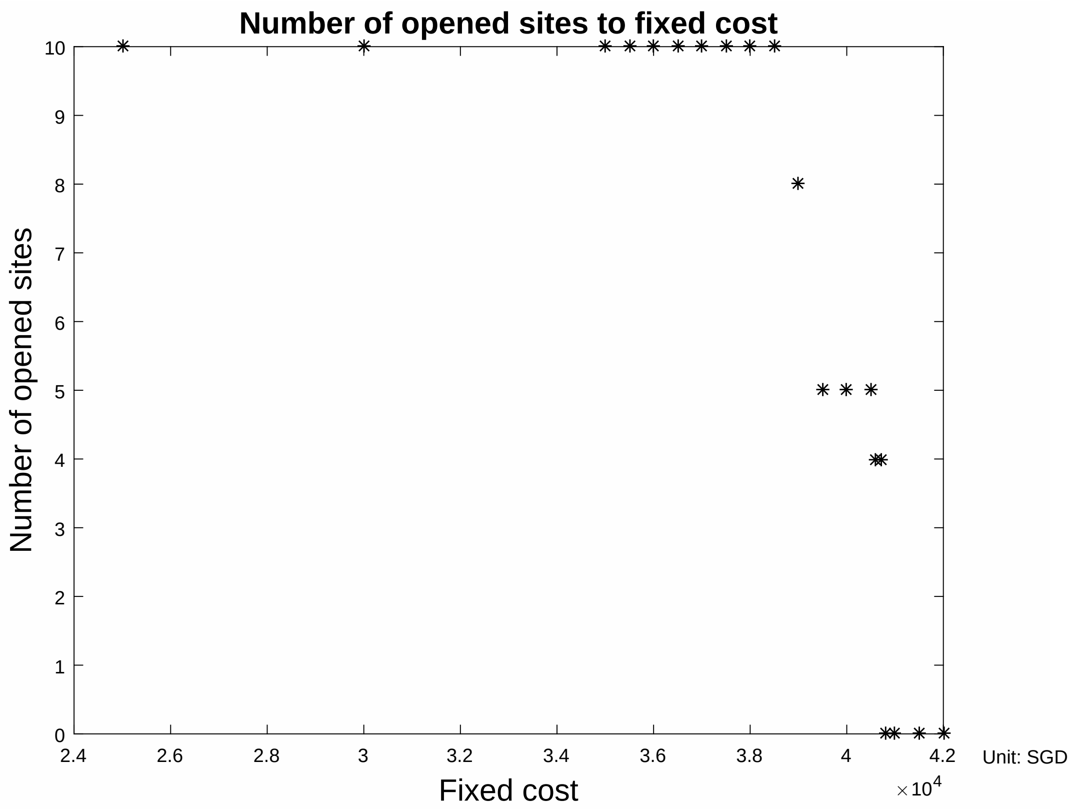

Figure 6.9: Number of opened facility to the fixed cost

It is shown in figure 6.9 the fixed cost is a factor to decide the amount of opened facility. When the fixed cost becomes large, the system tends to have centralized facility for the revenue of the feedstock may not be able to cover the expense of the opening facility.

6.5 Summary

In this chapter, simulations of different scales are first performed to evaluate the feasibility and scope of the solution approaches proposed in chapter 5. When and only when dealing with cases of small scale, MILP is distinguished by optimality of solution from other approaches and can be described with accurate and fast. While with the increase of the scale, parallel computing based on Map-Reduce method can improve the speed by managing a group of individual jobs separately in different clusters and the heuristic algorithm can reduce the amount of jobs significantly. However, lacking a criterion to evaluate the solution restricts its application range, while Lagrangian relaxation provides the criterion by relaxing a constraint and obtaining an upper bound and a lower bound to calculate the maximum possible error rate. The high requirement for computer configuration and the long solving time may be its restrictions. So it is clear presented the three solution approaches are better applicable to different conditions with varied requirements. After that, a case study simulated in Singapore is carried to validate the feasibility of approaches. And the results indicate their respective application range. The approaches would be applied balancing the scale of data, solving speed and solution accuracy.

