SPATIAL OPTIMIZATION OF BIOENERGY PRODUCTION

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March, 2014

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ABSTRACT

Biomass is a promising source for production of bioenergy; which has significant contribution in an attempt to reduce problems related to climatic change and energy security. However, to be a viable substitute for fossil fuel, bioenergy has to make a net energy gain and has to be produced in sufficient quantities without competing food supplies. Since biomass is distributed along the land escapes, it is also important to have a well-developed regional biomass supply chain system to exploit this resource. When we produce bioenergy, it takes energy cost to harvest, collect and transport biomass from the farm gate to the plant gate. There is also an energy cost to preprocess and operate a bio refinery plant and this should be analyzed and compared to the energy output.

In some cases, the production of bioenergy from biomass might be a loss, if there is no thorough accounting of energy input out-put analysis. Poorly placed processing plants can result in extra energy costs and can degrade the bioenergy production activity, no matter how good transportation plans are designed. As more plants are located, the plants tend to be closer to biomass source areas in lower transport costs, but higher building and opening costs. Thus, to examine the viability of biomass resource and estimate the maximum obtainable regional net energy from biomass (grass) it is quite essential to consider all energy inputs and outputs across the life cycle of biomass to bioenergy and determine the number, location and capacity of processing plants in accordance of the existing biomass resource. It is thus important to develop an optimization model along the whole energy production chain to make better decision.

Several studies in the past aimed primarily at maximizing the profitability of bioenergy production activity with respect to money. However, money invested and gained is not sufficient and reliable as measure of sustainable production. Because of inflation, price levels are changing while physical quantities (and energy cost) may not change. This research introduces a spatial optimization method in application to life cycle assessment model in the context of locating bio-gas plants and allocating available biomass (grass) to the active processing plants in a way that maximizes the net energy gain from biomass (grass). The study uses mixed integer optimization model to solve the biomass supply chain problem. The model utilizes raster data set of $1km \times 1km$ grid resolution. The developed model allows determining the number, location, size of a biofuel facility. It uses municipality of Enschede as a study area. The proposed methodology pointed out that, production of bioenergy from grass has positive energy gain. The sustainable growth of biomass (grass), using an optimized network of processing plants distributed in the municipality may significantly contribute to the local energy supply.

The proposed model can also be applied anywhere provided that both spatial and non-spatial data sets are available. Since regional based energy planning is important, the developed model may be a valuable tool for stakeholders and decision makers in order to decide the most favorable strategy regarding locations and capacity of new bioenergy production plants. The study will also be a basis for discussion and further improvement.

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Love will triumph!!!!

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CHAPTER 1

1. INTRODUCTION

1.1. Research Motivation

Concerns about energy security, rising costs of fossil fuel and a decrease for the volume of oil reserves, and change in global climate have largely stimulated a shift towards bioenergy production from biomass. Following the Kyoto protocol, many countries have set a plan for increasing the share of biofuel in the overall energy consumption. As an example, the European Union has aimed for a strong increase of renewable energy in the EU's overall energy mix to 20% by 2020 and for a significant increase of the share of biofuels in the transport sector with a target of 10% of fuel for transport by 2020 (Kopetz, 2007). Currently, more than 60% of Europe's renewable energy is obtained from bioenergy. Bioenergy is considered as the main energy sources for the 20% target in 2020 (EERA, 2013). Owing to EU goals, In Netherlands there is a 10% renewable energy target for the year 2020 and also a plan of 30% reduction in CO_2 by 2020 with reference to 1990 as mentioned by IEA (2012).

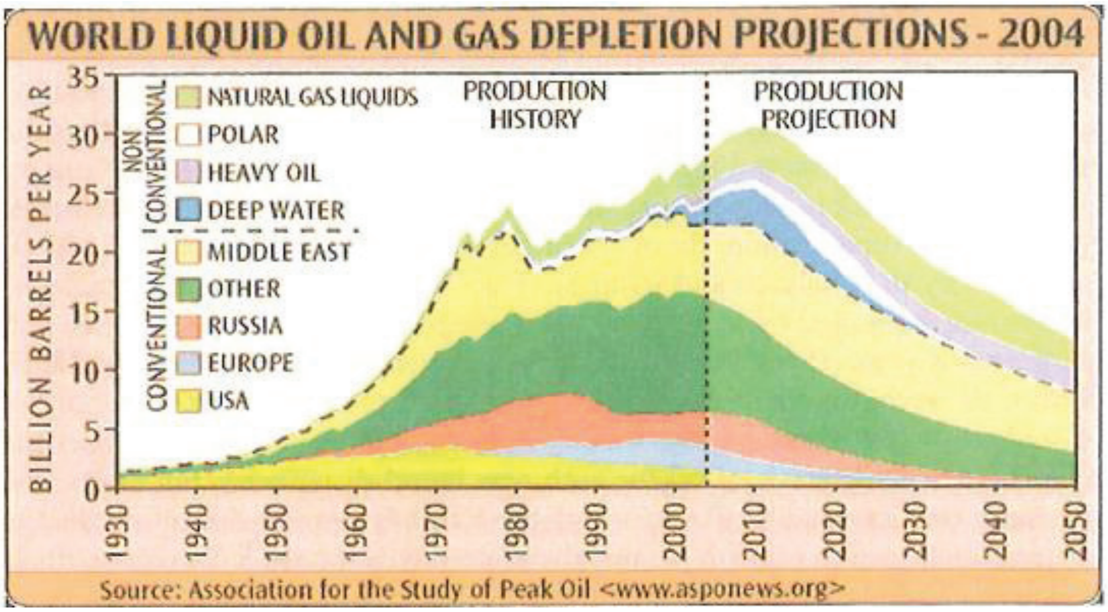


Figure 1: World oil and gas depletion projections: Source: (Campbell, 1995)

1.2. Benefits of Bioenergy

To reduce an increasing problem revolving around fossil fuel, regionally available biomass has been suggested as one of the solution to our dependence on petroleum. Producing sustainable renewable energy from biomass plays a key role in an attempt against global warming and strengthens the security of energy supply. Since, the use of biomass has several economic, societal and environmental benefits if biomass resources are sustainably managed. Unlike fossil fuel, biofuel is renewable energy because it can be replenished more quickly than fossil fuels. Bioenergy could also provide significant contributions to energy security since it can be used for heat, power, or transportation via different path ways (Faaij, 2006). Current security risks revolve around petroleum-based transportation fuels (Hirsch, Bezdek, & Wendling, 2005) can be substituted by ethanol and biodiesel. Bioenergy can help meet greenhouse gas (GHG) emission reduction targets by replacing fossil fuels with low-carbon alternatives. Furthermore, the life-cycle GHG emissions of bio-based heat, power, and transportation fuels are generally lower than their fossil fuel counterparts. Bioenergy can provide a new source of income for farmers through the sale of high-cellulose agricultural residues and purposely-grown energy crops on abandoned farmland (Flavin et al., 2006). Generally biomass energy has several benefits as compared to fossil and nuclear energy (Bassam, 1996).

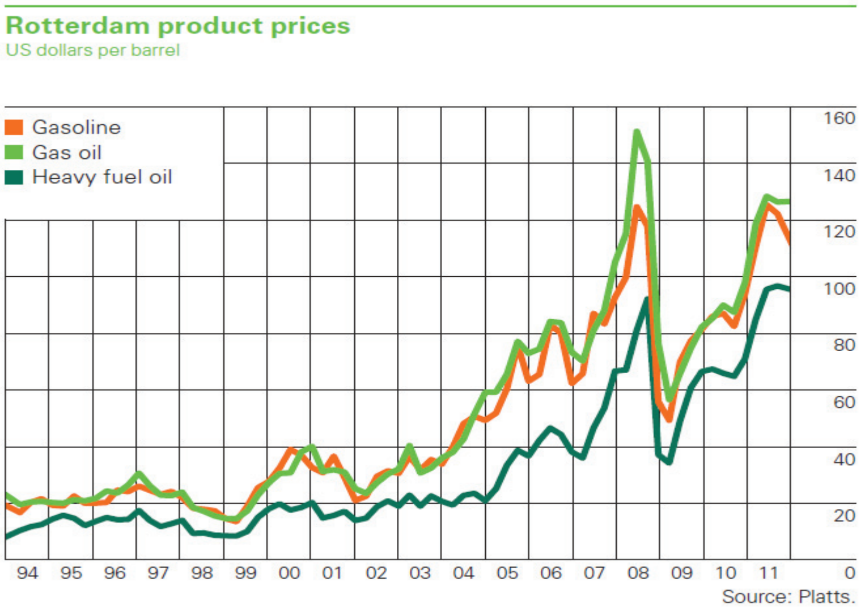


Figure 2: Rotterdam Product prices. Source: (Platts)

1.3. Research Problem

Though bioenergy has potential paybacks, production of bioenergy is not an easy task. There are several challenges to the infrastructure needed across all stages of the supply chain from biomass production, harvesting, storage, transportation, and processing to biofuel distribution and use. Biomass is geographically dispersed over the landscapes and has to be collected over considerable areas before it is economically viable to process it.

Bio refinery plants can be built in a wide range of capacities: as capacity increases, economies of scale in capital equipment are realized, but biomass procurement costs increase to ship the biomass to a location where the bio refinery plant is (Marrison & Larson, 1995) . Consequently, estimating the suitability of biomass transportation in realizing central plants are becoming the main issue. This is primarily important for biomass (grass) because of its low density and high volume for transportation.

In the past, several models have been developed to increase the performance of biomass supply chain issues related to production of bioenergy. Many of the studies were targeting on the economic aspect. Mainly their focus was to optimally siting a bio refinery processing plant so as to either maximize the net profit value or minimize the cost incurred along the production process. The question of how much net energy could be obtained from the source biomass, in accordance of the size, location and technology of the processing plant has been given less attention. However, money invested and gained is not sufficient and reliable as measure of sustainable production of bio-energy. Because, costs (money) invested at each stages of the supply chain are changing with time and are prone to lots of forces that are not related to energy (Beccali, Columba, D'Alberti, & Franzitta, 2009; van Rooijen & van Wees, 2006). Because of inflation, price levels are changing while physical quantities (and energy cost) may not change(Bullard, Penner, & Pilati, 1978)

Energy Balance/ Net Energy Analysis

In the conversion process of biomass to bioenergy/biofuels it is necessary to minimize the resource investments (labor, environmental services, energy, materials) and maximize the yield per hectare and increase conversion efficiency of a processing plant (Fredga & Mäler, 2010). More specifically, for bioenergy to be a viable alternative substitute for fossil fuel, a biofuel has to make a positive net energy gain, should have environmental benefits than traditional fossil fuel, be economically competitive, and capable of being produced in sufficient quantities to meet energy demands (Shie et al., 2011). Hence, reducing all energy inputs such as energy for farming, human labor, transport, machinery, conversion and distribution is important. Therefore, apart from financial analysis, addressing the net energy analysis is a better option.

One potentially useful alternative or supplement to the conventional economic cost-benefit analysis is net energy analysis*,* which is the analysis of how much energy is required to make a unit of the energy in question. Net energy is sometimes called energy surplus, energy balance, or "Net Energy Gain" (NEG). Some researchers also use the term "Energy Returned on Energy Invested" (EROEI). "Net energy analysis allows the possibility of a very useful approach for looking at the advantages and disadvantages of a given biofuel and allows the possibility of looking into the future in a way that markets seem unable to do"(C. Hall, 2008). The mathematical formulas to calculate NEG and EROEI and their interpretation are discussed in the following paragraphs:

Net Energy Gain (NEG)

NEG is a term used in energy economics that refers to the difference between energy invested into a biomass/bioenergy production activity and the energy output returned after production (Hill et al., 2006).

$$\boldsymbol{Net\ Energy\ gain = Energy\ output - Energy\ input}$$

NEG quantifies the amount of energy that will be gained after the biomass/bioenergy production activities. Net Energy Gain becomes a loss when it is less than 0. Whereas a positive NEG is an estimate of the energy gained for biofuel use in the production process. NEG is not a measure of the ability of the bioenergy production activity to support socioeconomic activity (C. Hall, 2008).

Energy Returned on Energy Invested (EROEI)

EROEI (energy efficiency) is the ratio of the energy output (expected return) obtained from a specific biomass/bioenergy production activity to the energy input (investment required) to get that energy (Hall et al., 2009). EROEI is calculated from the following simple mathematical equation. The value of EROEI can give information for decision makers. Often, if EROEI value is greater than 3 then, it is argued that the energy production activities are capable of supporting continuous socio-economic function (C. A. Hall, Balogh, & Murphy, 2009).

$$\boldsymbol{EROEI = \frac{Expected\ energy\ output}{Energy\ input}}$$

1.4. Scope of the study

The bioenergy production activity observed by this study is limited to the following biomass type and conversion technology:

1.4.1. Bioenergy from grass (alfalfa)

Bioenergy can be produced from various lignocellulose biomass types such as grass, wood, agriculture, residues and forest residues, municipal waste and manure. This study focuses on bioenergy production from grass. Grass (alfalafa) is a promising biomass source for bioenergy production. An alternative to grass that differ from conventional biomass sources mainly in that they are grown primarily as energy resource and not for food and most importantly that they have to be grown on marginal land that is not used for food production. Planting of alfalfa is not at cross purpose with nature conservation needs; because it conserves the soil structures, fixes nitrogenous nutrients from the atmosphere and enhances pasturelands biodiversity (Biemans, 2014). The production and use of grass does not compete in any way with food production, not for land, water, fertilisers or markets. Growing grass doesn't threaten the socioeconomic needs and well -being of the local people.

1.4.2. Conversion Technology

Biomass can be used in many energy-conversion processes to give power, steam, heat, electricity and liquid biofuel. Traditional biomass already offers the main source of energy for cooking and household heating in many developing countries. It is also used by animal feed industry, food processing industries, and the wood products industry, which consists construction and fiber products (paper and derivatives), along with chemical products made by these industries that have diverse applications including detergents, fertilizers, and erosion control products (Milbrandt & Uriarte, 2012).

The conversion technology addressed in this study is limited to anaerobic digestion (**AD)**. Anaerobic digestion is one of the convenient organic waste management ways which have significantly large resource recovery potentials. Biological process of AD is undertaken in without the use of oxygen with the help of microbes. Biogas and compost are produces from the anaerobic process. Biogas; consists of methane (ranging 55% to 70%) and carbon dioxide (CO_2) is produced from the process after 2-3 weeks. Compost can be used as organic fertilizer based on nutrient content.

