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Optimization Modeling Approach to Facilitate Decision Making Process of Energy Planning on College Campuses

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by

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Abstract

Increasing global environmental problems require a rapid response from universities (Sharp, 2002). Energy consumption of universities is increasing due to, for example, expansion in use of electronics and new building constructions (Levine, 2009; Sharp, 2002). There are increasing numbers of initiatives on university campuses to address climate change. The American College and University President's Climate Commitment (ACUPCC) is an effort by a group of colleges and universities that have pledged to eliminate greenhouse gas (GHG) emissions from their campus operations and become carbon neutral by a target date set by each university itself (ACUPCC, 2006).

This research presented an optimization approach to help decision makers of universities find an optimal energy plan that meet their environmental goals while minimizing costs associated with those energy plans. The optimization approach takes into consideration annual energy demand, budget constraints, and environmental constraints. This study analyzed the usefulness of a long-term planning approach. The results showed that a single long-term energy plan was better than integrated multiple short-term energy plans for a given planning horizon. However, long-term energy plans required higher capital investments. In addition, Monte Carlo simulation is used to analyze uncertainties associated with natural gas, electricity, and carbon prices. The optimization approach developed in this work can be used by university decision makers to make long-term decisions to meet their environmental goals in a cost effective manner.

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Dedicated to One of My Favorite Quotes:

“I think we risk becoming the best informed society that has ever died of ignorance”- Reuben Blades

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Chapter 1. Introduction

1.1 Motivation:

Increasing global environmental problems require a rapid response from universities (Sharp, 2002). Universities should not only be sustainable in their campus operations, but also provide leadership for the broader society (Sharp, 2002). Electricity consumption of universities is increasing due to, for example, expansion in use of electronics and new building constructions (Levine, 2009; Sharp, 2002).

There are increasing numbers of initiatives on university campuses to address climate change. The American College and University President's Climate Commitment (ACUPCC) is an effort by a group of colleges and universities that have pledged to eliminate greenhouse gas (GHG) emissions from their campus operations and become *carbon neutral* by a target date set by each university itself (ACUPCC, 2006). ACUPCC recommended that universities minimize GHG emissions and use carbon offsets to neutralize the remaining emissions (ACUPCC, 2006). Emissions reported in a GHG inventory are usually divided in three categories: Scope 1, Scope 2, and Scope 3 emissions (Klein-Banai & Theis, 2011). Emissions associated with on-site fuel consumption are categorized as Scope1 emissions. Emissions associated with purchased heat, cooling, steam, and electricity are considered as Scope 2 emissions. All emissions associated with air travel, transmission and distribution losses associated with purchased electricity, commuting, refrigerant, and waste are categorized as Scope 3 emissions (Klein-Banai & Theis, 2011). According to the analysis conducted by (Klein-Banai & Theis, 2011), Scope 1 and Scope 2 emissions constitute the majority of emissions in colleges.

The ACUPCC' commitment requires each participating university to prepare a Climate Action Plan (CAP) detailing methods and timelines to become carbon neutral in their operations by a

certain date set by the universities themselves (ACUPCC, 2006). According to (ACUPCC, 2006), the GHG inventory can provide a basis to develop a CAP because the inventory reveals what and how much emissions are created through every campus operation. (Levine, 2009; Simpson, 2009) propose a number of actions such as energy efficiency projects, renewable energy projects, carbon credits, and renewable energy credits (REC) that universities can consider to reduce their carbon footprint. A CAP should usually describe: i) which energy alternatives should be installed; ii) what is the size of the alternatives that need to be installed; iii) when should the alternative be installed during a given planning horizon. However, there is no standard approach for developing a CAP, and many universities find it difficult to complete such plans and they often lack the necessary resources for effective planning (Abbott, 2010; Rizzoa & Savinob, 2012).

There are many energy saving opportunities on college campuses such as using ENERGY STAR equipment, efficient lighting, and energy conservation that many universities have failed to capture (Levine, 2009; Simpson, 2009). A campus can be made more energy efficient by implementing such "low hanging fruit" projects that need modest capital investment and offer significant energy savings. Therefore, universities may prioritize such actions for short-term emission reductions. Simpson (2009) argued that universities usually prefer projects that have short payback period and may ignore projects with longer payback period. Moreover, Levine, (2009) suggested that there might be fewer such opportunities remaining in universities that have been part of campus sustainability initiatives for a long period and may already have exploited projects with quick payback period such as energy efficient lighting. According to Simpson (2009), once all opportunities of short payback period are exhausted, it becomes difficult for decision makers to justify projects with longer payback period because these projects appear to

be financially unattractive. However, projects with longer payback are essential for substantial reductions in GHG emissions (Simpson, 2009).

Another example of short-term thinking could be reliance on Renewable Energy Credits (RECs). ACUPCC commitment allows universities to purchase RECs and carbon offsets to neutralize their emissions (ACUPCC, 2006). Purchasing RECs may be an inexpensive way to reduce carbon footprint associated with the purchased electricity and support the development of clean energy sources. However, buying RECs may be cheaper in short-term, but may become expensive in the long run (Simpson, 2009). Despite many benefits of RECs, some skeptics argued that RECs purchasers receive nothing of value other than “bragging rights” (Simpson, 2009). Therefore, universities focusing on short-term benefits may be tempted to buy RECs and refrain from investing in long-term renewable energy projects.

Among the sustainability problems that university decision makers face are limited financial resources, emission constraints, and availability of a large number of energy supply options, and large number of energy efficiency measures. Selecting the optimal combination of supply options and efficiency measures is not an easy task. Uncertainties in future values of various cost parameters further complicate the decision making process to find an optimal plan. (Awerbuch, 2000) argued that economic models that ignore uncertainties may favor cheap fossil fuel technologies with cost streams that are very sensitive to fluctuations in the fuel prices over capital intensive technologies such as photovoltaic with expensive but a uniform cost stream.

Usually, planning is done by assuming a single future cost scenario. Such analysis produces a single optimal plan. However, there are a large number of possible cost scenarios due to the uncertainties in the future value of various input cost parameters. Such uncertainties in the future

value of various cost parameters also make it more complicated to find a lowest cost action plan in long-term investment strategies because each scenario may produce a different optimal plan (Awerbuch, 2000). According to Hobbs, (1995) it is possible to identify a robust plan that, although not optimal, performs satisfactorily well under all or most of the possible scenarios if uncertainties are also considered. There appears to be a need for methodologies that can help universities design a CAP that meets requirements of their decision makers such as annual budget constraints and environmental constraints. According to (Levine, 2009), decision makers of a university should consider available resources, uncertainties, and their risk attitudes while preparing their CAP. Financially risk-averse colleges may set interim as well as final goals they are certain to meet (Levine, 2009).

Application of optimization models in determining multi-period optimal energy mix in an energy system is not new. Several studies (Cormio, Dicorato, Minoia, & Trovato, 2003; Mirzaesmaeeli, Elkamel, Douglas, Croiset, & Gupta, 2010) propose energy optimization models to determine multi-period investment strategies for a typical energy system. The main purpose of such models consists of determining what energy alternatives should be installed, what size of an alternative should be installed, and how installed alternatives should be operated in order to satisfy energy demand and environmental constraints in each period. These studies failed to account for uncertainties in input parameters. Other studies use models based on Monte-Carlo Simulation to account for risks in electricity and gas prices (Dicorato, Forte, & Trovato, 2008; Feretic & Tomsic, 2005; Hawkes, 2010; Vithayasrichareon, MacGill, & Fushuan, 2009). However, these studies focus on single period rather than multi-period investment planning. This thesis will focus primarily on uncertainties in fuel prices, electricity prices, and carbon prices only.

However, the model developed in this study will be capable of incorporating other types of uncertainties as well.

1.2 Problem Statement

Suppose a university aims to determine what energy mix will satisfy partially or fully its annual energy demand (heat and electricity) in an environmentally responsible way. The costs to achieve carbon neutrality depend on the energy action plan of the institution. Each plan can be composed of a selection of different options that may differ from each other in economic and environmental factors. Some technologies such as fossil based generations have lower capital costs, fuel costs, and higher emissions. Some technologies such as renewable energy have higher capital cost, no fuel cost, and lower or zero emissions. In addition to generating energy, universities can also purchase electricity from the grid. Renewable energy credits and carbon offsets can also help to reduce carbon footprint of a university without investing in renewable energy technologies.

Based on available options and their characteristics, decision makers are required to find optimal contribution/share of each option in an energy plan. While developing an energy plan, decision makers may prefer to divide the planning horizon into multiple short-term planning periods and develop an optimal plan for each portion of that planning period. Such a strategy will produce multiple short-term optimal plans, which may be sub-optimal through a perspective of long-term planning period. On the other hand, decision makers may choose to develop an optimal plan by considering the entire planning horizon as a single planning period. However, such long-term plans may have high initial capital investments. There are financial constraints that must be met. Some universities may not have adequate financial resources to make large capital investments, which may force them to make sub-optimal choices.

In addition, some plans may be required to just focus on the ultimate goal of carbon neutrality that will ensure zero emissions after a certain date without any regards to the annual emission trajectory. Some plans may have additional constraints such as annual emission limits, which will lead to a gradual emission reduction trajectory to carbon neutrality. Different emission trajectories can have different impacts on the cost to achieve carbon neutrality (Mirzaesmaeeli et al., 2010). There are various energy alternatives available to choose from that might fulfill these constraints. However, developing an energy plan by selecting appropriate size and combination of alternatives, while simultaneously satisfying various constraints under uncertainties, is a very challenging task. Also, conventional practice of analyzing each single alternative independently for its net present value or cost-benefit ratio may not be effective in developing an optimal energy plan because there are many alternatives, and some of them are interdependent (George Mavrotas, Florios, & Vlachou, 2010). Therefore, the universities can use optimization models to develop an energy action plan that takes into consideration their objectives, budget constraints, and environmental constraints. The modeling approach can also help university decision-makers deal with the uncertainties.