Multiple parameters are changed to carry out the system's sensitivity analysis. There is a start point for capacity limit from where the system is profitable and tends to open WTE facility. And as the price of secondary feedstock is not profitable when taking penalty cost into account, the system tends to adopt a conservative capacity limit. Also the purity ratio to primary feedstock plays a more important role to profit, so it has a profound and lasting effect to prompt people's awareness to separate the waste precisely and consciously. Also, the fixed cost of facility affects the distribution of system and partly decides it is centralized or not. It indicates the distributed facilities are better built in remote districts or suburbs while centralized plant is adoptive mostly in downtown.

Chapter 7

Conclusions and Future Research

7.1 Conclusions

In this thesis, an incentive-location joint planning model is built up for sitting the recycling plant locations, and incentivization under uncertainty of residents' reservation incentives and waste volumes. The incentive policy here is designed to help prompt residents' environmental awareness and thus separate the residential waste precisely and actively as the quantity and quality of sorted waste are both essential to this waste management system. The general task is how to design jointly with multiple and sometimes contradictory decisions variables such as the location decision influences residents' incentives pricing, transporting cost and overall profit.

First a basic model with a sole feedstock is proposed to evaluate the economic feasibility of the WTE system framework under uncertain environment. Separated residential waste are taken in as the only source and both residents' incentive reservations and waste generations make the environment uncertain. And a mathematical model is formulated to optimize the system's configuration by maximizing the overall profit. Methodologies are also introduced for a better computational application. Then with the background in Shanghai, a special case is added for feasibility study and experiment test. The result is proved effective on environment of small scale and little variability. However, such a system may not be sustainable economically if feedstock collected from resident zones is insufficient to achieve a healthy capacity utilization. In that case, the model in chapter 3 would suffer the consequence of waste shortage because there is no buffer. IUT global's failure also reveals there is a huge risk to rely entirely on the waste collected for the factors influencing the waste generation are, to some degree, uncontrollable. Such a system may not be sustainable economically if feedstock collected from resident zones is insufficient to achieve a healthy capacity utilization.

Therefore, to enhance its resistance to environment variabilities and to provide a proper buffer to the system, waste from professional processing plants is introduced as secondary implement feedstock. Its poor purity ratio leading to low profitability establishes its introduction in secondary stage, as a way of back up. Thus two-stage mathematical programming model is formulated to fully describe the system including incentivation policy design.

Three solution approaches are then presented to enhance the computational compatibility especially on a large scale. Linearisation is applied to this two-stage optimizing problem to formulate a MILP model. It can generate the most accurate solution but the large data for megacities are often beyond its capability and causes failure. With enumeration, parallel computing with Map-reduced framework can split the large problem into many subproblems and allocate to multi processors but it still has a limitation for the data scale. Thus a heuristic technique is used to obtain much smaller tasks by placing a harder constraint. And the data from experiments indicates the error rate of solution is within acceptable value. Lagrangian relaxation does not only provide an upper bound for the problem but also is a good way to measure the accuracy of other methods.

A computational case study with the background of Singapore demonstrates how the system can be performed efficiently and sustainably. The result also provides a comprehensive comparison of three solution approaches on application range. MILP is optimal solution in cases of small scale and parallel computing based on Map-Reduce method with heuristic is fast and provide a feasible solution of high quality, while the quality can be measured by Lagragian relaxation approach. A wide range of scales and efficiency are covered by the three approaches, helping establish the system's outstanding competitiveness.

Multiple parameters are changed to carry out the system's sensitivity analysis. There is a start point for capacity limit from where the system is profitable and tends to open WTE facility. And as the price of secondary feedstock is not profitable when taking penalty cost into account, the system tends to adopt a conservative capacity limit. Also the purity ratio to primary feedstock plays a more important role to profit, so it has a profound and lasting effect to prompt people's awareness to separate the waste precisely and consciously. Last but not least, the fixed cost of facility affects the distribution of system and partly decides whether it is centralized or not. It indicates the distributed facilities are better built in remote districts or suburbs while centralized plant is adoptive mostly in downtown.

7.2 Future Work

In the context of this paper, there are many assumptions and simplifications used which can be reviewed by further studies on this topic. Firstly, target inventory levels are constants and are based on simplifying assumptions. Further studies may look into the impact of different target levels as imposed by the different members within the supply chain.

