GIS and Location Theory Based Bioenergy Systems Planning

by

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AUTHOR'S DECLARATION FOR ELECTRONIC SUBMISSION OF A THESIS

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Abstract

This research is concerned with bioenergy systems planning and optimization modelling in the context of locating biomass power plants and allocating available biomass feedstock to the active plants. Bioenergy, a promising renewable energy resource, has potentially significant benefits to climate change, global warming, and alternative energy supplies. As modern bioenergy applications in power production have the ability to generate cleaner electricity and reduce Green House Gas (GHG) emissions compared with traditional fossil fuels, many researchers have proposed various approaches to obtain competitive power generation prices from biomass in different ways. However, the highly dispersed geographical distribution of biomass is a big challenge for regional bioenergy systems planning.

This thesis introduces an integrated methodology combining Geographic Information Systems (GIS) and discrete location theories for biomass availability assessment, biomass power plant candidate selection, and location-allocation of power plants and biomass supplies. Firstly, a well known discrete location model – the p-Median Problem (PMP) model is employed to minimize the weighted transportation costs of delivering all collectable biomass to active power plants. Then, a p-Uncapacitated Facility Location Problem (p-UFLP) model for minimizing the Levelized Unit Costs of Energy (LUCE) is proposed and genetic algorithms (GAs) for solving these optimization problems are investigated. To find the most suitable sites for constructing biomass power plants, the Analytic Hierarchy Process (AHP) and GIS based suitability analysis are employed subject to economical, societal, public health, and environmental constraints and factors. These methods and models are aimed at evaluating available biomass, optimally locating biomass power plants and distributing all agricultural biomass to the active power plants.

The significance of this dissertation is that a fully comprehensive approach mixed with the applications of GIS, spatial analysis techniques, an AHP method and discrete location theories has been developed to address regional bioenergy systems planning, involving agricultural biomass potential estimation, power plants siting, and facility locations and supplies allocation scenarios. With the availability of the spatial and statistical data, these models are capable of evaluating and identifying electric power generation from renewable bioenergy on the regional scale optimally. It thus provides the essential information to decision makers in bioenergy planning and renewable bioenergy management. An application sited in the Region of Waterloo, Ontario Canada is presented to demonstrate the analysis and modelling process.

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To the memory of my dearest grandmother!

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Abbreviations

Abbreviation	Full Name
AD	Anaerobic Digestion
AHP	Analytic Hierarchy Process
CHP	Combined Heat and Power
CR	Consistency Ratio
DRG	Decentralized Renewable Generation
DC	Direct Combustion
DFD	Data Flow Diagram
DSS	Decision Support System
ESRI	Environmental Systems Research Institute
GA	Genetic Algorithm
GIS	Geographic Information Systems
GHG	Green House Gas
GRIA	Global Regional Interchange Algorithm
HTU	Hydro Thermal Upgrading
ILP	Integer Linear Programs
IEA	International Energy Agency
IGCC	Integrated Gasification/Combined Cycle
LUCE	Levelized Unit Costs of Energy
MSW	Municipal Solid Waste
MST	Minimum Spanning Tree
NBCD	National Biomass and Carbon Dataset
OM	Operation and Maintenance
PMP	p-Median Problem
P-UFLP	p-Uncapacitated Facility Location Problem
REPP	Renewable Energy Policy Project
RIBA	Regional Integrated Biomass Assessment
SGA	Simple Genetic Algorithm
TBA	Teitz and Bart Algorithm
WEC	World Energy Council

Chapter 1 Introduction

1.1 Research Motivation

Energy and environmental issues are two common concerns of modern society. Energy is a central part of every human being's daily life. In all its forms, such as chemical energy (food), thermal energy (heat), or electricity, energy has the ability to transform the daily lives of humans across the world by easing workloads, boosting economies and generally increasing the comfort of our lives. Worldwide energy consumption has been increasing rapidly. The increasing trend of energy consumption has been accelerated by the improvement of the quality of life that almost directly relates to the amount of energy consumed. At present, fossil fuels based energy resources, such as coal, gas, and oil, supply the majority of the total world energy requirement. According to the statistical data from the International Energy Agency (IEA), the world total final energy consumption is 7644 Mtoe[1]. As much as 66.7 percent is supplied by fossil fuels (i.e., Oil: 42.3%, Gas: 16.0%, and Coal: 8.4%). Combustible renewable and waste account for 13.7%, electricity for 16.2%, and other energy resources shares 3.4% of the total energy consumption (IEA, 2006).

Consuming fossil fuels has improved our lives in many ways, but burning fossil fuels has also created threats to our environment. Burning fossil fuels has provided us with energy for lights, refrigeration, air conditioning, and electronics- such as radio, TV, and computers. Yet the use of fossil fuel energy has also brought several problems. As Henry Ford II said, "The economic and technological triumphs of the past few years have not solved as many problems as we thought they would, and, in fact, have brought us new problems we did not foresee". Fossil fuels were thought to be a perfect energy resource when they were increasingly used since the industrial revolution. They are applied for electricity generation

[1] Mtoe: Million Tons of Oil Equivalent

in the 20th century, a period that is described as the golden era of fossil fuels. For example, the electricity generated by fossil fuels increased from less than 2% in 1900 to more than 30% by 2000 (Smil, 2000). Environmental implications began to emerge due to the exponentially increased applications of fossil fuels in the middle part of the 20th century (Venema, 2004). Fossil fuels consumption is believed to be the primary factor contributing to serious environmental problems, such as global warming, climate change and acid rain, which are a serious threat to the world's ecosystems and the prosperity of human civilizations. Figure 1.1 illustrates the world CO_2 emissions by fuel from 1971 to 2004. The IEA (2006) statistical data shows that about 26583 Mt of CO_2 was emitted to the atmosphere in 2004. 99.7% of these CO_2 emissions are contributed by fossil fuels, i.e. coal: 40.0%, oil: 39.9%, and gas: 19.8%. The other 0.3% CO_2 emissions are from industrial waste and non-renewable municipal waste. Therefore, climate scientists argue that in order to stabilize the earth's climate and prevent further global warming, the earth requires a 70% cut in present carbon dioxide emissions by 2050 [Flannery 2005].

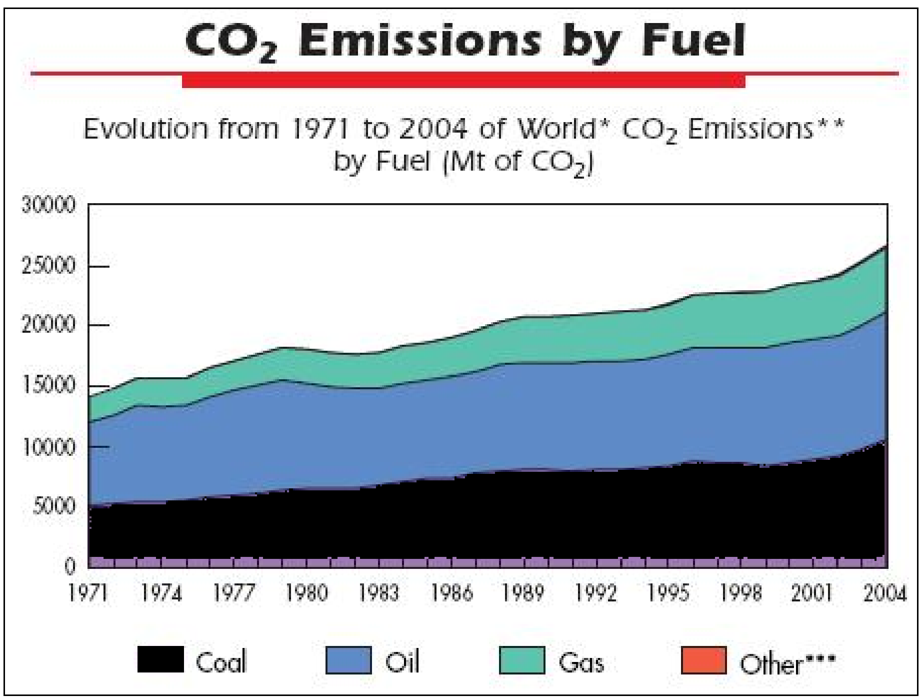


Figure 1-1 World CO_2 emissions by fuel (Source: IEA, 2006)

Besides the environmental fatigue or failure caused by the dominance of the current fossil-fuel-based single-energy system, Li (2005) claimed that energy diversification and localization can provide security for energy supply and distribution as well for the energy consumers. For example, the blackout in the northeastern states to the Midwest of the United States and part of Canada on August 12, 2003 could have been avoided or resolved faster. In the end, Li (2005) recommended that energy diversity should be promoted as the only sensible and feasible solution for sustainable development. In order to mitigate climate change and global warming, carbon dioxide emission must be reduced significantly. The applications of renewable energy resources, such as biomass energy, hydropower, geothermal, wind power, and solar, should be encouraged. In the executive summary of IEA 2006, it claims "Beyond 2020, the role of renewable energy in global energy supply is likely to become much more important".

Biomass energy is a traditional source of sustainable energy, which has been widely used in developing countries. As well, bioenergy will continue to be the major energy source in developing countries over the next two decades (IEA, 2006). Bioenergy is stored energy from the sun contained in materials such as plant matter and animal waste, known as biomass. Typical biomass resources include wood residues, generated from wood products industries; agricultural residues, generated by crops, agro industries and animal farms; energy crops, crops and trees dedicated to energy production; and municipal solid waste (MSW). From the latest final report prepared by Tremeer (2007), in 2004, renewable energy accounted for 12.1% of the 11059 Mtoe of the world total primary energy supply. Combustible renewable and waste, 97% of which is biomass, represented 79.4% of total renewable resources, meaning that in 2004 biomass accounted for about 10% of World Total Primary Energy (TPES) or 1100 Mtoe (OECD[2]/IEA 2006). The largest contribution to energy consumption, on average between a third and a fifth, is found in developing countries compared with 3% in industrialized countries (Voivontas, et al., 2001). In non-OECD countries, Europe and the

[2] The Organization of Economic Cooperation and Development, includes about 25 industrialized countries

former USSR[3] renewables contribute, according to IEA statistics for 2004, 10.6% and 3% of TPES, respectively.

The applications of biomass have great benefits on the environment if biomass resources are sustainably managed. Biomass energy is considered renewable because it is replenished more quickly when compared to the hundreds and millions of years required to replenish fossil fuels. Figure 1.2 illustrates the recycling of carbon as biomass accumulates in energy crops and forests and is consumed in a power station. First of all, the collected biomass from agricultural or forestry residues is transported from the field to a conversion facility (i.e. biomass power plant). The energy stored in the chemical bonds of the biomass are extracted and converted into electricity by initially combusting with oxygen (O_2). In this process, one of the products- carbon dioxide (CO_2) is released to the atmosphere. So far, this process is almost the same as coal fired power generation. However, the carbon dioxide generated from biomass combustion is absorbed by agricultural crops and forests through photosynthesis, where carbon dioxide is absorbed and oxygen is released to the atmosphere. This course of action occurs in a relatively short period of time and the process is cyclical as the CO_2 is available to produce new biomass. Nevertheless, fossil fuels which take millions of years to be converted from biomass are not deemed as renewable within a time-scale mankind can use. As McKendry (2002) has pointed out "burning fossil fuels uses 'old' biomass and converts it into 'new' CO_2 which contributes to the greenhouse effect and depletes a non-renewable resource".

[3] Union of Soviet Socialist Republics

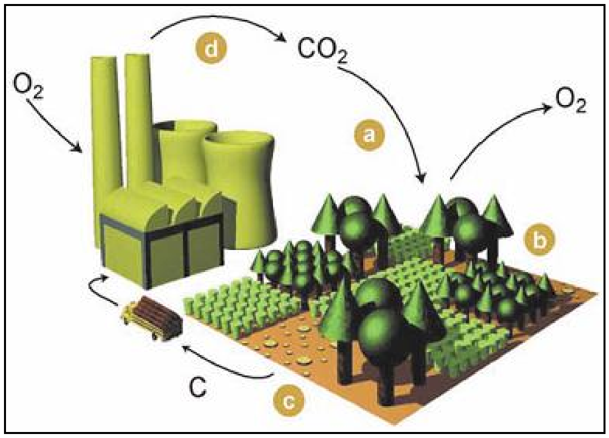


Figure 1-2 An illustration of the recycling of carbon in biomass application

(Source: Matthews and Robertson, 2002)

Besides the environmental benefits from biomass energy application, McKendry (2002) summarized two other factors that drive the usage of biomass energy:

- Firstly, technological developments relating to the conversion, crop production etc. promise the application of biomass at lower cost and with higher conversion efficiency than was possible previously. For example, when low cost biomass residues are used for fuel, the cost of electricity is already now often competitive with fossil fuel-based power generation. More advanced options to produce electricity are looking promising and allow a cost effective use of energy crops.

- The second main stimulus is the agricultural sector in Western Europe and in the US, which is producing food surpluses. This situation has led to a policy in which land is set aside in order to reduce surpluses. Related problems, such as the de-population of rural areas and payment of significant subsidies to keep land fallow, makes the introduction of alternative, non-food crops desirable. Demand for energy will provide an almost infinite market for energy crops grown on such potentially surplus land.

Venema (2004) presents a comprehensive discussion about the role of rural renewable energy design. He concluded: "alleviating rural energy poverty begins with improved management and use of local bioenergy resources". By adopting modern conversion technologies, existing biomass resources could be more efficiently converted into electricity, thereby addressing chronic energy shortages in the rural areas of some developing countries, where about two billion people have no access to electricity (Venema and Calamai, 2003). Biomass based decentralized renewable generation (DRG) may become the most plausible way to achieve rural electrification.

Despite the potential benefits from the applications of bioenergy, the large scale use of biomass is still controversial. Negative impacts of large scale uses of bioenergy may be imposed on land use, soil, biodiversity, hydrology energy and carbon balance, and natural scene when applying dedicated second generation biomass crops for power generation and liquid transportation (Rowe et al. (2007). Therefore, a local or regional scale of bioenergy application for power generation is more attractive. By only considering the agricultural and horticultural residues as the biomass feedstock to feed small scale of decentralized renewable generators, the impacts on the local environment and economics will be much reduced. However, the highly dispersed geographical distribution of biomass makes it difficult to estimate the potential biomass production, locate the best sites to construct decentralized bio-power plants and allocate available biomass to these selected plants optimally. The research presented in this thesis focuses on regional bioenergy systems planning for power generation, and introduces a set of optimization models which utilize GIS screening techniques and discrete location theory to assess agricultural biomass availability, and select optimized bio-power plant locations and biomass allocation scenarios. The results from this research are important in aiding spatial biomass energy system design practices.

1.2 Research Objectives

The goal of this thesis is to develop an integrated methodology combining Geographic Information Systems (GIS), Analytic Hierarchy Process (AHP), and discrete location theories to design spatially optimal biomass energy systems. The specific objectives of this research are to:

- Develop a land use based agricultural biomass potential availability assessment model to evaluate biomass production;

- Develop a GIS and Analytic Hierarchy Process (AHP) based suitability analysis for potential biomass power plant candidates selection to be used for power plants siting by considering multiple constraints and factors;
- Employ discrete location theories to formulate optimization models for spatially optimal bioenergy systems design;
- Employ Genetic Algorithms (GAs) to solve the location-allocation models and present the results using GIS map presentations.

The objectives are interrelated. The first two objectives provide not only the essential input parameters for the last two objectives, but also make it possible to achieve the last two objectives effectively.

1.3 Scope of the Thesis

This thesis consists of five chapters. This chapter introduces the background, motivation and objectives of this study. Chapter 2, Background and Literature Review, gives a detailed background introduction on biomass energy systems design and reviews different parts of the design procedure. Chapter 3, Basic Methodology, demonstrates the methodologies being applied in this research. GIS applications, biomass supplies evaluation model, suitability analysis methods, Analytic Hierarchy Process (AHP) method, p-median problem (PMP) model, and uncapacitated facility location problems (UFLP) are introduced in this chapter. A case study in the Region of Waterloo, Ontario Canada is completed in Chapter 4 by applying the proposed integrated methodology. Results from this study are illustrated in GIS maps. Chapter 5 presents the conclusions of this research and directions for future research work in bioenergy systems planning.

Chapter 2 Background and Literature Review

The bioenergy systems planning process requires some basic understanding of background information including: 1) bioenergy resources and conversion; 2) the relationship between bioenergy applications and energy consumption and environmental problems; and 3) current existing biomass applications associated with bioenergy systems design and modelling approaches. This chapter consists of four sections discussing the background and review items mentioned above. A summary is presented in the last section.

2.1 Bioenergy Resource and Conversion Technologies

Rapidly increased demand and consumption of world energy and our progressively deteriorated environment drive researchers to look for alternative energy resources and try to solve the environmental issue at the same time. As briefly discussed in Chapter 1, bioenergy is a promising renewable energy resource not only with significant benefits with respect to the environment compared with non-renewable fossil fuels, but also as an alternative energy to meet energy demands. This section will discuss how bioenergy applications can have the potential to support energy supplies and protect the environment.

2.1.1 Bioenergy Resources

Biomass energy is the oldest major source of energy for mankind and is presently evaluated to contribute about 10% to 14% of the world's energy supply (McKendry, 2002). Biomass is a scientific term for products derived from living organisms- wood from trees, harvested grasses, plant parts and residues such as twigs, stems and leaves, as well as aquatic plants and animal wastes. Domestic biomass resources include biomass processing residues, urban wood wastes, municipal solid wastes (MSW), animal wastes and energy crops. These biomass resources are described briefly in the following excerpt from the Renewable Energy Policy Project (REPP).

- Biomass processing residues include pulp and paper operation residues, forest residues, and agricultural or crop residues. All processing of biomass yields by-products and waste streams collectively called residues, which have significant energy potential. Agricultural and forest residues are the main categories of biomass residues that have been investigated. Agricultural residues consist of corn stover (stalks and leaves), wheat and rice straw, and processing residues such as nut hulls. Forest residues typically refer to those parts of trees unsuitable for forestry products or wood from forest thinning operations that reduce forest fire risk.

- Municipal solid waste (MSW) is the residues associated with human activity, such as waste rubber tire, waste plastic, wood waste and yard wastes, and waste paper. Urban wood waste is the largest source of waste from construction products [Seadi, 2002]. Most of the MSW is derived from plant matter and could be used for firing special MSW power systems. In the United States, approximate 2,500MW of MSW could be used for electric power generation.

- Animal manure is another type of biomass that includes cattle, chicken and pig waste. Animal waste can be converted into gas or burned directly for heat and power generation. In the developing world, dung cakes are used as a fuel for cooking. Since animal waste farms and animal processing operations create large amounts of animal wastes that constitute a complex source of organic materials with environmental consequences, utilizing the manure to produce energy properly lowers the environmental and health impacts.

- Energy crops are fast growing plants, trees and other herbaceous biomass which are harvested specially for energy production other than food or feed. They are considered as very important sources for obtaining biomass energy. Typical energy crops include herbaceous energy crops, woody energy crops, industrial crops, agricultural crops, and aquatic crops. These include switchgrass, hybrid poplars and willows, kenaf, soybean oil and meat, and algae.

From the sources of biomass presented above, it is obvious that biomass resources are distributed all over the lands, unlike fossil fuels which are concentrated in some particular spots. It is this characteristic that presents the biggest challenge in spatial bioenergy systems planning. Another important property of biomass energy is their bulk density, or volume, both as produced and as subsequently processed. Table 2.1 shows the comparisons of the bulk density and volumetric energy contents of some selected biomass and fossil fuels. In this table, we can observe that raw biomass, such as agricultural residues, rice hulls, net shells, and wood, has a relatively low bulk density and lower volumetric energy contents compared to coal. However, if the raw biomass is converted into bio-products, such as bio-diesel, pyrolysis oil, and ethanol, both the density and volumetric energy contents are very close or even higher than fossil fuels. In addition, it is apparent that transportation of raw biomass could be costly because of their low bulk density and volumetric energy contents compared to traditional fossil fuels. Thirdly, biomass has vast potential by world regions. The International Institute for Applied Systems Analysis (IIASA) produced a scenario for assessing the bioenergy potential based on economic criteria. Under this scenario, the bioenergy potential in 2020 could increase by 25% to 40% over 1990 reaching 67,557,569 Mtoe (International Energy Agency 2001). Some regions have more bioenergy potential. For example, according to the research of BIOCAP[4] Canada Foundation, Canada's vast forest resources are on a similar scale in energy terms to that of the Alberta oil sand if the resources are carefully managed to ensure their long term sustainability. BIOCAP Canada estimates the above ground biomass has an energy content of about 535 EJ or 50% of the proven reserves in the oil sands. The biomass potential in Ontario, estimated by BIOCAP, is sufficient to support at least 27% of the total current energy need of the province (Layzell, et al., 2006).

[4] A Canadian foundation dedicated to generating insights and technologies to inform the optimal use of Canada's '*biological capital*' (i.e. forests, farmlands, aquatic resources) to support the transition to a sustainable bioeconomy.

These two properties of biomass, i.e. highly spatial distribution and low density, increase the costs of harvesting, collecting and transporting of the agricultural and forestry residues and present a challenge in optimally locating conversion facilities and allocating available biomass feedstock to the facilities in biomass energy systems designed to reduce the costs of bioenergy production.

Table 2.1 Density and volumetric energy contents of various solid and liquid fuels

Fuel	Bulk Density (kg/m^3)	Volumetric Energy Contents (GJ/ m^3)
Ethanol	790	23.5
Methanol	790	17.6
Bio-diesel	900	35.6
Pyrolysis oil	1280	10.6
Gasoline	740	35.7
Diesel fuel	850	39.1
Agricultural residues	50-200	0.8-3.6
Hardwood	280-480	5.3-9.1
Softwood	200-340	4.0-6.8
Baled straw	160-300	2.6-4.9
Bagasse	160	2.8
Rice hulls	130	2.1
Nut shells	64	1.3
coal	600-900	11-33

(Source: Brown, 2003)

In this thesis, an integrated methodology for biomass energy systems design will be introduced applying a set of spatial analysis techniques and mathematical models. The following subsection discusses the biomass energy conversion technologies and their applications.

2.1.2 Biomass Conversion Technologies and Applications

In the previous subsection, biomass resources and two important characteristics impacting their viability as an energy source are discussed. In this subsection, fundamental biomass applications and conversion technologies are examined. As Venema (2004) points out: "energy intervention programs historically attempted to move people up the 'ladder of fuel preference'". Traditional biomass applications, for instance, cooking or heating with wheat straw, are associated with low efficiency and poverty. The *Energy ladder* was first introduced by Leach (1992) in the context of energy transition theory. Energy applications move up on "ladder" from biomass fuels (animal dung, crop residues, and wood) to cleaner, more efficient and more expensive liquid fuels (kerosene, gas) and electricity, as household possession increases. The fact that about two billion people (almost all of them live in the undeveloped rural areas) have little or no access to electricity and depend on biomass for their primary energy needs in the rural areas in some developing countries (Venema and Calamai 2003) reflects poor situations in their everyday life. It is essential to enhance the quality of life in the rural areas by converting the most accessible biomass into bio-fuels or electric power locally.

The purpose of a biomass conversion technology is to transform biomass into higher energy applications on the energy ladder. Biomass conversion can be classified into two main process technologies: thermo-chemical and bio-chemical conversions.

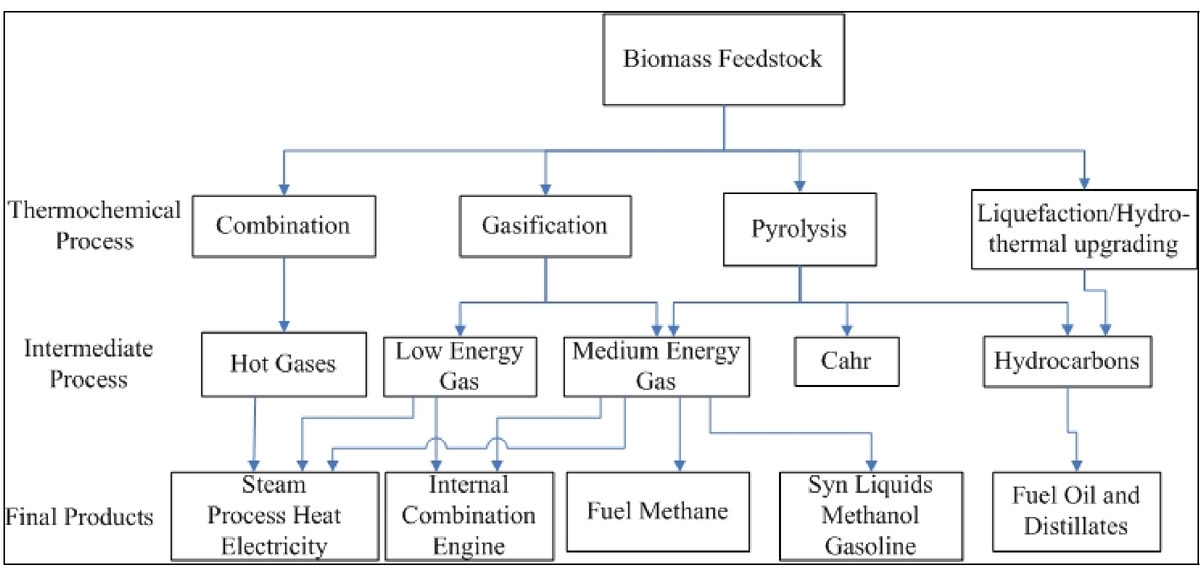


Figure 2-1 Main processes, intermediate energy carriers and final energy products from the thermo-chemical conversion of biomass (Source: Mckendry, 2002)

1) Thermo-chemical conversion

Three main processes are used for the thermo-chemical conversion of biomass together with two lesser used options. The main processes, the intermediate energy carriers and the final energy products from the thermo-chemical conversion procedure are illustrated in figure 2.1.

♦ Combustion

Combustion is the rapid oxidation of fuels to obtain energy in the form of heat. Since biomass resources are primarily composed of carbon, hydrogen, and oxygen, the main oxidation products are carbon dioxide (CO_2) and water (H_2O). Figure 2.2 shows the combustion process. The combustion process converts the chemical energy stored in biomass into heat, mechanical power, or electricity by applying various combustion equipments, e.g. combustors, boilers, steam turbines, turbo-generators, etc. The combustion of biomass is feasible only for biomass with a moisture content less than 50%, unless the biomass needs to be pre-dried (McKendry 2002). Therefore, field drying of biomass is desirable to reduce both transportation costs and heating penalties if direct combustion is selected for conversion. Co-combustion with coal is one option to generate electricity in the existing coal-fired power plants due to their high conversion efficiency. The net bioenergy conversion efficiency for biomass combustion power plant ranges from 25%-35% (1-100MW) and 35%-40% (larger than 100MW) (Layzell, Stephen et al. 2006).

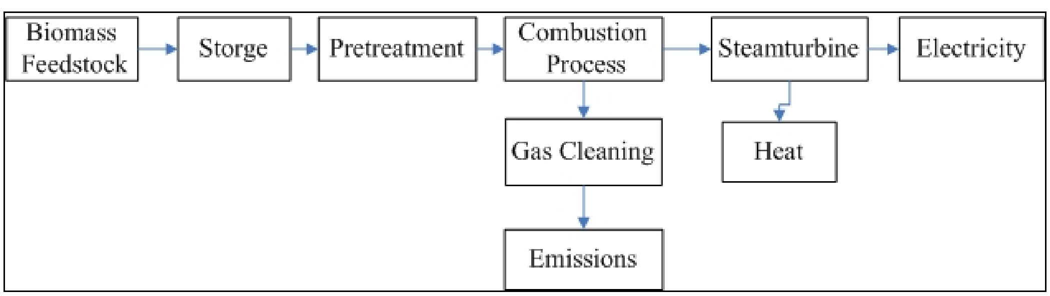


Figure 2-2 Schematic representation of the combustion process

♦ Thermal Gasification

Thermal gasification uses high pressure and temperature to convert solid biomass into gaseous and liquid forms. This gas consists of carbon monoxide (CO), hydrogen (H_2), methane (CH_4), nitrogen (N_2), carbon dioxide (CO_2), and small quantities of higher hydrocarbons. Figure 2.3 demonstrates the process of gasification. The produced gas can be burnt directly or used as a fuel for gas engines and gas turbines. The integrated gasification/combined cycle (IGCC) technology is considered to be a promising method of converting bioenergy. One advantage of IGCC gasification is to lower the emissions of particulate, NOx, and SOx (Layzell et al., 2006). Another important advantage of IGCC systems is that the gas is cleaned before being combusted in the turbine, allowing more compact and less costly gas cleaning equipment to be used, as the volume of gas to be cleaned is reduced (KcKendy, 2002).

The research of BIOCAP Canada (2006) indicates that the overall efficiencies of high pressure IGCC systems can reach 40-55% which are gradually improved compared with 35-38% in the research of Craig and Mann in 1997 and that of 40-50% in KcKendy's study in 2002. However, several technological issues, such as pre-treatment and tar removal, still need to be solved, resulting in a very slow development of biomass gasification in a rapid liberalised energy sector (Faaij 2006).

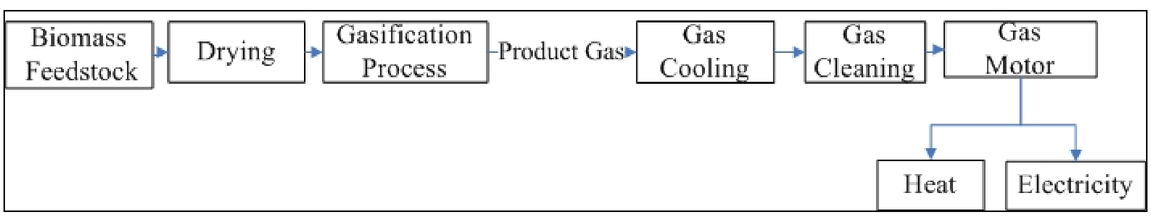


Figure 2-3 Schematic representation of the gasification process

- Pyrolysis

Pyrolysis is a complicated series of thermally driven chemical reactions that decompose organic compounds in the fuel. Pyrolysis proceeds at relatively low temperatures (around 500℃) in the absence of oxygen. Figure 2.4 depicts the range and possible yields of pyrolysis energy products. Pyrolysis is used to produce bio oil as a pre-treatment step to reduce the transportation costs in further conversion, such as efficient power generation or oil gasification for syngas production. Faaij (2006) has demonstrated that pyrolysis is less well developed than gasification. Problems with the conversion process and subsequent use of the oil, such as its poor thermal stability and its corrosivity still need to be overcome (McKendry, 2002). The conversion efficiency of pyrolysis ranges from 20% to 25%.

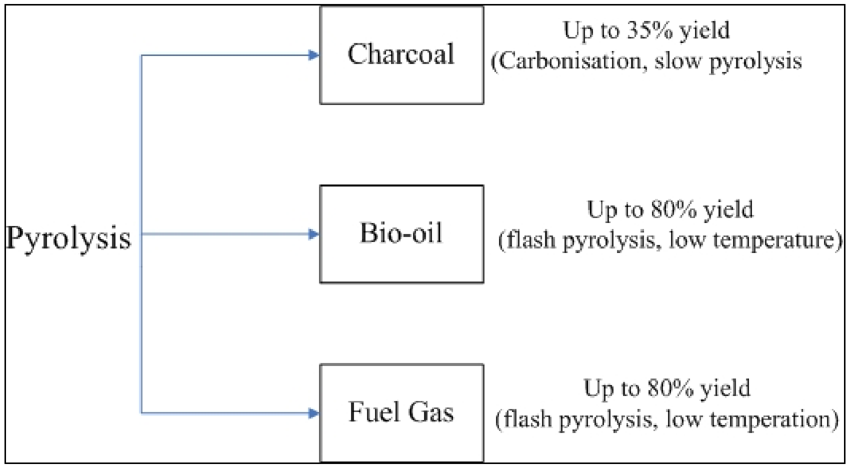


Figure 2-4 Energy products from pyrolysis (Adapted from McKendry 2002)

♦ Other conversion technologies

Other thermal chemical conversion technologies include hydro thermal upgrading (HTU) and liquefaction (conversion under high pressure) (Naber et al., 1997). HTU converts biomass in a wet environment at high pressure to partly oxygenated hydrocarbons. Liquefaction is the conversion of biomass into a stable liquid hydrocarbon using low temperatures and high hydrogen pressures. There are fewer applications of liquefaction mainly due to the fact that the reactors and fuel-feeding systems are more complex and more expensive than the pyrolysis processes (McKendry, 2002).

2) Bio-chemical conversion

There are three processes used in bio-chemical conversion of biomass: fermentation, anaerobic digestion (AD), and mechanical extraction/chemical conversion. Fermentation and AD are more popular than the mechanical extraction method.