1.4.3. Case Study Area

The area of analysis for this study is Enschede; it is one of the municipality and a city in the eastern Netherlands in the province of Overijssel and in the Twente region.

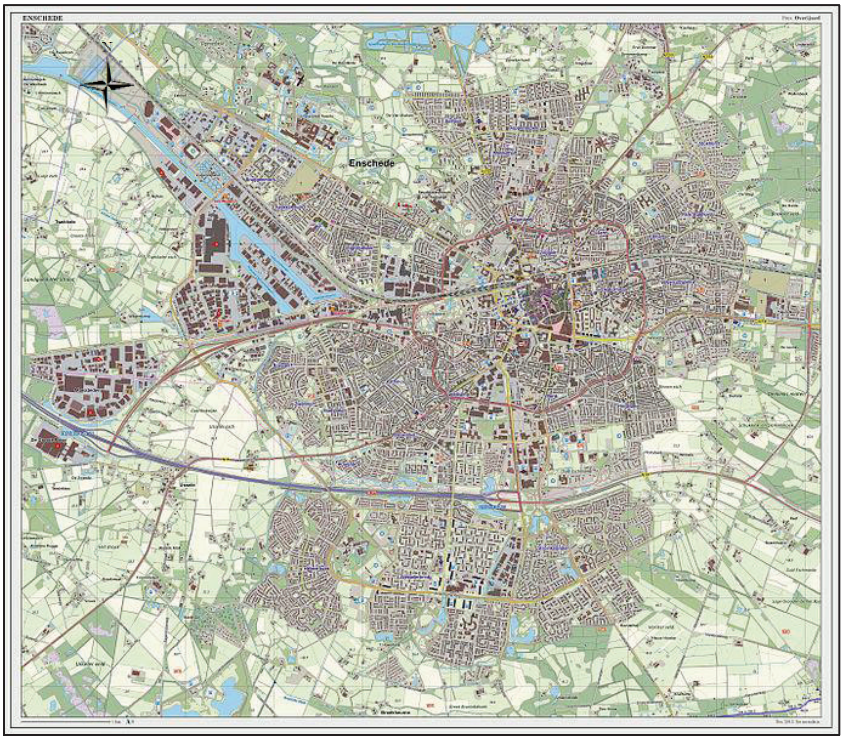


Figure 3: Dutch Topographic map of Enschede (city), Source(Wikipedia)

Geographically, the city lies a few kilometers away from Germany, which borders the municipality. In the west, Hengelo is the first immediate place and at the eastern side, Gronau plays that rolethe area. Enschede’s total area is 142.8 square kilometres (Wikipedia). Of this agricultural grass land is 51.57 square kilometres (36 % of the total area).

Energy target:

The energy target for the municipality of Enschede emerges from province Overijssel ambitious renewable energy plan. The ambition of the province is to make the energy supply more viable and decrease dependency on fossil fuels. The province of Overijssel has developed bioenergy production options based on EU and national standards, guidelines and legislation (Overijssel, 2008). With a target date of 2050 the province of Overijssel has a plan to meet a reduction in CO2 emissions of 80 %. Simultaneously, an ‘energy transition’ must have been achieved (Overijssel, 2008). Moreover, with a plan to be achieved in few years, the province of Overijssel has devoted itself to meet the EU emission reduction goal of 30 % by 2017 (reference to the 1990 emission level). For this reason, several renewable energy technologies, especially those associated to bio-energy, are considered as part of the policy approach. In addition to the goals mentioned, Overijssel targets to achieve a 20 % share of renewable energy sources in its energy mix. In total, the province of Overijssel aims to decrease emissions by 2,200 kton CO2 /yr. by 2020 (Hoppe, Kooijman-van Dijk, & Arentsen, 2011).

Bioenergy in Overijssel:

In the year 2011, 3.3 % of the regional energy consumption was obtained from renewable resources. Figure 4 displays the production of renewable energy in Overijssel, subdivided based on different sources. Waste incineration and bio-energy conversion takes the largest part of renewable energy production in the region. The Overijssel region has only one Wind Park. The natural conditions for wind energy production are not optimal in the inland region, but nor are the provincial authorities are willing to support wind energy. Heat and cold storage is also rather concentrated in the region, whereas hydro and solar energy sources are very few. Some river turbines are functional, but their production is less (only 6 TJ/year). Photovoltaic energy is hardly supported in the Netherlands since it is considered too expensive (Hoppe et al., 2011)

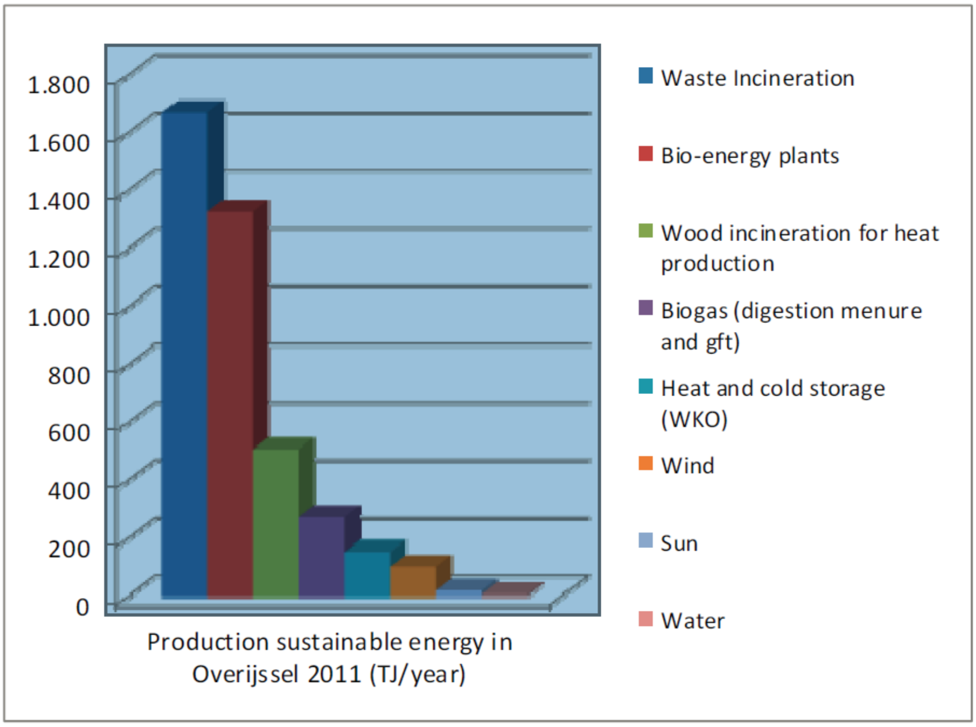


Figure 4: Production of renewable energy in Overijssel subdivided by sources (Overijssel., 2011)

Generally, 3% renewable energy production is not an impressive number that is why the province wants to have an ambitious renewable energy policy which concentrates on bio-energy.

1.5. Research objectives

The main objective of this research is to develop an optimization method in application to Life cycle assessment (LCA) model for the geographical location of bio refinery plants to satisfy the maximum Net Energy Gain (NEG) function.

1.5.1. Specific Objectives and Research Questions

The specific objectives and the respective research questions are outlined below:

1. To develop an LCA model of biomass for biofuel production
    a. Q1: what are the energy input components for the system boundaries of the LCA model?
2. To quantify the energy required throughout the biomass to bioenergy cycle and estimate the NEG value from grass.
    a. Q1: How much input energy is required to exploit the biomass resource of the study area?
    b. Q2: How much is the net energy balance?
3. To determine the optimal number, size and location of bio refineries needed to process the biomass resource of the study area.
    a. Q1: How big should each processing plant be? And how many plants are needed?
    b. Q2: Where should it be located?
    c. Q3. Which biomass supplying areas are shipping to which plant?
4. To analyze the solution obtained from MIP model?
    a. Q2: What are the comparison results of energy input versus energy output?
    b. Q: is the production of energy from grass viable?

1.6. Thesis structure

This thesis consists of six chapters. Of which the first chapter is Introduction. Second chapter is literature review; the third chapter focus on model formulation, chapter four deals on materials and methods and the fifth chapter talks about model results and analysis. Finally, conclusions, limitations of the study and suggestions for future work are assigned to the sixth chapter.

1.6.1. Concepts on each chapter

Chapter one is introduction, it introduces the motivation, objectives and scope of the study. In chapter two, an overview of spatial optimization problem, the two strategies (exact and heuristic) for solving spatial optimization problem are presented. Previous studies related to this thesis are reviewed. The strengths and shortcomings of the past literatures are also discussed.

An optimization model in application to life cycle assessment is formulated in chapter three. A detail description for the sets, parameters, decision variables, the goal function and constraints of the mixed integer programming model are given in this chapter. A conceptual model for life cycle assessment of biomass to bioenergy is also provided here.

Prior to discussing model implementation and results, the details of data acquisition techniques, methods and the used materials are presented in chapter four. In chapter five, main procedures to implement the mathematical model are listed. The techniques to validate the accuracy of the model are mentioned. Model results and analysis are also presented here. The sixth chapter is assigned to the conclusions, the strengths and limitations of the study. Finally, several suggestions are given for future research directions.

CHAPTER 2

2. LITERATURE REVIEW

In this chapter, a review of spatial optimization, structure of a spatial optimization problem and solution methods are presented. Previous studies related to this thesis are discussed.

2.1. Spatial Optimization

Spatial optimization is an important subspecialty in the area of geography, contributing to the fields of facility location modeling, bioenergy supply chain, land use planning, GIScience, school districting, and others. It is a discipline based on optimization techniques to define and solve problems where spatial context is important. "Spatial optimization is a decisive tool to prescribe the best spatial arrangement or allocation of resources, goods for a predefined planning period, but also to help understand the significance of a particular spatial arrangement or pattern" (Tong & Murray, 2012). The structure of spatial optimization problems and the solution methods are discussed in the following sections.

2.1.1. Spatial Optimization Problems

Similar to engineering and mathematics optimization problems (constrained), spatial optimization problems includes three building blocks of elements: an objective function, decision variables and constraint conditions. The objective associates to purpose of the problem context, often reflecting goals to be achieved, it could be minimizing costs (loss) or maximizing profits (gains) or benefits. The objective (goal) function can be structured using one or multiple objective functions. Decision variables relate to the decision(s) to be made. Constraints establish conditions necessary to be satisfied related to the problem under study. These constraints/forcing conditions might correspond to financial limitations, production capacities, environmental impacts, and so on.

A general spatial optimization problem with some conditions is specified by the following mathematical notations:

$$Maximize\ f(x) \qquad (1)$$

Subject to

$$g_i(x) \leq b_i \qquad (2)$$

$$x\ conditions \qquad (3)$$

Where x is a vector of decision variables, $x = (x_1, x_2, x_3, \ldots, x_n)$, f and g_i are functions of x, and b_i is a constant that bounds the value of each associated function g_i. The conditions on x (Equation 3) mainly includes some combination of real, integer, or binary requirements; non-negativity requirements; or both.

The unique feature that makes an optimization problem described in (1-3) spatial is that the specification(s) given to each of decision variables, functions, coefficients, and forcing conditions. Since geography and space become part of the model structure by design, this makes the defined optimization problem special. In other words, the variables, coefficients, functions, and forcing conditions that are geographically based have interdependent relationship. More specifically, they have spatially interdependent relationships and properties which are often difficult to figure out and model, but they also become challenging to solve as a result. Thus, spatial optimization problems have typical practical significance, either serving to describe or helping in planning decision making, as well as demanding substantial practical skill and expertise to properly structure and solve for a given substantive context (Tong & Murray, 2012).

The most evident spatial element of an optimization model is likely geographic decision variables. Usually spatial optimization problems give emphasis for problems that require decision where something is to be placed or located. The decision might need questions of how much should be located at some place, which path should be chosen, or even what kind of pattern of delivery or activity should be.

2.1.2. Solution Methods

There are two main strategies for solving spatial optimization problems, exact and heuristic methods (Church & Murray, 2009; Miller & Shaw, 2001; Scott, 1971). "Exact methods are those that exhaust all possibilities or exploit problem properties, ensuring that the optimal solution is found. Alternatively, heuristics are problem-specific ad hoc strategies, finding characteristically good solutions but generally lacking any capacity to verify or validate solution quality"(Tong & Murray, 2012).

i. Exact Methods

A solution method to an optimization problem is called exact method if the best possible, or optimal, solution is guaranteed to be known using this method. That is, it can be proven that the solution obtained by an exact method gives the best value, and hence no other decision variable values would give a better optimal value while preserving problem feasibility. There are many exact approaches, including derivative-based techniques, enumeration, linear programming, integer programming with branch and bound, and so on, as well as more problem-specific methods like the Hungarian algorithm, transportation simplex, Dijkstra's algorithm, and so on (A.T. Murray).

Enumeration is simple and direct, based on the problem type; it sorts out all feasible solutions, evaluates them, and then allows concluding which is the best. This makes a lot of sense, if solutions can be readily identified and the number of different solution combinations is not computationally prohibitive. Further, one can guarantee optimality or exactness. Unfortunately, many problems cannot be solved using enumeration technique for two reasons. First, some problems have an infinite number of possible solutions, making evaluation for each is impossible. Secondly, the number of possible solutions, although limited in number, might simply be too difficult to evaluate in a reasonable amount of time.(A.T. Murray)

Another most famous exact method is **linear programming** (LP) an approach that is based on linear algebra and solving a system of linear equations. It is an optimization method where both the objective function and the constraints are linearly dependent on the continuous decision variables. These days, there are several commercial software packages which are capable of solving LP problems with significantly large number of decision variables and many constraints (e.g. Gurobi, Cplex, LINDO, GAMS etc.). The only real drawback is that some problems do not preserve the assumption of linearity, either in the objective functions or decision variable. To resolve one aspect of limiting capabilities in linear programming, integer programming with branch and bound is a good option. It is an exact method for solving problems where decision variables are limited to integer values. Even though it is commercially available, the problem sizes that can be addressed are another limiting factor for integer programs (A.T. Murray).

ii. Heuristics

The concept of heuristic optimization methods is old and first appeared in the literature in the early 1940s (Polya, 1945). By the end of the early 1960s, it was a common concept in computer science. Heuristic methods were seen as 'provisional and plausible procedures whose purpose is to discover the solution of a particular problem at hand'(Gelernter, 1959). The most common features of all heuristic optimization (HO) methods is that they begin with a more or less random initial solution, iteratively produce new solutions by some generation rule and evaluate these new solutions, and finally report the best solution found during the search process. Heuristics makes few or no assumptions about the problem being optimized. Usually, heuristics do not guarantee that an optimal solutions need to be found nor do they determine how much better an optimum solution might be. On the other hand, heuristics are used to find approximate solutions for many complicated optimization problems (A.T. Murray).