Rizzoa & Savinob, (2012) asserted the importance of using linear programming models in developing optimal energy plans. The authors showed that short-term and long-term planning produce different optimal energy plans. The long-term planning required large capital investment and had more long-term benefits than short term planning, which required small capital investment. Several models have been proposed to study energy planning for an energy system (Cormio et al., 2003; Mirzaesmaeeli et al., 2010; Rizzoa & Savinob, 2012). These proposed deterministic models determine an optimal combination of energy options in an energy system by minimizing total cost under various budget and environmental constraints. However, the

various uncertain factors such as long term utility prices and carbon prices make quantifying actual cash flow for each plan uncertain. Therefore, under the budget and environmental constraints, choosing the right investment plan using deterministic models alone is not only difficult, but inadequate. This thesis proposes integrating the use of deterministic optimization models (e.g. Linear Programs) into a Monte-Carlo Simulation experiment to properly deal with planning uncertainties.

This thesis proposes and applies an optimization model to develop energy plan for Rochester Institute of Technology (RIT) and produce experimental results to address the following research questions:-

1) How and to what extent will the length of the planning period (no planning, every five years, every ten years, or once in every 20 years) affect an energy plan?

2) How and to what extent will the annual emission and/or carbon offset targets affect an energy plan?

3) How will an energy plan adopted for one particular scenario behave under different future cost scenarios?

This study does not generalize the experimental results to the planning of energy investments made by all universities, but it rather suggests an optimization based methodology that could be used to enrich and improve energy supply planning.

The remainder of the thesis is organized as follows: - Chapter 2 provides a literature review. Chapter 3 presents the section on methodology used to answer research questions mentioned above. Chapter 4 provides an experimentation of the model. Chapter 5 provides an analysis and discussions of the results. Chapter 6 concludes, and suggests future work.

Chapter 2. Literature Review

2.1 Mathematical Models in Energy Planning

Linear programming models are widely used tools in energy planning (Cormio et al., 2003; Hobbs, 1995; G. Mavrotas, Demertzis, Meintani, & Diakoulaki, 2003; Mirzaesmaeeli et al., 2010). A number of energy planning tools have been developed for national and regional level energy systems (S. Awerbuch & Berger, 2003; Cormio et al., 2003; Mirzaesmaeeli et al., 2010). There appears to be growing interest in applying similar models in the planning of small-scale and building level energy systems (Jackson, 2008; George Mavrotas et al., 2010; Rizzoa & Savinob, 2012). Some of these models consider uncertainties in input parameters (S. Awerbuch & Berger, 2003; Feretic & Tomsic, 2005; Vithayasrichareon et al., 2009), but focus on one-time investments. Some of these models do not consider uncertainties, but provide multi-year investment plans (Cormio et al., 2003; Mirzaesmaeeli et al., 2010). However, there appears to be a lack of studies that used energy models to analyze effects of uncertainties on multi-year investments plans.

Mirzaesmaeeli et al. (2010) proposed a deterministic non-linear multi period model, which was reduced to a linear model using an *exact linearized method*. George Mavrotas et al. (2010) developed a MILP model for energy planning in a hotel and applied Monte-Carlo simulation (MCS) technique to capture economic uncertainties. The model determines which and what size of energy alternatives should be installed to minimize annualized costs while meeting heating, cooling, and electricity load. George Mavrotas et al. (2010) conducted a case study in which electricity price, natural gas price, and discount rate were considered to be uncertain. According to the results, for a majority of the scenarios, a new Combined Heat and Power (CHP) unit was part of the every optimal solution obtained after each repetition of MCS. However, only for few

numbers of scenarios when prices of natural gas were high and prices of electricity were low, installation of CHP unit was not part of optimal solution. These results provide an interesting insight. If a decision maker solves the model for single instance of input parameters by assuming high gas prices and low electricity prices, then optimal solution would become sub-optimal in many future scenarios. However, application of MCS can help the decision maker realize how objective function and decision variables vary with the given uncertainties in the input parameters (George Mavrotas et al., 2010).

S. Awerbuch & Berger (2003) and Roques, Newbery, & Nuttall (2008) applied the portfolio approach to derive *efficient energy portfolios* for large energy systems. At any given time in an energy portfolio, generation costs of some technologies are higher than the generation costs of the other technologies in the portfolio. Over time, an optimal combination and share of technologies in the portfolio minimizes overall generation cost of the portfolio relative to the risk. Risk can be defined as yearly fluctuation in the generation costs of the technologies (Awerbuch, 2000). Each efficient portfolio has some cost and risk associated with it. A decision maker may choose any portfolio based on the risk attitude of the decision maker. However, the portfolio approach assumes that the generation costs of various technologies are normally distributed, which may not necessarily be true (S. Awerbuch & Berger, 2003).

Feretic & Tomsic (2005) used Monte-Carlo simulation to generate probability distribution of *levelized cost of energy* from three different power plants: coal, nuclear, and natural gas. Levelized cost of energy is defined as average cost of a unit of energy from a power plant over its lifetime. Its unit is $/kWh. The authors used probability distributions to describe uncertain input parameters such as investment cost, fuel cost, and operation life time of power plant. The authors analyzed the impact on energy costs due to externalities. Cost of energy from coal almost

doubled after introducing external costs such as environmental costs. Cost of energy from natural gas increased 30 percent due to external costs. One of the conclusions the authors drew was the importance of environmental and social costs of power plants. Therefore, any energy planning process should also consider environmental costs that may occur in future while evaluating economics of an energy plan. However, the method proposed in (Feretic & Tomsic, 2005) uses just Monte-Carlo Simulation, therefore, can only be useful in simulating generating cost of a given energy technology under uncertainty rather than finding an optimal combination of various technologies. Vithayasrichareon et al. (2009) proposed a linear programming model to determine optimal operation of a portfolio by minimizing operational costs. The authors also used Monte-Carlo Simulation to study the impact of various uncertainties on overall generation cost of various portfolios composed of one or more of following technologies: coal, combine cycle gas turbine, and open cycle gas turbine. The authors considered uncertainties in carbon price, coal price, and gas price by representing those uncertainties by normal distributions.

Hawkes (2010) proposed a deterministic linear programming model to determine the optimal installation capacity of various energy technologies in an energy system. The objective function minimized equivalent annual cost (EAC) of energy system. The author conducted the experiment in two steps. The first step performed deterministic optimization based on single estimates of energy prices. The second step used Monte-Carlo Simulation (MCS) for the combination of energy technologies obtained in the first step to account for uncertainties in electricity, natural gas, and wind speed. The results obtained through MCS showed that the deterministic optimization ignored economic risks. Therefore, it can be concluded that optimal solution based on a single estimate of fuel prices may become suboptimal under different prices scenarios. A simulation can provide a better insight into generation costs that a single deterministic analysis.

Rizzoa & Savinob, (2012) presented a deterministic linear programming model suitable for solving energy and environmental planning problems at small scale and municipal level. The authors illustrated the application of model by describing an optimal resource allocation problem to reduce emissions at school level. (Rizzoa & Savinob, 2012) also asserted that an optimal solution for a particular objective could not simply be obtained by finding optimal solution that meets half the objective, and then doubling the values of each decision variable to find the solution to meet the complete objective. For example, a best strategy to reduce emissions by 100 percent was different from a strategy to reduce emission from 0 to 50 percent, and then doubling the value of each decision variable. Therefore, according to the authors, the results implied that the decision makers should have a clear picture of objectives and available resources at the beginning of a planning horizon.

Cormio et al. (2003) proposed a dynamic linear programming model that finds the *optimal mix* of energy technologies for an energy system. The objective was to minimize present cost of the system over the entire planning period of 10-20 years. The system was subject to energy demand and environmental constraints. This model was then applied to a regional energy system in Italy. Mirzaesmaeeli et al. (2010) proposed a deterministic multi-period MILP model to determine optimal-mix of generation technology that will meet energy demand and CO2 emission targets at minimum cost. The objective function proposed seeks to minimize overall discounted cost over the planning horizon. The model though comprehensive did not account for uncertainties in future prices that would have affected investment decisions. As a college campus has a smaller, but similar energy system as a regional energy system, a model similar to the models proposed in (Cormio et al., 2003; Mirzaesmaeeli et al., 2010) can be formulated to study energy systems of college campuses.

In summary, Feretic & Tomsic (2005), Hawkes (2010), George Mavrotas et al (2010), and Vithayasrichareon et al. (2009) proposed energy models that consider uncertainties in various input cost parameters. However, these models focus on one time investment strategies. Cormio et al (2003), Mirzaesmaeeli et al (2010), and Zakerinia & Torabi (2010) proposed energy models that provided multi-period investment strategies, but failed to consider uncertainties. This thesis is proposing a deterministic multi-period optimization model to determine optimal mix of energy technologies in a small-scale energy system for a given demand. Moreover, the model will integrate Monte-Carlo Simulation (MCS) to account for uncertainties in electricity, natural gas, and carbon prices.

This work will not optimize operational schedule of various alternatives as done in previous studies (Cormio et al., 2003; Mirzaesmaeeli et al., 2010). The main reason for this limitation is inclusion of non-dispatchable technologies such as wind and solar. Power production from these technologies is unpredictable. Therefore, this work will use annual energy values only.

Chapter 3. Methodology

3.1 Mathematical Programming

Mathematical programming is a tool for solving optimization problems. A typical optimization problem has the following components (Winston & Goldberg, 1994):

i. Objective function: The objective function is the goal of the problem. It can be minimize or maximize a criterion (costs or benefits) or multiple criteria simultaneously (costs and risks).

ii. Decision variables: The decision variables describe decisions that have to be made in order to solve the problem

iii. Constraints: Constraints are conditions that must be met by any solution. In other words, constraints restrict the values decision variables can take.

Optimization problems can be represented by mathematical models, which try to determine values of decision variables that minimize or maximize the objective function among the set of all decision variables that satisfy given constraints. The constraints in most of the optimization models used in the energy sector usually ensure the power and energy demand of an energy system. Additional constraints such as technological limitations, environmental constraints, fuel consumption limits, and size limits are also considered. Usually, addition of each new constraint increases the cost of optimal solution. The decision variables in a typical optimization problem related to energy investments are finding the optimal size of various energy technologies in a given energy system, optimal operation of each technology, and/or sequence of additional installations of each technology required in order to satisfy the constraints such as energy demand (Hobbs, 1995). The typical objective in most of energy planning models is to minimize the discounted life cycle cost or net present value (NPV) of meeting energy needs of an energy

system over the entire planning horizon (Hobbs, 1995). This chapter develops an energy planning model that combines Mathematical Programming and Monte Carlo simulation in order to address research questions described in the first chapter. Combining deterministic mathematical models and Monte Carlo simulation is a challenging task. This work will use an approach similar to the one described in (Feretic & Tomsic, 2005; Hawk, 2010). The methodology is proposed in two parts. The first part develops a deterministic optimization model to represent an energy system. The second part experiments with Monte Carlo simulation based on the findings of the first part to account for uncertainties.