♦ Fermentation

Fermentation is a biological process in which enzymes produced by micro-organisms catalyze energy releasing reactions that break down complex organic substrates under anaerobic conditions. The major application in the fermentation industry is the production of ethanol, which is marketed to both fuel and beverage industries (Brown, 2003). It is commercially used on a large scale in various countries to produce ethanol from sugars crops. Several factors limit the use of the fermentation technology in the production of chemicals. Production rates by micro-organisms in aqueous media are inherently low. Most fermentation requires aseptic conditions, which can be difficult to achieve in large scale operations. Recovery of water soluble products from dilute solutions is expensive. The waste water in the process needs to be treated before being discharged due to the high biological oxygen demand (Brown, 2003).

- Anaerobic Digestion

Anaerobic digestion is the decomposition of organic wastes, including polysaccharides, proteins, and lipids, to gaseous fuel by bacteria in an oxygen-free environment. The desired product, known as biogas, is a mixture of CH_4, CO_2, and some trace gases. Figure 2.5 shows the general process of the anaerobic digestion application. Anaerobic digestion of biomass has been demonstrated and applied commercially with success in a multitude of situations and with a variety of biomass feedstock. As with natural gas, biomass sourced methane can be used in a turbine to produce power. Anaerobic digestion is particularly valuable for treatment of heterogeneous and high moisture biomass feedstock, such as organic domestic waste, organic industrial wastes, and manure. According to the study of Faaij (2006), the advanced, large scale anaerobic biomass digestion systems are developed in many countries, especially Denmark and Netherlands, to deal with various wet waste streams. As well, landfill gas is also deemed as a special source of biogas, which mainly contains methane (CH_4). Faaij claims that the collection and use of landfill gas for electricity production are profitable not only because useful energy (electricity or alternative fuel) is produced, but also because the landfill gas, which contributes to a build up of GHGs in the atmosphere, would be reduced. This utilization makes landfill gas an attractive GHG mitigation option and is widely adapted throughout the EU (Faaij et al., 1998). The conversion from biomass to biogas using AD has a relatively low efficiency at about 15-20%.

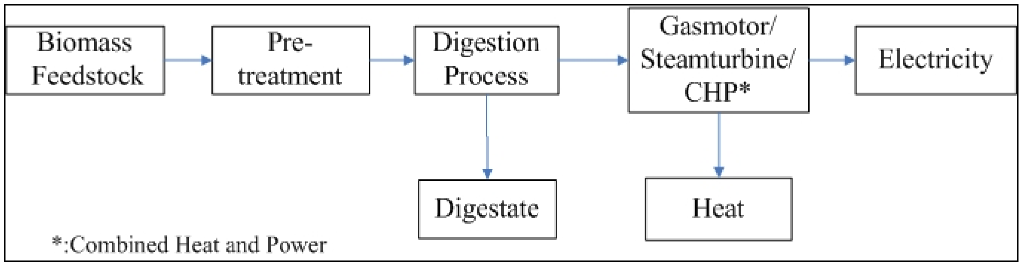


Figure 2-5 Schematic representation of the digestion process (Novem 2003)

3) Bio-renewable Resources Products

Bio-renewable resources can be transformed into a variety of products, including bioenergy, transportation fuels, chemicals and natural fibers (Brown 2003). The most popular products are power/heat generation and transportation fuels. The biomass applications mentioned in this subsection focuses on power/heat generation and briefly introduces other biomass products. Figure 2.6 summarizes conversion technologies and main final products.

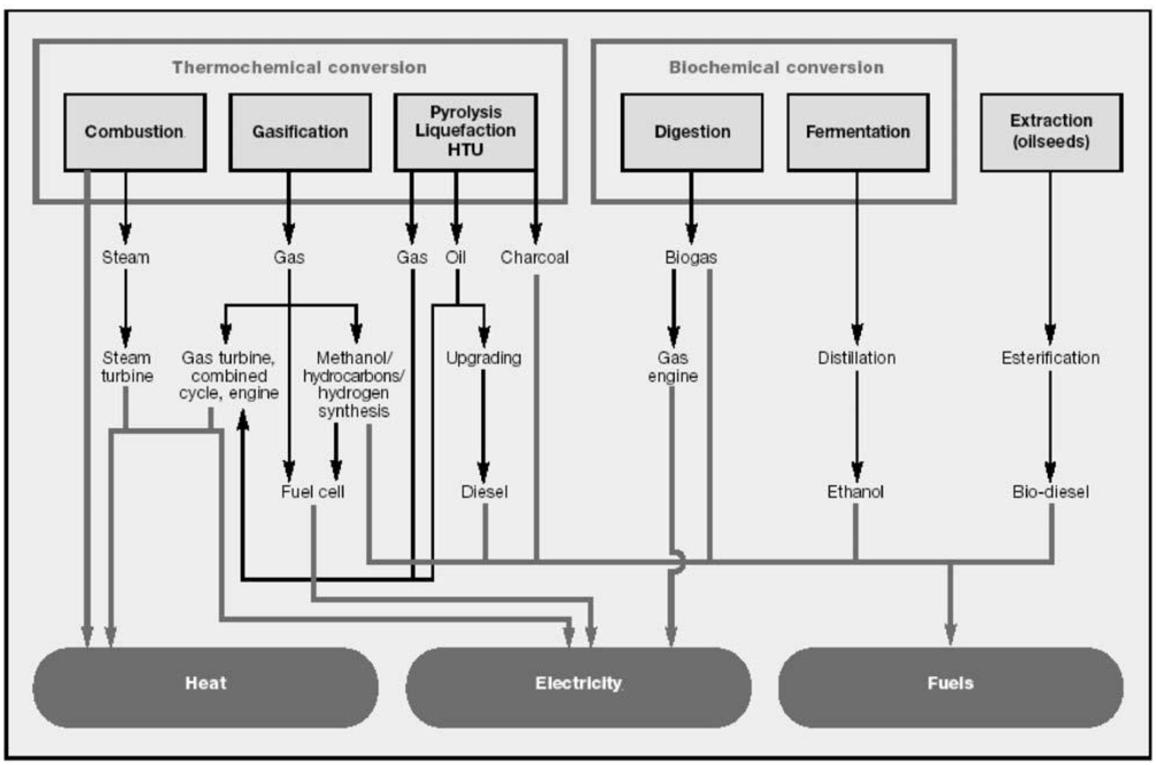


Figure 2-6 Main conversion options for biomass to secondary energy carriers (Turkenburg et al., 2000)

♦ Bioenergy –Heat/Electricity

Current heat and electricity generation that are primarily from fossil fuels are associated with negative environmental impacts. For example, in North America about 65% electricity and 95% heat were produced by fossil fuels in 2004, i.e. coal, oil, and gas (refer to table 2.2). Heat and power generated from biomass, referred to as bioenergy, are much lower than those from fossil fuels. Figure 2.7 illustrates that bioenergy (heat and electricity) is the main product in current biomass applications. Every conversion technology can directly or indirectly produce heat or electricity. Biomass power generation has experienced the greatest growth over the last two decades compared to the other renewable power generation alternatives. In 1995 biomass based power generation provided more than 50 billion kWh of electric energy from 10,000 MW of installed capacity (Swezey, 1995). According to IEA World Energy Outlook 2001, "the use of bioenergy in combined heat and power applications, where markets for heat exist, can be cost effective in some cases. Co-firing may be a low cost option for existing coal power plants, especially for low cost sources of biomass such as waste derived fuels. Bioenergy for heat applications may be cost effective in some OECD countries, especially where wood resources are available"

Table 2.2 Electricity and heat production in North America in 2004 (Data Source: IEA 2001)

Production from	Electricity (GWh)	Heat (TJ)	Percentage (%)	
			Electricity	Heat
Coal	2193547	38795	45.96	13.99
Oil	160907	17057	3.37	6.15
Gas	763625	208512	16	75.22
Biomass	55856	10299	1.17	3.72
Waste	24575	2551	0.51	0.92
Nuclear	903726	0	18.93	0
Hydro	638957		13.39	0
Geothermal	15487	0	0.32	0
Solar PV	29		0.0006	0
Solar thermal	587	0	0.01	0
Other sources	15699	0	0.33	0
Total Production	**4772995**	**277214**	**100**	**100**

The simplest way to get bioenergy is to burn biomass. This classic method of biomass application has been used for domestic heating in developing countries where people living in rural areas still use solid biomass, e.g. woods, straws, branches of trees, etc., for cooking and heating. But the traditional usage of biomass presents very low energy conversion efficiency, sometimes as low as 10% and generally goes with considerable emissions, e.g., dust and soot. Technology development has greatly improved this application with advanced heating systems which are automated, have catalytic gas cleaning and make use of standardized fuels (such as pellets). The efficiency of advanced domestic heating from biomass can be 70-90% with reduced emissions (Faaij, 2006). Natural Resources Canada's (NRCan's) Renewable Energy Deployment Initiative (REDI) promotes investments in renewable energy technologies, including biomass combustion systems that produce space heat and water heat for businesses. In addition, REDI will refund 25% of the purchase and installation costs of a biomass combustion system with high efficiency and low emissions as an allowance to encourage biomass application (Natural Resources Canada, 2001).

The utilization of biomass to generate heat and power in combined heat and power (CHP) plants has much higher electrical efficiencies and lower costs (Visser, 2004). In combined heat and power (CHP) plants, plant oil, solid biomass and biogas can be used for the distributed co-generation of heat and power. Large capacity bio-power plants are being developed worldwide by applying direct combustion, co-combustion, anaerobic digestion, and gasification technologies. An example of a basic system schematic of integrated gasification/combined cycle power plant (IGCC) is shown in figure 2.7. According to the studies of Layzell (2006), electric power production from biomass (bio-power) has the following key features:

1. May be used as base load power for the electrical grid;
2. Complements existing fossil fuel power generation, such as co-fired with coal within the existing infrastructure;
3. Can be used in centralized or distributed power systems.

Replacing coal with biomass in the existing coal-fired power plant is the single largest growing conversion route for biomass in many EU countries (Faaij, 2006). Also, in Canada, co-fired power generation projects are being considered. Case studies at Atikokan Power Generation Station (Ontario, Canada) , which has the ability to produce 900 million kWh per year, and at Nanticoke Power Generating Station, with the capacity of 3920 MW, show that the plants could be run on full/partly biomass energy at reasonable costs and have significant benefits to the regional economy (Layzell, 2006).

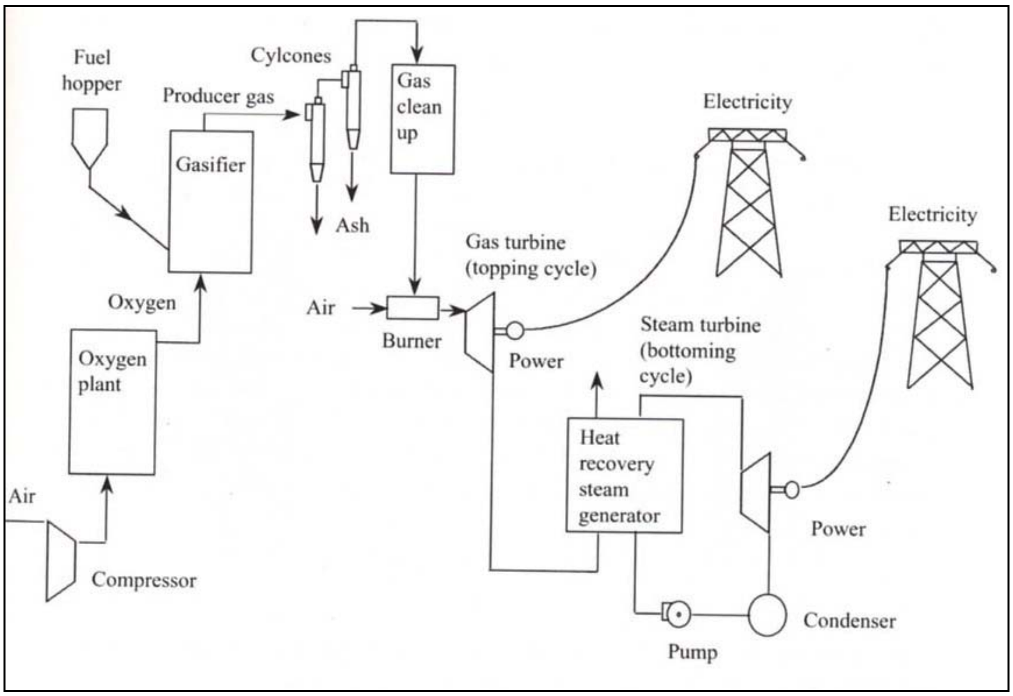


Figure 2-7 IGCC power plant based on a gas turbine topping cycle (Brown, 2003)

Another very important option to generate power from biomass is through Distributed Generation (DG) which has been used more and more frequently in recent years to meet different customer requirements. The DG plant can be designed to connect to the commercial power grids or be off-grid. Agrawal (2006) points out that "biomass has been considered one of the ideal energy resources for the DG mode of power generation" and lists the following advantages of utilizing biomass for power generation:

1. ability to produce firm and dispatchable power;

2. amenability to storage and use as per power demand
3. broadly similar combustion characteristics which may even enable partial co-firing with coal;
4. no need for elaborate pre-firing preparation

♦ Transportation Fuels

Transportation fuels are chemicals with sufficient energy densities and combustion characteristics to make them suitable for transportation applications. The primary candidates for biomass based transportation fuels are ethanol, methanol, and bio-diesel. From figure 2.6, three main routes can be distinguished to produce fuels from biomass. Ethanol can be produced by fermentation of sugar or starch crops. Methanol can be produced by gasification as transportation fuel. Bio-diesel can be produced by the processing of the fatty acids in vegetable oils which are produced from an agricultural crop. Almost one fourth of energy consumption in the United States is consumed by transportation needs. Ethanol is a good substitute for gasoline. A mixture of 10% ethanol blended with gasoline can be run on a conventional internal combustion engines without any engine modification. Recently, some North American car manufactures began offering vehicles that can use a blend of up to 85% ethanol in gasoline-E85 (REWP[5] report, 2003). Government allowance together with the technological advances in the production of biofuels, for example the use of woody bioenergy instead of agricultural crops, could reduce costs and increase renewables' market share in the longer term (IEA 2001).

♦ Other products from biomass

Other products from biomass include chemicals and fibers. Chemicals from biomass are deemed as the broadest class of products. Several oxygenated organic compounds are commercially produced from bio-renewable resources. Plant fibers can be used in the manufacture of textiles, paper products, and composite materials.

[5] Renewable Energy working Party

2.2 Bioenergy, Energy and the Environment

Energy and environmental issues are both very important in modern society. Energy consumption is related to the quality of life. As the energy consumption per capital increases, an indicator of quality of life, the Human Development Index (HDI) which is calculated using the United Nations standard, also increases accordingly (Fanchi, 2005). As well, energy is considered a prime agent in the generation of wealth and also a significant factor in economic development (Balat, 2006). With the increasingly development of some countries, the world energy demand will be increased by 57% between 1997 and 2020 and electricity demand will grow more rapidly than any other end-use fuel (IEA 2001). However, with the transition from woody fuels to fossil fuels, environmental issues begin to emerge such as climate change, global warming, rising sea level, ozone depletion, and increased pollution, which are associated with elevated consumption of fossil fuels. During the past two decades, the risk and reality of environmental degradation have become more apparent. With the relative advantages of bioenergy applications with respect to the environment and the progress in conversion technologies, bioenergy is becoming the most promising alternative to fossil fuels.

2.2.1 Bioenergy Application and Energy Supply

Energy application plays an important role in the world's future and affects all aspects of modern life. The demand for energy is increasing at an exponential rate due to the exponential growth of the world population. The IEA 2001 study indicates that the world primary energy demand is expected to continue to grow steadily, as it has over the last two decades. Energy resources have been divided into three categories: fossil fuels, renewable resources, and nuclear resources. As mentioned in subsection 2.1.2, biomass is a renewable resource that has the ability to be converted into almost all kinds of energy. This ability allows bioenergy to meet most energy demands, from traditional biomass combustion to electricity generation. However, due to the relatively high costs of generating bioenergy and the public opposition to biomass energy development (Upreti, et al., 2004), its share in total primary energy supply is much lower than fossil fuels. IEA 2001 summarized the current and future worldwide application of bioenergy as follows:

- The use of bioenergy in combined heat and power (CHP) applications, where markets for heat exist, can be cost-effective in some cases. Co-firing may be a low-cost option for existing coal power plants, especially for low-cost sources of bioenergy such as waste derived fuels. Bioenergy for heat applications may be cost effective in some OECD countries, especially where wood resources are available. On average, however, the development of bioenergy projects for electricity production will remain fairly costly.
- Bio-fuels currently account for only a small portion of global transport fuels. In most countries, they are only competitive if they enjoy government subsidies. Technological advances in the production of bio-fuels, for example the use of woody bioenergy instead of agricultural crops, could reduce costs and increase renewables' market share in the longer term.
- Bioenergy will continue to be a major energy source in developing countries over the next two decades. The level of demand for bioenergy will increase by nearly 25% in these countries, but its share in total primary consumption will fall.
- The share of bioenergy in residential energy demand in some developing countries is greater than 90%. Improving the efficiency of its use can lead to important savings in fuel-wood consumption and can prevent the rapid decline in forested areas.
- Availability and cost will remain key factors in bioenergy development. Competition from agricultural uses, the seasonality in bioenergy crop production and the distances from bioenergy sources and energy use are major factors influencing cost.
- The use of bioenergy can have many environmental benefits over fossil fuels if the resource is produced and used in a sustainable way. Environmental issues, resulting from airborne emission from solid bioenergy combustion will, however, increase in importance along with the use of this fuel. This is particularly important for waste incineration, which faces public opposition, and siting new facilities may be difficult.

Bioenergy can help to diversify the world energy supply and to increase energy security (Li, X., 2005). However, the costs of bioenergy generation limit its wide usage. Although the costs have largely fallen, further reductions are needed for them to compete with fossil fuels. The production costs will be more important to the long term energy supply outlook than the resource base (IEA 2001). Therefore, in order to increase bioenergy application toward total energy supply, all aspects of reducing bioenergy generation cost are essential. This research proposes integrated methodologies to reduce transportation costs of delivery biomass feedstock from fields to the biomass power plant facilities. Furthermore, the use of biomass as a source for power generation is investigated through the minimization of the Levelized Unit Costs of Energy (LUCE) (Venema, 2004).

2.2.2 Bioenergy Application and Environmental Issues

As a very important renewable energy source, the most significant contribution of bioenergy applications is to protect the environment via climate change mitigation, Green House Gas (GHG) emission reduction, as well as the reduction of acid rain and local or regional air pollution. The Kyoto Protocol to the United Nations Framework Convention on Climate Change (UNFCCC), agreed to in December 1997, marks an important turning point in efforts to promote the use of renewable energy worldwide. Since the original Framework Convention was signed at the Earth Summit in Rio de Janeiro in 1992, climate change has spurred many countries to increase their support of renewable energy. Even more ambitious efforts to promote renewable energies can be expected as a result of the Kyoto pact, which includes legally binding emissions limits for industrial countries, and for the first time, specially identifies promotion of renewable energy as a key strategy for reducing greenhouse gas (GHG) emissions (Demirbas, 2003). The risk of climate change due to emissions of carbon dioxide (CO_2) from fossil fuel is considered to be the main environmental threat from the existing energy system. Based upon the statistical data, the total world CO_2 emissions from the consumption of coal are 2427.14 million metric tons of carbon equivalents in 2001 (WEC[6], 2003). The use of bioenergy implies no net contribution to atmospheric greenhouse

[6] World Energy Council

gas CO_2, if the source biomass feedstock is sustainablely managed. (Ravindranath and Hall, 1995 and IEA Bioenergy, 2002). Since bioenergy can provide about 11% of total global primary energy supply, and approximately 35% in the developing countries (Jurgens, et al., 2006), the contribution to GHG reduction is significant if all the available biomass resources are sustainablely developed.

Much has been made of the negative environmental impact of using fossil fuels. The assumption has often been made that anything that reduces use of fossil fuels will automatically benefit the environment. However, the reality is much more complicated. Everything has two sides and every technology introduces both benefits and costs. Exploitation of bioenergy is no exception. The application of bioenergy may cause environmental issues which we are trying to prevent by careful management, such as deforestation, soil erosion (soil carbon degradation), land use competition, water and air pollution (Abmann et al., 2006 and Brown, 2003).

2.3 Review on Bioenergy Systems Design and Modeling

In order to meet rapidly increased energy demands and alleviate the pressure from environmental problems, much research has been conducted in almost every aspect of bioenergy application. These include improving the yields of agricultural products for food to leave more land for energy crops cultivation, increasing the yields of energy crops and shortening the harvest periods, researching bioenergy conversion technologies to make progress on conversion efficiency, and transportation modelling approaches for reducing the delivery costs of biomass. The development and application of personal computers have enabled the use of Geographic Information Systems (GIS) to manipulate spatial data and construct complicated numerical models and various scenario analyses to better understand bioenergy systems design problems. Despite the generally high spatial heterogeneity of biomass resources, applications of location theory to bioenergy systems design are seldom found in the relevant literature. Although almost all aspects of bioenergy applications have been investigated separately, very few references address an integrated methodology for bioenergy systems planning taking account of potential biomass assessment, power plant sites selection and biomass allocation –notable exceptions are Venema and Calamai (2003) , which have appeared in the operations research and rural development literature, not in bioenergy systems design literature. The section that follows provides a comprehensive review of existing research on biomass availability assessment, power plant siting, and discrete location theory based modelling approaches on spatial optimization. GIS based biomass assessment, biomass power plant siting, and location theory models are introduced in the sections that follow.

2.3.1 Biomass Availability Assessment

Biomass availability assessment is very important in the bioenergy systems planning process. Many previous studies have been conducted in this area. In 1998, an optimization model for energy generation from agriculture residues was developed by Kanniappan and Ranmachandran. By suitably allocating the land area for cultivation of various crops, their optimization model used linear programming to determine the maximum output of surplus biomass (agricultural residues) excluding the biomass assigned for fuel and fodder for animals. The optimal land use scenarios greatly increased power generation from agricultural residues. Graham et al. (2000) employed a GIS based modelling system for estimating potential biomass supplies from energy crops. They focus on the influence of geographic variation on the cost of biomass costs and supplies. Raster maps are presented showing the biomass feedstock delivering costs in eleven US states. Voivontas et al. (2001) have introduced a GIS based method to estimate the biomass potential for power production from agriculture residues. Their proposed Decision Support System (DSS), a computerized system used for decision making among alternatives, evaluates the theoretical potential, available potential, technological potential, and economical potential of biomass for electric power production. This DSS considers all possible restrictions and identifies candidate power plants. The required cultivated areas are established for biomass collection. Masera et al. (2006) used WISDOM, a GIS-based tool for analyzing wood fuel demand and supply spatial patterns, to assess the sustainability of wood fuel production as a renewable resource. Ramachandra and Shruthi (2007) applied GIS mapping tools to successfully map the renewable energy potential in Karnataka State, India. GIS is used in spatial and temporal analysis of the resources and demand and also aids the Decision Support System (DSS) for implementing location specific renewable energy technologies. Unal and Alibas (2007) evaluated the production of agricultural residues and their conversion to electrical energy via gasification in Turkey. Based on their studies, the quantity of biomass from agricultural residues are capable of meeting nearly 17% of national electricity consumption if all of the unused residues are converted into energy. Related studies on biomass availability evaluation can also be found in Grassi and Bridgwater (1993), Liang et al. (1995), Downing and Graham (1996), Rozakis et al. (2001), Goor et al. (2003), Hoogwijk et al. (2005), Tuck. et al. (2006), and Lewandowski et al. (2006).

Ways to decrease the biomass energy production costs are also studied in previous research. Noon et al. (1996) fully discussed Regional Integrated Biomass Assessment (RIBA) by analyzing transportation and site location in the United States. A series of costs related to biomass production and transportation are discuss in detail such as the hauling distance cost, the hauling time cost, the loading and unloading cost, and the marginal price for delivered energy crops. GIS-based continuous raster maps are derived from the costs model, representing feedstock costs of supplying energy crops feedstock upon the spatial variation. The RIBA systems also can select the sites of proposed conversion facilities and proximal bioenergy supply sites (pixels in the raster map). Graham et al. (2000) have investigated the effect of location and facility demand on the marginal cost of delivered wood chips from energy crops. Using the GIS-based decision support system-BRAVO (Noon and Daly, 1996), a spatial Decision Support System (sDSS) which is an interactive, computer based system designed to support a user or group of users in achieving a higher effectiveness of decision making while solving a semi-structured spatial problem, cost-supply curves were developed. BRAVO is designed to assist the spatial planner with guidance in making land use decisions. The study demonstrates one approach for quantifying the geographic complexity of biomass supplies and illustrates the need to consider the likely participation rate of farmers in projecting the possible costs of biomass feedstock. Swezey et al. (1995) discussed the potential impact of externalities considerations on the market for biomass power technologies in the U.S. The paper summarizes the work undertaken to assess the status of externalities considerations in states and utility electricity resource planning processes and to determine how externalities considerations might help or hinder future development of biomass power plants. They suggested the bioenergy industries should emphasize the environmental and non-environmental benefits of applying biomass energy to the states and the public in order to get more government subsidies. Moller and Nielsen (2007) analyzed transportation costs of forest wood chips in Denmark. GIS raster data based techniques are employed to screen the transportation costs surface map between the highly distributed forest wood biomass and selected bioenergy plants.

2.3.2 Biomass Power Plant Siting

In order to develop decentralized power generation from biomass feedstock, appropriate sites of power plants should be identified by taking into account a variety of criteria. The Public Service Commission of Wisconsin (1999) summarized common power plant siting criteria, which involved community impacts, public health and safety concerns, environmental impacts, land use impacts, and economic impacts. Siting analysis with GIS began in the 1970s and provided a variety of analytical tools for the integration of different spatial data, related to the parameters affecting the suitability of a location. GIS has been commonly used in many facility siting applications, such as power-plant locations, recreational and public facility location siting, ski resort sites, public school facility, and landfill sites identification. The best early examples of siting analysis with GIS involved identifying a power plant site in the state of Maryland. A variety of parameters were considered in a raster map presentation (Dobson, 1979). A GIS approach was utilized in order to apply the location criteria using three methods of overlay analysis, the process of combining spatial information from two or more maps from the same geographic area to derive a map considering of new spatial boundaries and entities or themes, for finding the most suitable locations for the siting of a coal power plant while considering all identified criteria, i.e. socio-economic and environmental. The results of their study outlined the areal extent of suitable versus non-suitable sites in Franklin County, Illinois and can be further used as a tool to assist planners and managers in the decision making process (Delaney and Lachapelle, 2003). Beheshtifar et al.

(2006) have introduced a method along with appropriate models and GIS mapping techniques to define the suitable areas for the construction of coal-fired power plants. The research considers many factors that may influence the power plant sites selection such as transportation accessibility, gas pipe network, earthquake and geological faults, topographic consideration, water resources, power demand centers and so on. Suitable locations for constructing new power plants areas are selected and presented using GIS maps.

The Analytic Hierarchy Process (AHP) is a structured technique for helping people deal with complex decisions. It was first developed by Thomas L. Saaty in the 1970s and has been extensively studied and successfully used in helping decision makers to structure and analyze a wide range of problems. However, it is rarely seen in the bioenergy systems planning literature. *Expert Choice*, a AHP based tools for decision making developed mainly by Saaty, was used in a particular biogas-fuelled combined heat and power (CHP) systems to evaluate the impacts of a variety of factors considered, such as air pollutants, GHG emissions, land use, economics, on the CHP system (Madlener, 2001). Delaney and Lachapelle, (2003) also proposed a scenario utilizing a pair-wise comparison matrix to determine the appropriate factor weights in a coal-fired power plant siting project. After applying AHP in the aquaculture/farming agent decision process, Pereira and Duarte, (2006) claimed that the AHP method is an easy way to help multi-criteria decision making adapt to each decision maker. The AHP was used for ranking of barriers to the adoption of improved cook stoves and biogas technology in Thailand in 2002. The results ranked the different barriers associated with the biomass based power generation. High initial cost, lack of financial aids, and lack of risk covering mechanisms have been found to be the three main barriers to biomass based power generation in Thailand (Asian Regional Research Programme in Energy, Environment and Climate Phase II, 2001). Ma et al. (2005) proposed a GIS combined with an AHP model for siting farm based centralized anaerobic digester systems for distributed power generation. A siting suitability map was produced to identify those areas that are most suitable for distributed bioenergy systems using animal manure. The results indicate that the integration of both spatial and non-spatial data allowed the GIS model to provide a broad-scale and multidimensional view on the potential bioenergy systems development in the study area accounting for environmental and social constraints as well as economic factors. In this thesis, an AHP method is used for determining the weights of the factors in the suitability analysis. Each factor is assigned a weight indicating the relative importance of the factors in the siting of power plants.

2.3.3 Spatial Optimization

Discrete location models are often classified in the literature based upon the number of facilities being located. Location models are widely employed in school planning and health care services planning (Rahman and Smith, 2000). But there is very little formal spatial optimization research in the field of bioenergy systems design, especially location-allocation models for minimizing the levelized unit cost of energy resulting from the application of different bioenergy conversion technologies. Venema and Calamai (2003) developed an approach for bioenergy systems planning using location-allocation and landscape ecology design principles to derive a two-stage p-median problem (PMP) model formulated to minimize domestic and commercial feedstock delivery costs. In a case study in India, the first stage of the model is to acquire domestic energy from proximal supply locations to feed the villages demand according to PMP location-allocation principles. A simultaneous PMP is also formulated between village demand locations and conversion facility locations to establish the commercial energy handling requirements at each active conversion location. The model is modified by adding a term that accounts for the cost of transporting biomass feedstock from the production zone to the centroid (biomass collection locations) to fully account for the weighted biomass flow-path distance in the designed systems. Their research focuses on developing bioenergy systems that address the rural socio-ecological problem rather than toward a tool for general bioenergy systems planning, i.e. biomass availability and location-allocation power plant and biomass resources.

Spatial optimization models are often combined with GIS screening techniques with the advantages of data acquisitions and manipulations. Venema et al. (2000) have addressed multi-objective spatial design principles for rural biomass energy planning. The paper aims at improving accessibility and ecological sustainability of biomass resources by applying remotely sensed landscape information, GIS analysis, spatial optimization, and landscape ecology design principles for decentralized landscape-based biomass energy systems planning. After a general discussion on the interface between GIS and location science, Church (2002) claimed that GIS will have a major impact on the field of location science in terms of model application and development. Moller-Jensen and Kofie (2001) employed a location-allocation model for health service planning in rural Ghana. The model was used to select an optimal location and provide statistics information on average distance to health centers and percentage of population covered. Many research papers employing location-allocation models in health service development planning in developing nations are fully reviewed by Rahman and Smith (2000). As an example, Pizzolato et al. (2004) studied school location problems and employed capacitated and uncapacitated p-median models for evaluating school locations. ArcView8.3[7] was used to handle large problems and improve the presentation and evaluation of their findings.

Location models applied in the field of bioenergy systems planning are rarely found in the literature. Li et al. (2005) introduced a method integrating genetic algorithms (GAs) and GIS for optimal location search. This research involves finding optimal sites for building one or more facilities based on various constraints and multiple-objectives. GIS tools are employed to get the detailed population and transportation data in the study area, and then use the derived information to facilitate the calculation of fitness functions. Finally, genetic algorithms are used to solve the non-constrained multiple-objectives optimization problems. The results indicate the proposed method has much better performance than either a standalone GIS approach or a simulated annealing search method.

The most comprehensive research in bioenergy systems planning in rural areas in the developing countries can be found in Venema's doctoral dissertation (Venema, 2004). A rural renewable energy design approach that employs spatial optimization techniques for rural bioenergy planning and bioenergy constrained hybrid rural renewable energy system

[7] ArcView 8.x is part of the ArcGIS Desktop software package developed by ESRI

design is fully discussed. In this thesis, location-allocation models (i.e. PMP and p-UFLP) are employed for bioenergy systems planning.

Bioenergy planning deals with a production chain with many links and bioenergy activities cross several traditional professional boundaries. Consequently, planning structures for bioenergy are often more complex than for other industries. This complexity calls for stringency and transparency of the planning methods (Hektor, 2000). In addition, the research on individual aspects of bioenergy application are usually studied by researchers from different disciplines and integrating each aspects associated with bioenergy applications into an optimal bioenergy system has not received much attention. Therefore, continued research on an integrated methodology for bioenergy systems planning is necessary. The research in this thesis focuses not only on decreasing the bioenergy production costs, but also on making significant contribution to the environment. Methodologies, principles, and results are integrated in designing an optimal bioenergy system.