There are many reasons why exact methods for solving an optimization problem might not be good or appropriate. Some problems are hard to solve and difficult to get an acceptable solution in a reasonable time. In such cases we usually prefer a not too bad solution much faster, by applying some arbitrary choices (reasonable guesses) which are a heuristic.

Many heuristics have been used for solving spatial optimization problems, such as interchange, greedy, simulated annealing, tabu search, and population-based heuristics, such as genetic algorithms and ant colony heuristics.

2.2. Review on Optimization Models for Biomass Supply Chain

The previous section has elaborated the unique features of spatial optimization techniques and the corresponding solution methods. This section will review literatures on optimization models for biomass supply chain.

The biomass supply chain has been modelled and analysed in the literature to increase model performance in terms of biomass transportation and the total delivery cost. In this context, a number of optimization models have been developed. Cundiff developed a linear programming (LP) model to design a biomass delivery system for switch grass producers which can provide feedstock for a central plant (Cundiff, Dias, & Sherali, 1997). The proposed optimization model determined a monthly shipment plan and capacity expansion schedule for each switch grass producer based on monthly harvest and four different weather scenarios.

A mixed-integer linear optimization model based on the dynamical evaluation of economic efficiency was developed by Nagel (2000) to find the most economical and ecological (based on CO2 emissions) energy supply structure for heating a small rural community. The main decision variable was whether they should build heating systems (individual energy supply), a heating plant, or a co-generation plant. The proposed model was used in the rural municipality of Brandenburg, Germany with 660 inhabitants. The results showed that the energy prices have the greatest influence on the economy. Individual heating systems became an attractive option with decreasing prices for biomass. The produced CO2 could decrease up to 25% by increasing the use of biomass. In addition, biomass would not be an economical feedstock with decreasing prices for fossil fuels.

Parker et al. (2010) has developed mixed integer-linear optimization model that determines the optimal locations, technology types and sizes of bio refineries to satisfy a maximum profit objective function applied across the biofuel supply and demand chain from site of biomass farm to the product fuel terminal. In the study, spatial information including biomass resources, existing and potential refinery locations and a transportation network model is incorporated to the model.

Kim, Realff, Lee, Whittaker, and Furtner (2011) presented a mixed integer linear programming model that enables the selection of fuel conversion technologies, capacities, biomass locations, and the logistics of transportation from the locations of forestry resources to the conversion sites and then to the final markets. The model targets to maximize the overall profit and considers various types of biomass, conversion technologies, and several feedstock and plant locations.An, Wilhelm, and Searcy (2011) formulates a model to maximize the profit of a lignocellulose biofuel supply chain ranging from feedstock suppliers to biofuel customers. Leduc, Lundgren, Franklin, and Dotzauer (2010) have developed a dynamic optimization model in order to find an appropriate geographic position of a methanol production plant to minimize the specific biofuel production cost.

A mixed integer mathematical programming model for the lignocellulose biomass-to-ethanol industry was developed (Gelson Tembo, 2003). The optimization model determined the most economical source of biomass, timing of harvest and storage, inventory management, bio refinery size, and bio refinery location. It also identified the breakeven price of ethanol for a gasification-fermentation process. The objective function of this model was to maximize the industry's net present value. The optimization model was applied in Oklahoma State where a variety of potential lignocellulose feedstock including plant residue, indigenous native prairies, and pastures are available. The primary finding of the study was that gasification-fermentation of lignocellulose biomass to bioethanol may be more economical than fermentation of corn grain with the further development of the conversion process to handle multiple feed stocks and reduction in the capital and operating costs of the plant.

Recently, with the growing interest towards renewable energy, geographical information systems (GIS) have been introduced in the analysis of biomass supply chains in order to estimate more accurately the expected biomass supply in a given region and the transportation distances and related costs and to assess the impacts of spatial feedstock subtraction of different chain designs (Geijzendorffer, Annevelink, Elbersen, Smidt, & de Mol, 2008). Sultana and Kumar (2012) have developed a model in GIS environment to locate bioenergy facility through integration of environmental and economic constraints in the province of Alberta, Canada. R. L. Graham, English, and Noon (2000) incorporated GIS –based modeling system and used it to estimate potential energy crop supplies and costs in eleven US states.

R. Graham et al. (1996) developed a GIS-based modeling system for analyzing the geographic variation in potential bioenergy-feedstock supplies and optimal locations for locating bioenergy facilities. The modeling system was designed for analyzing individual U.S. states, but it can be adapted to any geographic region. The modeling system has four basic components: mapping crop-land availability, calculating the expected yields and farm gate price, mapping the cost of the delivered energy-crop feedstock, and mapping the probable sites for the co-location of bioenergy facilities.

Graham constructed a regional-scale, GIS-based modeling system for estimating the potential biomass supplies from energy crops (R. L. Graham et al., 2000). The system considers the regions where energy crops could be grown, the spatial variability in their yield, and the transportation costs associated with acquiring the feedstock needed for an energy facility. The potential costs 17 and supplies of switch grass in 11 U.S. states are estimated by this system. They concluded that transportation costs are the lowest in Iowa, North Dakota, and South Dakota; and are the highest in South Carolina, Missouri, Georgia, and Alabama. They additionally estimated across 11 states, the costs of delivered feed stocks which ranged from \$33 to \$55 per dry ton for supplying a facility that requires 100,000 ton/year. Graham and Husain also made an insightful study on modeling for optimal biofuel sites (R. Graham et al., 1997; Husain, Rose, & Archibald, 1998).

2.3. Summary

In the bioenergy supply chain literature, several optimization methods have been applied. For the purpose of this study, we choose a mixed-integer programming (MIP) method. Since, mixed integer linear programming problems are often used to solve discrete location problems. This has also an advantage of simplicity and can guarantee in identifying global optimal solution (Cundiff et al., 1997; Tatsiopoulos & Tolis, 2003). The MIP model will represent decisions regarding the optimal number, locations, and sizes of the biofuel facilities, and the amounts of biomass to be transported between the harvesting areas and the biofuel facilities, and maximize the objective function of the delivered input energy costs.

CHAPTER 3

3. MODEL FORMULATION

As it has been discussed in the aforementioned chapter, several optimization methods have been reviewed to solve bioenergy supply chain issues. In this chapter a static Mixed Integer Programming (MIP) model in application to Life Cycle Assessment of biomass to bioenergy is introduced. Since, MIP models have the advantage of simplicity and can guarantee in identifying the global optimal solution (Cundiff et al., 1997; Tatsiopoulos & Tolis, 2003). The formulated MIP model represents decisions regarding the optimal number, locations, and sizes of the biofuel facilities and the amounts of biomass to be shipped between the biomass areas and the processing plants. The model maximizes the total Net Energy Gain (NEG) of the bio-refinery supply chain. It also reflects major thoughts and working conditions of the system. To simplify the presentation, the proposed model considers one time period (year), the technology and demand for biofuel chain are beyond the scope of this study. Before formulating an optimization model let us see what is meant by Life Cycle Assessment.

3.1. Life Cycle Assessment (LCA)

Generally, LCA involves the investigation and evaluation of the environmental impacts of a given product or service, based on the identification of energy and materials inputs and emissions released to the environment. In LCA, the energy inputs, output and the loss/gain and environmental impacts are calculated over the whole lifetime of the product 'from cradle-to-grave' – hence the name 'life cycle' (Guinée, 2002; von Blottnitz & Curran, 2007). The present LCA technique originates from `net energy analysis' studies, which were published for first time in the 1970s (Boustead, 1972; Bullard & Herendeen, 1975) LCA can also be integrated with optimization methods to provide a powerful tool for process design and optimization (Azapagic, 1999).

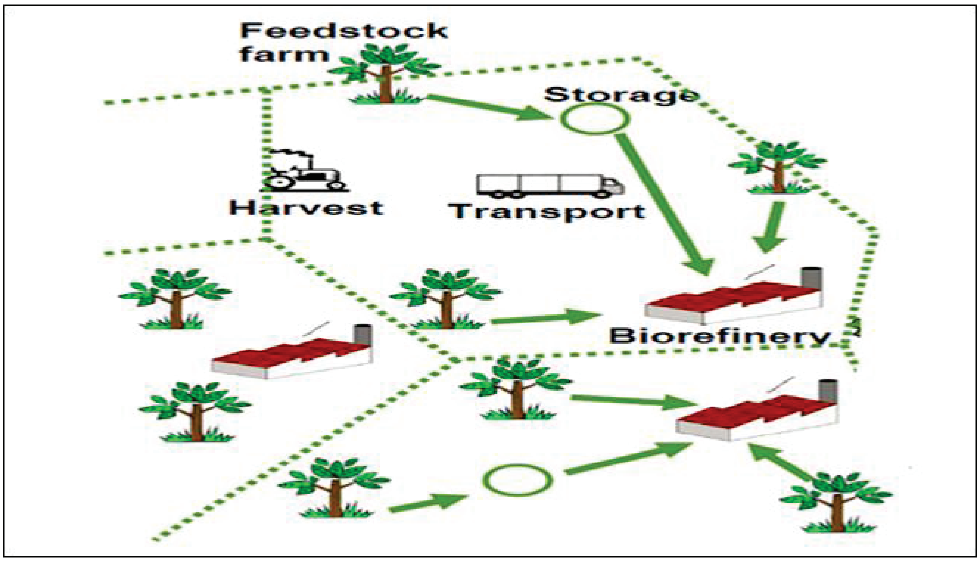


Figure 5: Biomass supply chain (Kang, Önal, Ouyang, Scheffran, & Tursun, 2010)

To define an LCA, determining the boundary is the crucial step. In this study, for production of bioenergy from biomass, only major energy input components such as energy cost to: collect and transport biomass, construct and operate the bio-refinery plant are getting consideration. These production stages are explained in more detail in the subsequent sections. The comparative analysis of energy spent to produce bioenergy versus energy out is cleared in the coming chapter.

The diagram in Fig 6 illustrates a generic bioenergy life cycle scheme; it shows the main sub-processes, and identifies the flows of materials and energy inputs.

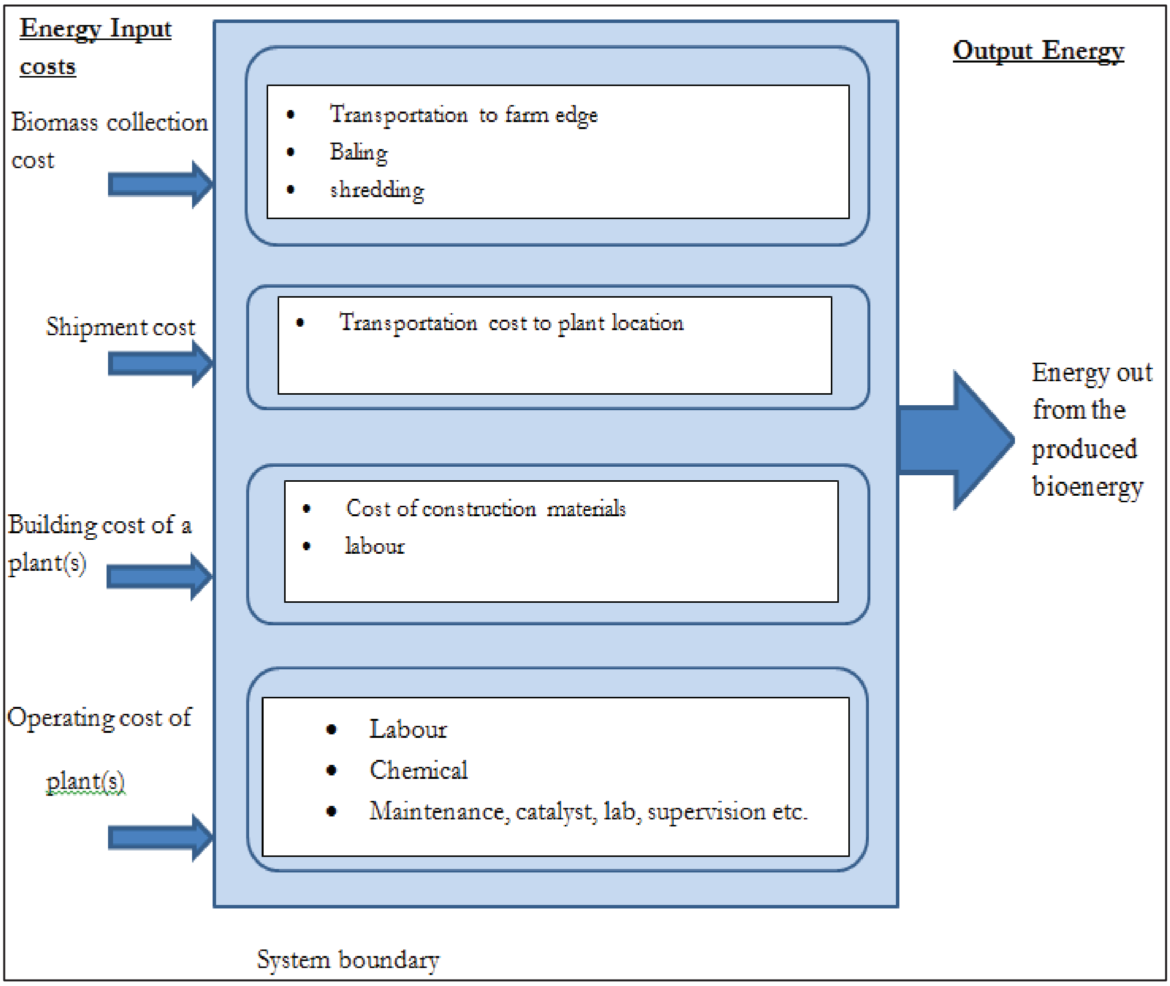


Figure 6: A life cycle scheme for the production of bioenergy

3.2. Mathematical Model Notations and Assumptions:

The following sets, indices, variables and units of measurements are used in the formulation of the Mathematical model.

1. Sets and indices

$R = \{(i, j), where\ i = 1, 2, \dots, m, j = 1, 2, 3, \dots, n\}$ Set of n x m grid cell coordinates for the study area.

$C = \{c_p : p \in R\}$ Vector of processing plant capacities in dry tone per year

$B = \{b_z : z \in R\}$ Vector of available biomass over each grid cell in kilo gram per/km^2

2. Model Parameters:

The parameters used in this formulation are:

ρ Energy cost to collect biomass in Mega Joule per kilogram

μ The unit energy cost of shipping agricultural crop residue from grid cell $z \in R\ to\ p \in R$ return trip included in Mega Joule/Km/kg.

