Abstract

Title: **OPTIMIZATION AND EQUILIBRIUM MODELING FOR RENEWABLE ENERGY: FOCUS ON WASTEWATER-TO-ENERGY APPLICATION**

Chalida U-tapao
Doctor of Philosophy, 2013

Directed By: **Professor Steven A. Gabriel**
Department of Civil and Environmental Engineering

This dissertation presents three novel optimization models for sustainable wastewater management. The Blue Plains Advance Wastewater treatment plant (AWTP) operated by the District of Columbia Water and Sewer Authority (DC Water) is used as a case study. The application to the Blue Plains AWTP is presented to illustrate the usefulness of the model and how wastewater treatment plants (WWTPs), solid waste disposal plants, community management groups can actively and positively participate in energy and agricultural markets. Besides the conversion of the solid end products into biogas and electricity via digesters, WWTP can also produce Class B biosolids for land application or Class A biosolids for use as fertilizer. Chapter 1 introduces the Blue Plains case study and other important aspects of wastewater management.

The first problem, discussed in Chapter 2, is a multi-objective, mixed-integer optimization model with an application to wastewater-derived energy. The decisions involve converting the amount of solid end products into biogas, and/or electricity for internal or external purposes. Three objectives; maximizing total value, minimizing energy purchased from external sources and minimizing carbon dioxide equivalent (CDE) emissions were presented via an approximation to the Pareto optimal set of

solutions. The second type of problem is a stochastic multi-objective, mixed-integer optimization model with an application to wastewater-derived energy and is presented in Chapter 3. This model considers operational and investment decisions under uncertainty. We also consider investments in solar power and processing waste from outside sources for revenue and other benefits. The tradeoff decision between operational and investment costs and CDE emissions are presented. The third type of optimization model is a stochastic mathematical program with equilibrium constraints (MPEC) for sustainable wastewater management and is presented in Chapter 4. This two-level optimization problem is a stochastic model with a strategic WWTP as the upper-level player. The lower-level players represent the fertilizer, natural gas, compressed natural gas (CNG) and electricity markets. All the lower-level players are price-takers. Chapter 5 considers a comparison of the three optimization models discussed above and highlights differences. Chapter 6 provides conclusions, contributions, and potential future directions.

OPTIMIZATION AND EQUILIBRIUM MODELING FOR RENEWABLE ENERGY: FOCUS ON WASTEWATER-TO-ENERGY APPLICATION

Chalida U-tapao

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2013

Advisory Committee:
Professor Steven A. Gabriel, Chair
Professor Shapour Azarm, Dean's representative
Professor Elise Miller-Hooks
Associate Professor Kaye L. Brubaker
Assistant Professor Stephanie Lansing

Acknowledgements

Apart from the efforts of myself, the success of this dissertation depends largely on the encouragement, guidelines and support of many others. First of all, I would like to express my greatest appreciation to my advisor, Professor Steven A. Gabriel for his tremendous helps and support. Without his encouragement, motivation and guidance this project would not have been possible.

Second, gratitude is also due to the members of my advisory committee, Professor Shapour Azarm, Professor Elise Miller-Hooks, Associate Professor Kaye L. Brubaker and Assistant Professor Stephanie Lansing for their valuable guidence.

Third, I wish to thanks my supervisors from the District of Columbia Water and Sewer Authority (DC Water), Mr. Christopher Peot and Mr. Mark Ramirez who were abundantly helpful and offered invaluable assistance, support and guidance. I am also thankful for the generous funding support of DC Water.

Forth, thanks also to all my graduate friends, David Prentiss, Seksun Moryadee, Andy Blohm, Hakob Advetisyan and Yilu Feng for sharing their ideas, work and invaluable assistance.

And last, but not least, I must not forget to thank my family, Mom, Dad, Aey, Aom, Ice, Atom and Mai, who always been behind me. “KOB KUN MAK KA”

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction and Motivation

1.1 Introduction

Many of the global issues facing us today such as air pollution, clean water, loss of biodiversity and sustainable energy (Filar and Haurie 2010) will have to be dealt with in a manner that addresses efficiency. Decision-makers facing these issues can use optimization for sustainable development planning. Optimization or more generally operations research (OR) has been applied to many fields of environmental management such as green supply chains (Bloemhof-Ruwaard et al. 1995), visualizing and solving environmental problems (van Beek et al. 1992), optimizing the cost for a Europe-wide reduction of the emissions of SO_2 (Amann et al. 1991), responding to strategies to counter climate change (Janssen 1993) and examining waste management. F. Talcott (1992) said "Environmental problems are substantial; the costs of dealing with them are imposing. Because our resources--natural and financial are limited, it is critical that we think smart and plan smart in dealing with environmental issues. Good analysis can pay off."

An important example of the use of OR to design sustainable development is the utilization of waste to supply energy. An ever-increasing volume of waste (solid waste and wastewater) is the trend for every country around the world making it a global issue. One important cause for this trend is the rise in world population. The last nine years (2003-2011) of data from the World Bank show explicitly that the world population increased from 6.35 billion in 2003 to 6.97 billion in 2011, or roughly a 10% increase. In the United States, the population[1] increased from 180.67 million in 1960 to 311.59 million in 2011. The solid waste generation rate also increased from 2.68 to 4.43 pounds per person per day [2] from 1960 to 2011 (EPA 2011). Because of the solid waste generation rate and rising population, the total amount of municipal solid waste in the U.S. increased from 88.4 million tons in 1960 to 251.9 million tons in 2011. Many researchers analyzed waste management problems including collection and disposal systems based on statistical and historical data and conducted their studies by using mathematical models (e.g., Chang and Wang 1996; Chang and Davila 2007; Filipiak et al. 2009; He et al. 2011b; Tan et al. 2012). Moreover, probabilistic optimization models were used to design waste management systems (Maqsood and Huang 2003; Li et al. 2008; Li and Huang 2011). Additionally, there is a close association between environmental issues (amount of waste and waste disposal) and economic factors (energy supply-demand and operational costs).

The projection of world energy consumption in the industrial, transportation, and electric power sectors respectively is about 2,760, 4,716, and 7,712 million tons of oil equivalent [3] in 2030, which is an increase from the current consumption level by about 31%, 25%, and 49%. Waste management systems also increase the total energy consumption. For example, fossil fuel is the primary raw material in the agricultural and industrial sectors. About 80 gallons of gasoline are used to produce one acre of corn in the U.S. (Pimentel et al. 1973) and waste management systems consume even more fossil fuel. Collection systems and the typical waste disposal processes such as incineration and

[1] http://www.multpl.com/united-states-population/table.
[2] English and SI units were used in this dissertation. English units were used in Chapters 1 to 6 because the case study WWTP uses English units. However, SI units were indicated in the Appendices for comparison purposes with outside sources.
[3] http://www.bp.com/energyoutlook2013.

landfill also consume high amounts of supplemental fuel and fuel for transportation. This also takes place in the power and transportation sectors. Therefore, processing energy from waste may be a sustainable way to reduce waste and fossil fuel consumption.

Because of increasing U.S. population, the total amount of wastewater and solid end products from wastewater treatment plant (WWTP) operational processes is also increasing. For example, the average U.S population uses about 80-100 gallons of water per person per day [4] of which 60-90% becomes wastewater (Vasilind 2003); we use 75% in the following calculation. In the U.S. there are about 3,171 WWTPs operated with flow rates [5] that vary from 5 mega gallons per day (MGD) up to 200 MGD to handle a total of approximately 21,000 MGD (311.59 million people multiplied by 90 gallons of water/person multiplied by 75%). This abundance of wastewater provides an excellent input to produce methane and/or electricity. Indeed, the potential to produce energy from digested biogas from solid end products of the wastewater treatment process was about 189.8 MW in 2011 and the cost of generated electricity ranged from 1.1 to 8.3 cents per kilowatt-hour (cent/kWh) (EPA 2011). Moreover, solid end products from wastewater treatment process could be produced either Class A or Class B biosolids (see more detail in the next section) and reused it to improve the quality of soil as nutrient-rich material. [6]

The U.S. Energy Information Administration (EIA 2009) indicated that in 2009 only 8% of U.S. energy production came from renewable energy sources and 50% of that came from biomass, which consists of bio-fuel, wood, and waste derived from biological materials. Producing energy from waste including solid waste and wastewater

---

[4] http://ga.water.usgs.gov/edu/qa-home-percapita.html.
[5] The 2008 CWNS is available through EPA's Office of Wastewater Management and can be accessed at: http://water.epa.gov/scitech/datait/databases/cwns/index.cfm.
[6] http://water.epa.gov/polwaste/wastewater/treatment/biosolids/index.cfm.

can increase renewable energy production. There are some existing mathematical models studied about biogas production from solid wastes. For example, ADM1 was mathematical model simulated anaerobic digestion process (IWA 2002). Biochemical and physico-chemical processes were applied to approximate the amount of biogas production. Using anaerobic digestion process to produce renewable energy from solid waste could become one from many ways of solid waste management system.

Many researchers used mathematical models to optimize decisions about solid waste management and waste-derived energy production for residential and industrial sectors, but few of them have focused on solid end products from wastewater and its derived energy. There are some mathematical models used in the analysis of wastewater treatment plant design and the quality of treated water (Ellis and Tang 1991; Draper et al. 2003; Cunha et al. 2009; Alvarez-Vázquez et al. 2010). Still others have considered optimization modeling of energy consumption in wastewater treatment plants and renewable energy harvests from water distribution (Ye and Soga 2012; Hu et al. 2013). However, few of those addressed high production volumes from WWTPs and the potential of the associated waste as a significant source of biomass for energy production (Ward et al. 2008).

The study of management wastewater-derived energy by applying OR to WWTPs is the main purpose of this dissertation. Renewable energy from solid end products from wastewater treatment plant is a small but sustainable part of energy production that can help to some extent to meet world energy demand and reduce fossil fuel consumption.

Management of wastewater-derived energy requires understanding the systems and an accurate modeling tool. This dissertation combines OR models and methods for sustainability decision-making related to WWTPs which ultimately helps these organizations towards a goal of being carbon neutral. In this context, the decision-makers can be one person or a group of people who make a decision for their organizations (DeCarolis et al. 2012; Schwarz 2005). As mentioned in the previous paragraphs, no prior research focused on studying sustainable management of solid end products from WWTP by using deterministic and stochastic optimization approaches. Both novel deterministic and stochastic optimization models for management of wastewater-derived energy are used in this dissertation and provide different vantage points. In addition, multiple objectives are considered to add realism to the problem area being studied. Examples of competing, multiple objectives in the context of WWTPs includes: minimizing the odor of the biosolids products sent to reuse sites (e.g., farms) while at the same time trying to minimize the plant operating and distribution costs (Gabriel et al. 2006a). The optimal solution is often a tradeoff among all objectives. The theory of multi-objective optimization is also included in this research to examine efficient solutions that can't be improved for one objective without worsening one or more of the other objectives. This dissertation is focused on the tradeoff between maximizing the benefits (also discussed as "value") from the operational and investment decisions and minimizing the net carbon dioxide equivalent emissions when purchased energy is considered at an average amount. Thirdly, the objective of just minimizing purchased energy is also considered.

These three objectives compete with each other and this is typified as follows. The small digester is chosen when maximizing expected benefits since it allows for lower costs than the big one but permits the WWTP to be active in the fertilizer, electric power, and CNG transportation markets. In fact, the highest level of Class A biosolids are produced (either from the digester or by composting) under this objective. By contrast, when minimizing expected carbon dioxide equivalent emissions, it is more effective to use a big digester. This choice of first-stage variables allows for selling the biogas-based electricity to the spot market and there is no activity in the CNG market. Lastly, when minimizing expecting purchased energy a big digester is also chosen. However, the uses are different for the output. In particular, the biogas-based electricity is used on-site and nothing is sold to the spot market. Moreover, there is also no CNG produced under this objective. For example, once maximum benefits (value) are considered, a small digester (lower costs than big digester) should be selected to product biogas and Class A biosolids. Biogas-based electricity, thus, these three objectives produce different first- and second-stage decisions for the WWTP.

The constraint method is operated by optimizing one objective while other objectives are constraints (Cohon 2003). The approximated Pareto optimal frontier is created with about 50 Pareto solutions from the stochastic optimization model.

Another approach included in the last section of this research is the study of mathematical programs with equilibrium constraints (MPEC) with an application to wastewater-derived energy. Such a framework (von Stackelberg 1934) can arise in many instances. Recently, MPECs have been used in energy applications to model the behavior of strategic players in the electric power sector (Hobbs et al. 2000; Lavigne et al. 2000, Gabriel and Leuthold 2010; Kazempour et al. 2010; Ruiz et al. 2012), in natural gas markets (Siddiqui 2011; Siddiqui and Gabriel 2012), in petroleum markets (Groot et al. 1992; Huppmann and Holz 2012) as well as in energy-efficiency studies (He et al. 2011a;

Lasaulce et al. 2009). There is no study on stochastic MPECs for sustainable wastewater management especially when a WWTP is considered to be the strategic player. In this part of the dissertation, the WWTP is modeled as the top-level player for methane, electricity, and biosolids production. As such, the WWTP's decisions can affect the bottom-level players in the agricultural market, transportation (compressed natural gas vehicles) sector, residential natural gas and electric power sectors. The collection of all the optimization problems for these players along with market-clearing conditions at the bottom level constitutes an MPEC with the top level a stochastic optimization model for the WWTP as Stackelberg leader. As such, the idea of prosumer (producer/consumer) is addressed from the integration between energy and transportation, electricity generation, agriculture and residential usage. The overall system is thus helpful for sustainable development.

1.2 Objectives of Dissertation

The objective of this dissertation is to develop and apply mathematical models to environmental management problems and provide results that can assist typical wastewater treatment plants to find optimal wastewater treatment management policies with respect to treatment processes, energy usage and carbon dioxide emissions and sustainability goals. The models are deterministic and stochastic optimization problems and a stochastic MPEC. Additionally, the results from the case study WWTP located in Washington, DC will provide estimates of the optimal total operational value (profit), net carbon dioxide equivalent emissions, energy purchased at the facility and tradeoffs between the various competing objectives. This case study appears in each of the main modeling sections as a further evidence of the applicability of the models.

1.3 Case Study

The Blue Plains Advanced Wastewater Treatment Plant (AWTP) is a wastewater and sewage treatment plant operated by the District of Columbia Water and Sewer Authority (DC Water). Blue Plains treats wastewater and sewage from jurisdictions in the District of Columbia, Maryland (Montgomery and Price George's counties) and Virginia (Fairfax and Loudoun counties) and serves approximately 1.6 million people. It has a capacity of 370 million gallons per day and a peak capacity of more than 1,000 million gallons per day [7] (Gabriel et al. 2006b). Blue Plains is one of the ten biggest WWTPs in the world. [8] Moreover, it is the largest advanced wastewater plant in the world [9], that is, the largest which operates nitrification and denitrification systems for removing nitrogen. Because of its size and prominence as an industry leader, Blue Plains is an ideal case study subject for this dissertation. To better acquaint the reader with the various processes going on at this advanced WWTP, the next few pages provide a briefly overview of the operations there.

The primary treatment process at this AWTP begins with physical procedures to separate insoluble solids (unsuspended solids) from wastewater. The debris is removed and trucked to a landfill. The remaining sewage flows into primary sedimentation tanks. More than half of the suspended solids are separated from the liquid. [10]

Wastewater with soluble solids flows to a secondary treatment process which uses

---

[7] http://www.dcwater.com/about/gen_information.cfm.
[8] http://enr.construction.com/infrastructure/water_dams/2012/extras/0328/slideshow.asp?slide=11. (Illustration: Justin Reynolds for Engineering News-Record (ENR.com)).
[9] http://www.dcwater.com/about/gen_information.cfm.
[10] http://www.dcwater.com/wastewater/process.cfm.

an activated sludge process to break down organic matter. The microorganisms working in this process consume organic matter as their food using a large amount of oxygen. Ammonia is converted by nitrification and denitrification into nitrogen gas. Solid end products are settled out and water is percolated down through a sand filter to remove the remaining suspended solids. However, before discharging water into the Potomac River, water is disinfected by dechlorination.

The solid end product from the primary treatment, called sludge, settles to the bottom and thickens by gravity and biological solids from the secondary and nitrification reactors are thickened by using flotation thickeners. The primary and secondary solids are combined and dewatered. The Blue Plains AWTP operational processes are shown in Figure 1.1.

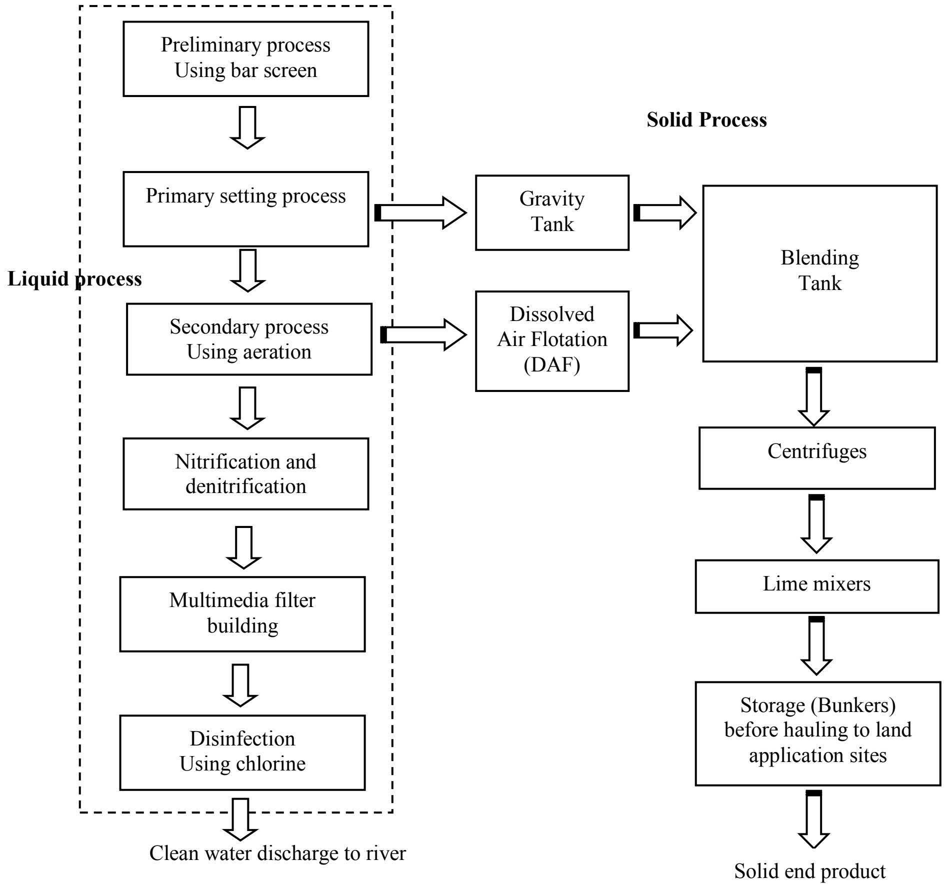


Figure 1.1 The Blue Plains AWTP operational processes.

Each day the Blue Plains facility produces approximately 1,200 wet metric tons of collected solids. Lime is added to remove pathogens by a process called lime stabilization. The treated sludge is distributed for use by several land application contractors and to several utilization facilities. About 90% is given to farmers for crop fertilization and 50 tons per day go to a compost production facility in Virginia. [11] The treated sludge is given away without obtaining revenues. Moreover, DC Water bares the costs associated with transportation and management. Waste-to-energy management models, which will be described in Chapters 2, 3 and 4 of this dissertation, will determine

[11] http://www.dcwater.com/education/biosolids_recycling.cfm.

the value (monetary or otherwise) of the treated sludge and thus, improve the long-term sustainability of operations at the Blue Plains facility.

The two valuable end products that result from the Blue plains AWTP facility are clean water and biosolids. The effluent clean water is discharged to the Potomac River and biosolids, generally called Class B biosolids, are lime-stabilized. Biosolids are transported to land application sites for several purposes such as agriculture, tree farming, and mine reclamation. [12]

The Environmental Protection Agency (EPA) classifies biosolids as either Class A or Class B. Class A biosolids require the total amount of pathogens to be below detectable levels and must meet the limitations of metal contaminants related to regulation 503 (the EPA part the 503 biosolids rule), which is the standard for the use or disposal of sewage sludge (EPA 1994). Class B biosolids are subject to less stringent requirements with respect to pathogens, but still require specific farm management practices and area restrictions before and after application (EPA 1994 and 2006). DC Water biosolids consistently meet Class A standards for coliform and are of significantly higher quality than Class B in general. However, Class B biosolids can be applied for slow release nitrogen fertilizer with low concentrations of other plant nutrients such as phosphorus, potassium, and essential micronutrients such as zinc and iron (approximately 4.4% Nitrogen, 1.36% Phosphorus and 0.16% Potassium of each metric ton of biosolids). [13] Moreover, organic matter can improve soil quality by controlling air and water content in soil structure while decreasing topsoil erosion (Wang et al. 2008). In addition to economic benefits from using biosolids as fertilizer, methane and heat are sources of

[12] Biosolids management program manual, issue date 10/21/2009.
[13] Biosolids statistic data from 2002-2010.

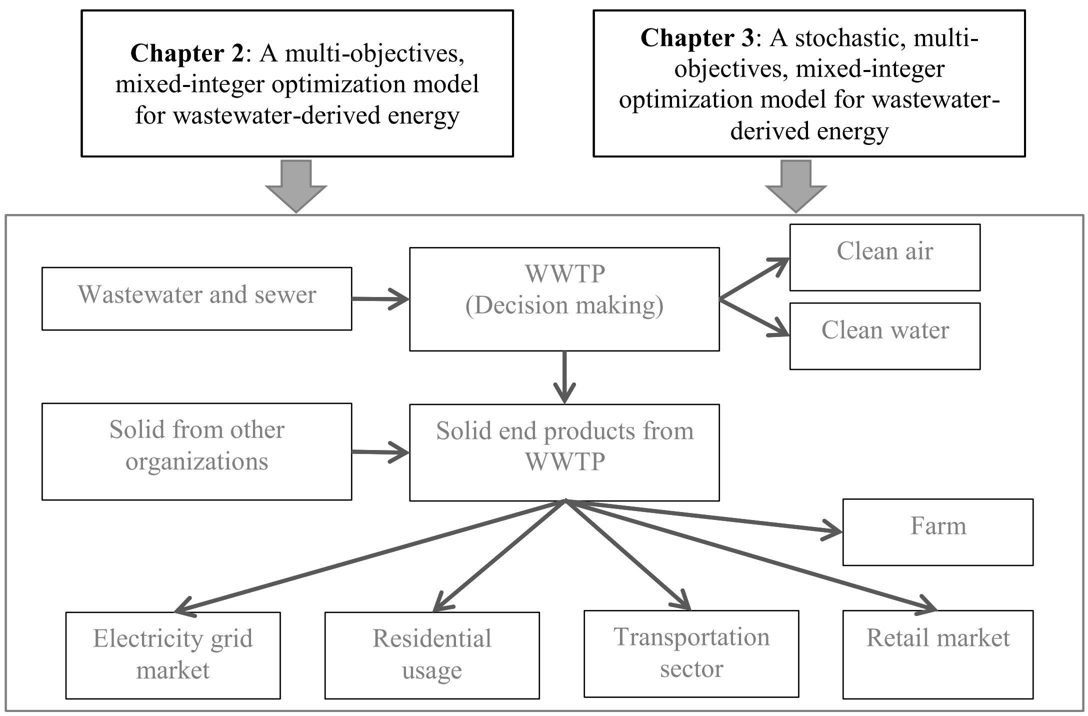
energy recovered from biosolids. Anaerobic digestion processing reduces the amount and volume of biosolids, and produces biogas, about 60% of which is methane gas CH_4 (Oleszkiewicz 2002). Pathogens are destroyed during the digestion process due to high temperatures. This digestion process also reduces problems associated with biosolids odor and result in Class A biosolids.

Incineration is another process to destroy solids end products from WWTP. The dewatered solids are fuel that reacts with oxygen (WEF 2012) through combustion. Therefore, incineration can be added to the solids treatment process if land application is not feasible (Brown 2007).

1.4 Organization of This Dissertation

Figure 1.2 displays the organization of this dissertation: Chapter 2 presents a deterministic, multi-objective, mixed-integer optimization model for wastewater-derived energy and also introduces details of the parameters used in this model. Chapter 3 presents a stochastic, multi-objective, mixed integer optimization version of the model with some of the data uncertain and therefore described by appropriate probability distributions. Chapter 4 presents a stochastic MPEC for sustainable wastewater management. Chapter 5 provides a comparison of the three optimization models (single-level problem for both the deterministic and stochastic models as well as the stochastic bilevel problem (MPEC)) and sensitivity analysis. Finally, Chapter 6 provides conclusions and directions for future research.

Three novel models were created with three specific types of problems associated with the management of wastewater-derived energy. Single-level problems, the deterministic optimization model in Chapter 2 and the stochastic optimization model in Chapter 3, are used to analyzed the optimal decision under not only the operational and investment aspects but also the end-use revenues, energy purchasing from external sources and carbon dioxide emissions. The two-level problem presented in Chapter 4 considered the WWTP as a strategic player at the upper level. The strategic player's decisions involve converting uncertain amounts of solid end products into biogas and/or electricity for internal or external purposes with first-stage decisions on the size of digester to build or other processing options. The lower-level players represent the retail fertilizer, wholesale electricity, residential natural gas and CNG markets.



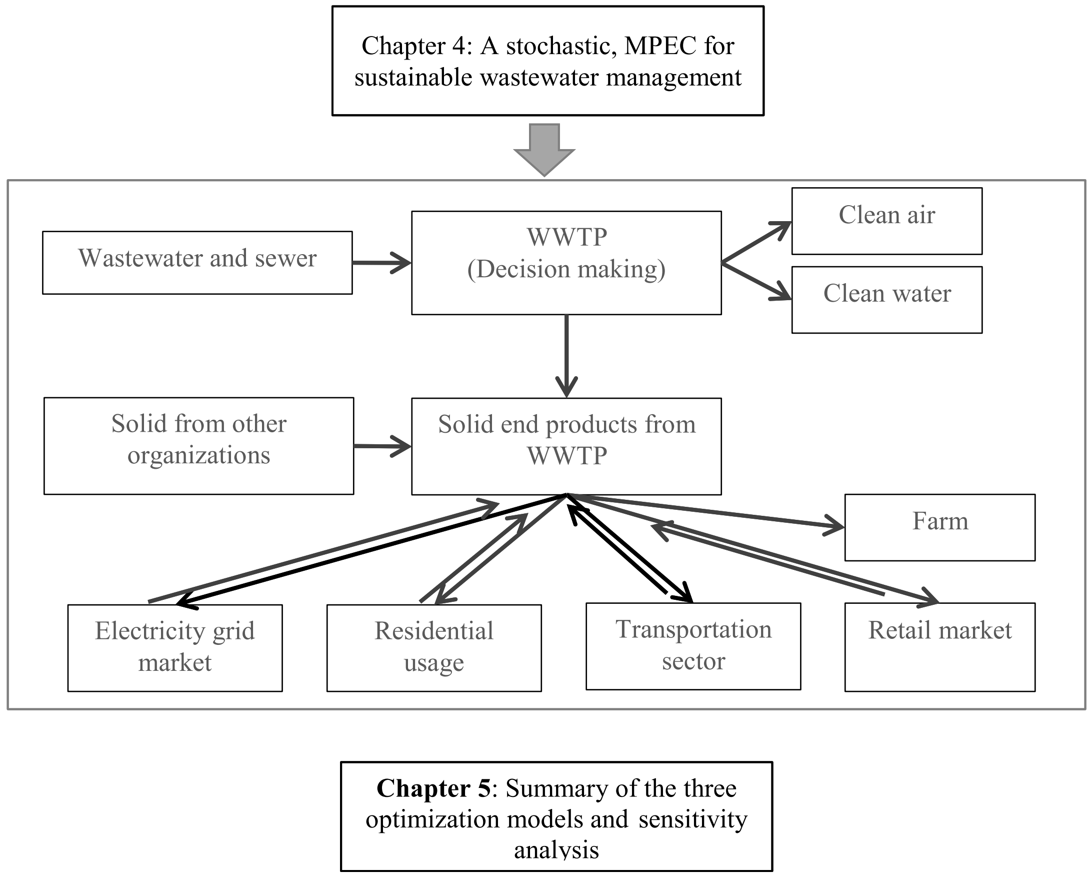


Figure 1.2 Organization of dissertation.

Chapter 2: A Multi-objectives, Mixed-integer Optimization Model for Management of Wastewater-derived Energy

Major cities in the world are facing environmental management problems from rapid population growth and excessive consumption of natural resources. Therefore, a critical goal for society is to find energy and natural resources that can be carefully managed in a way that sustainably mitigates water and air pollution.

Typically wastewater treatment plants produce clean water and biosolids (for land application) as end products from processing the wastewater. Wastewater solids offer an opportunity to produce renewable energy from digesting their carbon component (producing biogas and subsequently electricity) and at the same time recover costs by marketing the recovered nutrients to fertilize agricultural land in an environmentally friendly manner. This energy can be used directly at the plant to power mechanical systems such as aeration blowers, solids dewatering equipment as well as automated electronic process control. The treatment plant will not only benefit from a new low cost energy source but the revenue of using renewable energy generated from wastewater solids may reduce operational process costs as well.

The U.S. Energy Information Administration (EIA 2009) indicates that only 8% of the U.S. energy production came from renewable energy sources, and 50% of that 8% came from biomass, which consists of bio-fuel, wood and derived wood's residual, and waste derived from biological materials. The electric power sector accounts for 40% of this total energy (EIA 2009) and has an environmental incentive to use renewable energy. Furthermore, due to technological advances and cost competitiveness renewable energy's market share has increased in the past decades (Arent et al. 2011). Many previous studies have described the value and attributes of renewable energy investment (Bergman et al. 2006) and the benefits for investment in renewable energy for the power sector. Examples of recent works include: Traber and Kemfert (2011) and Genc and Thille (2011) respectively, for wind and hydropower. However, to our knowledge there has not been as much focus on biomass and in particular that derived from wastewater, which is the subject of this study.

Using solid end product from wastewater as a renewable energy source either in the form of biogas or as electricity derived from biogas will increase renewable energy production as well. Therefore, the production of wastewater-based biogas is an important consideration for wastewater treatment plants with competing goals such as reducing energy purchases, maximizing the value of the wastewater products, and minimizing the carbon dioxide emissions. Given the emphasis on producing energy from renewable sources (e.g., wind, solar, biomass), wastewater treatment plants can therefore be active participants in energy markets according to the huge amount of renewable energy sources from wastewater plants.

In the next section we discuss Advanced Wastewater Treatment Plant (AWTP), which is the subject of this study. This AWTP is considering converting wastewater to biosolids, methane and electricity via anaerobic digestion and in Section 3 we discuss an optimization model to assist AWTP management with this conversion process. The AWTP facility is one of the largest in the U.S. and this conversion to produce methane and electricity represents an environmentally friendly and possibly cost effective way to produce energy. AWTP is not alone in its intent to produce renewable energy from wastewater. Indeed, the U.S. Environmental Protection Agency (EPA) has estimated that there are roughly 3,500 facilities with wastewater flow greater than three million gallons per day (EPA 2007). As of EPA 2007 about 544 wastewater facilities were already using anaerobic digestion. These facilities may have the potential to produce biogas to generate electricity, which can be used by wastewater treatment plants (big consumers of energy) or sold to the power market. For example, West Point Wastewater Treatment Plant in New York serves a population of 670,000 and generates about 1.5-2 MW of electricity that it sells to local utilities. The Point Loma Plant, California, generates about 4.5 MW and as a result the City of San Diego saved more than $3 million in operational energy costs in 2000 (DOE 2004).

Optimization modeling has been extensively used in energy and environmental planning in the context of policy as well as operational considerations (DeCarolis 2011), taking into account the impact on the environment. For example, data analysis and optimization theory were applied (Tan et al. 2012). Li and Huang (2011) considered integrated modeling for solid waste management and showed trade-offs between system cost and feasibility in the presence of uncertainty. Other relevant environmental applications for water management have included: optimal flood control (Lee et al. 2009), optimization of large-scale water-distribution systems (Pezeshk 1994), groundwater supply management and conjunctive management of a large municipal and industrial water system (Parelta and Kalwij 2004). Moreover, optimization modeling has also been applied to study biological activity and chemical reactions for waste-treatment facilities (Alhumaizi and Ajbar 2006).

Renewable sources of energy figure prominently in this planning, especially in the U.S. and European markets e.g., renewable portfolio standards (Wiser and Barbose 2008), “20-20-20” policies (EU 2008) and wastewater-derived energy while currently small, could provide an efficient means to sustainability goals and lowering emissions from energy production (Elliot et al. 2010). Research on the more general category of biomass has concentrated on ethanol and biodiesel since they directly affect fossil fuel prices, e.g., ethanol from is used as an additive in gasoline in the U.S. (Rask 1998). Indeed, local state and federal entities in the U.S. have even stimulated local ethanol and biodiesel producers’ interest by increasing support for new production technologies (Kenkel and Holcomb 2006). Nevertheless, the economic effects from increasing prices of crops --European agricultural prices increased by 7% (Kretschmer et al. 2009)--may be a significant point for future study especially from a cost and environmental perspective vis-à-vis all forms of biomass including from wastewater. Despite this focus on renewable energy, there has not been a lot of research recently on wastewater-derived biogas for energy.

The objective of this study is to present a new multi-objective optimization model that provides guidance for wastewater treatment plants for processing wastewater solids taking into account sustainability, energy production and biosolids for land application. As such the model presented can assist wastewater treatment management in these areas. This model is tested using data from AWTP, which is located in the East coast of the U.S. The rest of this multi-objective optimization model is organized as follows: Section 2.1 presents operational processes at AWTP; Section 2.2 describes the multi-objective optimization model; Section 2.3 discusses the results of using the model and Section 2.4

provides concluding remarks. Lastly, there is an Appendix A showing supporting calculations.

2.1 Wastewater Treatment Plant Operational Processes

This section describes a wastewater treatment plant (WWTP) operational process. While a specific AWTP is the basis for the model, the processes and related decisions are generic enough to apply to a large number of other WWTPs. At the AWTP facility in question, approximately 1,406 million liters per day (370 million gallons per day) of wastewater and storm water flow into the AWTP via sewers. These flows come from municipal (domestic) wastewater in the Washington, D.C. metropolitan area, including parts of Maryland and Virginia (Gabriel et al. 2006). The AWTP operations are shown in Figure 1.1 and can be separated into two significant parts: the liquid and solid processes. Over 1,000 wet tons per day (wt/d [14]) of biosolids is the treated output of the influent that comes from the sewage. Biosolids from the AWTP facility are normally used as fertilizer by farms in Virginia and Maryland.

Biosolids, are the solid nutrient end product of the wastewater treatment process, and can be classified as either Class A or Class B biosolids by the Environmental Protection Agency (EPA). Class A biosolids require a total amount of pathogens to be lower than a detectable level and must meet the limitations of metal contaminants related to regulation 503, which is standard for the use or disposal of sewage sludge, (EPA 1994). Class B biosolids are less stringent relative to pathogens, but still require farm management practices and area restrictions before application (EPA 1994 and 2006). For example, the AWTP currently uses lime stabilization to improve the quality (i.e., reduce

[14] Weight in metric ton.

the amount of pathogen) of biosolids for land application resulting in Class B biosolids. Consequently, this material can be delivered to farms in nearby counties as fertilizer without cost. The solids stabilizing process by heat or chemical means can change wastewater solids from Class B to Class A biosolids by reducing the amount of pathogens. Being more stringent, Class A biosolids may therefore be used for field crops or marketed and sold for use by the general public with less risk than Class B biosolids (Kemp and Lynch 2009). Biosolids that meet pathogen-free Class A levels can provide wastewater treatment plants with many more options to utilize the market and collect revenues from the sale of biosolids.

This study focuses on management of the solid phase removed from wastewater. Solids from the primary and secondary treatment processes can be lime stabilized or can be processed through a "digester" to generate biogas. Stabilization of solids by digestion can be achieved by using a thermal hydrolysis, which prepares biosolids for anaerobic biodegradation, through digestion, (see Figure 2.1).

Thermal energy or chemical mechanisms can be used to pre-process sludge from operational processes, but at the AWTP, thermal energy will be used to stabilize soluble organic matter in wastewater and sewage. Consequently, this pre-treatment procedure is called thermal hydrolysis (Bonmat et al. 2001). Additionally, this procedure also improves accessibility of anaerobic bacteria by breaking down non-dissolved and dissolved compounds in wastewater to facilitate the digestion process (Kepp et al. 2000). Stabilized organic matter will pass to a digester under mesophilic anaerobic digestion, which operates at a temperature 33-37 degree C to destroy organic matter and produce several types of gas such as carbon dioxide and methane.