2.4 Summary

This chapter introduced the biomass resources, bioenergy conversion technologies, and products from biomass. The impacts of biomass energy applications on world energy supply and environmental issues are also briefly discussed. Previous research related to bioenergy systems planning are also reviewed such as biomass feedstock available assessment, bioenergy conversion facility locations siting, and spatial optimization design. The new methodology proposed in this thesis is intended to integrate the method and theories associated with bioenergy systems design and improve the performance of the systems by applying GIS screening techniques, Analytic Hierarchy Process (AHP), and discrete location models. The next chapter introduces the main methodologies and tools utilized in this research.

Chapter 3 Methodology

The methodologies used for developing the proposed integrated bioenergy systems planning strategy are described in this chapter. Figure 3.1 depicts the various aspects of the methodology that is developed. Basically, this methodology can be divided into three main parts: biomass availability assessment, suitability analysis and biomass power plant candidates selection, and spatial optimization models of bioenergy systems design. GIS spatial data will be manipulated in the biomass assessment and suitability analysis to find the approximate amount of collectable biomass and the locations of power plant candidates in suitable areas with different suitability will be identified by employing the AHP method and spatial analysis techniques. Afterwards, the statistical and spatial information (i.e. available biomass, distances between power plant candidates and biomass supplies, conversion technologies information) will be employed in spatial optimization models to identify different location-allocation scenarios.

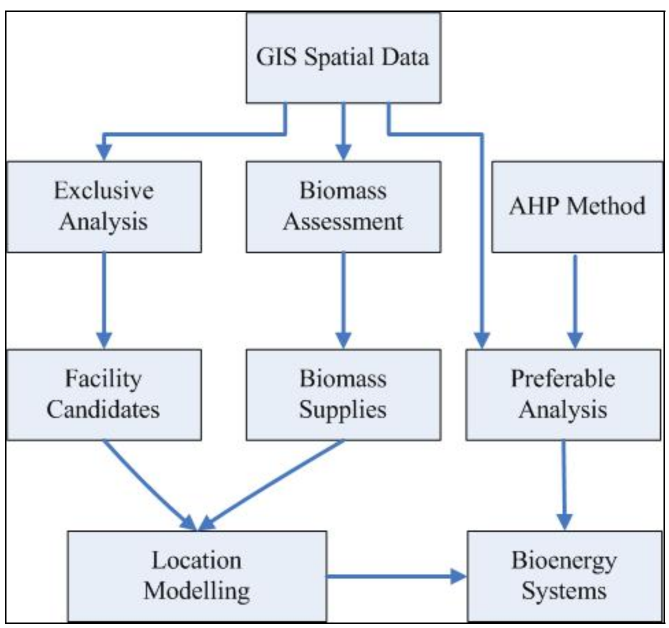


Figure 3-1 Overview of the methodology process

In the first section of this chapter, GIS and its applications in suitability analysis, site selection, network analysis, and spatial optimization are introduced. Then in the second section, an Analytic Hierarchy Process (AHP) method for obtaining the relative weights of the model constraints and factors is fully discussed. In the third section of this chapter, the discrete location models applied in this research are introduced. Genetic Algorithms (GAs) are discussed in the fourth section. These methods and tools form the basis of the integrated methodology for designing bioenergy systems. A summary of these methods is presented in the last section of this chapter.

3.1 Geographic Information Systems and Suitability Analysis

3.1.1 Geographic Information Systems

A Geographic Information System is a tool for making and using spatial information. Bolstad (2002) defines GIS as: *"a computer-based system to aid in the collection, maintenance, storage, analysis, output, and distribution of spatial data and information."* The first GIS was the Canada Geographic Information System which was designed in the mid-1960's as a computerized map measuring system to identify the nation's land resources and their existing and potential uses (Longley et al., 2005). With the development of information technology and the price of sufficiently powerful computers falling below a critical threshold, GIS has become widely used in the fields of government and public services, business and service planning, logistics and transportation, and environmental studies. Longley et al. (2005) state that a GIS is composed of six components: the network, which is the most fundamental part, hardware, software, spatial database, management and the participation of people.

GIS software provides the tools to manage, analyze, and effectively display and disseminate spatial data and spatial information. There are many commercial GIS packages, such as ArcGIS®, GeoMedia, MapInfo, ERDAS, and AUTOCAD MAP. The most popular one among them is ArcGIS®, major software from the Environmental Systems Research Institute (ESRI). In this research, the main components of ArcGIS® including ArcMap, ArcCatalog, and ArcInfo Workstation are employed for biomass availability assessment, suitability analysis and network analysis.

Although GIS is a useful tool, it has some challenges. Foremost of these is the need for suitable and available digital spatial data. Without this data GIS can make little or no contribution to the problems which face us. Fortunately, the improvements in GIS and related technologies and reductions in prices, along with various kinds of government stimulus, have led to the rapid growth of the GIS data industry. Most land use/land cover, road networks, and terrain digital maps are available in the U.S. and Canada. Even some specialized datasets are produced by governments and database vendors. For example, a particular project for producing the high-resolution “National Biomass and Carbon Dataset (NBCD)”, which is funded by NASA’S Terrestrial Ecology Program, has been carried out by the scientists at the Woods Hole Research Center (Braun 2005). Many bioenergy research projects have been conducted using Geographic Information Systems. One of the earliest applications is the analysis of woody biomass production potential in the south-eastern United States by Ranney and Cushman in 1980 (Graham et al., 2000).

The following subsections describe the spatial analysis applications of GIS in this research.

3.1.2 Suitability Analysis

Suitability analysis tools are commonly used for facility siting. In this thesis，the selection of suitable power plant candidate sites begins with identification of a set of criteria that can be used to differentiate those sites that are suitable from those which are not and to rank order suitable sites in terms of their desirability. Criteria that represent requirements that must be satisfied can be thought of as exclusionary because they eliminate certain areas from consideration. Other criteria may represent preferences rather than absolute requirements. Preferential criteria do not preclude development of a particular site but affect the site’s ranking in comparison to other potential sites.

1) Exclusive Analysis

In this thesis, exclusive analysis is used to identify areas where it would be unsuitable to construct power plants. In order to identify all those areas that are deemed unsuitable by exclusionary criteria, which are usually represented as buffer zones indicating suitable and unsuitable areas in a series of binary raster maps corresponding to each considered criterion. For each criterion, the cells falling within a constrained area which are unsuitable are assigned “0”, and cells falling in the suitable areas are assigned “1”. The cell values in the final exclusive analysis map are then calculated using the following equation.

$$C_{i,final} = \prod_{j=1}^{n} C_{i,j} \tag{1}$$

where, $C_{i,final}$ is the i^{th} Boolean cell value in the final exclusive analysis grid, $C_{i,j}$ is the i^{th} Boolean cell value in the grid of the j^{th} constraint, and n is the total number of exclusionary constraints considered. The multiplication of the Boolean constraint cell values result in the final exclusionary grid that will identify cells as unsuitable if they have value “0” in any one of the input layers. Only the cells that have a “1” in each input layer will have the value “1” in the final result, indicating a suitable cell.

2) Preferable Analysis

Unlike exclusionary criteria which have to be met absolutely, the preferable analysis is employed to measure the suitability (high, medium, or low) of each factor considered. In this thesis, for each factor map, the study area is classified into different cell values based on the corresponding criterion with a high cell value representing high suitability relative to the particular factor being considered. As well, each factor is assigned a weight representing its relative importance compared with the other factors in the suitability analysis. These weights are calculated through an Analytic Hierarchy Process (AHP) method which is described in section 3.2. The cell values in the final preferable analysis map are calculated using the following equation.

$$C_{i,final} = \sum_{j=1}^{m} w_j C_{i,j} \tag{2}$$

where, $C_{i,final}$ is the i^{th} cell value in the final preferable analysis grid, $C_{i,j}$ is the i^{th} cell value in the grid of the j^{th} preferable factor, w_j is the weight corresponding to the j^{th} preferable factor, and m is the total number of preferable factors considered. The final preferable analysis grid values indicate the overall rank preferences of each cell considering all the factors.

3.1.3 Network Analysis

Network analysis is a very important application in GIS. It is usually used to manage or optimize systems operation, such as utility, communication and transportation system operations. Utilities use network models to monitor and analyze their distribution systems and meter reading routes. Municipal public works departments use networks to analyze bus and trash routes and businesses use them to find the optimal routes for the delivery of goods and services.

The three main types of network analyses are: network tracing, network routing and network allocation. The purpose of network tracing is to find a particular path through the network based on criteria such as shortest distance, fastest distance and minimum cost. Network routing determines the optimal path along a network. Network allocation deals with the designation of portions of the network to supply centers or demand points. It is widely recognized that network analysis can provide crucial insight into geographic and real world networks, and can be employed to obtain more accurate and appropriate solutions in these networks.

In bioenergy systems planning, network analysis can be employed to find the lowest transportation costs in delivering biomass feedstock and in allocating all the collectable biomass to the conversion facilities, e.g. biomass power plants. In this study, ArcGIS® based network analysis was employed to:

1) find the shortest road network distance for the delivery path of biomass feedstock;
2) get the solutions of the p-median problem for locating the power plants and allocating the biomass supplies.

Many location-allocation problems are concerned with the provision of a service to satisfy a spatially dispersed demand which exists at a large number of widely distributed sites. To reduce costs, the service must be provided from a few, centralized locations to meet distributed demands.

3.2 Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a systematic procedure for representing the elements of any problem, hierarchically (Saaty and Kearns, 1985). It breaks a problem down into smaller and smaller parts and guides the decision making process through a series of pair-wise comparison between objectives or alternatives. This method was first introduced by Thomas Saaty in the 1970s and has become very successful in helping decision makers to structure and analyze a wide range of problems (Golden et al., 1989). The AHP enables the decision makers to express their qualitative judgments in a quantitative format, instead of assigning arbitrary weights to the qualitative factors. The mathematical foundations for AHP are established in references (Saaty, 1980) and (Saaty and Kearns, 1985).

The first task of the AHP process is to structure the decision problem hierarchically in a manner such as that illustrated in figure 3-3. The goal of the decision making problem is at the top of the hierarchy and the considered criteria associated with the problem are at the second level. At the bottom level are the decision alternatives. There could be some sub-criteria following the criteria if applicable.

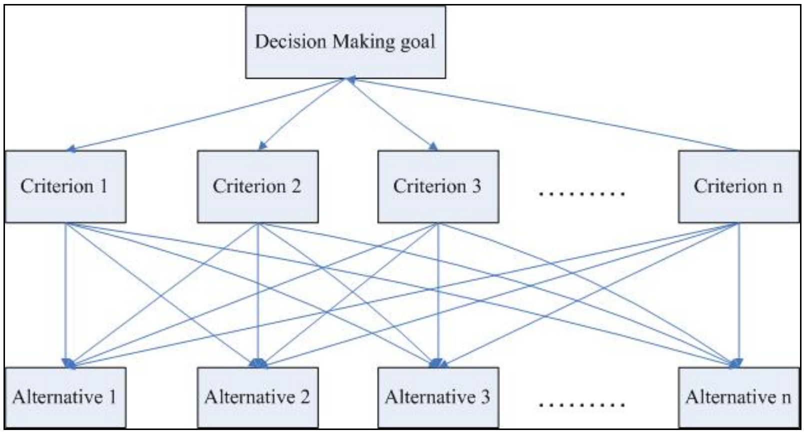


Figure 3-2 Hierarchy structure of the decision making process

Once this structuring of the problem is finished, the next step involves the elicitation of judgments for how “good” the decision alternatives perform under each criterion. The comparison of alternatives and criteria are conducted in a pair-wise fashion with respect to each item of the next higher level. In order to deal with the relative importance of each criterion, a scale of relative importance is defined, as shown in table 3-1. This table assigns quantitative numbers to measure the qualitative comparisons.

Table 3-1 Scale of relative importance (Saaty 1977)

Intensity of relative importance	**Definition**	**Explanation**
1	Equal importance	Two activities contribute equally
3	Moderate importance	Experience and judgment slightly favor one activity over another
5	Essential or strong importance	Experience and judgments strongly favor one activity over another
7	Demonstrated importance	An activity is strongly favored and its dominance is demonstrated in practice
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2,4,6,8	Intermediate values between the two adjacent judgments	When compromise is needed
Reciprocals of above numbers	If an activity has one of the above numbers (e.g. 3) compared with a second activity, then the second activity has the reciprocal value (i.e. 1/3) when compared to the first	

According to the judgment assigned to each criterion, a pair-wise comparison matrix A and a weights vector w can be computed as follows:

1. Let A_{ij} equals the intensity of relative importance between criterion i and criterion j, as defined in table 3.1 with $A_{ji} = \frac{1}{A_{ij}}$;
2. Compute $A_j = \sum_{i=1}^{n} A_{ij}$, the sum of each column of A;
3. Normalize A by dividing each element A_{ij} in the comparison matrix A by A_j;
4. Compute $w_i = \frac{1}{n}\sum_{j=1}^{n} A_{ij}$, the weight of criterion i;

where n is the total number of criterion (i.e. the dimension of A).

An example of the above procedure is shown in table 3-2 below.

Table 3-2 An example of pair-wise comparison matrix and weights

	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Weights
Criterion 1	1	2	5	6	0.536
Criterion 2	1/2	1	2	3	0.253
Criterion 3	1/5	1/2	1	2	0.130
Criterion 4	1/6	1/3	1/2	1	0.079

The numbers in the table represent the relative importance between the criteria. For instance, the relative importance of criterion 1 versus criterion 3 is 5 and between criterion 3 and criterion 1 is 1/5. This indicates that criterion 1 is strongly important compared with criterion 3. The numbers in the weights column show the relative weights of the corresponding criteria.

To evaluate the credibility of the estimated weights, Saaty (1977 and 1980) proposed an eigenvector which is considered a theoretically and practically proven method for evaluating the credibility of the weights (Golden et al. 1989). The method can be described as follows:

1. Calculate the maximum eigenvalue $\lambda_{\max}$ of the pair-wise comparison matrix A;

2. Compute the consistency index (C.I.) defined by Saaty as:

$$C.I. = \frac{\lambda_{\max} - n}{n-1} \quad (3)$$

3. Calculate the consistency ratio (C.R.)

$$C.R. = \frac{C.I.}{R.I.} \quad (4)$$

where the random index (R.I.) for different n can be obtained from Golden el al. (1989).

As a rule of thumb, a value of $C.R. \leq 0.1$ is typically considered acceptable. Larger values require the decision maker to reduce inconsistencies by revising judgments (Harker, 1987). The eigenvector approach can be used for determining whether the pair-wise comparison matrix is acceptable or not. For instance, the C.R. value of the example in table 3.2 is 0.009 which is much smaller than 0.1 indicating that the pair-wise comparison matrix and the computed weights are reasonable.

In this thesis, the AHP method is used to determine the weights of preferable criteria, instead of arbitrarily assigning intuitive or empirical weights, and the eigenvector approach is utilized for measuring the consistency of the proposed pair-wise comparison matrix.

3.3 Discrete Location Models

Mirchandani and Francis (1990) classified discrete location problems into four families: p-Median problems (PMP), p-Center problems (PCP), uncapacitated facility location problems (UFLP), and quadratic assignment problems (QAP). In this chapter, we will detail p-median and uncapacitated facility location problems which are used in this bioenergy systems planning research.

3.3.1 The p-Median Problem (PMP) Model

The p-median problem was first introduced by Hakimi (1965). A PMP model can be used to locate p facilities on a network among n candidates such that the total (weighted) distances traveled from demand points to their nearest facility sites are minimized.

The p-median problem can be described as follows: Given a complete, weighted and undirected graph or a network $G = (V, E)$ where V is the set of vertices and E is the set of edges, associate with each edge a weight $d(V_i, V_j)$ which is the shortest distance in the network between vertices V_i and V_j according to the metric d. Construct the n by n shortest distance matrix $d_{ij} = [d(V_i, V_j)]$. Assign a weight w_i to each vertex V_i and construct the weighted distance matrix $W_{ij} = w_i d_{ij}$. The problem is to find $V_p \subseteq V$ such that $|V_p| = p$, where p is the number of facilities to be built, and such that the sum of the shortest distances from the vertices in the set $\{V \setminus V_p\}$ to their nearest vertex in V_p is minimized (Reese, 2005).

ReVelle and Swain (1970) provided the following integer programming formulation for the discrete p-median problem.

$$\text{Minimize} \quad Z = \sum_{i=1}^{N} \sum_{j=1}^{M} \omega_{\mathrm{i}} d_{ij} x_{ij} \tag{5}$$

subject to

$$\sum_{j=1}^{M} x_{ij} = 1, \forall i \tag{6}$$

$$\sum_{j=1}^{M} y_j = p \tag{7}$$

$$x_{ij} \leq y_j, \forall i, j \tag{8}$$

$$y_j \in \{0,1\}, x_{ij} \in \{0,1\} \tag{9}$$

where

N = total number of demand points in the network

M = total number of candidate facilities

ω_{i} = demand at demand point i

d_{ij} = travel distance between demand point i and candidate facility j

$$x_{ij} = \begin{cases} 1 \text{ if demand } i \text{ is assigned to facility } j, \\ 0 \text{ otherwise,} \end{cases}$$

$$y_j = \begin{cases} 1 \text{ if a facility is located at candidate point } j, \\ 0 \text{ otherwise,} \end{cases}$$

p = number of facilities to be located.

The objective (5) expresses the desire to minimize the sum of the (weighted) distances between the demand points and the assigned facilities. The constraints (6) guarantee that the demand at a point is assigned to exactly one facility. The total number of assigned facilities is defined by constraints (7) to equal p . The constraints (8) ensure that demands are only allocated to active or open facilities. The last set of constraints ensure that the decision variables x_{ij} and y_j are binary.

The p-median problem is perhaps the most common facility location problem among researchers and practitioners. Since the p-median problem is an NP-hard combinatorial optimization problem (Kariv and Hakimi, 1979), optimal solutions to large sized problems are difficult to obtain. Solving NP-hard combinatorial optimization problems has been a core area in research for many communities in engineering, operational research and computer science (Dominguez and Munoz, 2005). Teitz and Bart (1968) first introduced the most well known interchange heuristic algorithm for the p-median problem. The algorithm starts with a random solution and improves it iteratively by swapping facilities in and out of the solution. It can achieve good solutions for small problems (Drezner and Hamacher, 2002). Other heuristics include the linear programming relaxation of Revelle and Swain (1970), the branch and bound algorithms of Khumawala (1972), Lagrangian relaxations methods proposed by Diehr (1972), Narula et al. (1977), and Cornuejols et al. (1977), the linear programming dual of Erlenkotter (1978), and a gamma heuristic approach by Rosing et al. (1999). Lorena and Senne (2003) introduced a column generation approach, using Lagrangean/surrogate relaxation to accelerate sub-gradient like methods, to solve capacitated p-median problems.

Modern heuristics applied to the p-median problem include simulated annealing algorithms designed by Murray and Church (1996) and a Tabu search algorithm developed by Rolland et al. (1997). More recently, Genetic algorithms (GAs), which are discussed in the following section 4.3, have appeared in the literature for solving facility location problems. Due to their representation scheme for search points, genetic algorithms are one of the most easily applicable representatives of evolutionary algorithms. Early attempts at applying GAs for solving facility location problems included direct binary encoding for the p-median problem (PMP) but the results were discouraging (Hosage and Goodchild, 1986). Recently, the use of integer encoding and some theory of set recombination have shown that genetic algorithms could potentially become competitive (Castro and Velazquez, 1999). Jaramillo et al. (2002) proposed using genetic algorithms to solve a variety of facility location problems, including the PMP and the UFLP. Very good approximate solutions compared with Lagrangian heuristics are achieved by using GAs. Correa et al. (2001), Bozkaya et al. (2002), Lorena and Senne (2003), ALP et al. (2003), Deominguez and Munoz (2005), and Fathali (2006) have proposed GAs with various GA operators for solving p-median problem and have obtained encouraging approximate solutions. A comprehensive survey with the aim of providing an overview on advances in solving the PMPs using recent procedures based on meta-heuristic rules are addressed by Mladenovic et al. in 2007.

3.3.2 The Uncapacitated Facility Location Problem (UFLP) Model

The uncapacitated facility location problem deals with the supply of a single commodity from a subset of potential facility locations. Facilities are assumed to have unlimited capacity such that any facility can satisfy all demands. For given costs associated with the facilities and given the transportation routes from potential facility sites to clients, a minimum cost of production and transportation plan can be obtained. Two features distinguish the UFLP from the p-median problem. One is that a nonnegative fixed cost is associated with each potential facility location in the UFLP and this cost exists only if a facility is actually established at that candidate location. Another feature is that the number of facilities to be established is not pre-specified in the UFLP.

If the number of facilities to be established is pre-specified (i.e. if p is specified), the formulation of the corresponding p -UFLP is given by

$$\text{Minimize } Z = \sum_{i=1}^{N}\sum_{j=1}^{M}\omega_i d_{ij} x_{ij} + \sum_{j=1}^{M} f_j y_j \tag{10}$$

subject to

$$\sum_{j=1}^{M} x_{ij} = 1, \forall i \tag{11}$$

$$\sum_{j=1}^{M} y_j = p \tag{12}$$

$$x_{ij} \le y_j, \forall i, j \tag{13}$$

$$y_j \in \{0,1\}, x_{ij} \in \{0,1\} \tag{14}$$

where

f_j is the fixed cost if a facility is established at candidate site j, and where the other variables and parameters are defined as they were for the p -median problem in subsection 3.3.1. Notice that if all $f_j = 0$, the p -UFLP becomes the PMP problem. Similarly, the UFLP is obtained if p is not pre-specified. Therefore, the p uncapacitated facility location problem is an extension of the p -median problem in that fixed costs like those encountered in the UFLP are associated with the potential facility sites.

The objective of the UFLP is to locate facilities on a network so as to minimize the total net cost (or maximize the total net benefit), including not only (weighted) transportation cost but also the fixed cost of setting up the active facilities and providing service to customers located on the nodes of the network. The UFLP is also an NP-hard problem (Cornuejols et al., 1990) and the integer restrictions of variables in these problems cause tremendous difficulty for classical optimization methods to find the optimal or a near-optimal solution. The popular branch-and-bound method is an exponential algorithm and faces difficulties in handling integer linear programs (ILPs) having thousands or tens of thousands of variables (Deb and Pal, 2004). Two type of decomposition- Lagrangian duality and Dantzig-Wolfe decomposition methods have been used for solving the UFLP (Cornuejols et al., 1990). A new method for solving UFLP based on the exact solution of the condensed dual of the strong linear programming relaxation for UFLP via orthogonal projections is recommended by (Conn and Cornuejols, 1990). Gao and Robinson (1994) presented a general model and dual-based branch and bound solution procedure to find optimal solutions for several uncapacitated location problems including UFLP. A Tabu search algorithm was developed by Al-Sultan and Al-Fawzan (1999) to solve the UFLP. The computational results show that the proposed algorithm produces optimal solutions for all test problems and it is very efficient in terms of time compared to existing algorithms. In 2004, Deb and Pal efficiently solved very large resource location-allocation problems including UFLP by applying customized genetic algorithms. They claimed that the exploitation of linearity in the objective function and constraints through genetic crossover and mutation operation is the main reason for success in solving such large scale applications. Their paper encourages further use of customized implementation of GAs in similar facility location problems. Villegas et al. (2006) applied a bi-objective uncapacitated facility location problem (BOUFLP) model to the Colombia coffee supply network. They designed and implemented three algorithms, including the Non-dominated Sorting Genetic Algorithm, the Pareto Archive Evolution Strategy, and an algorithm based on mathematical programming, for solving the BOUFLP.

In this thesis, PMP is solved by a commercial solver in ArcInfo Workstation and a GA is applied when the shortest path distances are used to represent the distances. The p-UFLP is solved using a GA based on the algorithm proposed by ALP et al. (2003).

3.4 Genetic Algorithms (GAs)

The concept of Genetic Algorithms was first proposed by Holland (1975) and described by Goldbery (1989). GAs are fundamentally stochastic search optimization techniques. Different from traditional optimization techniques, a GA seeks an optimal solution through the mechanism of natural selection. In GAs, each candidate solution is coded as a chromosome string and the search process starts from a group of these chromosomes referred to as populations. The chromosomes evolve through successive iterations, called generations. During each generation, the chromosomes are evaluated using some measures of fitness. In order to generate new solutions (offspring) in the next generation, the most popular GA operators, crossover and mutation, are used. The crossover operation exchanges some genes in the identical positions from two chromosomes in the current generation. The mutation operation modifies the gene in a chromosome from the current generation. A new generation is formed from this intermediate population by selecting some parents and offspring and rejecting others so as to keep the population size fixed. Fitter chromosomes have higher probabilities of being selected. The algorithm is terminated after a specified number of generations or the change in the fitness of the population after several generations between successive generations becomes acceptably small. A representation of the simple genetic algorithm (SGA) is shown in figure 3-4.

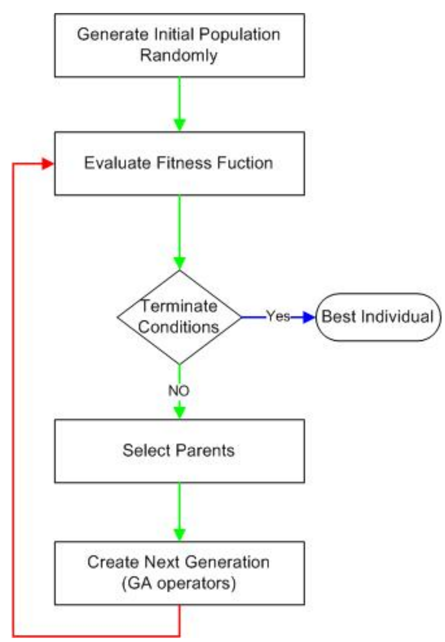


Figure 3-3 Overview of the simple genetic algorithm

GAs work well for complex optimization problems since they preserve the common sections of the chromosomes that have high fitness values, discard poor solutions, and evaluate more and more of the better solutions (ALP et al., 2003). However, there are no generic genetic algorithms that can be used in all GA applications, so users have to custom design the algorithm for their problem individually. Application of a GA to a specific problem requires the development of a fitness function and the representation, or encoding, of a candidate solution in a chromosome string. MATLAB provides a genetic algorithm toolbox for solving optimization problems. Many build-in functions can be used for generating initial population, fitness scaling, selection, reproduction, mutation, and crossover. For particular optimization problems, users can customize their own genetic algorithm process functions.

In this thesis, a custom genetic algorithm is developed in MATLAB. The components of genetic algorithm include:

- Encoding

The encoding of a solution is a critical decision since a poor choice will likely result in a poor algorithm regardless of its other features (Dominguez and Munoz, 2005). This issue has been investigated from many aspects. Gen and Cheng (2000) classified the encoding schemes into: binary encoding, real number encoding, integer or literal permutation encoding, and general data structure encoding. A string of bits is used to represent a solution of the problem in the binary encoding scheme. It is preferred by the majority of researchers (Back et al., 1997), however, binary encoding for function optimization problems has severe drawbacks limiting the applications of binary representation (Gen and Cheng, 2000). It has been demonstrated that real number encoding results in better performance than binary encoding for function optimization and constrained optimization whereas integer or literal permutation is best suited for combinatorial optimization problems since combinatorial optimization problems search for a best permutation or combination of elements subject to constraints. General data structure encoding can be used in more complicated problems to represent complex data structures.

- Population

The size of the population is an important parameter in the effectiveness of the genetic algorithm. Larger populations create a more diverse gene pool and enhance the probability of achieving the global optimum solution, but require more computation time. Smaller populations contain a less diverse gene pool and run the risk of premature convergence. Therefore, a compromise must be made between larger populations with more substantial computation efforts, and smaller populations that may converge to local solution but require less computing time. Many trials have to be completed to select a proper population size since there are no universal rules for determining the optimal population size for a specific problem.

- Selection

The purpose of selection is to pick parents from the current population. These parents will be modified by crossover or mutation to create offspring. Numerous selection rules have been proposed for GAs including Roulette wheel selection, ranking selection, and tournament selection. All methods rely on the fitness of individual members of the population and explicit requirements that all fitness values are positive and larger magnitude fitness values are superior to smaller magnitude fitness values. Populations that do not meet these requirements must have their fitness values mapped. Elitist selection is also often used to retain the best members in the population for subsequent generations. When elitism is applied to a genetic algorithm the best individuals survive to the next generation. Although introducing elitism increases the risk of being trapped in a local optimal solution, this method is useful for preserving the best individual through subsequent generations.

- Crossover and Mutation

Crossover and mutation are two basic operators in a genetic algorithm. The crossover operator exchanges genes between two parents to form two offspring that inherit the traits of both parents. Holland (1975) noted that it was crossover, and not random point mutations, which separated genetic algorithms from other evolutionary computation methods. The cutting point for separating the genes is randomly selected and the decision on whether or not to perform a crossover operation on two selected parents is determined randomly based on the crossover probability. A large crossover probability is commonly used in most GAs. The mutation operator alters one or more genes of a single parent. This can be done by randomly flipping bits from 1 to 0 or 0 to 1 in the binary encoding presentation. Mutation is generally considered as a method to recover lost genetic material rather than to search for better solutions. The decision on whether or not a given gene should be mutated is controlled by the mutation rate. Figure 3-5 illustrates crossover and mutation operations.

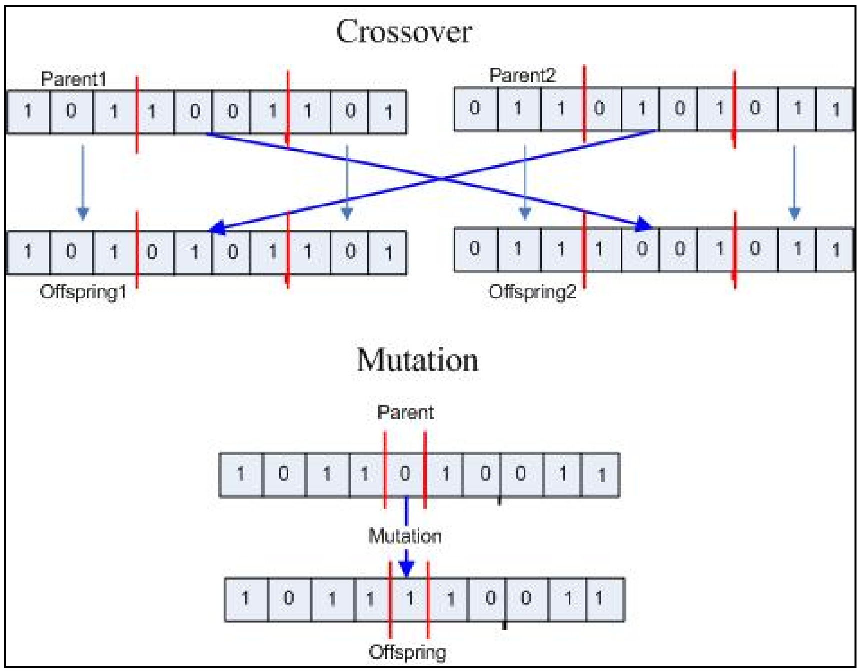


Figure 3-4 Crossover and mutation operations in GA

GAs are potentially powerful tools for solving large scale combinatorial optimization problems. Hosage and Goodchild (1986) developed a binary encoding genetic algorithm for solving discrete location-allocation problems. They observed that their algorithm is most likely to be trapped in a local optimum if the corresponding string is very dissimilar from the string of the true optimum. Jiang et al. (1997) solved two location models for physical distribution centers using genetic algorithms. Their results proved that both proposed models performed better than using the classical alternate location-allocation method (Jiang et al., 1997). Jaramillo et al., (2002) explored the use of GAs to solve location problems. In their paper, uncapacitated and capacitated fixed charge problems, the maximum covering problems, and competitive location models are solved by GAs and compared with the performance of other well known heuristics. Their research revealed that GAs were able to give good and robust solutions for each model except the capacitated fixed charge location problem. Bozkaya et al. (2002), Chaudhry et al. (2003), and ALP, et al. (2003) proposed efficient genetic algorithms for solving the p-median problem. In this thesis, GAs are employed and programmed for solving the proposed spatial optimization models as described in section 4.3. The attempts to solve discrete location-allocation problems using MATLAB are described in Chapter 4 and the script codes are presented in Appendix B.

3.5 Summary

In this chapter, GIS and its applications, the Analytic Hierarchy Process (AHP), discrete location models, and genetic algorithms and their application in location science, are introduced. GIS is an efficient data processing and analysis tool which can be used for biomass availability assessment, suitable sites selection when combined with the AHP method, and results visualization with GIS maps. In order to spatially locate the power plants and optimally allocate the available biomass, discrete location models are proposed. Genetic Algorithms capable of giving good solutions to the corresponding combinatorial optimization problems, when appropriate parameters are set, are also described.