3.2 Model Formulation

This section describes a model, which is a multi-period deterministic Linear Programming (LP) model. The section (3.2.1) details the various sets and notations used in the model. The model finds the values of decision variables (see section 3.2.3) such as capacities of energy alternatives that need to be installed and energy to be bought over a given planning period. The various constraints are described in section (3.2.5). The main constraints incorporated in the model include need to meet annual energy demand (3.2.5.1) and emission restrictions (3.2.5.4).

In order to keep the model simple and tractable without reducing its ability to address the research questions, it assumes that there is no year-to-year variability in energy generated from wind and solar. A typical power production[1] modeling of an energy system requires time resolution of one hour. However, hourly analyses of intermittent and unpredictable energy technologies such as solar and wind can make a model intractable. Therefore, this model analyzes annual energy generation and demand only. Also, the main aim of an energy plan for a

[1] Power production modeling finds when and how much power an alternative should produce during that time period (usually one hour)

college campus is to meet the energy demand at minimal most; therefore, option to export excess electricity back into the grid is not included.

3.2.1 Sets and Indices:

Notation 'I' is used to represent the set of different types of primary fuel available to meet energy demand. The set of various alternatives that are available is represented by notation 'B'. Each fuel-based alternative transforms primary energy into a secondary form of energy, which is either heat, electricity, or both. The secondary form of energy is used to meet the energy demand. Non-fuel based alternative such as wind and solar directly produces secondary form of energy, which can be used to meet the energy demand. Set 'W' represents different types of energy demand.

Set I represents set of primary fuel

$i = 1$ - Natural gas

$i = 2$ - Biomass

Set B represents set of different energy alternatives

fuel based generation

$b = 1$ - CHP_NG (natural gas fired)

$b = 2$ - CHP_B (biomass fired)

$b = 3$ - Boiler_NG (natural gas fired)

$b = 4$ - Boiler_B (biomass fired)

Non-fuel based energy alternatives

$b = 5$ - Wind

$b = 6$ - Photovoltaic

Set W represents set of different types of energy demand

$w = 1$ - Electricity

$w = 2$ - Heat energy

Set T represents time period in years (t= 0, 1, 2, 3….19 representing time period 2015 to 2034)

3.2.2 Parameters:

This section describes the parameters that were used in the model. Different types of input data were represented by different types of parameters. The parameters used in our work can be classified into three main categories: cost parameters, technical parameters, and constraint parameters.

The following is the list of notations used to represent the cost parameters followed by a small description about each parameter.

C_{bt} - Investment cost of alternative $b \in B$ in period $t \in T$ ($/unit)

FOM_{bt} - Fixed operation and maintenance cost of alternative $b \in B$ in year $t \in T$ ($/unit)

VOM_{bt} - Variable O&M cost of alternative $b \in B$ in year $t \in T$ ($/unit)

FP_{it} - Price of fuel $i \in I$ in year $t \in T$ ($/MMBtu)

EP_{wt} - Price of purchased energy type $w \in W$ in year $t \in T$ ($/MMBtu)

RP_{wt} - Price of renewable energy credits energy type $w \in W$ in year $t \in T$ ($/kWh)

FI_{bt} - Financial incentive for alternative $b \in B$ in year $t \in T$ ($ or $/kW or $/kWh)

CCP_{t} - Carbon credit price in year $t \in T$ ($/ton of CO2 equivalent)

d - Real discount rate

The following is the list of notations used to represent technical parameters followed by a small description about each parameter. The technical parameters were used to represent technical information related to each energy alternative.

CF_b - Capacity factor of alternative $b \in B$

η_{wb} - Conversion efficiency of alternative $b = (1,2,3,4)$ w.r.t. energy $w \in W$

α_{wb} - Output energy coefficient of alternative $b = (5,6)$

$\alpha_{wb} = 1$ if alternative b produces w type of energy, 0 otherwise

LB_b - Operational life time of alternative $b \in B$ (years)

LTB_b - Lead time of alternative $b \in B$ (years)

M - Large Number

The following is the list of notations used to represent constraint parameters followed by a small description about each parameter. The constraint parameters were used directly or indirectly to represent information related to resource constraint, size constraint, or environmental constraints.

EC_{bt} - Capacity of alternative $b \in B$ existing at the beginning of planning horizon and still operational in year $t \in T$ (units)

$Llimit_b$ - Lower limit on total capacity of alternative $b \in B$

$Ulimit_b$ - Upper limit on total capacity of alternative $b \in B$

$Lbound_b$- Lower bound on minimum size of alternative $b \in B$

$Ubound_b$- Upper bound on maximum size of alternative $b \in B$

ED_{wt} - Demand of energy type $w \in W$ in year $t \in T$ (kWh)

CFF_i - GHG emission from unit consumption of fuel $i \in I$ (kg of CO2/unit)

CFE_{wt} - Carbon footprint of purchased energy type $w \in W$ in year $t \in T$ (kg of CO2/MMBtu)

$Glimit_t$ - Limit on GHG emissions in year $t \in T$ (kg of CO2 equivalent)

$Share_t$ - Limit on share of carbon offsets and RECs in year $t \in T$ (kg of CO2 equivalent)

3.2.3 Decision Variables:

Y_{bt} - If an alternative $b \in B$ should be installed in year $t \in T$ (0 if no, 1 if yes)

NC_{bt} - New installation capacity or size of alternative $b \in B$ in year $t \in T$ (kW or kW_{th})

AEB_{wbt} - Annual energy type $w \in W$ produced from alternative $b \in B$ in year $t \in T$ (kWh)

E_{wt} - Amount of energy type $w \in W$ purchased in year $t \in T$ (kWh)

FU_{ibt} - Amount of fuel $i \in I$ used by alternative $b = (1,2,3,4)$ in year $t \in T$ (kWh)

REC_{wt} - Renewable energy credits for energy type $w \in W$ purchased in year $t \in T$ (kWh)

CC_t - Carbon credits purchased in year $t \in T$ (tons of CO2 equivalents)

3.2.4 Objective Function

The goal of this model is to determine how much and when to invest in each alternative of an energy system, subject to energy demand and emission constraints. Our objective minimizes the sum of the present value of annual energy expenditures occurred during the each year of the specified planning horizon. The following expression provides a mathematical formulation of the objective function.

$$\text{Minimize } Total\ Cost = \sum_{t \in T} \frac{Cost_t}{(1+d)^t} \tag{3.1}$$

The term $Cost_t$ represents total annual cost associated with energy in year *t*. The annual cost can be broken down into the following cost components.

$$Cost_t = INV_t + FOM_t + VOM_t + Energy_t + RECCost_t + Fuel_t + CreCost_t - Incentive_t$$

Where, INV_t is total investment cost occurred in any year t and is calculated by equation (3.2). The investment cost represents the total money spent on installing new alternatives each year. It

depends on type and size of alternatives installed and their capital cost. In the following equation, NC_{bt} represents the type and size of alternative installed in year 't' and C_{bt} represents respective capital cost.

$$INV_t = \sum_{b \in B} NC_{bt} \cdot C_{bt} \qquad \forall\, t \in T \qquad (3.2)$$

It is assumed that there is no difference between O&M costs of older equipment and newer equipment. Though it may not necessarily reflect reality as older equipment has higher maintenance cost that an equivalent newer one, this assumption is necessary to keep the tractability of the model. Equipment that retires during the planning horizon will not incur any operation and maintenance costs beyond their useful life. Also, it is assumed that the equipment that is still under construction will not have any operation and maintenance costs until it starts producing energy. Therefore, in any year t, set SA_{bt} limits the installed capacity that has been commissioned by the beginning of the year and still in operation in the year. LB_b is operational life of an alternative *b*. LTB_b is the lead time of installation for alternative *b*.

$$SA_{bt} = [\max(1, t - LB_b - LTB_b + 1) \ldots, (t - LTB_b)]$$

FOM_t and VOM_t represent *fixed operation and maintenance* and *variable operation and maintenance* cost occurred any year *t*. These costs can be obtained by expressions (3.3) and (3.6) respectively. EC_{bt} is the total capacity of an alternative that was installed before planning period begun and still operational in year *t*. $NC_{b\tau}$ is the total installed capacity of an alternative that is operational in year *t*.

$$FOM_t = \sum_{b \in B} FOM_{bt}(EC_{bt} + \sum_{\tau \in SA_{bt}} NC_{b\tau}) \qquad \forall\, t \in T \qquad (3.3)$$

The *variable operation and maintenance (VOM)* cost depends on the energy produced by an alternative (AEB_{wbt}) in any energy *t*. The VOM is represented by two components. The first component (3.4) calculates VOM costs of non-CHP alternatives. The second component (3.5) calculates VOM cost of CHP alternatives. The VOM of CHP technologies is expressed in terms of electricity production only. Therefore, constraint (3.6) accounts for total VOM_t cost, which is sum of these two components.

$$VOM1_t = \sum_{b \in B} \sum_{w \in W} VOM_{bt} AEB_{wbt} \qquad b - (1,2) \qquad \forall\, t \in T \qquad (3.4)$$

$$VOM2_t = \sum_{b \in B} \sum_{w \in W} VOM_{bt} AEB_{wbt} \quad b = (1,2)\ \ w = 1\ \ \forall\, t \in T \qquad (3.5)$$

$$VOM_t = VOM1_t + VOM2_t \qquad (3.6)$$

$Energy_t$ represents cost of energy purchased from utilities in year *t*. It depends on amount of each type of energy purchased (E_{wt}) and its price (EP_{wt}) in that year. It can be calculated by expression (3.7).

$$Energy_t = \sum_{w \in W} E_{wt} EP_{wt} \qquad \forall\, t \in T \qquad (3.7)$$

The cost component associated with fuel costs incurred in year *t* is obtained by expression (3.8). The fuel costs are dependent on fuel prices (FP_{it}) and amount of fuel used (FU_{ibt}) in that year.