γ Unit energy cost of processing in Mega Joule per ton (MJ/ton).

α Conversion efficiency of a processing plant in Mega Joule per ton (MJ/ton).

d_{zp} The Euclidean distance from cell z to cell p

f_p fixed cost of locating a plant at cell p $\in$R

Model inputs are:

b_z Amount of biomass from each grid cell

Decision variables:

a_{zp} Fraction of biomass to be shipped from cell z to cell p.

c_p Capacity of processing plant at location p.

x_p Indicator variable for the opening of a plant at location p,

$$x_P = \begin{cases} 1 & \text{if we locate a plant at cell p } \in \text{ R} \\ 0 & otherwise \end{cases}$$

For notational convenience we define A, C and X, as vectors that denote the collection of decision variable a_{zp} , c_p and x_p respectively. The controlling parameters (independent variables) are the grid coordinates for the candidate locations, the capacity of the processing plant and an indicator variable for the location of processing plant.

The general frame of the objective function is formulated as follows:

$$\text{Max}_{(\text{C,A})}(E_{out} - E_{in}) \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where, $E_{out}\ and\ E_{in}$ are the total energy output and total energy inputs respectively

Energy output:

The energy output (gained) after the biomass is converted to energy (E_{out}) considers plant capacity as its variable. It is assumed that the energy out is directly proportional to the production capacity of the plant.

Mathematically

$$E_{out} = \alpha \sum_{p \in R} c_p \quad is\ the\ total\ energy\ output\ from\ the\ selected\ bio\ refinery(ies).$$

Energy input (E_{in})

The input energy (E_{in}) includes the energy cost for collection, hauling, operating, building the plant, and the fixed energy cost for opening of a plant(s). It is the sum of the following five terms.

$$E_{in} = E_{collection} + E_{transportation} + E_{operate} + E_{build} + E_{fixed\ cost} \cdot$$

The description for each term is explained in the following subsections

Energy cost for Collection of biomass ($E_{collection}$)

Collection involves operations pertaining to shredding, baling, and moving bales to the field age or transporting biomass to a nearby site for temporary storage. The quantity of biomass resource that can be gathered at a specific time depends on several factors. In case of agricultural biomass (grass), these considerations include the type and sequence of collection operations, the efficiency of collection equipment, tillage and crop management practices, and environmental restrictions, such as the need to protect soil erosion, preserve soil productivity, and maintain soil carbon levels. In this study biomass collection cost includes, the cost for gathering, shredding, baling and transporting biomass to the field edge. For the purposes of this study we assume that the total energy cost to collect biomass is proportional to the total available biomass.

$$E_{collection} = \rho \sum_{z \in R} b_z$$

Figure 7: Round bale biomass. Source: (Consult, 2014)

Energy cost for Transportation:

One major concern for the economic viability of energy production from biomass is transportation cost. Transportation is a key element of the biomass feedstock supply chain system. Biomass may be transported by truck on existing roads or by barges and trains on waterways or existing rail networks (Hess, Foust, Hoskinson, & Thompson, 2003). Transporting biomass more than 80 km (50 mile) by road are not considered to be economically viable (Paine et al., 1996). In fact the markets are also influenced by geography (Lunnan, 1997). Therefore, supply at distant locations may not be favorable for exploitation due to higher costs (Fischer & Schrattenholzer, 2001). Hence, it is always better to search for a nearby market for the biomass; if possible, so that the energy cost related to biomass transportation over large distance can be reduced. For our study, it is assumed that biomass is transported to a processing plant by truck, since truck transport is generally well developed in Netherlands and is often the cheapest mode of transport but it turns out to be expensive as travel distance increases (Cundiff et al., 1997). Transport costs which cover the distance from the biomass farm to the plant gate is the crucial part of the total costs. They are increasing function of distance and depend on the yield and density of the biomass, the size of processing plant and a given truck-hauling rate (Gallagher et al., 2003).The cost of transporting biomass is often the factor that limits the capacity of a processing plant. Large scale processing plants can get advantage from economies of scale and lower unit capital costs. However, the largely dispersed biomass(grass) through the landscape, and relatively low conversion efficiencies of existing plants have tended to restrict the size of bio-energy plants (Larson, 1993). Transportation cost includes loading/unloading cost.

Maintenance and Operating cost

Operating cost estimation is not easy since it varies from place to place based on labour rates, availability of skilled man power, accessible infrastructure etc. Thus, direct comparison of operating cost from literature is not always exact. The typical number of operating labourers required for the operation and maintenance of plants can be compared directly and scaled more accurately from literature. For the purpose of this study, an overall estimation given by Uellendahl et al. (2008) were used as basis for operating cost estimation.

The operating cost considers variable costs of operations including labor, supervision, utilities, maintenance, supplies, lab charges, royalties, catalyst, solvents, taxes, and insurance. For the purpose of analysis to our model, it is assumed that all of these charges are directly linearly dependent upon production capacity of a plant.

Construction/building cost: it contains both fixed and variable costs. The fixed cost includes all expenses which are not varying; it covers taxes, insurance costs and rent (for parcel and buildings). These costs are not dependent with the capacity of a plant. The variable cost consists of the energy costs of labour, construction material and machinery cost. This cost depends on processing plant capacity. For the case of simplicity, a linear cost function is considered to this study.

Thus, an explicit formulation for the objective function described in equation (1) is given below

$$\underset{(C,A)}{\text{Maximize}} \quad \overbrace{\alpha \sum_{p\in R} c_p}^{Energy\ out} - \overbrace{\rho \sum_{z\in R} b_z}^{Energy\ to\ collect} - \overbrace{\mu \sum_{z\in R} \sum_{p\in R} b_z d_{zp}\, a_{zp}}^{Energy\ to\ transport} - \overbrace{\beta \sum_{p\in R} f(c_p)}^{Energy\ to\ build(variable\ cost)}$$

$$- \overbrace{\sum_{p\in R} f_p * X_p}^{fixed\ cost} - \gamma \overbrace{\sum_{p\in R} c_p}^{energy\ to\ operate} \qquad (2)$$

$$subject\ to \quad \sum_{z} b_z\, a_{zp} = c_p \qquad \forall p \in R \qquad (3)$$

$$\sum_{P} a_{zp} = 1 \qquad \forall z \in R \qquad (4)$$

$$a_{zp} \leq x_p \qquad \forall p \in R \qquad (5)$$

$$x_p \in \{0,1\} \qquad \forall p \in R \qquad (6)$$

$$0 \leq a_{zp} \leq 1 \quad , c_p \geq 0 \qquad \forall\, z, p \in R \qquad (7)$$

The objective function in (2) maximizes the net energy gain by minimizing the total energy input cost of all operations. Which is, the sum of output energy from each selected processing plant of capacity c_p (provided that the plant is to be located at p) less the energy cost to collect biomass, the energy required to transport the biomass from fields (agricultural grid cells) to processing plants, energy to build a processing plant of capacity c_p, energy needed to operate a plant.

Constraint (3) limits the amount of biomass shipped to processing plant is as equal as the capacity of the processing plant. Constraint (4) assures that if biomass is shipped from grid cell z to processing plant, then the biomass is assigned to only single processing plant. Constraint (5) will ensure that biomass at cell z are not shipped to a plant at location p if we have not selected location p. Constraint (6) and (7) are the integrality and non-negativity constraints, respectively.

The energy cost to build a processing plant is a function of capacity. In reality, this cost is non- linear function, however for the sake simplicity a linear function is assumed in this study. The total energy cost to collect biomass is fixed, as both ρ and b_z are constants and hence the second summand can be excluded from the objective function in (2). However, in the calculation of maximum energy gain it will be considered after the optimization problem is solved. Thus, an equivalent MIP model to expressions (2) to (7) is:

$$\underset{(C,A)}{\text{Maximize}} \quad \overbrace{\alpha \sum_{p\in R} c_p}^{Energy\ out} - \overbrace{\mu \sum_{r\in R} \sum_{p\in R} b_z d_{zp}\, a_{rp}}^{Energy\ to\ transport} - \overbrace{\beta \sum_{p\in R} f(c_p)}^{Energy\ to\ build\ (variable)} - \overbrace{\sum_{p\in R} f_p * X_p}^{fixed\ cost}$$

$$- \gamma \overbrace{\sum_{p\in R} c_p}^{energy\ to\ operate} \qquad (8)$$

Subject to the previously discussed constraints

Note: the fixed cost of locating a processing plant has to be considered; otherwise the model would seek to place a plant at every grid cell in order to reduce the shipment costs.

CHAPTER 4

4. MATERIALS AND METHODS

4.1. Materials

4.1.1. Data

Several data sets are required as model input, including the quantity of biomass supply from each grid cells, unit costs for collection of biomass, unit cost of transportation of feedstock from biomass areas to processing plant locations and the unit energy costs to operate as well as to build a plant. The techniques used to generate these data are justified below.

Energy Input Data
Measuring all of the input energy requirements for bio energy production from biomass is difficult and beyond the scope of this theses project. Instead, assumptions and estimations have been derived from available data in order to approximate actual energy Inputs. A discussion on the energy calculations for input and energy conversion parameter values is included in the subsection below. The data is presented for each input as well as the cumulative energy demand is expressed in MJ of energy input per kg of biomass (grass) produced. The weight of the grass (biomass) produced is measured in kilogram.

Table 1: Data for energy inputs

Inputs	Biomass type	value	Unit of measure	Reference(s)
Energy to transport the biomass to the processing plant (μ)	Agricultural crop residue.	0.001968	MJ/km/kg	Ghafoori, Flynn, and Feddes (2007)
Energy to collect /transport to local storage (ρ)	Agricultural crop residue.	0.232	MJ/kg	V. and Tiffany. (2010)
Average lower heating value (α)	Agricultural crop residue.	16.6	MJ/kg	http://www.biofuelsb2b.com/useful_info.php?page=Typic
Energy cost to operate biogas plant (γ)	Agricultural crop residue.	0.293	MJ/Kg	Uellendahl et al. (2008)
Average biomass yield	grass	7×10^6	kg/km^2/year	Holland (2010)
Transportation cost by heavy trucks		2.426	MJ/ton/km	(Wikipedia)

The scale factor for the energy cost to build a processing plant was taken to be 600MJ/tone/year. An assumption is also derived for the fixed energy cost to open a plant to be 28,000MJ/tone.

Distance Matrix Data:
The **Euclidean distance** from the centroid of each rectangular grid coordinates of a biomass cell to the other grid cells of the study area are generated by writing a code in Matlab. The code to obtain grid coordinates and calculate the Euclidean distance matrix is shown in the appendix section. The figure below is an illustration for rectangular grid coordinates.

(1,1)	(2,1)	(3,1)	(4,1)	(5,1)	(6,1)
(1,2)	(2,2)	(3,2)	(4,2)	(5,2)	(6,2)
(1,3)	(2,3)	(3,3)	(4,3)	(5,3)	(6,3)
(1,4)	(2,4)	(3,4)	(4,4)	(5,4)	(6,4)
(1,5)	(2,5)	(3,5)	(4,5)	(5,5)	(6,5)
(1,6)	(2,6)	(3,6)	(4,6)	(5,6)	(6,6)
(1,7)	(2,7)	(3,7)	(4,7)	(5,7)	(6,7)

Figure 8: Sample representation of rectangular grid coordinates

Biomass data:

Top10NL Cadastral Level (1-10m) Vector Shape files for 28 East, 28 Wests, 29 West, 34 East, 35 West blocks of Western Holland land use data were used. This vector data was projected to RD New coordinate system and adjusted to Geographic Coordinate System Amersfoort. To determine the study area, the six blocks of layers are merged to one layer, and then the resulting layer was clipped by the boundary of Enschede. Only areas covered by grass are taken in to consideration as input data. The whole study area was discretized in to a raster map of 1km x 1Km grid points. The dimension of 1 km ^{2} for each cell was chosen because an area of 1 km^2 ensures to build a processing plant and is good enough to compromise the tradeoff between computational complexity and level of detail for biomass estimation. Applying the regular grid, as shown the in figure 6, to the study area, it is obtained a total of (15 by 14 rectangular grid) 210 square grid cells. Biomass (grass) resources are not evenly distributed throughout the municipality. The maps below show where the biomass resources are located.

Figure 9: Map showing grass land areas of Enschede

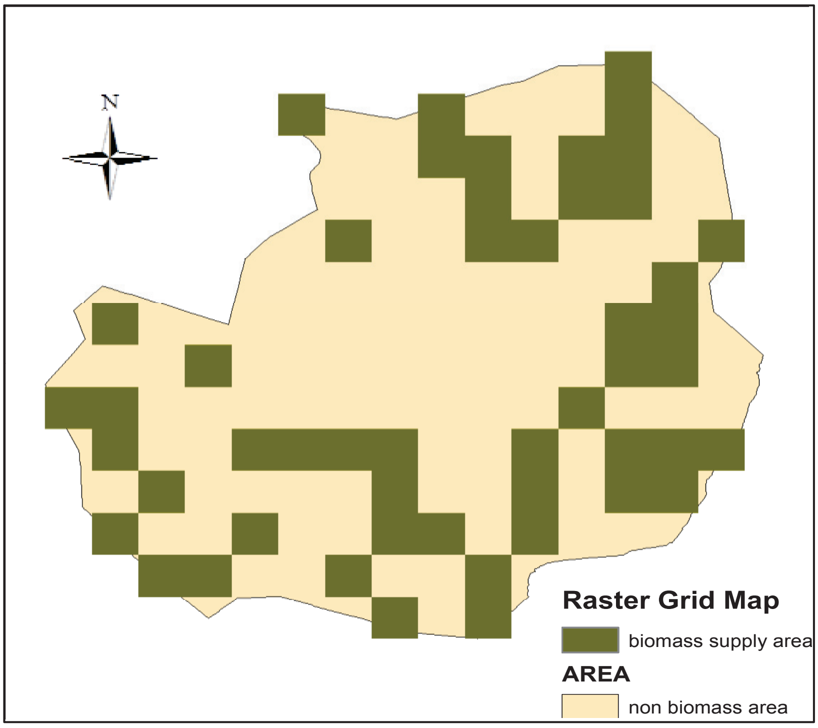


Figure 10: 1km x 1km raster grid biomass map

Based on an estimate made by Holland (2010), the average amount of biomass yield from each grid cell was taken to be 7 tons per hectare (700 tones/ km^2).