Chapter 4 Model Implementation: A Case Study

In this chapter, the integrated models of bioenergy systems planning are demonstrated with a case study in the Region of Waterloo, Ontario, Canada. The tools and methods described in the previous chapter are implemented in this case study and some results are presented using maps. Agricultural biomass availability estimation is conducted in the first section. The second section describes the implementation process and the criteria used in the selection of biomass power plant candidates using the GIS and AHP applications. Discrete location theory based spatial optimization models are formulated in the third section. A brief summary is presented in the last section of the chapter.

The reason for selecting Waterloo region as the study area is to take advantage of the readily available GIS data and because it is an agricultural dominated region. However, the proposed methodology in this thesis can be carried out in any regions subject to the availability of spatial and statistical data.

4.1 Biomass Availability Assessment Method and Implementation

The proposed methodology for optimal bioenergy systems planning was applied to the Region of Waterloo which is located in the Southwest region of Ontario, Canada (approximate population 506,800 in 2006). The Region is made up of the cities of Cambridge, Kitchener and Waterloo as well as the Townships of North Dumfries, Wellesley, Wilmot and Woolwich.

In this thesis, biomass availability is estimated based on the land use in this region. There are 26 land use categories in the study area including urban areas, agricultural areas, grain system, and idle agricultural land. The spatial distribution of land use in this region is illustrated in figure 4-1 and statistically summarized in a table in Appendix A. By observing the figure and table, it is obvious that not all the lands are suitable for producing biomass. In this thesis, the biomass feedstock available for power production was assumed to come primarily from crops residues and energy crops through combustion, co-combustion or gasification techniques. Other kinds of biomass, such as forestry wood residues, animal manure, and municipal solid waste are not taken into account in this biomass potential evaluation. This is because animal manure and municipal solid waste, which have more moisture content, are more suitable to conversion through anaerobic digestion, and forestry wood residues availability is associated with the forestry sustainable management and landscape ecology design problems which are beyond the scope of this research.

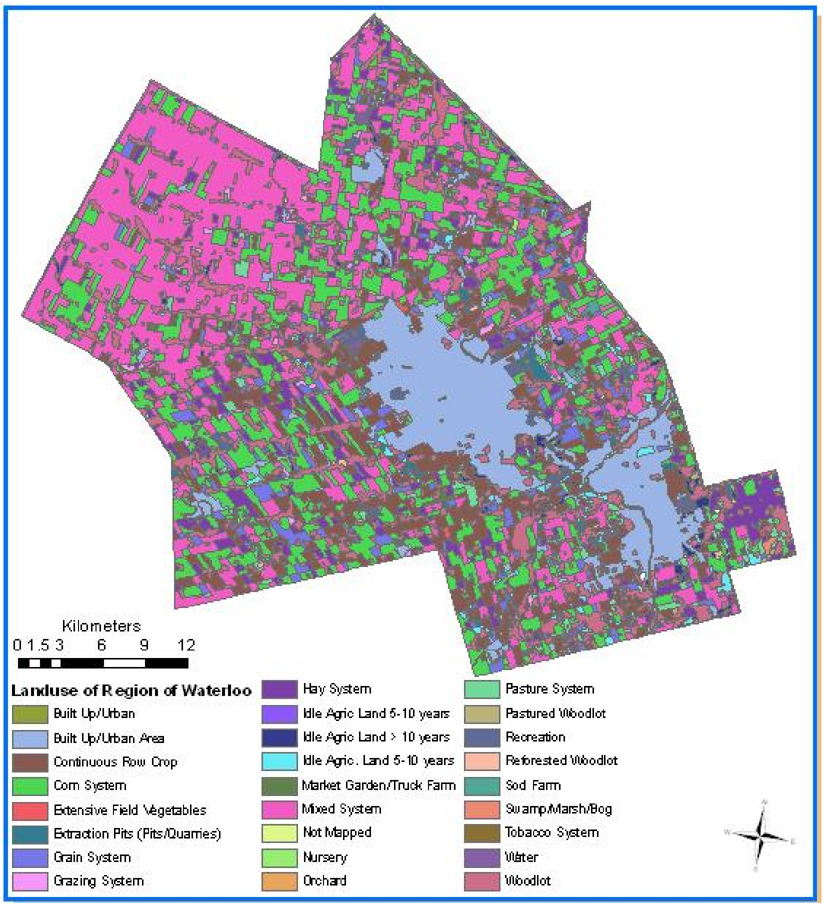


Figure 4-1 Land use in the Region of Waterloo, Ontario, Canada

(The Ontario Ministry of Natural Resource, 2002)

The procedure used to evaluate agricultural biomass supply in the study area involves the following three stages:

- Assess the theoretical biomass production from each suitable land use category;
- Partition the study area into several biomass supply zones based on the filtered power plant candidate locations (see section 4.2);
- Overlay with the biomass production points data to determine the biomass supply of each zone.

In the first stage, before calculating the available biomass, the land use categories that are not appropriate for producing biomass (such as built up urban areas, water, extensive field vegetables, etc.) are excluded from the land use map. After this exclusion, 14 land use categories are left as suitable land for biomass production. These are summarized in table 4-1.

Table 4-1 Land use considered for biomass production

Landuse Catalogues	Number of polygons	Total Areas(Ha)
Continuous Row Crop	359	17135.198
Corn System	383	24347.501
Grain System	232	5270.384
Grazing systems	52	741.525
Hay system	294	8665.026
Idle Agric Land 5-10 years	160	1693.575
Idle Agric Land >10 years	107	1300.416
Mixed Systems	274	35844.838
Pasture system	94	1834.93
Pastured Woodlot	13	152.596
Reforested Woodlot	17	167.926
Sod Farm	7	309.594
Swamp/Marsh/Bog	15	161.491
Horticultural System	828	18115.913
Sum	2835	115740.913

Depending on the land use categorization (represented in the GIS by polygons showing the usages of each parcel in figure 4-1), the theoretically obtainable biomass in polygon n is calculated as follow:

$$B_n = A_n \sum_{i=1}^{m} (y_i \times p_{ni}) \tag{15}$$

where, B_n is the biomass production in polygon n (dry-ton), A_n indicates the area of polygon n (Ha), y_i is the biomass yield of crop *i* (dry-ton/Ha), p_{ni} is the percentage of available biomass from crop i in polygon n, and m is the number of crops planted in polygon n. With the historical agricultural statistical data and biomass yield data (refer to Appendix A), y_i and p_{ni} can be obtained. These data were then used in equation (15) to compute biomass production in each land use polygon. In order to more conveniently calculate the yields of the biomass production zone in the second stage, these polygons were then converted to points by applying GIS feature conversion tools. The computed biomass potential associated with each polygon was stored in the "bio-production" field of the attribute table of the biomass production points. Figure 4-2 illustrates the distribution of suitable land use categories (excluding the unsuitable land use categories) for agricultural biomass production over the entire Region of Waterloo. Notice that the white areas in the map represent the filtered unsuitable land use categories for producing agricultural biomass. They are not considered in this study.

In the next stage of assessing biomass availability, the study area is divided into several zones corresponding to the number of power plant candidate locations (see section 4.2). The purpose of this action is to create the same numbers and locations of biomass collection sites as the number of power plant candidates. It is neither practical nor feasible in the real world to collect and transport biomass in every land parcel in the study area to the assigned biomass power plant. A more viable way is to collect the biomass in several land parcels and send them to a selected closer site for preparation before transport to the conversion facilities.

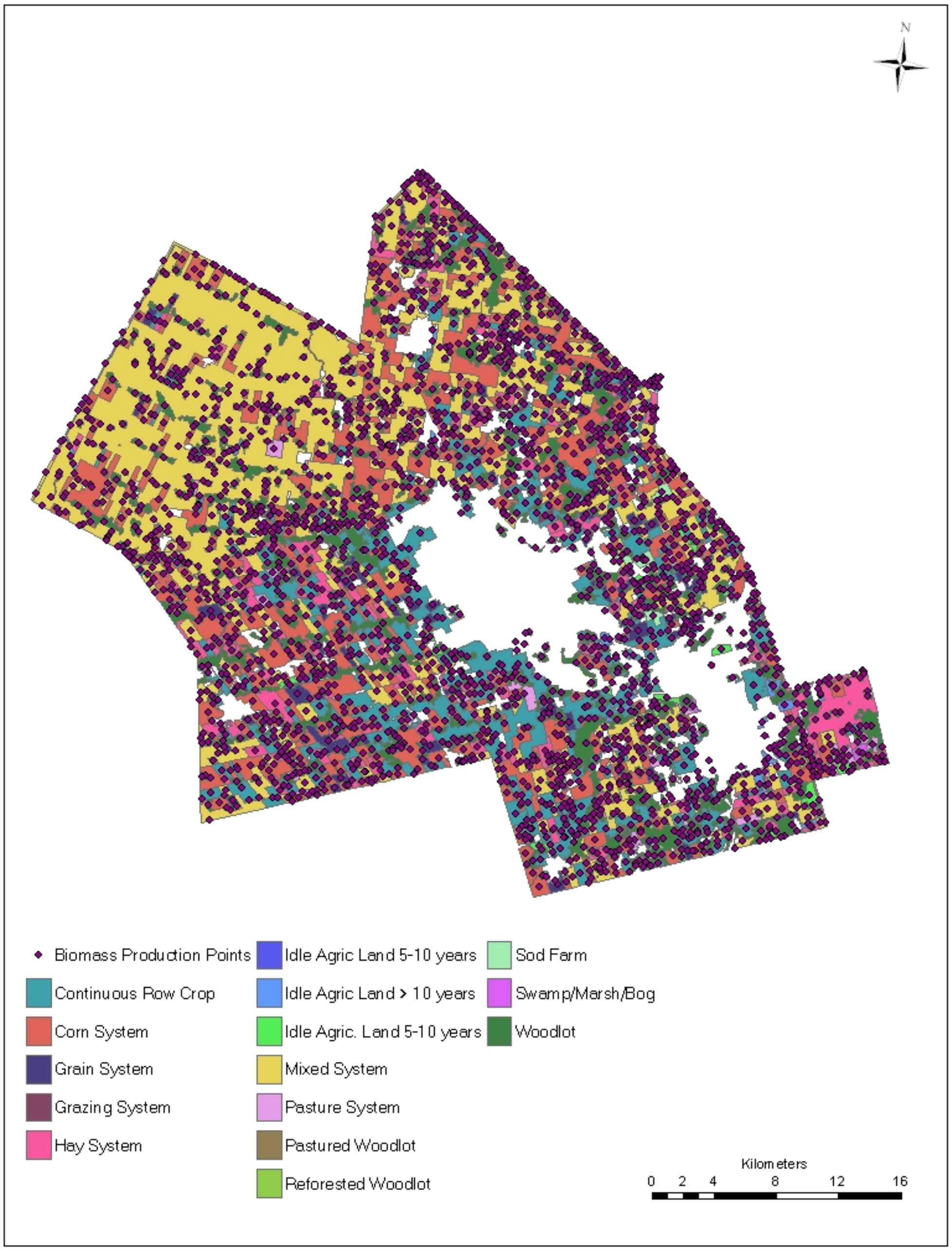


Figure 4-2 Suitable land use for biomass production in the Region of Waterloo

In addition, an advantage of using the same candidate sites for both the collection and power plant candidate sites is that it ensures that the biomass collected in a zone need not be transported to constructed power plants in a different geographic location. The process of allocating the available biomass feedstock is conducted by applying the "Euclidean Allocation" tool in ArcMap 9.1. The Euclidean Allocation tool allocates each cell to the closest input sources (i.e. "SOURCE_GRID" in figure 4-3) based on Euclidean distance. Figure 4-3 illustrates this spatial distance tool in ArcMap. The input source in the Euclidean allocation can be either a vector or raster dataset. If the input source data is a feature class, it will first be converted internally to a raster before the Euclidean analysis is performed. In this thesis, the input sources are the candidate sites of the biomass power plants and the purpose is to allocate the biomass production areas (represented as raster cells) to the nearest power plant candidates.

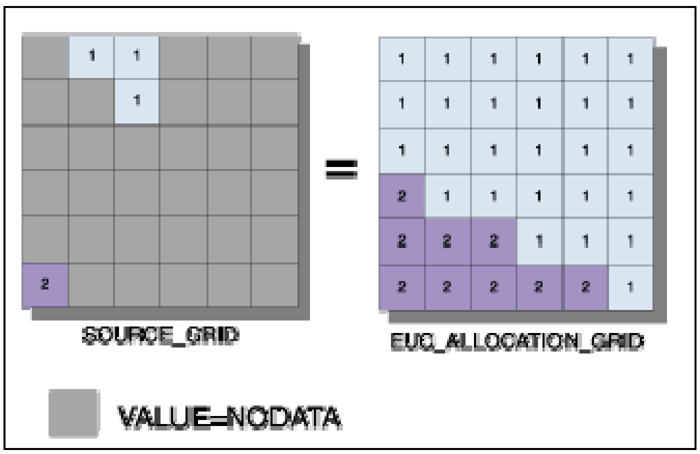


Figure 4-3 Basic illustration of Euclidean Allocation

By applying this tool, the study area is partitioned into several zones based on the power plant candidates as the input sources. Furthermore, the biomass production points are allocated to the proximal biomass collection sites, which have the same geographic coordinates as the biomass power plant candidates derived from section 4.2. An example result of this process with 87 power plant candidates is illustrated in figure 4-4.

In figure 4-4, the Voronoi diagram indicates how the Region of Waterloo has been partitioned into several biomass supply zones where each zone contains several biomass production points.

In the last stage of biomass availability estimation, the “bio-production” quantities for all biomass production points, identified in the first stage, within each biomass production zone are summed to obtain the biomass supply potential in each zone.

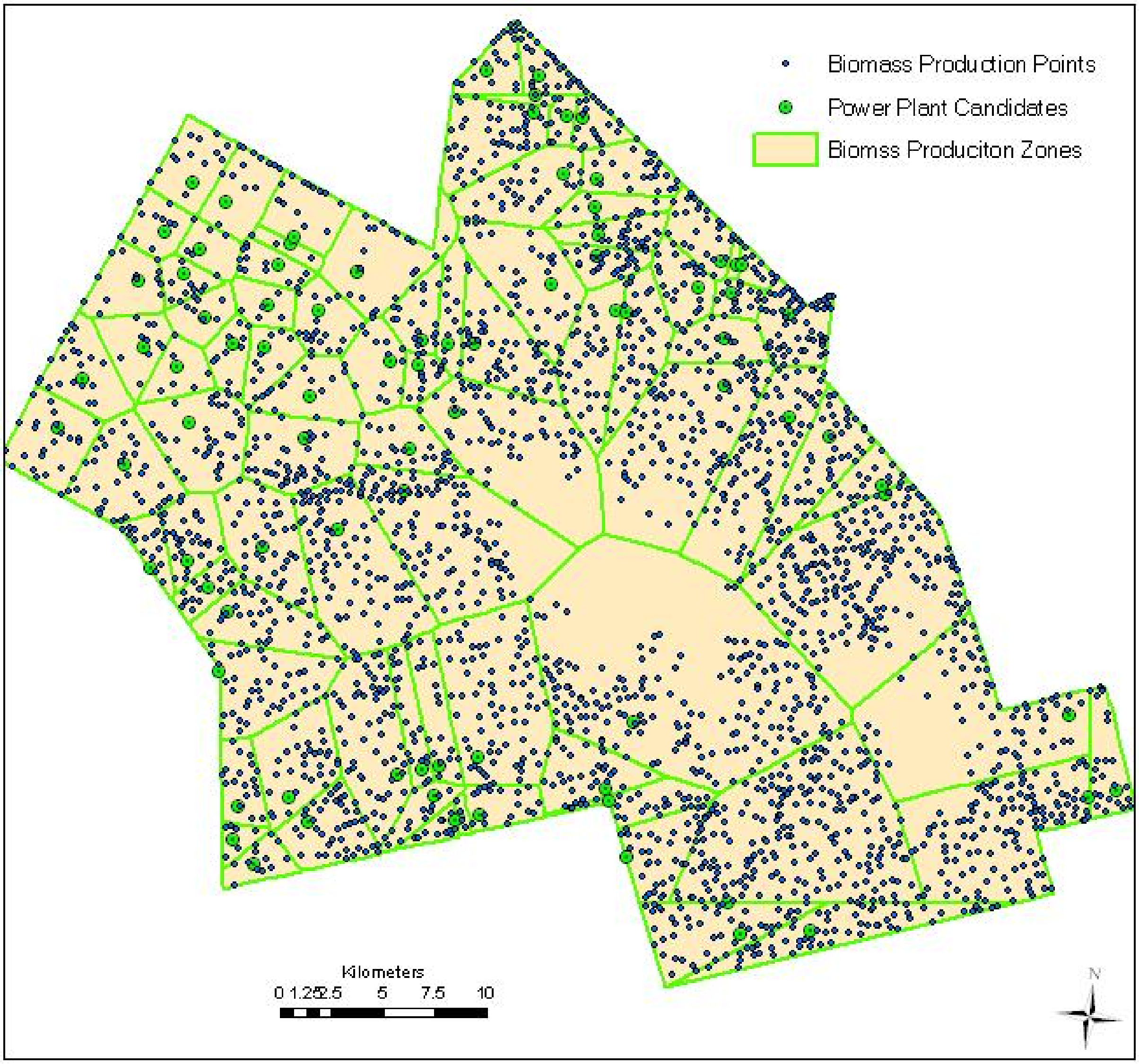
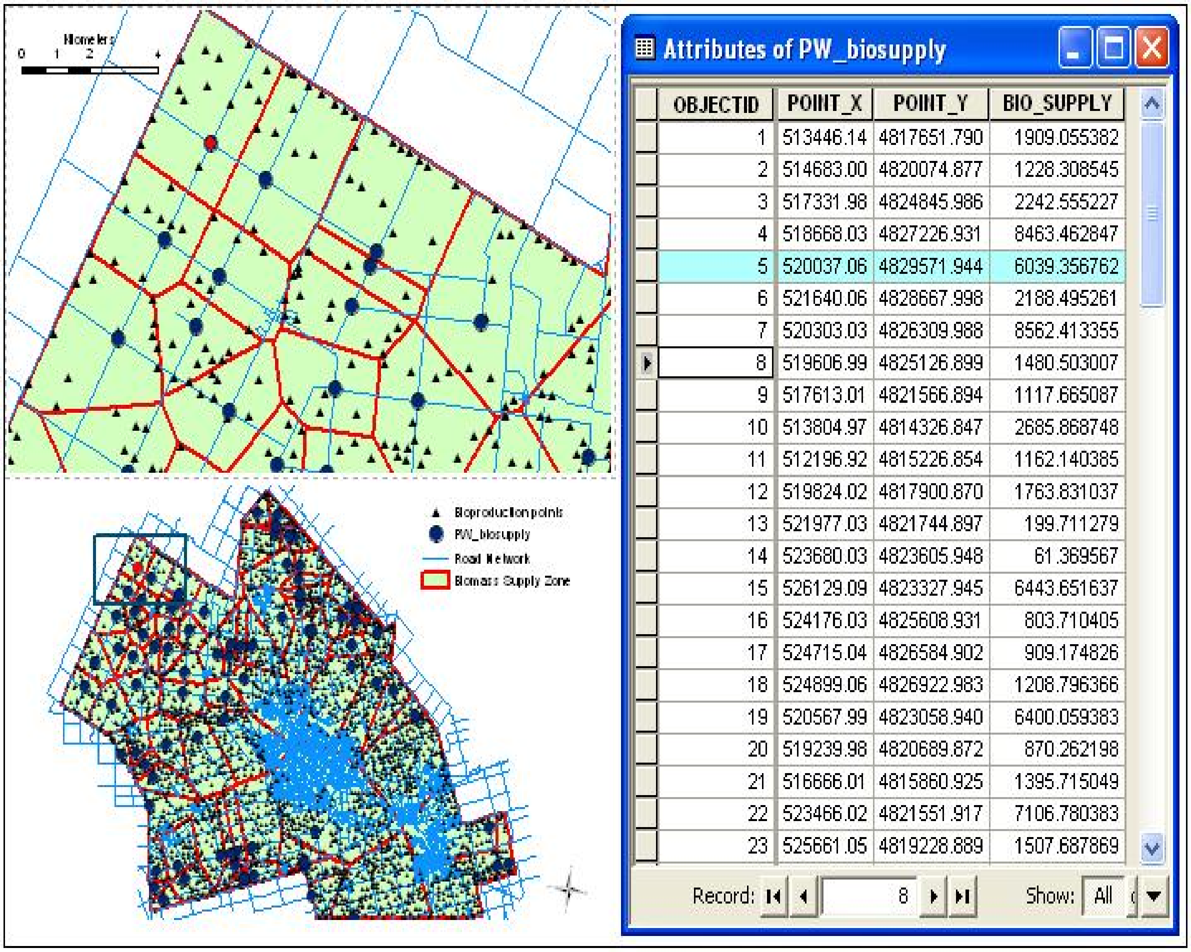


Figure 4-4 An illustration of biomass supply zones in the Region of Waterloo

The total biomass supply for each such zone is then computed based on its geographic distribution (using scripts written in Python[8] and running in the ArcCatalog® of ArcGIS®,

[8] A dynamic object-oriented programming language that can be used for many kinds of software development

refer to Appendix B) by simply summing the corresponding "bio-production" field values of all of the biomass production points in each such zone. A new field "BIO_SUPPLY" is added to the power plant candidate attribute table where the summed values are stored. Figure 4-5 shows the results of the biomass potential calculation in each biomass supply zone.



OBJECTID	POINT_X	POINT_Y	BIO_SUPPLY
1	513446.14	4817651.790	1909.055382
2	514683.00	4820074.877	1228.308545
3	517331.98	4824845.986	2242.555227
4	518668.03	4827226.931	8463.462847
5	520037.06	4829571.944	6039.356762
6	521640.06	4828667.998	2188.495261
7	520303.03	4826309.988	8562.413355
8	519606.99	4825126.899	1480.503007
9	517613.01	4821566.894	1117.665087
10	513804.97	4814326.847	2685.868748
11	512196.92	4815226.854	1162.140385
12	519824.02	4817900.870	1763.831037
13	521977.03	4821744.897	199.711279
14	523680.03	4823605.948	61.369567
15	526129.09	4823327.945	6443.651637
16	524176.03	4825608.931	803.710405
17	524715.04	4826584.902	909.174826
18	524899.06	4826922.983	1208.796366
19	520567.99	4823058.940	6400.059383
20	519239.98	4820689.872	870.262198
21	516666.01	4815860.925	1395.715049
22	523466.02	4821551.917	7106.780383
23	525661.05	4819228.889	1507.687869

Figure 4-5 Results of biomass assessment in the Region of Waterloo

In figure 4-5, the bottom left figure illustrates the results of the biomass assessment in the Region of Waterloo and the upper left figure shows the details for the boxed in area of the lower figure. The locations of biomass supply zones are fixed to the locations of power plant candidates, which represent the supply input parameters to the location-allocation models described in section 4.3. The attribute table on the right of figure 4.6 shows how the attributes associated with each zone (i.e. the biomass supply and the point location) are stored.

4.2 Power Plant Candidates Selection and Results

In this thesis, we first assume that all the intersections in the road network of the study area are biomass power plant candidate sites. This is mainly because the optimal solutions of discrete location models are always found at the vertex of a network (Hakimi, 1964). As well, this assumption facilitates maximizing accessibility without unnecessarily increasing costs for road construction. However, this assumption may negatively impact on the efficacy of the location-allocation process in two ways.

1) Not all road network intersections are feasible sites for constructing biomass power plants. Neither thermal power plants nor landfill gas power plants are suitable at every intersection. Environmental or public health constraints should ultimately be taken into account when selecting power plant sites (Public service commission of Wisconsin, 1999). For instance, it is unacceptable in most situations for a power plant to be located in an environmental sensitive protection area (ESPA), floodplains, or in an urban area near residential zones.

2) Since the number of intersections in road networks is normally very large (9760 intersections in the road network of the Region of Waterloo), the computational burden in solving the corresponding location-allocation models could make their solutions intractable. Consequently, since many intersections are in urban areas that are often unsuitable for power plant sites, it would be beneficial to conduct the suitability analysis process to reduce the number of suitable candidate sites.

In this section, the Analytic Hierarchy Process and GIS based suitability analysis are utilized to limit the problem size by filtering out intersections in unsuitable areas and applying preferable criteria to rank order the areas that are most suitable for locating biomass power plants. The original spatial data of the study area used for the suitability analysis are listed in table 4-2.

Table 4-2 Spatial data

Data Layers (Vector and Raster)		
Land use	Water body	Elevation
Floodplain	Road network	Airports
Water discharge	Water supply	Existing Substations
Distribution network	Urban areas	Biomass supply

4.2.1 Implementation and Results of Exclusive Suitable Analysis

GIS based suitability analysis consists of exclusive and preferable analysis. This subsection describes the details of the implementation of exclusive analysis and presents the results derived from this spatial analysis process.

Many criteria could be considered as exclusionary constraints which must be satisfied in the process of selecting suitable sites for building power plants. General considerations are listed in table 4.3 as the exclusive siting criteria (Public service commission of Wisconsin, 1999, Delaney et al., 2003 and Beheshtifar et al., 2006). The constraints and regulations aim to minimize the negative impact on the environment, to protect public health and safety and to keep the constructed power plants operating at lower costs and in more stable conditions.
Depending on the concerns of the decision makers and the regulations in different regions or nations, some of the criteria summarized in table 4-3 could be chosen as particular exclusive constraints.

Table 4-3 Siting criteria for power plants by major category

Considerations	Major Categories
Site Requirements	• Accessibility • Site Geography • Topography • Site expandability • Solid waste management • Fuel delivery
Community Impacts	• Archaeological and historical sites • Community service costs • Aesthetics • Public attitude • Labour availability • Effects on wells • Numbers of relocations
Public Health and Safety Concerns	• Air quality • Electric and Magnetic Fields (EMF) • Noise • Operational odors • Traffic safety • Water treatment
Environmental Impacts	• Air and drink water quality • Groundwater impacts-recharge, discharge, quantity, quality • Protect species • Wetlands • Waste water treatment • Waste minimization, recycling ,reuse
Economic Impacts	• Delivered costs of energy • Future development • Jobs and purchases • Transmission and distribution changes • Property values
Land Use Impacts	• Industrial forests • Land acquisition • Land use compatibility • Previous land use • Prime agricultural land • Recreational areas

The regional official policies plan for the Region of Waterloo (1994) states: "Any infrastructure planning should meet the planning policies of the Region of Waterloo, the Region of Waterloo will review and comment on Environmental Assessment Studies (EAS), and may participate in the Environmental Assessment Process, for major hydro-electric power lines, oil lines, gas lines, communication lines or lines conveying other liquids or energy, to ensure that regional interests concerning impacts on the Natural Habitat Network, Heritage resources, sensitive groundwater areas, City and Township Urban Areas, Rural Settlement Areas, and natural resources are addressed. " The goal is to achieve a Sustainable Regional Community.

In this thesis, five constraints are taken into account as the exclusionary criteria according to the geographic characteristic and regulations of the region. Each exclusive constraint is implemented by separating the suitable areas and unsuitable areas using buffers. The intent of buffering is to minimize the negative effects of the plant by increasing the distance to neighbours through use of surrounding land that provides a "buffer". Buffer area refers to the strips of land between the plant facilities and adjacent property owners, especially residential property owners. Generally, sites with large or higher quality buffer areas are more desirable. All the constraints considered in the exclusive suitability analysis are illustrated in figure 4-6 and are described as follows:

1) Residential zones (built up urban areas)

In order to minimize the impacts of constructing new power plants on the residents in the local area, the plant sites should be buffered from residential zones. The considerations of public health and safety, such as noises, operational odors, traffic safety issues, EMF, dust etc., ought to be reduced to a minimum level. Appropriate buffers can provide not only relatively quiet safe isolation, but also avoid residents' relocation.

2) Floodplain

It is important to reduce the potential for flood damage and plant shut down. Designs typically locate critical equipment above the 100-year flood level. Non-critical portions of the plant systems (e.g., road) below the 100-year level can be raised or protected (Public service commission of Wisconsin, 1999). In this study, the zones within the floodplain buffers are excluded as potential power plant candidate sites.

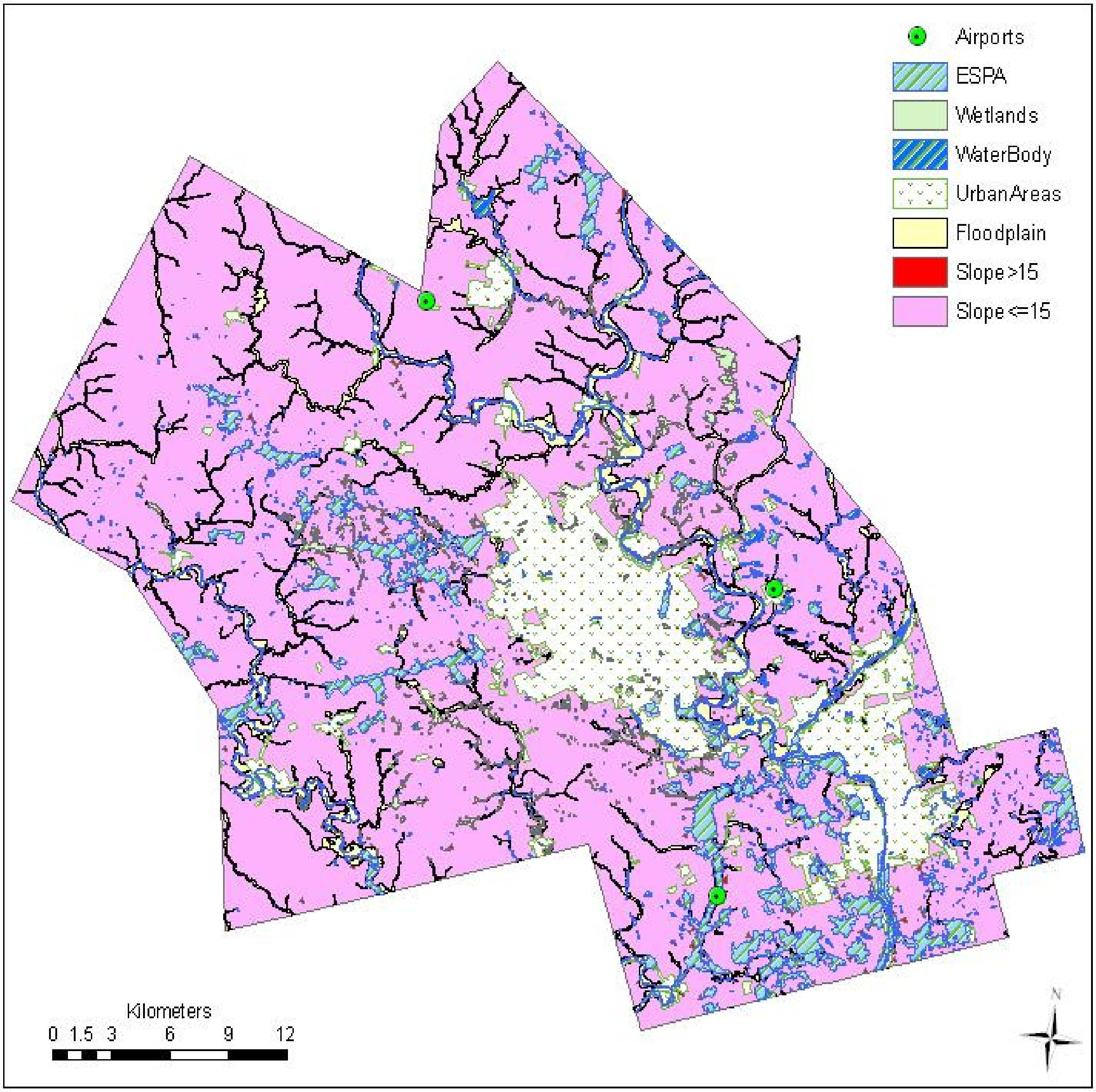


Figure 4-6 Constraints in the exclusive suitability analysis

3) Slope

It is obvious that other types of area which are unsuitable for construction are those liable to catastrophic slope movements such as landslides, rockslides, deep-seated creep etc.

Therefore, the slope of the land should be considered in the exclusive suitability analysis. The slope map in the study area is calculated in ArcGIS® and certain slope-angles are selected. Areas with slope-angles beyond 15° are excluded from the suitability map (Demek and Kalvoda, 1992).

4) Distance to airports

Usually, a power plant has high towers and chimneys and discharges large volumes of gas. Consequently for safety reasons and to comply with air space restrictions and regulations, plants should be located away from airports. Generally, sites at greater distances from airports and designated as clear zones are desirable, as are sites offset from runway alignments (Public service commission of Wisconsin, 1999).

5) Water body/environmentally sensitive areas

Water bodies include all lakes, rivers, wetlands and ponds in the region. They are considered environmentally sensitive areas. In order to protect water quality, biodiversity, and the natural habitat network, the proposed power plants should not be constructed near water bodies or environmentally sensitive areas.