$$Fuel_t = \sum_{b \in B-(5,6)} \sum_{i \in I} FU_{ibt} FP_{it} \qquad \forall\, t \in T \qquad (3.8)$$

$RECCost_t$ cost component represents the cost of purchasing renewable energy credits, and can be obtained by expression (3.9). It can be calculated by multiplying amount of energy credits purchased (REC_{wt}) and the price of each credit (RP_{wt}).

$$RECCost_t = \sum_{w \in W} REC_{wt} RP_{wt} \qquad \forall\, t \in T \qquad (3.9)$$

The expression (3.10) calculates cost of purchasing carbon credits in year t. It depends on amount of carbon credits purchased (CC_t) and its price (CCP_t) in that year.

$$CreCost_t = CCP_t \cdot CC_t \qquad \forall\, t \in T \tag{3.10}$$

$Incentive_t$ represents the total financial incentive/grants/tax benefits received from any entity for each alternative.

$$Incentive_t = \sum_{b \in B} FI_{bt} \qquad \forall\, b \in B \quad \forall\, t \in T \tag{3.11}$$

3.2.5 Model Constraints

3.2.5.1 Energy Production and Demand

The following constraint (3.12) ensures that the total annual energy production (AEB) of each type of energy is more than the demand of that type of energy in any given year in the planning period. The energy supply includes on-campus energy generation by alternatives (AEB_{wbt}) and energy purchase (E_{wt}). The overall energy demand (ED_{wt}) is assumed to be known for each year.

$$\sum_{b \in B} AEB_{wbt} + E_{wt} \geq ED_{wt} \quad \forall\, w \in W \qquad \forall\, t \in T \tag{3.12}$$

It is also assumed that the performance of any alternative does not degrade over time. It means that older equipment will perform just as well as an equivalent newer one.

3.2.5.2 Maximum Energy Production

In any given year, the energy produced by an alternative (AEB_{wbt}) cannot exceed its maximum energy generation capacity. The output energy coefficient (α_{wb}) in constraint (3.13) is multiplied to impose an upper limit on the kind of energy the alternatives (5 and 6) can supply.

$$AEB_{wbt} \leq 8760 * \alpha_{wb}\, CF_b \left(EC_{bt} + \sum_{\tau \in SA_{bt}} NC_{b\tau} \right) \ \forall\, w \in W, b = (5,6) \quad t \in T \tag{3.13}$$

Additional constraints (3.14) and (3.15) ensure that the energy generated from fuel-based alternatives does not exceed maximum possible generation from total installed capacity[2]. A Combined Heat and Power (CHP) technology is rated in terms of electricity production capacity. Therefore, heat recovery from a CHP technology is dependent on amount of electricity produced by that technology. Therefore, constraint (3.12) is defined over single index (w=1) only. 8760 represents number of hours in a year.

$$AEB_{wbt} \leq 8760 * CF_b\left(EC_{bt} + \sum_{\tau \in SA_{bt}} NC_{b\tau}\right) \quad \forall\, w = 1, b = (1,2) \quad t \in T \tag{3.14}$$

$$AEB_{wbt} \leq 8760 * CF_b\left(EC_{bt} + \sum_{\tau \in SA_{bt}} NC_{b\tau}\right) \quad \forall\, w = 2 \;\; b = (3,4) \quad t \in T \tag{3.15}$$

The constraint (3.16) ensures that the energy generated from alternatives (1, 2, 3, and 4) is in balance with the annual fuel consumption by the alternatives. It should be noted that the constraint (3.16) also makes sure that ratio[3] of heat and electrical power by CHP alternative is in accordance with the characteristics of the CHP technology. It is assumed that this ratio remains unchanged throughout the operational phase of CHP alternative. In constraint (3.16) the number 293 represents unit conversion factor: 1MMBtu=293kWh

$$AEB_{wbt} = 293 * \sum_{i \in I} FU_{ibt}\eta_{wb} \;\; \forall\, w \in W, \forall\, b = (1,2,3,4) \;\; \forall\, t \in T \tag{3.16}$$

3.2.5.3 Maximum Capacity Constraint

The total installed capacity of any alternative should be within its allowable limit. The constraint (3.17) will keep the total installed capacity of an alternative above its minimum limit and below its upper limit. The minimum limit can be defined by decision makers. For example,

[2] Inequality in constraint (3.12, 3.13, and 3.14) is modeled to include all feasible solutions. However, it is always sub-optimal to utilize less energy than what is available if money has already been invested to install new capacity.
[3] This ratio is only defined for a cogeneration technology.

there can a requirement to have at least some photovoltaic or wind turbines in energy systems even if they are not cost effective.

$$Llimit_b \leq EC_{bt} + \sum_{\tau \in SC_{bt}} NC_{b\tau} \leq Ulimit_b \qquad \forall\, b \in B,\ \forall\ t \in T \tag{3.17}$$

$$SC_{bt} = [\max(1, t - LB_b + 1) \ldots, t]$$

Rizzoa & Savinob (2012) recognized that there are certain *economy-of-scale* issues in small scale energy systems related to size of energy alternatives that affect unit cost. The relationship between size and unit cost is often non-linear, which can be approximated by linear relationships. The authors suggested that each size-scale (for example small, medium or large) of every generation technology can be considered as a separate decision variable. Each size-scale can be represented by a range where size and unit cost exhibit linear relationship. Furthermore, George Mavrotas et al., (2010) also used similar piecewise linear approximation as described in constraints (3.18 and 3.19) to account for non-linear cost-size relationship. The decision variable Y and NC in the constraints express whether or not an alternative should be installed in any given year and what capacity should be installed respectively. The parameters $Lbound$ and $Ubound$ capture the range of values the decision variables are allowed to take without violating linearity assumption.

$$NC_{bt} - Y_{bt} Lbound_b \geq 0 \quad \forall\, b \in B, \qquad \forall\ t \in T \tag{3.18}$$

$$NC_{bt} - Y_{bt} Ubound_b \leq 0 \quad \forall\, b \in B, \qquad \forall\ t \in T \tag{3.19}$$

Constraint (3.20) limits the amount of renewable energy credits (REC_{wt}) purchased, which cannot exceed the amount of purchased energy (E_{wt}). Factor '1000' in (3.20) is conversion factor from MWh to kWh because RECs are usually bought in MWh units.

$$E_{wt} \geq 1000 * REC_{wt} \; \forall \, w \in W \;\; \forall \, t \in T \tag{3.20}$$

3.2.5.4 Emission Constraint

Total carbon footprint of the system should not exceed annual carbon footprint limit ($Glimit_t$) on the system imposed by decision maker. The following constraint accounts for emissions associated with burning of fuel. It depends on fuel use (FU_{ibt}), amount of emissions emitted by burning one unit of fuel (CFF_i) in boilers, amount of energy purchased (E_{wt}), and carbon footprint of purchased energy (CFE_{wt}). Purchasing *Renewable Energy Credits (REC_{wt})* can reduce the carbon footprint associated with purchased energy. Additionally, overall carbon footprint of the system can also be reduced through carbon credits (CC_t). One carbon credit is equivalent to 1000kgs of CO2. Constraint (3.22) limits share of carbon offsets and RECs towards meeting the emission targets. This constraint can indirectly increase the share of renewable energy in an energy system.

$$\sum_{b \in B-(5,6)} \sum_{i \in I} CFF_i FU_{ibt} + \sum_{w \in W} CFE_{wt}(E_{wt} - 1000 * REC_{wt}) - 1000CC_t \leq Glimit_t \; \forall \, t \in T \tag{3.21}$$

$$\sum_{w \in W} CFE_{wt}(1000 * REC_{wt}) + 1000CC_t \leq Share_t \; \forall \, t \in \; T \tag{3.22}$$

3.2.5.5 Fuel Use Constraint

Any boiler or CHP unit is assumed to use only one type of fuel throughout its operation. The following constraint will ensure that no boiler uses multiple fuels in any year.

$$FU_{12t} = 0 \quad \forall \, t \in T \tag{3.23}$$

$$FU_{14t} = 0 \quad \forall \, t \in T \tag{3.24}$$

$$FU_{21t} = 0 \quad \forall \, t \in T \tag{3.25}$$

$$FU_{23t} = 0 \quad \forall \, t \in T \tag{3.26}$$

3.3 Monte Carlo Simulation (MCS)

There are multiple ways to analyze uncertainties in input parameters. Some of the ways to analyze uncertainties are sensitivity analysis and scenario analysis. Sensitivity analysis measures the change in output variable with respect to change in values of input parameters one at a time (Spinney & Watkins, 1996). One of the strengths of sensitivity analysis is that it can be helpful in screening the parameters that have biggest impact on the output. However, one of the limitations of using sensitivity analysis is that it analyzes only one uncertain parameter at a time. Such analysis may ignore the interaction among various input parameters.

Another way to analyze uncertainties is scenario analysis. Decision makers can analyze multiple scenarios to account for uncertainty. One common ways to classify scenarios can be 'best case', 'base case', and 'worst case' scenario (Spinney & Watkins, 1996). Each scenario is associated with a particular combination of input parameters. The advantage of using scenario analysis over sensitivity analysis is that decision makers can analyze impacts on the output by changing multiple uncertain parameters simultaneously. However, drawback of this approach is that if uncertainties in input parameters are large, or there are too many uncertain parameters are large, the number of possible scenarios can be very large.

Monte Carlo simulation (MCS) is a very helpful way to experiment with a large number of possible combinations of input parameters (Spinney & Watkins, 1996). In MCS experiment, all input parameters are expressed as probability distribution. Then, the experiment is run for a certain number of trials. In each trial, the value of each uncertain parameter is randomly chosen from its probability distribution to find corresponding value of the output. Repeating the process for certain number of trials results in a probability distribution of the output. Another main

advantage of using MCS is that it also gives information on the distribution of the output as compared to scenario analysis, which only gives a range of values of the output.

In an energy planning, there can be many uncertain parameters such as, but not limited to capital costs of wind and PV, electricity, gas, and carbon prices. As number of uncertain parameters or range of uncertainties in the values of some parameter increases, choice of MCS over scenario analysis can be very helpful in determining cost distribution of an energy plan.