Table 2: Estimated biomass data

Area of land covered by biomass (grass)	Harvestable biomass	Reference
50km^2	35000drytone/year	Holland (2010)

4.1.2. Software Used and their Purpose

Various tools and software have been utilized in this thesis project for analysis and report writing. Among these, AIMMS ("Advanced Interactive Multidimensional Modeling System") software has been used to solve the optimization problem. We choose AIMMS because, the free AIMMS Academic License allows in using unrestricted world-class solvers such as CPLEX, GUROBI, MOSEK, XA, CP Optimizer, CONOPT, MINOS, SNOPT, LGO, AOA, PATH, CP Optimizer, and, through COIN-OR, CBC and IPOPT with no extra installation required, and free of charge. Table 3 shows list of software used in the theses project.

Table 3: Software used and their purpose

Software	Purpose
ArcGIS10.1	• Layer clipping • Map preparation • Biomass data extraction • Geo processing (Vector →Raster→ASCII)
Matlab13a	• Writing code to generate rectangular coordinates and calculate distance matrix • To Write code that converts the output solution to an equivalent ASCII representation of map
AIMMS/GUROBI	• To solve an optimization model
Microsoft Excel	• To enable AIMMS read biomass data, distance matrix data. Read results from AIMMS.
Microsoft Word	• To write the report
Microsoft power point	• To prepare slides for presentation

CHAPTER 5

5. MODEL IMPLEMENTATION AND RESULTS

This section discusses model validation, implementation and obtained results. As mentioned in chapter one, the area of analysis for this model is Enschede. It utilizes raster data format of 1km grid cell resolution with 14 rows and 15 columns, where the land use of each cell is homogenous. Each cell covered by biomass is considered as a harvesting site and each grid cell of the study area are candidate location for a plant. The model is validated by using a hypothetical data set and implemented for two cases over the study area. In each case the optimum NEG value and other energy costs are analyzed. The optimal location, size and the number of plants over the study area are determined for two cases.

5.1. Main Procedures

Main Procedures utilized in Arc GIS, MATLAB, Microsoft Excel and AIMMS for data preprocessing and Model implementation:
A variety of sequential steps have been applied to preprocess data, write code and execute model outputs. The list below shows the steps to be followed to obtain desired model output.

In Arc GIS:

1. Extraction of Grassland Area in Enschede Municipality
    - Load all the 'Terrain Land Cover' Shape files for the six regional blocks onto ArcGIS.
    - Merge six blocks of Top10 land use layers (different parts of Netherlands) to one layer
    - Use 'Select by Attribute' feature to select only those areas belonging to the 'Grassland' category. Create a layer that contains only the area selected and then export this layer to your personal or file geodatabase as a shape file.
    - Clipped by the boundary of Enschede.
2. Change the biomass vector data to raster then to ASCII.
3. Change ASCII data to csv format

In Matlab:

4. Load the csv data obtained in step 3 to Matlab and convert to column vector
5. Write code to generate rectangular grid coordinates of the study area.
6. Write code to calculate Euclidean distance matrix.

In Microsoft Excel

7. Import the obtained Euclidean distance matrix in step6 to Microsoft excel
8. Import the biomass data obtained in step 4 to Microsoft Excel
9. Generate location points in Microsoft Excel

In AIMMS

10. Introduce a set of indices, parameters, variables, constraints and objective function
11. Write code to read data from Microsoft Excel
12. Read data for location points, biomass and distance matrix from Microsoft Excel.
13. Run the AIMMS model, execute the solution

To convert the solution into map information

14. Export the solution to excel—then change to csv format, load to MATLAB, then write a code to change this data to ASCII representation of a map and

15. Convert the ASCII to Raster map by using Arc GIS conversion tool.

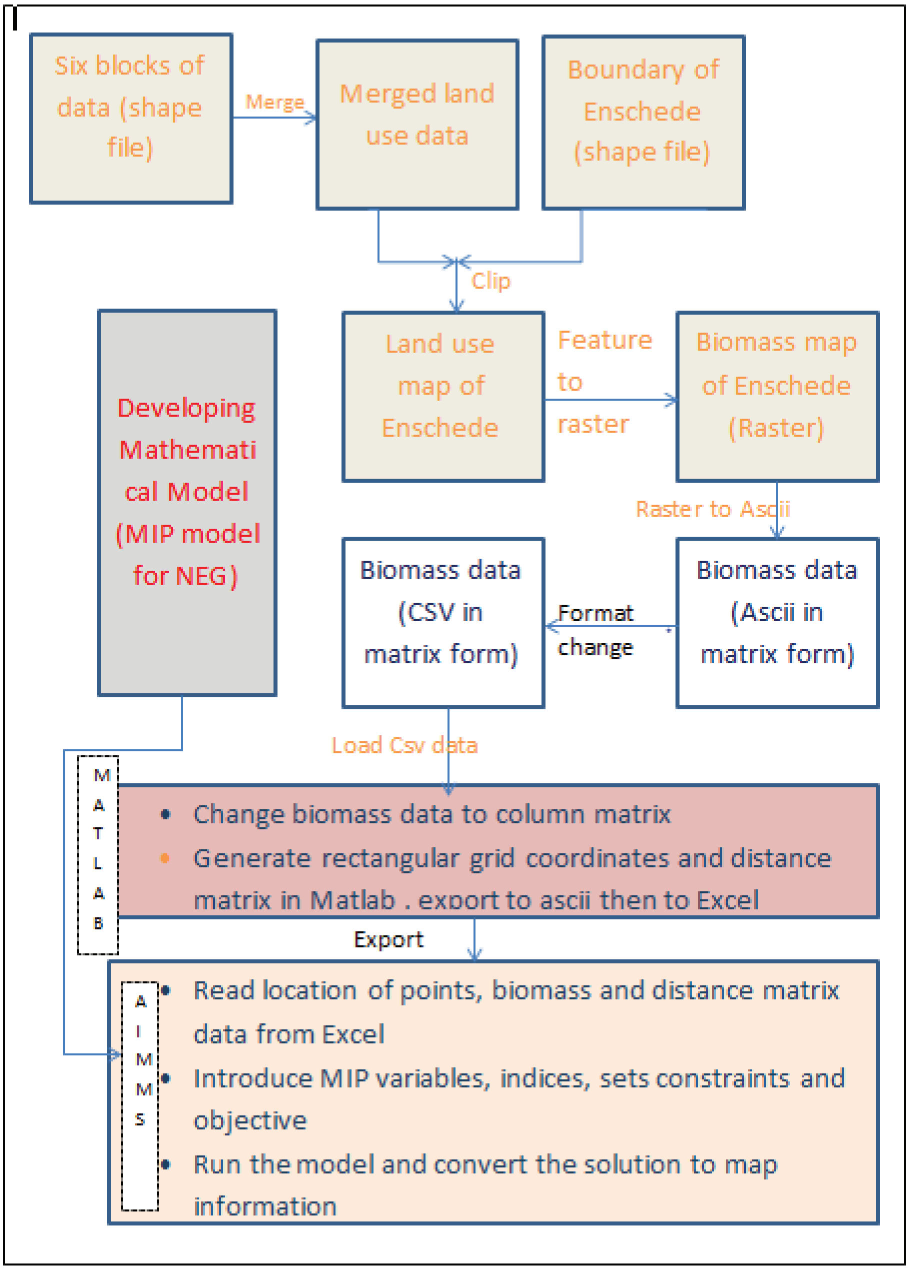


Figure 11: Flow chart for the methodology

5.2. Model Validation:

It is important to establish and execute a mechanism for validating the accuracy of the model. This has been done by making analysis of an illustration example scenario using the realistic input data and model parameters described above. For this purpose, a simple hypothetical data set of 7 by 7 rectangular grid cells was designed, which can also be solved manually. This validation is important in order to make comparison with the results of the model to real world system behavior. The validation assumes the building cost function in the optimization problem linear and is employed for the following cases:

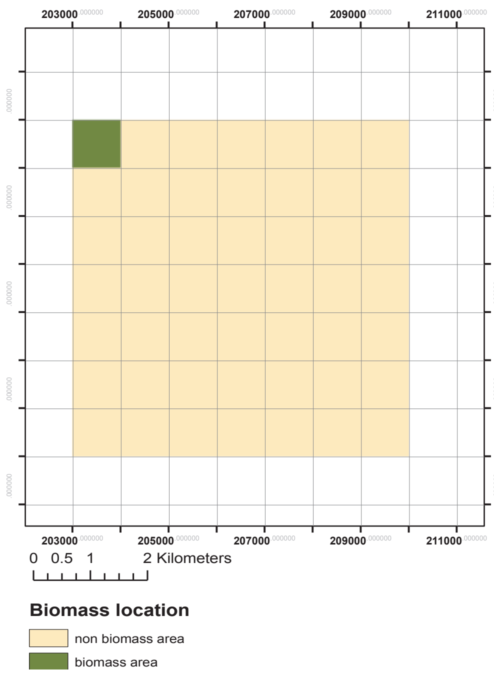
Case 1: when this data set has only one grid cell covered by biomass.
Case 2: when only 2 grid cells which are in opposite corners of the data set are covered by biomass.
Case3: when the hypothetical dataset is homogeneously covered by biomass.
Note: to see the effect of the opening cost (fixed cost) case 3 is employed for two fixed cost values (28000 and 40000).

1. **Case 4:** to see the effect of transportation cost, three sub cases are considered. (i,e, When the unit cost of transportation is:
    a. $\mu = 1\text{MJ}/\text{km}/\text{ton}$
    a. $\mu = 2\text{MJ}/\text{km}/\text{ton}$ and
    b. $\mu = 4\text{MJ}/\text{km}/\text{ton}$

5.2.1. Model Validation Results:

Case 1: when the data set has only one grid cell covered by biomass.
As shown from the figures below, the location of a plant in this case is the same as the biomass supplying grid cell. Obviously, since we have only one biomass source cell, we get a plant with capacity of 700 dry tone/year which lies exactly on biomass cell itself.

Biomass Map



Location of Plant

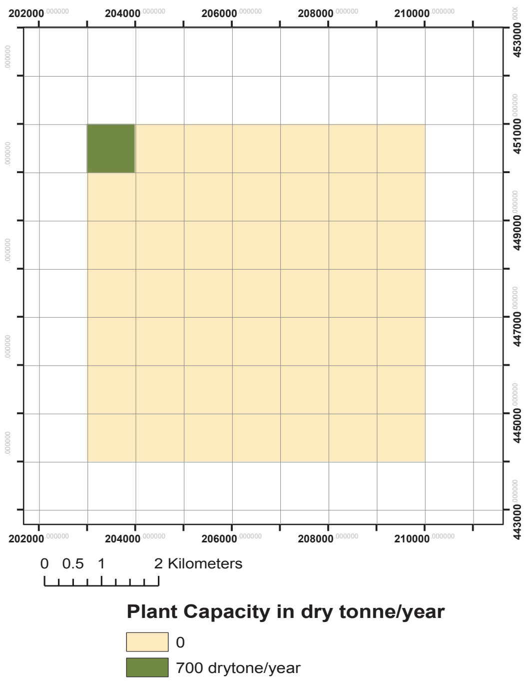


Figure 12: Biomass map (left) and plant location (right)

Case 2: when only 2 grid cells, which are in opposite corners of the data set are covered by biomass.

Biomass Map Location and capacity of plants

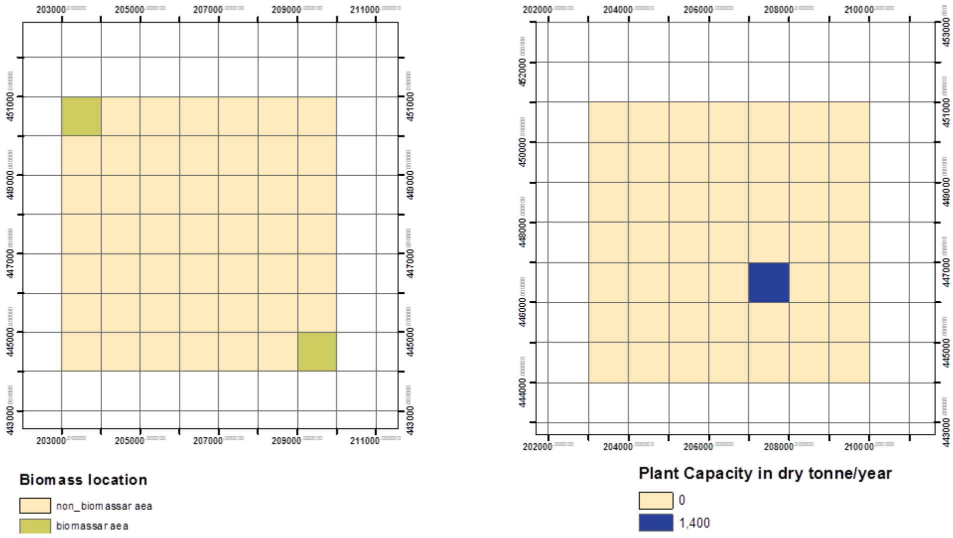


Figure 13: Biomass supplying areas and optimal location and capacity of a plant.

The diagram above illustrates, biomass supplying areas (left) and the optimal location and capacity of a plant (right). In this case the model gives only one plant with capacity of 1400dry tone/year. From the solution report, we observe that biomass from each grid cell is assigned to only one plant. Moreover, the resulting plant can exploit all the resources. The optimal location of a plant is on one of the diagonal grid cells between the biomass sources. If we do this manually the optimal location is clearly on one of the diagonal cells hence, this makes feasible.