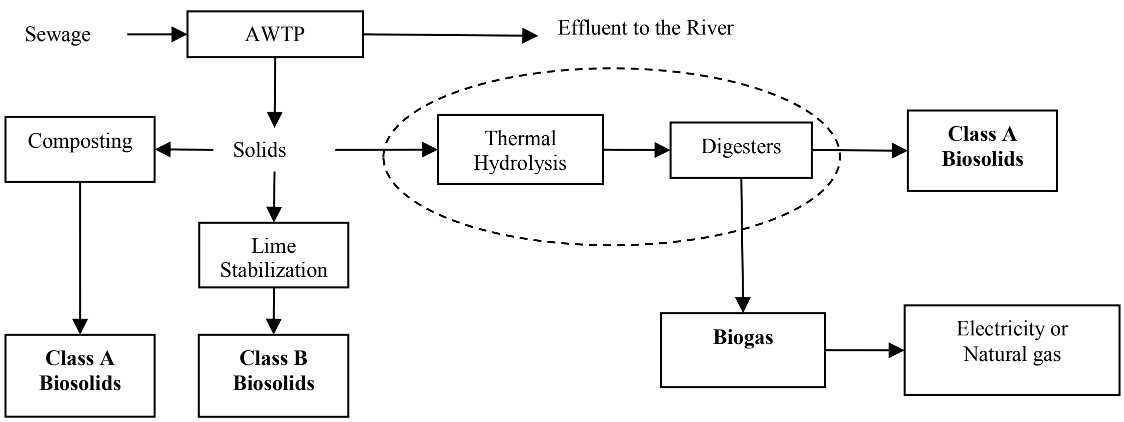


Figure 2.1 Solid phase management flow diagram.

2.1.1 Amount of Solids Produced [15]

One of the key inputs to the multi-objective optimization model to be presented below is the amount of solids contained in the influent to the AWTP. For this study the annual average amount of solids is estimated from historical data at AWTP for 2007-2009. Solids are separated from wastewater when they pass through the primary treatment process called gravity thickeners (GT) and secondary treatment process called dissolved air flotation thickener water activated sludge (DAF TWAS).

However, many new facilities and operational techniques have been installed at AWTP in order to upgrade water and sewer treatment, which affects the solids production. For example, the biological treatment techniques and facilities used for reducing secondary mean cell residence time (MCRT), use thermal hydrolysis and anaerobic digester and also using enhanced nitrogen removal facilities (ENRF) and use enhanced clarification facility (ECF) will directly impact solids product. Another

[15] Data in this model were collected, analyzed and used as the daily variables; all units are calculated for an average day.

important parameter that impacts the solids amount would be population growth around the service area. The size of the population obtained from the Metropolitan Washington Council of Governments (MWCOG) is 2,227,446 in 2009 will be used as a baseline and 2,386,665 in 2015, 2,505340 in 2020, 2,596,791 in 2025 and 2,651,750 in 2030 will be calculated from 2009 and projected to 2030, respectively. [16]

From the estimates stated above, the average daily maximum solids influent (based on the year 2030) can be calculated as 428 dry tons (dt). Additionally, the minimum solids influent is computed as 383 dt, according to thermal hydrolysis and anaerobic digestions starting in 2014. These two values will be respectively, upper and lower bounds on the total solids amount to be described in the model formulation below.

2.1.2 Energy Consumption for Operations at AWTP

Normally, wastewater treatment operational processes use electricity to run their facilities, natural gas for space heating, and fuel for biosolids transportation and service vehicles similar to AWTP. This plant does not generate electricity, but purchases it from external sources. Historically, the energy used at this facility fluctuates each day and month depending on influent amounts. For this study, 634,000 kWh is used [17], representing the average amount of electricity used for all the operational processes from 2005-2009. The average amount of natural gas consumed for space heating from 2007-2009 was [18] 172,240 cubic feet (cf). Also, transporting biosolids to the land application sites is another area of big energy consumption. The fuel for biosolids transportation in gallon (gal) was calculated relative to the amount of biosolids produced in dt. For the

[16] Brown and Caldwell, Technical memorandum number 1 to DC Water, March 2010.
[17] Blue Plains AWTP energy consumption historical data from 2007-2010.
[18] Energy saving report for DC Water, MWH Americas, December 2010.

purpose of the model below, the natural gas for heat and fuel for transportation is expressed in kWh. The natural gas in cf is changed to kWh to describe the energy recovered from bio-methane. The fuel for transportation in gallon is calculated assuming a round-trip delivery distance.

2.1.3 Biogas Production by Anaerobic Digestion Processes

Biosolids are the nutrient resource end products of the wastewater treatment process and are used on farms as fertilizer. However, this material can also be highly odorous and may contain pathogens therefore utilization sites may need to be highly regulated. Many wastewater treatment plants such as the one in case study spends large parts of their budget to properly utilize Class B biosolids. One approach to improve the quality of biosolids is to digest the solids and produce biogas for generation of electric power (and other uses). The digestion process may reduce problems associated with biosolids odors and improves Class B Class A biosolids. For these reasons, the AWTP facility is considering using thermal hydrolysis and anaerobic digestion to improve the quality of biosolids and to promote recycling instead of only using lime stabilization. Such an approach could also be appealing to other WWTP.

Solids will be digested in an anaerobic environment and produce biogas and stabilized biomass (Class A biosolids) using the following chemical reaction (Rosso and Stenstrom 2008):

$$\text{Solids} + \text{Carbon substances} \longrightarrow CH_4 + CO_2 + H_2O + \text{trace gases} + \text{Class A biosolids}$$

The biogas (CH_4 + CO_2 + H_2O + trace gases) can be broken down into the following component shares: 55-65% methane gas (CH_4), 30-40% carbon dioxide gas (CO_2), and 0-5% water vapor, traces of hydrogen sulfide H_2S and hydrogen H_2 (Appels et al. 2008). Consequently, in the model presented below, an average 60% of methane composition in biogas will be used, and called bio-methane. However, total amount of biogas production from thermal hydrolysis and anaerobic digesters will be calculated relative to design criteria. The thermal hydrolysis process will first stabilize solids and the anaerobic process will digest organic substance in the form of volatile solids. Only 15 cf of biogas are contained in a pound of volatile solids, so the approximated amount of biogas is 4.4 million cf per day calculated from a digester maximum of 370 dt (Metcalf & Eddy and AECOM 2008).

2.1.4 Energy Recovered from Methane Gas

AWTP buys electricity for its operational processes from an external contractor averaging 634,000 kWh at $0.086 per kWh and uses it to operate all facilities, including treating wastewater and biosolids. Generating electricity from biogas, which is produced by anaerobic digestion of biosolids, may be a better economic choice for the AWTP facility and other wastewater treatment plants to reduce external electricity costs. The approximate amount of electricity generated from biogas can be estimated and converted to kilowatt-hours by using the heat value of biogas.

Biogas produced from the digestion process still needs a further step of separating sulfurs and siloxanes to clean the biogas to eventually get bio-methane. The amount of bio-methane (Ryckebosch et al. 2011) remaining after the cleaning process is about 55-

65% or on average 60% (Appels et al. 2008) of the original biogas produced. AWTP may use this bio-methane on-site for heat or power generation, or take it off-site by injecting it into natural gas pipelines, gas storage facilities, or for use in fleet vehicles as compressed natural gas (bio-CNG (Ryan and Caulfield 2010)) [19]. After the high pressure compressing and cleaning process, the amount of CNG amount will be about 96.5% of the original bio-methane. [20]

2.1.5 Carbon Dioxide Equivalent (CDE) Emissions

WWTPs are huge sources of greenhouse gas (GHG) emissions including carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) and hydro fluorocarbon (HFC-134a). Indeed, WWTP operations in 2005 generated over 2% of total U.S. greenhouse gas emissions from solids processing and disposal activities, which include landfill and wastewater processing (CH2MHILL 2007). WWTPs that use aerobic and/or anaerobic biodegradation emit CO_2, CH_4 and N_2O from degrading soluble organic matters in wastewater as well as via the land application biosolids to agricultural fields.

The large WWTPs may find it's advantageous to generate energy from wastewater and obtain benefits from renewable energy credits (RECs) or carbon dioxide credits related to CO_2 allowances. In this study, the carbon dioxide equivalents [21] (CDE) offset relating to the anaerobic digestion process and the biosolids land application

[19] The Washington Metropolitan Area Transit Authority (WMATA) as the fourth largest transit system in U.S. for combined rail and bus transit having 1,500 square mile service area includes 3.5 million people within Washington, DC, and parts of Maryland and Virginia, do support using CNG for transit bus, according to result of studied show reducing carbon dioxide emission (NREL 2006) and saving some of fuel cost (detail will be in NREL 2006).
[20] http://www.environmental-expert.com/products/biogas-to-compressed-natural-gas-35510.
[21] The international standard practice expresses GHG in the term of carbon dioxide equivalent (CDE). Other GHGs than carbon dioxide emission will be converted to CDE by using global warming potential (GWP), which express 1 for CO_2, 21 for CH_4, 310 for N_20 and 1300 for HFC-134a (EPA 2004).

process are deducted from carbon dioxide emissions from operational processes. For instance, the model described below estimates CDE emissions from electricity consumption at AWTP by multiplying electricity used by 0.00055 tons CDE per kWh (The climate registry 2008). The electricity if generated from end product of wastewater can create CDE reduction (get credits) for AWTP since it was renewably generated instead of purchased from the outside with fossil fuel such as coal and petroleum larger amounts of CDE. AWTP would get renewable energy credit or CO_2 credits.

An additional benefit for AWTP is that the CO_2 credits from the land application process will decrease 0.1 tons of CDE per dry ton of biosolids when using biosolids as fertilizer (Brown and Leonard 2004). Other advantages from CO_2 credits include using natural gas for a variety of sectors including compressed natural gas (CNG) for the transportation sector. For example using one cubic meter of natural gas, WWTP will offset 0.00197 tons CDE for producing electricity and selling CNG to the transportation sector will offset 0.001908 tons CDE. (The climate registry 2008).

2.2 A Multi-objective, Mixed-integer Optimization Model

Given the above discussion about wastewater-derived energy and carbon dioxide emissions, the model we propose will: maximize the total value of wastewater treatment plant operational processes, minimize the amount of energy to be purchased, and minimize the net carbon dioxide equivalent emissions. As such, it will be a multi-objective, mixed-integer optimization model. Figure 2.2 describes the overall set-up to be modeled with the first step being wastewater flow to the various operational process and passed to the liquid and solids phases normally. As discussed above, between 383-428 dt of biosolids can be produced based on historical data. The amount of biosolids influent denoted I_B is thus bounded between these two values. The model will select which value in the range [383, 428] is best given the competing three objectives and other constraints.

In the next step of the flowchart in Figure 2.2, sludge influent can go three directions: digestion (I_G,"G" for gas), land application as Class B biosolids (I_B, "B" for Class B), or directly as Class A material (I_A, "A" for Class A). In the first case, biosolids sent to the digester will produce biogas and generate electricity as well as some Class A material. In the second case, the biosolids will be processed for land application as fertilizer. In the third case, biosolids will be stabilized by heat to reduce the amount of pathogens before going to other processes. The model will decide optimal values for I_G, I_B and I_A given other constraints with respect to the three objectives.

The next decision that the model makes is to divide up the digested product between production of the Class A biosolids, natural gas for sale on the spot market (G_{NG}), compressed natural gas for transportation usage (G_{CNG}^{T}) and electricity from biogas (G_E). For the quantity of Class A biosolids destined for land application, the model will select if it should be given to farms to use as plant nutrients (B_A^L, "L" for land application) or sold on the fertilizer market (B_A^{AM}, "AM" for agricultural market).

Lastly, the model will make all decisions for sales to end-use spot markets, for natural gas non-transportation, CNG, electricity, fertilizer, or use the power at AWTP along with the renewable energy credits and carbon allowance market considerations. In the next sections, we describe the variables and constraints that make up the model, which will be solved as a mixed-integer, linear program, using the General Algebraic Modeling System (GAMS). [22]

2.2.1 Decision Variables

The following is a description of the variables used in the model with the main ones also shown in Figure 2.2. Note that the model is solved for a typical day. Hence, the values for all the variables are in units per day. [23]

I_T = total solids produced (dt)

I_G = solids used to produce biogas (dt)

I_B = solids used to produce Class B biosolids from lime stabilization to be land applied (dt)

I_A = solids used to produce Class A biosolids without digestion (dt)

G_E = biogas from solids for generating electricity (cf)

G_{NG} = biogas from solids sold to the natural gas spot market (cf)

G_{CNG} = biogas from solids sold to transportation sector as CNG (cf)

B_A^L = biosolids Class A produced for land application (dt)

B_A^{AM} = biosolids Class A sold in the agricultural market (dt)

E^E= electricity bought from external sources and used at AWTP (kWh)

E_B^{WWTP} = electricity generated from biogas and used at AWTP (kWh)

E_B^{SM} = electricity generated from biogas and sold to the spot market (kWh)

---

[22] http://www.gams.com

[23] Variables bearing the superscript "DC" refers to quantities produced and consumed at AWTP as opposed to buying from the outside.

NG_H^E = natural gas purchased from external sources (cf) [24]

V_{CR} = revenue from carbon dioxide credits or renewable energy credits ($)

V_D = digester processing costs ($)

x_{ij} = amount of solids processed by digester i and segment j (dt)

w_{ij} = binary variables equal to 1 if digester i and segment j used 0 otherwise (dt)

2.2.2 Parameters

I_T_min minimum solid end product from operational process (dt)

I_T_max maximum solid end product from operational process (dt)

Cap maximum amount of Class B production (dt)

f_G biogas production factor (cf)

f_{NG} methane production factor (unitless) [25]

f_{CNG} CNG production factor (unitless) [26]

f_B dry tons of Class A biosolids per dry ton of solids influent (dt/dt)

$WWTP_E$ average electricity consumption at AWTP (kWh)

f_E factor used to calculate generated electricity from biogas (kwh/cf)

$WWTP_{NG}$ average daily natural gas consumption at AWTP (cf)

f_C^E factor used to calculate carbon dioxide emissions from electricity (t/kWh)

f_C^{NG} factor used to calculate carbon dioxide emissions from used natural gas for heat (t/cf)

---

[24] This variable is fixed at 172,240 cf/d but is presented here as a variable for generality.

[25] The biogas (CH_4 + CO_2 + H_2O + trace gases) can be broken down into the following component shares: 55-65% methane gas (CH_4), 30-40% carbon dioxide gas (CO_2), and 0-5% water vapor, traces of hydrogen sulfide H_2S and hydrogen H_2 (Appels et al. 2008). Consequently, in the model presented below, an average 60% of methane composition in biogas is used.

[26] The reduction from 100% is due to further processing for gas quality outside of WWTP (http://www.environmental-expert.com/products/biogas-to-compressed-natural-gas-35510).

f_C^{CNG} factor used to calculate carbon dioxide offset from sold CNG for transportation sector (t/cf)

f_C^f factor used to calculate carbon dioxide offset from biosolids used as fertilizer (t/dt)

f_C^t factor used to calculate carbon dioxide emissions from transportation of biosolids to land application field (t/dt)

f_P^T factor used to calculate fossil fuel consumption to transport Class A and/or B biosolids to land application fields (kWh/dt)

f_E^P electricity purchasing prices (\$/kWh)

f_{NG}^P natural gas selling prices (\$/cf)

f_E^{Gen} electricity generation costs (\$/kWh)

f_{CNG}^{Com} CNG compression costs (\$/cf)

f_B^T factor used to calculate biosolids transportation cost to land application field (\$/dt)

$f_A^{Compost}$ Class A biosolids composted costs (\$/dt)

f_B^f fertilizer prices (\$/t)

f_E^S electricity selling prices (\$/kWh)

f_{CNG}^S CNG prices (\$/cf)

C_{allow}^{WWTP} CDE allowance (t)

f_C^S carbon credits (\$/t CDE)

f_{REC}^S renewable energy credits (\$/t)

F is equal to 0 or 1

h_{ij} digester fixed cost

a_{ij} digester variable cost

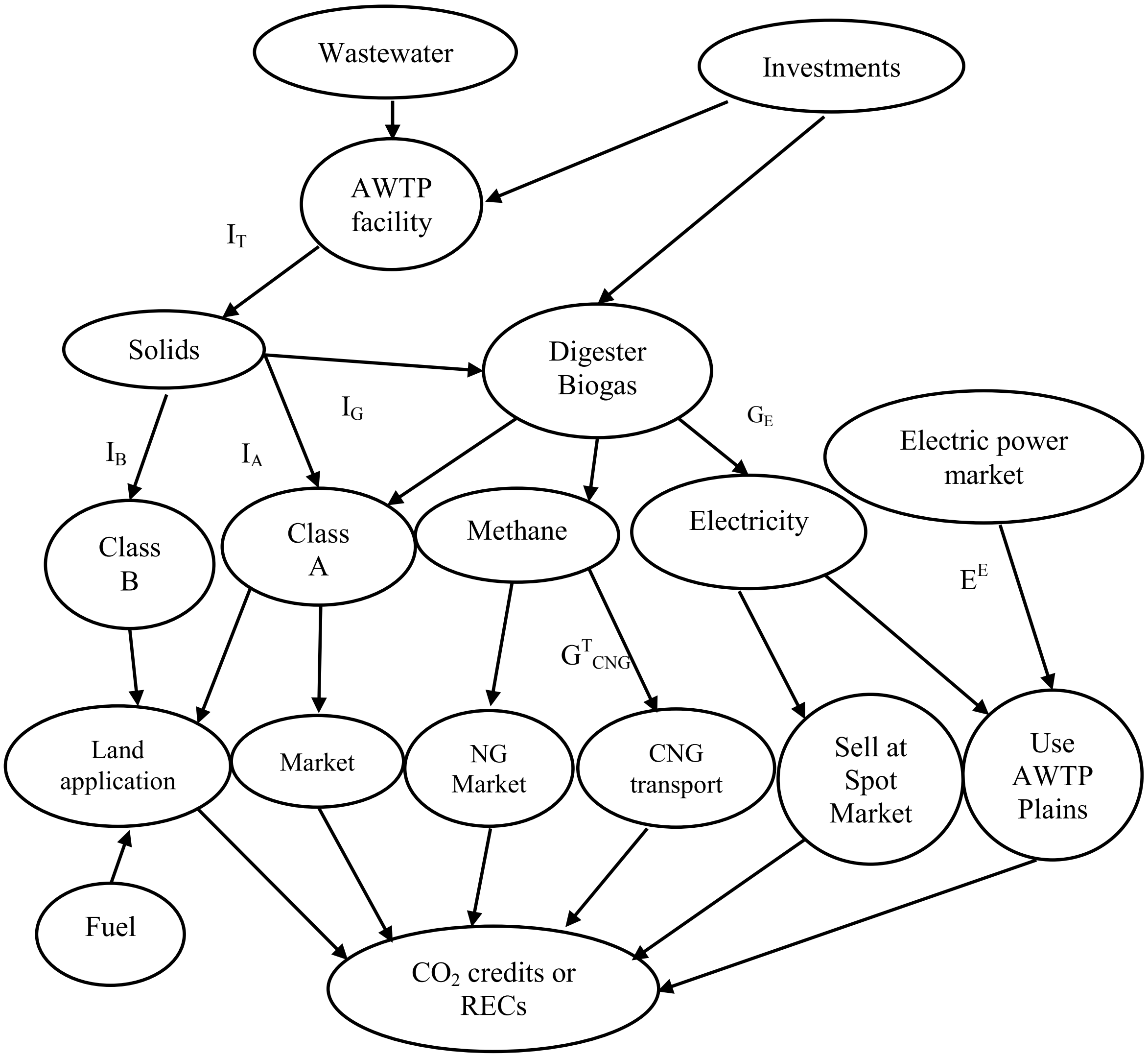


Figure 2.2 Process diagram of the multi-objective optimization model for the biosolids management program at the AWTP.

2.2.3 Constraints

All constraints are linear and represent conservation some quality.

2.2.3.1 First-stage Constraints

The cost of the digester V_D is calculated for four different combinations of thermal hydrolysis/digestion (TH&digester) and lime stabilization (LS) (Metcalf & Eddy and AECOM 2008):

- Digester type 1: one large digester (four trains of thermal hydrolysis [27] and anaerobic digester [28]) plus lime stabilization, called "4 TH&digester + LS",
- Digester type 2: one small digester (two trains of thermal hydrolysis and anaerobic digester) plus lime stabilization, called "2 TH&digester + LS",
- Digester type 3: one large digester and one small digester, called "4 TH&digester + 2 TH&digester", or
- Digester type 4: only lime stabilization.

For each of these four types of digesters ($i=1,2,3,4$) the cost function is split into two segments ($j=1,2$) reflecting the cost of lime stabilization for inflow exceeding a certain threshold unique to each type. For example, for digester type 2, lime stabilization begins at 250 dt of inflow. Figure 2.3 shows the costs of the four possible digester cases;

From the details mentioned above, each digester cost will have a fixed cost [29], denoted by h_{ij} and a variable cost (operation and maintenance costs) related to the solids influent amount, denoted by a_{ij}. Only one digester will be picked according to the binary variable w_{ij}.

[27] Thermal hydrolysis is a solid conditioning process including thickened, steam, pressure and cooled down solids before anaerobic digestion (Metcalf & Eddy and AECOM 2008). The end-products are solids that are ready to be processed by anaerobic digestion (mesophilic or thermophilic).
[28] Mesophilic anaerobic digestion is a process that is operated from 91 to 99 degrees Fahrenheit to reduce the quantity of solids, pathogens and odor (Metcalf & Eddy and AECOM 2008). Anaerobic biodegradation breaks down organic substances into the following component shares: 55-65% methane gas (CH_4), 30-40% carbon dioxide gas (CO_2), 0-5% water vapor, traces of hydrogen sulfide H_2S and hydrogen H_2 and class biosolids (Appels et al. 2008).
[29] Fixed costs included construction, thermal hydrolysis facility, boiler, digested gas, CO_2 scrubber, overhead of construction processes, and insurance.

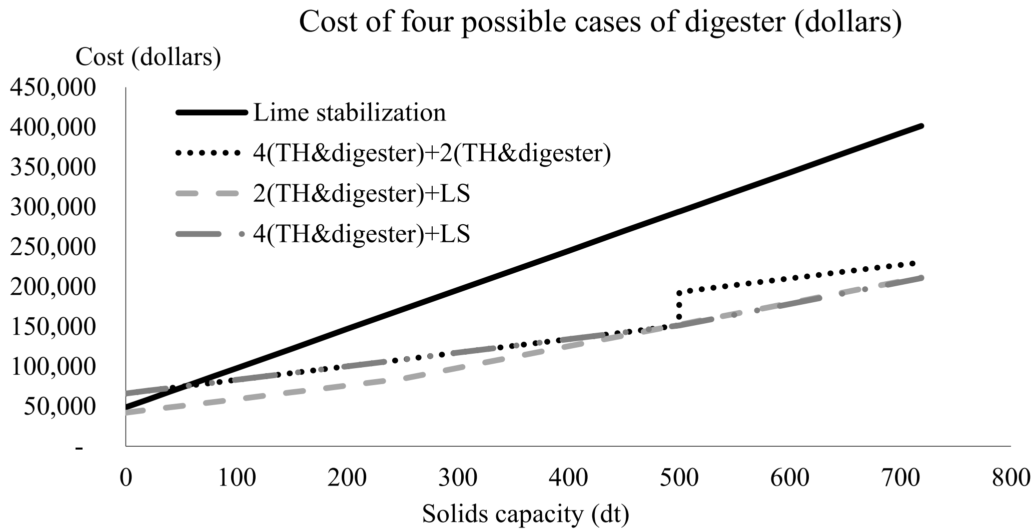


Figure 2.3 Cost of four possible cases of digester.

(a 50-year digester lifetime is assumed).

2.2.3.2 Second-stage Constraints

$I_T = I_B + I_A + I_G$ dt (2.1a)

$I_{T}\_min \leq I_T \leq I_{T}\_max$ dt (2.1b)

$I_G \leq \sum_i \sum_j x_{i,j}$ dt (2.1c)

$I_G \leq Solid_{gas}(1 - w_{41} - w_{42})$ dt (2.1d)

$I_B \leq Cap - I_G - I_A$ dt (2.1e)

$I_A \leq Cap - I_G - I_B$ dt (2.1f)

$\sum_i \sum_j w_{i,j} = 1$ (2.1g)

$w_{i,j} \epsilon \{0,1\}. \forall i, j$ (2.1h)

$x_{i,j} \leq CAP_{i,j} w_{i,j}$ (2.1i)

$x_{i,j} \geq l_{i,j} w_{i,j}$ (2.1j)

Constraint (2.1a) defines the conservation of produced solids expressed in dt.

Constraint (2.1b) defines the amount of solids produced from wastewater in dt. The maximum 428 dt is based on the design for the digester. The minimum 383 dt is historically based.

Constraints (2.1c) and (2.1d) define the amount of solids in dt that will go to the digester to produce biogas .The maximum 370 dt is based on a design for the digester (Metcalf & Eddy and AECOM 2008). Note that, w_{41} or w_{42} = 1 means only lime stabilization is used, hence no digestion. Also at most one of w_{41} or w_{42} = 1

Constraint (2.1e) defines the amount of solids in dt that will use the lime stabilization process to produce Class B biosolids. The maximum amount of Class B [30] production 719 dt will be delivered to the land application site in case the operational process faces the maximum peak flow. Constraint (2.1f) is similarly defined, but for maximum amount of Class A.

Constraint (2.1g) defines at most one of the w_{ij} variables is equal to 1

The binary constraint is (2.1h) and constraints (2.1i) and (2.1j) refer to upper bounds on the biosolids amount, constrained respectively by the maximum solids capacity and the minimum solids used to produce biogas. $l_{i,j}$ indicates solids used to produce biogas in dt.

$$f_G I_G = G_E + G_{NG} + G_{CNG} \qquad \text{cf} \qquad (2.2a)$$

$$G_{NG} \leq f_{NG} f_G I_G \qquad \text{cf} \qquad (2.2b)$$

$$G_{CNG}^T \leq f_{CNG} f_G I_G \qquad \text{cf} \qquad (2.2c)$$

[30] 719 dt is the maximum peak flow based on historical data from the AWTP operational process and digester design.

Constraint (2.2a) defines the total amount of biogas in cf produced from the solids influent. The maximum biogas of about 4.4×10^6 cf comes from the digester design, which is also equal to the product of factor f_G and the dry ton of solids influent. See Appendix A.

Constraint (2.2b) defines the amount of bio-methane in cf produced from the solids influent. The amount of bio-methane is 60% of total biogas produced. The reduction from 100% is due to further processing needed for methane quality outside of AWTP. Constraint (2c) is similarly defined, but for CNG.

$$f_B I_G + I_A = B_A^L + B_A^{AM} \qquad \text{dt} \qquad (2.3)$$

The left-hand side of constraint (2.3) defines the total amount of Class A biosolids from the digester or composting processes in dt. The right-hand side represents the destination of the Class A biosolids, either land application or sold to the agricultural market. The factor of f_B is the amount of dry tons of Class A biosolids per unit of solids influent. See Appendix A.

$$WWTP_E \leq E^E + E_B^{WWTP} \qquad \text{kWh} \qquad (2.4a)$$

$$E_B^{WWTP} + E_B^{SM} = f_E G_E \qquad \text{kWh} \qquad (2.4b)$$

Constraint (2.4a) defines the average daily amount of electricity used at AWTP for operations, which is 634,000 kWh from historical data. This electricity may be bought from external sources (E^E) or generated from biogas (E_B^{WWTP}) and used at AWTP.

Constraint (2.4b) defines the electricity in kWh generated from the biogas produced during the digestion process and used at AWTP. The maximum electricity generated from biogas is calculated from the maximum solids transferred from the influent multiplied by factor of f_E calculated from the efficiency of one type of power generator using biogas. See Appendix A.

$$WWTP_{NG} = NG_H^E + G_{NG} \qquad \text{cf} \qquad (2.5)$$

Constraint (2.5) defines the total natural gas used at AWTP for operations expressed in cf. The average daily amount of natural gas consumption at AWTP from historical data is 172,240 cf. This natural gas may be purchased from external sources (NG_H^E) or generated at AWTP as bio-methane (G_{NG}).

$$C_T = f_C^E(E^E - E_B^{WWTP} - E_B^{SM}) + f_C^{NG}(NG_H^E - G_{NG}) + \left(f_C^t - f_C^f\right)(I_B + B_A^L + B_A^{AM}) - f_C^{CNG} G_{CNG}^T \qquad \text{t CDE } (2.6)$$

Constraint (2.6) defines the net total carbon dioxide equivalent emissions in t CDE. This constraint can be broken down as follows:

- $f_C^E(E^E - E_B^{WWTP} - E_B^{SM})C_T$ the carbon emissions less offset from electricity usage both generated at the AWTP and purchased ;
- $f_C^{NG}(NG_H^E - G_{NG})$ the carbon emissions from natural gas purchased from outside the AWTP less what is generated internally ;

- $\left(f_C^t - f_C^f\right)(I_B + B_A^L + B_A^{AM})$ the net carbon emissions resulting from transporting the biosolids to the reuse sites (net emissions relative to biosolids credits received)
- $f_C^{CNG} G_{CNG}^T$ the credits accrued from selling the digester-derived methane to the CNG transportation sector

The carbon emissions and/or offset from various sources are listed in Appendix A.

$$P_T = f_P^T (I_B + B_A^L + B_A^{AM}) + E^E + f_P^T NG_H^E \qquad \text{kWh} \quad (2.7)$$

Constraint (2.7) defines the total energy purchased, which includes energy for transportation of Class A and/or Class B biosolids to land application sites, electricity and natural gas consumption in kWh. The factors used to calculate fossil fuel consumption to handle Class A and/or B biosolids to land application fields and to the market in kWh, and the natural gas consumption at AWTP in kWh are given in Appendix A.

$$V_D = \sum_i \sum_j a_{i,j} x_{i,j} + \sum_i \sum_j h_{i,j} w_{i,j} \qquad \$ \qquad (2.8a)$$

$$V_{CR} = f_C^S (C_{allow}^{WWTP} - C_T) F - f_{REC}^S (C_{allow}^{WWTP} - C_T)(1 - F) \qquad \$ \qquad (2.8b)$$

$$V_T = Revenues - Costs \text{ where :} \qquad \$ \qquad (2.8c)$$

$$Revenues = [f_B^f B_A^{AM}] + [f_E^S E_B^{SM}] + [f_{CNG}^S G_{CNG}^T] + [V_{CR}]$$

$$Costs = V_D + [f_E^P E^E] + [f_{NG}^P NG_H^E] + [f_E^{GEN} (E_B^{WWTP} + E_B^{SM})] + [f_{CNG}^{COM}\ G_{CNG}^T] +$$

$$[f_B^T (B_A^L + I_A + \ I_B)] + [f_A^{Compost}\ I_A]$$

Constraint (2.8a) defines the digester cost.

Constraint (2.8b) defines the carbon dioxide and renewable energy credits.

Contraint (2.8c) defines the AWTP total value in dollar ($). It is composed of the following revenues: sales of Class A biosolids to the agricultural market, sales of electricity to the spot market, CNG from the digestion process sold to the spot market or transportation sector and carbon dioxide and renewable energy credits constraint (2.8b). In addition, the total value includes the following costs: digester cost, cost of electricity and natural gas bought externally from the spot market, electricity generation cost, production cost of CNG, cost of transporting Class A and B biosolids to land application fields, and composting costs. The coefficients are listed in Appendix A.

2.2.4 Objective Functions

1. *Minimize* $Z = C_T$ t CDE (2.9a)

2. *Minimize* $Z = P_T$ kWh (2.2.9b)

3. *Maximize* $Z = V_T$ $ (9c)

Equation (2.9a) defines the objective function of minimizing net carbon dioxide emissions calculated from carbon dioxide equivalent emitted by all operational processes and carbon dioxide offsets from digestion and land application.

Equation (2.9b) defines the objective function of minimizing total energy purchased at AWTP calculated from three sources: fossil fuel for transporting biosolids to land application fields, electricity for operational processes and natural gas for heat.

Equation (2.9c) defines the objective function of maximizing the total AWTP value calculated from operational costs and revenues.

2.3 Results and Discussion

The summary of results of the multi-objective, optimization model taking each objective separately are shown in detail in Table 2.1.

For maximizing the total value objective, the type of digester and the amount of biosolids influent are key variables. For example, an optimal solution uses type 2 digester (two trains of thermal hydrolysis & anaerobic digestion with lime stabilization), which has the lowest operational cost, producing biogas from solids (I_G) at the level of 250 dt. Furthermore, Class A biosolids from composting and digestion will be sold as fertilizer. All of the biogas generated from digestion is used for electricity and space heat at the AWTP operations.

For minimizing the carbon dioxide emissions objective, using digested biogas to generate electricity resulted in the greatest reduction in CDE emissions. At optimality 428 dt of solids influent (I_G) will be processed by digester type 3 (four trains Thermal hydrolysis & anaerobic digester and two trains Thermal hydrolysis & anaerobic digester) to produce biogas. Digester-based electricity is used for the AWTP operations. From used digester-based electricity, AWTP will receive carbon dioxide offsets and from biogas for heat. These results support AWTP's goal of a low carbon dioxide equivalent emissions.

For the objective of minimizing energy purchased, the amount of biogas-based electricity is an important variable. At optimality 428 dt of solids are digested to produce biogas and generate 293,040 kWh of electricity. The result of this is that only 340,960 kWh out of AWTP's total consumption of 634,000 kWh needs to be bought from the outside.

Table 2.1 Model results with three objective functions.

Decision variables	Unit	Lower bound	Upper bound	Maximizing total value	Minimizing net CDE emissions	Minimizing energy purchasing
Total solids influent	dt	383	428	428	428	428
Solids produced biogas (I_G)	dt	0	428	250	428	428
Solids for Class B (I_B)	dt	0	428	0	0	0
Solids for Class A (I_A)	dt	0	428	178	0	0
Biogas generated electricity	cf	0	5,141,136	1,092,000	4,968,900	5,141,100
Bio-methane used as NG	cf	0	3,084,682	172,240	172,240	0
CNG sold to transportation	cf	0	2,976,718	1,738,700	0	0
Class A to land application	dt	0	428	0	207	207
Class A sold spot Market	dt	0	428	299	0	0
Electricity purchasing	kWh	340955	634000	571,750	350,770	340,960
Generated Electricity and use	kWh	0	293045	62,245	283,230	293,040
Generated Electricity and sell	kWh	0	293045	0	0	0
NG purchasing	cf	0	172,240	0	0	172,240
REC revenue	$	0	654	264	563	547
Digester cost	$	84,540	401,551	84,540	193,240	230,520
Optimal value				**-104,500**	**48**	**365,990**
Digester type				2	3	3

The above results indicate the benefits of generated biogas from solid end products of wastewater. The total value (profits) could be increased from the internal renewable energy production revenue (selling generated bio-CNG and biogas-based electricity) and Class A biosolids sold as fertilizer. However, the small digester (digester type 2) option was selected to produce biogas if the objective were to maximize total value.

However, when either minimizing the expected purchased energy from outside sources or minimizing the expected net CDE emissions are used as objectives, there is a different digester investment option. In particular, with both these objectives, the big digester is preferred.

One difference between these two objectives is the use of the output from the big digester. When minimizing purchased energy is chosen as the objective, the big digester allows for more internally generated electricity and thus offsets the outside energy that needs to be bought than minimizing CDE is chosen as the objective.

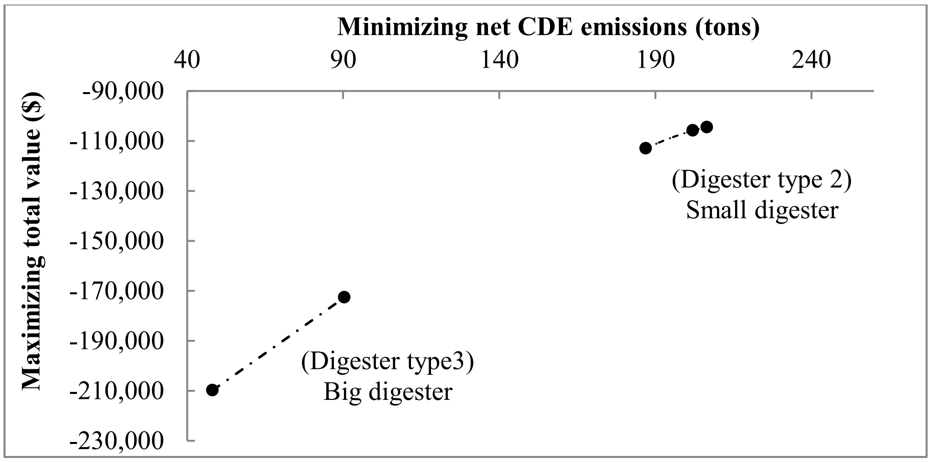


Figure 2.4 An approximation of the Pareto optimal points when analyze minimizing CDE emissions and maximizing total value objectives.

The next step is to generate and then analyze an approximation of the Pareto optimal frontier. Figure 2.4 depicts the relationship of the maximizing total value and minimizing net CDE emissions objectives. The AWTP can reduce the amount of carbon dioxide emissions when the operational cost is increased. For example, to reduce CDE emissions, the AWTP can move from a small digester (three most northeastern points in Figure 2.4) to a big digester (remaining two points). This switching from a smaller to a bigger digester results in 97 fewer tons of emissions (187 to 90) but $618 per day more per ton of CDE emissions. However, if the same digester is used (big or small), a different trade-off results. For example, staying with the big digester, the top southwestern-most points indicate that to reduce one ton of CDE emissions, it costs $880 per day. Conversely, if staying with the small digester, the corresponding figure is $311 per day. These figures indicate that producing more biogas with the big digester has a positive environmental benefit.