The purpose of the exclusive suitability analysis is to exclude all intersections located in unsuitable areas by considering the constraints above. The process is conducted in the environment of the model builder in ArcCatalog. The Data Flow Diagram (DFD) consisting of all spatial data taken into account in the model builder is illustrated in the following figure 4-7.

In particular, the buffer distance for urban areas is set to 1.0 kilometre. Water body/environmental sensitive areas and floodplain have a buffer distance of 300 meters. Intersections with slope-angle greater than 15° are excluded and intersections within 3 kilometres of airports are prohibited. After applying the exclusive suitability analysis to the spatial data as described in the DFD in figure 4.8, an exclusive suitability map is generated. All the road network intersections in the region are overlaid with the derived exclusive suitability map to identify the power plant candidates in the Region of Waterloo as illustrated in figure 4-8. These filtered power plant candidate sites are identified as the facilities in the location-allocation models and used as the locations for partitioning the study area into several biomass supply zones in section 4.1.

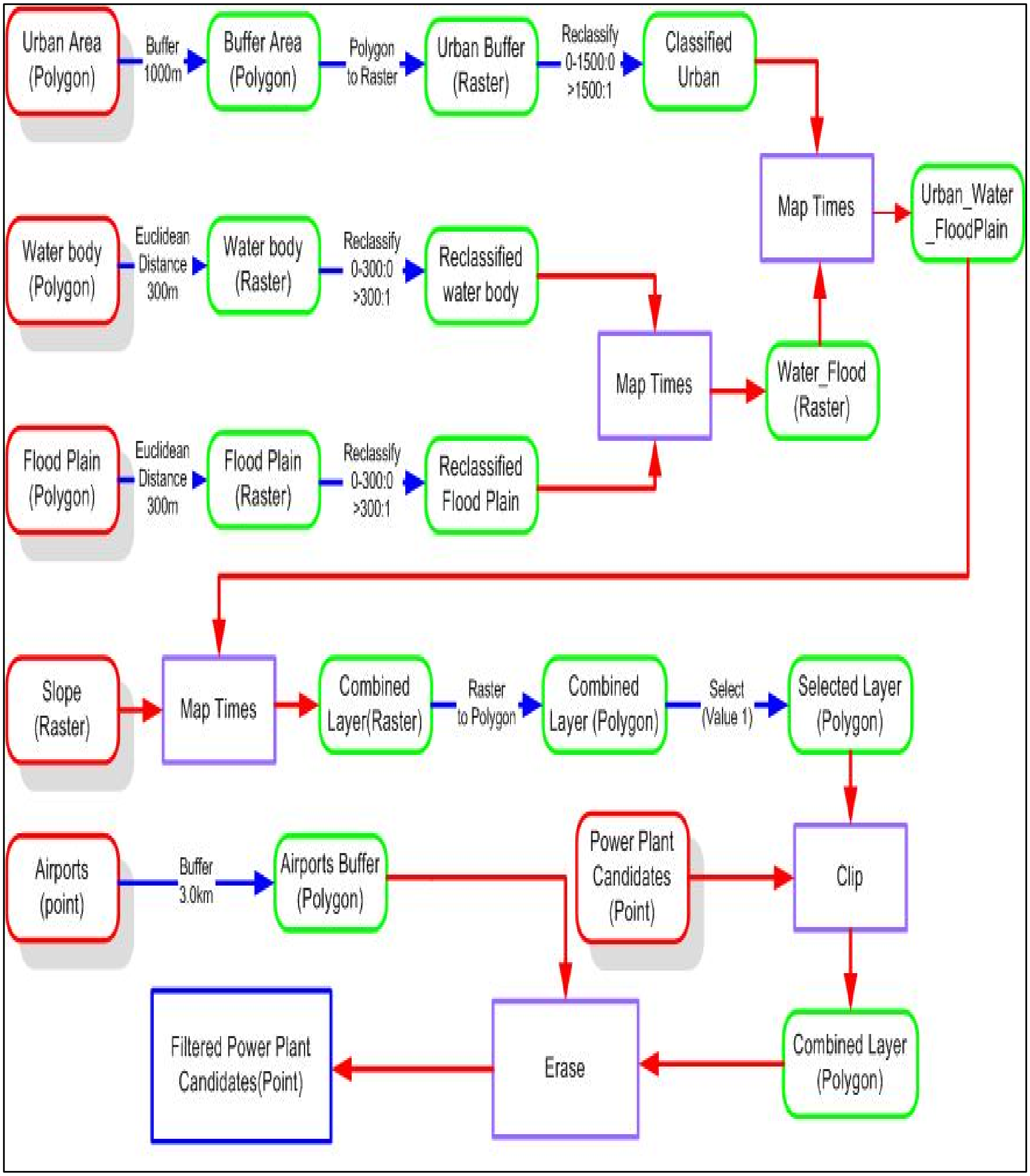


Figure 4-7 Data flow diagram of the exclusive suitability analysis

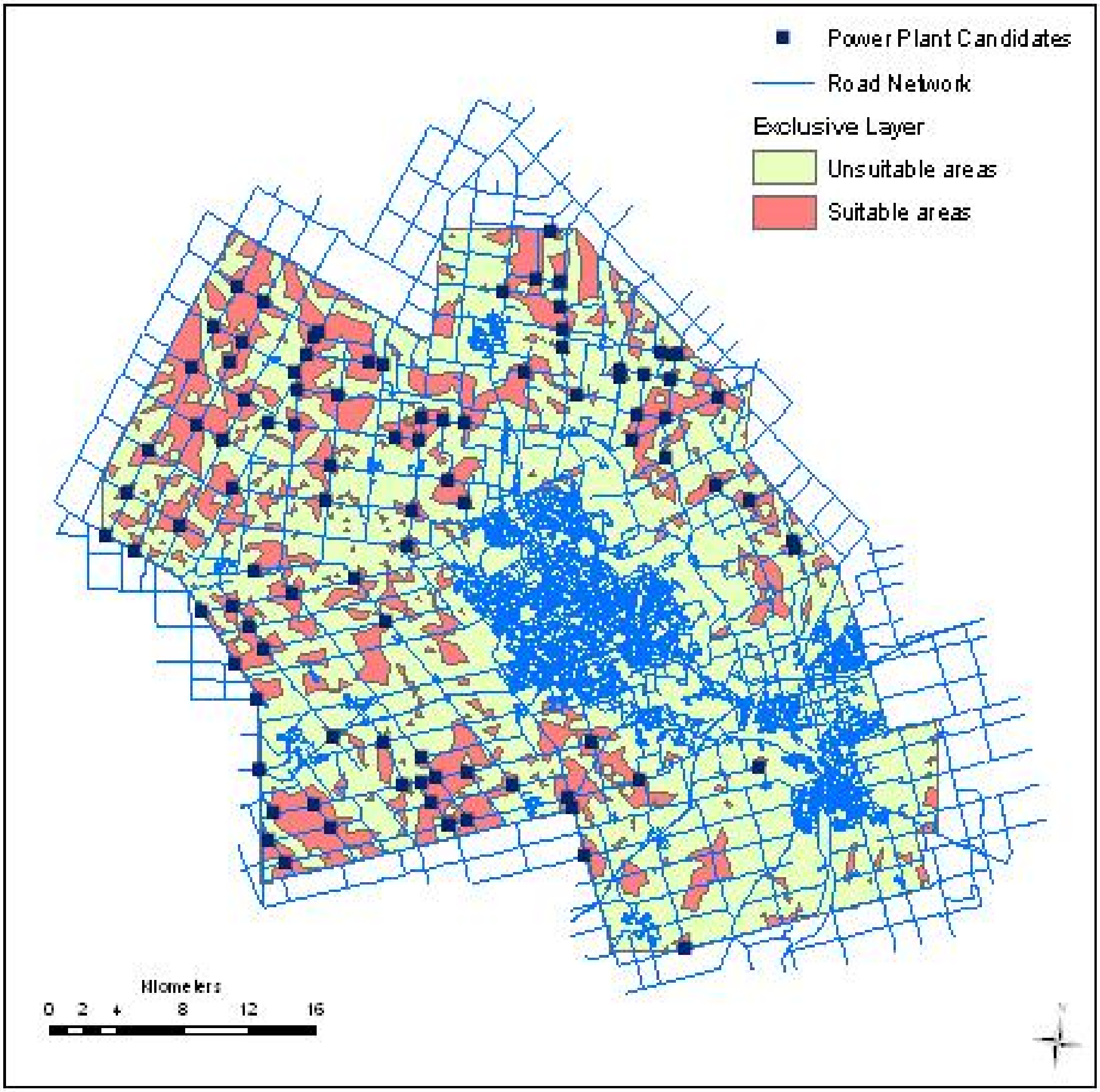


Figure 4-8 An example of exclusive suitability analysis results

To facilitate this process, an exclusive analysis toolbox was developed for conducting the exclusionary suitability analysis process interactively. By entering the buffer distances or slope-angles to this toolbox, a corresponding exclusive suitability analysis result is generated and presented in a GIS map. The toolbox was developed in Python 2.1 and runs in ArcCatalog 9.1. With this toolbox, the decision makers can conveniently get the analysis results without knowing much about ArcGIS® and Python. The interface to the toolbox is shown in Figure 4-9 and the detailed scripts for this toolbox appear in Appendix B of this thesis.

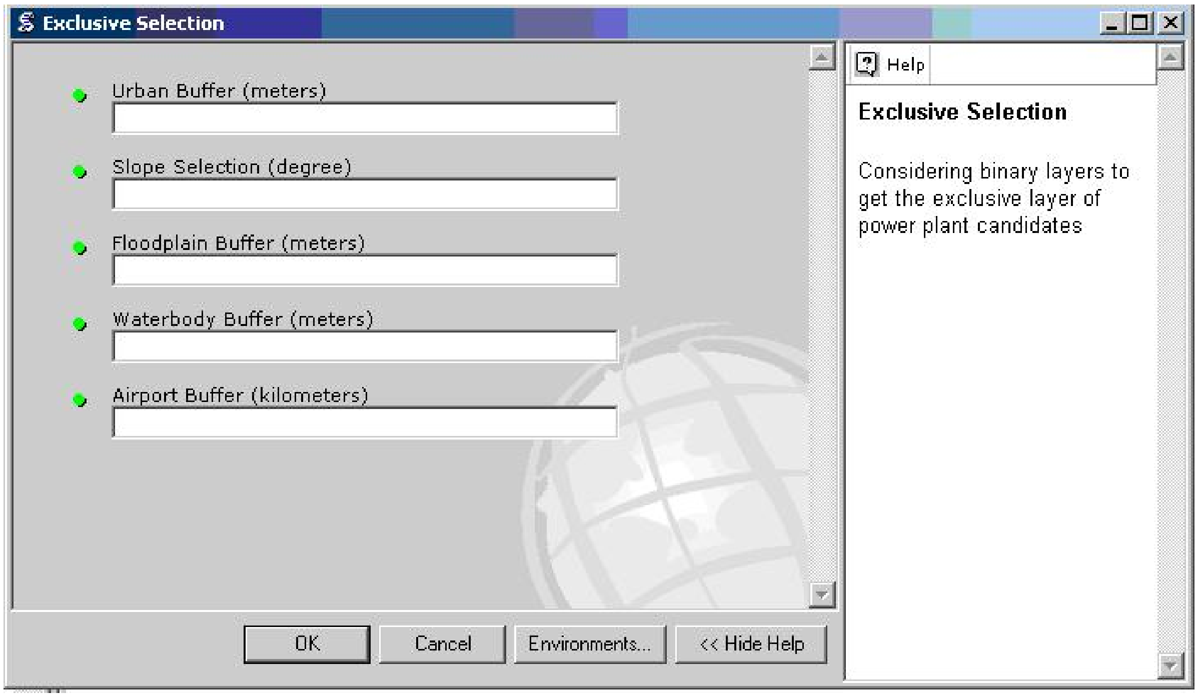


Figure 4-9 Interface of the exclusive analysis toolbox

It is this exclusionary analysis that reduces the numbers of potential biomass power plant candidates from 9760 to a relatively small number (in this example, the number shrinks to 87). In addition to accounting for power plant selection criteria this analysis also reduces the computational effort required to solve the spatial optimization models by reducing their size. The preferable suitability analysis described in the next section ranks the suitability of the remaining candidates for the construction of biomass power plants and provides some direction to the decision makers in cases where multiple solutions are obtained.

4.2.2 Implementation and Results of Preferable Suitable Analysis

There are six preferable factors, which rank the candidate areas based on their suitability considered in this case study. They are presented in table 4-4.

Table 4-4 Criteria in preferable suitability analysis

Preferable Suitability Analysis			
Factors	**Description**	**Criteria**	**Weights**
Biomass supply	Indication of high, medium, and low biomass supply	3 levels classifications	0.438
Substations	Indication of the distance to the existing substations (the closer, the better)	2,3,4,5,10km buffers	0.258
Urban areas	Indication of the distance to the urban areas (the further, the better)	1.5,2,3,5km buffers	0.152
Water supply	Indication of high, medium, and low water supply	3 levels classifications	0.082
Slope	Indication of different level of slopes (the small, the better)	5 levels classifications	0.035
Water discharge	Indication of high, medium, and low water discharge	3 levels classifications	0.035

In the preference analysis, each area is placed (by factor) into one of several buffers or classes. Each buffer or class has a preference rank relative to the factor being considered. For example, 3 classifications in the "biomass supply" factor indicate high, medium or low levels of available biomass feedstock and areas having a high, medium or low stock are assigned values 3, 2 or 1 respectively. It is obvious that it is more attractive to construct biomass power plants in areas with higher values. When these assigned values are multiplied by the corresponding weight (0.438) the resulting biomass supply contribution becomes part of the final preference layer where areas with higher numbers are more preferable than areas with lower numbers. Similarly, it is preferable to build biomass power plants in areas near to existing substations in order to reduce the electric power delivery expenses.

In order to combine the preferable factors considered in this study, a Weighted Overlay tool is applied to integrate the effects of all the preference factors and to derive the final preferable analysis result which are reported using a map that shades areas of low, medium, and high suitability. The results of the preferable analysis combined with the location allocation model solutions, showing quantitative results of minimizing biomass power generation costs, can provide the decision making supports for decision makers.

The weights associated with the factors in table 4-4 are attained using the Analytic Hierarchy Process (Ma. et al. 2005). AHP, a systematic method for comparing a list of objectives or alternatives, was introduced in section 3.2. The AHP enables the decision makers to express their qualitative judgments in a quantitative format, instead of assigning arbitrary weights to the qualitative factors.

Based on the relative importance of the factors affecting the suitability of areas in the bioenergy systems planning process, the pair-wise comparison matrix A, shown in table 4-5, was derived.

Table 4-5 Pair-wise comparison matrix A in AHP

	Biomass supply	Substations	Urban areas	Water supply	Slope	Water discharge	Weights
Bio_supply	1	3	4	5	9	9	0.438
Substations	1/3	1	3	4	7	7	0.258
Urban areas	1/4	1/3	1	3	5	5	0.152
Water supply	1/5	1/4	1/3	1	3	3	0.082
Slope	1/9	1/7	1/5	1/3	1	1	0.035
Water	1/9	1/7	1/5	1/3	1	1	0.035

The meaning of each element in the matrix is described in table 3.1 and the weights in the last column, which represent the weight ranks of the factors considered by the decision makers, are computed following the procedure described in section 3.2. For example, since the distance from the plants to the biomass supply sites was considered most important, this factor was assigned the highest weight (0.438) by the AHP. In order to evaluate the credibility of the estimated weights, the consistency ratio (C.R.) was computed using the eigenvector method proposed by Saaty in 1977. The corresponding results were obtained using the procedure described in section 3.2 and are summarized in table 4-6 below.

The computed consistency ratio, 0.039, indicates that the pair-wise matrix A is reasonable and the weights derived from A are acceptable. The scripts for computing the weights and the C.R. are presented in Appendix B.

Table 4-6 Computation results of consistency ratio

Related variables	λ_{max}							C.I.					C.R.		
Values	6.2418							0.0484					0.0390		
n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
R.I.	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

After all these weights and criteria were computed, a number of GIS screening techniques were conducted in ArcGIS® to produce a preferable layer following the procedure in the data flow diagram illustrated in figure 4-10.

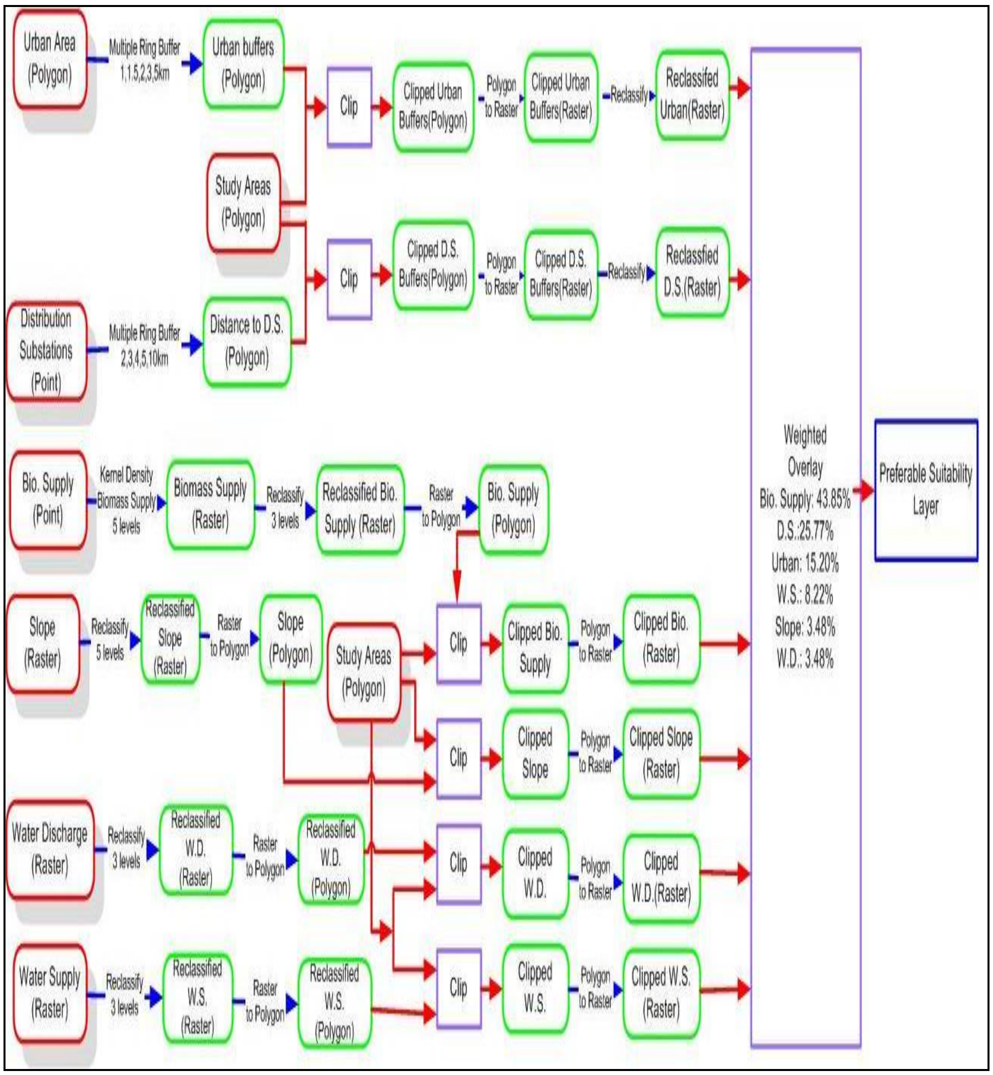


Figure 4-10 Data flow diagram (DFD) of preferable suitability analysis

In the last procedure of the DFD, Weighted overlay, an important spatial analysis tool is employed. It is a technique for applying a common measurement scale to diverse and dissimilar inputs to create an integrated analysis. Geographic problems often require the analysis of many different factors that exist in different raster layers with different value scales: distances, degrees, and so on. You can't add a raster of slope (degrees) to a raster of distance to facilities (meters) and obtain a meaningful result. Additionally, the factors may not be equally important. For example, in our study the distance to biomass supply points is more important than the distance to substations. The principal of a weighted overlay is presented in the following figure 4-11.

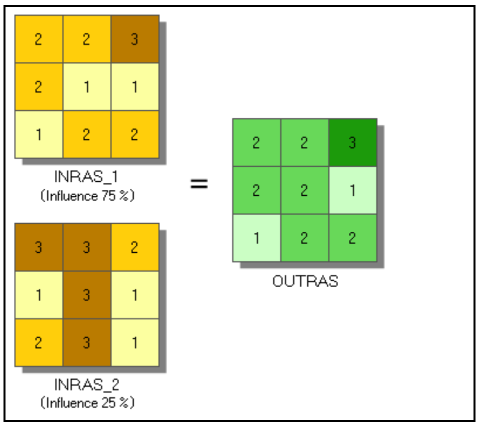


Figure 4-11 Illustration of weighted overlay

In the illustration, the two input raster are first reclassified to a common measurement scale of 1 to 3. Each raster is then assigned a percentage influence. The resulting cell values are then multiplied by their percentage influence, and the results are added together and then rounded to create the output raster. For example, consider the top left cell. The values for the two inputs become (2 * 0.75) = 1.5 and (3 * 0.25) = 0.75. The sum of 1.5 and 0.75 is 2.25 which is then rounded to 2. The preferable suitability analysis layer, obtained after all factor layers were overlaid using weighted overlay, is shown in figure 4-12.

The derived preferable suitability layer ranks the study area into four basic zones based on their preferable suitability. The filtered power plant candidate sites are scattered in each zone. If the optimal solutions from the location-allocation models are not unique or if the weighted costs corresponding to alternate optimal solutions are very close the selection of sites in the areas with high suitability take priority and the decision makers can use this analysis to make appropriate choices.

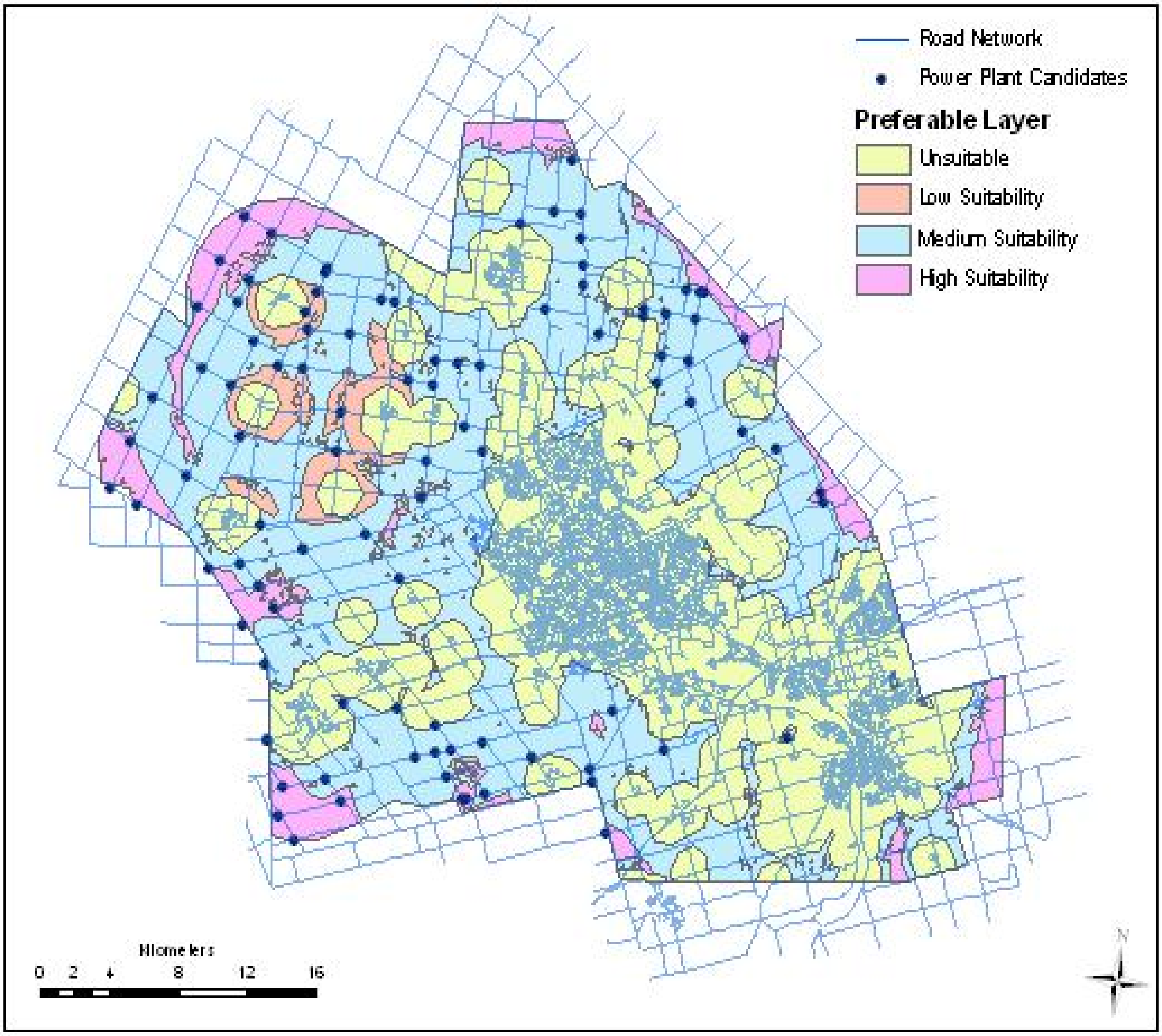


Figure 4-12 Results of the preferable suitability analysis

Power plant selection and suitability analysis are very important steps in designing bioenergy systems. On one hand, they prepare the input data for the spatial optimization models and reduce the number of variables to improve computational performance. On the other hand, these processes consider multiple factors, including environmental, public health and safety, feasibility, and community impacts in selecting the most suitable areas as candidates for the construction of biomass power plants. The methodologies, such as exclusive analysis, AHP, and preferable analysis, employed in the processes are easily performed and the decision makers do not require significant knowledge of GIS or AHP.

The following section describes how the locations of the power plants and the allocation of the biomass supplies to these plants are computed to minimize the weighted transportation costs and levelized unit cost of energy (LUCE).

4.3 Spatial Optimization Models of Bioenergy Systems

4.3.1 Optimization Problems Identification

In the previous section, a variety of factors are investigated for bioenergy systems design. In this section, the economics of designing bioenergy systems is addressed through the use of location-allocation models based on geographic variations. Firstly, a p-median problem model is proposed for minimizing the weighted transportation costs of delivering biomass feedstock from biomass supply zones to the selected power plants. Then a p-uncapacitated facility location problem (p-UFLP) model is used for minimizing the LUCE. The built-in PMP solver in ArcInfo, based on the Teitz and Bart (1968) Algorithm (TBA) and the Global Regional Interchange Algorithm (GRIA), is used to solve the p-median problem. Customized GAs, based on Alp et al. (2003), are used to obtain approximate solutions of the PMP and the p-UFLP models. These optimization models attempt to select the best power plant sites from the power plant candidates and to optimally allocate all available biomass supplies to those proximal located power plants by minimizing different costs (i.e. weighted transportation costs and LUCE). Finally, the selected power plants are connected to the existing power distribution network. The problem is depicted in figure 4-13.

In figure 4-13, power plant candidates and biomass supplies points have the identical geographic coordinates. The existing distributed substations in this area are connected by high power transmission lines. The objectives of the optimization problem are to select the best sites on which to build biomass power plants and to distribute all biomass supplies to those active power plants by optimizing the total weighted transportation costs or the LUCE. Once the active power plants are selected, these power plants are connected to the existing distributed substations to provide alternative "Green Electricity" to the local areas.

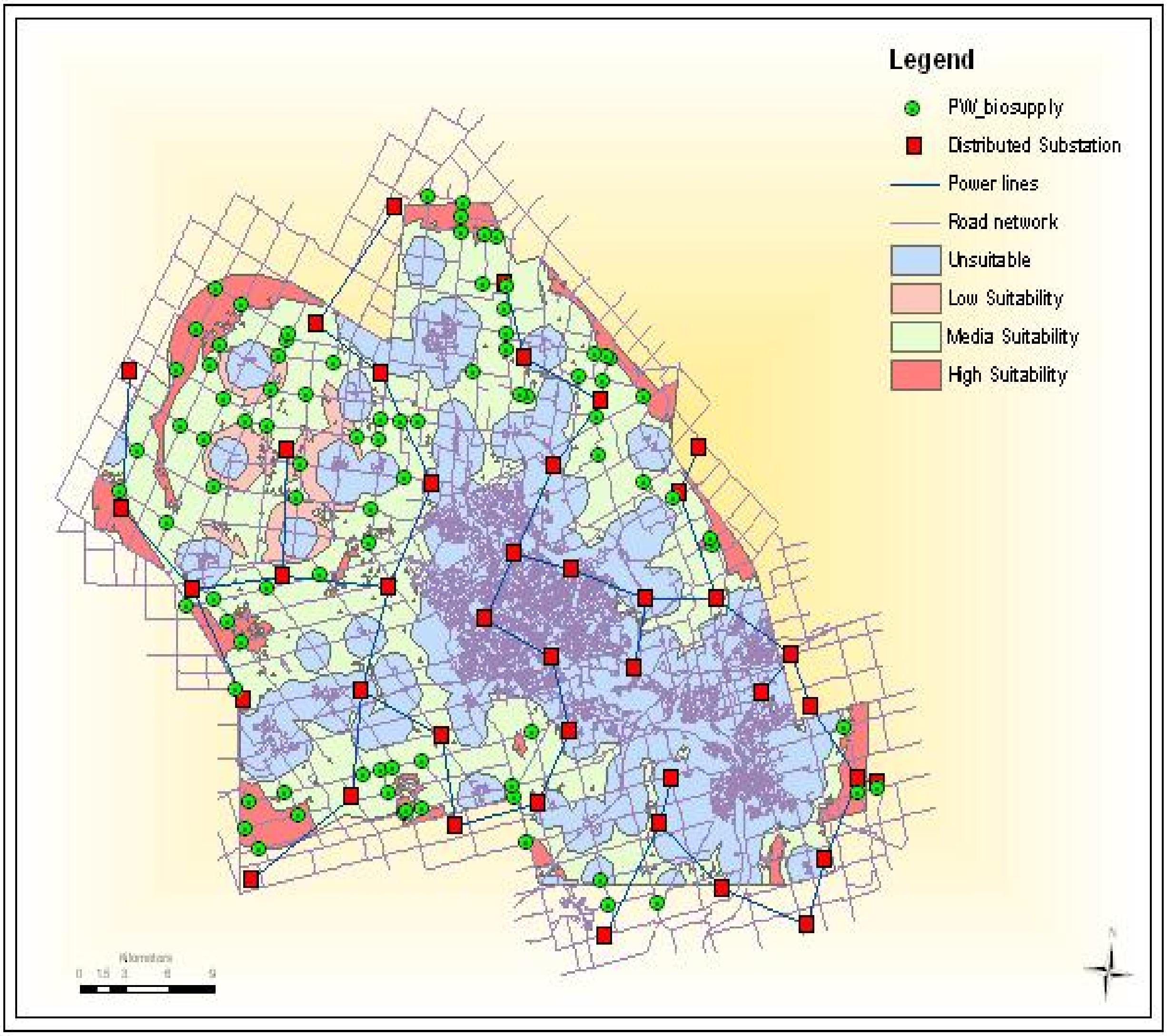


Figure 4-13 Illustration of the spatial optimization problem

Since the actual spatial data for the distributed power system in the region were not accessible, a distribution network was generated by applying the Minimum Spanning Tree (MST) algorithm and using the corresponding tree nodes to represent the locations of distributed substations in the study area. The procedure for creating the distribution network involves the following steps (detailed scripts are presented in Appendix B).

1) Randomly generate a specified number of points in the study area;
2) Use the kruskal MST algorithm (Minieka 1978, Brassard and Bratley, 1988) in MATLAB to find the solutions of the minimum spanning tree by connecting the points generated in the first step;
3) Use ArcGIS to create a distribution network representing the distributed substations and power lines using the solutions derived from step 2.

In the location-allocation models, two types of distances, Euclidean distance and shortest paths in the networks are applied and compared. Euclidean distance can be easily computed from the following equation:

$$D_{Euc} = \sqrt{(X_2^2 - X_1^2)^2 + (Y_2^2 - Y_1^2)^2} \tag{16}$$

where, (X_1, Y_1) and (X_2, Y_2) are the coordinates of two points.

Finding the shortest or least-cost path in a network connecting to points is more complicated. One approach to finding the least-cost path between an origin and a destination is to examine all possible paths between them and to choose one path with the least cost. However, computational consideration makes it impractical to examine all possible paths between two points since in many networks there are literally hundreds of thousands of possible paths between an origin and a destination. Therefore Dijkstra’s algorithm (Dijkstra, 1959), one of the simplest greedy path finding algorithms (ArcInfo Help, 2006), is employed in ArcGIS to find an approximate shortest path.