In the existing literature on energy planning, MCS technique has been used in two different ways. George Mavrotas et al (2010) used Monte Carlo simulation to solve the optimization model by randomly choosing values of input parameters from their respective probability distribution. The results of objective function and decision variables are recorded after each repetition of the simulation. In this type of application, MCS produces a probability distribution of the objective function and decision variable by repeated sampling of the input parameters. Therefore, the decision maker can see how the objective function and the decision variables can vary, given the specific uncertainty on the model's parameters. With this type of application of the simulation users can explore and understand which decision variables are important and which have negligible effects on the system under uncertainty. However, choosing an appropriate set of decision variables from the distribution is challenging. Also, further experimentation must be done in order to describe how a particular energy plan will behave under uncertainty once a particular set of decision variables (combination of energy alternatives) has been chosen.

Hawks (2010) applied MCS technique to analyze economic performance of a single combination of technologies. In this type of application, simulations were performed by repeated sampling of input parameters from their distribution for a particular combination of technologies obtained

with a single estimate of uncertain parameters through deterministic optimization. The output of the simulation was the distribution of objective function, which was savings in energy cost.

In our work, the second type of application can be more useful in determining economic behavior of one particular mix of technologies under uncertainty. The Monte Carlo simulation experiment conducted in this thesis is similar to the application proposed in Hawks (2010). We aim to use MCS to find how the total cost of a particular energy plan (combination of energy alternatives or technology mix) may be affected by uncertainties in input parameter. In this study, we limit our analysis to only three uncertain parameters, electricity, natural gas, and carbon prices to test the effectiveness of MCS in energy planning. The next chapter applies the methodology to develop energy plan for an energy system.

An overall guide to apply above methodology is shown in figure 9-1 (see appendix).

Chapter 4. Experiment

The methodology described in the previous chapter has two parts. The modeling part that finds the values of decision variables (energy plan) such as capacities of energy alternatives that need to be installed and energy to be bought over a given planning period for a particular cost scenario. Monte-Carlo Simulation experiment, then, helps to assess the effects of uncertainties in natural gas, electricity, and carbon prices on an energy plan. This methodology can be useful for universities interested in assessing the effects of certain aspects of energy planning such as the length of the planning period, uncertainties in costs, and certain constraints on investment decisions. This methodology mainly requires snapshot of existing energy system, knowledge of future annual energy demand of campus that must be satisfied, and types of fuel and energy alternatives available to decision makers in order to meet the energy demand. Uncertainty analysis requires knowledge of probability distribution of uncertain parameters. In order to answer the research questions mentioned in the first chapter, the methodology was tested through its application to develop an energy plan for Rochester Institute of Technology (RIT) campus.

The following section (4.1) provides details on RIT campus and its energy system. The next section (4.2) discusses what the most likely decisions are that RIT may have to make in order to develop its energy plan. It also describes how the experiment was set up and all the scenarios that were considered. The last section (4.3) of this chapter provides the data on energy system of RIT, various energy alternatives, and uncertainties.

4.1 Background Information on the Campus

RIT is a private university located in suburban Rochester. Its campus occupies 1300 acres of land (RIT, 2012b). In the past few decades, student enrollment increased by more than 20-30 percent (RIT, 2012b). RIT offers many doctoral, masters, and bachelor level degree programs. Moreover, many more additional new programs and courses are now being offered. Many new construction projects such as Institute Hall, Institute for Sustainability, and Gene Polisseni Arena have already been completed or about to be completed in near future (RIT, 2012a) . Therefore, due to the increasing size of campus and increment in student enrollment, RIT faces sustainability challenges such as increasing energy consumption, waste generation, and environmental emissions. Rising costs of electricity and natural gas can also put additional financial burden on the university's budget. Currently, the university spends more than $10 million on utilities annually (RIT, 2012c).

Share of Greenhouse Gas (GHG) emissions resulting from various activities related to the campus is shown in figure 4-1. The majority of RIT's greenhouse gas emissions in 2010 resulted from purchased electricity, associated transmission and distribution loss, and combustion of natural gas on campus (RIT, 2011). Emissions resulting from commuting and travel also constitute a large portion of overall emissions. However, these emissions, which are considered Scope3 emissions, are beyond the scope of this work because policies or initiatives focusing on reducing Scope1 and Scope2 emissions may have little impact on Scope3 emissions and vice-versa. Emissions related to commuting can be reduced through a green transportation policy rather than the campus's energy policy.

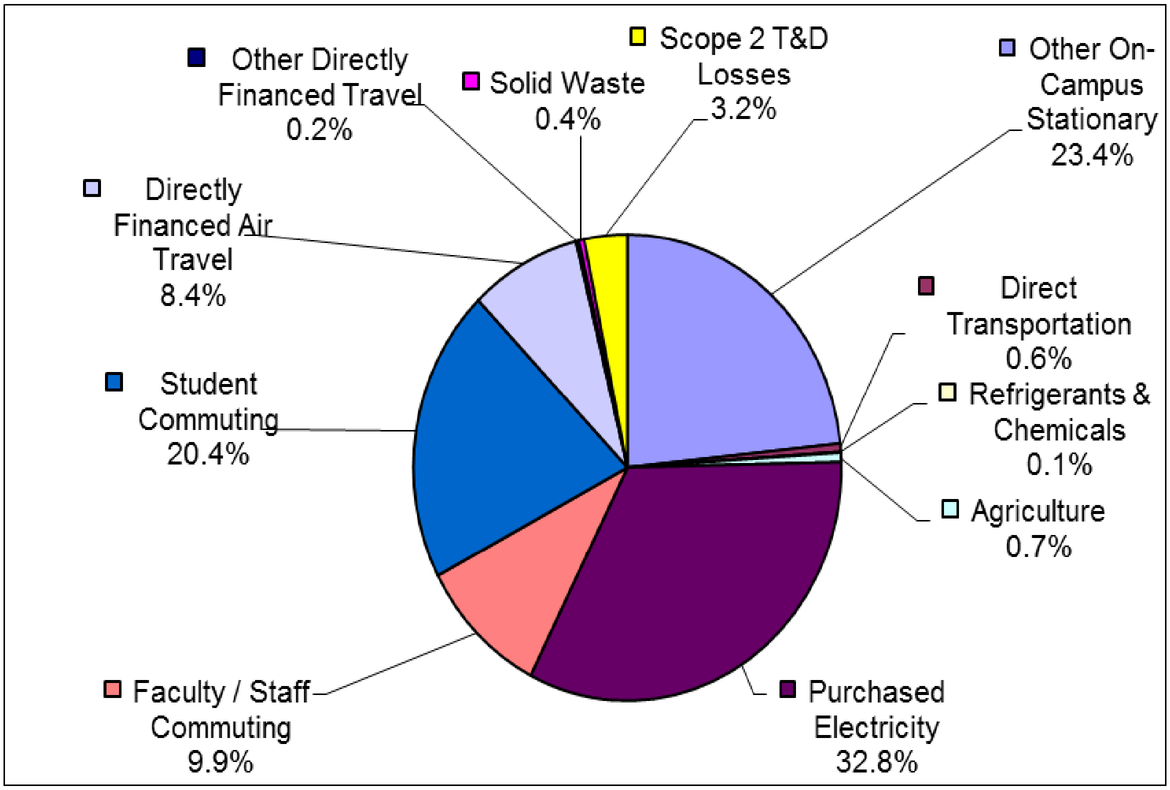

Figure 4-1 GHG Emission Pie Chart-2010 Source: (RIT, 2011)

RIT pledged to become carbon neutral by the end of year 2030 (RIT, 2011). One of the main focuses of RIT is to develop a list of projects and implementation timeline for those projects that will reduce carbon emissions. Some of the actions RIT may take in the future to reduce its emissions include investments in renewable energy and natural gas based power plants in addition to improving energy efficiency. The goal of becoming carbon neutral can be met through different ways. These ways include producing all energy through renewable energy sources, purchasing carbon offsets and RECs, or in combination of both. However, renewable energy requires large capital investments, which might limit the implementation of some of the projects. On the other hand, strategy of relying just on carbon offsets and RECs to meet the goal may turn out be expensive in the long run if carbon and RECs prices rise in the future. Therefore,

decision makers may have to find a desirable combination of these two ways to meet long-term targets. Therefore, it also becomes necessary to invest in long-term projects, which requires long-term planning because some of those decisions must be made much sooner than the target-date. Therefore, decision makers at RIT need to compare costs associated with long-term planning strategies and short-term planning strategies and also analyze uncertainties in various parameters.

The following section explores importance of such decisions using methodology proposed in previous chapter to help decision makers at RIT to find an optimal alternative mix (energy plan) that can meet their emission objectives and financial constraints.

4.2 Analysis Method

Suppose decision makers at RIT want to reduce their emissions related to energy consumption. They are looking for the cost effective ways to meet their emission targets and energy demand. In other words, they need an energy plan. An energy plan basically describes what projects should be implemented and when they should be implemented. However, before making any planning decisions to develop an energy plan, they must consider exploring costs of some of the planning strategies. These planning strategies include length of planning period, annual investment limits, and rate of annual emission (basically share of carbon offsets and RECs). It is possible that choosing different planning strategies individually or combining multiple strategies together, will result in different energy plan and different planning decisions. Also, decision makers must also consider uncertainties in various parameters such as electricity prices, natural gas prices, and carbon prices before making any large capital investments.

Next section describes the experimental setup. It was assumed that the energy demand reflected the improvements achieved through energy efficiency and conservation. However, if decision makers want to consider energy efficiency and conservation projects along with energy

alternatives to find optimal mix, it can be achieved by considering energy efficiency and conservation projects as alternatives in the model. This will require much more data on each individual energy efficiency or conservation project. The planning horizon was assumed to span from the starting of year 2015 to the end of year 2034, a period of 20 years. The deadline to achieve carbon neutrality was by the end of year 2030.