2.4 Conclusions

In this study, we have developed a model to analyze optimizing three different objectives: maximizing total value, minimizing net carbon dioxide equivalent emissions and minimizing energy purchasing. In addition, various solids management operational activities at AWTP have been modeled. The first decisions involve selecting the type of digester option (four in all including just lime stabilization). Based on which of these four choices are selected, AWTP should then choose from producing biogas from digestion to generate electricity, selling the biogas directly to the spot market, composting to produce Class A biosolids or stabilize solids to produce Class B biosolids.

The results indicate that AWTP is able to process the maximum amount of 428 dt of solids while benefitting from carbon dioxide credits. Additionally, the analysis indicates that there is a Pareto tradeoff between the environmental and energy market benefits of larger digesters vs. the greater associated investment and operational costs for digestion. What is optimal depends on the objective being considered. For example, when maximizing total value the smallest digester is best. However, when minimizing either energy purchasing or carbon dioxide emissions, the largest digester option is optimal.

This study shows that optimal investment and operational decisions for an advanced wastewater treatment plant taking into account energy and environmental considerations can be complicated. Given the increasing environmental and renewable energy concerns, this type of model is likely to assist both wastewater and energy managers.

Chapter 3: A Stochastic, Multi-objective, Mixed-integer Optimization Model for Wastewater-derived Energy

Sustainability is a concept of increasing significance and valuable to a number of organizations. However, modeling investment decisions for sustainable energy production is challenging due to the many factors that need to be considered. Decision-makers can use optimization models to explore sustainability infrastructure decisions (DeCarolis et al. 2012; Schwarz 2005).

Mathematical programming models have been applied for waste management generally speaking, due in part to an increasing amount of waste over the years. Indeed, from 1960 to 2010, municipal solid waste (MSW) generation in the U.S. has increased from 88.1 million tons to 249.9 million tons in 2010 (EPA 2011). No doubt this is due in part to population increases but it may also be the result of more waste per person. From a modeling perspective, there is a great opportunity to guide waste managers and other interested parties on how best to make use of this untapped resource. To that end there have been many research works on this topic. Some recent works include multi-objective programming models of solid waste management (Perlack and Willis 1985; Chang and Wang 1996), optimization models for solid waste management (Filipiak et al. 2009; Rawal et al. 2012), a game-theoretic approach for analyzing strategies of waste management for old computers (Kaushal and Nema 2013) to name a few. The perspective of these and other works were both environmental and economic goals with sustainable management as an overall objective. Results of these models indicate that decision-makers could benefit from the waste by recovering a high amount of energy, reducing

CO_2 emissions, etc. For this research, we implemented a stochastic, multi-objective optimization model to manage solid end products from a wastewater treatment plant that considered both economic and environmental benefits. The current topic goes beyond a deterministic optimization version of the model (Gabriel et al. 2012) in several important ways. First, it includes ten stochastic inputs (e.g., electricity consumption and prices) based on actual fitted probability distribution. These stochastic data elements then led to 59,049 scenarios that became part of a two-stage, stochastic recourse model, which took into account hedging of decisions unlike the deterministic version of the model. Additionaly, a scenario-reduction approach (Dupacova et al. 2003; Heitsch and Romisch 2003) was used to balance the tradeoff of solution quality vs. computational time. Lastly, the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS) were obtained and analyzed to provide guidance.

For waste in the form of solid end products from wastewater treatment plants (WWTPs), there is also a huge potential for resource recovery. In the U.S. there are some 3,171 plants (http://water.epa.gov/scitech/datait/databases/cwns/index.cfm) that have up to 757 million liters per day of influent waste with a resulting huge amount of potential solid end products to be used as fertilizer on farms or to produce methane and/or electricity, renewably. Unlike biomass derived from crop waste, which takes up valuable land and therefore is in some competition with an increasing population, wastewater-derived energy is positively correlated with population growth but with less land constraints as compared to traditional bio-fuels from crops. That is, the larger the population, all things being equal, the greater the amount of wastewater hence more bio-gas for use in the power, transportation, or other sectors. To get more electricity from traditional biofuels would likely require more land. As such, in the move to a Smart Grid in which renewable energy will no doubt play a large role, wastewater-to-energy represents a sustainable part of the energy supply portfolio in the face of larger and larger populations.

The focus of the research in this dissertation is the sustainable management of WWTPs in which the energy consumption of the plant, the carbon dioxide emissions, as well as the revenues and costs are examined. The wastewater treatment plant used for the case study is one of the largest in the world and has some ability to generate its own electricity. This sustainability option is important for this WWTP. Carbon dioxide (CO_2) emissions and fossil fuel-based energy can be reduced if anaerobic digestion is applied to produce solids end product. However, a small digester offers a choice with less operational costs. The tradeoff between operational costs and CO_2 emissions provides a possible option to reduce operation costs per ton of CO_2 emissions and vice-versa. As such, the model considers many aspects of the Smart Grid such as: integration between energy and transportation, electricity generation by atypical prosumers (producer/consumer), the connection between energy and agriculture, and overall system planning to reduce negative environmental externalities, to name a few. The work considers a set of stochastic elements (e.g., power prices, influent, energy consumption) and includes scenario-reduction techniques to efficiently solve the resulting mixed-integer, linear stochastic program. The model is tested using the data from the biggest advanced wastewater treatment plant (AWTP) on the East Coast of the United States but in addition, the areas under study are also applicable to other WWTPs attesting to the generality of the modeling and results.

The main energy supplied to the wastewater treatment plant examined in this research is generated from coal power plants. The operational costs of the WWTP are subject to the price of energy purchased from an outside source and to the onsite investment in clean energy. The estimated levelized costs of electricity (LCOE) for electricity generated from a conventional coal plant is around $0.098 per kilo-watt-hour (kWh) (www.eia.gov), and the greenhouse gas (GHG) emissions, especially carbon dioxide (CO_2), from coal burning can be as high as 93.44 kilograms per million BTU (EIA 2012). The LCOE for biomass, wind, solar PV (photovoltaic), hydropower, and geothermal are respectively $0.115, $0.096, $0.153, $0.089, and $0.098 per kWh (EIA 2012), all of which emit much less CO_2 to the atmosphere than conventional coal plants. For example, the U.S. total CO_2 emissions from the electric power sector were 2,160.3 million tons of CO_2 in 2009. About 80.6% emissions were from coal-based electricity and only 0.6% emissions were from municipal solids waste (biomass) and geothermal-based electricity (http://www.eia.gov). Therefore, the WWTP should produce and use renewable energy from locally available natural resources in light of sustainability goals. This research looks into the benefits derived from the use of solar energy and solid end products from WWTP as a biomass source.

More than 60% of wastewater treatment plants in the United States used solid end products to: i) fertilize land, and/or ii) fuel boilers or generate electricity using methane gas from an anaerobic digestion process (www.insinkerator.com). For using as fertilizer, carbon, nitrogen and phosphorus (important substances for organic fertilizer) from solid end products compositions can increase environmental benefits of land application in agricultural fields (Wang et al. 2008). An additional benefit of using solid end products from WWTP is the reduced amount of carbon dioxide equivalent (CDE) emissions from using solid end products as a renewable energy source (Peters and Rowley 2009).

Uncertain outcomes associated with wastewater treatment operations as well as market conditions (prices and costs of products) are the main aspects to consider in a stochastic optimization for sustainability decision-making. The solid end product coming from the wastewater treatment processes is called “solids” and the level is uncertain due to many factors such as: usage patterns by day of the week, season of the year, and discrete weather-related events (Flores-Alsina et al. 2008) and for this study, the level of solids has been statistically fit to an appropriate probability distribution and input into the model as random parameters. Consequently, there is an uncertain amount of biogas. Energy consumption related to the operations also varies as solar electricity generated from uncertain solar radiation. The issues of electricity, fossil fuel, natural gas, agricultural market conditions as well as carbon dioxide credits are also fit to probability distributions.

To analyze the tradeoffs for a WWTP, we present a two-stage, stochastic optimization model with recourse. The first-stage considers which type of digester or other process should be implemented. The digester converts wastewater to Class A biosolids (see the next section for a discussion) as well as methane as a byproduct. The second-stage involves operational constraints for each of the 59,049 ($=3^{10}$) scenarios reflecting 10 uncertain aspects and three levels for each as an approximation of the fitted probability distribution. Examples of the recourse decisions are to sell or use generated electricity from renewable energy sources (biogas or solar), to sell biosolids end product to the agricultural market or land apply them as plant nutrients. In addition, multiple objectives are considered to add realism to the problem area being studied. The optimal solution is often a tradeoff among all objectives. The theory of multi-objective optimization is also included in this research to examine efficient solutions that can't be improved for one objective without worsening one or more of the other objectives. This dissertation is focused on the tradeoff between maximum benefit from the operational and investment decision and minimum net CDE emissions when purchased energy is considered at average amount. For example, once maximum benefits are considered, small digester (lower costs than big digester) should be selected to product biogas and Class A biosolids (see the detail about each type of digester in Section 3). Biogas-based electricity, bio-CNG (compressed natural gas (CNG) produced from biogas) and Class A biosolids are produced from biogas and sold to the electric power, CNG for transport and fertilizer markets, respectively, to increase the revenues. On the other hand, big digester, which is higher costs than small digester, is preferred to produce more biogas and related products such as biogas-based electricity and bio-CNG. Either an option to sell to the relevant markets or use internal WWTP is selected due to minimizing net CDE or minimizing purchased energy, respectively.

For computational purposes reduction of the 59,049 scenarios was needed. Many methods could be used to decrease the size of the full scenario tree (59,049 scenarios) such as conditional sampling, random sampling and scenario-reduction approaches. In this study the scenario-reduction approach was used wherein a reduced form of the scenario tree is generated to decrease computational time (see Section 4 for more detail). The scenario-reduction procedure produces a smaller tree but still contains original data and probabilities related to all scenarios (Morales et al. 2009; Gabriel et al. 2009). The

GAMS scenario reduction package ‘‘GAMS/SCENRED2” (www.gams.com) was used to create a reduced tree with specialized algorithms (Dupacova et al. 2003; Heitsch and Romisch 2003).

The rest of this chapter is organized as follows: Section 3.1 presents the operational parameters of the WWTP. Section 3.2 describes the stochastic, multi-objective optimization model and Section 3.3 explains the scenario reduction method. Section 3.4 discusses the results of the model while Section 3.5 provides concluding remarks. Lastly, the Appendixes contain additional details.

3.1 Case Study of a Large Wastewater Treatment Plant

In this study, ten groups of uncertain data were involved such as solids end product from wastewater treatment operational process, energy consumption (mention in Section 3.1.1), energy prices and costs, e.g., carbon dioxide credits. The resulting stochastic optimization model also considers investments in solar power (mentioned in Section 3.1.1) and consideration of disposal of incremental solid waste coming from outside organizations (mentioned in Section 3.1.3) as well as incineration as an option.

3.1.1 Energy Consumption at AWTP

A WWTP uses electricity to run its facilities, natural gas for space heating, and fossil fuel to transport biosolids and for service vehicles. For the case study WWTP, the electricity consumption during 2004-2010 varied between 564,000 and 838,000 kilowatt hours (kWh) per day. Purchased energy from external sources is the biggest cost item for the case study WWTP. Therefore, adopting alternative energy sources is one crucial option by which the WWTP can reduce its energy costs.

The Atlantic County Utilities Authority (ACUA), [31] Falmouth's wastewater treatment plant (Town of Falmouth wind energy project, summer 2012.), San Elijo (EPA-832-F-05-014 2005) and the Deer Island treatment Plant (DITP) (Crowe et al. 2009) are examples of WWTPs that produce their own renewable energy for internal use and supply left over energy for households. The WWTP in this study has two possible options of renewable energy sources: biogas and solar energy. Biogas from solid end products is likely to be its main source of renewable energy. Furthermore, the plant has the potential to generate electricity from solar energy as solar radiation varies between 0.19 and 2.65 kWh/m^2 for its location. This is the solar capacity that is used in the study.

3.1.2 Biogas Production from Biosolids

In addition to the economic benefits of using biosolids as fertilizer, the recovery of methane from solid end products is posssible (see details in Fig. 3.1.). An anaerobic digestion process reduces the amount and volume of solids to produce biogas with methane gas as its main composition (Oleszkiewicz and Mavinic 2002). Thermal energy is used to stabilize organic matters in the solids influent for digestion (Bonmati et al. 2001) and then passes them through the anaerobic digestion process to eliminate organic matters and then produce several types of gases, such as carbon dioxide and methane. This process is called thermal hydrolysis and anaerobic digestion (TH & anaerobic

[31] http://www.acua.com/acua/uploadedFiles/Home/ACUA_Information/Files/Fact_Sheets/WWFactSheet0609.pdf

digestion). The end products are principally methane (CH_4), carbon dioxide (CO_2), and stable organic residues (Wang et al. 2007; Rosso and Stenstrom 2008).

The resulting biogas can then be converted into several forms of energy, such as compressed natural gas (CNG) for cars, natural gas for heating, and electricity. CNG can replace gasoline in motorized vehicles and fossil fuel, such as coal and crude oil, in electricity production.

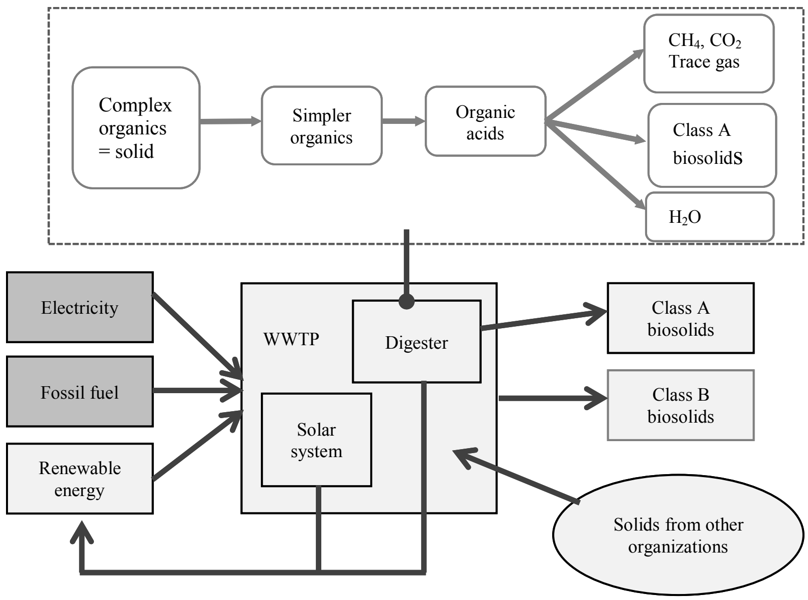


Figure 3.1 Wastewater treatment plant model considered.

3.1.3 The Incremental Solids Disposal for Additional Environmental and Economic Benefits

Long-term investments in a digester for disposal of specific types of solid waste requires careful consideration. Hence, purchasing the disposal service from an outside source may be a better alternative for some organizations (Green 2008). With the huge capacity of a digester (details in the next section), the case study AWTP has the potential to process solids from nearby organizations and get waste management tipping fees, i.e., an outsourcing payment to the AWTP.

3.1.4 Carbon dioxide Equivalent Emissions

In addition to economic benefits, solid end products from wastewater operations are helpful in reducing greenhouse gas emissions such as carbon dioxide and methane. Land application biosolids for the agricultural sector reduce carbon sequestration in soil. For example, District of Columbia Water and Sewer Authority [32] reduced 1,941 metric tons of CDE (ton CDE) [33] emissions by land application of Class B biosolids. Also, the WWTP can receive benefits from offsetting carbon dioxide from using biogas-based electricity generated from digested biogas. This study considered a generator capacity of 2.02 kWh/m^3 to generate electricity from digested biogas. The associated electricity generations costs are shown in Appendix B but do not include transporting the biogas to the electricity generation site. For instance, each megawatt hour (MWh) of used or sold biogas-based electricity can offset 0.00055 tons of CDE (EPA 2004). Using heat produced from biogas offsets 0.00197 tons of CDE per cubic meter (t/m^3) or 0.000056 tons of CDE per cubic foot (t/cf), and using CNG from biogas for transportation reduces 0.001908 t/m^3 or 0.000054 t /cf (The climate registry 2008).

3.2 A Stochastic, Multi-objective, Optimization Model

---

[32] http://www.dcwater.com/news/publications/2011_08_biosolids_report.pdf

[33] The international standard practice expresses GHG in the term of carbon dioxide equivalent (CDE). Other GHGs than carbon dioxide emission are converted to CDE by using a global warming potential (GWP), which expresses 1 for CO_2, 21 for CH_4, 310 for N20 and 1300 for HFC-134a (EPA 2004).

To model the various engineering and uncertain parameters discussed above, a stochastic, multi-objective optimization is developed. Specifically, the model simultaneously maximizes the total value (i.e., revenues less costs) of the AWTP operational processes, minimizes the amount of energy to be purchased, and minimizes the net carbon dioxide emissions. Fig. 3.2 describes the overall model with the first step being the modeling of wastewater from the sewage sent to the various operational processes and produced liquid (clean water flowing to the river) and solids (solid end products) phases.

The solid end product from the case study WWTP facility varies between 113-814 dry tons (dt) per day. A Weibull probability distribution was the best fit for capturing the (residual) amount of solids and is denoted by $I_{WWTP}(s)$ with "s" the index for the 59,049 scenarios. Additionally, the total amount of solids to the digester includes possible inflow from outside organizations. Specifically, we consider 60 dt per day from organization 1, as denoted by $I_{OR1}(s)$ and 50 dt per day from organization 2 ($I_{OR2}(s)$).

In the next step of the process diagram in Fig. 2, solid influent can go to one of three directions: digester ($I_G(s)$), incineration ($I_I(s)$), land application as Class B biosolids ($I_B(s)$), or directly as Class A material ($I_A(s)$). In the first case, solids sent to the digester will result in biogas, electricity, and some Class A material, or being disposed of by incineration. In the second case, the solids will be processed for land application as fertilizer. In the third case, solids will be stabilized by a composting process to reduce the amount of pathogens before going to other processes. The model will decide optimal values for $I_{OR1}(s)$, $I_{OR2}(s)$, $I_G(s)$, $I_I(s)$, $I_B(s)$, and $I_A(s)$, given the constraints and the three objectives to be optimized.

The next set of decisions to be made by the model is to divide the digested product into Class A product, biogas from biosolids ($G_{NG}(s)$), compressed natural gas for transportation ($G_{CNG}(s)$), and electricity from the biogas ($G_E(s)$). For the quantity of Class A biosolids destined for land application, the model will select whether the biosolids should be land applied on farms ($B_A^L(s)$) or sold in the agricultural market ($B_A^{AM}(s)$).

Due to the potential to generate electricity from solar energy, investments in solar power are described in another set of decisions. $S_{radia}(s)$ and $S_{generate}(s)$ respectively, representing the set of generated electricity from solar radiation and solar electricity generation costs.

Lastly, the model selects sales to end-use, spot markets: natural gas non-transportation, CNG, electricity, fertilizer, or using the wastewater-derived the power at the WWTP along with the renewable energy credits and carbon allowance market considerations. In the next sections, we describe the objective functions, variables, and constraints of the model, which is a mixed-integer linear program, solved using the General Algebraic Modeling System (GAMS). [34]

3.2.1 Decision Variables

The following is the description of the sets and variables used in the model with the main variables shown in Fig. 3.2. Note that the model solves for values of only one typical day; hence, all the variable values are in units per day.

[34] www.gams.com.

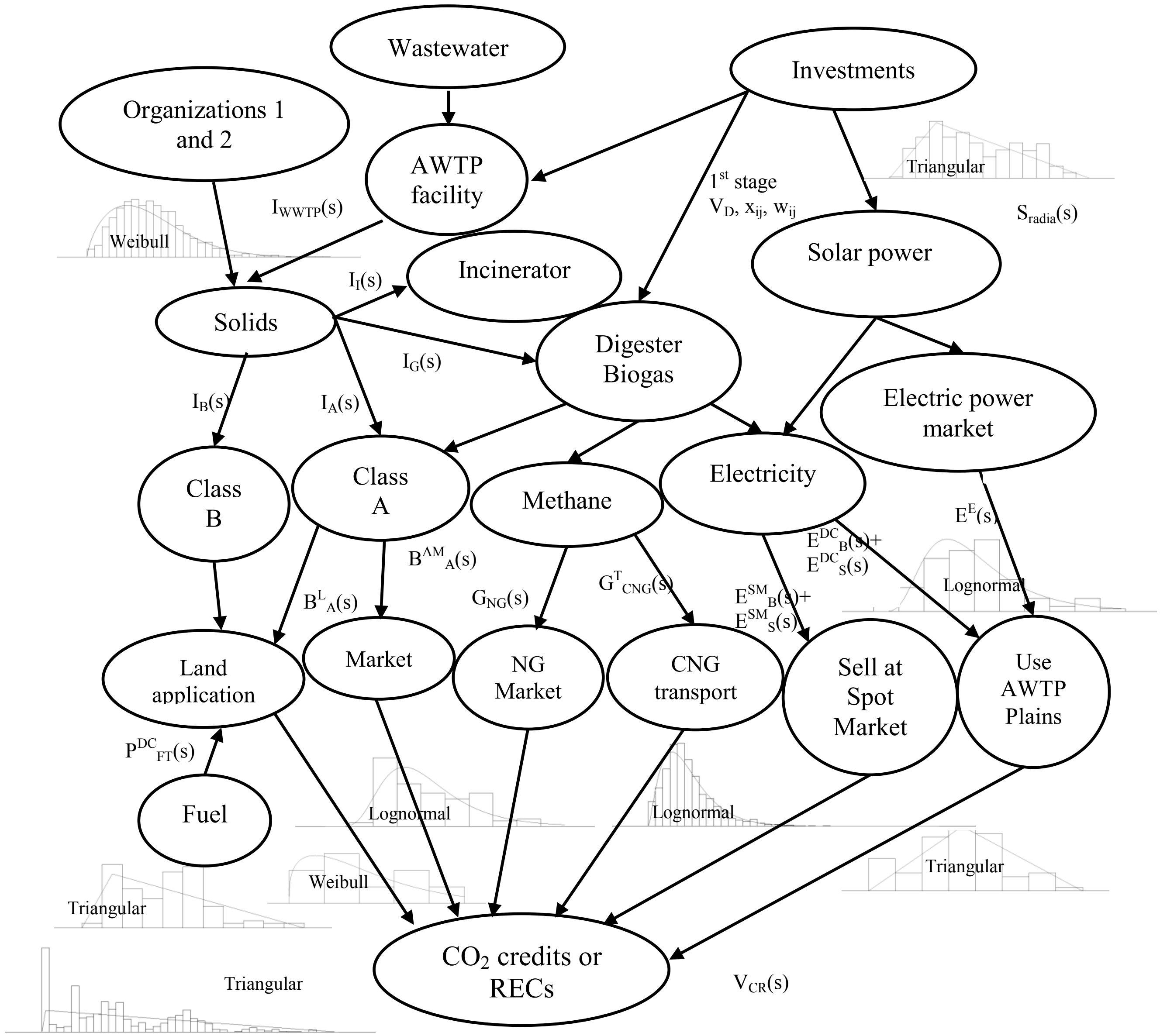


Figure 3.2 Process diagram of the stochastic, multi-objective optimization model for the biosolids management program at the AWTP.

Sets

i ϵ {1,2,3,4,5} options for five types of digester-lime stabilization, and incineration

j ϵ {1,2,3} Three segments for the digester cost curve

s ϵ {1,2,..59,049} scenarios

First-stage decision variables (all variables are assumed to be nonnegative unless specified otherwise.)

$x_{i,j}$ amount of solids processed by digester i and segment j (dt)

$w_{i,j}$ $\begin{cases} 1 \text{ if digester/incinerator option i and cost segment j is selected} \\ 0 \text{ otherwise} \end{cases}$

Intermediate first-stage decision variable

V_D cost of digester ($)

Second-stage decision variables

$I_G(s)$ solids used to produce biogas (dt)

$I_B(s)$ solids used to produce Class B biosolids from lime stabilization for land application (dt)

$I_A(s)$ solids used to produce Class A biosolids not from the digester (dt)

$I_I(s)$ solids incinerated (dt)

$I_{OR1}(s)$ solids brought in from organization 1 (dt)

$I_{OR2}(s)$ solids brought in from organization 2 (dt)

$G_E(s)$ biogas generated from biosolids for generating electricity (cf)

$G_{NG}(s)$ biogas generated from biosolids (cf)

$G_{CNG}^T(s)$ biogas generated from biosolids sold to the transportation sector CNG (cf)

$B_A^L(s)$ biosolids Class A produced for land application (dt)

$B_A^{AM}(s)$ biosolids Class A sold in the agricultural market (dt)

$E^E(s)$ electricity bought from external sources and used at WWTP (kWh)

$E_B^{WWTP}(s)$ electricity generated from biogas and used at WWTP (kWh)

$E_B^{SM}(s)$ electricity generated from biogas and sold to the spot market (kWh)

$E_S^{WWTP}(s)$ electricity generated from solar energy and used at WWTP (kWh)

$E_S^{SM}(s)$ electricity generated from solar energy and sold to the spot market (kWh)

$NG_H^E(s)$ natural gas purchased from external sources (cf)

3.2.2 Parameters [35]

CAP maximum amount of Class B production (dt)

S_{OR1} maximum amount of solids from organization 1 (dt)

S_{OR2} maximum amount of solids from organization 2 (dt)

S_{gas} maximum amount of solids used to produce biogas (dt)

f_G biogas production factor (cf)

f_{NG} methane production factor (unitless) [36]

f_{CNG} CNG production factor (unitless) [37]

f_B amount of dry tons of Class A biosolids per dry ton of solids influent

f_E factor used to calculate generated electricity from biogas (kwh/cf)

$WWTP_{NG}$ average daily amount of natural gas consumption at WWTP[38] from historical data (cf)

f_C^E factor used to calculate carbon dioxide emissions from electricity (t/kWh)

---

[35] See details on Appendix B.

[36] The biogas ($CH_4 + CO_2 + H_2O$ + trace gases) can be broken down into the following component shares: 55-65% methane gas (CH_4), 30-40% carbon dioxide gas (CO_2), and 0-5% water vapor, traces of hydrogen sulfide H_2S and hydrogen H_2 (Appels et al. 2008). Consequently, in the model presented below, an average 60% of methane composition in biogas is used.

[37] The reduction of CNG from 100% of natural gas is due to further processing for gas quality outside of WWTP (http://www.environmental-expert.com/products/biogas-to-compressed-natural-gas-35510).

[38] The highest natural gas consumption obtained from the energy saving plan report of December, 2010.

f_C^{NG} factor used to calculate carbon dioxide emissions from used natural gas for heat (t/cf)

f_C^{I} factor used to calculate carbon dioxide emissions from incineration (t/dt)

f_C^{CNG} factor used to calculate carbon dioxide offset from sold CNG for the transportation sector (t/cf)

f_C^{f} factor used to calculate carbon dioxide offset from biosolids used as fertilizer (t/dt)

f_C^{t} factor used to calculate carbon dioxide emissions from transportating biosolids to the land application field (t/dt)

f_P^{T} factor used to calculate fossil fuel consumption to transport Class A and/or B biosolids to land application fields (kWh/dt)

f_P^{G} factor used to calculate natural gas consumption at WWTP (kWh/cf)

f_P^{I} supplementary fuel for incineration process factor (kWh-$/dt-gal)

f_I^{T} factor used to calculate fossil fuel consumption for transportation Class A and/or B biosolids to land application fields and to agricultural market in gallon per dry ton (gal/dt)

f_E^{Gen} electricity generation costs ($/kWh)

f_{CNG}^{Com} CNG compression costs ($/cf)

f_A^{Com} Class A biosolids composted costs ($/dt)

f_{Ash}^{I} ash disposal cost ($/dt)

f_{CNG}^{T} CNG prices ($/cf)

f_I^{TIP} tipping fees ($/dt of biosolids)

C_{allow}^{WWTP} CDE allowance (t)

S_{panel} installation area of solar panels (m^2)

RES credits from renewable electricity standard ($/kWh)

f_{on}^{off} parameter used to turn on REC or CO_2 credits and it is equal to 0 or 1

REC renewable energy credits ($/t CDE)

Random parameters

$Pr(s)$ probability for each scenario [39]

$I_{WWTP}(s)$ uncertain solids influent to digester (dt)

$E_{consump}(s)$ uncertain electricity consumption at WWTP (kWh)

$E_{purchased}(s)$ uncertain electricity purchasing prices ($/kWh)

$E_{sold}(s)$ uncertain electricity selling prices ($/kWh)

$NG_{purchased}(s)$ uncertain natural gas purchasing prices ($/cf)

$P_{fossil}(s)$ uncertain fossil fuel prices to transport Class A and B bisolids ($/gal)

$F_{prices}(s)$ uncertain fertilizer prices ($/t)

$R_{CO2}(s)$ uncertain carbon credits ($/t CDE)

$S_{radia}(s)$ uncertain solar radiation (kWh/m^2)[40]

$S_{generate}(s)$ uncertain generated solar electricity cost ($/kWh)

3.2.3 Constraints

All constraints except for those defining binary variables are linear and the majority of them represent some form of conservation of product.

[39] See details in Appendix B.
[40] While the amount of solar radiation is a random variable, the amount of solar power generated from it is an upper-level, second-stage decision variable.

3.2.3.1 First-stage Constraints

For the digester cost, V_D, the model selects one digester design from five possible cases: 1) four trains of thermal hydrolysis (TH) and anaerobic digestion (4TH & digester) and a lime stabilization (LS), 2) two trains of thermal hydrolysis and anaerobic digestion (2TH & digester) and a lime stabilization (LS), 3) four trains of thermal hydrolysis and anaerobic digestion (4TH & digester) with another two trains of thermal hydrolysis and anaerobic digestion (2TH & digester) and a lime stabilization, 4) only a lime stabilization process, or 5) only a incineration process. Each of these five types of digesters (*i=1,2,3,4,5*) has three cost curve segments (*j=1,2,3*) relating to a change in the process with different costs. For example, x_{11} corresponds to segment one for digestion option number one (thermal hydrolysis and anaerobic digestion with lime stabilization). Fig. 3.3 and the analysis below show the costs of the five possible digester cases.

The costs of each digester consist of a fixed cost, denoted by h_{ij}, and variable costs related to the solids influent amount, denoted by $a_{ij.}$ Only one digester can be selected and this is controlled by the binary variable w_{ij}. Constraint (3.1) defines the investment cost of the digester.

$$V_D = \sum_i \sum_j a_{i,j} x_{i,j} + \sum_i \sum_j h_{i,j} w_{i,j} \qquad \$ \qquad (3.1)$$

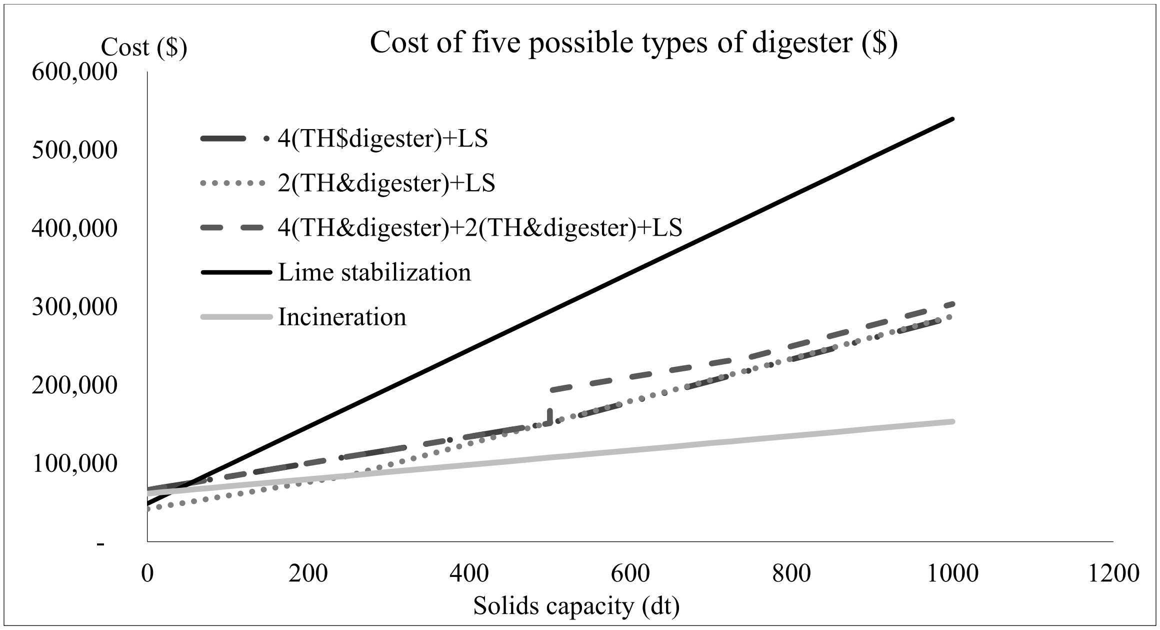


Figure 3.3 Cost of five possible types of digester

(a 50-year digester lifetime is assumed).

Note that this 50-year lifetime is an assumption and specifically used for this case study.

3.2.3.2 Second-stage Constraints

Influent constraints

$I_B(s) + I_A(s) + I_I(s) + I_G(s) = I_{WWTP}(s) + I_{OR1}(s) + I_{OR2}(s)$ dt (3.2a)

$I_B(s) \leq CAP - I_A(s) - I_I(s) - I_G(s)$ dt (3.2b)

$I_G(s) \leq \sum_i \sum_j x_{i,j}$ dt (3.2c)

$I_G(s) \leq S_{gas}(1 - w_{41} - w_{42} - w_{43})$ dt (3.2d)

$I_G(s) \leq S_{gas}(1 - w_{51} - w_{52} - w_{53})$ dt (3.2e)

$I_{OR1}(s) \leq S_{OR1}$ dt (3.2f)

$I_{OR2}(s) \leq S_{OR2}$ dt (3.2g)

$\sum_i \sum_j w_{i,j} = 1$ (3.2h)

$w_{i,j} \epsilon \{0,1\}. \forall i, j$ (3.2i)

$x_{i,j} \leq CAP_{i,j} w_{i,j}$ (3.2j)

$x_{i,j} \geq l_{i,j} w_{i,j}$ (3.2k)

Constraint (3.2a) defines the conservation of produced solids expressed in dt.

Constraint (3.2b) defines the amount of solids in dt required in the lime stabilization process to produce Class B biosolids.

Constraints (3.2c), (3.2d) and (3.2e) define the amount of solids in dt that will go into the digester to produce biogas. The binary variables $\mathrm{w}_{41}, \mathrm{w}_{42}$ or w_{43} = 1 mean that only lime stabilization option is used and $\mathrm{w}_{51}, \mathrm{w}_{52}$ or w_{53} = 1 means that only incineration is used, thereby no biogas.

Constraints (3.2f) and (3.2g) define the maximum amount of solids from outside sources in dt.

Constraint (3.2h) defines at most one of the w_{ij} variables is equal to 1

The binary constraint is (3.2i) and constraints (3.2j) and (3.2k) refer to upper bounds on the biosolids amount, constrained respectively by the maximum solids capacity and the minimum solids used to produce biogas. $l_{i,j}$ indicates solids used to produce biogas in dt.

Biogas constraints

$f_G \, I_G(s) = G_E(s) + G_{NG}(s) + G_{CNG}^T(s)$ cf (3.3a)

$G_{NG}(s) \leq f_{NG} f_G \, I_G(s)$ cf (3.3b)

$G_{CNG}^T(s) \leq f_{CNG} f_G \, I_G(s)$ cf (3.3c)

Constraint (3.3a) defines the total amount of biogas in cf generated from the solids influent. Constraint (3.3b) defines the amount of bio-methane gas [41] from the solids influent in cf. Constraint (3.3c) is similarly defined but for CNG.

Biosolids constraints

$$B_A^L(s) + B_A^{AM}(s) = f_B\, I_G(s) + I_A(s) \qquad \text{dt} \qquad (3.4)$$

Constraint (3.4) defines the total amount of Class A biosolids from the digester and composting processes in dt that can be land applied or sold to the agricultural market.

Electricity constraints

$$E_{consump}(s) \leq E^E(s) + E_B^{WWTP}(s) + E_S^{WWTP}(s) \qquad \text{kWh (3.5a)}$$

$$E_B^{WWTP}(s) + E_B^{SM}(s) = f_E G_E(s) \qquad \text{kWh (3.5b)}$$

$$E_S^{WWTP}(s) + E_S^{SM}(s) = (S_{Panel})(S_{radia}(s)) \qquad \text{kWh (3.5c)}$$

Constraint (3.5a) defines the daily amount of electricity used at the AWTP for operations, which is an uncertain data element and is denoted by “$E_{consump}(s)$”. The electricity may be bought from external sources ($E^E(s)$) or generated from biogas ($E_B^{WWTP}(s)$) and used at the AWTP. In addition, it is possible to generate electricity from solar power ($E_S^{WWTP}(s)$) to be used at the AWTP.

[41] Bio-methane is one part of biogas which also includes carbon dioxide and other gases.

Constraint (3.5b) defines the electricity in kWh from the biogas produced during the digestion process and use at the AWTP or sold to the spot market. Constraint (3.5c) defines the electricity in kWh from solar power and used at the AWTP or sold to the spot market.