Case 3: Now let us see the case for which the entire land is covered by biomass. We did this by taking low value for opening cost (fixed cost) and large value fixed cost.

a) When the opening cost (fixed cost) for a plant is $f_p = 28000MJ$(low value)

Biomass Map Location and capacity of Plants

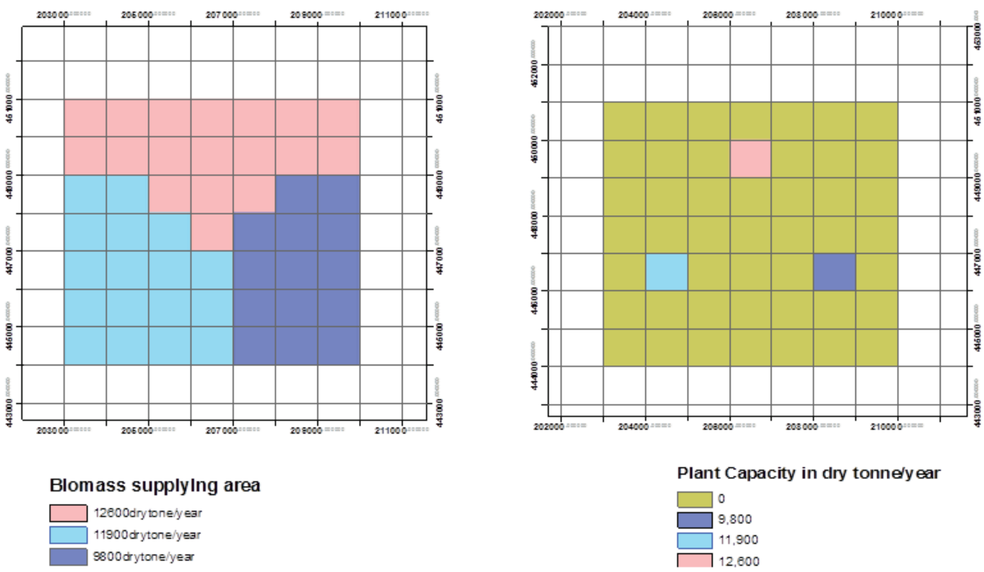


Figure 14: Biomass supplying areas and optimal location and capacity of processing plants.

b) When the opening cost (fixed cost) for a plant is $f_p = 40000MJ$(large value)

Biomass Map | Location of Plants and capacity

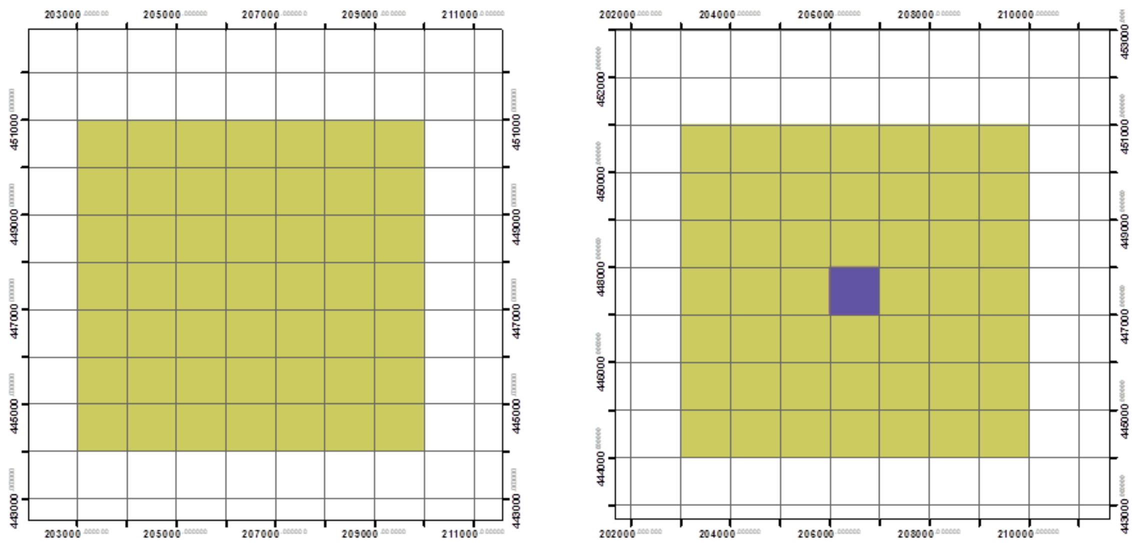


Figure 15: Biomass supplying areas and optimal location and capacity of a plant.

When the entire area is homogeneously covered by biomass, model outputs of Case 3 a. and 3 b. demonstrates that, depending on the fixed cost value, either three plants are needed or one big plant would be placed in the middle. From the two cases, we can see that the capacity of a plant is directly dependent on the opening cost of a plant. Obviously when the cost gets higher and higher, instead of opening smaller size plants; opening one bigger size plant is a better option. This is reasonably true and matches with reality, hence, this makes sense.

Case 4: To see the robustness of the location and capacity of a plant, three transportation costs, such as $\mu = 1$MJ/km/ton, $\mu = 2$MJ/km/ton and $\mu = 4$MJ/km/ton were considered and the model was tested for each value. In such a case, the model gives one plant, three plants and four plants. Figure below shows number and location of plants for the mentioned subcases.

$\boldsymbol{\mu = 1\text{MJ/km/ton}}$

Biomass source | Plant location

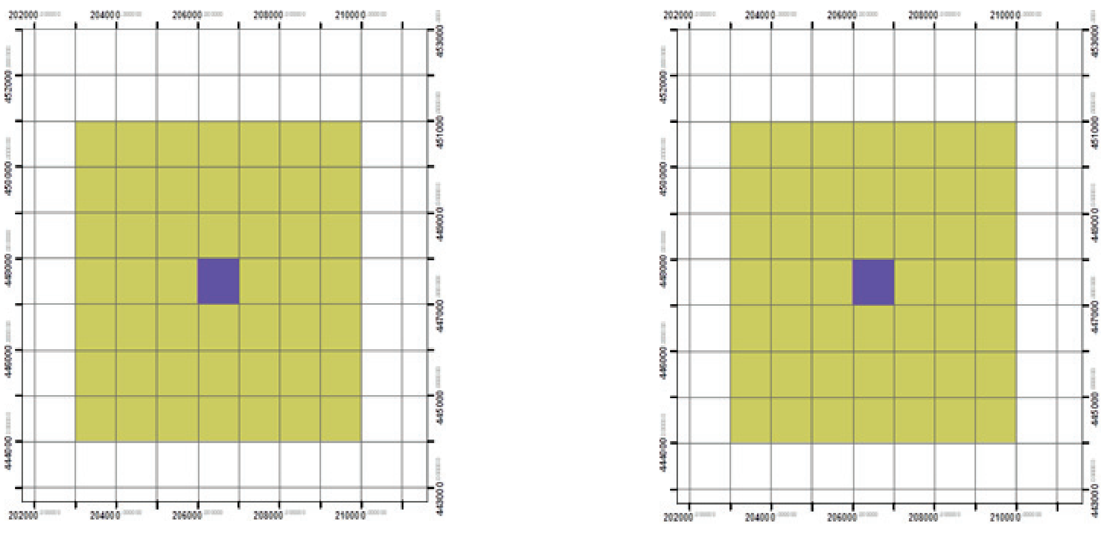


Figure 16: Biomass supplying areas and optimal location and capacity of a plant.

$\mu = 2MJ/km/ton$

Biomass supply area　　　　　　　　　　Plant location

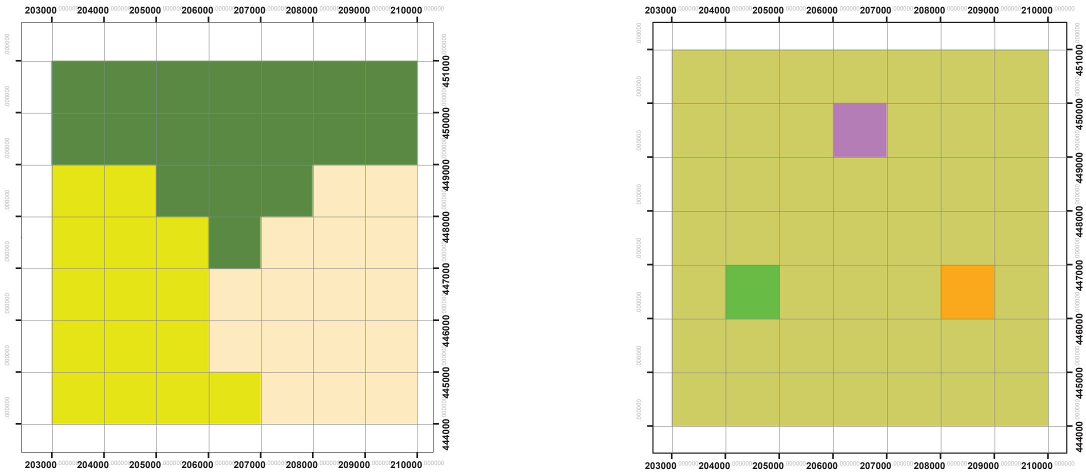


Figure 17: Biomass supplying areas and optimal location and capacity of a plant

$\mu = 4MJ/km/ton$

Biomass supply area　　　　　　　　　　Plant location

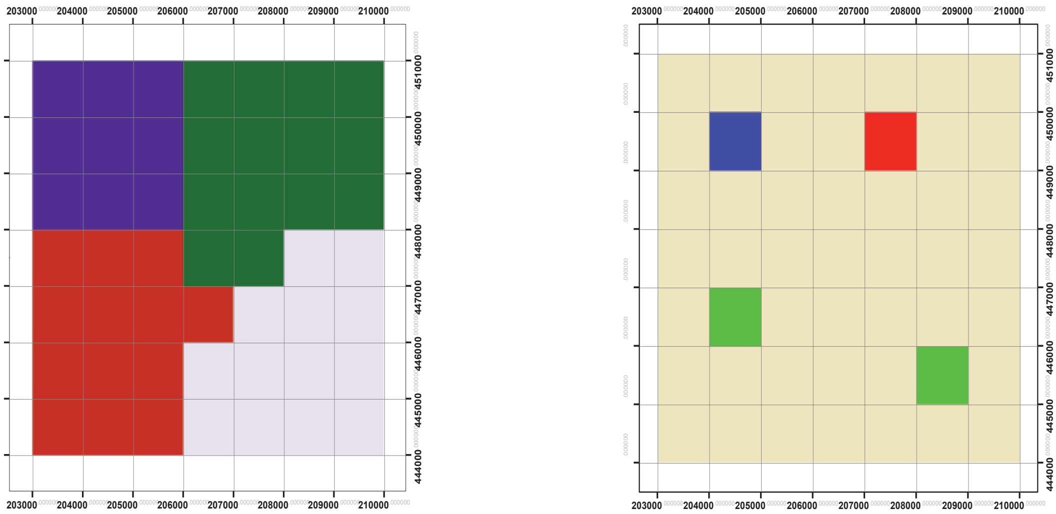


Figure 18: Biomass supplying areas and optimal location and capacity of a plant

Summary:

Result outputs of case 3 and case 4 reveals that: the optimal number of plants decreases as the cost for opening a plant increases. Case 4 demonstrates that, the higher energy cost for transportation the less optimal number of plants. This shows the model can optimally balance energy cost of transportation and opening cost of processing plant.

Now, having the above illustrations for validity of the model; let us implement the model and make analysis with some ground truth data set.

5.3. Optimization Model Results and Analysis

The previously mentioned method of estimation, assumptions and data are fed into an optimization model and implemented over Enschede area, for two cases:

Case 1: When the Energy Cost function has linear relation with capacity of a plant and the opening cost is 28,000MJ.

This case assumes the building cost as a linear function of capacity. The fixed cost is set to 28,000 MJ. The model consists of 44310 integer variables, 211 continuous variables, and 44521 constraints to give an MILP problem that was programmed in the software AIMMS and it was solved in 2.84 s of CPU time using core i7 processor speed 2.67 GHz with 8 GB of RAM.

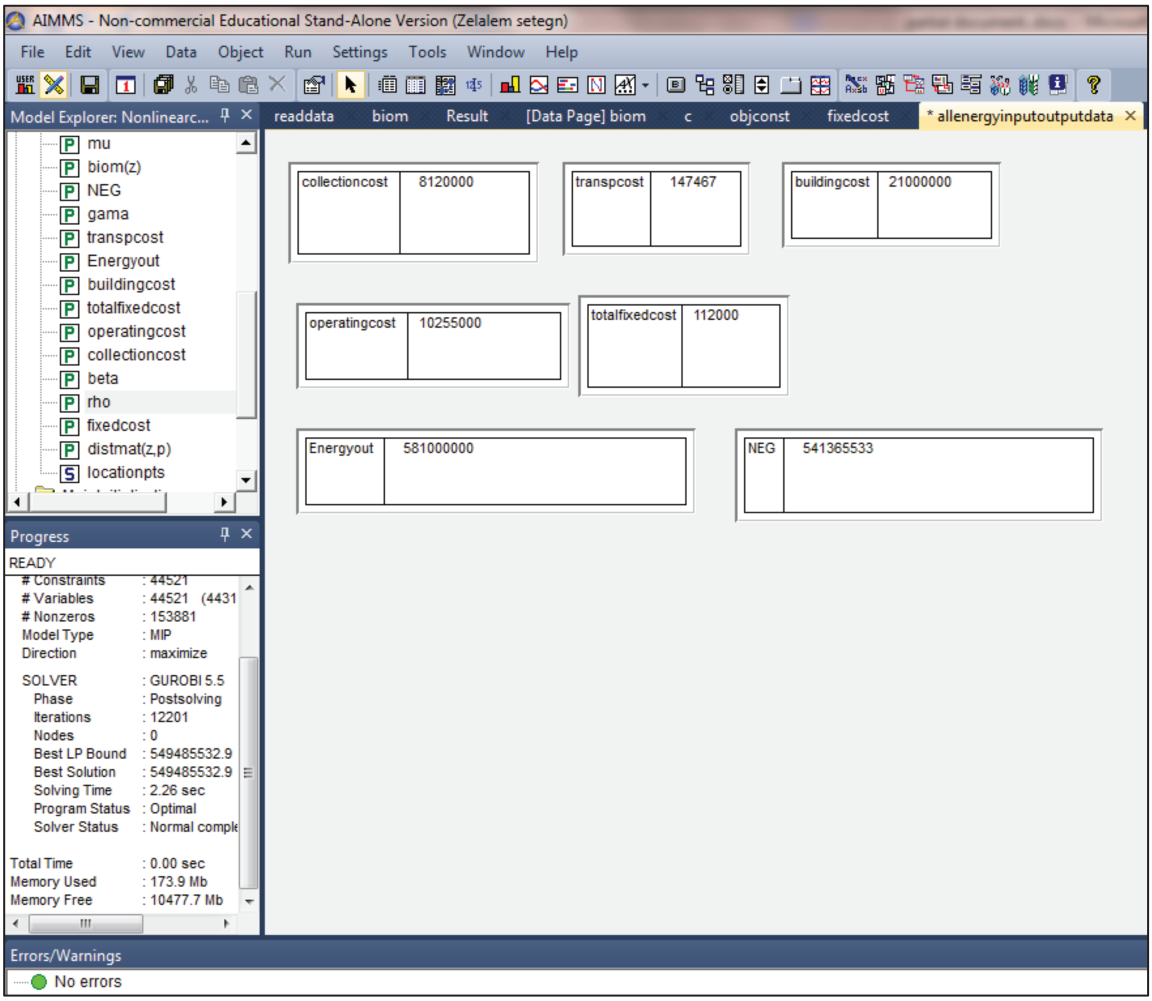


Figure 19: Progress report of the model

The model gives four optimal plants; among this only one plant has a capacity of 9800dry tone/year and each of the remaining three plants have a capacity 8400 dry tone/year. The list of total energy input output is shown in the table 4.