4.2.1 Deterministic Analysis

Main purpose for this analysis was to test the effects of length of planning period, annual investment limits, and rate of annual emission reduction on planning decisions by comparing total present costs associated with each type of planning strategy. The analysis approach taken in this work is shown in figure 4-2

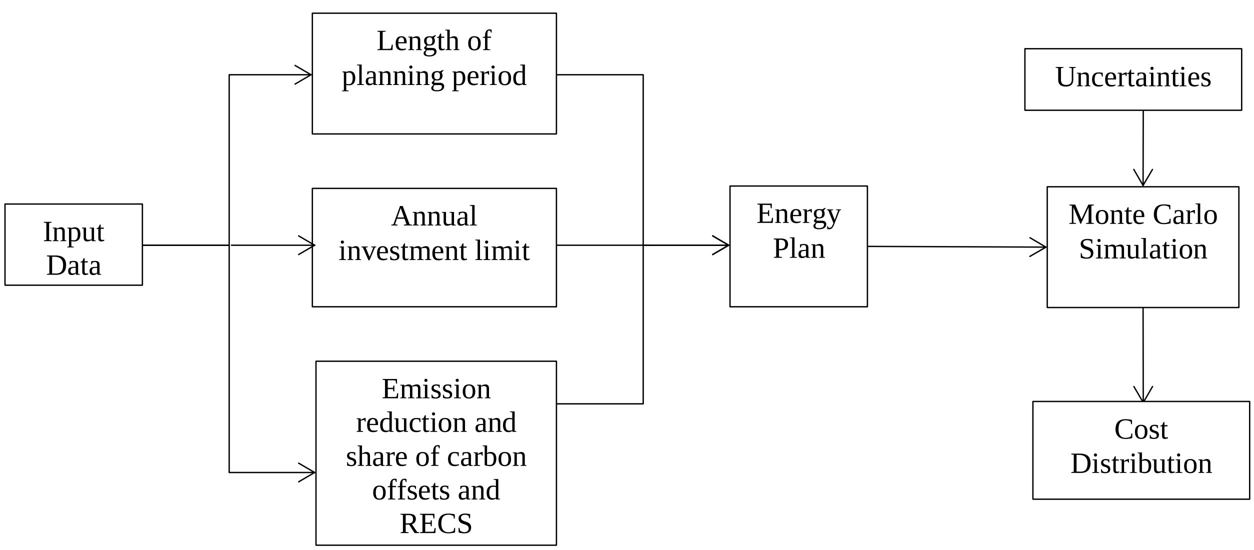

Figure 4-2 Analysis Method

4.2.1.1 Length of Planning Periods

Length of the planning period can be an important part of planning strategy. A planning period is length of time period shorter or equal to the planning horizon. Decision makers may choose to plan for different length of planning periods (every five years or ten years) to develop

an energy plan. A solution which is optimal during a particular planning period may not be optimal if analyzed over the entire planning horizon. Five or ten year planning approach will find a solution that is optimal (the lowest cost solution) based only on five or ten year of data respectively. Therefore, using either five year or ten year planning approach decision makers will have to run the model sequentially four times (once in every five years) or two times (once in every ten years) during the planning horizon of 20 years. Decisions in next five or ten years will depend on decisions taken in previous five or ten years. On the other hand, 20 year planning approach (MP) will find a solution based on analysis of 20 years, and decision makers will have to run the model only once to find optimal solution. The deterministic optimization model was used to find optimal energy plans for RIT through different planning period strategies for a certain number of known cost scenarios (total four cost scenarios described in section 4.3.3). For each of the cost scenarios and each of the planning period strategies, an optimal energy plan was developed. Then total present costs associated with each of the optimal plan were compared to draw conclusions.

4.2.1.2 Limit on Annual Investment

Long-term energy plans require may huge capital investments. In reality, due to resource constraints it may not be possible to implement energy plans that require significant capital investments. Suppose decision makers limit their maximum annual investments to certain amount. The decision makers may not either have or be willing to invest large capitals. They might be interested in making more gradual investments. This approach may give them more flexibility because as more data become available on energy demand, cheaper energy alternatives, or energy prices, it might be easier to adopt partially or fully better energy mix of alternatives by running the model one more time. However, this flexibility comes at a certain

cost. Investing not enough capital may develop energy plans that may become more expensive over the period of planning horizon.

4.2.1.3 Emission Trajectories

Based on the findings of previous section, the next step for decision makers can be setting up desired environmental targets. Different emission trajectories i.e. rate of annual emission reduction can also be an important part of planning strategy to achieve carbon neutrality that decision makers may have to consider. Focusing on just final neutrality objective without any interim emissions targets may give decision makers more flexibility in choosing and implementing certain projects. On the other hand, gradual reduction in emissions may require additional expenditures on either purchasing offsets or installing renewable energy alternatives. However, graduate reduction may help decision makers keep track of progress towards final goal. The deterministic optimization model was used to find optimal energy plans for RIT through different emission trajectories for a certain number of known cost scenarios (described in section 4.3.3). For those cost scenarios, total present costs associated with each of the emission reduction strategies were compared to draw conclusions.

4.2.2 Uncertainty Analysis

In this part of the analysis Monte Carlo simulation experiment was conducted to analyze effects of uncertainties. Monte-Carlo simulation was performed by randomly choosing values of uncertain parameters from their respective probability distributions. As argued in the first chapter, cost analysis should also consider uncertainties associated with some parameters such as natural gas, carbon, and electricity prices. It is possible to identify a robust plan that may not be optimal for any single future outcome, but will perform satisfactorily well under all or most of the possible scenarios if uncertainties are also considered. For this part of the analysis, certain

energy plan can be chosen based on the findings of the previous two sections (4.2.1.1 and 4.2.1.2) and MCS was used for each of the optimal plans (technology mix) to find how uncertainties change the cost of that energy plan.

4.3 Data for the Analysis

4.3.1 Different Planning Periods

Four different planning periods were tested: i) Business As Usual (BAU) ii) Every five years iii) Every ten years iv) 20 years (Master Plan-(MP)). The university's decision makers have a choice to continue on a business as usual (BAU) path for next 20 years, plan periodically every five years, ten years, or 20 years (Master Plan-MP). In BAU case, the university will continue to purchase all of its electricity from grid apart from the electricity generated through 15kW PV installation. It will continue to use gas-only boilers to meet it heating requirements. However, there are no additional on-campus electricity generation units of any other alternatives. Every year, the university will continue to purchase RECs equivalent to 15 percent of its electricity usage to neutralize some of the emissions associated with purchasing electricity. Every year after 2030, it will purchase carbon offsets and/or RECs to neutralize the remaining emissions.

4.3.2 Annual Investment Limits

Three annual investment limits were chosen: 2 million dollar, 5 million dollars, and 'no limit' to test the impacts of capital constraints. The rational for choosing these limits was that first two of these limits are almost equal to 20 percent and 50 percent of money RIT currently spends on utilities. It is reasonable to expect at least 20 percent of additional money every year to make capital investments in order to develop an energy plan. 'No limit' condition was only considered to compare how capital constraints affect an energy plan.

4.3.3 Different Emission Trajectories

Two emission trajectories that were considered for the analysis are shown in figure 4-3. An Emission trajectory was assumed to provide an upper limit on how much annual emission should be allowed each year until year 2030, after which emissions must be zero. 'No Limit' (NL)

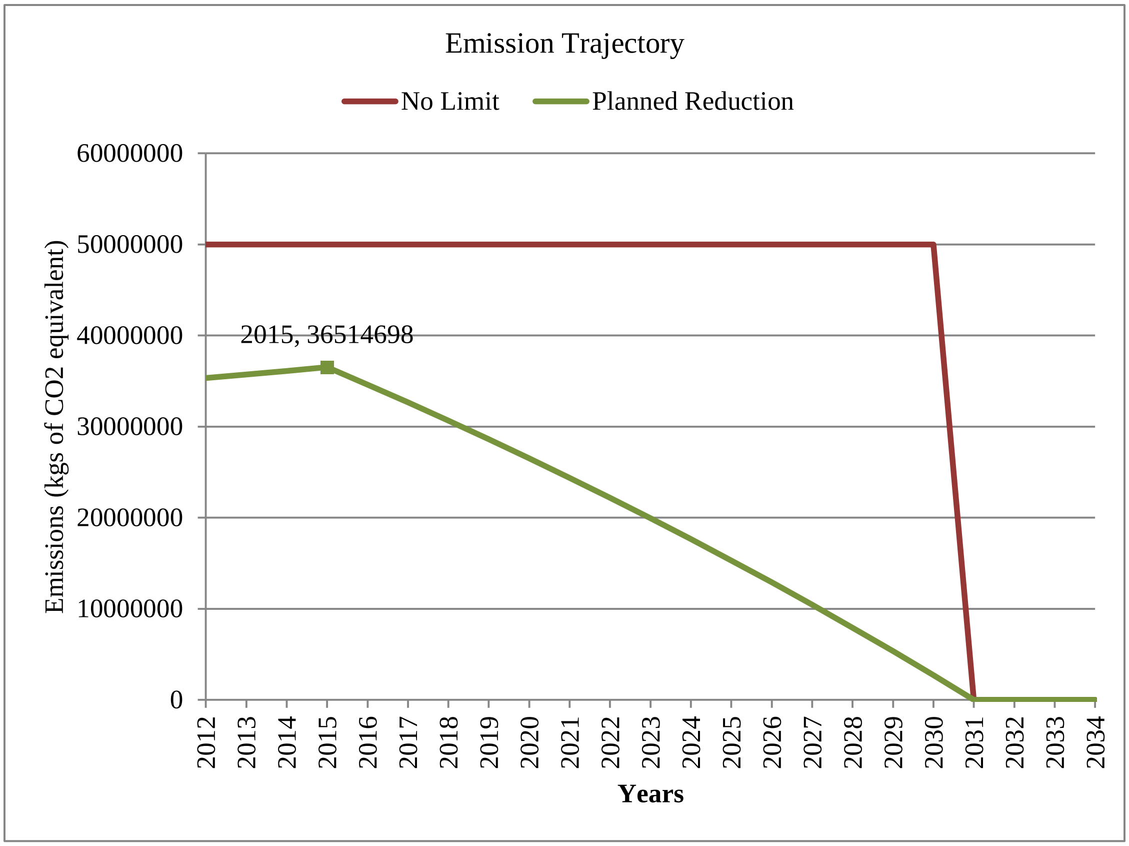

Figure 4-3 Emission Trajectory

emission trajectory had no restrictions on annual emissions. The second emission trajectory, 'Planned Reduction (PR)', was considered had a planned upper limit on emissions that would decrease to zero by the end of 2030 (beginning of year 2031) from their starting values in 2015.