In the following two subsections, the implementation and results of the optimizations are addressed.

4.3.2 Total Weighted Transportation Costs Minimization

Since the setup cost of building the facilities and equipping a facility in the study region is assumed to be independent of their location when a certain conversion technology is selected, only the costs of delivering biomass feedstock from the fields to the active power plants are considered in this thesis. Different scenarios for locating of power plants and allocating biomass supplies affect the main costs of biomass power generation. Therefore, a PMP formulation is applied to model this particular discrete location problem. Expressions (17) to (21) formulate this problem.

$$\text{Minimize } \mathrm{T}_{\text{costs}} = \sum_{i=1}^{n}\sum_{j=1}^{n} \alpha c_{\mathrm{i}} d_{ij} x_{ij} \tag{17}$$

subject to

$$\sum_{j=1}^{n} x_{ij} = 1, \forall i \tag{18}$$

$$\sum_{j=1}^{n} y_j = p \tag{19}$$

$$x_{ij} \le y_j, \forall i, j \tag{20}$$

$$x_{ij} \in \{0,1\} \text{ and } y_j \in \{0,1\} \tag{21}$$

where, in equation (18), n is the number of power plant candidates, which is the same as the number of biomass supply points, α is the average biomass delivery price (\$/ton-km), c_i is the biomass supply in location i, d_{ij} is the transportation distance between location i and location j, x_{ij} is the decision variable representing the decision to allocate available biomass between supply i and power plant candidate j, y_j represents whether candidate site j is selected as an active power plant site or not. Constraints (18) through (21) have the same interpretation as in constraints (6) through (9).

In ArcInfo, there are two algorithms used for solving the PMP (i.e. TBA and GRIA). TBA is a robust heuristic used for solving location-allocation problems. Even though it is not guaranteed to find optimal solutions, it does so in many instances. TBA will usually find a very good solution referred to as a ‘local optimum that is close to optimal.’ However, there is no hard and fast rule to determine how close TBA solutions are to optimal (ArcInfo Help, 2006). Teitz and Bart (1968) developed the first heuristic for the p-median problem. This heuristic was based on the interchange or substitution process that was developed by Shin Lin (1965) for the Travelling Salesman Problem. Essentially, the process starts with a pattern or configuration of p locations. Then the process begins by selecting a candidate (but unused) site and considers swapping this candidate for each of the current p-facility locations. If any swap is encountered that improves weighted distance, then the best of those possible p swaps is made. The process then continues by selecting another candidate site and testing swaps. When no swap between candidate and a facility location, which can improve the objective, exists, the heuristic stops. The GRIA is a relatively new heuristic used for solving location-allocation problems. It begins with a 'starting solution', or 'seed', of m candidates. The algorithm then goes through a global phase and a regional phase of candidate substitutions to arrive at a local optimum. In the global phase, a solution site is selected that makes the least increase in the total weighted distance once it is removed from the solution. It is replaced with the unselected candidate that decreases the total weighted distance the most. These substitutions are repeated until no further reduction in the total weighted distance can be achieved in this manner. The regional phase involves looking at the candidates allocated to each site. If a site can be replaced by one of these candidates to reduce the total weighted distance, the substitution is made. These substitutions are repeated until there is no further reduction in the total weighted distance. The degree of optimality obtained with GRIA is, like TBA, dependant on the data and the size of the problem.

Many Genetic Algorithm approaches are proposed for solving the PMP. In this thesis, a genetic algorithm based on the study of ALP et al. in 2003 has been developed for solving the PMP model. This algorithm was compared to the commercial TBA and GRIA algorithms using the same dataset and parameters from the PMP model. It produced acceptable solution results for our particular PMP models. The GA is described in details as follow:

♦ **Encoding scheme:**

Instead of using binary encoding, this algorithm employs an integer string representation. Each solution is encoded as an integer string of length p, where each gene of the chromosome indicates the index of the facility selected as an active power plant. For instance, the string [12, 23, 35, and 56] represents a candidate solution for the 4-median problem where sites 12, 23, 35 and 56 are selected as active power plant sites. This encoding scheme ensures that constraints (19) are always satisfied.

- **Fitness function computation:**

The fitness function is directly related to objective function (17). More specifically, the fitness of an individual is given by the expression (22) (Deminguez and Munoz, 2005).

$$f(s) = \sum_{i=1}^{n} \alpha c_i (\min_{1 \le j \le p} \{d(i, s_j)\}) \tag{22}$$

where, s is an individual solution, n is the number of supply points, α is the average biomass delivery price ($/dry-ton·km), c_i is the biomass supply in location i (dry-ton), and $d(i, s_j)$ is the distance between supply point i and site represented by the j^{th} component of s. This fitness value is easily computed using the problem data. The calculation assumes that every demand point would be allocated to the closest open facility. This ensures that constraints (18) and (20) are always satisfied. Hence, the selection of the fitness function and the encoding satisfy all constraints and no additional effort is needed in the implementation of the algorithm to enforce the constraint set.

- **Population size, initial population, and parents selection**

The population size should ensure that:

(1) All possible genes of the approximate solution must be contained in the initial population. The initial gene pool greatly affects whether the best solution can be reached in the algorithm.

(2) The population size should be proportional to the problem size. A larger problem should correspond to a larger population size.

By considering these two properties of the population size, ALP et al. give the following expression to determine the population size of the algorithm.

$$PopSize = \max\left\{2, \left\lceil \frac{n}{100} \cdot \frac{\ln(S)}{d} \right\rceil\right\} d \qquad (23)$$

where, PopSize denotes the population size, n is the number of supply points, $S = C\binom{n}{p}$ is the number of all possible solutions to the corresponding problem p is the number of active power plants, $d = \left\lceil \frac{n}{p} \right\rceil$ is the minimum integer number of elements required to represent each gene in the initial population. By applying this population size determination scheme, every gene appears at least twice in the initial population and the size increases with the problem size.

The initial population contains all genes of the problem and the frequency of the appearance of genes in the initial population is initially nearly constant. Suppose that the population size kd is computed by (23) for some constant k. For the first set of $\frac{n}{p}$ members, genes 1, 2,…, p are assigned to the first member, genes $p+1, p+2, \ldots\ldots, 2p$ are assigned to the second member, and so on. For the second set of $\frac{n}{p}$ members, similar assignments are made, but an increment of two in the sequences are used. For instance, for a problem with $(n, p, k) = (12,4,2)$, the initial population is set as:

$$\begin{bmatrix} 1 & 2 & 3 & 4 \\ 5 & 6 & 7 & 8 \\ 9 & 10 & 11 & 12 \\ 1 & 3 & 5 & 7 \\ 9 & 11 & 2 & 4 \\ 6 & 8 & 10 & 12 \end{bmatrix}$$

If $\frac{n}{p}$ is not an integer number, random genes are allocated to fill the empty places in the initial population matrix.

After the initial population is computed, the next step randomly selects parents form this population and manipulates their genes to produce offspring. The process is described in what follows.

- **Offspring generation, Mutation, and replacement**

The GA employs a greedy algorithm to generate offspring for the next generation. Firstly, the offspring generator forms the union of the genes in the two parents (called the draft member) and classifies its genes into "fixed genes" which are in both parents and "free genes" which are all others. Then the generator calculates the fitness value of the draft member f_{draft} , and removes whichever free gene results in the least increase in the fitness function value compared with f_{draft} . This process is repeated until the length of the draft member equals p and the chromosome (called candidate member) derived is the child of the parents for the following generation. In this GA, no mutation is used since all the genes are present in the initial population. It should be noted that ALP et al. claim that the mutation operator does not improve the performance of their algorithm.

In order to keep a good average fitness value for the population, a replacement operator is used to discard the current child if it is identical to another member in the current population or if its fitness value is worse than the chromosome with the worst fitness in the current population. The algorithm is terminated if the generated children have not made an improvement to the fitness after a given number of successive iterations determined by $\left| n\sqrt{p} \right|$ $(n > 2p)$ or $\left| n\sqrt{n-p} \right|$ $(n \le 2p)$.

- **Results**

The optimization results are obtained by applying TBA and GA with the spatial data derived from the previous sections. Maps are used to illustrate some of these results with different p values and distance measurements, i.e. Euclidean distance and shortest path distance. Figures 4-14, 4-15 and 4-16, show the results where Euclidean distance and the shortest path route distance are used respectively, the power plants are selected among all the candidates with pre-determined p values (i.e. 1, 4 and 15), and the available biomass in the area is allocated to the selected power plants so as to minimize the weighted transportation costs. Both the TBA algorithm and the proposed GA converge to the same approximate solutions but the solutions are different when different distance representations are employed.

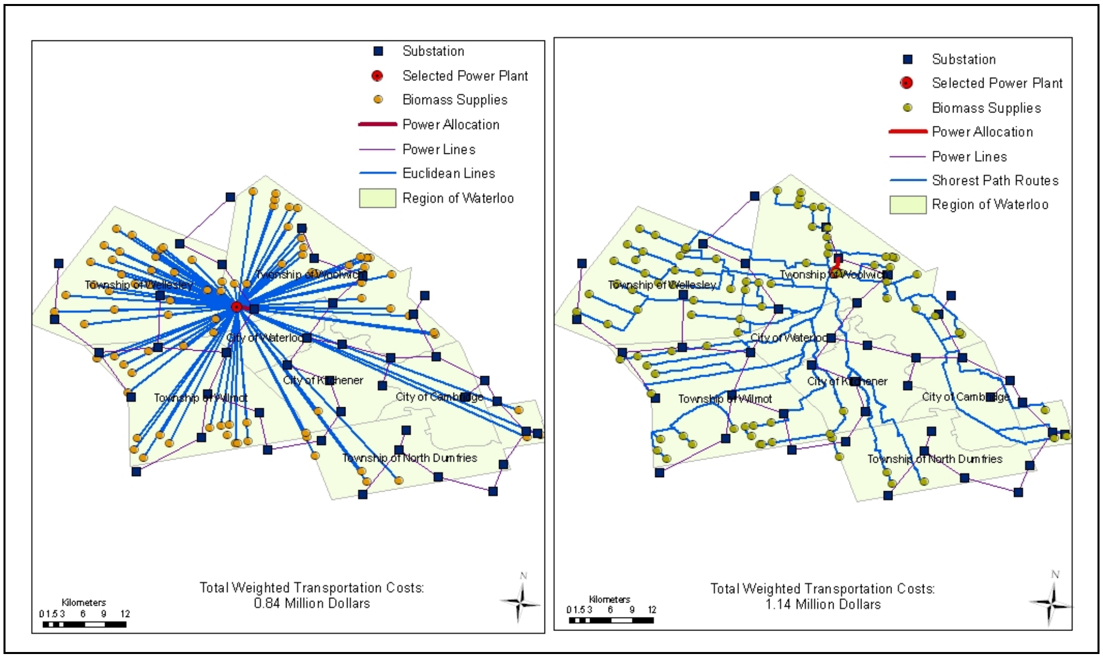


Figure 4-14 PMP solutions with Euclidean distances and shortest distances n **=87,** p **=1**

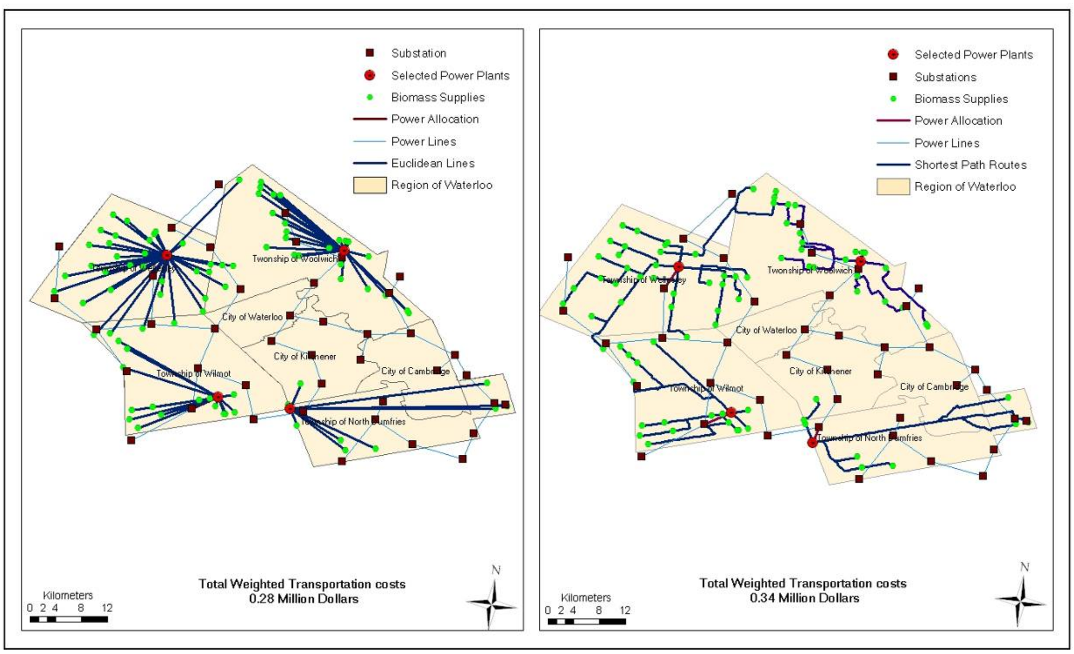


Figure 4-15 PMP solutions with Euclidean distances and shortest distances n **=87,** p **=4**

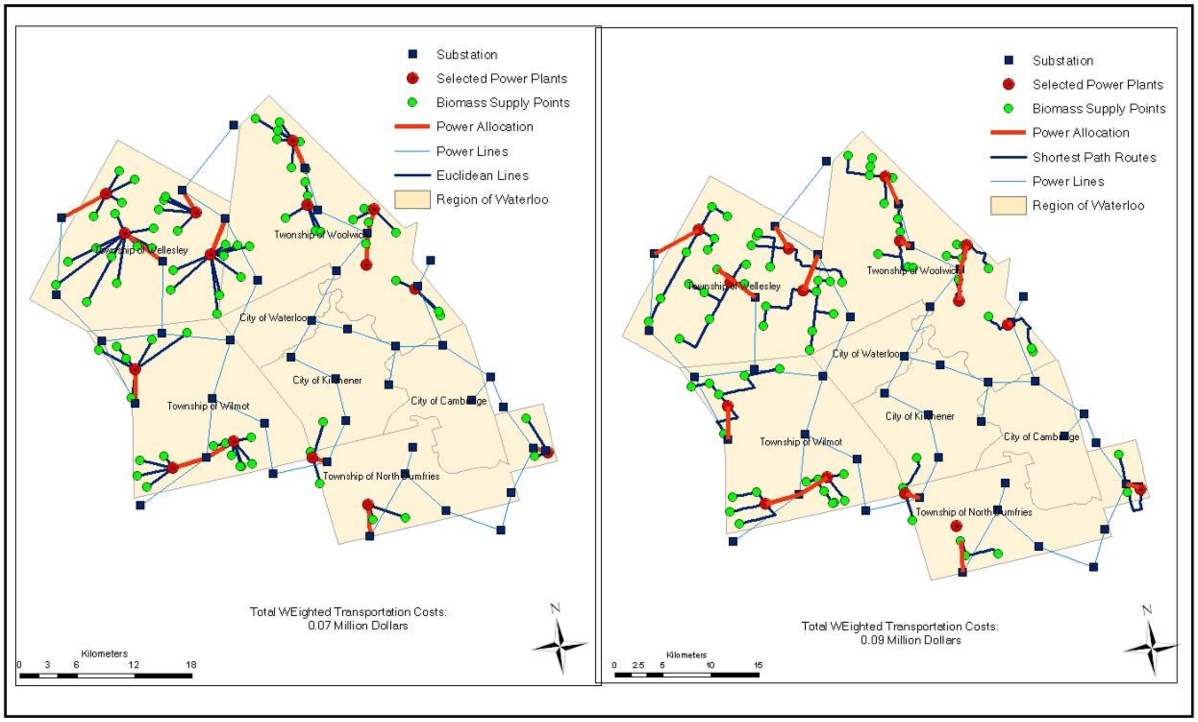


Figure 4-16 PMP solutions with Euclidean distances and shortest distances, n=87, p=15

Figures 4-17 through 4-19 present statistical information associated with the solution of the PMP models for different values of p using the proposed methods. As expected when the number of selected power plants p is increased, both the average transportation distances and the furthest distance to be traveled initially decrease gradually. However for values of p larger than 13, the average transportation distance changes very little (see figure 4-17). The same trends are observed in the weighted distance comparison (see figure 4-18) and weighted transportation cost comparison in figure 4-19 with various p values. This indicates that as more power plants are constructed, the transportation costs become less dominant as the total capital costs increase.

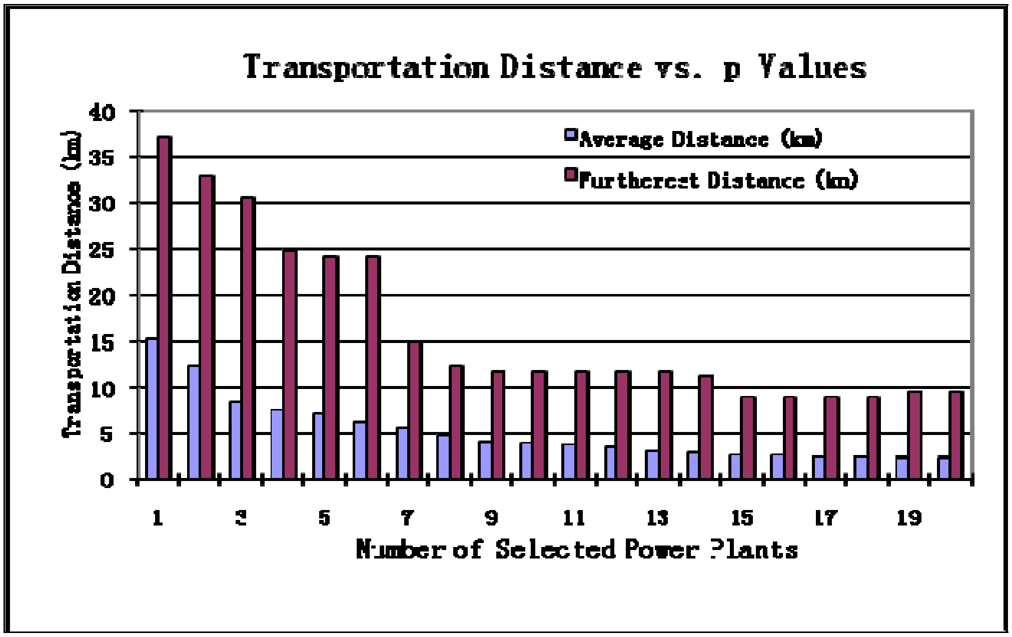


Figure 4-17 Average and furthest transportation with different p values

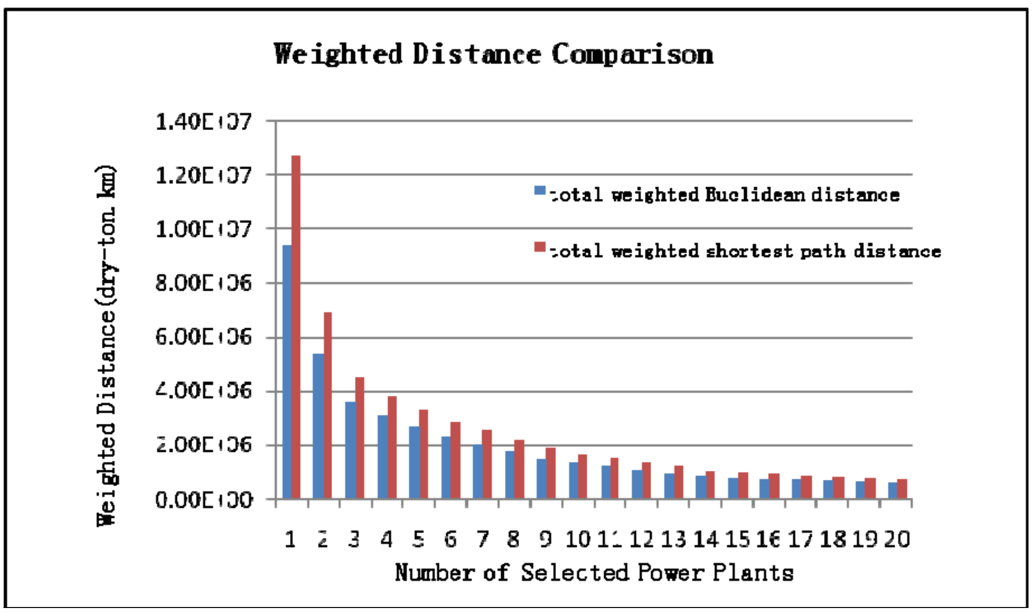


Figure 4-18 Comparison of weighted distance with different p values

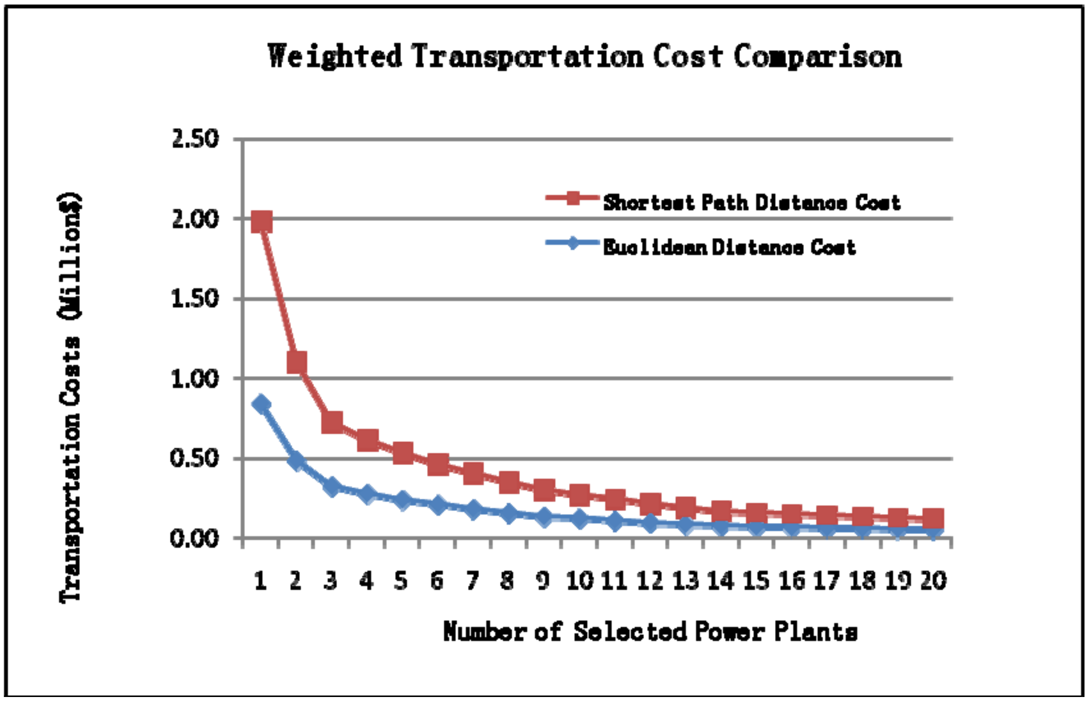


Figure 4-19 Comparison of transportation costs between different distances

Figure 4-19 shows the weighted transportation costs using the shortest network path distances and Euclidean distances for various values of p. Although both decrease with increasing values of p, the shortest network path distances are, as expected, always greater than the Euclidean distances for each value of p. In both cases, the transportation cost reaches zero when p equals 87 since each biomass supply will be assigned to a power plant sharing the same physical location with it. As p values increase, the installation and capital costs of constructing power plants will dominate the total energy cost and the costs of delivering biomass feedstock have fewer effects on the total energy generation price.

In order to evaluate the overall power generation price in designing optimal bioenergy systems, an uncapacitated facility location problem model for minimize the levelized unit cost of energy is introduced in the following subsection.

4.3.3 Levelized Unit Cost of Energy (LUCE) Minimization

One way of representing the overall cost of electricity generation is by way of the levelized unit cost of energy (LUCE). LUCE is comprised of capital costs, transportation costs, operation and maintenance costs, and fuel costs (Venema, 2004). Use of a LUCE calculation can assist decision makers in comparing various supply options- e.g. to compare the selections of energy conversion technologies (combustion, co-combustion, gasification, anaerobic digestion, or pyrolysis), and sources (coal, biomass, wind, nuclear etc.). The location-allocation model proposed in this thesis attempts to minimize the LUCE of generating electricity through biomass by using different bioenergy conversion technologies. It is assumed that two main bioenergy conversion technologies, Direct Combustion (DC) and Integrated Gasification/Combined Cycle (IGCC) which have different conversion efficiencies, are selected for comparison in this study. The general bioenergy spatial design problem is then to strike the optimum balance between transportation costs and capital costs realizing that many geographically-dispersed small plants will decrease transportation costs but incur relatively higher capital costs. In this thesis, a p-UFLP model is used to compare by considering both transportation costs and capital costs to minimize the levelized unit cost of energy through converting biomass to electric power.

With the spatial data from the sections on biomass assessment and power plant candidate selection, a p-UFLP based location-allocation model is specifically formulated to minimize the LUCE ($/kWh) as follows.

$$\text{Minimize LUCE} = \frac{1}{\sum_{i=1}^{N} \beta c_i} \left(\sum_{i=1}^{N} \sum_{j=1}^{N} \alpha c_{\mathrm{i}} d_{ij} x_{ij} + \sum_{j=1}^{N} (IC_j cap_j y_j) + C_x \right) \tag{24}$$

subject to

$$\sum_{j=1}^{N} x_{ij} = 1, \forall i \tag{25}$$

$$\sum_{j=1}^{N} y_j = p \tag{26}$$

$$x_{ij} \le y_j, \forall i, j \tag{27}$$

$$IC_j = \left(\sum_{i=1}^{N} \beta c_j x_{ij}\right) / (8760 lf), \qquad \forall j \tag{28}$$

$$y_j \in \{0,1\}, x_{ij} \in \{0,1\} \tag{29}$$

where N is the number of biomass supply points which is also the number of candidate power plant locations, α is the unit biomass feedstock transportation cost ($/dry-ton/km), c_i is the quantity of biomass supply in the location i (dry-tons), β is the conversion coefficient between energy and biomass potential (kWh/dry-ton), IC_j is the installed capacity of power plant j (kW), lf is the load factor representing the percentage of the electricity generated from biomass over the designed capacity of the power plant, cap_j is the annualized capital and installation cost ($/kW) at location j which varies in different locations depending on the bioenergy conversion technologies (i.e. direct combustion or gasification) applied and the capacity of power plant j, C_x is the total cost ($) of purchasing biomass fuel and operation and maintenance (O&M) for the selected biomass power plants, which is assumed to be a constant value in this study, x_{ij} is the decision variable representing the allocation decisions of available biomass between supply i and power plant candidate j, y_j represents whether candidate site j is selected as an active power plant site ($j = 1$) or not ($j = 0$). The parameters used in this model are listed in table 4-7 (Layzell et al., (2006), IEA Bioenergy, (2007), Khrushch et al. (1999)).

Table 4-7 Parameter values used in the p-UFLP model

Conversion Technology	Capacity IC (MW)	Conversion Efficiency β	Capital Cost cap ($/kW)	Load Factor
Direct Combustion	5-25	30%-35%	3000-5000	0.6 or 0.9
Integrated Gasification Combined Cycles(IGCC)	10-30	40%-55%	2500-5500	0.6 or 0.9

Energy conversion coefficient			
Energy conversion	**Description**	**Number**	**Units**
Electrical Energy	Joules to electrical energy	3.6	MJ/kWh
Energy content of Crops(dry)	Energy Content of Crops	18	GJ/dry-ton
Trucking Transportation Cost α	Trucking Transportation Cost	0.125	$/dry-ton/km
Biomass Cost (crop residues)	Bio-fuel Cost	3	$/GJ
O&M Cost	Operation and Maintenance cost	16	$/MWh
Policy Incentives	Federal Renewable Power Production Incentive	10	$/MWh

The parameter values from table 4-7 were used to define the objective function (24) of the p-UFLP model in a MATLAB coded genetic algorithm solution approach. For different model settings, such as conversion technologies and load factors, the data from the following table were used in these genetic algorithms. “High”, “medium” and “low” in the table represent the relative capacity of the biomass power plants. As indicated the relative capital cost ($/kW) of building higher capacity power plants is lower than building small power plants.

Table 4-8 Data selection for different conversion technologies

Conversion Technology	Load Factor	Power Plant Capacities (MW)			Capital Costs ($/kW)			Conversion Efficiency
IGCC	0.6	high	Medium	low	high	Medium	low	0.55
	0.9	>30	10-30	<10	2500	4000	5500	
Direct Combustion	0.6	high	Medium	low	high	Medium	low	0.35
	0.9	>25	5-30	<25	3000	4000	5000	

The p-UFLP can be decomposed into two interdependent sub-problems – the location sub-problem and the allocation sub-problem (Al-Sultan and Al-Fawzan, 1999). The location sub-problem selects the facilities to be established (i.e., corresponding to $y_j = 1$) and the allocation sub-problem determines the demand distribution pattern for those established facilities (i.e., corresponding to $x_{ij} = 1$). In this thesis, it is assumed that the operation and maintenance cost is fixed for each power plant candidate. However, the capital costs vary with respect to the conversion technology selected and the power plant capacity. Generally, a larger power plant has higher conversion efficiency and lower capital and installation cost ($/kW) and vice versa.

When a p-UFLP model is solved using genetic algorithms, the fitness of a chromosome in the population can be calculated by evaluating the two components of the objective function (i.e. the weighted transportation cost and the fixed facility cost). The fitness of any particular solution (chromosome) is given by the following expression which was obtained by combining the ideas of (Jaramillo et al., 2002) and (Dominguez and Munoz, 2005):

$$f(s) = \frac{1}{\sum_{i=1}^{N} \beta c_i} \left(\sum_{i=1}^{N} \alpha c_i \left(\min_{1 \le j \le p} \{ d(i, s_j) \} \right) + \sum_{j=1}^{p} f_{s_j} \right) \tag{30}$$

where s is an individual feasible solution (a chromosome) in the current generation and s_j is the j^{th} gene in this chromosome. c_i is the biomass supply at location i, f_{s_j} is the fixed cost of establishing a plant at site s_j, α is the unit biomass feedstock transportation cost ($/dry-ton/km), β is the conversion coefficient between energy and biomass potential (kWh/dry-ton), and $d(i, s_j)$ is the distance between supply point i and site represented by the j^{th} component of s.

The procedures for solving this p-UFLP using a GA are different from those used in solving the PMP model. The steps of the overall algorithm are stated in what follows, where the number of power plant candidates is N, the number of power plants is p, and the population size is $PopSize$:

1. Generate a initial population $(PopSize \times p)$ and calculate the allocation solution for each individual chromosome in this population with respect to minimizing the weighted transportation costs;
2. With the allocation solutions calculated from step 1, compute the bio-power capacities (MW) of the selected power plants for the population $(PopSize \times p)$. The capacity in each selected power plant can be calculated by summing all the biomass supplies (dry-ton) according to the allocation solution. Based on the power plant capacities, assign the capital and installation costs for the power plants and calculate the fitness value for each individual based on equation (30);
3. Repeat while $MaxIter \le m, where\, \mathrm{m} = \begin{cases} \mathrm{n}\sqrt{\mathrm{p}}, \mathrm{n} > 2\mathrm{p} \\ \mathrm{n}\sqrt{\mathrm{n - p}}, \mathrm{n} \le 2\mathrm{p} \end{cases}$

   3.1 calculate the best and worst fitness values in the current population;

   3.2 select parents from the current population using random selection;

3.3 generate a new child from the parents selected in 3.2 and compute the corresponding UFLP fitness value for the new child;

3.4 if the child is not identical to any other chromosomes in the current generation, replace the chromosome having the worst fitness value in the current population with the child if its fitness is better than the worst, otherwise return;

3.5 find the best individual in the new population. If it is same as the best individual in the previous generation, set MaxIter=MaxIter+1, otherwise, set MaxIter=MaxIter;

3.6 output the best individual as the sub-problem solution in the current generation, repeat 3.1 -3.6 until MaxIter is greater than m.

4. Select the best member from the population as the final location sub-problem solution;
5. Based on the location sub-problem solution from step 4, calculate the corresponding allocation solutions and the LUCE considering operation and maintenance and fuel costs.