Natural gas consumption constraint

$$NG_H^E(s) + G_{NG}(s) = WWTP_{NG} \qquad \text{cf} \qquad (3.6)$$

Constraint (3.6) defines the total natural gas used at the AWTP for heat expressed in cf ($WWTP_{NG}$). Natural gas may be purchased from external sources ($NG_H^E(s)$) or produced at AWTP in the form of bio-methane ($G_{NG}(s)$).

Carbon dioxide equivalent emission constraint

$$C_T(s) = f_C^E\ (E^E(s) - E_B^{WWTP}(s) - E_B^{SM} - E_S^{WWTP}(s)) + f_C^{NG}(NG_H^E(s) - G_{NG}(s)) +$$
$$f_C^I(\ I_I(s) + (f_C^t - f_C^f)(\ I_B(s) + B_A^L(s) + B_A^{AM}(s)) - f_C^{NG} G_{CNG}^T(s) \qquad \text{t CDE} \quad (3.7)$$

Constraint (3.7) defines the net total carbon dioxide equivalent emissions in t CDE, consisting of CDE emissions from AWTP operations ($f_C^E\ E^E(s)$), natural gas heating ($\mathrm{f_C^{NG}}(\mathrm{NG_H^E}(s))$, transportation of biosolids ($f_C^t(I_B(s) + B_A^L(s) + B_A^{AM}(s))$) and incineration ($f_C^I\ I_I(s)$) less offsets from renewable electricity generated ($f_C^E(E_B^{WWTP}(s) + E_B^{SM} + E_S^{WWTP}(s))$) and used at AWTP, sold CNG ($f_C^{NG} G_{NG}(s)$), used/sold bioslids as fertilizer ($f_C^f\ (I_B(s) + B_A^L(s) + B_A^{AM}(s))$).

Energy purchasing constraint

$P_T(s) = f_P^T(I_B(s) + B_A^L(s) + B_A^{AM}(s) + I_{OR1}(s) + I_{OR2}(s)) + f_P^G NG_H^E(s) + E^E(s) + f_P^I/P_{fossil}(s)I_I(s)$ kWh (3.8)

Constraint (3.8) defines the total purchased energy of AWTP, which includes energy for transportation of Class A and/or Class B biosolids to land applied sites ($f_P^T(I_B(s) + B_A^L(s) + B_A^{AM}(s))$), transportation of solids from organizations 1 and 2 ($f_P^T\left(I_{OR1}(s) + I_{OR2}(s)\right)$), natural gas consumption ($f_P^G NG_H^E(s)$), electricity consumption ($E^E(s)$), and supplement fuel for incineration ($f_P^I/P_{fossil}(s)I_I(s)$) in kWh.

Value constraints

$V_{CR}(s) = R_{CO2}(s)\left(C_{allow}^{WWTP} - C_T(s)\right)f_{0n}^{off} + REC\left(C_{allow}^{WWTP} - C_T(s)\right)\left(1 - f_{on}^{off}\right)$ \$(3.9a)

$V_T(s) = Revenues(s) - Costs(s)$ where: \$ (3.9b)

Constraint (3.9a) defines the revenue from carbon dioxide or renewable energy credits.

Constraint (3.9b) defines the net AWTP total value in \$. It is composed of the following costs (with a negative sign in front): digester cost (V_D), cost of electricity ($E_{purchased}(s)E^E(s)$) and natural gas bought externally from the spot market ($NG_{purchased}(s)NG_H^E(s)$), solar electricity generation cost ($S_{generate}(s)(E_S^{WWTP}(s) + E_S^{SM}(s))$), production cost of CNG ($f_{CNG}^{COM}\ G_{CNG}^T(s)$), ash disposal cost ($f_{ASH}^I\ I_I(s)$), cost of transporting Class A and B biosolids to land application fields ($f_I^T\ P_{fossil}(s)(B_A^L(s) +$

$B_A^{AM}(s) + I_B(s)))$, transporting cost from organization 1 and 2 $(f_I^T\ P_{fossil}(s)(I_{OR1}(s) + I_{OR2}(s))$, supplement fuel cost $(f_I^T\ P_{fossil}(s)I_I(s))$ and composting cost $(f_A^{COM}\ I_A(s))$. In addition, the total value includes the following revenues: sales of Class A biosolids to the agricultural market $(F_{prices}(s)B_A^{AM})$; sales of electricity $(E_{sold}(s)E_B^{SM}(s)$ and $E_{sold}(s) + RES)E_S^{SM}(s))$, CNG from the digestion process to the spot market or transportation sector $(f_{CNG}^T\ G_{CNG}^T(s))$; tipping fees from both organizations $(f_I^{TIP}(I_{OR1}(s) + I_{OR2}(s)))$; and carbon dioxide and renewable energy credits $(V_{CR}(s))$.

3.2.4 Objective of a Stochastic Model

There are three objectives to be optimized: maximizing expected total value, minimizing expected net CDE emissions and minimizing expected purchased energy. As is the case with two-stage recourse models, the objective(s) is (are) applied to the full model (i.e., the deterministic equivalent). The expectation is taken over all the scenarios considered after discretizing the fitted probability distributions shown in Fig. 3.2.

This study is focused on the tradeoff between maximizing the benefits (also discussed as "value") from the operational and investment decisions and minimizing the net carbon dioxide equivalent emissions when purchased energy is considered at an average amount. Thirdly, the objective of just minimizing purchased energy is also considered.

These three objectives compete with each other and this is typified as follows. The small digester is chosen when maximizing expected benefits since it allows for lower costs than the big one but permits the WWTP to be active in the fertilizer, electric power, and CNG transportation markets. In fact, the highest level of Class A solids are produced (either from the digester or by composting) under this objective. By contrast, when minimizing expected carbon dioxide equivalent emissions, it is more effective to use a big digester. This choice of first-stage variables allows for selling the biogas-based electricity to the spot market and there is no activity in the CNG market. Lastly, when minimizing expecting purchased energy a big digester is also chosen. However, the uses are different for the output. In particular, the biogas-based electricity is used on-site and nothing is sold to the spot market. Moreover, there is also no CNG produced under this objective. For example, once maximum benefits (value) are considered, a small digester (lower costs than big digester) should be selected to product biogas and Class A biosolids. Biogas-based electricity, thus, these three objectives produce different first- and second-stage decisions for the WWTP

1. Maximize $z = V_T(s)$	dollar
2. Minimize $z = C_T(s)$	ton CDE
3. Minimize $z = P_T(s)$	kWh

3.3 Scenario Reduction

The model as stated above contains 59,049 scenarios resulting from the 10 groups of uncertainties that were transformed from continuous distributions (see Fig. 3.2) to three-point, discrete distributions (Keefer 1994; Hoyland and Wallace 2001). Each distribution function was discretized to low, medium and high values with the corresponding probabilities. The scenario-based optimization then takes into account the resulting three-point distributions and related probabilities of 10 uncertain elements (3^{10} = 59,049 scenarios used). This stochastic optimization model has been solved using an

Intel(R) Core (TM) i7-2670QM computer with a CPU@2.2 GHz and 8 GB of RAM. The computational time required to solve this problem for one objective at a time was about 56 minutes for maximizing total value, 153 minutes for minimizing purchased energy and 165 minutes for minimizing carbon dioxide emissions. However, the computational time increased to about 2.5 hours when two objectives were optimized at the same time (multi-objective optimization) to obtain one Pareto optimal point. The constraint method was used optimizing one objective while other objectives were constrained (Cohon 2003). The approximated Pareto optimal frontier was created with about 50 Pareto solutions from the stochastic optimization model. For computational purposes, a scenario-reduction approach (Morales el al. 2009; Conejo el al. 2010) was used to reduce the computational time and effort.

Scenario reduction begins with a subset of the full set of 59,049 scenarios. In this research the distance functions between the reduced scenario tree and the original one, i.e., the monitoring function, are computed internally by GAMS/SCENRED2 (GAMS/SCENRED2 2007; Dupacova et al. 2003; Heitsch and Romisch 2003 and 2009). This is done in an iterative fashion until convergence criteria are met. The scenario reduction method is shown step by step in Fig. 3.4.

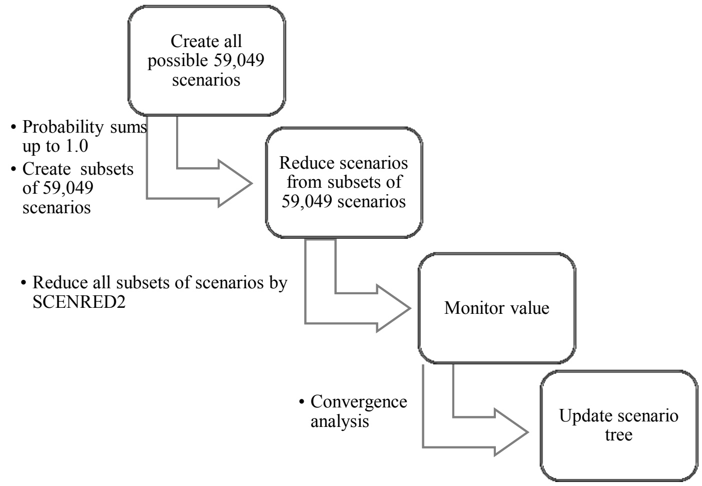


Figure 3.4 The scenario reduction method

As described in (Conejo et al. 2010), a large scenario tree can be reduced to a smaller one via a probability measure distance (relative distance for GAMS/SCENRED2). It can be shown that the optimal value of the objective function of the reduced scenario tree is close to the optimal value of the objective function of the initial scenario tree if the reduced scenario tree is properly chosen (Conejo et al. 2010). A convergence analysis (Dupacova et al. 2003) was run by varying the percentage of relative distance of the reduced scenario tree relative to the initial probability measure. The reduced tree could be run between 0% of the relative distance (the original scenario tree) and 100% (having only one scenario). Fig. 3.5 shows maximizing the expected WWTP total value objective function as a function of the number of scenarios in the reduced tree. The reduced tree was obtained by varying the relative distance measure. The full scenario tree was only used in this case to test the quality of the scenario-reduction approach. In general, one would not have access to the full scenario tree.

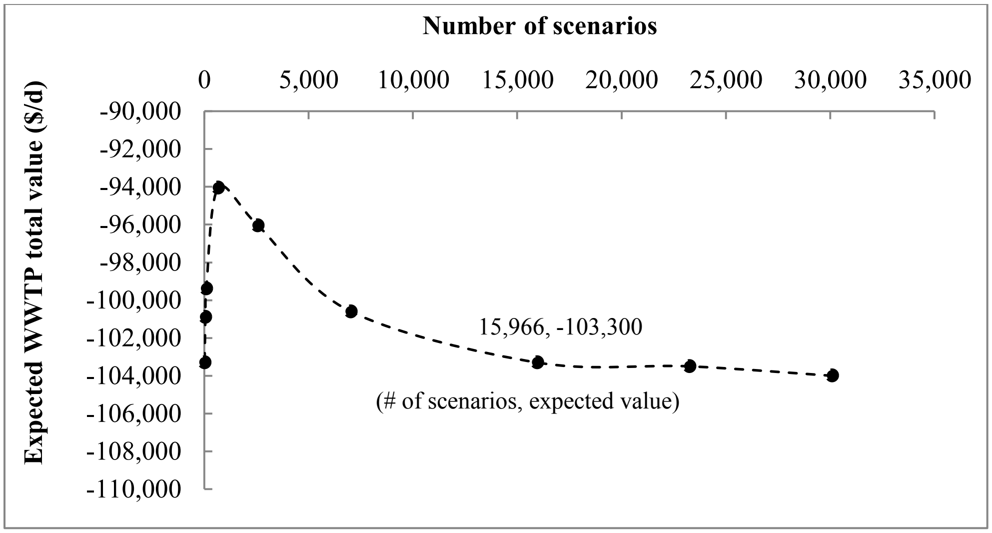


Figure 3.5 Results from the stochastic model varying the number of scenarios

The reduced tree was estimated by assigning percent reduction on GAMS subroutine GAMS/SCENRED2 (GAMS/SCENRED2 2007; Heitsch and Romisch 2003 and 2009). In Figure 3.5, for all the reduced-scenario outputs shown, the model selected two trains of a thermal hydrolysis and anaerobic digestion (2TH & digester) and a lime stabilization (LS) for the first-stage decision (i.e., the small digester). As the size of the reduced set of scenarios increases, excluding pathological cases, the objective function (expected total value) should after some point be close to that of the model with the full set of scenarios. However, more scenarios generally means more computational time is needed. Thus, there is a tradeoff in the quality of the solution when a reduced set of scenarios is used and the computational time. In this study, a tolerance of 2% from the optimal objective function value for the full set of scenarios was used in conjunction with the GAMS/SCENRED2 subroutine, which automatically selected the subset of scenarios. The expected total value -$103,300 of the reduced tree was 98.9% accurate relative to the optimal objective function value of -$104,371 for the tree with the full set of scenarios. With this procedure, the number of scenarios was reduced from 59,049 to 15,966.

3.4. Results and Discussion

In this section, we summarize the results of the stochastic optimization model by analyzing each of the three objectives one at the time. Also we compare the optimal objective function value between the deterministic and the stochastic optimization models.

For each of the three objectives, four cases were considered as shown in Figures 3.6, 3.7, and 3.8.

1. $0 per dry ton of biosolids for tipping fee from the two outside organizations, no solar power from on-site.
2. $0 per dry ton of biosolids for tipping fee, and solar power allowed on-site.
3. $50 per dry ton of biosolids for tipping fee, and solar power allowed on-site.
4. $100 per dry ton of biosolids for tipping fee, and solar power allowed on-site.

When maximizing the expected value to the WWTP, the second digester strategy (two TH & anaerobic digester and lime stabilization) with the maximum amount of solids (250 dt) was selected to produce biogas. The cost of this digester was a key item because the chosen option has the lowest operational and maintenance costs (costs per dry ton of solids) for operated solid end products for 0-250 dt compared to other digester types (shown in Fig. 3.3). The optimal objective function value without tipping fees and solar power had a cost of $109,808 per day (shown in Fig. 3.6). However, the tipping fee and solar power were important options for the WWTP to increase its value (profit). For example, if a \$0 tipping fee and solar power were considered, the operational costs decreased to \$109,742. However, with solar power but tipping fees of \$50 or \$100, the value increased to only \$104,371 and \$98,871 per day of costs, respectively.

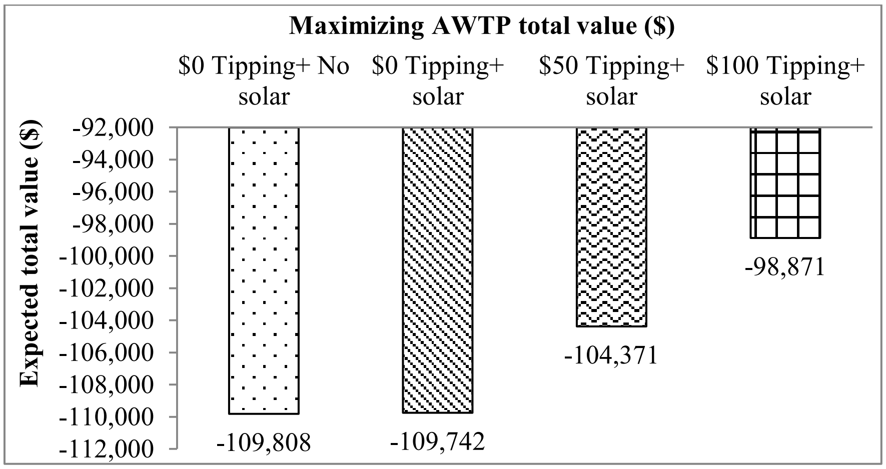


Figure 3.6 Optimal objective value of the maximizing expected AWTP total value in dollars.

Fig. 3.7 shows the results when minimizing the second objective of expected purchased energy. The third digester option (four TH & anaerobic digester and two TH & anaerobic digester) with a maximum capacity of 620 dt was selected to produce biogas. The optimal objective function value without tipping fee and solar power showed that 430,984kWh per day of energy was purchased, and this amount was reduced to 412,263 kWh if on-site solar power was generated in combination with a \$100 tipping fee.

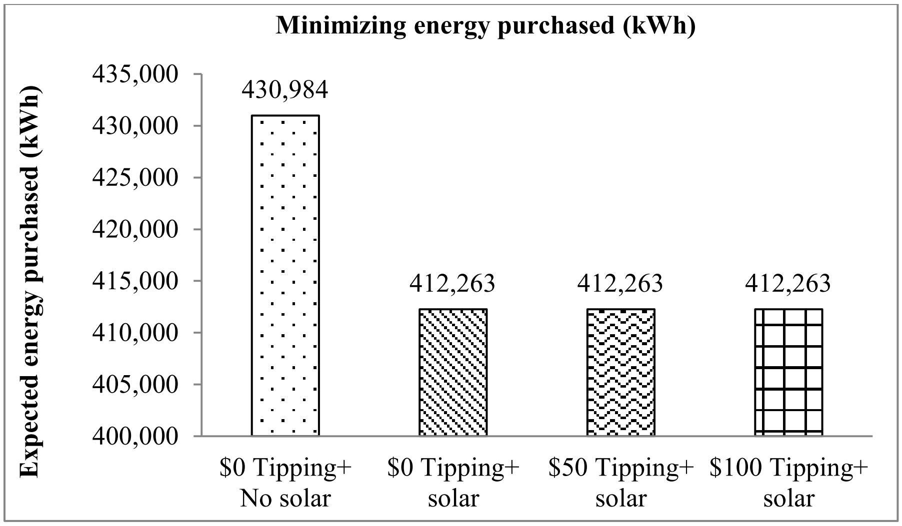


Figure 3.7 Optimal objective value of the minimizing expected purchased energy in kWh.

Figure 3.8 shows the results when minimizing the third objective of expected net CDE emissions. The third digester option (four TH & anaerobic digester and two TH & anaerobic digester plus LS) was selected. Electricity from solar power was also generated. The optimal objective function value for the specific case that did not include tipping fees and solar power was 288 tons CDE emissions per day. The expected net CDE emissions could be offset to 268 tons per day if solar power was generated and used at AWTP.

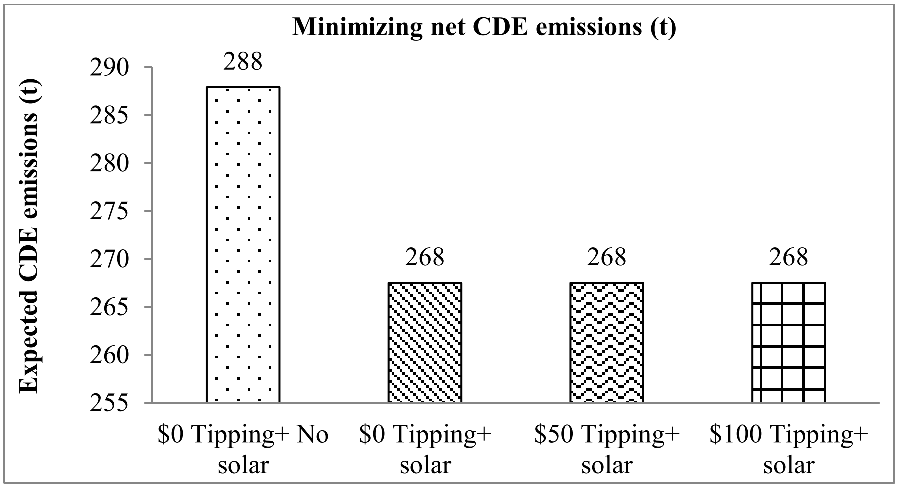


Figure 3.8 Optimal objective values of the minimizing expected net CDE emissions in ton.

The above results indicate the benefits of generated biogas from wastewater; solar power generated on-site, and tipping fees. The expected WWTP total value could be increased from the internal renewable energy production revenue (selling generated electricity and CNG) and tipping fees. However, the small digester (digester type 2) option was selected to produce biogas if the objective were to maximize total value. The amount of solids end product if higher than the digester capacity (250 dt), are composted and sold to the agricultural market as Class A biosolids (fertilizer) when maximizing value.

However, when either minimizing the expected purchased energy from outside sources or minimizing the expected net CDE emissions are used as objectives, there is a different first-stage solution. In particular, with both these objectives, the big digester is preferred.

One difference between these two objectives is the use of the output from the big digester. When minimizing purchased energy is chosen as the objective, the big digester allows for more internally generated electricity and thus offsets the outside energy that needs to be bought. When minimizing CDE, the big digester has another function. Namely, more of the internally produced electricity is sold to the outside power market. Table 3.1 shows optimal solutions for the three, conflicting objectives where the expected amounts of various model outputs are shown.

Table 3.1 The expected amount of related products from solid end products

Objective	Max VT	Min CT	Min PT
Digester type	Small	Big	Big
Class A biosolids sold as fertilizer (dt)	274	158	107
Renewable-based electricity used at WWTP (kWh)	79,006	18,547	171,615
Renewable-based electricity sold to the outside power market (kWh)	101,319	218,897	0
CNG sold (cf)	86,540	0	0

An approximation of the Pareto optimal frontier was generated to show the relationship between the expected AWTP total value in $ and the expected net CDE emissions in ton by fixing the values of the expected purchased energy at 634,000 (average energy consumption) kWh. Figure 3.9 provides some insights on trading off CDE emissions with operational costs. The second digester option was selected and the expected net CDE emissions were grouped into three portions based on a statistical regression analysis. According to the three equations shown in Figure 3.9, the AWTP needs to spend about $36, $173, or $371 on operational costs to reduce 1 ton of CDE emissions at average energy consumption when the range of CDE emissions were considered [154,160] for the first portion, (160, 177] for the second portion and (177, 202] for the third portion.

Clearly, WWTP managers must carefully balance the tradeoffs between environmental/sustainability goals and profitability in making decisions concerning wastewater-to-energy programs. These decisions in turn, can affect the external energy markets as well as the CNG and agricultural markets. In terms of the Smart Grid, since WWTPs are prosumers, this balancing of goals could have important effects on the power sector if WWTPs' generation scales up.

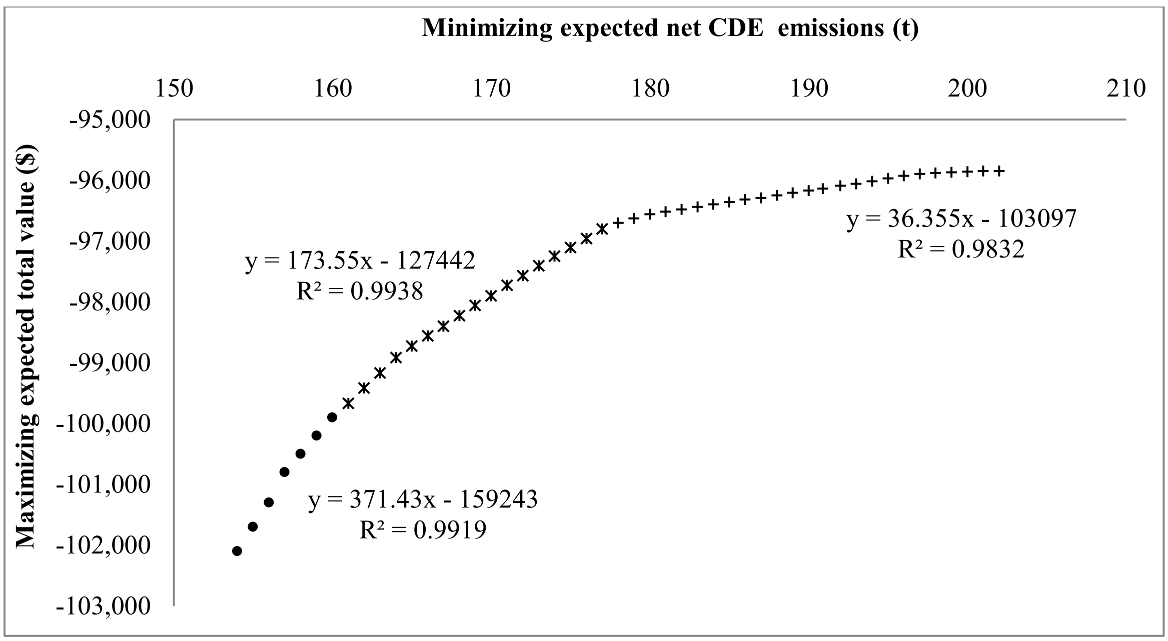


Figure 3.9 Approximation of the Pareto optimal frontier showing the relationship between maximizing expected AWTP total value and minimizing expected net CDE emissions when the expected purchasing energy 634,000 kWh.

3.5 Conclusions

In this study, we have developed a two-stage stochastic optimization model to analyze three different objectives: maximizing expected WWTP total value (i.e., profit), minimizing expected net carbon dioxide equivalent emissions, and minimizing expected purchased energy. The first-stage decisions involve selecting one of five possible digester-lime stabilization cases : four thermal hydrolysis & digester and a lime stabilization, two thermal hydrolysis & digester and a lime stabilization, four thermal hydrolysis & digester with two thermal hydrolysis & digester and a lime stabilization, a only lime stabilization and an only incinerator. The WWTP can then either choose to produce biogas from digestion, dispose of it by incineration, compost it to obtain Class A biosolids, or stabilize it by lime to produce Class B biosolids.

The results show that the WWTP could reduce CDE emissions and decrease purchased energy from outside sources by using a big digester (four thermal hydrolysis & digester with two thermal hydrolysis & digester and a lime stabilization) to produce biogas from biosolids. On the other hand, the smallest digester (two thermal hydrolysis & digester and a lime stabilization) was selected to minimize operational and investment costs for maximizing the expected WWTP total value. Additionally, the analysis shows that incremental digestion of solid waste from nearby organizations increases the revenue. By using solar energy on-site, the analysis shows a decreased dependence on purchased energy from outside sources. Further analysis indicates that there is a Pareto optimal tradeoff for the WWTP between the environmental and the associated investment and operational costs for digestion.

This study shows that optimal investment and operational decisions for a wastewater treatment plant taking into account energy and environmental considerations (CDE emissions) can be complicated. Given the increasing concerns for social, economic, environment and interest in renewable energy, the stochastic optimization model presented however, could be of great use to wastewater treatment plants and energy managers to guide them with evaluating all the tradeoffs.

Chapter 4: A Stochastic MPEC for Sustainable Wastewater Management

Models to assist decision-makers for environmental management have been considered by a number of researchers. In this study, we present a novel, stochastic mathematical program with equilibrium constraints (MPEC) model for wastewater management. The area of wastewater management is studied not only in the environmental area but also in energy, transportation and agriculture given the various end products from wastewater. Some research by others has considered various aspects of wastewater management. For example, wastewater treatments plant design and the quality of treated water (Ellis and Tang 1991; Draper et al. 2003; Cunha et al. 2009; Alvarez-Vázquez et al. 2010). Others have considered optimization modeling of energy consumption in wastewater treatment plants and renewable energy harvests from water distribution (Ye and Soga 2012; Hu et al. 2013). However, it is rare that other research has concentrated on the end products of wastewater treatment plants. From the perspective of MPECs, there have been many works in the last 20 or 30 years. Many of them focused on energy or other markets structure area but not wastewater (Luo et al. 1996; Gabriel et al. 2013). Some of these MPECs have also been stochastic in nature such as a stochastic Stackelberg equilibrium model for the European natural gas market (De Wolf and Smeers 1997) and a stochastic MPEC approach for electricity markets (Wogrin et al. 2011), to name two examples.

The model is based on the Blue Plains Advanced Wastewater Treatment Plant (AWTP) run by the District of Columbia Water and Sewer Authority (DC Water). This plant's ammonia is converted by nitrification and denitrification into nitrogen gas, and through this nitrogen removal process a treatment plant is considered an AWTP. Without this procedure, it is considered as just a wastewater treatment plant (WWTP). We use this latter definition for the more general case in this study. The Blue Plains AWTP is listed as the one of the largest wastewater treatment plants in the world[42] [43] and as such provides an excellent test bed. The stochastic MPEC encompasses both the investment and operational aspects of converting wastewater to: biosolids (Class B) for land application, biosolids (Class A) for plant fertilizer, compressed natural gas for transportation, and methane for electric power production or other uses in the residential natural gas sector. As such the model is a stochastic MPEC where the stochasticity arises from the probabilistic nature of many of the inputs such as: natural gas prices, electricity prices, solid end products from wastewater operational process, etc. As described in a later section, the various probability distributions for these inputs are discretized leading to a scenario-tree approach. The overall size of this stochastic MPEC can therefore be large, depending on the number of scenarios and processes considered. Indeed, in the case of used a reduced number of 2,187 scenarios, the upper-level problem has 102,789 continuous variables and 32,805 binary variables and the lower-level problem has 166,212 continuous variables, 247,131 binary variables and 30,618 SOS1 (special ordered sets of type 1) variables, thus making this a very large-scale problem.

The general formulation for a mathematical program with equilibrium constraints is given by the following:

---

[42] http://enr.construction.com/infrastructure/water_dams/2012/extras/0328/slideshow.asp?slide=11 (Illustration: Justin Reynolds for Engineering News-Record (ENR.com)).

[43] The 2008 The Clean Watersheds Needs Survey (CWNS) is available through EPA's Office of Wastewater Management and can be accessed at: http://water.epa.gov/scitech/datait/databases/cwns/index.cfm.

$$
\begin{gathered}
\min f(x, y) \\
\text{s.t. } (x, y) \in \Omega \qquad (4.1) \\
y \in S(x)
\end{gathered}
$$

where there are two sets of continuous variables $x \in \Re^{n_x}$, $y \in \Re^{n_y}$ respectively, the vector of upper-level and lower-level variables. The overall objective function is $f(x, y)$ and Ω represents the joint feasible region between the upper- and lower-level variables. The challenging constraints are that the lower-level variables y belong to $S(x)$, the solution set of the lower-level problem. This bottom-level problem can be one or more optimization problems, a complementarity problem (Cottle et al. 2009) or variational inequality problem (Luo et al. 1996). Even if all other parts of (4.1) are linear, the last set of constraints are non-convex and can cause computational difficulties unless a specialized MPEC approach is applied, rather than just treating (4.1) as a regular nonlinear program (Bazaraa et al. 1993).

Much research has been devoted over the last 25-30 years to efficiently solving MPECs (Luo et al. 1996; Scheel and Scholtes 2000). Some recent approaches include the works by Fletcher et al. (2004, 2006), Leyffer et al. (2006) and Anitescu et al. (2007) that search for stationary points of these problems. These methods have been shown to obtain local solutions to moderately sized MPECs. However, given the non-convexity of MPECs, it may work for small problems might not work for large instances. As described by Chen et al. (2006), a two-stage process was needed to solve their large energy market MPEC. There have been general algorithms that provide global solutions (Gumus et al. 2001; Hu et al. 2007; Mitsos 2010) to MPECs proposed in the literature as well. Other methods (Steffensen and Ulbrich 2010; Uderzo 2010) also exist but have not been shown to work for large-scale models.

In this study, we make use of the new SOS1 (Beale and Tomlin 1970) approach of Siddiqui and Gabriel (2012) to transform the complementarity conditions of the lower-level problem appropriately. This work, partially based on (Gabriel et al. 2006) reformulates an MPEC into a single-level, SOS1-constrained optimization problem or one with a penalty-like term. It has been used in combination with a heuristic adjustment procedure (Siddiqui and Gabriel 2012) to solve an MPEC of approximately 9,400 variables for the North American natural gas market. Thus, it appears that it can scale to larger problems. This is important in the current application which, depending on the number of scenarios used for the upper-level problem, could be rather large. Moreover, this approach has been shown in (Siddiqui and Gabriel 2012) to be numerically superior (at least on the problems tried) than the method of disjunctive constraints (Fortuny-Amat and McCarl 1981).

At the top level of this MPEC is the depiction of the wastewater treatment plant (WWTP) whose activities are modeled as a two-stage, stochastic optimization problem with recourse. The first-stage variables include investments in digesters (different capacities) that convert the solid end products from the wastewater treatment process to methane and Class A biosolids.

The first-stage decisions are combined with recourse actions such as how much methane to produce from the digestion process, how much electricity to produce from the methane, how much compressed natural gas (CNG) to sell to the Washington, DC CNG bus system, how much natural gas to sell to the residential sector, and how much high-end (Class A) or Class B fertilizer [44] (biosolids) to produce and sell in retail stores or land apply at reuse sites, respectively.

Given the proximity to Washington, DC's CNG fleet of buses, local farms, and the possibility to generate its own electricity (to some extent), the Blue Plains facility has the potential to influence (at least locally) several related markets. First, currently in the Washington, DC CNG bus market, 1.98 million cubic feet per day of this fuel is used. The Blue Plains potential production of CNG is about 2.55 million cubic feet per day so that in principle it could be enough to entirely cover this market (Chandler et al. 2006). In addition, a CNG station could be established at DC Water to support other CNG vehicles. At present, the District of Columbia has no public stations, two private ones, and the State of Maryland has three public and six private ones. Virginia has five public and 12 private ones. [45]

DC Water can also be a player in the natural gas market beyond CNG by selling its digester-based methane to natural gas consumers. Burning the methane to produce electricity is also another recourse option for the Blue Plains WWTP. At present, this facility buys about 15 MW from its local supplier (PEPCO) and potentially as much as 10 MW could be produced from digested-based methane (Metcalf & Eddy and AECOM 2008).

Lastly, as Class A biosolids are an organic fertilizer, Blue Plains could also be an important influence in the high-end, fertilizer market. On average, Blue Plains produces some 370 dt per day, which is about 18% of an average U.S. state's fertilizer

---

[44] See the next section for an explanation of Class A and class B biosolids.
[45] http://www.afdc.energy.gov/fuels/natural_gas_locations.html.

consumption.[46] If DC Water decides to sell its digester-derived, Class A biosolids in this market for the Washington metro area, it could have a significant effect on fertilizer market prices.

The MPEC nature of the model arises since decisions that DC Water can make (e.g., how much Class A biosolids to produce) can have a significant effect on the various, lower-level markets outlined above. From that perspective, DC Water has a Stackelberg leader position in these markets (Gabriel et al. 2013) so that the MPEC paradigm is appropriate. Moreover, as DC Water represents one of the largest WWTPs in the world, other wastewater treatment plants may follow their lead in innovate thinking vis-à-vis expanding the role of wastewater management. Lastly, as a renewable energy source (and transportation fuel), certain renewable energy credits (RECs) and carbon credits are available to WWTPs that pursue this wastewater-to-energy route. Moreover, such a renewable energy source increases with population growth and generally does not compete for arable land as do crop-based biofuels. From that perspective, wastewater and the resulting products offer a renewable energy source that correlates positively with population growth and is thus a sustainable approach.

In summary, this study offers the following. First, it provides a novel model for wastewater management at WWTPs on how to be active in several markets such as energy, agriculture and transportation. Moreover, the model allows for the WWTP to be a local Stackelberg leader in the market application. The study also provides a novel formulation for a stochastic MPEC. Lastly, the numerical results indicate that such a model can successfully be solved with a representative number of scenarios.

[46] The U.S. fertilizer consumption in 2009 was 37 Mega tons/year which when divided by 50 (for the U.S. States) yields 748,000 tons/year/state, http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx#26720.

4.1 The Blue Plains Advanced Wastewater Treatment Plant (AWTP) Operational Processes

The Blue Plains facility is located on the banks of the Potomac River in Washington, DC and covers an area about 150 acres (60.7 hectares). This location has the potential to produce renewable energy from photovoltaic (PV) solar power [47] in addition to its primary wastewater treatment function. Based on a growing U.S. population, it is expected that the Blue Plains treatment capacity will be increased to an average amount of 370 million gallons/day (MGD) (1,400.6 liters/day) [48]. The treatment processes are divided into separate parts, each with a distinct function. The solid end products from the primary, secondary, nitrification and denitrification are thickened separated and dewatered. These products can be used to produce Class B biosolids [49] by lime stabilization, Class A biosolids [50] by composting and/or biogas from the digestion process (Oleszkiewicz and Mavinic 2002).

4.2 Overview of Model Formulation

The overall model is a two-level, stochastic MPEC with a wastewater treatment plant as the Stackelberg leader at the top level and four separate markets at the bottom level. At this top level, the investment and operational decisions of the wastewater treatment plant are depicted as a two-stage stochastic optimization problem with

[47] NREL, Solar radiation data manual for flat-plate and concentrating collectors http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2005/targzs/targzs_by_state.html#M.
[48] http://www.dcwater.com/about/gen_information.cfm.
[49] Class B biosolids require farm management practices and area restrictions before application, even though they already have a reduced amount of pathogens (EPA 1994 2006).
[50] Class A biosolids require a total amount of pathogens to be lower than a detectable level and must meet the limitations of metal contaminants related to regulation 503 (EPA 1994).

recourse. The wastewater treatment plant is modeled as maximizing its profit for a typical day. The uncertainty stems from certain inputs (e.g., prices, influent) that are random and the various probability distributions are described below. The wastewater treatment plant's first-stage investment decisions include what size of digester to build to convert the influent into methane and Class A biosolids. The recourse decisions relate to levels of the various outputs to produce such as methane, electricity, Class A or Class B biosolids. The second-stage involves scenario-based decisions about how much revenue less costs WWTP is able to produce. Lastly, the lower level consists of profit-maximization problems for each of the four markets considered (high-end fertilizer, CNG transportation, residential natural gas sector, power sector) as well as related market-clearing conditions.