Also, in this study of information sharing scheme, in order to keep things simple, a simple two-tiered supply chain is considered. This is not the case with many real-life supply chains which are much more complex and connects many more echelons and stakeholders. Further studies can deal with a supply chain with more layers and look into the effect of the increase in complexity of the supply chain.

In this thesis many assumptions and approximations are adopted to simplify the model process. These can be viewed as possible extensions or explorations in future works. For instance, purity ratios can be separated to be viewed as uncertainties, which maybe more specific and practical for different populations' behaviour and thus influence the incentivation pricing making. Customized incentive design may be applied to resident zones for a better resource utilization.

In addition, multiple periods of planning can be considered as the system is supposed to last for tens of years in which people's behaviours may be subjected to change under future rules and society state. Multiple periods of planning may react fast to environment changes in premise of not affecting the basic framework, thus resulting in a better optimization and then making a contribution to long-term sustainability and profitability.

Also, in the stage of reallocation, inter communications may be added with the development of green transporting. In this study, the concern about environment pollution during loading and transporting is still outstanding. But when the technologies get mature and applied widely, the inter communication parts may be included in this framework to get a better utilization of waste to avoid wasting of resources, and more directly, to reduce penalty cost and get more profit. Future studies can significantly improve the waste utilization by adopting an advanced inner communication system at low cost.

Moreover, the methodologies may be improved by taking some more precise heuristic method to enhance the quality of feasible solution in parallel computing with heuristic and Lagrangian relaxation. To get a better speed we placed a harder constraint into the model in former approach and remove one from constrains in latter approach. Both of the restriction and relaxation have exploring potential to improve. And future study may look into how the heuristic steps influence the system' s overall performance including speed and accuracy.

Last but not least, due to realistic constraints, all computation performance is based on the computer's equipment. The trend would not change but the data may varies with different machines. And the data for the test is regional hence the result of the cases are not necessarily identical.

The function for incentive may be too general as the behaviour of residents are complicated and changeable to many factors like weather and transportation condition. It can be more specified in detail.

Bibliography

Al-Othman, W. B., Lababidi, H. M., Alatiqi, I. M., and Al-Shayji, K. (2008). Supply chain optimization of petroleum organization under uncertainty in market demands and prices. *European Journal of Operational Research*, 189(3):822–840.

Baetz, B. W. and Neebe, A. W. (1994). A planning model for the development of waste material recycling programmes. *Journal of the Operational Research Society*, pages 1374–1384.

Barney, B. (2015). Introduction to parallel computing. `https://computing.llnl.gov/tutorials/parallel_comp/`.

Berger, C., Savard, G., and Wizere, A. (1999). Eugene: an optimisation model for integrated regional solid waste management planning. *International Journal of Environment and Pollution*, 12(2-3):280–307.

Bogh, M. B., Mikkelsen, H., and Wøhlk, S. (2014). Collection of recyclables from cubes–a case study. *Socio-Economic Planning Sciences*, 48(2):127–134.

Brunner, P. H. and Rechberger, H. (2015). Waste to energy–key element for sustainable waste management. *Waste Management*, 37:3–12.

Bruvoll, A., Halvorsen, B., and Nyborg, K. (2002). Households recycling efforts. *Resources, Conservation and Recycling*, 36(4):337–354.

Carneiro, M. C., Ribas, G. P., and Hamacher, S. (2010). Risk management in the oil supply chain: a cvar approach. *Industrial & Engineering Chemistry Research*, 49(7):3286–3294.

Chang, N.-B. and Wei, Y. (1999). Strategic planning of recycling drop-off stations and collection network by multiobjective programming. *Environmental Management*, 24(2):247–263.

Chen, C. and Liu, L. Q. (2014). Pricing and quality decisions and financial incentives for sustainable product design with recycled material content under price leadership. *International Journal of Production Economics*, 147:666–677.

Chen, C.-W. and Fan, Y. (2012). Bioethanol supply chain system planning under supply and demand uncertainties. *Transportation Research Part E: Logistics and Transportation Review*, 48(1):150–164.

Chu, C., Kim, S. K., Lin, Y.-A., Yu, Y., Bradski, G., Ng, A. Y., and Olukotun, K. (2007). Map-reduce for machine learning on multicore. *Advances in neural information processing systems*, 19:281.