The computational efforts of solving the p-UFLP model are much heavier than those required to solve the PMP model. It takes much longer CPU time to get approximate optimal solution than that required for solving the PMP model of the same size (i.e. N and p are the same). This complexity of the computation is basically due to the introduction of the varied capital costs. The genetic algorithm runs for each pre-determined p value with different conversion technologies, conversion efficiencies, and load factors. The corresponding results are obtained and illustrated in the figures that follow.

Figures 4-20 through 4-23 illustrate the location of the biomass power plants and the allocation of the biomass feedstock to these power plants. In these example solutions, p is fixed to 11, either Integrated Gasification/Combined Cycle (IGCC) or Direct Combustion (DC) conversion technologies are selected for biomass conversion and load factors of either 0.6 or 0.9 are used. The LUCE for those combinations are summarized in table 4-9.

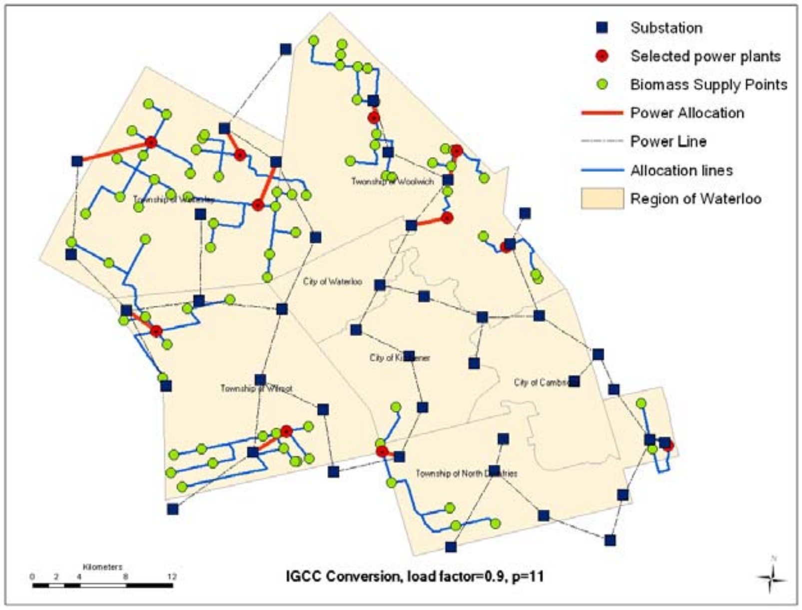


Figure 4-20 Location-Allocation solution with Integrated Gasification/Combined Cycle (IGCC) conversion, load factor=0.9, p=11

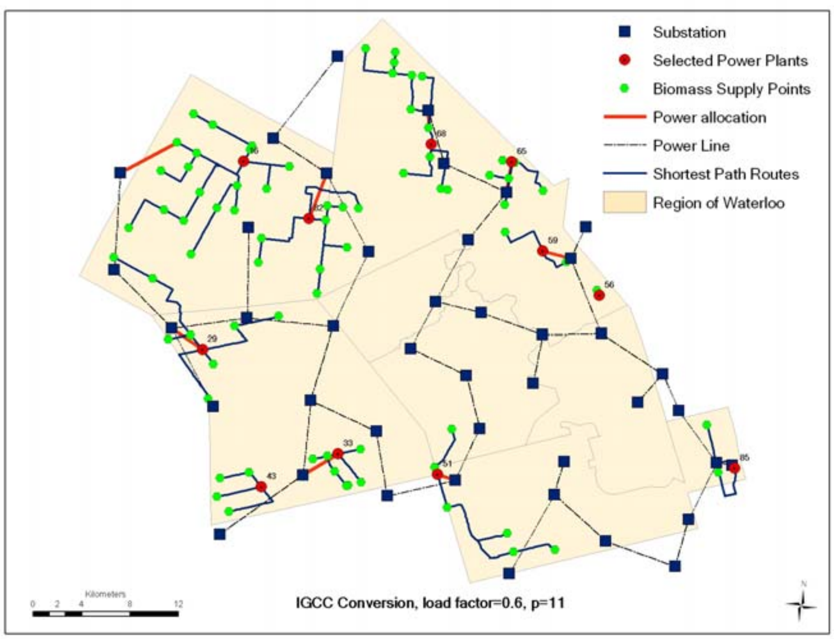


Figure 4-21 Location-Allocation solution with Gasification/Combined Cycle IGCC conversion, load factor=0.6, p=11

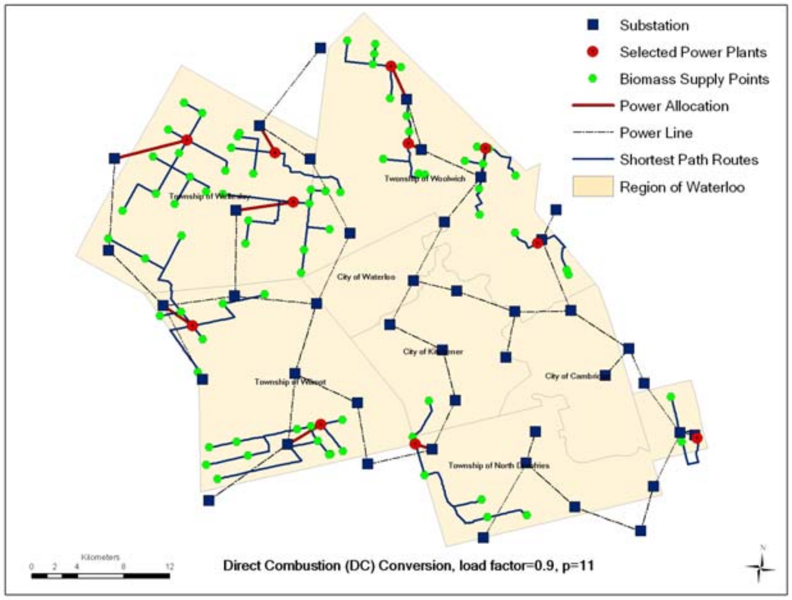


Figure 4-22 Location-Allocation solution with Direct Combustion (DC) conversion, load factor=0.9, p=11

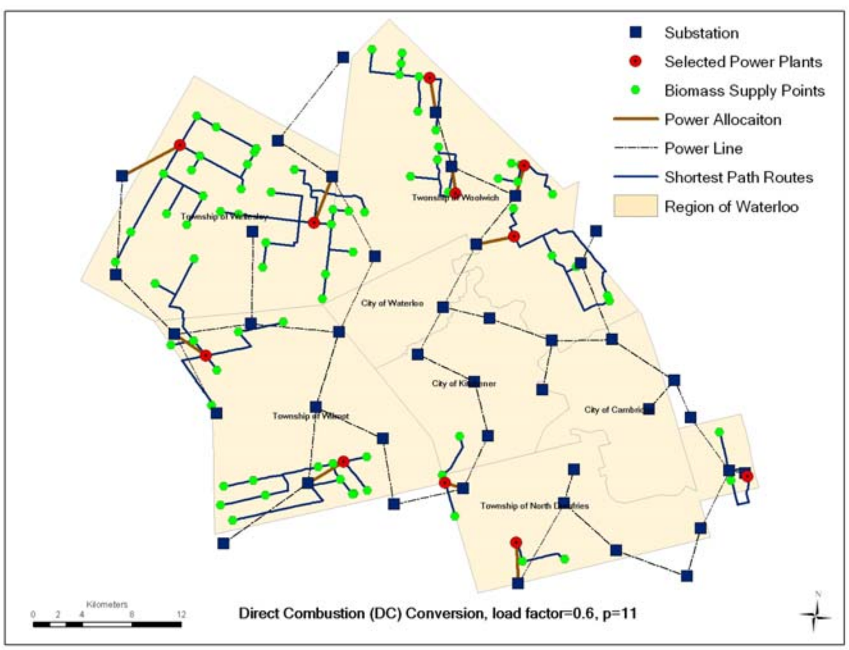


Figure 4-23 Location-Allocation solution with Direct Combustion (DC) conversion, load factor=0.6, and p=11

It is apparent that the IGCC conversion technology has lower LUCE costs than direct combustion for the same load factors. Although IGCC has a 10% higher conversion expense (5500$/kW) than DC (5000$/kW) when the capacity of the plant is small, IGCC conversion has a much higher conversion efficiency (0.55) than direct combustion (0.35). As well, the p-UFLP model solutions have lower LUCE costs for higher load factors. The explanation for this is that the biomass power plants with high load factors convert a higher percentage of bioenergy to electric power and this causes the capital, maintenance and operation cost to be relatively low, therefore, resulting in lower LUCE costs.

Table 4-9 Summary of a example p-UFLP solution with p=11

Conversion Technology	Load Factor	LUCE Cost ($/kWh)
IGCC	0.6	0.4360
	0.9	0.2411
Direct Combustion	0.6	0.5008
	0.9	0.2580

By computing the solutions of the UFLP models when different p values are specified, the optimal number of biomass power plants (i.e. the value of p corresponding to the lowest LUCE cost) can be found along with the corresponding optimal allocation solution. Figures 4-24 through 4-27 plot the LUCE as a function of the number, p, of power plants to be constructed for both IGCC and DC conversion technologies and load factors of 0.6 and 0.9. Based on these results, the optimal numbers of active power plants corresponding to the minimum LUCE are summarized in table 4-10.

Table 4-10 LUCE costs of optimal number of power plants with different parameters

Conversion Technology	Load Factor	Optimal Number of Selected Power Plants	LUCE Cost ($/kWh)
IGCC	0.6	9	0.4282
	0.9	11	0.2411
Direct Combustion	0.6	15	0.4925
	0.9	17	0.2518

Although Figures 4-24 through 4-27 exhibit similar trends, the LUCE in each situation is quite different. The costs initially decrease sharply as the number of plants is increased but this change becomes much more gradual for larger values of p as the increase in capital, operation and maintenance costs start offsetting the reduced transportation costs. These figures also show that a higher load factor yields a lower LUCE and vice versa.

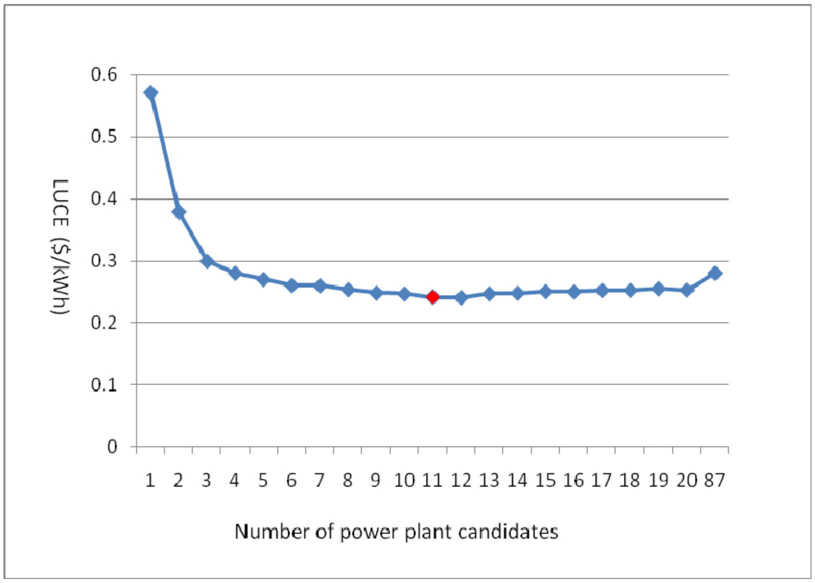


Figure 4-24 p-UFLP model solutions, Gasification/Combined Cycle (IGCC) conversion, load factor=0.9, efficacy= 0.55

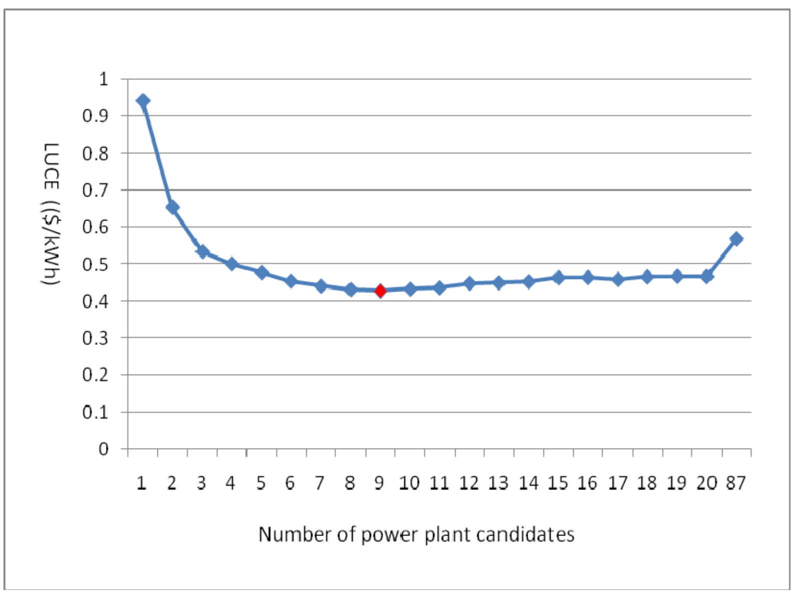


Figure 4-25 p-UFLP model solutions, Gasification/Combined Cycle (IGCC) conversion, load factor=0.6, efficacy= 0.55

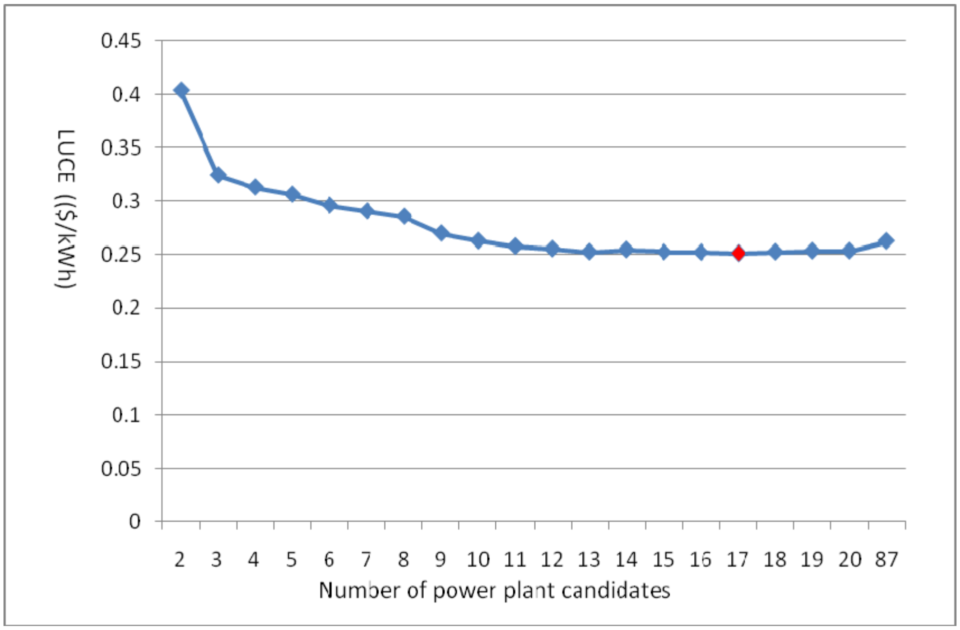


Figure 4-26 p-UFLP model solutions, Direct Combustion (DC) conversion, load factor=0.9, efficacy: 0.35

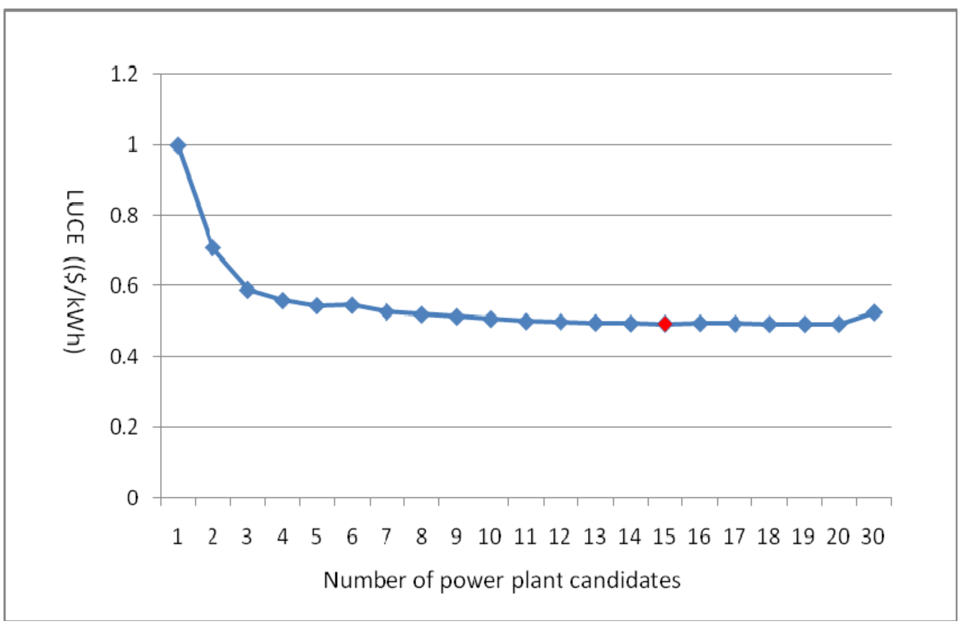


Figure 4-27 p-UFLP model solutions, Direct Combustion (DC) conversion, load factor=0.6, efficacy: 0.35

The weighted transportation costs keep on decreasing and will reach zero when p equals N. On the other hand, the capital costs of constructing these selected power plants increase because the capacities of the power plants decrease and power plants with larger capacities have lower capital costs per kW. These relationships are illustrated in figures 4-28 through 4-30 for DC conversion with load factor 0.6 and the solutions with different parameters are presented in Appendix C. Similar results will be achieved with different conversion technologies and load factors.

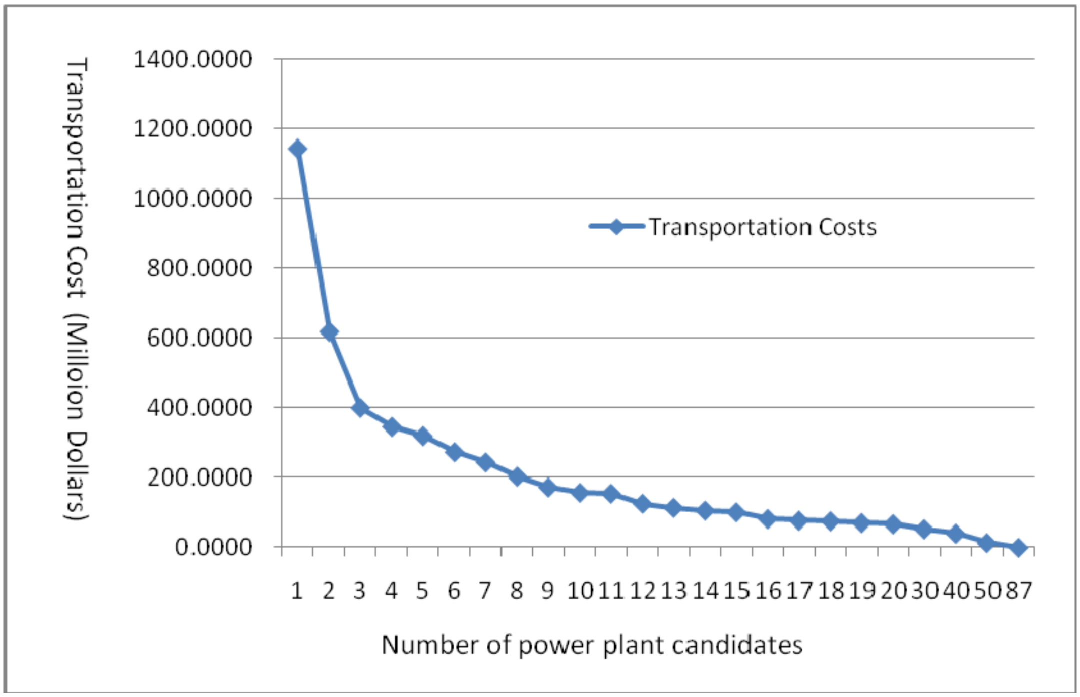


Figure 4-28 Transportation costs with different p values, Direct Combustion, load factor=0.6

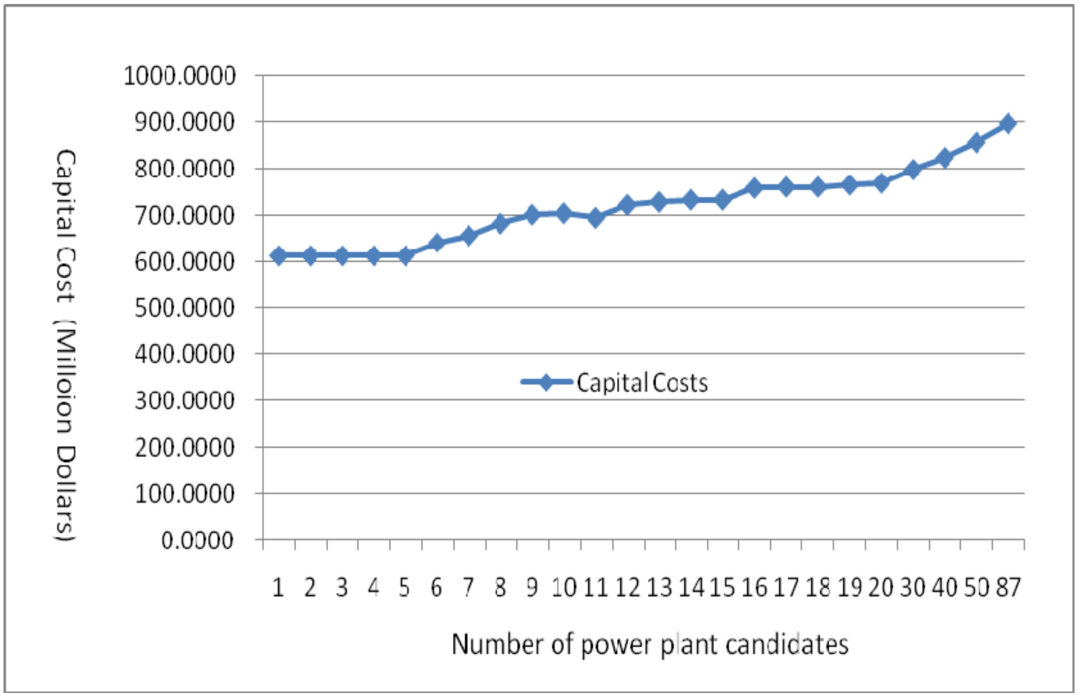


Figure 4-29 Capital costs with different p values, Direct Combustion, load factor=0.6

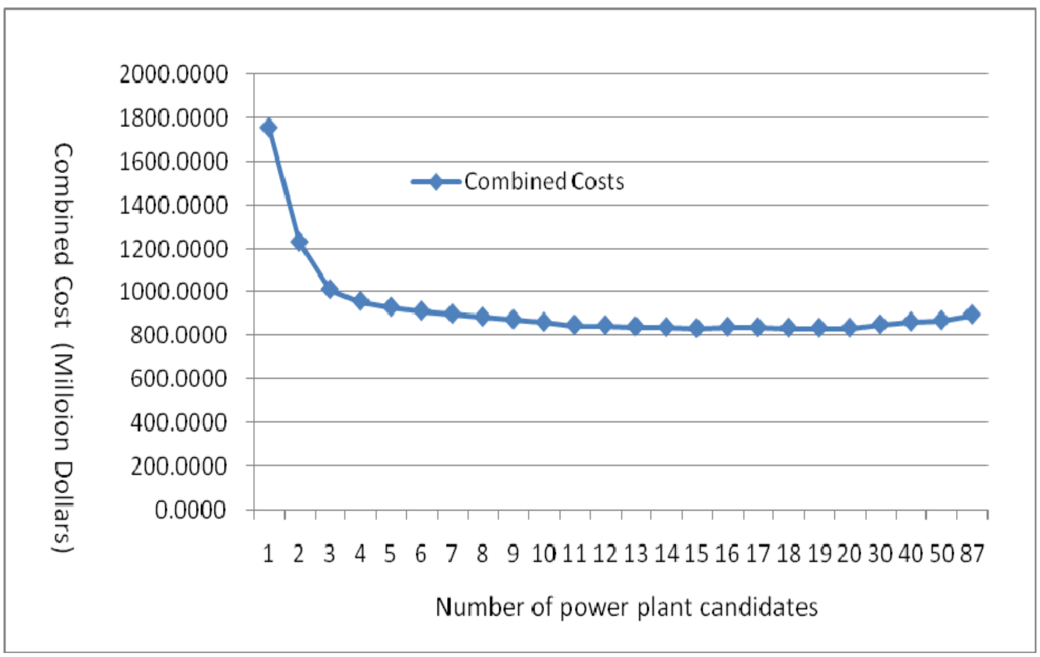


Figure 4-30 Combined costs (sum of transportation costs and capital costs) with different p values, Direction Combustion, load factor=0.6

The results of the LUCE optimization, together with the consequences of the AHP and preferable analysis, assist decision makers in making scientific biomass energy systems planning decisions by considering not only environmental, public health, and social factors, but also economic concerns.

4.3.4 The LUCE Minimization and Preferable Analysis Results Application

Compared with the use of coal fired electric power, the application of biomass power does not only meet the electricity demands of the local area, but also benefits the local environment by improving air quality and reducing of CO_2 emission. Since the LUCE minimization approach using location-allocation models provides quantitative measurements associated with the generation of biomass power, the solutions are appropriate when considering the economics of biomass energy systems design. On the other hand, the AHP and GIS based preferable suitability analysis, described in the previous subsections, addresses environmental, public health, and social considerations. The preferable analysis results illustrate the suitability levels of constructing biomass power plants in the study area using GIS map presentations. Therefore, in designing optimal bioenergy systems, the combination of LUCE minimization and preferable analysis results can provide valuable information for decision makers.

Generally, there are many approximate “optimal” solutions to the p-UFLP model which LUCE costs that are very close to the optimal solution. Although they are not economically optimal for LUCE minimization, they may have more environmental, public health, and social benefits than the optimal solution resulting from their location in the preferable maps. The more power plants constructed in areas with higher preferable suitability levels, the more environmental credits can be achieved. Since the LUCE optimal solution to the p-UFLP model computed by the genetic algorithm is uncoupled from the preferable analysis, decision makers should consider these near optimal (LUCE) solutions in making trade offs between economical consideration and environmental, public health and social impact concerns.

The following example is chosen to demonstrate the application of designing an optimal bioenergy system. Direct combustion is selected for biomass conversion, load factor equals 0.6 and p is fixed to 15 since these values yield the best solution in the corresponding spatial optimization model (see figure 4-27). The preferable analysis results illustrated in figure 4-12 are selected for environmental consideration. For this demonstration, three 15-UFLP solutions, including the optimal solution, are chosen for comparison using the preferable suitability map. Each selected power plant is labelled with a unique number to assist in discriminating different locations, as shown in the following figures 4-31 and 4-32. The location (by number) of the selected power plants of each solution with corresponding LUCE cost is summarized in the following table 4-11.

Table 4-11 Solutions of p-UFLP model in case of DC conversion, load factor=0.6, p=15

Conversion Technology	Load Factor	LUCE Cost ($/kWh)	Selected Power Plant Location Label Numbers
Direct Combustion	0.6	**0.4925 (optimal)**	4 13 31 33 43 51 58 61 66 67 79 81 82 85 86
		0.4930	4 14 31 33 43 51 53 58 59 61 65 67 79 82 85
		0.4986	4 14 31 33 43 51 58 61 66 67 79 81 82 84 86

The economically optimal solution (0.4925 $/kWh of LUCE cost) and the corresponding locations of other two solutions (0.4930 $/kWh and 0.4986 $/kWh of LUCE cost) are compared in the preferable analysis map as shown in figure 4-31 and 4-32. Firstly, from figure 4-31 which is the comparison of optimal solution (0.4925 $/kWh) and solution (0.4930 $/kWh), there are four pairs of power plants (i.e., 13 and 14, 66 and 65, 81 and 59, 86 and 53) that have different locations based on the LUCE costs. Observing each pair of locations, we see that the locations of power plants in the first three pairs are in areas with the same suitability levels (i.e. all are in medium preferable suitability areas). However, the power plant labelled number 86 in the optimal LUCE solution is located in a medium suitability level area whereas the power plant labelled number 53 is located in a high suitability level area, as clearly illustrated in the zoom-in chart of figure 4-31.

This suggestion that the alternate solution (0.4930 $/kWh with LUCE costs) in figure 4-31 may be the preferred bioenergy system design solution if the decision makers are more concerned with the environmental impacts of the system.

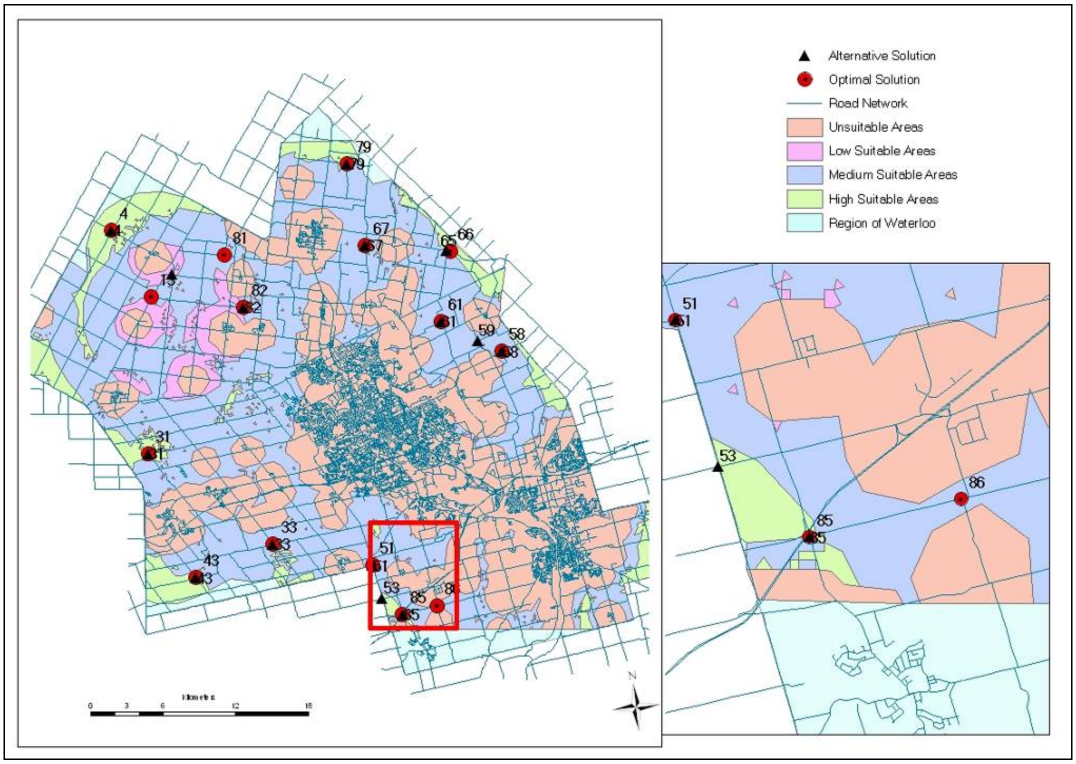


Figure 4-31 Bioenergy systems design using the result of preferable analysis and the solutions of LUCE cost optimization (1)

The comparison of the optimal solution and the second alternate solution is shown in figure 4-32. There are two pairs of power plant sites selected in different locations, i.e., 13 and 14, 85 and 84. The power plant labelled 13 in the optimal LUCE cost solution is in a medium preferable analysis suitability level area whereas the power plant labelled 14 in the alternate solution is in a low suitability level area. The other pairs of power plants (85 and 84) are both located in a medium suitability level area. Therefore, it is apparent that the alternate solution with LUCE cost of 0.4986 \$/kWh is neither more economical nor more environmentally suitable than the optimal LUCE solution.