4.2.1 Upper-Level Problem: Stochastic Optimization Model

The top-level, stochastic optimization problem for the wastewater treatment plant is shown in Figure 4.1. The first step in this flowchart represents the inflow of wastewater directly to the plant facility. Solid end products from primary treatment, secondary treatment nitrification and denitrification are collected and inflow to digester, incinerator, lime stabilization or composting processes. The model also considers solids from outside organizations that are outsourcing their wastewater treatment.

Based on a goodness-of-fit test, a Weibull distribution function is used to represent the range of the solid end products (influent) between 113-814 dry tons [51] (dt) from the Blue Plains facility and is denoted by $I_{WWTP}(s)$ with "s" the scenario index. There are 6,561 scenarios described in the next section, resulting from discretizing this

[51] All units are calculated for an average day.

and other probability distributions. In addition to this random inflow, solids (waste) from two outside organizations are also considered for the digester. In particular, there are decisions variables of solids from organization 1, $I_{OR1}(s)$ or organization 2, $(I_{OR2}(s))$, which have respectively, a maximum 60 dt and maximum 50 dt per day.

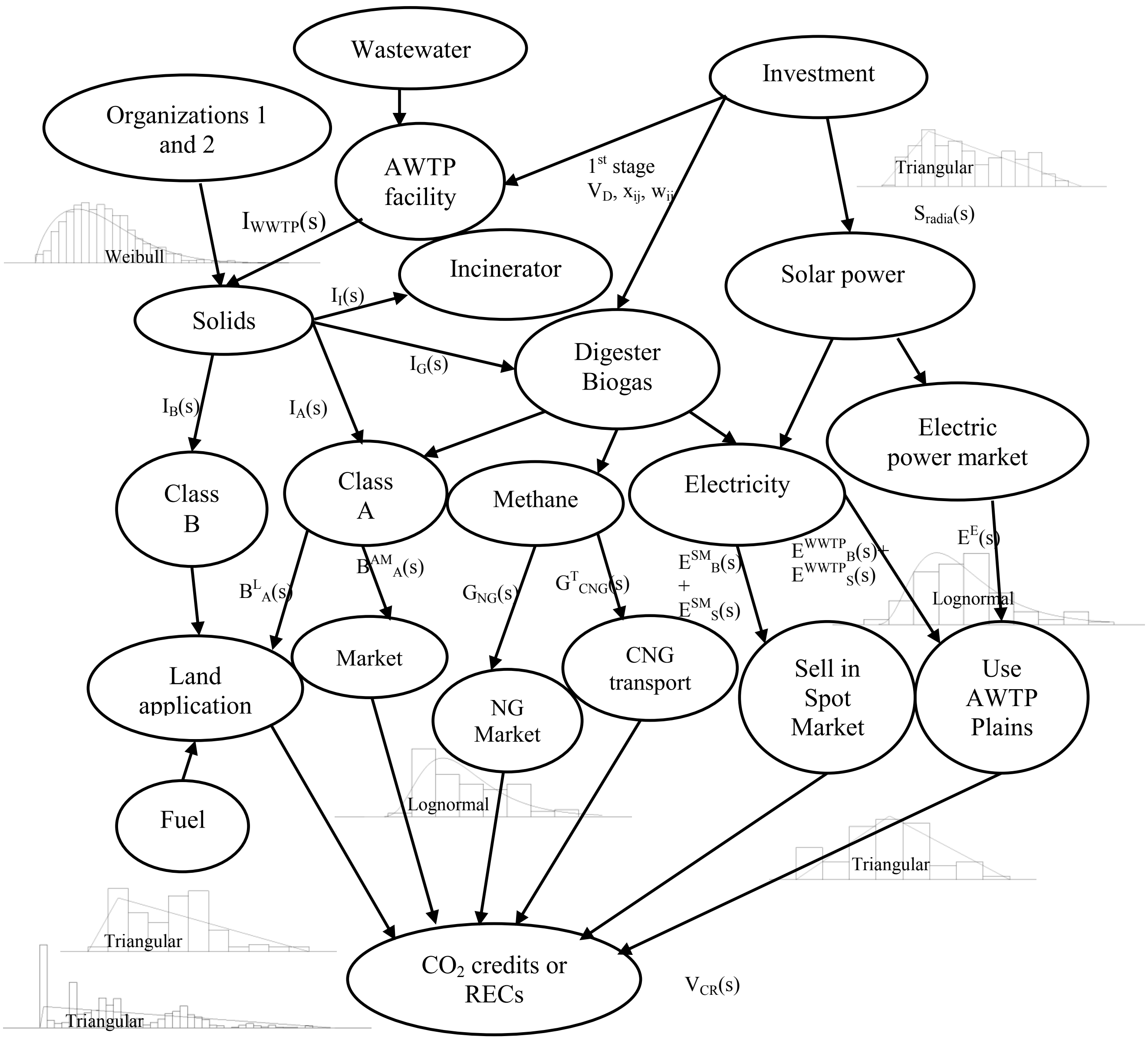


Figure 4.1 Flowchart of the stochastic optimization model for biosolids management program at the Blue Plains AWTP

From Figure 4.1, it can be seen that solids influent can flow to the anaerobic digester ($I_G(s)$), be incinerated ($I_I(s)$), lime-stabilized into Class B biosolids ($I_B(s)$), or composted as Class A bisolids. ($I_A(s)$). The resulting products from the digestion process are biogas and Class A biosolids ($B_A^{AM}(s)$ and $B_A^{L}(s)$). Lime stabilization is used to produce Class B biosolids for land application, but the composting process produces Class A biosolids for fertilizer.

The biogas from the digester can be cleaned up to make bio-methane ($G_{NG}(s)$), compressed natural gas for transportation ($G_{CNG}^{T}(s)$), and gas to generate electricity ($G_E(s)$). For the quantity of Class A biosolids, the model will select whether the biosolids should be land applied on farms ($B_A^{L}(s)$) or sold in the agricultural market ($B_A^{AM}(s)$). According to the potential to generate electricity from solar energy, solar radiation is described by the variable $S_{radia}(s)$ and solar power generation costs are given by $S_{generate}(s)$.

The model selects sales to relevant markets at the lower-level: residential natural gas sector, CNG for the transportation market, electricity, fertilizer, or using the wastewater-derived power along with the renewable energy credits and carbon allowance market considerations.

4.2.1.1 Decision Variables and Parameters

The following is the description of the sets, variables and parameters used in the model with the main variables shown in Figure 4.1. Note that the model solves for values of only one typical day; hence, all the variable values are in units per day.

Sets

$i \in \{1,2,3,4,5\}$ options for five types of digester, lime stabilization, and incineration [52]

$j \in \{1,2,3\}$ three segments for the digester cost curves

$s \in \{1,2,..6,561\}$ scenarios

Main upper-level variables [53]

$I_G(s)$ solids used to produce biogas (dt)

$I_B(s)$ solids used to produce Class B biosolids from lime stabilization for land application (dt)

$I_A(s)$ solids used to produce Class A biosolids not from the digester (dt)

$I_I(s)$ solids incinerated (dt)

$I_{OR1}(s)$ solids brought in from organization 1 (dt)

$I_{OR2}(s)$ solids brought in from organization 2 (dt)

$G_E(s)$ biogas generated from biosolids for generating electricity (cf)

$G_{NG}(s)$ methane gas transformed from biogas generated from the digestion process, called bio-methane (Ryckebosch et al. 2011) and used in the residential natural gas sector (cf)

$G_{CNG}^T(s)$ CNG transformed from biogas generated from the digestion process, called bio-CNG (cf) (Ryan and Caulfield 2010)

$B_A^L(s)$ biosolids Class A produced for land application (dt)

$B_A^{AM}(s)$ biosolids Class A sold in the agricultural market (dt)

$E^E(s)$ electricity bought from external sources and used at the AWTP (kWh)

[52] Each digester type is described in Figure 4.2 and defined in a later section.
[53] All variables are assumed to be nonnegative unless specified otherwise. Also, only the main primal variables are shown. The endogenously determined prices (dual variables) are not shown here but are described later in the text.

$E_B^{WWTP}(s)$ electricity generated from biogas and used at the WWTP (kWh)

$E_B^{SM}(s)$ electricity generated from biogas and sold to the spot market (kWh)

$E_S^{WWTP}(s)$ electricity generated from solar energy and used at the WWTP (kWh)

$E_S^{SM}(s)$ electricity generated from solar energy and sold to the spot market (kWh)

$NG_H^E(s)$ natural gas purchased from external sources (cf)

$C_T(s)$ total net carbon dioxide equivalent (t)

$P_T(s)$ total energy purchased at WWTP (kWh)

$V_T(s)$ total WWTP value, which is the revenue minus costs ($)

$x_{i,j}$ amount of solids processed by digester i and segment j (dt)

$w_{i,j}$ $\begin{cases} 1 \text{ if digester/incinerator option i and cost segment j is selected} \\ 0 \text{ otherwise} \end{cases}$

Parameters [54]

CAP maximum amount of Class B production (dt)

$\bar{G}_{NG}$ maximum amount of bio-methane production (cf)

$\bar{G}_{CNG}^{T}$ maximum amount of bio-CNG production (cf)

$\bar{B}_A^{AM}$ maximum amount of Class A biosolids sold in the agricultural market (dt)

$\bar{E}_B^{SM}$ maximum amount of electricity generated from biogas and sold to the grid (kWh)

$\bar{E}_S^{SM}$ maximum amount of electricity generated from solar radiation and sold to the grid (kWh)

S_{OR1} maximum amount of solids from organization 1 (dt)

S_{OR2} maximum amount of solids from organization 2 (dt)

[54] See the Appendix D for values of the parameters.

S_{gas} maximum amount of solids used to produce biogas (dt)

f_G biogas production factor (cf/dt)

f_{NG} bio-methane production factor (average 60% methane gas is produced from biogas) (unitless) [55]

f_{CNG} bio-CNG production factor (average 57.6% CNG is produced from biogas) (unitless) [56]

f_B amount of dry tons of Class A biosolids per dry ton of solids influent (dt/dt)

f_E factor used to calculate generated electricity from biogas (kwh/m^3)

$WWTP_{NG}$ average daily amount of natural gas consumption at WWTP [57] from historical data (cf)

f_C^E factor used to calculate carbon dioxide emissions from electricity (t CDE /kWh)

f_C^{NG} factor used to calculate carbon dioxide emissions from natural gas used for heating at the Blue Plains facility (t CDE /cf)

f_C^I factor used to calculate carbon dioxide emissions from incineration (t CDE /dt)

f_C^{CNG} factor used to calculate carbon dioxide offset from sold CNG for the transportation sector (t CDE / cf)

---

[55] The biogas ($CH_4 + CO_2 + H_2O$ + trace gases) can be broken down into the following component shares: 55-65% methane gas (CH_4), 30-40% carbon dioxide gas (CO_2), and 0-5% water vapour, traces of hydrogen sulphide H_2S and hydrogen H_2 (Appels et al. 2008). Consequently, in the model presented below, an average 60% of methane composition in biogas is used.

[56] The reduction of CNG from 100% of natural gas is due to further processing for gas quality outside of WWTP (http://www.environmental-expert.com/products/biogas-to-compressed-natural-gas-35510). CO_2 scrubbing is and other purification steps are needed in order to prepare the bio-methane for use as CNG. See Appendix A and Figure A-1 for more details.

[57] The highest natural gas consumption obtained from the energy saving plan report of December, 2010.

f_C^f factor used to calculate carbon dioxide offset from biosolids used as fertilizer (t CDE /dt)

f_C^t factor used to calculate carbon dioxide emissions from transportating biosolids to the land application field (t CDE/dt)

f_P^T factor used to calculate fossil fuel consumption to transport Class A and/or B biosolids to land application fields (kWh/dt)

f_P^G factor used to calculate natural gas consumption at WWTP (kWh/cf)

f_P^I supplementary fuel for incineration process factor (kWh-\$/dt-gal)

f_I^T factor used to calculate fossil fuel consumption for transportation Class A and/or B biosolids to land application fields and to agricultural market in gallon per dry ton (gal/dt) [58]

f_E^{Gen} electricity generation costs (\$/kWh)

$\gamma_{bio-CNG}$ CNG compression costs (\$/cf) [59]

$\gamma_{bio-methane}$ non-transportation natural gas production costs (\$/cf)

f_A^{Com} biosolids Class A production costs (\$/dt)

f_{Ash}^I ash from incineration disposal cost (\$/dt)

f_I^{TIP} tipping fees (\$/dt of biosolids)

C_{allow}^{WWTP} CDE allowance (ton CDE)

S_{panel} installation area of solar panels (m^2)

RES credits from renewable electricity standard (\$/kWh)

---

[58] Note that the transportation cost factor is given independent of distance to the reuse site. This was done to approximate the costs based solely on volume rather than having the model keep track of all the reuse sites and delivery of product there.

[59] The convention is to use γ only for lower-level, unit production costs.

f_{on}^{off} parameter used to turn on REC or CO_2 credits (mutually exclusive options) and it is equal to 0 or 1, respectively (fixed for any given run)

REC renewable energy credits ($/t CDE)

$\bar{q}_{ino}$ maximum amount of inorganic fertilizer in the market (dt)

$\bar{q}_{org}$ maximum amount of organic fertilizer in the market (dt)

$\bar{q}_{fossil}$ maximum amount of fossil fuel-based electricity sold to the grid (kWh)

$\bar{q}_{nuclear}$ maximum amount of nuclear-based electricity sold to the grid (kWh)

$\bar{q}_{hydro}$ maximum amount of fossil-fuel based electricity sold to the grid (kWh)

$\bar{q}_{CNG}$ maximum amount of CNG for transportation sold to the natural gas grid (cf)

$\bar{q}_{NG}$ maximum amount of natural gas sold to the natural gas grid (cf)

γ_{ino} inorganic fertilizer production costs ($/dt)

γ_{org} organic fertilizer production costs ($/dt)

γ_{fossil} fossil fuel based-electricity production costs ($/kwh)

$\gamma_{nuclear}$ nuclear based-electricity production costs ($/kwh)

γ_{hydro} hydropower based-electricity production costs ($/kwh)

γ_{CNG} CNG for transportation production costs ($/cf)

γ_{NG} non-transportation natural gas production costs ($/cf)

Random parameters

Pr(s) probability for each scenario

$I_{WWTP}(s)$ uncertain solids influent to digester (dt)

$E_{consump}(s)$ uncertain electricity consumption at WWTP (kWh)

$E_{purchased}(s)$ uncertain electricity purchasing prices ($/kWh)

$NG_{purchased}(s)$ uncertain natural gas purchasing prices ($/cf)

$P_{fossil}(s)$ uncertain fossil fuel prices to transport Class A and B bisolids ($/gal)

$R_{CO2}(s)$ uncertain carbon credits ($/t CDE)

$S_{radia}(s)$ uncertain solar radiation (kWh/m^2) [60]

$S_{generate}(s)$ uncertain generated solar electricity cost ($/kWh)

4.2.1.2 Constraints

All constraints except for those defining binary variables are linear and the majority of them represent some form of conservation of product. [61] The first-stage constraints define the five possible types of digester costs V_D (constraint (14a) shown in the next section), where i=1,2,3,4,5 represent the five type of digesters each having three cost curve segments indexed by j=1,2,3 (see Figure 4.2).

- Type 1 is four trains of thermal hydrolysis (TH) and anaerobic digestion (4TH & digester) and lime stabilization (LS)
- Type 2 is two trains of thermal hydrolysis and anaerobic digestion (2TH & digester) and lime stabilization (LS)
- Type 3 is four trains of thermal hydrolysis and anaerobic digestion (4TH & digester) with another two trains of thermal hydrolysis and anaerobic digestion (2TH & digester) and lime stabilization (LS)
- only a lime stabilization process (LS)
- only an incineration process

[60] While the amount of solar radiation is a random variable, the amount of solar power generated from it is an upper-level, second-stage decision variable.
[61] This does not include complementarity constraints arising from the lower-level problem.

The costs of digesters consist of a fixed cost, denoted by h_{ij}, and variable costs related to the solids influent amount, denoted by $a_{ij.}$ Only one digester and segment j of a cost curve can be selected and this is controlled by the binary variable $w_{ij.}$

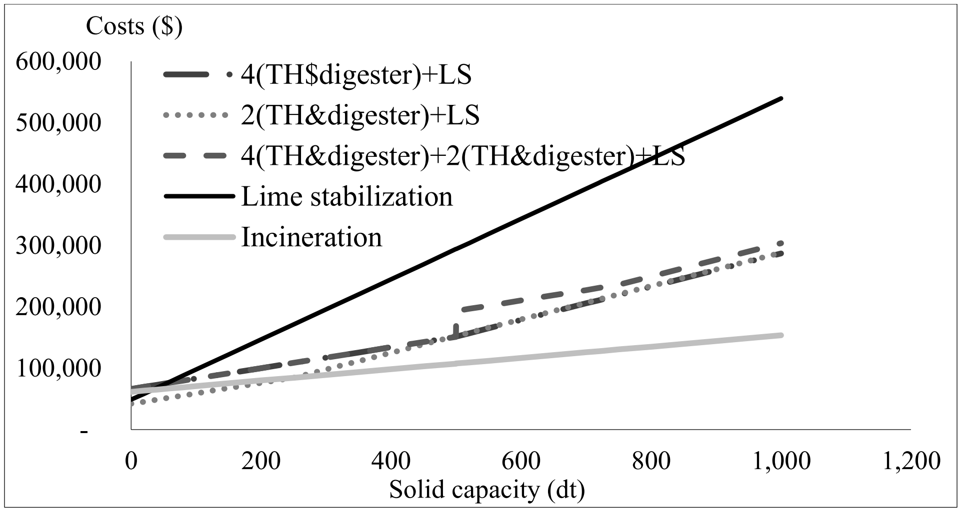


Figure 4.2 Costs of five possible types of digesters ($)

Second-stage constraints relate to biosolids influent, biogas production, biosolids Class A production, natural gas consumption, electricity, carbon dioxide equivalent emissions, energy purchased and value constraints. All constraints consider the 6,561 scenarios from eight groups of uncertain data. Appropriate probability density functions (pdf) are created [62] using goodness-of-fit techniques (Sheldon 2012). Using Blue Plains' historical data, a Weibull pdf best represented solid end products inflow to the digester and a triangular pdf was selected for energy consumption. Solar radiation, solar generated costs, fossil fuel costs and CO_2 credits were also fitted with triangular pdfs based on historical data. Lognormal pdfs were used for the natural gas and electricity prices.

[62] http://highered.mcgraw-hill.com/sites/0073376280/student_view0/arena_software_download.html.

The uncertainties were transformed from continuous distributions to three-point, discrete distributions (Keefer 1994; Hoyland and Wallace 2001) to serve as input in the upper-level problem. Each distribution function was discretized to low, medium and high values with the corresponding probabilities. For example, the three discrete numbers representing Blue Plains' energy consumption are 615.5, 701.0 and 786.5 MWh per day with 0.321, 0.429 and 0.250 probabilities, respectively. As described in the Appendix C, these probabilities were determined by picking key cut-off values. The scenario-based optimization then takes into accounts the resulting three-point distributions and related probabilities [63] of eight uncertain elements [64] (3^8 = 6,561 scenarios used).

4.2.1.3 Objective of the Stochastic Optimization Model

Maximizing expected total value is the objective to be optimized expressed in dollars for the upper-level problem. The expectation is taken over all the scenarios considered after discretizing the fitted probability distributions shown in Figure 4.1 and described above.

4.2.2 Lower-Level Problem

The objective of the lower-level separate optimization problems is to maximize expected profit (in dollars). There is one optimization problem for each of the relevant markets including fertilizer, electricity, residential natural gas and CNG for transportation. Markets are assumed to be perfectly competitive, so players are price-takers (Shy 1995). These prices are determined by market-clearing conditions for each

[63] Pr(s) represents probability for each scenario.
[64] Uncertain elements include $I_{WWTP}(S)$,$E_{consump}(S)$,$E_{purched}(S)$,$NG_{sold}(S)$,$P_{fossil}(S)$,$R_{CO2}(S)$,$S_{radia}(S)$, $S_{generate}(S)$.

market at the lower level which together with the KKT conditions of these separate optimization problems constitute the lower-level problem. [65]

4.2.2.1 Lower-Level Optimization Problem of Selling Class A Biosolids to the Fertilizer Market.

The U.S. Department of Agriculture categorizes plant nutrients (fertilizer) into three different groups: 1) single (nitrogen, phosphate) nutrient, 2) multiple (mono ammonium-phosphate) nutrients, 3) secondary and micronutrients (manure, compost, and sewage sludge) [66], dependent on the end-use purposes. This research didn't consider the end-use purposes but focused on compositions of fertilizer by categorizing them into two groups: 1) inorganic fertilizer and 2) organic fertilizer. The objective of this part of the lower-level problem is to maximize the expected profit of the fertilizer market. Considering both the inorganic and organic fertilizer producers, expected profits of each player are calculated from the difference of revenues based on fertilizer prices ($\$\pi_F(s)\ per\ dt$) [67], and linear production costs of inorganic and organic fertilizer [68] ($\$\gamma_{ino}, \$\gamma_{org}$). In addition, the quantities of inorganic and organic fertilizer should be less than or equal to the maximum amount of supply in the fertilizer market. Problem (4.2) describes the optimization problem for the fertilizer markets.

[65] Note that due to the assumption of perfect competition, the separate profit-maximization problems of both players can be put together into one overall fertilizer problem since the resulting KKT conditions are the same. A similar line of reasoning applies to the other lower-level optimization problems.
[66] http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx#26720.
[67] Note that there is a just one fertilizer price but two quantities: inorganic and organic fertilizers (see (Abrell and Weigt 2012) for similar reasoning in the electricity market).
[68] See the Appendix D.

$$max_{q_{ino}(s),q_{org}(s)} \sum_s P\,r(s)\,\{\pi_F(s)\left(q_{ino}(s)+q_{org}(s)\right)-\gamma_{ino}q_{ino}(s)-\gamma_{org}q_{org}(s)\}$$

(4.2a)

s.t.

$$q_{ino}(s) \leq \bar{q}_{ino} \qquad \left(\lambda_{ino}(s)\right) \quad \forall s \tag{4.2b}$$

$$q_{org}(s) \leq \bar{q}_{org} \qquad \left(\lambda_{org}(s)\right) \forall s \tag{4.2c}$$

$$q_{ino}(s), q_{org}(s) \geq 0 \qquad \forall s \tag{4.2d}$$

where:

$q_{ino}(s)$ = amount of inorganic fertilizer in dt

$q_{org}(s)$= amount of organic fertilizer in dt

$\lambda_{ino}(s)$ = dual price of inorganic fertilizer constraint

$\lambda_{org}(s)$= dual price of organic fertilizer constraint

4.2.2.2 Lower-Level Optimization Problem of Selling Electricity to the Grid

The objective function for this part of the lower-level problem is to maximize the expected profit of selling electricity to the grid; three types of power generators are considered: fossil fuel (coal, natural gas and petroleum), nuclear, and renewables (hydropower). Expected profits of each of the three players (fuel types) are calculated from the difference between revenues based on electricity sold ($\$\pi_E(s)$ per kWh), and linear production costs of fossil, nuclear and hydro-based electricity[69] ($\$\gamma_{fossil}, \$\gamma_{nuclear}, \$\gamma_{hydro}$). The quantities of generated electricity from each source

[69] See the Appendix D for particular values.

should be less than or equal to the maximum amount of supply in the power market. The associated optimization problem is shown in (4.3).

$$max_{q_{fossil}(s)q_{nuclear}(s),q_{hydro}(s)} \sum_s Pr(s) \{ \pi_E(s) \left(q_{fossil}(s) + q_{nuclear}(s) + q_{hydro}(s) \right) - \gamma_{fossil} q_{fossil}(s) - \gamma_{nuclear} q_{nuclear}(s) - \gamma_{hydro} q_{hydro}(s) \} \tag{4.3a}$$

s.t.

$$q_{fossil}(s) \leq \bar{q}_{fossil} \qquad \left(\lambda_{fossil}(s)\right) \quad \forall s \tag{4.3b}$$

$$q_{nuclear}(s) \leq \bar{q}_{nuclear} \qquad \left(\lambda_{nuclear}(s)\right) \quad \forall s \tag{4.3c}$$

$$q_{hydro}(s) \leq \bar{q}_{hydro} \qquad \left(\lambda_{hydro}(s)\right) \quad \forall s \tag{4.3d}$$

$$q_{fossil}(s), q_{nuclear}(s), q_{hydro}(s) \geq 0 \quad \forall s \tag{4.3e}$$

where:

$q_{fossil}(s)$= amount of fossil fuel-based electricity in kWh

$q_{nuclear}(s)$= amount of nuclear-based electricity in kWh

$q_{hydro}(s)$= amount of hydropower-based electricity in kWh

$\lambda_{fossil}(s)$= dual price of fossil fuel-based electricity constraint

$\lambda_{nuclear}(s)$= dual price of nuclear-based electricity constraint

$\lambda_{hydro}(s)$= dual price of hydropower-based electricity constraint

4.2.2.3 Lower-Level Optimization Problem of Selling CNG to the Transportation Sector

In this lower-level problem, the objective is to maximize the expected profit of selling CNG to the transportation sector. This form of natural gas is produced from the methane coming as an output of the digester. Profits are calculated as the difference between revenues using natural gas prices ($\$\pi_{CNG}(s)\ per\ m^3$), and linear production costs [70] ($\$\gamma_{CNG}$). The quantities of CNG actually sold should be less than or equal to the maximum amount of supply in the CNG transportation market. Formulation (4.4) is the associated optimization problem.

$$max_{q_{CNG}(s)} \sum_s Pr(s)\{\pi_{CNG}(s)q_{CNG}(s) - \gamma_{CNG}q_{CNG}(s)\} \tag{4.4a}$$

s.t.

$$q_{CNG}(s) \leq \bar{q}_{CNG} \qquad (\lambda_{CNG}(s)) \quad \forall s \tag{4.4b}$$

$$q_{CNG}(s) \geq 0 \qquad \forall s \tag{4.4c}$$

where:

$q_{CNG}(s)$=amount of natural gas for transportation sector in cf

$\lambda_{CNG}(s)$=dual price of natural gas for transportation sector constraint

4.2.2.4 Lower-Level Optimization Problem for Selling Natural Gas to the Residential Natural Gas Sector

The objective in this lower-level problem is similar to the CNG one, namely maximizing the expected profit of selling natural gas to residential sector. Here the

[70] See the Appendix D for particular values.

related gas prices are ($\$\pi_{NG}(s)\, per\, m^3$), and the linear production costs [71] are γ_{NG}. Quantities of natural gas sold should be less than or equal to the maximum amount of supply in this market. Formulation (4.5) depicts this lower-level optimization problem.

$$max_{q_{NG}(s)} \sum_s Pr(s)\,\{\pi_{NG}(s)q_{NG}(s) - \gamma_{NG}q_{NG}(s)\} \tag{4.5a}$$

s.t.

$$q_{NG}(s) \leq \bar{q}_{NG} \qquad (\lambda_{NG}(s)) \quad \forall s \tag{4.5b}$$

$$q_{NG}(s) \geq 0 \quad \forall s \tag{4.5c}$$

where:

$q_{NG}(s)$= amount of natural gas for the residential sector in cf

$\lambda_{NG}(s)$=dual price of natural gas for the residential sector constant

4.2.3 Market-Clearing Conditions for the Lower-Level Markets

In addition to the lower-level optimization problems just described, there are market-clearing conditions (MCC) for each of the markets as shown in (4.16). For each market, these MCC stipulate that total supply (either from the lower- or upper-level or exogenously) must equal demand. The latter is described by linear demand function. Lastly, for each of these MCC, there is an associated Lagrange multiplier or price that is used by the lower-level players in each of the markets.

[71] See the Appendix D for particular values.

4.3 Mathematical Formulation of the stochastic MPEC

As described above, this study considers DC Water as the strategic player at the upper-level of a stochastic MPEC, modeled as maximizing expected profit (expected total value) subject to operational and investment constraints. The upper-level player decides on how much to produce of the following end products: 1) biosolids Class A, 2) biogas- and solar-based electricity, 3) bio-CNG and 4) bio-methane to be supplied to the relevant markets at the lower-level problem (see Figure 4.3). In addition, the upper-level player determines the amount of Class B biosolids that go to land application.

Maximize expected DC Water total value ($)
s.t.
First-stage constraints related to digester investment cost ($)
Five possible types of digesters
- 4 TH&digester and lime stabilization
- 2 TH&digester and lime stabilization
- 4 TH&digester, 2 TH&digester and lime stabilization
- lime stabilization
- incineration

Second-stage constraints related to the 6,561 scenarios

Solids influent constraints	(dt)
Biogas constraints	(cf)
Biosolids Class A constraints	(dt)
Natural gas consumption constraints	(cf)
Carbon dioxide emission constraints	(t CDE)
Energy consumption constraints	(kWh)
Electricity constraints	(kWh)
Value constraints	($)

Upper-level problem

$B_A^{AM}(s)$ $E_B^{SM}(s)$ $E_S^{SM}(s)$ $G_{CNG}^{T}(s)$ $G_{NG}(s)$

$\pi_F(s)$ $\pi_E(s)$ $\pi_{CNG}(s)$ $\pi_{NG}(s)$

Lower-level problem

Maximize expected profit of the fertilizer market	($)
Maximize expected profit of the residential natural gas market	($)
Maximize expected profit of natural gas for CNG transportation	($)
Maximize expected profit of electricity sold to the grid	($)
Market-clearing conditions for relevant markets	($)

Figure 4.3 Over all structure of the Stochastic MPEC.

The upper-level player will first make a decision on one of five possible types of digester and optimize the amount of Class A biosolids *($B_A^{AM}(s)$)* in dt, the amount of electricity generated from solar energy ($E_S^{SM}(s)$) and biogas sold to the spot market *($E_B^{SM}(s)$)* in kWh, as well as the amount of CNG (bio-CNG) production *($G_{CNG}^{T}(s)$)* and natural gas (bio-methane) for residential usage $G_{NG}(s)$ in cf. The lower-level will consider those quantities as fixed and solve the respective optimization problems in addition to the MCC to produce equilibrium prices of fertilizer *($\pi_F(s)$)* in \$/dt, electricity ($\pi_E(s)$) in \$/kWh, CNG ($\pi_{CNG}(s)$) and natural gas ($\pi_{NG}(s)$) in \$/cf. The structure of the two-level problem is shown in Figure 4.3 and the formulation of the two-level problem [72] are shown in (4.6) - (4.16).

The complete upper-level of the Stochastic MPEC is shown in (4.6)-(4.14) where the intermediate variables revenues and costs are defined as follows:

revenues = $\pi_F(s)B_A^{AM}(s)$+$\pi_E(s)E_B^{SM}(s)$+ $E_S^{SM}(s)(\pi_E(s) + RES)$

+ $\pi_{NG}(s)G_{NG}(s)$+$\pi_{CNG}(s)G_{CNG}^{T}(s)$+$f_I^{TIP}(I_{OR1}(s) + I_{OR2}(s))$+$V_{CR}(s)$

where $V_{CR}(s)$ are the renewable energy or CO_2 credits described in (14b). [73]

costs = $V_D +\ E_{purchased}(s)E^E(s) +\ NG_{purchased}(s)NG_H^E(s) +$

$S_{generate}(s)(E_S^{WWTP}(s) + E_S^{SM}(s) +\ \gamma_{bio\_CNG}\ G_{CNG}^{T}(s) + \gamma_{bio\_methane}G_{NG}(s) +$

$f_{ASH}^{I}\ I_I(s) + f_I^T\ P_{fossil}(s)(B_A^L(s) + B_A^{AM}(s) + I_B(s)) + f_I^T\ P_{fossil}(s)(I_{OR1}(s) + I_{OR2}(s)$

$+\ f_I^T\ P_{fossil}(s)I_I(s) + \gamma_{org}\ I_A(s)$

---

[72] Related constants and parameters are in the Appendix D.

[73] There are three sources of renewable energy revenue being modeling. First, RES is the renewable energy standard paid by the government for using renewable energy except biogas. Second, as shown in (14b) there are two mutually exclusive options for renewable energy credits: either carbon credits or renewable energy credits.

where V_D are the digester (and related) costs described in (4.14a).

$$Max \sum_s Pr(s)(revenues(s) - costs(s)) \qquad \$ \qquad (4.6)$$

s.t.

Solids influent constraints

$$I_B(s) + I_A(s) + I_I(s) + I_G(s) = I_{WWTP}(s) + I_{OR1} + I_{OR2} \qquad \text{dt} \qquad (4.7a)$$

$$I_B(s) \leq CAP - I_A(s) - I_I(s) - I_G(s) \qquad \text{dt} \qquad (4.7b)$$

$$I_G(s) \leq \sum_i \sum_j x_{i,j} \qquad \text{dt} \qquad (4.7c)$$

$$I_G(s) \leq S_{gas}(1 - w_{41} - w_{42} - w_{43}) \qquad \text{dt} \qquad (4.7d)$$

$$I_G(s) \leq S_{gas}(1 - w_{51} - w_{52} - w_{53}) \qquad \text{dt} \qquad (4.7e)$$ [74]

$$I_{OR1} \leq S_{OR1} \qquad \text{dt} \qquad (4.7f)$$

$$I_{OR2} \leq S_{OR2} \qquad \text{dt} \qquad (4.7g)$$

$$\sum_i \sum_j w_{i,j} = 1 \qquad (4.7h)$$ [75]

$$w_{i,j} \epsilon \{0,1\}. \forall i, j \qquad (4.7i)$$

$$x_{i,j} \leq CAP\ w_{i,j} \qquad (4.7j)$$ [76]

$$x_{i,j} \geq l_{i,j}\ w_{i,j} \qquad (4.7k)$$ [77]

Biogas production constraints

---

[74] Constraints (7c)-(7e) define the amount of solids in dt that will go into the digester to produce biogas. The binary variables w_{41}, w_{42} or w_{43} = 1 mean that only the lime stabilization option is used and w_{51}, w_{52} or w_{53} = 1 means that only the incineration option is used, therefore no biogas.

[75] Constraint (7h) is a constraint to enforce mutual exclusivity of the digester-segment options.

[76] Constraint (7j) refers to upper bounds on the biosolids amount by the maximum solids capacity in dt.

[77] Constraint (7k) refers to the minimum solids used to produce biogas. $l_{i,j}$ indicates solids used to produce biogas in dt.