It must be mentioned here that though NL emission trajectory seems to restrict annual emissions at 50,000,000 kgs of CO_2 equivalent, it is a sufficiently large number and does not interfere with the modeling results in anyway. It should also be noted that the second emission trajectory provided an upper limit on annual emissions and might not be the actual emission trajectory. It

meant that the actual emissions in a planning strategy intended to reduce emissions gradually were less than or equal to the upper limit defined by the second emission trajectory. It is possible to have any kind of planned emission trajectory because it has to be decided by decision makers depending on how fast or slow they intend to reduce the emissions.

4.3.4 Energy and Carbon Prices for Various Scenarios

Currently, the college pays[4] approximately \$0.08/kWh for electricity and \$6/MMBtu for natural gas. These values were assumed to represent best-case scenario (A) (low prices, zero escalation rate) in this thesis because these prices are lower than the prices in any scenario described in (EIA, 2012b) for commercial sector in East North Central region . Energy price escalation rate was assumed to be zero. Carbon prices[5] in the best case scenario were assumed to be constant throughout the period and were equal to \$15/tonne (EIA, 2012b; Johnston, Hausman, Biewald, Wilson, & White, 2011) . The cost of biomass for every scenario was assumed to be equal to \$5/MMBtu, including biomass transportation costs (Haq, 2002). These prices weren't subject to change during the planning horizon under any scenario.

In scenario (B) (low prices, but high escalation rate), electricity, natural gas, and carbon prices were assumed to be escalating from the base prices in scenario A at a rate of 1.5 percent, 1.2 percent, and 5 percent respectively due to high economic growth. Higher economic growth may increase the energy demand, which will increase the energy prices. The important reason for choosing this scenario was to analyze how energy and carbon prices will affect the costs of planning if present prices of the electricity, natural gas, and carbon are low, but will rise rapidly in future.

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[4] Information is based upon an interview with a college facility management staff.
[5] Carbon prices implies cost of purchasing carbon credits by the college

In scenario (C) (high prices, but no escalation rate), which is based on reference case scenario, estimates of electricity price and natural gas price presented in The Annual Energy Outlook (AEO)-2012 (EIA, 2012b) for year 2015 in East-North-Central region are $0.0970/kWh and $8/MMBtu. It was assumed that future restrictions on emissions imposed on utilities may lead to higher energy prices to consumers. However, these prices will stay constant throughout the planning horizon. The carbon prices were assumed to be constant at $25/tonne throughout the period. The reason for choosing this scenario was to analyze how energy and carbon prices will affect the costs of planning if present prices of the electricity, natural gas, and carbon are high, but are not expected to rise in future.

In scenario (D) (high prices, high escalation rate), electricity, natural gas, and carbon prices were assumed to be escalating from the scenario (C) prices at a rate of 1.5 percent, 1.2 percent, and 5 percent respectively. These values were assumed to represent **worst-case** scenario These escalation rates were sourced from GHG price scenario considered in (EIA, 2012a). The carbon price escalation rate is sourced from (Johnston et al., 2011) and presented in table 4-6. The higher starting prices as compared to low prices in scenarios A and B could be due to the restrictions on emissions imposed on utilities may lead to higher energy prices to consumers. The higher economic growth will lead to more energy demand, which will increase the costs of energy. The reason for choosing this scenario was to analyze how high energy and carbon prices as well as high escalation rate will impact the planning.

Four different cost scenarios were considered for the deterministic analysis. The best-case cost scenario represents the lowest gas, electricity, and carbon prices during the entire planning horizon. The worst-case cost scenario represents highest gas, electricity, and carbon prices. Another reason for choosing these cost scenarios was to find how sensitive optimal energy plans

were to electricity, gas, and carbon prices. Also, higher sensitivity may justify the need to use Monte Carlo Simulation to mitigate the effects of uncertainties.

The electricity, natural gas, and carbon prices assumed for various scenarios (A to D) are summarized in table 4-1.

Table 4-1 Cost and Emission factor of fuel, carbon credits, and purchased electricity (in 2010 dollars)

	Purchased Electricity	Escalation Rate	Natural Gas	Escalation Rate	Carbon Credits	Escalation Rate
Reference Unit	1kWh	Percent	1MMBtu	Percent	1000kgs of CO2	Percent
Scenario (A)	$ 0.080	0	$6	0	$15	0
Scenario (B)	$ 0.080	1.5	$6	1.2	$15	5
Scenario (C)	$ 0.097	0	$8	0	$25	0
Scenario (D)	$ 0.097	1.5	$8	1.2	$25	5
Carbon Footprint/unit (in kgs of CO2)	1.06 *0.226 = 0.240		53		-	

4.3.5 Uncertainty in Electricity, Natural gas, and Carbon prices

Uncertainties in the future electricity, natural gas, and carbon prices were represented by uniform probability distribution. The main reason for choosing uniform distribution was that it only required knowledge of minimum and maximum values, which are easier to obtain. Also, the uniform distribution also expresses maximum uncertainty (George Mavrotas et al., 2010). Historical data on energy prices does not reflect environmental costs or carbon prices. However, there is no credible information on how exactly government regulations on carbon prices will affect the energy prices. Therefore, it is safe to assume maximum uncertainties in planning decisions. In the second part, the findings of the first part were used to conduct Monte Carlo Simulation experiment to analyze effects of uncertainties. Monte-Carlo simulation was

performed by randomly choosing yearly prices of these parameters from a distribution. As argued in the first chapter, cost analysis should also consider uncertainties associated with gas, carbon, and electricity prices. It is possible to identify a robust plan that may not be optimal for any single future outcome, but will perform satisfactorily well under all or most of the possible scenarios if uncertainties are also considered. In this part of the analysis, certain optimal solutions are chosen based on the findings and results of the first part and MCS was used for each of the optimal plan to find how uncertainties change the cost of that energy plan

4.3.6 Energy System of the Campus

The Institute purchases almost all of its electricity from grid. There are very small photovoltaic installations on campus (15kW in total). The institute has taken various initiatives to reduce its carbon emissions. Since 2009, RIT has been purchasing RECs (renewable energy credits) equivalent to 15 percent of its electricity consumption (RIT, 2011). In addition, in the past few years, many conservation initiatives such as efficient lighting, occupancy sensors, daylight harvesting, ENERGY STAR equipment purchasing policy, retro-commissioning have made campus operation more energy efficient (RIT, 2012c). Campuses similar to RIT that have been implementing energy efficiency and energy conservation measures for some years may have fewer opportunities left to further save energy. Levine, (2009) and Simpson, (2009) note that these universities also need to focus on long-term investments such as renewable energy projects for substantial reduction in emissions along with energy conservation projects.

The present snap-shot of the campus energy system was considered to be the starting point of the planning horizon. As mentioned previously, the college purchases all of its electricity. It does not purchase any heat energy (steam or hot water), and hence, meets all of its thermal energy needs

by burning natural gas using gas-only boilers[6] installed on campus. Therefore, it is assumed that the thermal energy requirements will continue to be met through on-campus fuel combustion. No amount of thermal energy (steam or hot water) will be purchased throughout the planning horizon. The historical energy consumption[7] of RIT is presented in table 9-3 (see appendices). The graphical representation of the data is shown in figure 4.4.

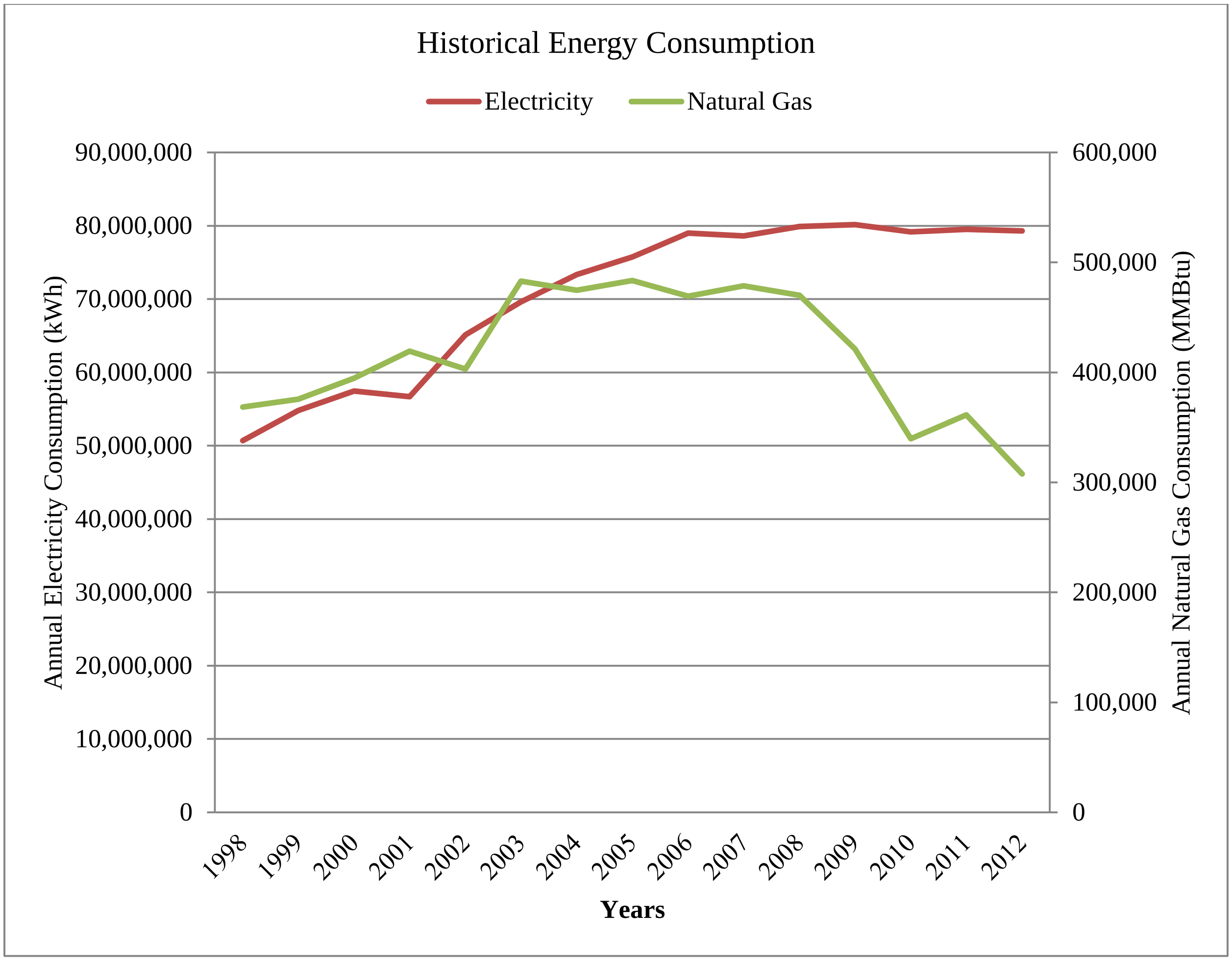

Figure 4-4 Historical Energy Consumption Source: (RIT, 2013)

It is clear from the data that electricity consumption for the past few years has been stable despite growth in campus size and student enrollment. The improvements in energy efficiency and

[6] These data are based on information provided by facility management staff of the campus through email exchanges.