Dean, J. and Ghemawat, S. (2008). Mapreduce: simplified data processing on large clusters. *Communications of the ACM*, 51(1):107–113.

Dempster, M., Pedron, N. H., Medova, E., Scott, J., and Sembos, A. (2000). Planning logistics operations in the oil industry. *Journal of the Operational Research Society*, 51(11):1271–1288.

Ekins, P., Simon, S., Deutsch, L., Folke, C., and De Groot, R. (2003). A framework for the practical application of the concepts of critical natural capital and strong sustainability. *Ecological economics*, 44(2):165–185.

Erkut, E., Karagiannidis, A., Perkoulidis, G., and Tjandra, S. A. (2008). A multicriteria facility location model for municipal solid waste management in north greece. *European Journal of Operational Research*, 187(3):1402–1421.

Escudero, L. F., Quintana, F. J., and Salmerón, J. (1999). Coro, a modeling and an algorithmic framework for oil supply, transformation and distribution optimization under uncertainty. *European Journal of Operational Research*, 114(3):638–656.

Everett, J. W. and Modak, A. R. (1996). Optimal regional scheduling of solid waste systems. i: Model development. *Journal of Environmental Engineering*, 122(9):785–792.

Faghri, A., Lang, A., Hamad, K., and Henck, H. (2002). Integrated knowledge-based geographic information system for determining optimal location of park-and-ride facilities. *Journal of urban planning and development*, 128(1):18–41.

Fullerton, D. and Kinnaman, T. (2002). The economics of household garbage and recycling behavior.

Geist, A. (1994). *PVM: Parallel virtual machine: a users' guide and tutorial for networked parallel computing*. MIT press.

Ghose, M., Dikshit, A. K., and Sharma, S. (2006). A gis based transportation model for solid waste disposal–a case study on asansol municipality. *Waste management*, 26(11):1287–1293.

Gottinger, H. W. (1988). A computational model for solid waste management with application. *European Journal of Operational Research*, 35(3):350–364.

Grama, A. (2003). *Introduction to parallel computing*. Pearson Education.

Grossmann, I. E. and Guillén-Gosálbez, G. (2010). Scope for the application of mathematical programming techniques in the synthesis and planning of sustainable processes. *Computers & Chemical Engineering*, 34(9):1365–1376.

Guide Jr, V. D. R., Teunter, R. H., and Van Wassenhove, L. N. (2003). Matching demand and supply to maximize profits from remanufacturing. *Manufacturing & Service Operations Management*, 5(4):303–316.

Harder, M. and Woodard, R. (2007). Systematic studies of shop and leisure voucher incentives for household recycling. *Resources, conservation and recycling*, 51(4):732–753.

Hong, S., Adams, R. M., and Love, H. A. (1993). An economic analysis of household recycling of solid wastes: the case of portland, oregon. *Journal of environmental economics and management*, 25(2):136–146.

Huang, Y., Chen, C.-W., and Fan, Y. (2010). Multistage optimization of the supply chains of biofuels. *Transportation Research Part E: Logistics and Transportation Review*, 46(6):820–830.

Inghels, D., Dullaert, W., and Vigo, D. (2016). A service network design model for multimodal municipal solid waste transport. *European Journal of Operational Research*, 254(1):68–79.

IUTgroup (2008). National energy globe for ados process. http://www.theiutgroup.com/index.php?option=com_content&task=view&lang=en&id=146.

Jakus, P. M., Tiller, K. H., and Park, W. M. (1996). Generation of recyclables by rural households. *Journal of Agricultural and Resource Economics*, pages 96–108.

Jenkins, R. R., Martinez, S. A., Palmer, K., and Podolsky, M. J. (2003). The determinants of household recycling: a material-specific analysis of recycling program features and unit pricing. *Journal of environmental economics and management*, 45(2):294–318.

Jennings, A. A. and Suresh, P. (1986). Risk penalty functions for hazardous waste management. *Journal of Environmental Engineering*, 112(1):105–122.

Johansson, O. M. (2006). The effect of dynamic scheduling and routing in a solid waste management system. *Waste management*, 26(8):875–885.