Table 4: List of Energy Inputs, Output and Optimal NEG and EROEI value

List of Energy Inputs and Outputs	Unit	Energy Value	Optimal number of plants
Total energy cost for collection	MJ/dry ton	8120000.00	4
Total energy cost for transportation	MJ/km/ton	147467.13	
Total energy cost to built	MJ	21000000.00	
Total energy cost to operate	MJ	10255000.00	
Total Fixed cost to open a plant	MJ	112000.00	
Total energy input	MJ	39634467.13	
Total energy output	MJ	581000000.00	
Maximum Net Energy gain	MJ	541365532.9	
EROEI	No unit	14.65896	

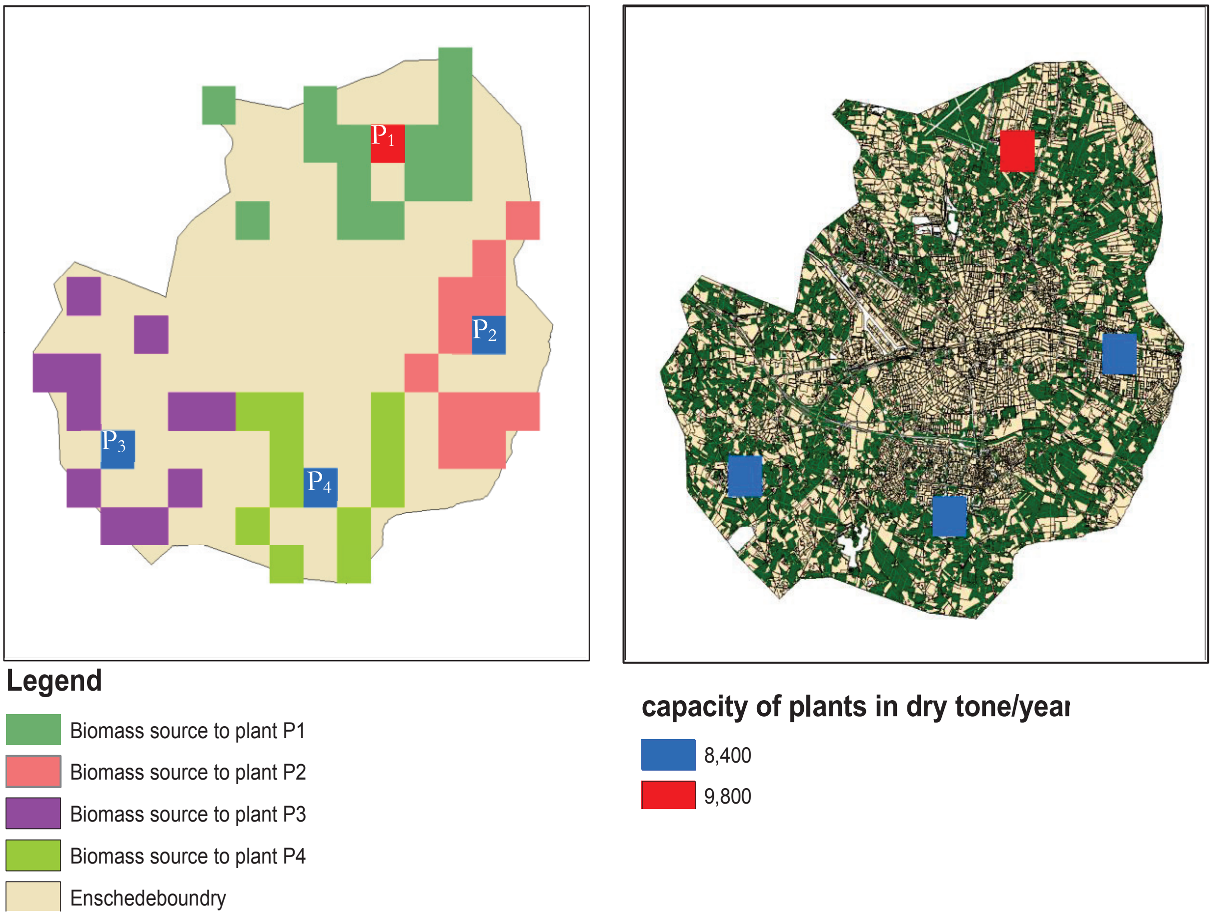


Figure 20: Map showing biomass supply area and location and capacity of processing plants.

The map to the left shows the land that could possibly deliver biomass to the plant whose annual capacity is displayed in the right map.

Table 4: lists the total energy requirement (input) and production (output) of the four assessed bioenergy production facilities in the municipality of Enschede. The total input energy (energy consumption) for the four processing plants is 39634467.13MJ/year. Regardless of the expansive nature of the system boundary

for LCA (energy inputs), the results of this study reveals that the production of biofuel from grass has a positive NEG value (i.e., biofuel energy content exceeds the total energy input). The total input energy is about 6.82 % of the total output energy and the value of the NEG is 541365532.9MJ/year. The ratio of energy output to input (EROEI) value is 14.658. Besides, energy cost to build and operate a bio-refinery and the cost to collect biomass are seen as the main components in the total input energy with the percentages about 53%, 25.87% and 20.4% of the total input energy cost, respectively. The cost of transportation is the least (below 1% of the total input energy cost) this is because the coverage of the study area is small and the optimal location of bio-refineries is not too far from the biomass farms.

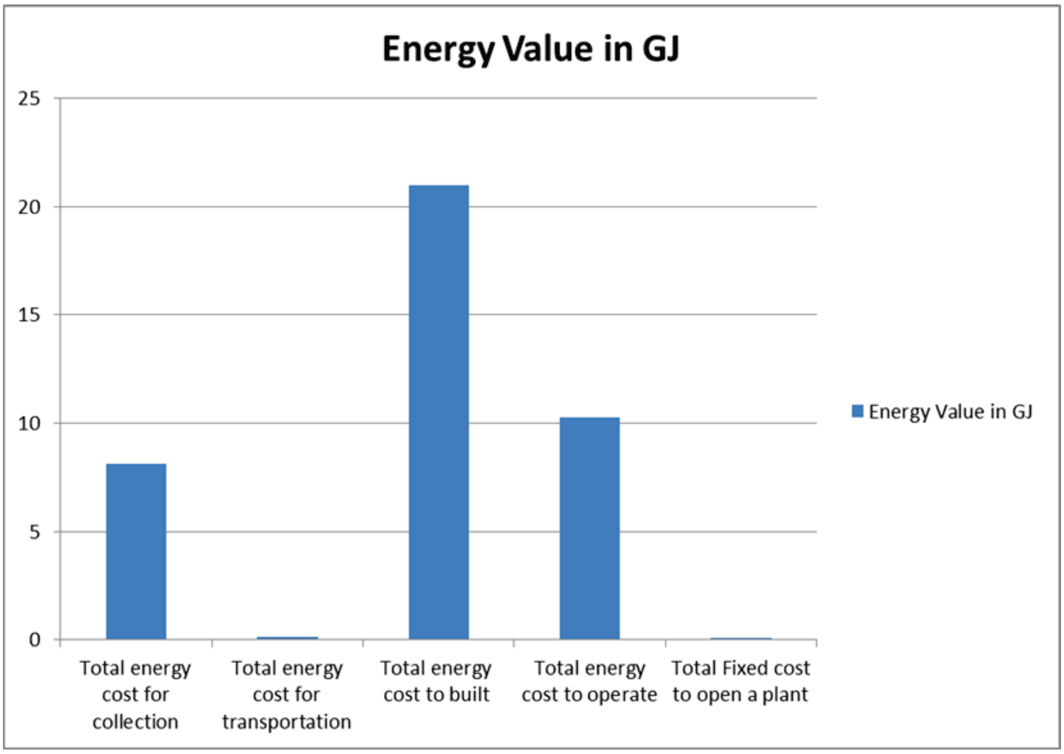


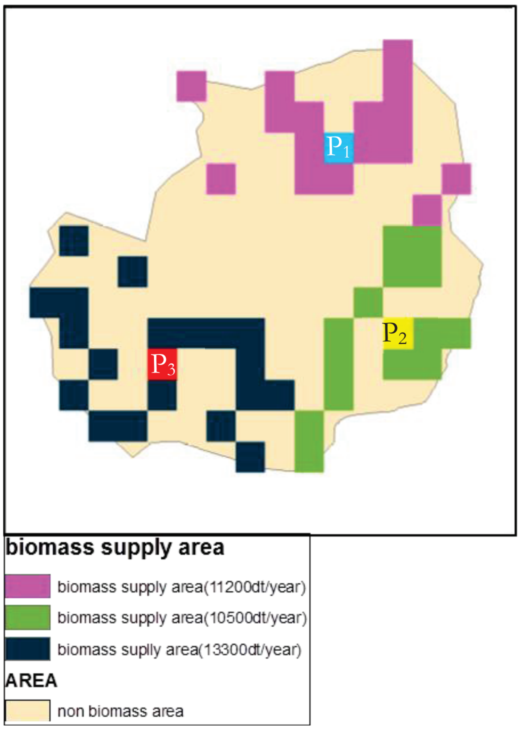
Figure 21: Energy input break down in Giga Joule.

Table 5: Results for the optimal location of processing plants in the municipality of Enschede

	Units	**P1**	**P2**	**P3**	**P4**
Plant capacity	Dry ton/year	9800	8400	8400	8400
Area of grass land share	Km^2	14	12	12	12
Energy cost for transportation	MJ/Km/ton	45041	32826	37868	31732
Energy cost for collection	MJ/ton	2273600	1948800	1948800	1948800
Building cost	MJ/year	5880000	5040000	5040000	5040000
Opening cost	MJ	28000	28000	28000	28000
Operating cost	MJ/year	2871400	2461200	2461200	2461200
Total energy input	MJ/year	11098041	9510826	9515868	9509732
Total energy output	MJ	162680000	139440000	139440000	139440000
NEG	MJ	1511699959	129929174	129924132	12993027
EROEI	No unit	14.65844287	14.66118716	14.6534189	14.66287

Table5: Presents the energy cost break down for the four assessed processing plants. A plant with highest production capacity would then be obtained with the plant located in the northern part of the municipality of Enschede, where the total input energy cost is around 1098041MJ/year. The highest NEG (1511699959MJ) value is assigned to a plant with bigger capacity. However the EROEI value per each plant is almost the same.

Case 1.b when the fixed cost is 40, 000MJ



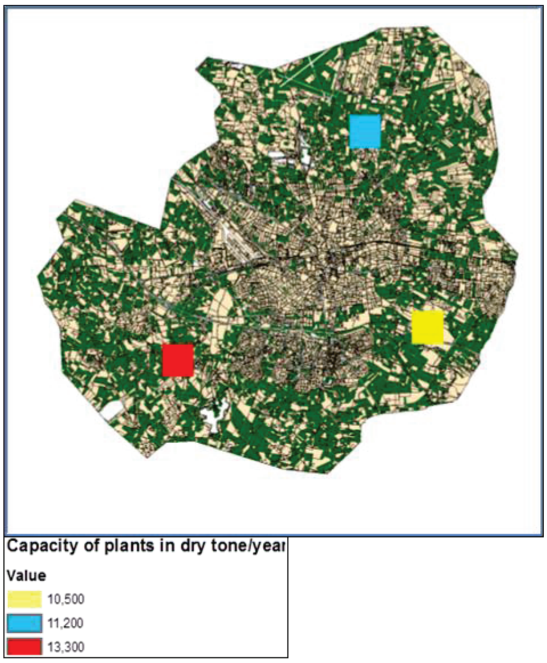


Figure 22: Map showing biomass supply area and location and capacity of processing plant

Table 6: List of energy input output

List of Energy Inputs and Outputs	Energy Value in MJ/year	Optimal number of plants
Total energy cost for collection	8120000.00	3
Total energy cost for transportation	181364.4611290346	
Total energy cost to built	21000000	
Total energy cost to operate	10255000	
Total Fixed cost to open a plant	120000	
Total energy input	39676364.46	
Total energy output	581000000	
Maximum Net Energy gain	541365532.9	
EROEI	14.64	

The displayed results in table 6 shows, as the opening cost of a plant increases from 28000 to 40000, the optimal number of plants gets decreased. However, there is no significant difference in the final NEG value. Besides, similar to the above case, the highest costs are contributed by the costs to build and operate the plant as well as the energy cost to collect biomass. The EROEI value is also the same as the previous case.