$f_G\ I_G(s) = G_E(s) + G_{NG}(s) + G_{CNG}^T(s)$ cf (4.8a)

$G_{NG}(s) \leq f_{NG} f_G\ I_G(s)$ cf (4.8b)

$G_{CNG}^T(s) \leq f_{CNG} f_G\ I_G(s)$ cf (4.8c)

$G_{NG}(s) - \bar{G}_{NG}(s) \leq 0$ cf (4.8d)

$G_{CNG}^T(s) - \bar{G}_{CNG}^T(s) \leq 0$ cf (4.4.8e)

Class A biosolids production constraints

$B_A^L(s) + B_A^{AM}(s) = f_B\ I_G(s) + I_A(s)$ dt (4.9a)

$B_A^{AM}(s) - \bar{B}_A^{AM}(s) \leq 0$ dt (4.9b)

Electricity consumption constraints

$E_{consump}(s) \leq E^E(s) + E_B^{WWTP}(s) + E_S^{WWTP}(s)$ kWh (4.10a)

$E_B^{WWTP}(s) + E_B^{SM}(s) = f_E G_E(s)$ kWh (4.10b)

$E_S^{WWTP}(s) + E_S^{SM}(s) = (S_{Panel})(S_{radia}(s))$ kWh (4.10c)

$E_B^{SM}(s) - \bar{E}_B^{SM}(s) \leq 0$ kWh (4.10d)

$E_S^{SM}(s) - \bar{E}_S^{SM}(s) \leq 0$ kWh (4.10e)

Natural gas residential sector consumption constraints

$WWTP_{NG} \leq NG_H^E(s) + G_{NG}(\mathrm{s})$ cf (4.11)

Conservation of CDE emissions

$C_T(s) = emissions - offsets$ ton (4.12)

where

Emissions = $f_C^E\ E^E(s)$+$f_C^{NG} NG_H^E(s)$+ $f_C^t(I_B(s) + B_A^L(s) + B_A^{AM}(s))$+($f_C^I\ I_I(s)$)

Offsets = $f_C^E(E_B^{WWTP}(s) + E_B^{SM} + E_S^{WWTP}(s))$+ $f_C^{CNG} G_{CNG}^T(s)$ +$f_C^{NG} G_{NG}(s)$+$f_C^f(I_B(s) + B_A^L(s) + B_A^{AM}(s))$

Conservation of energy purchased

$$P_T(s) = f_P^T\left(I_B(s) + B_A^L(s) + B_A^{AM}(s)\right) + f_P^T\left(I_{OR1}(s) + I_{OR2}(s)\right) + f_P^G NG_H^E(s) + E^E(s) + f_P^I / P_{fossil}(s) I_I(s) \quad \text{kWh} \quad (4.13)$$

Digester costs

$$V_D = \sum_i \sum_j a_{i,j} x_{i,j} + \sum_i \sum_j h_{i,j} w_{i,j} \quad \$ \quad (4.14a)$$ [78]

Revenue from CDE emissions or renewable energy credits

$$V_{CR}(s) = SC(s)\left(C_{allow}^{WWTP} - C_T(s)\right) f_{0n}^{off} + REC\left(C_{allow}^{WWTP} - C_T(s)\right)(1 - f_{on}^{off}) \quad \$ \quad (4.14b)$$

Karush–Kuhn–Tucker (KKT) conditions of the lower-level individual optimization problems by market

Fertilizer market:

$$0 \le Pr(s)(-\pi_F(s) + \gamma_{ino}) + \lambda_{ino}(s) \ \perp\ q_{ino}(s) \ \ge 0 \quad (4.15a)$$

$$0 \le \bar{q}_{ino} - q_{ino}(s) \ \perp\ \lambda_{ino}(s) \ge 0 \quad (4.15b)$$

[78] Values of $a_{i,j}$ and $h_{i,j}$ are shown in Appendix D.

$$0 \leq Pr(s)\left(-\pi_F(s) + \gamma_{org}\right) + \lambda_{org}(s) \perp q_{org}(s) \geq 0 \qquad (4.15c)$$

$$0 \leq \bar{q}_{org} - q_{org}(s) \perp \lambda_{org}(s) \geq 0 \qquad (4.15d)$$

Electricity market:

$$0 \leq Pr(s)\left(-\pi_E(s) + \gamma_{fossil}\right) + \lambda_{fossil}(s) \perp q_{fossil}(s) \geq 0 \qquad (4.15e)$$

$$0 \leq \bar{q}_{fossil} - q_{fossil}(s) \perp \lambda_{fossil}(s) \geq 0 \qquad (4.15f)$$

$$0 \leq Pr(s)(-\pi_E(s) + \gamma_{nuclear}) + \lambda_{nuclear}(s) \perp q_{nuclear}(s) \geq 0 \qquad (4.15g)$$

$$0 \leq \bar{q}_{nuclear} - q_{nuclear}(s) \perp \lambda_{nuclear}(s) \geq 0 \qquad (4.15h)$$

$$0 \leq Pr(s)\left(-\pi_E(s) + \gamma_{hydro}\right) + \lambda_{hydro}(s) \perp q_{hydro}(s) \geq 0 \qquad (4.15i)$$

$$0 \leq \bar{q}_{hydro} - q_{hydro}(s) \perp \lambda_{hydro}(s) \geq 0 \qquad (4.15j)$$

CNG market:

$$0 \leq Pr(s)(-\pi_{CNG}(s) + \gamma_{CNG}) + \lambda_{CNG}(s) \perp q_{CNG}(s) \geq 0 \qquad (4.15k)$$

$$0 \leq \bar{q}_{CNG} - q_{CNG}(s) \perp \lambda_{CNG}(s) \geq 0 \qquad (4.15l)$$

Residental natural gas market:

$$0 \leq Pr(s)(-\pi_{NG}(s) + \gamma_{NG}) + \lambda_{NG}(s) \perp q_{NG}(s) \geq 0 \qquad (4.15m)$$

$$0 \leq \bar{q}_{NG} - q_{NG}(s) \perp \lambda_{NG}(s) \geq 0 \qquad (4.15n)$$

Market-clearing conditions of the relevant markets:

$$q_{ino}(s) + q_{org}(s) + B_A^{AM}(s) = 315{,}730.8 - 769.23\pi_F(s), (\pi_F(s)\ free) \qquad (4.16a)$$

$$q_{fossil}(s) + q_{nuclear}(s) + q_{hydro}(s) + E_B^{SM}(s) + E_S^{SM}(s) =$$

$$0.4878 - 7x10^{-7}\pi_E(s), (\pi_E(s)\ free) \qquad (4.16b)$$

$$q_{CNG}(s) + G_{CNG}^{T}(s) = 3.78x10^{7} - 3x10^{-9}\pi_{CNG}(s),\ \pi_{CNG}(s)\ free) \qquad (4.16c)$$

$$q_{NG}(s) + G_{NG}(s) = 4.23x10^{7} - 3x10^{-9}\pi_{NG}(s),\ (\pi_{NG}(s)\ free) \qquad (4.16d)$$

An objective function (4.6) computes the expected profit in dollars (net value). It is composed of the following revenues as a function of scenario: sales of Class A biosolids to the agricultural market ($\pi_F(s)B_A^{AM}(s)$); sales of electricity to the grid ($\pi_E(s)E_B^{SM}(s)$) and ($E_S^{SM}(s)(\pi_E(s) + RES)$), bio-methane or bio-CNG from the digestion process sold to the natural gas spot market ($\pi_{NG}(s)G_{NG}(s)$) or transportation sector ($\pi_{CNG}(s)G_{CNG}^{T}(s)$); tipping fees from both outsourcing organizations ($f_I^{TIP}(I_{OR1}(s) + I_{OR2}(s))$); and carbon dioxide and renewable energy credits ($V_{CR}(s)$). In addition, the expected net value includes the following costs: digester cost (V_D), cost of electricity ($E_{purchased}(s)E^{E}(s)$) and natural gas bought externally from the spot market ($NG_{purchased}(s)NG_H^{E}(s)$), electricity generation costs ($S_{generate}(s)(E_S^{WWTP}(s) + E_S^{SM}(s)$), production costs of bio-CNG ($\gamma_{bio\_CNG}\ G_{CNG}^{T}(s)$), production costs of bio-methane ($\gamma_{bio\_methane}G_{NG}(s)$), ash disposal costs ($f_{ASH}^{I}\ I_I(s)$), cost of transporting Class A and B biosolids to land application fields ($f_I^{T}\ P_{fossil}(s)(B_A^{L}(s) + B_A^{AM}(s) + I_B(s))$), transporting costs from organizations 1 and 2 ($f_I^{T}\ P_{fossil}(s)(I_{OR1}(s) + I_{OR2}(s)$), supplementary fuel costs ($f_I^{T}\ P_{fossil}(s)I_I(s)$) and composting costs ($\gamma_{org}\ I_A(s)$).

Conservation of CDE emissions (4.12) defines the net total carbon dioxide equivalent emissions in tons. The CDE emissions from AWTP operations ($f_C^{E}\ E^{E}(s)$), natural gas heating $f_C^{NG}(NG_H^{E}(s))$, transportation of biosolids ($f_C^{t}(I_B(s) + B_A^{L}(s) + B_A^{AM}(s))$) and incineration($f_C^{I}\ I_I(s)$) and the offsets from renewable electricity generated ($f_C^{E}(E_B^{WWTP}(s) + E_B^{SM} + E_s^{WWTP}(s))$) and used at the AWTP, sold bio-CNG

$(f_C^{CNG} G_{CNG}^T(s))$, sold bio-methane $f_C^{NG} G_{NG}(s)$, used/sold biosolids as fertilizer $(f_C^f (I_B(s) + B_A^L(s) + B_A^{AM}(s)))$.

Conservation of purchased energy (4.13) defines the total purchased energy of the AWTP including energy for transportation of Class A and/or Class B biosolids to land application sites $(f_P^T(I_B(s) + B_A^L(s) + B_A^{AM}(s)))$, transportation of solids from organizations 1 and 2 $(f_P^T(I_{OR1}(s) + I_{OR2}(s)))$, natural gas consumption $(f_P^G NG_H^E(s))$, electricity purchased from outside sources $(E^E(s))$, and supplementary fuel for incineration $((f_P^I / P_{fossil}(s)) I_I(s))$ in kWh.

The right-hand sides of (4.16) represent the inverse demand equations for each of the markets. These equations were determined from least-squares regression using data from the following sources: fertilizer market[79] (Mankiw 2007), electricity market (Bernstein and Griffin 2006; EIA 2013), CNG market[80] [81] (Bernstein and Griffin 2006; DOE 2013), residential natural gas market (Bernstein and Griffin 2006; DOE 2013).

The SOS type 1 variables (SOS1) are used to transform the complemenarity conditions of the lower-level optimization problems into integer linear constraints. [82] For example, constraints (4.15a) and (4.15b) were transformed and shown in (4.17).

$$zp_{ino}^1(s) = Pr(s)\{-\pi_F(s) + \gamma_{ino}\} + \lambda_{inor}(s) \tag{4.17a}$$

$$2SOS_{ino}^{1+}(s) + 2SOS_{ino}^{1-}(s) = zp_{ino}^1(s) + q_{ino}(s) \tag{4.17b}$$

$$2SOS_{ino}^{1+}(s) - 2SOS_{ino}^{1-}(s) = zp_{ino}^1(s) - q_{ino}(s) \tag{4.17c}$$

[79] http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx#26720.
[80] http://www.afdc.energy.gov/fuels/properties.html.
[81] Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model, version 1.7. 2007. Input Fuel Specifications. Argonne National Laboratory. Chicago, IL., and *www.afdc.energy.gov.*
[82] See detail on Appendix D.

$$zp_{ino}^2(s) = \bar{q}_{ino} - q_{ino}(s) \tag{4.17d}$$

$$2SOS_{ino}^{2+}(s) + 2SOS_{ino}^{2-}(s) = zp_{ino}^2(s) + \lambda_{ino}(s) \tag{4.17e}$$

$$2SOS_{ino}^{2+}(s) - 2SOS_{ino}^{2-}(s) = zp_{ino}^2(s) - \lambda_{ino}(s) \tag{4.17f}$$

$$zp_{ino}^1(s), zp_{ino}^2(s) \geq 0 \tag{4.17g}$$

$$q_{ino}(s) \geq 0 \tag{4.17h}$$

$$\lambda_{ino}(s) \geq 0 \tag{4.17i}$$

$SOS_{ino}^{1+}(s), SOS_{ino}^{1-}(s), SOS_{ino}^{2+}(s), SOS_{ino}^{2-}(s)$ are SOS1 variables

The objective function has computationally difficult bilinear (non-convex) terms. For instance, the revenue from biosolids Class A sold to the fertilizer market ($\pi_F(s)B_A^{AM}(s)$) is a bilinear term as it is the produce of price and quantity which are both variables. These bilinear terms can be linearly approximated using discrete levels for one of the variables in the manner described in (Gabriel et al. 2009; Gabriel and Leuthold 2010). For example, in the bilinear term above, the continuous variable $B_A^{AM}(s)$ measuring the production of Class A biosolids can be discretized to a set of possible production levels. We follow the linearization procedure from (Gabriel and Leuthold 2010) and apply it to the bilinear terms: $\pi_F(s)B_A^{AM}(s)$, $\pi_E(s)E_B^{SM}(s)$, $\pi_E(s)E_S^{SM}(s)$, $\pi_{CNG}(s)G_{CNG}^T(s)$ and $\pi_{NG}(s)G_{NG}(s)$. [83] Note that there are alternative ways to "convexify" these bilinear terms but they may depend on a special structure (e.g., Ruiz and Conejo 2009).

[83] See details on Appendix D.

4.4 Generation of Subset of Scenarios

Reduction of the 6,561 scenarios was needed for computational purposes. Many methods could be used to decrease the size of the full scenario tree (6,561 scenarios). In this study conditional (random) sampling and scenario reduction approaches were both tried.

Scenario-reduction approaches (Morales el at. 2009; Conejo el at. 2010) are used to find a reduced scenario tree that is close to the original one and finding such a reduced tree is a computationally challenging problem (Dupacova et al. 2003; Heitsch and Romisch 2003 and 2009). The monitoring function, which results from the distance between the original scenario tree and the reduced one, was used to generate reduced scenario trees and GAMS/SCENRED2 [84] was used to that end. Convergence analysis was run by varying the percentage of the relative distance between the original and the reduced trees until convergence criteria were met (see Figure 4.4). The reduced tree could be generated by using between 0% of the relative distance (original scenario tree) and 100% (having only one scenario) or desired number of preserved scenarios. Results in Figure 4.4 indicated how to select the number of scenarios. Using a reduced number of 2,187 scenarios, the expected total value stabilized (Figure 4.4). This number of scenarios was then used given computational considerations.

[84] www.gams.com/dd/docs/solvers/scenred2.pdf.

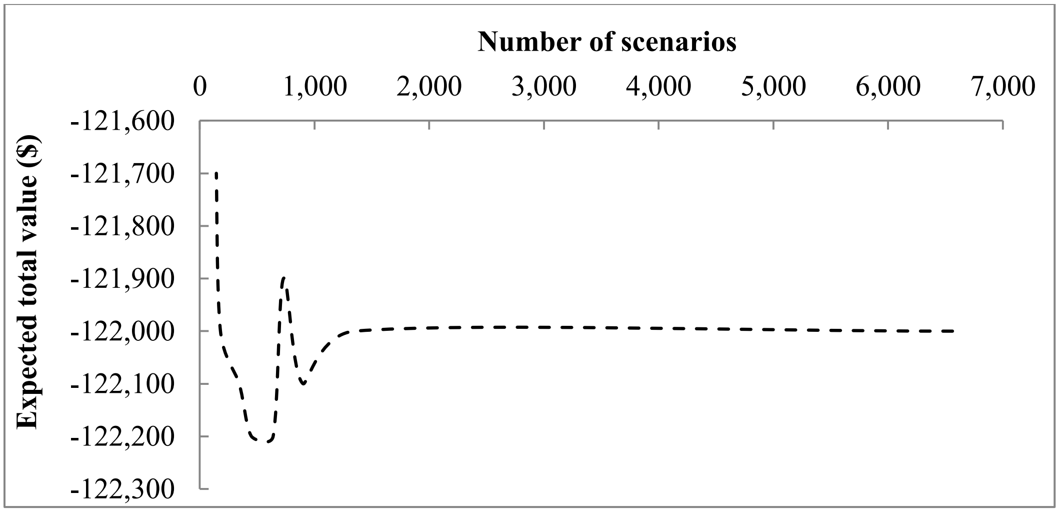


Figure 4.4 Results from the two-level model varying the number of scenarios (Key: (number of scenarios, optimal objective function value))

Another approach besides scenario reduction is conditional (random) sampling.[85] This is a common method to produce a subset of scenarios by sampling from the full scenario tree (Kaut and Wallace 2007; Kouwenberg 2001). Figure 4.5 compares the expected total value of the sample of reduced scenarios (27, 81 and 243 of the 6,561 scenarios) using conditional (random) sampling and scenario reduction approaches as mentioned above. The number of reduced scenarios in conditional (random) sampling was selected by fixing some groups of uncertain data such as carbon dioxide credits, electricity consumption, solar radiation, solar power generation costs and/or fossil fuel costs. For example, of the eight uncertain data elements, when three of them were fixed, a scenario tree from the remaining four elements gave a resulting $3^4 = 81$ scenarios. [86]

[85] http://ntnu.diva-portal.org/smash/get/diva2:122673/FULLTEXT01.pdf.

[86] In fact, there are 8 choose 3= 56 ways of getting 243 scenarios as described above same as 8 choose 5 of getting 27 scenarios. It would be computationally prohibitive to try all those 56 ways so three such ways were chosen and are displayed as circles in Figure 4.5. When four of the random variables are fixed, there

Similarly, when three of the eight random variables were fixed, $3^5 = 243$ scenarios resulted. The purpose of this test is to see when different random variables are fixed (It can be the 27, the 81 or the 243 cases), does the optimal objective function vary considerably. If yes, it means that the particular scenarios selected are important. Otherwise, any 27, 81 or 243 could be used. Figure 4.5 shows that there is not much variation between the three optimal objective function values shown as circles. This reinforces the fact that the particular 27, 81 or 243 scenarios are not so important. Consequently, scenario reduction via GAMS/SCENRED2 which itself picks the scenarios in the reduced tree can be trusted as long as the number of scenarios is greater than 27. From Figure 4.4, the number of scenarios where the optimal objective function stabilized was 2,187 and thus this was the chosen value for the reduced number of scenarios.

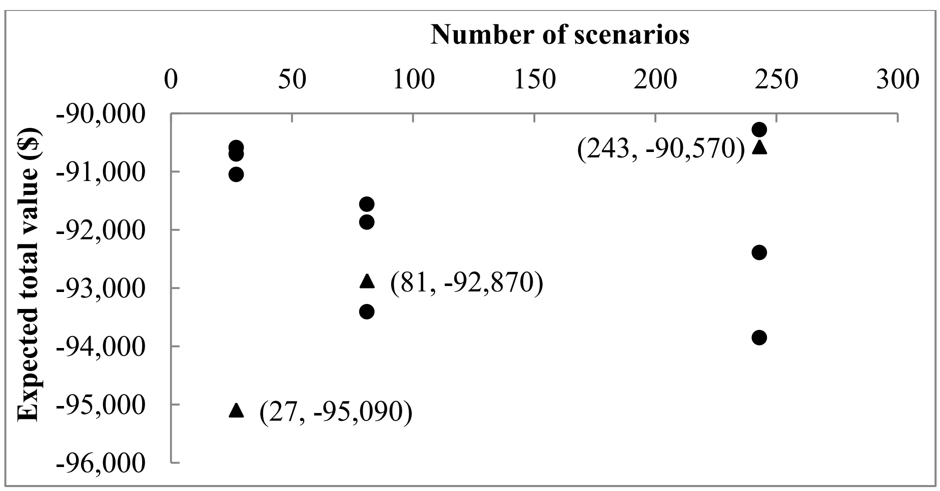


Figure 4.5 the optimal solutions of scenario reduction and conditional sampling approach

---

are 70 ways to choose the 81 scenarios. Again, for computational reasons only three were chosen and shown in Figure 4.5.

The reduced scenario tree had 2,187 scenarios [87] because of the convergence analysis and the computational time (see next section). Note that in general, one would not necessarily be able to solve the problem with the full scenario tree as we did to compare against a solution with a reduced tree. However, the GAMS routine does not in general need the full scenario tree to operate.

4.5 Results and Discussion

4.5.1 Numerical Results

Figure 4.6 shows the numerical results from solving the stochastic MPEC. The maximum expected total value (profit) is -$93,270. [88] The model selected a small digester, namely the 2 thermal hydrolysis & anaerobic digestion and lime stabilization processes. In this case, a larger digester is not necessarily better. One reason is that a smaller digester is less expensive in terms of investment and operational costs in spite of producing less methane for the downstream CNG and electricity markets. Also, a smaller digested amount of material allows for more high-end biosolids to be sold as organic fertilizer where the unit profit could be higher.

The expected amount of biosolids of 106 dt were delivered to land application fields (delivered biosolids had some of Class A and Class B). Biogas from the digestion process produced bio-methane, bio-CNG and generated biogas-based electricity. Bio-methane and bio-CNG were sold to the natural gas market, but the expected amount of

[87] The number of 243 leaves in the reduced scenario tree were input to arrive at a total of 2,187 scenarios to be used by GAMS.
[88] The optimal profit is negative in part because only an important subset of the AWTPs activities are modeled. For example, fees from customers to treat the wastewater are not included as they don't vary but they do represent a revenue source.

biogas-based electricity of 171,170 kWh was used internally as was the solar-based electricity that was generated the expected amount 18,722 kWh.

The expected amount of Class A biosolids of 206 dt were sold as high-end fertilizer with a market-clearing price of $249.60 per dt equal to the marginal production cost for organic fertilizer in the lower-level problem. The expected amount of bio-CNG was 348,930 cubic feet per day and bio-methane was 370,210 cubic feet per day and were sold in the CNG and residential sectors, with expected prices $0.009 and $0.003 per cubic feet, respectively. All of the biogas-based and solar-based electricity generated at Blue Plains was used there none of it was sold to the spot market. Figure 4.6 shows a summary of the output.

It is interesting to note that the bio-CNG (for the transportation sector) and the bio-methane (for the residential sector) selected by the model were smaller than their maximum values of 5,652,751 and 5,888,282 cubic feet per day indicating that all things being equal, these sectors were less important to the AWTP than the high-end fertilizer market. This is an interesting observation that may provide guidance to AWTP managers. [89]

[89] This analysis assumes that if there are multiple solutions that the same reasoning relative to maximum production quantities holds.

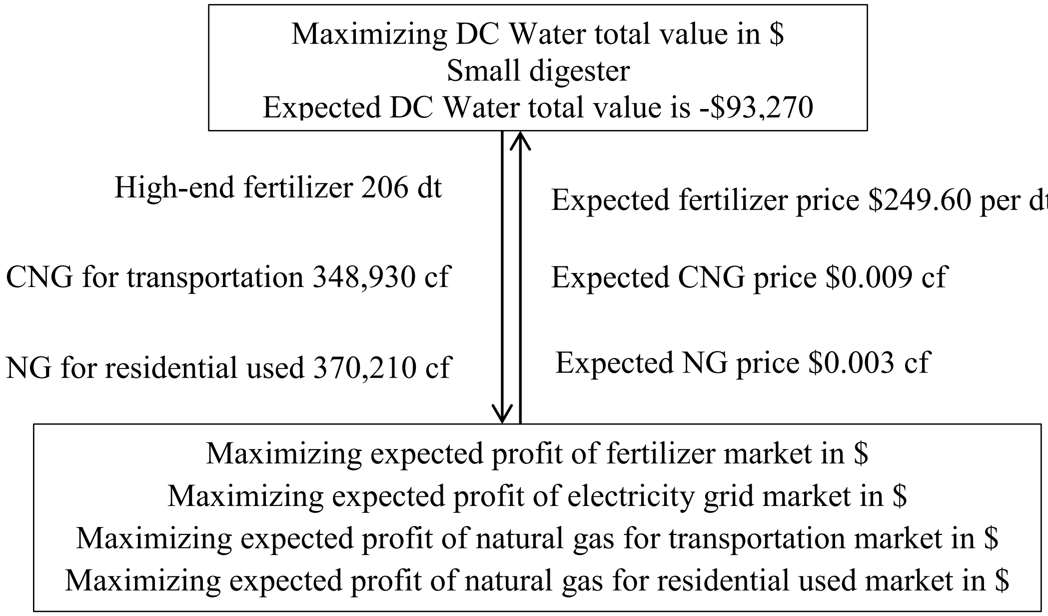


Figure 4.6 the expected amount of results from Stochastic MPEC

4.5.2 Computational Issues

This stochastic MPEC has been solved using XPRESS with GAMS on an Intel(R) Core (TM) i7-2670QM computer with a CPU@2.2 GHz and 8 GB of RAM. The computational time required to solve this problem with different number of scenarios (size of problem) are shown in Table 1. Not only the size of the problem but also the linearization of the bilinear terms in the objective function influenced the computational time (see (Ruiz and Conejo 2009) for a similar discussion of computational time with bilinear terms). Two linearization schemes for bilinear terms were selected. Case 1 was a two-point linearization that had a lower value of zero and an upper value at the maximum generation level of $B_A^{AM}(s), E_B^{SM}(s), E_S^{SM}(s), G_{CNG}^{T}(s)$ and $G_{NG}(s)$. Case 2 had four values (depending on the bilinear terms) used in the linearization. The CPU time of case 1 was less than for case 2 and significantly less when a large number of scenarios were used. Therefore, it appears that the appropriate selection of how many terms in the bilinear linearization to use as well as the number of scenarios in the reduced tree is important in order to solve larger problems. [90]

Table 4.1 Computational time with different number of scenarios

No. Scenarios	2,187 [91]	729	343
CPU time* (s)	95	70	44
CPU time(s)**	302	82	66

Note that * represents case one, and ** represents case two.

4.6 Summary and Conclusions

In this study, we have introduced a novel stochastic MPEC model for wastewater management at a large advanced wastewater treatment plant (AWTP). From maximizing expected total value (profits) of the AWTP, the numerical results indicate that a small digester is preferred. This digester is used to produce biogas and then produce products such as bio-methane, bio-CNG, electricity-based biogas and Class A biosolids. The AWTP is a regional Stackelberg leader since it can influence the fertilizer, compressed natural gas and residential natural gas markets by the level of the products it produces: Class A biosolids, CNG, methane.

This study also explored a scenario reduction and conditional sampling procedure given the large number of scenarios (6,561) to use in the complete scenario

[90] For 27 scenarios, we also ran a case where the bilinear terms were not linearized. After two days of wall clock time, the solution procedure had not finished. From that perspective, the linearization of the bilinear terms seems quite important.
[91] For the 2,187-scenario case, the upper-level problem has 102,789 continuous variables and 32,805 binary variables; the lower-level problem has 166,212 continuous variables, 247,131 binary variables and 30,618 SOS1 variables.

tree. It was found that 2,187 sufficed since at that number, the optimal objective function stabilized.

It could be concluded from this study that this stochastic two-level problem could be of great use to wastewater managers who need to consider many factors beside just wastewater in the face of profitability and sustainability goals.

Chapter 5: Summary of the Three Optimization Models Developed and Sensitivity Analysis Comparing Their Output

Decision-making problems often involve uncertainty in the inputs. With an assumption of certain data, the deterministic formulation of the problem suffices. However, in the face of uncertainty, a stochastic formulation of the problem is required (Conejo et. al. 2010). Furthermore, for some problems, an optimal decision depends not only on the outcome of uncertain events, but also on the decisions made by potentially different players being modeled. This situation is the case for a typical WWTP. In Chapter 4 of this dissertation, an MPEC was formulated to account for both the uncertainty of events and the dependency of the lower-level players' decisions on the upper-level decisions.

The three models discussed in Chapters 2, 3 and 4 have different approaches: deterministic, stochastic and two-level, stochastic modeling, respectively. Average data were optimized in the deterministic model (Chapter 2). One of four types of digesters (anaerobic digester or lime stabilization) was chosen and the amount of the related products such as biogas, biosolids, electricity, natural gas were decided regarding solid end products.

For the single-level, stochastic optimization model (Chapter 3), 10 groups of uncertain data were used with a two-stage, recourse formulation. The uncertainty was used in the second-stage problem for corrective (recourse) actions based on three-point probability mass functions used to approximate calibrated continuous probability distributions (e.g., lognormal).

Finally, in Chapter 4, a two-level stochastic MPEC model was developed to account for first-mover advantages by the upper-level WWTP. DC Water, as the strategic, upper-level player, made value-maximizing decisions at the upper-level, which included the type of digester, the amount of biosolids Class A, the amount of bio-methane, the amount of bio-CNG, the amount of biogas-based and solar-based electricity. The lower-level players also optimized their respective profit-maximization decisions in the electricity grid market, fertilizer, CNG and natural gas for residential markets.

This chapter summarizes and compares the results of the three approaches (same decision variables and constraints), the benefits of each model, the value of information while considering stochasticity and different optimal solutions while considering the two-level problem. Additionally, the last part of this chapter considers a sensitivity analysis of the single and two-level (MPEC) stochastic optimization models' output.

5.1 Single-level Optimization Problems Analysis

5.1.1 Comparison of Deterministic and Stochastic approaches for single-level optimization problems

Based on the information available to DC Water, decision makers face uncertainty. As such the stochastic optimization approach is ideal. However, there are computational issues to consider when uncertain data are included. For example, the computational time to find an optimal solution for a stochastic optimization model with differing objectives for wastewater derived energy was about 60-180 minutes. [92] On the other hand, for a given set of data, the deterministic optimization model for wastewater-

[92] This stochastic model has been solved using XPRESS with GAMS on an Intel(R) Core (TM) i7-2670QM computer with a CPU@2.2 GHz and 8 GB of RAM.

derived energy only required about 2-10 minutes to solve using the same computer. Stochastic optimization is more computationally challenging but more revealing in terms of tradeoffs and risk.

Two theoretical concepts can explain the accuracy of the optimal objective value: the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS). The EVPI is the amount that decision makers would find reasonable to pay (in terms of their objective) in return for complete and accurate information about the future (Birge and Louveaux 1997). The VSS is the benefit of using a stochastic rather than a deterministic model (Birge and Louveaux 1997; Escudero et al. 2007).

The EVPI, by definition, is the difference between the wait-and-see (WS) and the here-and-now recourse problem (RP) solution (Birge and Louveaux 1997) and is defined below assuming a minimization problem formulation.

$$EVPI = RP - WS \tag{5.1}$$

where:

$$WS = E_{\xi}[\min_x z(x, \xi)] \tag{5.2}$$

$$RP = \min_x E_{\xi} z(x, \xi) \tag{5.3}$$

x = the levels of the five possible types of digester in the first-stage constraints

ξ = the random data vector resulting in 59,049 scenarios

The VSS, is the difference between the here-and-now (RP) solution and the expected result of using mean values (EV) problem (EEV) (Birge and Louveaux 1997).

$$VSS = EEV - RP \tag{5.4}$$

where:

$EV = \min_x z(x, \bar{\xi})$ (5.5)

$EEV = E_\xi(z(\bar{x}(\bar{\xi}), \xi))$ (5.5)

$\bar{\xi} = E(\xi)$ (5.6) [93]

$\bar{x}(\bar{\xi})$ = optimal solution to (5.5)

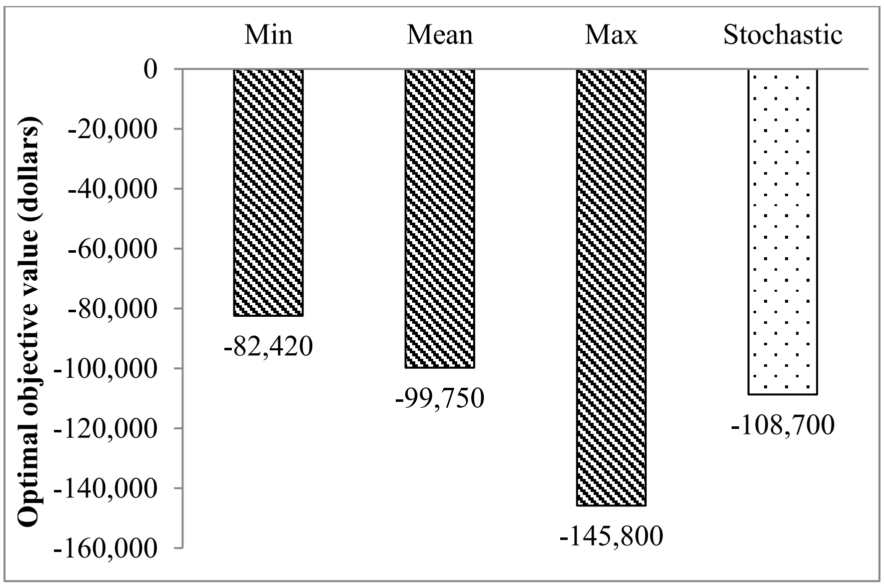


Figure 5.1 A comparison of the optimal objective values (Maximizing total value in dollars) of the three deterministic cases to that of the stochastic case.

For the purpose of evaluating the EVPI and VSS, three deterministic cases were constructed that differ by the value of the inputs. The inputs to the three cases were chosen to represent the minimum, mean and maximum value of each input. For each case, the optimal objective values were -\$82,420, -\$99,750 and -\$145,800 respectively (see Figure 5.1). The optimal objective value is negative in part because only an

[93] $E(\xi)$ denotes the expectation of ξ.

important subset of the WWTPs activities is modeled such as biosolids management costs and revenues. However, some other operational costs and revenues were not included. For example, fees from customers to treat the wastewater are not included as they do not vary but they do represent a revenue source.

The wait-and-see optimal objective function value was -$99,557, [94] while the here-and-now (recourse) optimal objective function value was -$108,700. The EVPI for this maximizing DC Water total value problem was thus $9,143.

A much simpler approach to solve the WS problem was obtained by replacing all random variables by their expected value (mean value). The measure of utility, or lack thereof, of optimization by mean values is expressed in the value of the stochastic solution.

The here-and-now (recourse) solution value was -$108,700, while the expected result of using mean value (EEV) was -$112,036. Thus, the VSS was $3,336 indicating how much better the WWTP could do by considering a stochastic rather than a deterministic model. In this case, the optimal objective value of stochastic model represents 2.9% improvement over the expected result of using the mean value solution (EEV).

The deterministic and stochastic models indicated the use of the small digester to produce biogas and related products such as Class A biosolids, bio-CNG, bio-methane and biogas-based electricity. The small digester is less expensive in terms of investment and operational costs. Bio-CNG and bio-methane were produced and sold to the markets when the deterministic model was used. However, with the stochastic model, biogas-

[94] The objective function value is based on maximizing different from the suggested WS approach shown earlier.

based electricity was also produced and sold.

5.1.2 Risk measurement in stochastic optimization model

The stochastic optimization model was considered with uncertainty, so the total values (profits) were random variables based on scenarios. Using only the expected value in the objective function ignores any risk associated with the WWTPs decisions. Consequently, a risk measure is also needed and the conditional Value-at-Risk (CVaR) was used. CVaR is one of many types of risk measures and has been shown to be coherent (Conejo et al. 2010). CVaR (α,x) defines the expected value of the profits smaller than the (1-α)-quantile [95] of the distribution of total profits (Conejo et al 2010). Mathematically, CVaR for a generic two-stage problem is given below in (5.7). CVaR elements are given by: $\eta - \frac{1}{1-\alpha}\sum_{\omega\in\Omega}\pi(\omega)s(\omega))$ in the objective function as well as the constraints $\eta - \left(c^T x + q(\omega)^T y(\omega)\right) \leq s(\omega), \forall\omega \in \Omega$ and $s(\omega) \geq 0, \forall\omega \in \Omega$ that enforce the necessary definition of CVaR (see (Conejeo et al. 2010) for more details).

$$CVaR(\alpha, x) = max\left\{\eta - \frac{1}{1-\alpha}\varepsilon_\omega\{max\{\eta - f(x,\omega), 0\}\}\right\}, \forall\alpha \in (0,1) \qquad (5.7)$$

$$\max_{x,y(\omega),\eta,s(\omega)}(1-\beta)(c^T x + \sum_{\omega\in\Omega}\pi(\omega)q(\omega)^T y(\omega)) + \beta(\eta - \frac{1}{1-\alpha}\sum_{\omega\in\Omega}\pi(\omega)s(\omega))$$

s.t.
$$Ax = b \qquad (5.8)$$

$$T(\omega)x + W(\omega)y(\omega) = h(\omega), \forall\omega \in \Omega \qquad (5.9)$$

$$\eta - \left(c^T x + q(\omega)^T y(\omega)\right) \leq s(\omega), \forall\omega \in \Omega \qquad (5.10)$$

$$s(\omega) \geq 0, \forall\omega \in \Omega \qquad (5.11)$$

$$x \in X, y(\omega) \in Y, \forall\omega \in \Omega \qquad (5.12)$$

[95] $\alpha \in (0,1)$.

where: x is the first-stage decision variable

y is the second-stage decision variable and related with scenarios

$(y = \{y(\omega);\ \forall\omega \in \Omega\}$

η = auxiliary variable

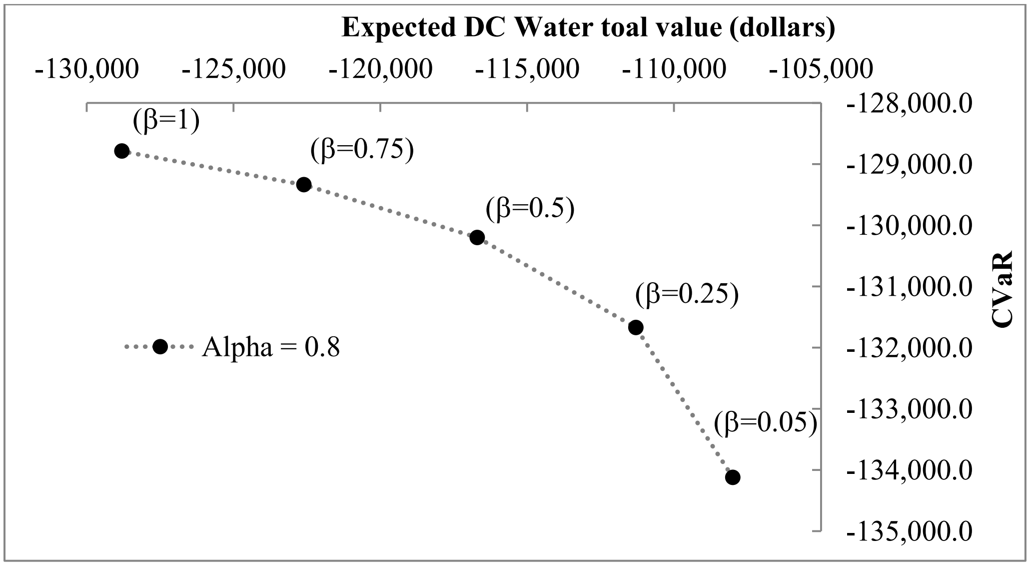


Figure 5.2 The efficient frontier represented in the term of expected total value and CVaR when α was 0.8.

Figure 5.2 shows the efficient frontier represented in terms of expected total value and CVaR when α was 0.8 (0.2-quantile). The tradeoff between expected total value and CVaR was generated by varying the weighting parameter β. [96] The risk in the model will increase if β is reduced to zero since it won't be accounted for in the objective function. According to the analysis of risk measure for this stochastic model, the expected total value was -\$108,000 (cost) when β was 0.05 and the expected total value was reduced to -\$128,800 (increased costs) for β equal to 1. The higher the risk (more negative CVaR)

[96] $\beta \in (0,1)$.

the higher the expected total value as shown in Figure 5.2.

It is also important to see how the solution changes as a function of β. Table 3.2 shows optimal solutions when CVaR was considered with different values of β. Regardless of the value of β, a small digester was always selected. However, what is interesting, is the different solutions chosen by the model as β varied. When the model was optimized with high risk (β close to zero), a relatively higher amount of biogas was used to generate electricity which was then sold to the electric power market. On the other hand, a significantly larger amount of digested biogas was used to produce bio-CNG and sold to the transportation market when the model considered small risk (β was close to one). Why is this happening? One explanation is that in the face of risk, the WWTP will devote much more of its activities to the CNG market where the price was deterministic instead of to the power market whose prices are stochastic. This is a nice example of how the WWTP's strategies can shift to avoid risk.