Khor, C. S., Elkamel, A., Ponnambalam, K., and Douglas, P. L. (2008). Two-stage stochastic programming with fixed recourse via scenario planning with economic and operational risk management for petroleum refinery planning under uncertainty. *Chemical Engineering and Processing: Process Intensification*, 47(9):1744–1764.

Lee, S. and Paik, H. S. (2011). Korean household waste management and recycling behavior. *Building and Environment*, 46(5):1159–1166.

Lu, L.-T., Hsiao, T.-Y., Shang, N.-C., Yu, Y.-H., and Ma, H.-W. (2006). Msw management for waste minimization in taiwan: The last two decades. *Waste Management*, 26(6):661–667.

MacDonald, M. L. (1996). Solid waste management models: a state of the art review. *Journal of solid waste technology and management*, 23(2):73–83.

Macharis, C., Vanhaverbeke, L., van Lier, T., Pekin, E., and Meers, D. (2012). Bringing intermodal transport to the potential customers: An interactive modal shift website tool. *Research in Transportation Business & Management*, 5:67–77.

Marufuzzaman, M., Ekşioğlu, S. D., and Hernandez, R. (2014a). Environmentally friendly supply chain planning and design for biodiesel production via wastewater sludge. *Transportation Science*, 48(4):555–574.

Marufuzzaman, M., Eksioglu, S. D., and Huang, Y. E. (2014b). Two-stage stochastic programming supply chain model for biodiesel production via wastewater treatment. *Computers & Operations Research*, 49:1–17.

Mikac, N., Cosovic, B., Ahel, M., Andreis, S., and Toncic, Z. (1998). Assessment of groundwater contamination in the vicinity of a municipal solid waste landfill (zagreb, croatia). *Water Science and Technology*, 37(8):37–44.

Morrissey, A. J. and Browne, J. (2004). Waste management models and their application to sustainable waste management. *Waste management*, 24(3):297–308.

Muckstadt, J. A. and Koenig, S. A. (1977). An application of lagrangian relaxation to scheduling in power-generation systems. *Operations research*, 25(3):387–403.

Mulvey, J. M. and Crowder, H. P. (1979). Cluster analysis: an application of lagrangian relaxation. *Management Science*, 25(4):329–340.

Niziolek, A. M., Onel, O., and Floudas, C. A. (2016). Municipal solid waste to liquid transportation fuels, olefins, and aromatics: Process synthesis and deterministic global optimization. *Computers & Chemical Engineering*.

Oliveira, F., Grossmann, I. E., and Hamacher, S. (2014). Accelerating benders stochastic decomposition for the optimization under uncertainty of the petroleum product supply chain. *Computers & Operations Research*, 49:47–58.

Olson, M. (2009). *The logic of collective action*, volume 124. Harvard University Press.

Palak, G., Ekşioğlu, S. D., and Geunes, J. (2014). Analyzing the impacts of carbon regulatory mechanisms on supplier and mode selection decisions: An application to a biofuel supply chain. *International Journal of Production Economics*, 154:198–216.

Paleologos, E. K., Caratelli, P., and El Amrousi, M. (2016). Waste-to-energy: An opportunity for a new industrial typology in abu dhabi. *Renewable and Sustainable Energy Reviews*, 55:1260–1266.

Pan, S.-Y., Du, M. A., Huang, I.-T., Liu, I.-H., Chang, E., and Chiang, P.-C. (2015). Strategies on implementation of waste-to-energy (wte) supply chain for circular economy system: a review. *Journal of Cleaner Production*, 108:409–421.

PropertyGuru (2015). Singapore hdb estate clementi. `http://www.propertyguru.com.sg/singapore-property-listing/hdb/clementi`.

Reschovsky, J. D. and Stone, S. E. (1994). Market incentives to encourage household waste recycling: paying for what you throw away. *Journal of policy analysis and management*, 13(1):120–139.

Rogner, H., Zhou, D., Bradley, R., Crabbé, P., Edenhofer, O., and Hare, B. L. kuijpers and m. yamaguchi (2007)introduction in metz, b., or davidson, pr bosch, r. dave and la meyer (eds) climate change 2007: Mitigation. contribution of working group iii to the fourth assessment report of the intergovernmental panel on climate change.