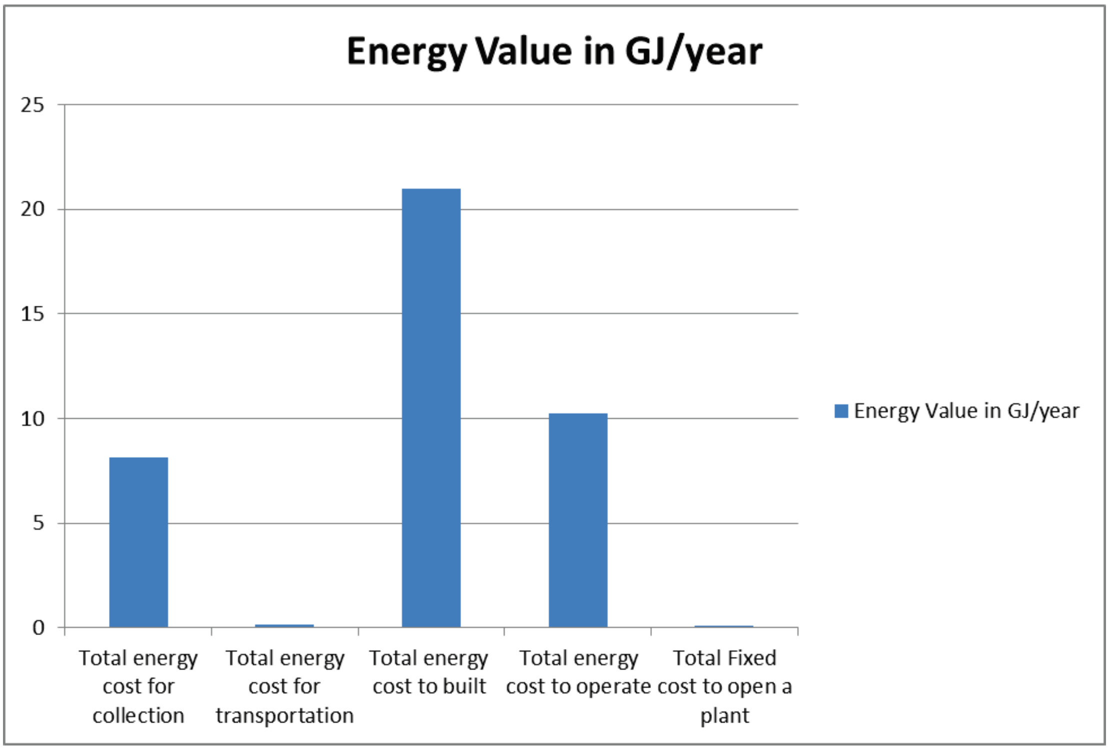


Figure 23: Energy cost break down

Table 7: Results for the optimal location of plants in the municipality of Enschede

	Units	P1	P2	P3
Plant capacity	Dry ton/year	11200	10500	13300
Area of grass land share	Km^2	16	15	19
Energy cost for transportation	MJ/Km/ton	56299.7533	46947.47197	78117.2358
Energy cost for collection	MJ/ton	2598400	2436000	3085600
Building cost	MJ/year	6720000	6300000	7980000
Opening cost	MJ	40000	40000	40000
Operating cost	MJ/year	3281600	3076500	3896900
Total energy input	MJ/year	12696299.75	11899447.47	15080617
Total energy output	MJ/year	185920000	174300000	220780000
Maximum Net Energy gain	MJ	173223700.3	162400552	205699383
EROEI	No unit	14.643637	14.6477389	14.6399846

Result from table 7 signifies that a plant located in the south west of Enschede would have highest capacity and higher energy input consumption as a result a maximum NEG value (205699383MJ/year) will be obtained. However, EROEI value per each plant is almost the same which is 14.64.

Summary:

Generally from the above two cases it can be seen that the overall regional NEG and EROEI values obtained in case one and in case two are almost equal, that is the regional NEG and EROEI values for both cases are 541365532.9MJ/year and 14.56 respectively. This is because of the linear relations in the objective function. However the NEG value per each plant has shown a difference. Since the production capacity of the optimal processing plants is not the same. Plants with highest production capacity have higher NEG value and small size plants have lower NEG value.

CHAPTER 6

6. CONCLUSIONS AND RECOMENDATIONS

6.1. Conclusions

In this study we have concentrated on developing an optimization method in application to life cycle assessment model that determines the optimal number, sizes and geographical location of bio-refinery plants to maximize the regional net energy gain from biomass (grass). In order to meet our objective; we have comprehensively reviewed previous literatures related to spatial optimization problems, solution methods to these problems and optimization methods on bioenergy supply chain. Finally, a mixed integer optimization model was formulated. An application sited in the province of Overijssel, municipality of Enschede was presented to establish analysis. The defined model was solved by "Advanced Interactive Multidimensional Modeling System" (AIMMS).

Thus, the methodology presented in this study was useful and has answered all the proposed research questions listed in the first chapter as follow:

- The energy input components for the system boundaries of the LCA model was determined to: energy cost to collect and transport biomass as well as the energy cost to build and preprocess the biomass feedstock plant.
- For the purpose of analysis the developed model was implemented for two cases: where case one is for small opening cost value of a plant (28000MJ) case two was for opening cost value 40000MJ. The study output for both cases reveals that the costs of producing biofuel depend on the geographical distribution of biomass to be exploited and the size of the processing plant. Moreover, the deployment of an optimization solution signifies that production of bioenergy from grass has a positive NEG value. Using the optimized supply chain, there is a considerable potential of biomass from grass to support plants with total capacity 35000 dry ton/year that gives an energy yield of 541365532.9MJ/year.
- The total energy input requirements for case one and case two are 39634467.13MJ/year and 39676364.46MJ/year respectively. Furthermore, the corresponding net energy gains from each system are 541365532.9MJ/year and 541365532.9MJ/year.

- The model is able to determine the number, size and location of processing plants as well as the corresponding biomass supply areas in the territory. The optimal number, size and location of processing plants are seen in the map information displayed by figure 19 and 21.

- From the study it can also be concluded that, the energy production activity from grass is viable and can support socioeconomic functions. Since, the EROEI value from grass is significantly large (14.64).

It has been discussed in chapter one section 1.4.3 that, to meet the renewable energy targets of province Overijssel as well as municipality of Enschede; production of bioenergy is the main policy approach. However to use the widely distributed regional resource sustainably, establishing well organized biomass supply chain system is indispensable. Based on this study (using the developed optimized supply chain network), it can be seen that, there is much more energy potential from unconventional biomass source (grass). This will make significant contribution to meet the energy target goals of province Overijssel in general and municipality of Enschede in particular.

6.2. Research Merit:

This study will contribute the investigation of a wide variety of conditions that promise sustainable biomass utilization in the renewable bio-energy industry. With the availability of spatial and non-spatial data, the developed methodology can help to guarantee the viability and sustainability of the biofuel supply chain defined in this study. The information obtained from this result could also be a basis for discussion and can also be applied anywhere as long as both the spatial and non-spatial data inputs are available.

6.3. Research Limitation:

In this research we are able to develop an optimization method that can determine the number, location and size of a biomass based processing plants with respect to energy maximization from grass. However, this research has some limitations that can be further improved by future works. Due to shortage of time we are not fully addressing some concepts in our methodology. For instance, in the formulation of our model we use only Euclidean distance approach (a real route is not included), only a linear cost function for energy cost to build a plant was considered, we do not perform suitability analysis for the location of the plant also we never account the environmental impact assessment to reduce greenhouse gas emissions in the boundary of LCA of biomass to bioenergy.

6.4. Recommendation:

- The integration of energy indices like EROEI and NEG along the biomass supply chain
- Integrating LCA with optimization methods is a good option to estimate the energy potential of a given region. Because, it can provide a powerful tool for process design and optimization (Azapagic, 1999)
- We believe that further research is required to increase the performance of the developed optimization model. It is recommended to include road network distance. Moreover, for the sake of comparison and better analysis, it is good to introduce a nonlinear building cost function to the optimization model and environmental impact assessment to the boundary of the LCA model. Since, the greenhouse gas balance of the bioenergy production chain should be positive.

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7. APPENDICES:

7.1. Matlab code to generate grid coordinates and calculate distance matrix

Editor - D:\all D\Matcode\outputcode.m*

outputcode.m* × outputresult.m ×

```
%% Read data

%% load biomassdata(asciiform)
B = load('D:\results\whenfixedcost60000\originalbiomdata\newbiomassdata.txt'); % biomass data in ascii form
bi    =    350*reshape( B' ,1,numel(B));
m                                         =   size(B,1);      % numberof rows in B (rows in the raster map)
n                                         =   size(B,2);      % number of columns(columns in the raster map)
%% generate grid coordinataes
[N,Y]                                     =   deal(ones((m*n),1));

for j = 1:(m*n)
    N(j, 1)                               =   mod(j-1, n)+1;
end

for k = 1:m
    Y((k-1)*n+ 1 :n*k,1)                  =   k;
end

K                                         =   [N Y];          % the rectangular coordinates of a raster dta along row.
R                                         =   [N Y];          % the rectangular coordinates of a raster dta along row.

%% Calculate distance Matrix
[D,T]                                     =   deal(zeros(m*n, m*n));                          %distance matrix function

for i = 1 : length(K),
    for j = 1 : length(R),
        D(i,j)                            =   sqrt((K(i,1)-R(j,1)).^2 + (K(i,2)-R(j,2)).^2);   % distance from ith cell to jth grid cell

    end
end
```

Figure 24: A snap shot of the code to generate grid coordinates and distance matrix.

7.1. Matlab code to convert solution (in AIMMS) to ascii representation of map information.

Editor - D:\all D\Matcode\outputresult.m*

outputcode.m* | outputresult.m*

```
%% Load solutions from AIMMS( plant capcity and biomass allocation data)

A  =  load('D:\results\whenfixedcost60000\originalbiomdata\allocation.csv');          % biomass allocation to plants( solution obtained from AIMMS)
C  =  load('D:\results\whenfixedcost60000\originalbiomdata\capacityoutput.csv');      % capacityoutput
%% load biomassdata(asciiform)
B = load('D:\results\whenfixedcost60000\originalbiomdata\newbiomassdata.txt');        % biomass data in ascii form
bi   =   700*reshape( B' ,1,numel(B));
m                                        =   size(B,1);                                % numberof rows in B (rows in the raster map)
n                                        =   size(B,2);                                % number of columns(columns in the raster map)

M = zeros(m*n,1);                                                                       % column vector
for z = 1:m*n;
    for p = 1:m*n;
      if A(z,p) == 1 && Q(z, 1)>0;
        M( z,1) = p;
      end
    end
end
M;
L = reshape(M, n, m);                                                                  % number of column of raster data and m number of rows of raster data
Cap = reshape(C, n, m);
F =(Cap)';                                                                             % map for the location of plants( matrix form)
L';                                                                                    % Biomass supplying areas as matrix form
q = L';
%%save ascii dta for both biomass supply area and plant location and capacity
save('biomsupplyarea57.txt','q','-ascii')
type('biomsupplyarea57.txt')
save('plantlocation57.txt','F','-ascii')
type('plantlocation57.txt')
```

Figure 25: Matlab code to convert solution to ascii

7.2. AIMMS main report

```
MAIN MODEL

  PROCEDURE
    identifier :  readlarge
    body       :
      empty locationpts;
      empty x(p), obj, a(z,p), c(p), biom(z);

      Spreadsheet::SetActiveSheet("biomas.xlsx","biomas");

      Spreadsheet::RetrieveSet("biomas.xlsx",locationpts, "A2:A1321");
      Spreadsheet::RetrieveTable("biomas.xlsx",biom, "C1324:C2643", "B1324:B2643");

      Spreadsheet::RetrieveTable("biomas.xlsx",Distmat, "D2:AXW1321", "C2:C1321",
"D1:AXW1");


      Spreadsheet::CloseWorkbook("biomas.xlsx", 0);

  ENDPROCEDURE  ;

  PROCEDURE
    identifier :  hypotheticaldta
    body       :
      empty locationpts;
      empty x(p), obj, a(z,p), c(p), biom(z);

      Spreadsheet::SetActiveSheet("dataforAIMMhyp.xls","sheet1");

      Spreadsheet::RetrieveSet("dataforAIMMhyp.xls",locationpts, "A2:A50");
      Spreadsheet::RetrieveTable("dataforAIMMhyp.xls",biom, "C214:C262",
"B214:B262");

      Spreadsheet::RetrieveTable("dataforAIMMhyp.xls",Distmat, "D2:AZ50", "C2:C50",
"D1:AZ1");


      Spreadsheet::CloseWorkbook("dataforAIMMhyp.xls", 0);

  ENDPROCEDURE  ;

  PROCEDURE
    identifier :  readdata
    body       :

      empty locationpts;
      empty x(p), obj, a(z,p), c(p), biom(z);

      Spreadsheet::SetActiveSheet("dataforAIMMS.xls","sheet1");

      Spreadsheet::RetrieveSet("dataforAIMMS.xls",locationpts, "A2:A211");
      Spreadsheet::RetrieveTable("dataforAIMMS.xls",biom, "C214:C423", "B214:B423");

      Spreadsheet::RetrieveTable("dataforAIMMS.xls",Distmat, "D2:HE211", "C2:C211",
"D1:HE1");


      Spreadsheet::CloseWorkbook("dataforAIMMS.xls", 0);

  ENDPROCEDURE  ;
```

```
  DECLARATION SECTION

    PARAMETER:

    MATHEMATICAL PROGRAM:
       identifier   :  optim
       objective    :  obj
       direction    :  maximize
       constraints  :  AllConstraints
       variables    :  AllVariables
       type         :  Automatic
       comment      :  "optim.CallbackAOA := 'OuterApprox::BasicAlgorithm';
                        solve optim;" ;

    CONSTRAINT:
       identifier   :  objconst
       definition   :  obj = sum(p, alfa*c(p))-sum(p, gama*c(p))-
sum((z,p),mu*biom(z)*distmat(z,p)*a(z,p))-beta*sum(p, (c(p)))-sum(p, fixedcost*x(p))
;

    CONSTRAINT:
       identifier   :  binaryrelate
       index domain :  (z,p)
       definition   :  a(z,p)<=x(p) ;

    CONSTRAINT:
       identifier   :  fraction
       index domain :  z
       definition   :  sum(p,a(z,p))=1 ;

    CONSTRAINT:
       identifier   :  sumofbiom
       index domain :  p
       definition   :  sum(z,biom(z)*a(z,p))=c(p) ;

    VARIABLE:
       identifier   :  obj
       range        :  free ;

    VARIABLE:
       identifier   :  x
       index domain :  p
       range        :  binary ;

    PARAMETER:
       identifier   :  Energyout
       definition   :  sum(p, alfa*c(p)) ;

    VARIABLE:
       identifier   :  a
       index domain :  (z,p)
       range        :  binary ;

    VARIABLE:
       identifier   :  c
       index domain :  p
       range        :  nonnegative ;

    PARAMETER:
       identifier   :  alfa ;

    PARAMETER:
       identifier   :  mu ;

    PARAMETER:
       identifier   :  biom
       index domain :  z ;
```

```
  PARAMETER:
     identifier   :  NEG
     definition   :  obj-collectioncost ;

  PARAMETER:
     identifier   :  gama ;

  PARAMETER:
     identifier   :  transpcost
     definition   :  mu*sum((z,p), biom(z)*distmat(z,p)*a(z,p)) ;

  PARAMETER:
     identifier   :  buildingcost
     definition   :  beta*sum(p,c(p)) ;

  PARAMETER:
     identifier   :  totalfixedcost
     definition   :  sum(p, fixedcost*x(p)) ;

  PARAMETER:
     identifier   :  operatingcost
     definition   :  gama*sum(p, c(p)) ;

  PARAMETER:
     identifier   :  collectioncost
     definition   :  rho*sum(z,biom(z)) ;

  PARAMETER:
     identifier   :  beta ;

  PARAMETER:
     identifier   :  rho ;

  PARAMETER:
     identifier   :  fixedcost ;

  PARAMETER:
     identifier   :  distmat
     index domain :  (z,p) ;

  SET:
     identifier   :  locationpts
     subset of    :  Integers
     indices      :  z, p ;

ENDSECTION  ;

PROCEDURE
  identifier :  MainInitialization

ENDPROCEDURE  ;
```