Table 3.2 The expected amount of products of digested biogas when considered CVaR with different β.

Beta	**0.0**	**0.25**	**0.5**	**0.75**	**1.0**
CVaR	-543,533	-131,669	-130,197	-129,336	-128,786
Expected value ($)	-108,700	-111,323	-116,656	-122,569	-128,786
Class A sold as fertilizer (dt)	121	121	121	121	98
Biogas-based electricity sold to the outside power market (kWh)	84,247	73,215	67,081	62,402	46,475
Solar-based electricity sold to the outside power market (kWh)	17,858	15,683	15,919	16,064	11,255
CNG sold to the outside transportation market (cf)	8,154	303,169	442,327	530,276	351,516

5.2 Comparison of Stochastic Optimization and Stochastic MPEC approaches

The 2.6% ($2,936 per day) improvement in value resulting from the stochastic model provides the motivation to further study the impact of uncertainty in wastewater-to-energy management. In this section, the stochastic, mathematical model with equilibrium constraints (two-level optimization model) was compared with the stochastic optimization model (one-level optimization model).

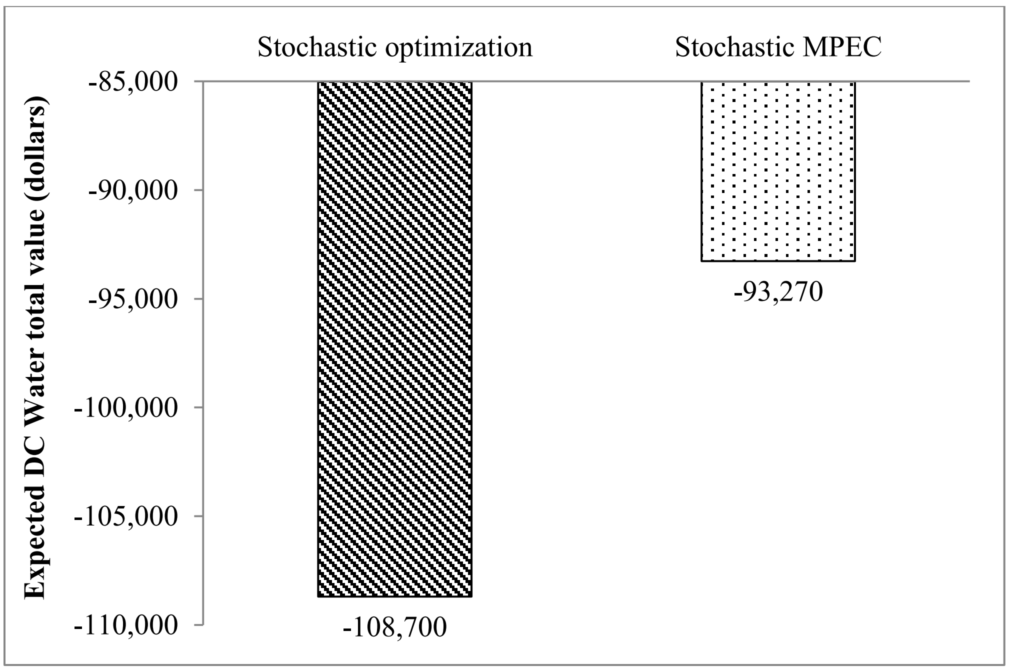


Figure 5.3 The difference between the expected DC Water total value of the stochastic optimization model and stochastic MPEC.

Figure 5.3 shows the difference between the optimal objective value of the stochastic MPEC and the stochastic optimization model. The stochastic MPEC indicated 14% lower value (lower costs) compared to the results from the stochastic optimization model. Both models selected a small digester for maximizing the DC Water total value. However, when market equilibrium was considered, that is, in the MPEC, the proportion of end-products had the effect of raising the prices of some of the associated products of biogas such as Class A biosolids, bio-methane and bio-CNG, thus accounting for the higher expected objective value.

The endogenous prices of fertilizer, CNG and NG taken from market-clearing conditions of the relevant markets were assigned as exogenous prices in the stochastic optimization model. The expected DC Water total value increased from -$108,700 to -$84,340 because the prices of products were raised and were closer to the real market. For example, high-end fertilizer prices were increased from $62 to $249.60 per dry ton and the fertilizer prices in agricultural market was $252 per dry ton in 2010. [97] These limited results indicate the influence of the top-level player (the WWTP) on determining market prices (and other things) to their advantage.

5.3 Sensitivity Analysis

Uncertain information about the parameters in the stochastic optimization model and stochastic MPEC were represented by probability distributions. It is important to state that the underlying probability distributions are generally unknown (Fente et al. 1999; Van Groenendaal and Kleijnen 2002) and thus they have to be estimated with a goodness-of-fit measure. The dependence of the model's behavior on its parameters (uncertain information) could be found by sensitivity analysis from using different probability density functions (pdf) e.g., the triangular distribution, probability mass functions (pmf) and/or using different data from cumulative density functions (cdf). However, not all of these sensitivity analyses could be shown in this dissertation. An example of quantified values of distribution functions was presented to study the

[97] http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx#26720.

sensitivity analysis of the models. Two different sets of distribution functions that were selected by the best and the second best fit were studied as an initial sensitivity analysis.

The next part of this chapter presents a sensitivity analysis of the case study where the optimal objective values are compared against two different sets of probability distributions for both the stochastic optimization model and the stochastic MPEC.

- Case 1 (Base Case) had ten distribution functions and was shown in Figure 5.4.
- Case 2 had ten distribution functions and was shown in Figure 5.5.

Table 1 shows the different probability distributions used for each of the uncertain data elements. Two cases were considered as part of a sensitivity analysis that included how the optimal objective functions changed.

Table 5.1 Uncertain data used for Cases 1 and 2.

Uncertainty data	**Case 1**	**Case 2**
Solid influent to digester (dt)	Weibull pdf	Lognormal pdf
Natural gas costs ($/cf)	Lognormal pdf	Weibull pdf
Electricity consumption (kWh)	Triangular pdf	Weibull pdf
Electricity prices ($/kWh)	Lognormal pdf	Triangular pdf
Electricity costs ($/kWh)	Lognormal pdf	Triangular pdf
Fossil fuel prices ($/gal)	Triangular pdf	Weibull pdf
Fertilizer prices ($/ton)	Weibull pdf	Triangular pdf
Solar electricity costs ($/kWh)	Triangular pdf	Weibull pdf
Solar radiation (kWh/m^2)	Triangular pdf	Weibull pdf
CO_2 credits ($/ton)	Triangular pdf	Lognormal pdf

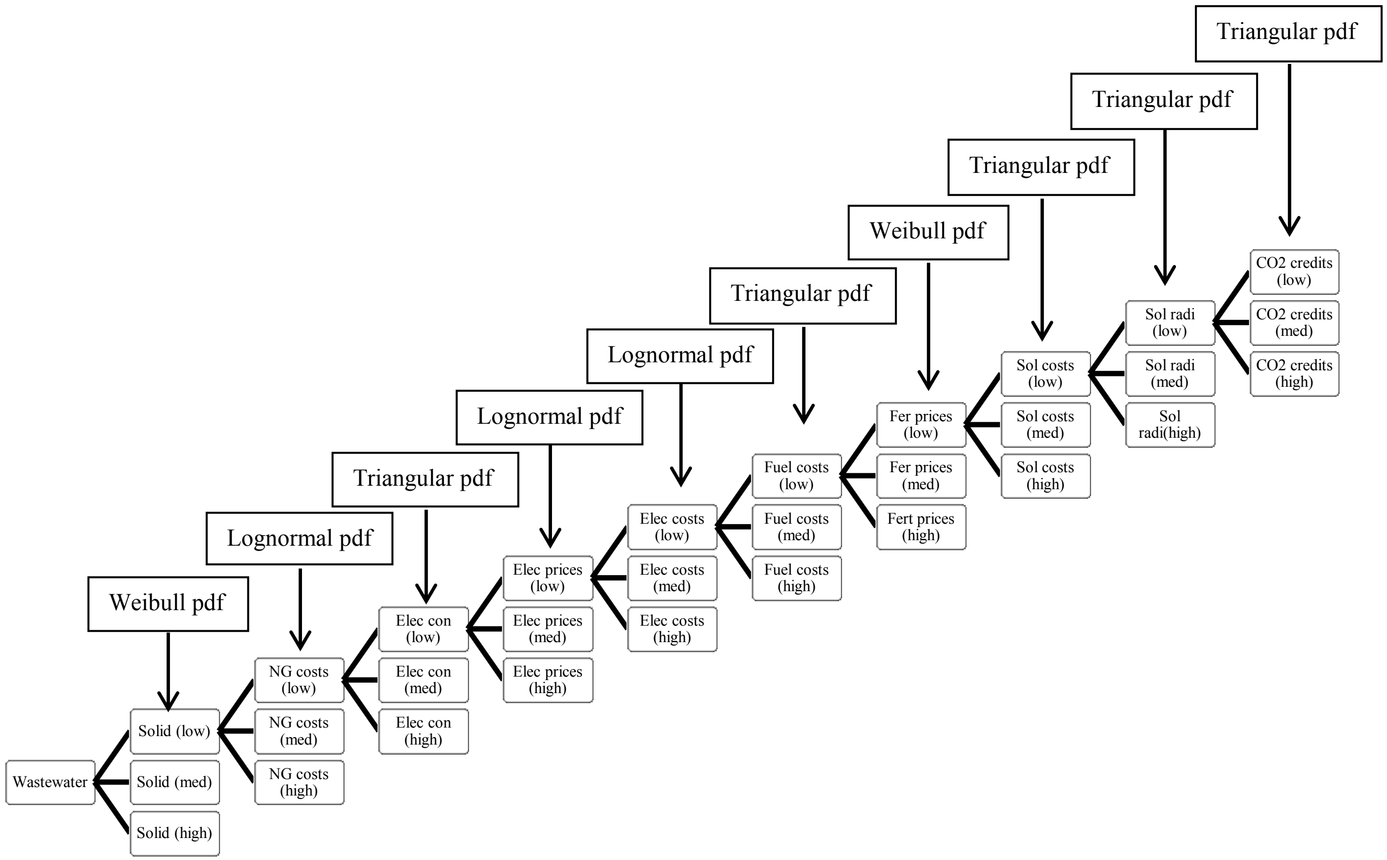


Figure 5.4 Diagram showing all probability density functions for Case 1.

Note that low = low amount, med = medium amount, high = high amount

Solid = solid end products, Elec = electricity, Fuel = fossil fuel, Fer = fertilizer, sol = solar electricity.

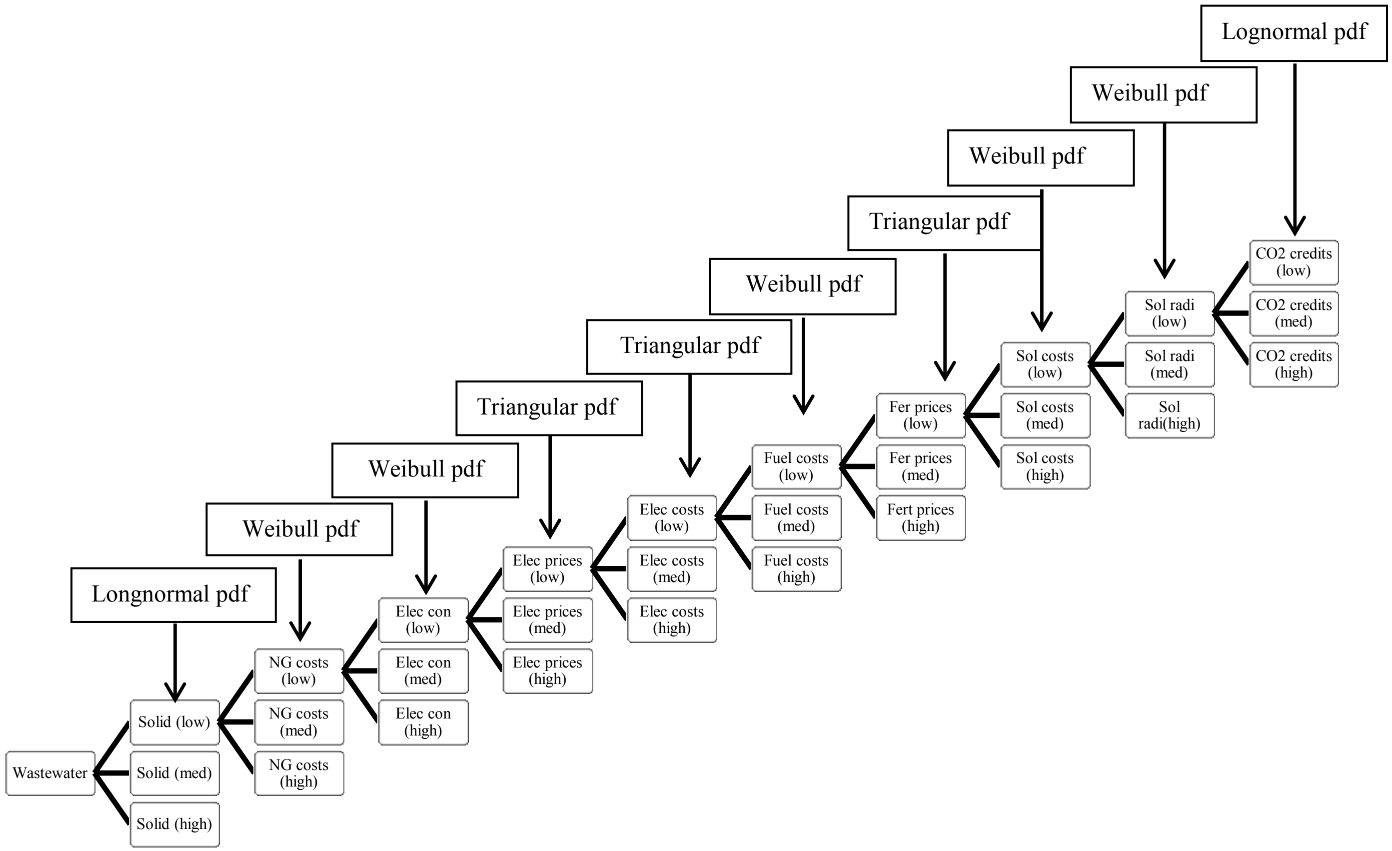


Figure 5.5 Diagram showing all probability density functions for Case 2.

Note that low = low amount, med = medium amount, high = high amount

Solid = solid end products, Elec = electricity, Fuel = fossil fuel, Fer = fertilizer, sol = solar electricity.

For both cases, the stochastic model and the stochastic MPEC indicated that DC Water should invest in a small digester to produce biogas in the first stage, use biogas-based electricity internally and sell the related products such as Class A biosolids, bio-methane and/or bio-CNG in the second stage. However, the different distribution functions that represented uncertain data provided slightly different optimal objective values as shown in Figure 5.6. The stochastic, mixed-integer optimization model for wastewater-derived energy indicated a 4.3% difference between the Base Case (Case 1) and Case 2 when optimized to maximize the DC Water total value. For the stochastic MPEC, the optimal objective values of the Base Case and Case 2 differed by 0.63%. Lastly, the Base Case (Case 1) had a better optimal objective function value than Case 2 for the single-level problem but this was slightly reversed for the stochastic MPEC.

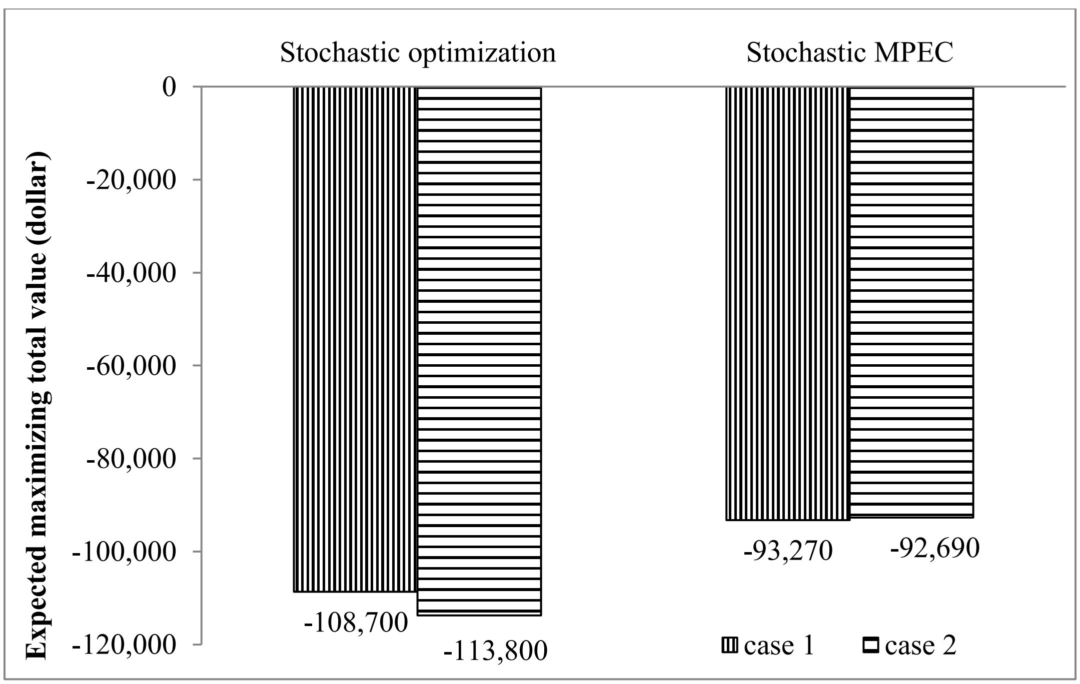


Figure 5.6 The difference of the expected maximizing total value of the stochastic optimization model and stochastic MPEC when optimized based on two different sets of distribution functions.

Moreover, parameters such as conversion rates of biogas, prices for solar panels, renewable energy credits, lifetime of equipment, etc., fixed costs for equipment could also be captured in the sensitivity analysis. However, the study of sensitivity analysis of these parts did not be included in this dissertation.

5.4 Conclusions

The purpose of the sensitivity analysis quantified above was to show the dependence of the model behavior on its parameters. However, from the given data in the two cases chosen, since there was a small difference (below 5%) in the results, this suggests that the model is not very sensitive to the selected data. However, a more extensive sensitivity analysis with different parameters values for the same distributions, different distributions, or other different model parameters might show very different results. For example, conversion rates of biogas, prices for solar panels, renewable energy credits, lifetime of equipment, etc., fixed costs for equipment could also be captured in the sensitivity analysis. However, the study of sensitivity analysis of these parts did not be included in this dissertation.

The comparisons between the stochastic and deterministic analyses show the significance of explicit consideration of the probabilistic information (Gunawan et al. 2005) for these optimization problems. The value of the stochastic solution provided an improvement of about 2.9% on the optimal objective value.

Moreover, the stochastic MPEC showed an increased sales level of products from the digester to the relevant markets over that shown by the stochastic optimization problem. In both models, a small digester was preferred to produce biogas and sell bio-

CNG as well as bio-methane to the relevant markets DC Water was able to gain more revenues from solids end products of wastewater treatment operation process. However, the expected optimal objective value of the stochastic MPEC showed $15,830 per day or $5.77 million per year lower costs than the single-objective stochastic optimization model by selling associated products from biogas to relevant markets. Exogenous prices of bio-CNG, bio-methane and biosolids Class A were taken into account when the stochastic model (single-level problem) was optimized. These downstream markets were not influenced by the decisions of the upper-level player (DC Water). On the other hand, for the two-level, stochastic MPEC, the top-level player was able to exert its influence to achieve a higher profit.

Chapter 6: Conclusions and Possible Future Directions

This dissertation presented novel one-level deterministic and stochastic optimization models as well as an innovative stochastic MPEC and compared the relative benefits of each model (Chapter 5). An application of the model of a wastewater treatment plant was provided to show the benefit for each approach and the Blue Plains facility was used as a testbed. In this section, the conclusions regarding each model are presented, the contributions of this dissertation are enumerated and proposals for future work as an extension of the current work are provided.

6.1 Contribution of This Dissertation

The models and applications presented in this dissertation address the complexity of operational and investment decisions in a typical WWTP and the interaction with many markets such as agricultural, carbon dioxide, and energy markets.

The first major contribution of this research is the development of a deterministic, multi-objective optimization model for wastewater-derived energy to maximize WWTP total value, minimize net carbon dioxide equivalent (CDE) emissions, and minimize energy purchased from external sources. These models can assist DC Water as well as other WWTPs in defining optimal wastewater treatment management policies and operational systems.

A second major contribution of this research is the development a stochastic, multi-objective optimization model for wastewater-derived energy meeting the same three objectives (maximizing WWTP total value, minimizing net CDE emissions, and minimizing energy purchased from external sources). This model can assist WWTPs, in particular, to find the optimal solutions under uncertain conditions (e.g. solid end products resulting from uncertain wastewater inflow, energy consumption internal operating plant and related markets conditions). In this second thrust, scenario-reduction techniques and certain computational aspects are also considered given the large-scale nature of the work.

A third major contribution presents a stochastic MPEC where DC Water is the top-level player interacting with the agricultural, natural gas for transportation, natural gas for residential used and power markets at the bottom level. This type of problem, which is concerned with making an optimal decision with other players present in a non-cooperative competitive environment, is known in economics as a Stackelberg Game. Other WWTPs, solid waste disposal plants, and community management groups can apply this model to find their usefulness decisions and sustainable development.

A fourth contribution of this dissertation is in Chapter 5 where a comparison of the various one- and two-level optimization models is performed. Besides clarifying the advantages of each of the three models described, it is anticipated that decision makers, project managers, and plant operators who design wastewater systems will also benefit from this comparative analysis.

In sum, these three novel models provide DC Water with an optimal wastewater solids management strategy. Other WWTPs, solid waste disposal plants, and community management groups can apply the model to make better waste management decisions under uncertain conditions. Also, future investigators such as decision makers and plant operators can compare the relative benefits of the deterministic optimization, the stochastic optimization and the stochastic MPEC within the WWTP context. The end result is that WWTP management can be better guided towards sustainability and other goals.

6.2 Conclusions

A multi-objective, mixed-integer optimization model for wastewater-derived energy has been developed in Chapter 2 using the Blue Plains advanced wastewater plant (AWTP) as a case study. The results of the deterministic model can assist DC Water, the operator of Blue Plains, and operators like it to achieve environmental and economic goals. Since DC Water can reduce its CDE emissions as well as reduce the energy purchased from external sources, using electricity from digested biogas to supply the Blue Plains facility is a sustainable and environmentally friendly course of action. One result from the analysis of the output of these models was that using a small digester was advantageous when total plant value (revenues less costs) was maximized.

The deterministic optimization model shows that DC Water should use electricity from digested biogas internally. Using biogas and biogas-based electricity produced from the digester on site at Blue Plains is an environmental friendly choice (reducing CDE emissions). However, each ton of CDE offsets results in higher operational costs so there is an interesting tradeoff that can be made. The models and the resulting guidance could greatly help decision-makers at the other 3,171 WWTPs around the U.S. and in other countries.

In addition, solar power could be a significant renewable energy option to reduce energy purchased from outside sources and reduce the total amount of CDE emissions.

Also, tipping fees from organizations that outsourced their wastewater processing to Blue Plains could be another important source of revenue for DC Water.

Perfect decisions require perfect information. However, not every case can find the complete information necessary to make such a decision. In Chapter 3, a stochastic optimization version of the model was presented using 59,049 scenarios resulting from uncertain data. Many stochastic parameters were considered such as the amount of solids end product, the level of energy consumption, energy prices and costs, and CO_2 credits. Decision-makers can use this type of model to hedge their decisions against an uncertain future. A stochastic optimization model could be of great use to wastewater managers who need to consider many factors besides wastewater in the face of profitability (maximizing total value) and sustainability goals (environment, economics and social).

In Chapter 4, a stochastic MPEC for sustainable wastewater management presented, which was developed. The upper level of this two-level problem was the WWTP. The bottom level was composed of the various downstream market players that could be influenced by the WWTP's choices of producing fertilizer, methane or electricity as well as market-clearing conditions. This large-scale, complex two-level problem presented a computational challenge. A scenario-reduction approach was adopted to reduce the number of scenarios. Additionally, SOS1 variables were used to transform the optimality conditions of the lower-level to a more tractable form. Also, for computationally efficiency a linearization of bilinear terms (of the form price times quantity) was used. There are a variety of other disciplines, such as process engineering in chemical engineering, pipeline operations and solid waste management that could also develop and apply both the SOS1 and linearization of bilinear terms approaches to solve large-scale, complex problems.

In Chapter 5, a comparison of the three optimization models is developed. Specifically, we provide a sensitivity analysis of the model inputs, the benefits of each model and advantages of each approach (the deterministic optimization, stochastic optimization and stochastic MPEC). The deterministic optimization model was used to optimize the complicated systems by using average data. However, the stochastic optimization approach was applied to optimize when uncertainty was involved. Incorporating stochasticity showed an improvement and a motivation to use a stochastic MPEC to maximize total value for the top-level player (the wastewater treatment plant).

6.3 Future Research

6.3.1 Decomposition Aspects

The stochastic optimization and the stochastic MPEC models contained a large number of scenarios because 10 and 8 uncertain groups of data were involved, respectively. A scenario-reduction approach was employed to reduce the computational time for the resulting large-scale problem. With the goal of speeding up computation, decomposition strategies like Benders method/L-shaped method (Birge and Louveaux 1997) could be applied to allow for more probabilistic details. Further decomposition efforts would not only yield computational benefits, but also allow the model to make better use of uncertain information and/or include multiple time periods in the model. For example, allowing the model to consider a multi-year timeframe instead of just a current "typical day" for a planning horizon relative to investment decisions would be an improvement. Also, decision makers can consider more detail on seasonal aspects of the relevant markets conditions. Development of computationally efficient decomposition (or other_ methods) for stochastic MPECs like the one developed in this dissertation would therefore be an interesting line of future research.

6.3.2 More Detail on the Lower-level Problems of a Stochastic MPEC for Sustainable Wastewater Management

The lower level players of the MPEC represent the downstream markets that can be influenced by the WWTP by its choices of producing high-end fertilizer, methane or electricity. These markets include: agriculture, compressed natural gas (CNG) transportation, residential natural gas, and electricity. A second area of potential future research would be to enhance these lower-level models from what was developed in this dissertation to allow for more realism in the formulation.

For example, DC Water may consider investing in an internal CNG station infrastructure. According to the digester design (Metcalf & Eddy and AECOM 2008), DC Water has the potential to produce and supply about 2.55 million cf/d of bio-CNG to the transportation sector in Washington, DC. The demand for CNG for buses in the Washington D.C. metro area is about 1.98 million cf/d consumption in 2006. In addition, a CNG station could be established at DC Water to support other CNG vehicles. At present, the District of Columbia has no public stations, two private ones, and the State of Maryland has three public and six private ones. Virginia has five public and twelve private ones. [98]

[98] http://www.afdc.energy.gov/fuels/natural_gas_locations.html

Appendices

Appendix A: Parameters Used for the Deterministic Optimization Model

I_{T_min} = 383 dt

I_{T_max} = 428 dt

Cap = 719 dt

f_G = 12,012 cf/dt (339.94 m^3/dt)

f_{NG} = 0.6 (See detail in A-1)

f_{CNG} = 0.579

f_B = 0.4838 dt/dt solid

$WWTP_E$ = 634,000 kWh

f_E = 0.057 kWh/cf (2.02 kwh/m^3)

$WWTP_{NG}$ = 172,240 cf (4,874.39 m^3)

f_C^E = 0.00055 t/kWh (See A-2)

f_C^{NG} = 0.000056 t/cf (0.00197 t/m^3) (The climate registry 2008)

f_C^{CNG} = 0.000054 t/cf (0.001908 t/m^3) (The climate registry 2008)

f_C^f = 0.1 t/dt (Brown 2004)

f_C^t = 0.2 t/dt (Brown 2004)

f_P^T = 73.50 kWh/dt

f_E^P = \$0.086 per kWh

f_{NG}^P = \$0.00529 per cf (\$0.187 per m^3)

f_E^{Gen} = \$0.00506 per kWh

f_{CNG}^{Com} = \$0.002876 per cf (\$0.1016 per m^3)

f_B^T = \$ 2.1 per dt

$f_A^{Compost}$ = \$36 per dt

f_B^f = \$69.86 per dt

f_E^S = \$0.052 per kWh

f_{CNG}^S = \$0.0116 per cf (\$0.408 per m^3)

C_{allow}^{WWTP} = 346.18 t CDE

f_C^S = \$0.05 per t CDE

f_{REC}^S = \$1.89 per t CDE

F = 0

Digester fixed costs ($h_{i,j}$) in dollars

Digester/segment	1	2	3
1	66,145.68	15,670.68	15,670.68
2	41,982.36	16,744.86	16,744.86
3	66,145.68	108,128.04	32,415.54
4	48,658.94	48,658.94	48,658.94

Operation and Maintenance costs ($a_{i,j}$) in dollars

Digester/segment	1	2	3
1	170.23	271.18	271.18
2	170.23	271.18	271.18
3	170.23	170.23	271.18
4	490.81	490.81	490.81

Minimum solids use to produce biogas $(l_{i,j})$ in dt

Digester/segment	1	2	3
1	500	500.001	750.001
2	250	250.001	750.001
3	500	500.001	750.001
4	500	500.001	750.001

A.1 The calculation of bio-methane and bio-CNG from biogas

Anaerobic digestion of organic matter, especially from landfill, waste, sewage and wastewater, produces biogas, which methane and carbon dioxide gas are the main compositions. Methane from biodegradation can also call bio-methane. Bio-methane can be used as energy like natural gas by using it on-site for heat or power generation, or take it to off-site by injecting into nearly natural gas pipeline or trucking in two different forms, which are compressed natural gas (CNG) and liquefied natural gas (LNG). [99]

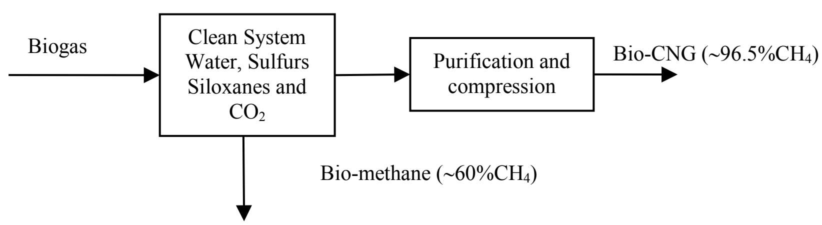


Figure A-1 Composition of bio-methane and bio-CNG on biogas [100] [101] (Appels et al. 2008)

A.2 The calculation indirect CDE emissions from electricity

Emission factors for Washington, DC	1,095.53	lbs CO_2/MWh
	0.028	lbs CH_4/MWh
	0.017	lbs N_20/MWh

[99] http://suscon.org/cowpower/biomethaneSourcebook/biomethanesourcebook.php
[100] http://www.environmental-expert.com/products/biogas-to-compressed-natural-gas-35510.
[101] www.biocng.us.

(The climate registry 2008)

CDE emission factors from electricity are calculated as follows taking into account the molecular weight of each compound:

$$1095.53 + 0.028 \times 21 + 0.017 \times 310 = 1{,}101.388 \text{ lbs CDE/MWh}$$

$$= 0.00055 \text{ t CDE/kWh}$$

This constant is used for parameter $f_C^{\boldsymbol{E}}$.

A.3 The calculation CDE emissions/offsets from land application process

CO_2 emissions from transportation (Brown 2004), (f_C^t) = 0.2 t CDE/dt of biosolids

CO_2 offsets from using biosolids as fertilizer (Brown, 2004), (f_C^f) = 0.1 t CDE/dt of biosolids

A.4 The calculation of CDE emissions for using bio-methane as natural gas

CO_2 emissions from natural gas = 53.06 kg CDE/mmBTU

= 0.000056 t CDE/cf

This constant is used for parameter f_C^{NG}.

A.5 The calculation of CDE offsets for selling CNG for transportation sector

CO_2 offsets from selling CNG = 0.000054 t CDE/cf of CNG (The climate registry 2008)

This constant is used for parameter $f_C^{\boldsymbol{CNG}}$.

Appendix B: Parameters and Density Functions Used for the Stochastic Optimization Model

CAP = 1000 dt

S_{OR1} = 60 dt [102]

S_{OR2} = 50 dt [103]

S_{gas} = 620 dt (Metcalf & Eddy and AECOM 2008)

f_G = 12,012 cf/dt [104]

f_{NG} = 0.6

f_{CNG} = 0.579

f_B = 0.4838 (Metcalf & Eddy and AECOM 2008)

f_E = 0.057 kwh/cf [105]

$WWTP_{NG}$ = 172,240 cf [106]

f_C^E = 0.00055 t/kWh (The climate registry 2008)

f_C^{NG} = 0.000056 t/cf (The climate registry 2008)

f_C^I = 1.44 t/dt (Brown, et al. 2010)

f_C^{CNG} = 0.000054 t/cf (The climate registry 2008)

f_C^f = 0.1 t/dt (Brown 2004)

f_C^t = 0.2 t/dt (Brown 2004)

---

[102] 1,400,000 population, 1.4 x 10^{-4} wet tons per day produced sludge rate, and 70% water content

[103] Wastewater influent 60 MGD and the solid production rate 0.82

[104] The maximum biogas of approximately 4.4×10^6 cf comes from the digester design, which is equal to 12,012 cf/dt times each dry ton of solids influent.

[105] Calculated from the efficiency of one type of power generator using biogas (Metcalf & Eddy and AECOM 2008).

[106] The highest natural gas consumption obtained from the energy saving plan report of December, 2010.

f_P^T = 73.5 kWh/dt

f_P^G = 0.057 kWh/cf

f_P^I = 26.58 kWh-$/dt-gal

f_I^T = 0.56 gal/dt

f_E^{Gen} = $0.00506 per kWh

f_{CNG}^{Com} = $0.002876 per cf

f_A^{Com} = $36 per dt

f_{Ash}^I = $27.85 per dt

f_{CNG}^T = $0.0116 per cf

f_I^{TIP} = $0, $50, $100 per dt of biosolids influent to digester

C_{allow}^{WWTP} = 346.2 t

S_{panel} = 14,944 m^2

RES = $0.05 per kWh [107]

f_{on}^{off} = 0

REC = $1.89 per ton CDE

Digester fixed costs ($h_{i,j}$) in dollars

Digester/segment	1	2	3
1	66,145.68	15,670.68	15,670.68
2	41,982.36	16,744.86	16,744.86
3	66,145.68	108,128.04	32,415.54
4	48,658.94	48,658.94	48,658.94
5	61,504.25	61,504.25	61,504.25

[107] EIA, 2009 mentioned that the generated electricity from rooftop photovoltaic and small wind turbines will earn 1 credit per kWh after 2014, and gain $0.05 per kWh as market value for each credit.

Operation and Maintenance costs ($a_{i,j}$) in dollars

Digester/segment	1	2	3
1	170.23	271.18	271.18
2	170.23	271.18	271.18
3	170.23	170.23	271.18
4	490.81	490.81	490.81
5	92.00	92.00	92.00

Minimum solids use to produce biogas ($l_{i,j}$) in dt

Digester/segment	1	2	3
1	500	500.001	750.001
2	250	250.001	750.001
3	500	500.001	750.001
4	500	500.001	750.001
5	500	500.001	750.001

$I_{WWTP}(s)$ = solids influent to digester (113-814 dt) fitted with weibull distribution function (113+weibull (202, 1.98)).

$E_{consump}(s)$ = electricity consumption at WWTP (564,000-838,000 kWh) fitted with = triangular distribution function (triangular (564,000, 684,000, 838,000)).

$E_{purchased}(s)$ = electricity purchasing costs ($ 0.030-0.136 per kWh) fitted with log normal distribution function (0.01 + lognormal(0.0598, 0.0259)).

$E_{sold}(s)$ = electricity selling prices ($0.019-0.288 per kWh) fitted with log normal distribution function (0.019 + lognormal(38.5, 31.6)).

$NG_{purchased}(s)$ = natural gas purchasing costs ($0.0029-0.013 per cf) fitted with log normal distribution function (0.0029 + lognormal(4.51, 2.27)).

$P_{fossil}(s)$ = fossil fuel prices to transport Class A and B ($1.43-5 per gallon) fitted with triangular distribution function (triangular(1.09, 1.62, 5)).

F_{prices} (s) = fertilizer prices (\$30.92-92.52 per ton) fitted with weibull distribution function (30 + weibull(28.8, 1.3)).

$R_{CO2}(s)$ = carbon credits (\$0.05-8 per ton CO_2) fitted with triangular distribution function (triangular (0, 0.1, 8)).

$S_{radia}(s)$ = solar radiation (0.19-2.65 kWh/m^2) fitted with triangular distribution function (triangular (0, 0.677, 2.9)).

$S_{generate}(s)$ = generated solar electricity cost \$0.12, \$0.13 and \$0.15 per kWh (triangular (16, 17.7, 22.9))

Appendix C: Probability for 59,049 Scenarios Using in the Stochastic Model

Probability for each scenario is calculated by multiplying the probability of ten groups of uncertainty together (the details of each uncertainty probability are shown in Figure B). For example, scenario 1 was multiplied 0.295, 0.338, 0.321, 0.260, 0.136, 0.289, 0.338, 0.180, 0.530 and 0.037 (respectively, the probabilities for the low case of each uncertainty), with a final result of 4.479×10^{-7}. Pr(s) denotes the probability for each scenario and is used to calculate expected values in the three objective functions.