Rondinelli, D. A. and Berry, M. A. (2000). Environmental citizenship in multinational corporations: social responsibility and sustainable development. *European Management Journal*, 18(1):70–84.

Roni, M. S., Eksioglu, S. D., Searcy, E., and Jha, K. (2014). A supply chain network design model for biomass co-firing in coal-fired power plants. *Transportation Research Part E: Logistics and Transportation Review*, 61:115–134.

Saphores, J.-D. M., Nixon, H., Ogunseitan, O. A., and Shapiro, A. A. (2006). Household willingness to recycle electronic waste an application to california. *Environment and Behavior*, 38(2):183–208.

Sazvar, Z., Akbari Jokar, M. R., and Baboli, A. (2014a). A new order splitting model with stochastic lead times for deterioration items. *International Journal of Systems Science*, 45(9):1936–1954.

Sazvar, Z., Mirzapour Al-e hashem, S., Baboli, A., and Jokar, M. A. (2014b). A bi-objective stochastic programming model for a centralized green supply chain with deteriorating products. *International Journal of Production Economics*, 150:140–154.

Seik, F. T. (1997). Recycling of domestic waste: early experiences in singapore. *Habitat International*, 21(3):277–289.

Shaw, P. and Maynard, S. (2008). The potential of financial incentives to enhance householders kerbside recycling behaviour. *Waste Management*, 28(10):1732–1741.

Sundberg, J., Gipperth, P., and Wene, C.-O. (1994). A systems approach to municipal solid waste management: a pilot study of goteborg. *Waste management & research*, 12(1):73–91.

Tanskanen, J.-H. (2000). Strategic planning of municipal solid waste management. *Resources, conservation and recycling*, 30(2):111–133.

TheStraitTimes (2011). Zero waste in singapore. http://www.zerowastesg.com/tag/iut-global/.

Tiller, K. H., Jakus, P. M., and Park, W. M. (1997). Household willingness to pay for dropoff recycling. *Journal of Agricultural and Resource Economics*, pages 310–320.

Times, S. (2015). Singapore budget 2015: Two trials to start this year to get people to recycle food waste. http://www.straitstimes.com/singapore/environment/singapore-budget-2015-two-trials-to-start-this-year-to-get-people-to-recycle.

Timlett, R. and Williams, I. (2009). The impact of transient populations on recycling behaviour in a densely populated urban environment. *Resources, Conservation and Recycling*, 53(9):498–506.

Timlett, R. E. and Williams, I. D. (2008). Public participation and recycling performance in england: A comparison of tools for behaviour change. *Resources, Conservation and Recycling*, 52(4):622–634.

Tınmaz, E. and Demir, I. (2006). Research on solid waste management system: to improve existing situation in corlu town of turkey. *Waste management*, 26(3):307–314.

Today, A. (2013). South korea's food waste solution : You waste, you pay. http://www.asiatoday.com/pressrelease/south-koreas-food-waste-solution-you-waste-you-pay.

Today, R. (2012). Seoul's example. http://www.recyclingtoday.com/article/rtge1112-municipal-recycling-seoul/.

Tsai, T.-h. (2008). The impact of social capital on regional waste recycling. *Sustainable development*, 16(1):44–55.

Wallace, R., Ibsen, K., McAloon, A., and Yee, W. (2005). Feasibility study for co-locating and integrating ethanol production plants from corn starch and lignocellulosic feedstocks (revised). Technical report, National Renewable Energy Lab., Golden, CO (US).

Wang, S., Watada, J., and Pedrycz, W. (2014). Granular robust mean-cvar feedstock flow planning for waste-to-energy systems under integrated uncertainty. *Cybernetics, IEEE Transactions on*, 44(10):1846–1857.

Wojanowski, R., Verter, V., and Boyaci, T. (2007). Retail–collection network design under deposit–refund. *Computers & Operations Research*, 34(2):324–345.

Yau, Y. (2010). Domestic waste recycling, collective action and economic incentive: The case in hong kong. *Waste Management*, 30(12):2440–2447.

ZeroWasteSingapore (2015). Singapore waste statistics 2014. http://www.zerowastesg.com/2015/03/18/singapore-waste-statistics-2014/.