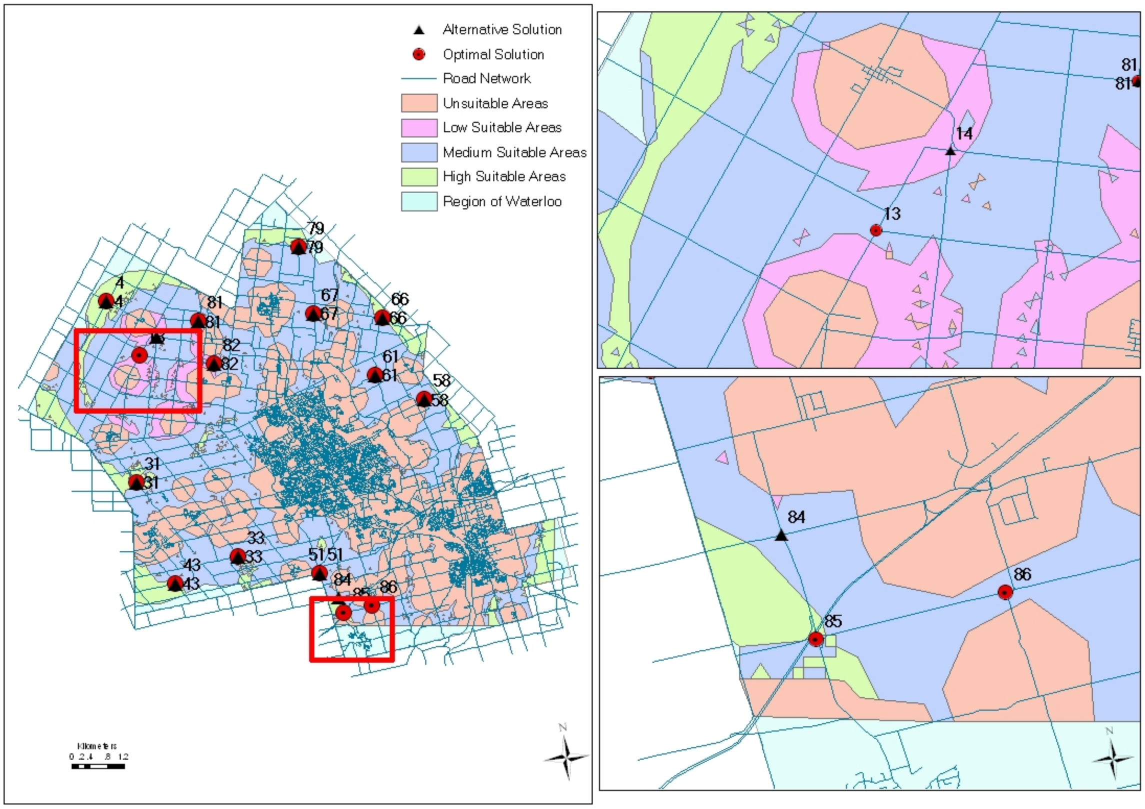


Figure 4-32 Bioenergy systems design using the result of preferable analysis and the solutions of LUCE cost optimization (2)

4.4 Summary

The main objective of this case study was to demonstrate the proposed integrated methodology implementation and the process of assessing biomass availability, power plant candidate selection, and spatial optimization of bioenergy systems. By reviewing the current bioenergy systems planning status and by considering the particular situation in the Regional Municipality of Waterloo, we can conclude that the integrated approach for bioenergy systems planning should be considered as part of the region's development strategy.

Through this case study and analyses, various aspects of the methodology have been examined. It is established that the models are capable of providing essential decision support information to the planners for regional bioenergy systems planning and management.

Biomass availability from agricultural residues, suitable areas for constructing decentralized biomass power generation, and optimally allocations of biomass feedstock can be qualitatively and quantitatively identified.

By introducing the AHP method to the suitability analysis, qualitative factors are converted into quantitative measures and used to assign weights that reflect the relative importance of the factors. In doing so, more accurate and scientific results identifying the most suitable areas can be derived from the GIS based suitability analysis model. GIS is a useful tool in processing and analyzing large amounts of spatial data for bioenergy systems design. In this study, GIS applications were implemented for basic data processing and information gathering, spatial analysis, and visualizing design results. Advanced GIS applications, such as the location-allocation solver, network analysis tools are also used for solving the p-median problem model.

In order to analyze the impact of the design parameters on the solutions of the location-allocation design problems, experiments with varying numbers of established biomass power plants, conversion technologies and load factors have been conducted. Corresponding results associated with these different parameters are achieved and analyzed. At the end of this section, the application of the AHP and preferable analysis results combined with LUCE optimization solutions is also introduced. Planners will get important decision making supports for bioenergy systems planning through this application process.

In this thesis, a comprehensive integrated approach is proposed for biomass energy planning. However, some of the acknowledged limitations of the research include: 1) Facility site selection, suitability analysis, and discrete location modeling are not programmed in the integrated environment (different software have to be applied for different analysis); 2) suitability analysis and AHP exercises have to be repeated when the input parameters are changed; 3) the optimization model does not consider the generated electricity distribution costs. These limitations should be addressed in the future studies in these fields.

Chapter 5 Conclusion, Contributions and Future Work

5.1 Conclusions and Contributions

As one of the most promising renewable energy resource, bioenergy for power generation has a lot of benefits from both an environmental point of view or in terms of energy security and energy balance. An integrated methodology combining GIS, AHP, and discrete location-allocation models is introduced. This comprehensive design approach for bioenergy system planning addresses the difficulty resulting from the highly distributed biomass resources and promotes economically and environmentally sustainable development at the local or regional scale.

An agricultural residues based biomass availability estimation model assesses the collectable biomass feedstock available to biomass power plants. By only including annual agricultural wastes, this model will consider plans having little impact on the environment and economics in the local area. GIS based suitability analysis, network analysis and AHP methods have effectively promoted the design performance. The results obtained can not only provide decision making support for planners but also decrease the computational efforts in the spatial optimization models. This study demonstrated the potential of GIS and AHP as efficient methods for bioenergy systems planning.

This research work has investigated the overall process of bioenergy system design. Some key aspects related to bioenergy systems planning, from biomass availability assessment to locating power plants and distribution of biomass, have been investigated and a review of previous research on the corresponding fields (i.e. biomass assessment, power plant siting, and spatial optimization) was conducted. P-median models for finding the optimal location of power plants and allocation of biomass feedstock with the least weighted transportation costs are discussed. Another facility location problem model - the p-uncapacitated facility location problem model was also employed to minimize the levelized unit cost of energy to assess the viability of using bioenergy for electric power generation. The modeling results demonstrate that these models are effective ways for spatial optimization in bioenergy systems design.

The main contributions of this research include the following aspects:

1. Prior to this study, an integrated model for regional scale bioenergy systems design has never been fully addressed in the bioenergy literature. This study fills this gap by proposing an integrated method for comprehensive bioenergy systems planning at the regional scale;
2. The use of GIS based suitability analysis, network analysis and AHP for power plant siting;
3. The utilization of a p-UFLP location-allocation model for LUCE minimization in bioenergy systems design;

5.2 Future Work

Future research on bioenergy systems planning should include modelling of the distribution of generated bio-power so that: (1) all acquired bio-power can be optimally injected into the local distribution grid, and (2) power plants and distribution substations can be selected by considering the local power demand to minimize power delivery costs. In addition, more bioenergy resources, such as MSW and wood residues, in the regional scale for power generation will be taken into account for bioenergy systems planning. Further development of the bioenergy systems design model may consider uncertainties and develop corresponding algorithms for solving the stochastic spatial optimization models.

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Appendix A

Statistical Data for Biomass Availability Assessment

Table A- 1 Land use catalogues in the Region of Waterloo

Land Use Catalogues	Number of Polygon	Area (Ha)
Not Cataloged	277	37.98
Built Up/Urban	5	41.83
Built Up/Urban Area	95	17404.38
Continuous Row Crop	359	17595.07
Corn System	383	26203.87
Extensive Field Vegetables	26	331.86
Extraction Pits(pits/Quarries)	54	1033.95
Grain System	232	5432.57
Grazing System	52	771.77
Hay System	294	10150.04
Idle Agric Land 5-10 years	160	1792.95
Idle Agric Land >10 years	107	1313.07
Market Garden/Truck Farm	10	177.16
Mixed System	274	25618.92
Not Mapped	56	107.43
Nursery	7	80.56
Orchard	5	41.77
Pasture System	94	2102.50
Pastured Woodlot	13	155.55
Recreation	35	1265.17
Reforested Woodlot		209.02
Sod Farm	7	317.26
Swamp/Marsh/Bog	15	178.09
Tobacco System	2	14.79
Water	252	1681.91
Woodlot	828	19571.52
Sum	3659	133630.99

The statistical data appearing in Appendix A are from the online dataset at Statistics Canada (http://www40.statcan.ca/l01/ind01/l2_920.htm), the Regional Municipality of Waterloo spatial data from the University of Waterloo Map Library, and from Voivontas et al. (2001) and Layzell, et al. (2006).

Table A- 2 Yields of crop residues in the Region of Waterloo (2005 data)

Crops species	Areas (Ha,2005)	Crop Planted (%)	Average yield (t/Ha)	Potential Bioenergy (dry-ton)
Winter Wheat(straw)	11929	12.67	2.95	35189.51
Spring Wheat(straw)	1988	2.11	2.87	5704.53
Fall Rye(straw)	626	0.65	1.26	788.83
Oats(straw)	1078	1.15	1.26	1358.33
Barley(straw)	2442	2.59	2.12	5177.97
Mixed Grain(straw)	1477	1.57	2.94	4341.48
Grain Corn(straw)	18122	19.25	7.17	129933.11
Canola	138	0.15	2.5	343.91
Soybeans	24711	26.25	3.5	86487.60
Dry White Beans	1044	1.11	3.5	3655.24
Colored Beans	828	0.88	3.94	3263.04
Fodder Corn	3296	3.50	2.5	8239.72
Hay	26471	28.12	6.18	163590.67

Table A- 3 Yields of horticultural residues in the Region of Waterloo (2005 data)

Wood species	Areas (Ha,2005)	Crop Planted (%)	Average yield (t/Ha)	Potential Bioenergy (dry-ton)
Apples	6,78	36.46	4.77	32340.84
Apricots	29	0.16	16.92	491.58
Blueberries, High bush	138	0.74	2.94	404.30
Blueberries, Low Bush	15	0.08	2.12	32.85
Cherries, (branches)	695	3.74	5.11	3553.19
Cherries, (branches)	251	1.35	5.11	1281.72
Grapes, Labrusca	1,61	8.64	1.26	2024.37
Grapes, Vinifera	3,99	21.43	1.26	5022.49
Nectarines(branches)	255	1.37	5.61	1428.87
Peaches (branches)	1,98	10.64	5.61	11104.95
Pears (branches)	705	3.79	16.92	11929.01
Plums (branches)	333	1.79	6.21	2068.82
Raspberries(branches)	314	1.70	5.11	1603.39
Strawberries	1,16	6.23	1.26	1456.96

Table A- 4 Yields of biomass based on the land use in the Region of Waterloo

Land use catalogs	Areas (Ha)	Average biomass yield (dry-ton/Ha)	Potential bioenergy (dry-ton)
Continuous Row Crop	17135.20	3.04	52133.84
Corn System	24347.50	2.5	60868.75
Grain System	5270.38	5.06	26641.79
Grazing systems	741.53	6.18	4582.62
Hay system	8665.03	6.18	53549.86
Idle Agric Land > 5 years	2994.00	15	44909.86
Mixed System	35844.84	3.28	117708.93
Pasture system	1834.93	6.18	11339.87
Pastured Woodlot	152. 06	5.73	874.27
Reforested Woodlot	167.93	5.73	962.10
Sod Farm	309.60	6.18	1913.29
Swamp/Marsh/Bog	161.50	2	322.98
Woodlot	18115.91	5.73	103791.24

Appendix B Scripts and MATLAB Codes Developed in This Thesis

Appendx B-1. Scripts for Biomass Availability Assessment

```
# ---------------------------------------------------------------------------
# bioselectfrompw.py
# Created on: Sun Mar 25 2007 01:13:03 PM  (generated by ArcGIS/ModelBuilder)
# ---------------------------------------------------------------------------

# Import system modules
import sys, string, os, win32com.client

# Create the Geoprocessor object
gp = win32com.client.Dispatch("esriGeoprocessing.GpDispatch.1")

# Load required toolboxes...
gp.AddToolbox("C:/software/arcgis/ArcToolbox/Toolboxes/Analysis Tools.tbx")
gp.overwriteoutput = 1

# Local variables...
landArea_FeatureToPoint_shp =
"F:\\Suitability_analysis\\biomass_production\\landArea_FeatureToPoint.shp"
rastert_eucallo3_shp = "F:\\Suitability_analysis\\test\\rastert_eucallo6area.shp"
rastert_eucallo3_Select_shp = "F:\\Suitability_analysis\\test\\rastert_eucallo6area_Select.shp"
select_clip_shp = "F:\\Suitability_analysis\\test\\select_clip.shp"
select_clip_Statistics_dbf = "F:\\Suitability_analysis\\test\\select_clip_Statistics.dbf"
rows=gp.InsertCursor("F:\\Suitability_analysis\\test\\select_clip_Statistics.dbf")
#searchrows=gp.SearchCursor(select_clip_Statistics_dbf)
searchPolygons=gp.SearchCursor("F:\\Suitability_analysis\\test\\rastert_eucallo6area.shp")
searchBuf=searchPolygons.Next()

while searchBuf:
    #select one polygon from biosupply zones by its FID field
    i=int(searchBuf.GetValue("FID"))+1
    stringFID="\"rastert_eucallo3_shp.FID\"= " + str(i)
    # Process: Select...
    gp.Select_analysis(rastert_eucallo3_shp, rastert_eucallo3_Select_shp, stringFID)
    # Process: Clip...
    gp.Clip_analysis(landArea_FeatureToPoint_shp, rastert_eucallo3_Select_shp, select_clip_shp, "")
    # Process: Summary Statistics...
    select_clip_Statistics_dbf="F:\\Suitability_analysis\\test\\"+str(i)+".dbf"
    print i
    gp.Statistics_analysis(select_clip_shp, select_clip_Statistics_dbf, "Bio_sup SUM", "")
    searchrows = gp.SearchCursor(select_clip_Statistics_dbf)
    # Give the value to a new row, and insert the row intor the select_clip_Statistics.dbf
    row = rows.NewRow()
    searchrow = searchrows.Next()
```

```
    #row.OID = i
    row.FREQUENCY = int(searchrow.GetValue("FREQUENCY"))
    row.SUM_Bio_su = float(searchrow.GetValue("SUM_Bio_su"))
    rows.InsertRow(row)
    searchBuf=searchPolygons.Next()
```

Appendx B-2. Scripts for Exclusive Suitability Analysis Toolbox

```
# ---------------------------------------------------------------------------
# exclusive.py
# Created on: Tue Feb 13 2007 04:53:15 PM  (generated by ArcGIS/ModelBuilder)
# ---------------------------------------------------------------------------

# Import system modules
import sys, string, os, win32com.client

# Create the Geoprocessor object
gp = win32com.client.Dispatch("esriGeoprocessing.GpDispatch.1")

# Set the necessary product code
gp.SetProduct("ArcInfo")

# Check out any necessary licenses
gp.CheckOutExtension("spatial")
gp.OverwriteOutput = 1

# Load required toolboxes...
gp.AddToolbox("C:/software/arcgis/ArcToolbox/Toolboxes/Spatial Analyst Tools.tbx")
gp.AddToolbox("C:/software/arcgis/ArcToolbox/Toolboxes/Analysis Tools.tbx")
gp.AddToolbox("C:/software/arcgis/ArcToolbox/Toolboxes/Conversion Tools.tbx")

#setup the inputs and outputs variables
#inputs
n1 = sys.argv[1]#Urban buffer length
n2 = sys.argv[2]#slope degree
n3 = sys.argv[3]#floodplain buffer
n4 = sys.argv[4]#waterbody buffer
n5 = sys.argv[5]#airport buffer
n11=str(n1)
n22=str(n2)
n33=str(n3)
n44=str(n4)
n55=str(n5)

# Local variables...
clipslope = "F:\\Suitability_analysis\\clipslope"
Floodplain_shp = "F:\\Suitability_analysis\\Floodplain.shp"
waterbody_shp = "F:\\Suitability_analysis\\waterbody.shp"
```

```
dis_flplain = "F:\\Suitability_analysis\\scratch\\dis_flplain"
Output_direction_raster__2_ = ""
dis_waterbody = "F:\\Suitability_analysis\\scratch\\dis_waterbody"
Output_direction_raster__3_ = ""
recdis_wbody = "F:\\Suitability_analysis\\scratch\\recdis_wbody"
recdis_fplain = "F:\\Suitability_analysis\\scratch\\recdis_fplain"
time_Wbl = "F:\\Suitability_analysis\\scratch\\time_wbl"
exclusive = "F:\\Suitability_analysis\\scratch\\exclusive"
time_1 = "F:\\Suitability_analysis\\scratch\\time_1"
exclusive_shp = "F:\\Suitability_analysis\\scratch\\exclusive.shp"
sele_exclu_shp = "F:\\Suitability_analysis\\scratch\\sele_exclu.shp"
pwcliped_shp = "F:\\Suitability_analysis\\scratch\\pwcliped.shp"
urbanland_shp = "F:\\Suitability_analysis\\urbanland.shp"
buff_urban_shp = "F:\\Suitability_analysis\\scratch\\buff_urban.shp"
raster_buffer = "F:\\Suitability_analysis\\scratch\\raster_buffer"
rec_buffer = "F:\\Suitability_analysis\\scratch\\rec_buffer"
airports_shp = "F:\\Suitability_analysis\\airports.shp"
buffer_ap_shp = "F:\\Suitability_analysis\\scratch\\buffer_ap.shp"
pwcandidates_shp = "F:\\Suitability_analysis\\scratch\\pwcandidates.shp"
power_plant_candidats_shp = "F:\\Suitability_analysis\\power plant candidats.shp"

# Process: Euclidean Distance (2)...
gp.EucDistance_sa(Floodplain_shp, dis_flplain, n3, "25", Output_direction_raster__2_)
# Process: Euclidean Distance ...
gp.EucDistance_sa(waterbody_shp, dis_waterbody, n4, "25", Output_direction_raster__3_)
# Process: Buffer...
gp.Buffer_analysis(urbanland_shp, buff_urban_shp, " n11 Meters", "FULL", "ROUND", "ALL", "")
# Process: Feature to Raster (2)...
gp.FeatureToRaster_conversion(buff_urban_shp, "Id", raster_buffer, "25")
# Process: Reclassify...
gp.Reclassify_sa(raster_buffer, "Value", "0 0;NODATA 1", rec_buffer, "DATA")
# Process: Reclassify (3)...
gp.Reclassify_sa(dis_flplain, "Value", "0 n33 0;NODATA 1", recdis_fplain, "DATA")
# Process: Reclassify (2)...
gp.Reclassify_sa(dis_waterbody, "Value", "0 n44 0;NODATA 1", recdis_wbody, "DATA")

# Process: Times...
gp.Times_sa(recdis_fplain, recdis_wbody, time_Wbl)
# Process: Times (4)...
gp.Times_sa(rec_buffer, time_Wbl, time_1)
# Process: Times (3)...
gp.Times_sa(time_1, clipslope, exclusive)
# Process: Raster to Polygon...
gp.RasterToPolygon_conversion(exclusive, exclusive_shp, "SIMPLIFY", "Value")
# Process: Select...
gp.Select_analysis(exclusive_shp, sele_exclu_shp, "\"GRIDCODE\" =1")
# Process: Clip...
gp.Clip_analysis(power_plant_candidats_shp, sele_exclu_shp, pwcliped_shp, "")
```

```
# Process: Buffer ...
gp.Buffer_analysis(airports_shp, buffer_ap_shp, "n55 Kilometers", "FULL", "ROUND", "ALL", "")
# Process: Erase...
gp.Erase_analysis(pwcliped_shp, buffer_ap_shp, pwcandidates_shp, "")
```

Appendx B-3. Python Scripts for Shortest Path Routes

```
# ---------------------------------------------------------------------------
# Routes87.py
# Created on: dj. set 06 2007 01:27:56
#   (generated by ArcGIS/ModelBuilder)
# ---------------------------------------------------------------------------

# Import system modules
import sys, string, os, arcgisscripting

# Create the Geoprocessor object
gp = arcgisscripting.create()

# Check out any necessary licenses
gp.CheckOutExtension("Network")
gp.OverwriteOutput = 1

# Load required toolboxes...
gp.AddToolbox("C:/software/arcgis/ArcToolbox/Toolboxes/Analysis Tools.tbx")
gp.AddToolbox("C:/software/arcgis/ArcToolbox/Toolboxes/Network Analyst Tools.tbx")
gp.AddToolbox("C:/software/arcgis/ArcToolbox/Toolboxes/Data Management Tools.tbx")
gp.AddToolbox("C:/software/arcgis/ArcToolbox/Toolboxes/Conversion Tools.tbx")

# Local variables...
Facilities_Select_shp = "D:\\Suitability_analysis\\ShortestRoute\\Facilities_Select.shp"
pwcandidates87_shp = "D:\\Suitability_analysis\\test\\pwcandidates87.shp"
Closest_Facility = "Closest Facility"
row_roadnetwork_ND = "D:\\Suitability_analysis\\row_roadnetwork.nd"
Facilities = "Closest Facility"
Incidents = "Closest Facility"
Routes = "Closest Facility"
Scratch = "D:\\Suitability_analysis\\ShortestRoute\\Scratch"
Routes__3_ = "D:\\Suitability_analysis\\ShortestRoute\\Routes"
Scratch__3_ = "D:\\Suitability_analysis\\ShortestRoute\\Scratch"
Routes__2_ = "Closest Facility\\Routes"

#The following scripts are designed for calculating the Shortest Routes representing
#the real distances between Facilities and demands

for n in range(87):

   k=n+1
```

```
    stringId="\"pwcandidates87_shp.OBJECTID\"= "+str(k)

    # Process: Make Closest Facility Layer...
    gp.MakeClosestFacilityLayer_na(row_roadnetwork_ND, "Closest Facility", "Length",
"TRAVEL_FROM", "", "1", "", "ALLOW_UTURNS", "", "NO_HIERARCHY", "",
"TRUE_LINES_WITH_MEASURES")

    # Process: Select...
    gp.Select_analysis(pwcandidates87_shp, Facilities_Select_shp, stringId)

    # Process: Add Locations...
    gp.AddLocations_na(Closest_Facility, "Facilities", Facilities_Select_shp, "CurbApproach #
0;Attr_Length # 0", "500 Meters", "", "rd_slrn SHAPE;row_roadnetwork_Junctions NONE",
"MATCH_TO_CLOSEST", "APPEND", "NO_SNAP", "5 Meters")

    # Process: Add Locations (2)...
    gp.AddLocations_na(Closest_Facility, "Incidents", pwcandidates87_shp, "CurbApproach #
0;Attr_Length # 0", "5000 Meters", "", "rd_slrn SHAPE;row_roadnetwork_Junctions NONE",
"MATCH_TO_CLOSEST", "APPEND", "NO_SNAP", "5 Meters")

    # Process: Solve...
    gp.Solve_na(Closest_Facility, "SKIP")

    # Process: Save To Layer File...
    gp.SaveToLayerFile_management(Routes, Routes__3_)

    # Process: Feature Class To Shapefile (multiple)...
    gp.FeatureClassToShapefile_conversion("'Closest Facility\\Routes'", Scratch)
```

Appendx B-4. MATLAB Codes for Consistency Check in AHP

```
%calculate the weights and C.R.of the pair-wise conparison matrix A
function [w,cr]=crcom(A)
n=size(A,1);
for i=1:n
    a(i)=sum(A(:,i));
end
for j=1:n
    B(:,j)=A(:,j)/a(j);
end
for k=1:n
    w(k)=mean(B(k,:));
end
eigvalue=max(eig(A));
ri=[0 0 0.58 0.90 1.12 1.24 1.32 1.41 1.45 1.49 1.51 1.48 1.56 1.57
1.59];
ci=(eigvalue-n)/(n-1);
cr=ci/ri(n);
```

```
if cr>0.1
    display 'consistence ratio is not acceptable'
else
    display 'weights and consistence ratio are:'
end
```

Appendx B-5. MATLAB Codes for Minimum Spanning Tree (MST)

```
%% random points generating for the biomass production areas in the
Region of Waterloo
clear;
format long
n=100;%number of points generated
%x coordintes range
a=510686.32;b=565707.99;%range of the x
%y coordinates range
c=4790684.67;d=4837391.63;%range of the x
%generating random x,y coordinates between ranges
x=a+(b-a).*rand(n,1);
y=c+(d-c).*rand(n,1);
ds=[x,y];%coordinates of the generated substations

%% Creat substation point features
% After obtaining the coordinates, create a new file named
"substation.shp" by adding the x,y coordinates
% to the points

%% calculate the distance matrix of substions and generate the MST
graph
%coordinates of substation points
s=shaperead('L:\M.Sc at UW\Research Work\data preparation\MST and
Landuse\data folder\substation.shp');
sizes=size(s);
n=sizes(1);
for m=1:n
    C(m,1)=[s(m).X];
    C(m,2)=[s(m).Y];
end
x1=C;
for n=1:size(x1,1)
   for m=1:size(x1,1)
   dis(n,m)=sqrt((x1(m,2)-x1(n,2)).^2+(x1(m,1)-x1(n,1)).^2);
   end
end
A=sparse(dis);%distance matrix
T=mst(A);%generate the MST graph, where MST is a agrithm of
generating MST graph with respect to the given A
```

Appendx B-6. MATLAB Codes for Solving p-UFLP Models

```
% Main program for solving p-UFLP model
Clear
for jj=1:30
n=87;pbar=17;lf=0.9;
load weights.mat;
load shortestRoute.txt;
dis=shortestRoute;
%%
load inipop17;
inipopulation=qq;
P=size(inipopulation,1);
%%
for i=1:P
    iniallocation{i}=allocapmp(inipopulation(i,:),n,w,dis,pbar);
end
%%
for i=1:P
for j=1:pbar
capacity(i,j)=(sum(w(iniallocation{i}{j}))*18/3.6)*0.35/(8670*lf);%assume
the conversion efficency is 55% of IGCC
if capacity(i,j)>25
    fxcap(i,j)=3000;
else if capacity(i,j)>5 & capacity(i,j)<=25
        fxcap(i,j)=4000;
    else
        fxcap(i,j)=5000;
    end
end
end
end
%%
for i=1:P
inifitness_values(i)=LUCEfitness(inipopulation(i,:),w,dis,lf,fxcap(i,:),in
iallocation{i});
end
%%
MaxIter=0;
while MaxIter<=1500
    MaxIter;
    [bestvalue1,best1]=min(inifitness_values);
    solution1=sort(inipopulation(best1,:));
    [p1,p2]=selectchild(P,inipopulation);

[pchild,allocation_pchild,pchild_fitness]=LUCEchildgen(w,dis,n,pbar,p1,p2,
lf);%

[newpopulation]=LUCEreplacement(inipopulation,pchild,w,dis,P,pbar,pchild_f
itness,lf,fxcap,iniallocation);
inipopulation=newpopulation;
    for i=1:P
        iniallocation{i}=allocapmp(inipopulation(i,:),n,w,dis,pbar);
```

```
    end
    for i=1:P
        for j=1:pbar

capacity(i,j)=(sum(w(iniallocation{i}{j}))*18/3.6)*0.35/(8670*lf);%assume
the conversion efficency is 55% of IGCC,0.35 for DC
            if capacity(i,j)>25
                fxcap(i,j)=3000;
              else if capacity(i,j)>5 & capacity(i,j)<=25
                fxcap(i,j)=4000;
              else
                fxcap(i,j)=5000;
              end
            end
        end
    end
    for k=1:P

inifitness_values(k)=LUCEfitness(inipopulation(k,:),w,dis,lf,fxcap(k,:),in
iallocation{k});
    end
    [bestvalue,best]=min(inifitness_values);
    solution=sort(inipopulation(best,:));
    if all(solution==solution1)
        MaxIter=MaxIter+1;
    else
        MaxIter=MaxIter;
    end
end
%%
solution_allocation=allocapmp(solution,n,w,dis,pbar);
fx_solution=fxgen(solution_allocation,w,lf);
f=LUCEfitness(solution,w,dis,lf,fx_solution,solution_allocation);
%%
ftranscap=f;
totalw=sum(w);
%fuel costs and OM cost
ffuel=3*totalw*18;%3$/GJ
%ffuel=3.5*totalw*18;%3.5$/GJ
fom=(18000*totalw/3.6)*0.016*lf;
%fom=(18000*totalw/3.6)*0.025*lf;
%LUCE cost
f=1/((18000*totalw/3.6)*lf)*(ftranscap+ffuel+fom);
solution;
jjj(jj,:)=[solution f ftranscap fom ffuel];
end
[f,solutionindex]=min(jjj(:,pbar+1));
solution=jjj(solutionindex,1:pbar)
solution_allocation=allocapmp(solution,n,w,dis,pbar);
```

Appendix C Solutions of p-UFLP Model

Table C- 1 Summary of solutions in case of DC conversion, load factor=0.6

p	LUCE ($/kWh)	Transportation Costs($)	Capital Costs($)
1	0.9985	1142862903.33	612103213.89
2	0.7104	618616213.90	612103213.89
3	0.5905	400395397.72	612103213.89
4	0.5607	346226781.35	612103213.89
5	0.5461	319617865.97	612103213.89
6	0.5472	273648996.98	640752315.23
7	0.5288	244353521.16	655850658.31
8	0.5210	204030345.00	681925140.93
9	0.5144	173011188.88	701093993.52
10	0.5077	157700151.51	704244978.00
11	0.5008	155231462.64	694156531.7
12	0.5001	126224392.60	721812664.48
13	0.4971	114320394.03	728254335.73
14	0.4951	106117606.94	732880008.70
15	0.4925	101365734.56	732880008.70
16	0.4960	82371572.62	758288606.13
17	0.4946	77649149.75	760504306.17
18	0.4937	75970983.81	760504306.17
19	0.4933	70973856.33	764907078.65
20	0.4939	67565285.51	768904096.89
30	0.5018	52980612.89	798163580.37
40	0.5088	40072711.49	823781250.30
50	0.5123	13592047.65	856636746.32
87	0.5270	0	896926471.31

Table C- 2 Summary of solutions in case of DC conversion, load factor=0.9

p	LUCE ($/kWh)	Transportation Costs($)	Capital Costs($)
1	0.5963	1142862903.33	534375821.65
2	0.4042	618616213.90	534375821.65
3	0.3249	402160188.11	534375821.65
4	0.3136	349384673.56	534375821.65
5	0.3067	297804309.21	572129188.99
6	0.2964	266749123.14	819195256.40
7	0.2908	229044159.06	875813337.73
8	0.2859	201371329.70	892659950.68
9	0.2701	173011188.88	914017893.73
10	0.2630	157935267.90	1354399614.38
11	0.2580	144574472.75	1184554700.57
12	0.2555	131842479.38	1542436201.45
13	0.2529	117982588.29	1590659877.23
14	0.2548	107279521.09	2339959275.70
15	0.2531	111604918.02	2488201677.02
16	0.2524	107284092.12	2656554276.08
17	0.2518	106003591.54	3050357941.06
18	0.2527	93500381.36	3192319160.65
19	0.2536	104458889.18	3105173540.33
20	0.2537	87797236.56	3683358702.63
87	0.2628	0	640910706.38

Table C- 3 Summary of solutions in case of IGCC conversion, load factor=0.6

p	LUCE ($/kWh)	Transportation Costs($)	Capital Costs($)
1	0.9424	1142862903.33	612103213.89
2	0.6543	618616213.90	612103213.89
3	0.5344	400395397.72	612103213.89
4	0.5008	346226781.35	612103213.89
5	0.4773	319617865.97	612103213.89
6	0.4544	273648996.98	640752315.23
7	0.4409	244353521.16	655850658.31
8	0.4315	204030345.00	681925140.93
9	0.4282	173011188.88	701093993.52
10	0.4324	157700151.51	704244977.99
11	0.4360	155231462.64	694156531.71
12	0.4484	126224392.59	721812664.48
13	0.4499	114320394.03	728254335.73
14	0.4531	106117606.94	732880008.70
15	0.4635	101365734.56	732880008.70
16	0.4641	82371572.62	758288606.13
17	0.4588	77649149.75	760504306.17
18	0.4657	75970983.81	760504306.17
19	0.4674	70973856.33	764907078.65
20	0.4667	67565285.51	768904096.89
87	0.5687	0	11749566939.96

Table C- 4 Summary of solutions in case of IGCC conversion, load factor =0.9

p	LUCE ($/kWh)	Transportation Costs($)	Capital Costs($)
1	0.5713	1142862903.33	408068809.26
2	0.3793	618616213.90	408068809.26
3	0.2999	402160188.11	408068809.26
4	0.2807	339240874.67	424085389.35
5	0.2705	300456354.17	434123600.93
6	0.2608	272268311.44	437206421.74
7	0.2602	229044159.06	451188002.23
8	0.2540	201371329.70	458335050.14
9	0.2486	172569628.57	488077868.47
10	0.2472	153243658.06	488077868.47
11	0.2412	138282479.27	489519498.93
12	0.2413	128205133.45	492832079.65
13	0.2474	112181245.33	501510554.24
14	0.2484	113190757.66	505864326.41
15	0.2510	108063775.27	506296114.29
16	0.2506	83656144.55	528662011.51
17	0.2528	79914899.10	530762667.83
18	0.2531	74351025.40	539012810.91
19	0.2556	73584471.80	542275478.18
20	0.2534	66784660.97	549320614.56
87	0.2805	0	8614349450.77