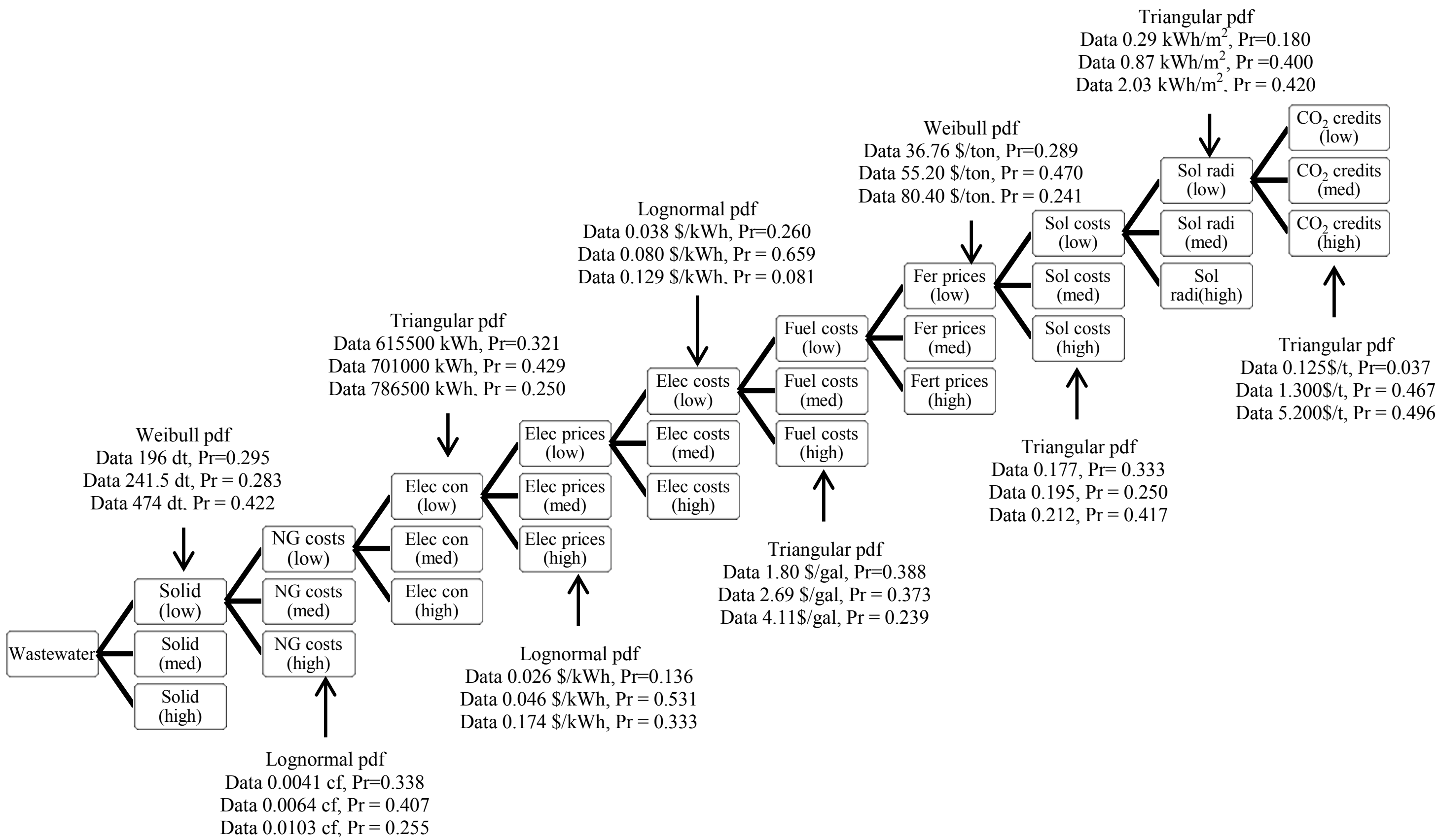


Figure C-1 scenarios tree show probability of uncertain data
Note that low = low amount, med = medium amount, high = high amount
Solid = solid end products, Elec = electricity, Fuel = fossil fuel, Fer = fertilizer, sol = solar electricity.

Appendix D: Parameters and Density Functions Used for the Stochastic MPEC

CAP = 1,000 dt

$\bar{G}_{NG}$ = 166,738 m^3 (5,888,282 cf)

$\bar{G}_{CNG}^{T}$ = 160,068 m^3 (5,652,751 cf)

$\bar{B}_{A}^{AM}$ = 814 dt

$\bar{E}_{B}^{SM}$ = 250,800 kWh

$\bar{E}_{S}^{SM}$ = 30,340 kWh

S_{OR1} = 60 dt

S_{OR2} = 50 dt

S_{gas} = 620 dt (Metcalf & Eddy and AECOM 2008)

f_G = 339.94 m^3/dt (12,012 cf/dt)

f_{NG} = 0.6

f_{CNG} = 0.579

f_B = 0.4838 (Metcalf & Eddy and AECOM 2008)

f_E = 2.02 kwh/m^3 (0.057 kwh/cf)

$WWTP_{NG}$ = 4,874.39 m^3 (172,240 cf)

f_C^E = 0.00055 t CDE/kWh (The climate registry 2008)

f_C^{NG} = 0.00197 t CDE /m^3 (0.000056 t/cf) (The climate registry 2008)

f_C^I = 1.44 t CDE /dt (Brown, et al. 2010)

f_C^{CNG} = 0.001908 t CDE /m^3 (0.000054 t/cf) (The climate registry 2008)

f_C^f = 0.1 t CDE /dt (Brown 2004)

f_C^t = 0.2 t CDE /dt (Brown 2004)

f_P^T = 73.5 kWh/dt

f_P^G = 2.02 kWh/m^3 (0.057 kWh/cf)

f_P^I = 26.58 (kWh-$/dt-gal)

f_I^T = 0.56 gal/dt

f_E^{Gen} = $0.00506 per kWh

$\gamma_{bio-CNG}$ = $0.1016 per m^3 ($0.0058 per cf)

$\gamma_{bio-methane}$ = $0.1765 per m^3 ($0.005 per cf)

f_A^{Com} = $249.6 per dt

f_{Ash}^I = $27.85 per dt

f_I^{TIP} = $0, $50, $100 per dt of biosolids influent to digester

C_{allow}^{WWTP} = 346.2 t

S_{panel} = 14,944 m^2

RES = $0.05 per kWh [108]

f_{on}^{off} = 0

REC = $1.89 per ton CDE

$I_{WWTP}(s)$ = solids influent to digester (113-814 dt) fitted with a Weibull distribution function

$E_{consump}(s)$ = electricity consumption at WWTP (564,000-838,000 kWh) fitted with a triangular distribution function

$E_{purchased}(s)$ = electricity purchasing prices ($ 0.03-0.136 per kWh) fitted with a lognormal distribution function

[108] In (EIA, 2009) it was mentioned that the generated electricity from rooftop photovoltaic and small wind turbines will earn 1 credit per kWh after 2014, and gain $0.05 per kWh as market value for each credit.

$NG_{purchased}(s)$= natural gas purchasing prices (\$0.102-0.459 per m^3) or (\$0.0029-0.013 per cf) fitted with a lognormal distribution function

$P_{fossil}(s)$ = fossil fuel prices to transport Class A and B (\$0.38-1.32 per liter) or (\$1.43-5 per gallon) fitted with a triangular distribution function

$R_{CO2}(s)$ = carbon credits (\$0.05-8 per ton CO_2) fitted with a triangular distribution function

$S_{radia}(s)$ = solar radiation (0.19-2.65 kWh/m^2) fitted with a triangular distribution function

$S_{generate}(s)$ = generated solar electricity cost \$0.12, \$0.13 and \$0.15 per kWh

Random parameter values	Low		Medium		High	
	value	probability	value	probability	value	probability
$I_{WWTP}(s)$ (dt)	196	0.295	241.5	0.283	474	0.422
$E_{consump}(s)$ (kWh)	615,500	0.321	701,000	0.429	786,500	0.250
$E_{purchased}(s)$ (\$/kWh)	0.038	0.260	0.080	0.659	0.129	0.081
$NG_{purchased}(s)$(\$/m^3)	0.148	0.338	0.226	0.407	0.364	0.255
$P_{fossil}(s)$ (\$/litter)	0.48	0.388	0.71	0.373	1.09	0.239
$R_{CO2}(s)$ (\$/ton CO_2)	0.125	0.037	1.30	0.467	5.20	0.496
$S_{radia}(s)$ (kWh/m^2)	0.29	0.180	0.87	0.400	2.03	0.420
$S_{generate}(s)$ (\$/kWh)	0.15	0.333	0.13	0.250	0.12	0.417

Note that the key cut-off value depends on two criteria:

- it should be about the 30th, 60th, or the 100th percentiles (for representativeness)
- the exact percentile is approximated by where a "bin" ends from the goodness-of-fit.

Digester fixed costs ($h_{i,j}$) in dollars

Digester/segment	1	2	3
1	66,145.68	15,670.68	15,670.68
2	41,982.36	16,744.86	16,744.86
3	66,145.68	108,128.04	32,415.54
4	48,658.94	48,658.94	48,658.94
5	61,504.25	61,504.25	61,504.25

Operation and Maintenance costs ($a_{i,j}$) in dollars

Digester/segment	1	2	3
1	170.23	271.18	271.18
2	170.23	271.18	271.18
3	170.23	170.23	271.18
4	490.81	490.81	490.81
5	92.00	92.00	92.00

Minimum solids use to produce biogas ($l_{i,j}$) in dt

Digester/segment	1	2	3
1	500	500.001	750.001
2	250	250.001	750.001
3	500	500.001	750.001
4	500	500.001	750.001
5	500	500.001	750.001

$\bar{q}_{ino}$ = 122,019 dt [109]

$\bar{q}_{org}$ = 1,899.8 dt

$\bar{q}_{fossil}$ = 35,476 kWh [110] (71.31% of average daily retail sales in 2012)

$\bar{q}_{nuclear}$ = 84,920 kWh (16.85% of average daily retail sales in 2012)

$\bar{q}_{hydro}$ = 54,482 kWh (10.81% of average daily retail sale in 2012)

$\bar{q}_{CNG}$ = 1,197,608 m^3(42,293,151 cf) [111] (EIA 2013)

[109] U.S. department of agricultural (USDA) data from 2000 to 2010 (http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx#26720)

[110] An average daily amount of retail sales of electricity to the District of Columbia residential sector is 504,109.6 kWh (EIA 2013)

[111] http://www.eia.gov/oil_gas/natural_gas/data_publications/natural_gas_monthly/ngm.html.

$\bar{q}_{NG}$ = 1,197,608 m^3(42,293,151 cf)

γ_{ino}= $224 per dt [112]

γ_{org}= $249.6 per dt [113]

γ_{fossil} = $0.047 per kWh (EIA 2013)

$\gamma_{nuclear}$= $0.025 per kWh

γ_{hydro}= $0.011 per kWh

γ_{CNG}= $0.671per m^3($0.019 per cf) (included $0.0058 per cf production unit, operation, and maintenance costs [114] and $0.013 per cf natural gas [115] cost)

γ_{NG}=$0.459per m^3($0.013 per cf)

---

[112] http://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx#26720.

[113] The composting process cost in 2008 is $208 per dry ton of fertilizer, which included $8 per dry ton for capital cost and $200 per dry ton for operation and maintenance cost (EPA 2002; Harkness et al. 1994; Wang et al. 2009), and 20% of management cost was added.

[114] www.biocng.us.

[115] http://www.eia.gov/oil_gas/natural_gas/data_publications/natural_gas_monthly/ngm.html.

Bibliography

Abrell, J., and H. Weigt, 2010, Combining Energy Networks.

Alhumaizi, K., and A. Ajbar, 2006, Optimization of an unstructured first-order kinetics model of cyclically operated bioreactors: Journal of environmental engineering, v. 132, p. 453-462.

Alvarez-Vázquez, L. J., N. García-Chan, A. Martínez, and M. Vázquez-Méndez, 2010, Multi-objective Pareto-optimal control: an application to wastewater management: Computational Optimization and Applications, v. 46, p. 135-157.

Amann, M., Klaassen, G., & Schopp, W. International Institute for Applied Systems Analysis, Laxenburg., 1991, Un/ece workshop on exploring european sulfur abatement straegies (Status report SR-91-03).

Anitescu, M., P. Tseng, and S. J. Wright, 2007, Elastic-mode algorithms for mathematical programs with equilibrium constraints: global convergence and stationarity properties: Mathematical programming, v. 110, p. 337-371.

Appels, L., J. Baeyens, J. Degrève, and R. Dewil, 2008, Principles and potential of the anaerobic digestion of waste-activated sludge: Progress in Energy and Combustion Science, v. 34, p. 755-781.

Arent, D. J., A. Wise, and R. Gelman, 2011, The status and prospects of renewable energy for combating global warming: Energy Economics, v. 33, p. 584-593.

Batstone, D.J., Keller, J., Angelidaki, R.I., Kalyuzhnyi, S.V., Pavlostathis, S.G., Rozzi, A., Sanders, W.T.M., Siegrist, H., Vavilin, V.A., 2002, Anaerobic Di-gestion Model No.1 (ADM1), IWA Task Group for Mathematical Modelling of Anae-robic Digestion Processes, STR No. 13, *IWA Publishing*, London, UK. ISBN: 9781900222785

Bazaraa, M. S., H. D. Sherali, and C. M. Shetty, 2013, Nonlinear programming: theory and algorithms, John Wiley & Sons.

Beale, E. M. L., and J. A. Tomlin, 1970, Special facilities in a general mathematical programming system for non-convex problems using ordered sets of variables: OR, v. 69, p. 447-454.

Bergmann, A., N. Hanley, and R. Wright, 2006, Valuing the attributes of renewable energy investments: Energy Policy, v. 34, p. 1004-1014.

Bernstein, M. A., and Griffin, J. The U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, under contract No. DE-AC02-05CH11231, 2006, Regional differences in the price-elesticity of demand for energy (DE-AC36-99-GO10337). Retrieved from website: http://www.osti.gov/bridge.

Birge, J. R., and F. V. Louveaux, 1997, Introduction to stochastic programming, Springer.

Bloemhof-Ruwaard, J. M., P. Van Beek, L. Hordijk, and L. N. Van Wassenhove, 1995, Interactions between operational research and environmental management: European Journal of Operational Research, v. 85, p. 229-243.

Brown, S., 2007, Green'incineration: Biocycle, v. 48, p. 21.

Brown, S., and P. Leonard, 2004, Building carbon credits with biosolids recycling: BioCycle, v. 45, p. 25-29.

Brown, S., N. Beecher, and A. Carpenter, 2010, Calculator tool for determining greenhouse gas emissions for biosolids processing and end use: Environmental science & technology, v. 44, p. 9509-9515.

Bonmat, A., X. Flotats, L. Mateu, and E. Campos, 2001, Study of thermal hydrolysis as a pretreatment to mesophilic anaerobic digestion of pig slurry: Water Science & Technology, v. 44, p. 109-116.

CH2MHILL. (2007). Discussion paper for a wastewater treatment plant; sector greenhouse gas emission reporting protocol 15.

Chandler, K., Eberts, E., & Melendez, M. the United States Department of Energy, National Renewable Energy Laboratory, 2006, Washington metropolitan area transit authority: Compressed natural gas transit bus evaluation (NREL/TP-540-37626). Retrieved from website: http://www.nrel.gov/docs/fy06osti/37626.pdf.

Chang, N.-B., and E. Davila, 2007, Minimax regret optimization analysis for a regional solid waste management system: Waste Management, v. 27, p. 820-832.

Chang, N.-B., and S. Wang, 1996, Solid waste management system analysis by multiobjective mixed integer programming model: Journal of Environmental Management, v. 48, p. 17-43.

Chen, Y., B. F. Hobbs, S. Leyffer, and T. S. Munson, 2006, Leader-follower equilibria for electric power and NO x allowances markets: Computational Management Science, v. 3, p. 307-330.

Cohon, J. L., 2003, Multiobjective programming and planning. New York, NY: Academic Press.

Composting, A., and O. Recycling, 2008, The whey to renewable energy: BioCycle, v. 49, p. 40.

Conejo, A. J., M. Carriâon, and J. M. Morales, 2010, Decision making under uncertainty in electricity markets, v. 153, Springer.

Cottle, R., Pang, J., Stone, R., 2009, "The Linear Complementarity Problem," SIAM, Philadelphia, PA.

Cunha, M. C., L. Pinheiro, J. Zeferino, A. Antunes, and P. Afonso, 2009, Optimization model for integrated regional wastewater systems planning: Journal of water resources planning and management, v. 135, p. 23-33.

Crowe, J., R. Hambrick, J. Snell, and W. Rickerson, 2009, Wastewater plants as green power producers: BioCycle, v. 50, p. 36-39.

DeCarolis, J. F., 2011, Using modeling to generate alternatives (MGA) to expand our thinking on energy futures: Energy Economics, v. 33, p. 145-152.

DeCarolis, J. F., K. Hunter, and S. Sreepathi, 2012, The case for repeatable analysis with energy economy optimization models: Energy Economics.

Draper, A. J., M. W. Jenkins, K. W. Kirby, J. R. Lund, and R. E. Howitt, 2003, Economic-engineering optimization for California water management: Journal of water resources planning and management, v. 129, p. 155-164.

Dupačová, J., N. Gröwe-Kuska, and W. Römisch, 2003, Scenario reduction in stochastic programming: Mathematical programming, v. 95, p. 493-511.

Elliott, R. J., M. R. Lyle, and H. Miao, 2010, A model for energy pricing with stochastic emission costs: Energy Economics, v. 32, p. 838-847.

Ellis, K., and S. Tang, 1991, Wastewater treatment optimization model for developing world. I: Model development: Journal of environmental engineering, v. 117, p. 501-518.

Energy Information Administration (EIA), 2009, Impacts of a 25-percent renewable electricity standard as proposed in the American Clean Energy and Security Act Discussion Draft, Office of Integrated Analysis and Forecasting, U.S. Department of energy, Washington, DC 20585

Energy information administration (EIA), 2009, Renewable Energy Consumption and Electricity 12 Preliminary Statistics. Office of Coal, Nuclear, Electric and Alternate Fuels. U.S. Department of Energy. Retrieved from http://www.eia.gov/fuelrenewable.html.

Energy information administration (EIA), 2011, Annual energy outlook 2011.

Energy Information Administration (EIA), 2012, Annual energy outlook 2012. Retrieved from website: www.eia.gov/forecasts/aeo.

Energy information Administration (EIA). U.S. Department of Energy, 2013, Electric power monthly with data for january 2013. Retrieved from Independent statistics&analysis website: http://www.eia.gov/electricity/monthly/pdf/epm.pdf.

Energy information administration (EIA). U.S. Department of Energy, 2013, Electric power annual 2011. Retrieved from Independent statistics&analysis website: http://www.eia.gov/electricity/annual/pdf/epa.pdf.

Escudero, L. F., A. Garín, M. Merino, and G. Pérez, 2007, The value of the stochastic solution in multistage problems: Top, v. 15, p. 48-64.

European Union (EU). (2008). Climate change: Commission welcomes final adoption of Europe's climate and energy package. Retrieved from http://europa.eu/rapid/press-release_IP-08-1998_en.htm.

Fente, J., K. Knutson, and C. Schexnayder, 1999, Defining a beta distribution function for construction simulation: Simulation Conference Proceedings, 1999 Winter, p. 1010-1015.

Filar, J. A., and A. Haurie, 2010, Uncertainty and environmental decision making, Springer.

Filipiak, K. A., L. Abdel-Malek, H.-N. Hsieh, and J. N. Meegoda, 2009, Optimization of municipal solid waste collection system: case study: Practice Periodical of Hazardous, Toxic, and Radioactive Waste Management, v. 13, p. 210-216.

Fletcher, R., S. Leyffer, D. Ralph, and S. Scholtes, 2006, Local convergence of SQP methods for mathematical programs with equilibrium constraints: SIAM Journal on Optimization, v. 17, p. 259-286.

Fletcher, R., and Leyffer, Sven, 2004, Solving mathematical programs with complementarity constraints as nonlinear programs: Optimization Methods and Software, v. 19, p. 15-40.

Flores-Alsina, X., I. Rodriguez-Roda, G. Sin, and K. V. Gernaey, 2008, Multi-criteria evaluation of wastewater treatment plant control strategies under uncertainty: Water research, v. 42, p. 4485-4497.

Fortuny-Amat, J., and B. McCarl, 1981, A representation and economic interpretation of a two-level programming problem: Journal of the operational Research Society, p. 783-792.

Gabriel, S., P. Sahakij, M. Ramirez, and C. Peot, 2006a, A multiobjective optimization model for processing and distributing biosolids to reuse fields: Journal of the Operational Research Society, v. 58, p. 850-864.

Gabriel, S. A., A. J. Conejo, J. D. Fuller, B. F. Hobbs, and C. Ruiz, 2010, Complementarity modeling in energy markets, Springer.

Gabriel, S. A., R. García-Bertrand, P. Sahakij, and A. J. Conejo, 2005, A practical approach to approximate bilinear functions in mathematical programming problems by using Schur's decomposition and SOS type 2 variables: Journal of the Operational Research Society, v. 57, p. 995-1004.

Gabriel, S. A., and F. U. Leuthold, 2010, Solving discretely-constrained MPEC problems with applications in electric power markets: Energy Economics, v. 32, p. 3-14.

Gabriel, S. A., Y. Shim, A. J. Conejo, S. de la Torre, and R. García-Bertrand, 2009, A benders decomposition method for discretely-constrained mathematical programs with equilibrium constraints: Journal of the Operational Research Society, v. 61, p. 1404-1419.

Gabriel, S. A., S. Vilalai, C. Peot, and M. Ramirez, 2006b, Statistical modeling to forecast odor levels of biosolids applied to reuse sites: Journal of environmental engineering, v. 132, p. 479-488.

Gabriel, S. A., J. Zhuang, and R. Egging, 2009, Solving stochastic complementarity problems in energy market modeling using scenario reduction: European Journal of Operational Research, v. 197, p. 1028-1040.

GAMS, 2009, Generalized Algebraic Modeling System, www.gams.com.

Genc, T. S., and H. Thille, 2011, Investment in electricity markets with asymmetric technologies: Energy Economics, v. 33, p. 379-387.

Greer, D., The whey to renewable energy, Biocycle energy, (2008). pp. 40-44.

Groot, F., C. Withagen, and A. De Zeeuw, 1992, Note on the open-loop von Stackelberg equilibrium in the cartel versus fringe model: The Economic Journal, v. 102, p. 1478-1484.

Gunawan, R., Y. Cao, L. Petzold, and F. J. Doyle III, 2005, Sensitivity analysis of discrete stochastic systems: Biophysical Journal, v. 88, p. 2530-2540.

Gümüş, Z. H., and C. A. Floudas, 2001, Global optimization of nonlinear bilevel programming problems: Journal of Global Optimization, v. 20, p. 1-31.

Harkness, G. E., C. C. Reed, C. J. Voss, and C. I. Kunihiro, 1994, Composting in the Magic Kingdom: Water environment & technology, v. 6, p. 64-67.

He, G., S. Lasaulce, and Y. Hayel, 2011a, Stackelberg games for energy-efficient power control in wireless networks: INFOCOM, 2011 Proceedings IEEE, p. 591-595.

He, L., G. Huang, and H. Lu, 2011b, Greenhouse gas emissions control in integrated municipal solid waste management through mixed integer bilevel decision-making: Journal of hazardous materials, v. 193, p. 112-119.

Heitsch, H., and W. Römisch, 2003, Scenario reduction algorithms in stochastic programming: Computational optimization and applications, v. 24, p. 187-206.

Heitsch, H., and W. Römisch, 2009, Scenario tree modeling for multistage stochastic programs: Mathematical Programming, v. 118, p. 371-406.

Hobbs, B. F., C. B. Metzler, and J.-S. Pang, 2000, Strategic gaming analysis for electric power systems: An MPEC approach: Power Systems, IEEE Transactions on, v. 15, p. 638-645.

Hu, Q., G. Huang, Y. Cai, and Y. Xu, 2013, Energy and Environmental Systems Planning with Recourse: An Inexact Stochastic Programming Model Containing Fuzzy-Boundary Intervals in Objectives and Constraints: Journal of Energy Engineering.

Hu, J., J. E. Mitchell, J.-S. Pang, K. P. Bennett, and G. Kunapuli, 2008, On the global solution of linear programs with linear complementarity constraints: SIAM Journal on Optimization, v. 19, p. 445-471.

Huppmann, D., and F. Holz, 2012, Crude Oil Market Power—A Shift in Recent Years?: The Energy Journal, v. 33.

Høyland, K., and S. W. Wallace, 2001, Generating scenario trees for multistage decision problems: Management Science, v. 47, p. 295-307.

Janssen, M., 1993, Climate change: an optimization approach. Paper prepared for the IFORS XIII conference, 12-16 July, Lisbon.

Kaushal, R. K., and A. K. Nema, 2012, Strategic Analysis of Computer Waste Management Options: Game-Theoretic Approach: Journal of Environmental Engineering, v. 139, p. 241-249.

Kaut, M., and S. W. Wallace, 2007, Evaluation of scenario-generation methods for stochastic programming: Pacific Journal of Optimization, v. 3, p. 257-271.

Kazempour, S., A. J. Conejo, and C. Ruiz, 2011, Strategic generation investment using a complementarity approach: Power Systems, IEEE Transactions on, v. 26, p. 940-948.

Keefer, D. L., 1994, Certainty equivalents for three-point discrete-distribution approximations: Management Science, v. 40, p. 760-773.

Kemp, J. S., and D. L. Lynch, 2009, Evaluation of Class A vs. Class B Processes for Beneficial Use of Biosolids: Proceedings of the Water Environment Federation, v. 2009, p. 1147-1162.

Kenkel, P., and R. B. Holcomb, 2006, Challenges to producer ownership of ethanol and biodiesel production facilities: Journal of Agricultural and Applied Economics, v. 38, p. 369.

Kepp, U., I. Machenbach, N. Weisz, and O. Solheim, 2000, Enhanced stabilisation of sewage sludge through thermalhydrolysis-three years of experience with full scale plant: Water Science & Technology, v. 42, p. 89-96.

Kouwenberg, R., 2001, Scenario generation and stochastic programming models for asset liability management: European Journal of Operational Research, v. 134, p. 279-292.

Kretschmer, B., D. Narita, and S. Peterson, 2009, The economic effects of the EU biofuel target: Energy Economics, v. 31, p. S285-S294.

Lasaulce, S., Y. Hayel, R. El Azouzi, and M. Debbah, 2009, Introducing hierarchy in energy games: Wireless Communications, IEEE Transactions on, v. 8, p. 3833-3843.

Lavigne, D., R. Loulou, and G. Savard, 2000, Pure competition, regulated and Stackelberg equilibria: Application to the energy system of Quebec: European Journal of Operational Research, v. 125, p. 1-17.

Lee, S.-Y., A. F. Hamlet, C. J. Fitzgerald, and S. J. Burges, 2009, Optimized flood control in the Columbia River Basin for a global warming scenario: Journal of Water Resources Planning and Management, v. 135, p. 440-450.

Leyffer, S., G. López-Calva, and J. Nocedal, 2006, Interior methods for mathematical programs with complementarity constraints: SIAM Journal on Optimization, v. 17, p. 52-77.

Li, Y., and G. Huang, 2011, Integrated Modeling for Optimal Municipal Solid Waste Management Strategies under Uncertainty: Journal of Environmental Engineering, v. 137, p. 842-853.

Li, Y., G. Huang, Z. Yang, and S. Nie, 2008, An integrated two-stage optimization model for the development of long-term waste-management strategies: Science of the total environment, v. 392, p. 175-186.

Luo, Z.-Q., J. Pang, D. Ralph, 1996, Mathematical programs with equilibrium constraints, Cambridge University Press.

Mankiw, N. G., 2012, Principles of microeconomics, Cengage Learning.

Maqsood, I., and G. H. Huang, 2003, A two-stage interval-stochastic programming model for waste management under uncertainty: Journal of the Air & Waste Management Association, v. 53, p. 540-552.

Metcalf&Eddy and AECOM, 2008, Biosolids management program summary report for the Blue Plains Advance Wastewater Treatment Plants.

Mitsos, A., 2010, Global solution of nonlinear mixed-integer bilevel programs: Journal of Global Optimization, v. 47, p. 557-582.

Morales, J. M., S. Pineda, A. J. Conejo, and M. Carrion, 2009, Scenario reduction for futures market trading in electricity markets: Power Systems, IEEE Transactions on, v. 24, p. 878-888.

National Renewable Energy Laboratory (NREL), 2006, 75 Largest Transit Agencies, fiscal year 2002 Ranked by Passenger Miles (Thousands), American Public Transit: Technical report NREL/TP -540-37626,http://www.apta.com/research/stats/overview/75largest.cfm.

Oleszkiewicz, J., and D. Mavinic, 2002, Wastewater biosolids: an overview of processing, treatment, and management: Journal of Environmental Engineering and Science, v. 1, p. 75-88.

Pannell, D. J., 1997, Sensitivity analysis of normative economic models: theoretical framework and practical strategies: Agricultural economics, v. 16, p. 139-152.

Peralta, R., and I. M. Kalwij, 2004, Mathematically optimizing water management: EWRI 2004 Groundwater Symposium.

Perlack, R. D., and C. E. Willis, 1985, Multi-objective decision-making in waste disposal planning: Journal of environmental engineering, v. 111, p. 373-385.

Peters, G. M., and H. V. Rowley, 2009, Environmental comparison of biosolids management systems using life cycle assessment: Environmental science & technology, v. 43, p. 2674-2679.

Pezeshk, S., 1994, Data management for large-scale water-distribution optimization systems: Journal of Water Resources Planning and Management, v. 120, p. 116-120.

Pimentel, D., L. Hurd, A. Bellotti, M. Forster, I. Oka, O. Sholes, and R. Whitman, 1973, Food production and the energy crisis: Science, v. 182, p. 443-449.

Rask, K. N., 1998, Clean air and renewable fuels: the market for fuel ethanol in the US from 1984 to 1993: Energy Economics, v. 20, p. 325-345.

Rawal, N., R. M. Singh, and R. Vaishya, 2011, Optimal management methodology for solid wastes in Urban Areas: Journal of Hazardous, Toxic, and Radioactive Waste, v. 16, p. 26-38.

Rosso, D., and M. K. Stenstrom, 2008, The carbon-sequestration potential of municipal wastewater treatment: Chemosphere, v. 70, p. 1468-1475.

Ross, S., 2012, Simulation. Academic Press.

Ruiz, C., A. J. Conejo, and Y. Smeers, 2012, Equilibria in an oligopolistic electricity pool with stepwise offer curves: Power Systems, IEEE Transactions on, v. 27, p. 752-761.

Ruiz, C., and A. J. Conejo, 2009, Pool strategy of a producer with endogenous formation of locational marginal prices: Power Systems, IEEE Transactions on, v. 24, p. 1855-1866.

Ryan, F., and B. Caulfield, 2010, Examining the benefits of using bio-CNG in urban bus operations: Transportation Research Part D: Transport and Environment, v. 15, p. 362-365.

Ryckebosch, E., M. Drouillon, and H. Vervaeren, 2011, Techniques for transformation of biogas to biomethane: Biomass and bioenergy, v. 35, p. 1633-1645.

Scheel, H., and S. Scholtes, 2000, Mathematical programs with complementarity constraints: Stationarity, optimality, and sensitivity: Mathematics of Operations Research, v. 25, p. 1-22.

Schwarz, H.-G., 2005, Modernisation of existing and new construction of power plants in Germany: results of an optimisation model: Energy economics, v. 27, p. 113-137.

Shmoys, D. B., and C. Swamy, 2004, Stochastic optimization is (almost) as easy as deterministic optimization: Foundations of Computer Science, 2004. Proceedings. 45th Annual IEEE Symposium on, p. 228-237.

Siddiqui, A, S., 2011, Solving two-level optimization problems with applications to robust design and energy markets.

Shy, O., 1996, Industrial organization: theory and applications: MIT Press Books, v. 1.

Siddiqui, S., and S. A. Gabriel, 2012, An SOS1-based approach for solving MPECs with a natural gas market application: Networks and Spatial Economics, p. 1-23.

Stamatakis, M., and N. V. Mantzaris, 2009, Comparison of Deterministic and Stochastic Models of the lac Operon Genetic Network: Biophysical journal, v. 96, p. 887-906.

Steffensen, S., and M. Ulbrich, 2010, A new relaxation scheme for mathematical programs with equilibrium constraints: SIAM Journal on Optimization, v. 20, p. 2504-2539.

Tan, Q., G. Huang, and Y. Cai, 2011, Robust planning of environmental management systems with adjustable conservativeness under compound uncertainty: Journal of Environmental Engineering, v. 138, p. 208-222.

The climate registry, 2008, General reporting protocols for the voluntary reporting program: version 1.1.

Tolcott, F. W.,1992, Environmental agenda; the time is ripe for an analytical approach to policy problems. OR/MS Today, (June), 18-24.

The U.S. Department of Energy, 2004, Federal Energy Management Program, Biomass and alternative methane fuels (BAMF) super ESPC fact sheet.

The U.S. Environmental Protection Agency (EPA), 1994b, Land Application of Sewage Sludge: A Guide for Land Appliers on the Requirements of the Federal Standards for the Use or Disposal of Sewage Sludge, 40 CFR Part503, Office of Enforcement and Compliance Assurance, EPA, Washington, DC. Report no. EPA 831-B-93-002b.

The U.S. Environmental Protection Agency (EPA), 2002, Office of Water, EPA 832-F-02-024.

The U.S. Environmental Protection Agency (EPA), 2004, Metrics for expressing greenhouse gas emissions: Carbon equivalents and carbon dioxide equivalents: The U. S. Environmental Protection Agency Office of Transportation and Air Quality, EPA 420-F- 05-2002.

The United States Environmental Protection Agency (EPA), 2005, Auxiliary and supplemental power fact sheet: microturbines, EPA-832-F-05-014.

The U.S. Environmental Protection Agency (EPA), 2006, Status Report: Land Application of Biosolids, Office of Inspector General, EPA, Washington, DC. Report no. 2002-S-000004.

The United States Environmental Protection Agency (EPA), 2006, Status Report: Land Application of Biosolids (Report no. 2002-S-000004). Office of Inspector General, EPA, Washington, DC.

The U.S. Environmental Protection Agency (EPA), 2007, Opportunities for and benefits of combined heat and power at wastewater treatment facilities. EPA-430-R-07-003.

The United States Environmental Protection Agency (EPA), 2007, eGRID2006 Version 2.1 (2004 data); CH_4 and N_2O factors provided by EPA Climate Leaders based on eGRID2006 fuel consumption and electricity generation data and U.S. EPA's Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2005

The U.S. Environmental Protection Agency (EPA), Combined Heat and Power Partnership, 2011, Opportunities for combined heat and power at wastewater treatment facilities: Market analysis and lessons from the fields.

The U.S. Environmental Protection Agency (EPA), Solids Waste and Emergency Response (5306P), 2011, Municipal solid waste generation, recycling, and disposal in the United States: Facts and figures for 2010. Retrieved from website: www.epa.gov/wastes.

The U.S. Department of energy, 2013, Energy efficiency and renewable energy: Clean cities alternative fuel price report.

Traber, T., and C. Kemfert, 2011, Gone with the wind?—Electricity market prices and incentives to invest in thermal power plants under increasing wind energy supply: Energy Economics, v. 33, p. 249-256.

Uderzo, A., 2010, Exact penalty functions and calmness for mathematical programming under nonlinear perturbations: Nonlinear Analysis: Theory, Methods & Applications, v. 73, p. 1596-1609.

Van Beek, P., L. Fortuin, and L. Van Wassenhove, 1992, Operational research and the environment: Environmental and Resource Economics, v. 2, p. 635-639.

Van Groenendaal, W. J., and J. P. Kleijnen, 2002, Deterministic versus stochastic sensitivity analysis in investment problems: an environmental case study: European Journal of Operational Research, v. 141, p. 8-20.

Vesilind, P. A., 2003, Wastewater treatment plant design.[1]. Textbook, IWA publishing.

Von StackelberG, H., 2011, Market structure and equilibrium, Springer.

Wang, H., S. L. Brown, G. N. Magesan, A. H. Slade, M. Quintern, P. W. Clinton, and T. W. Payn, 2008, Technological options for the management of biosolids: Environmental Science and Pollution Research-International, v. 15, p. 308-317.

Wang, L. K., N. C. Pereira, and Y. T. Hung, 2009, Biological treatment processes, v. 8, Springer.

Ward, A. J., P. J. Hobbs, P. J. Holliman, and D. L. Jones, 2008, Optimisation of the anaerobic digestion of agricultural resources: Bioresource Technology, v. 99, p. 7928-7940.

Wiser, R., & Barbose, G., 2008, "Renewables energy standards in the united states: A status report with data through 2007," Lawrence Berkeley National Laboratory, report LBNL 154-e. Retrieved from http://eetd.lbl.gov/ea/ems/reports/lbnl-154e.pdf.

WEF. (2012). Solids process design and management. Mc Graw Hill.

Ye, G., and K. Soga, 2011, Energy harvesting from water distribution systems: Journal of Energy Engineering, v. 138, p. 7-17.