[7] The information is based up on an email exchange between the author of this thesis and one of the people at RIT's facility management staff.

conservation initiatives in past few years appear to be important factors that may have offset the growth in electrical energy consumption. As campus is operating more efficiently than it was operating few years ago, it is assumed that average annual growth in electricity consumption will be less than 3.24 percent, the historical average growth in electricity consumption during past years as presented in table 9-3. It is also safe to assume that due to campus expansion and more student enrollment in the future the annual growth rate in electricity consumption will be greater than zero percent. In addition, it is also possible that energy conservation initiatives in the future may continue to offset the growth of electricity consumption at least to a certain degree as there might be fewer opportunities left to save energy. Therefore, it is assumed that electricity consumption will rise at a rate of 1.6 percent per year, which is approximately average of zero growth and 3.24 percent growth.

The natural gas consumption has declined significantly in past 3-4 years. The major renovations in the institute's heating and cooling plant and/or warm winters appear to have affected the natural gas consumption (RIT, 2012c).

The heat requirement can be calculated simply by multiplying natural gas consumption and efficiency of gas-only boiler (80 percent in this case; see table 4-2). It should be noted that heat generated through natural gas combustion can either be used for heating purposes directly or cooling purposes using absorption chiller. In the past, natural gas has been the only source to meet heating and cooling requirements, therefore, natural gas consumption reflects actual overall

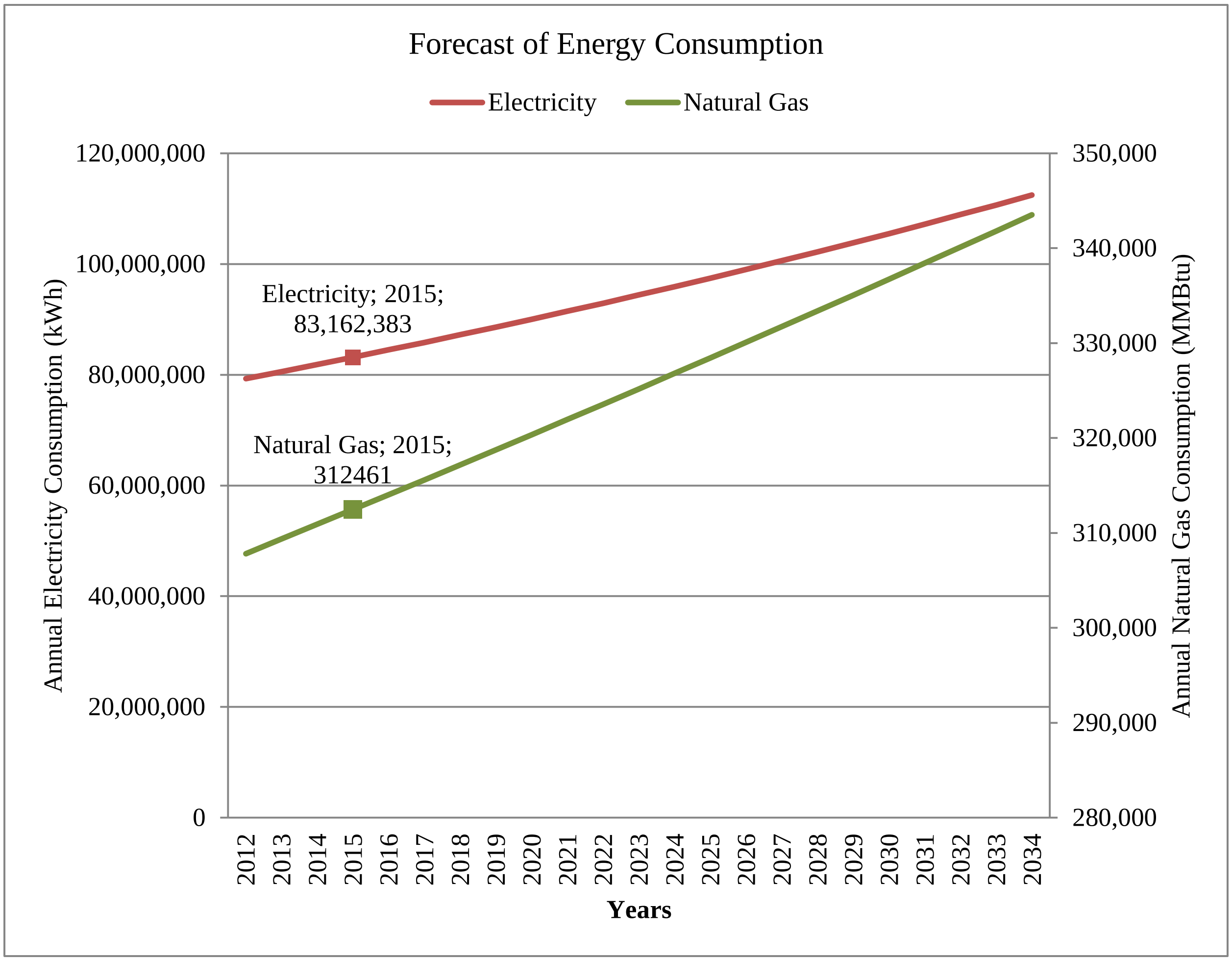

Figure 4-5 Forecast of Energy Consumption

heat requirement on the campus. Based on the past consumption data and potential improvements in energy conservation, it was assumed that the growth rate in heat requirement may lie between zero percent and 1.28 percent. However, planned expansion of campus discussed above may increase overall demand of natural gas because existing buildings are still

operational and the planned construction of new buildings is taking place. Therefore, it was assumed that the natural gas consumption in the future will rise at rate of 0.50 percent. Forecast of energy consumption is shown in figure 4-5. These forecasts are based on assumption that electricity consumption will rise at a rate of 1.6 percent and natural gas consumption will rise at a rate of 0.50 percent. Forecast values of the energy consumption of starting year of the planning horizon, 2015, are also shown in the same figure.

4.3.7 Cost and Technical Data of Energy Alternatives

There are many alternatives that can be used to generate energy on college campuses. However, the purpose of this work is to test the model and address the research questions described in the first chapter. Therefore, only some alternatives are considered here. It should be mentioned that the cost of any alternative may vary depending upon the geographical location as each state has different costs such as labor costs, permit costs etc. Therefore, there might be variations in overall costs of each alternative depending on location of the installation. This thesis only uses generic estimates based on existing literature.

4.3.7.1 Boiler and Combined Heat and Power (CHP)

Conversion of primary fuel such as biomass, coal, or natural gas into electricity using boilers is not efficient as compared to CHP technologies. CHP technologies are very efficient in converting fossil fuel and biomass into useful heat and electricity (ETSAP, 2010b). The principle of CHP (also called cogeneration) is to recover energy that would otherwise be released into the atmosphere as waste heat, thus increasing overall efficiency of the conversion process (EPA, 2008). Therefore, CHP generation has significant environmental benefits over separately producing fossil-based electricity and on-site fossil-based thermal energy. The overall efficiency of a CHP system can be around 70-80 percent (EPA, 2008). A typical commercial scale CHP

unit can be used on a college campus to meet its partial or full energy needs. The useful heat recovered could be sent into a central heating loop for space heating during winter or to absorption chillers to provide space cooling during summer (EPA, 2008). Various fuels such as natural gas, biomass can be used in a CHP technology

Table 4-2 summarizes various parameters of different boilers and CHP alternatives used in this thesis. For the purposes of illustration, this thesis will include gas boiler, biomass boiler, gas-turbine based CHP, and biomass based CHP technologies. It should be noted that all the data in table 4-2 are estimates based on the information provided in (EPA, 2007, 2008; ETSAP, 2010a, 2010b; Hawkes, 2010; WBDG, 2012). It is also assumed that lead time for adding gas boilers is one year because no system modifications are necessary. However, adding CHP units or biomass boilers may require major modification of existing system. Therefore, lead time for systems is assumed to be two years.

Table 4-2 Existing generation capacity (in kW)

Alternative	Investment Cost	Fixed O&M Cost	Variable O&M Cost	Capacity Factor	Lead Time	Lifetime	Efficiency (Electricity, Heat)
CHP_NG	$2000[8]/kWe	$ 30/kWe	$0.006/kWh	0.90	2 Years	20	(28%, 41%)
CHP_B	$5200[9]/kWe	$100/kWe	$0.001/kWh	0.90	2 Years	20	(18%, 52%)
Boiler_NG	$66/kWth	$7/kWth	$0.001/kWh	0.90	1 Years	15	(0, 80%)
Boiler_B	$500/kWth	$14/kWth	$0.001/kWh	0.90	2 Years	15	(0, 70%)

4.3.7.2 Renewable Energy Alternatives

Universities can generate electricity by harnessing wind energy on campus. Gradual decrease in investment costs has made wind energy financially attractive and more competitive with

[8] The investment cost of CHP_NG is complex installation cost, which refers to the installation cost at existing customer site requiring added engineering and construction cost due to major modifications in existing system (EPA, 2008; ETSAP, 2010b).
[9] Actual cost of biomass based CHP is about $4500/kW (EPA, 2007). However, additional $700/kW is modification cost to existing system based on the approximate cost difference in simple and complex installation mentioned in (EPA, 2008)

conventional energy sources (UNEP, 2006). Table 4-3 summarizes cost and technical data of various renewable energy alternatives. This thesis considered PV and wind for the analysis. The data estimates in the table is based on the information provided in (Tidball, Bluestein, Rodriguez, & Knoke, 2010). It was assumed that none of the alternatives received any financial incentives.

Table 4-3 Data on cost parameters of the alternatives

Alternative	Investment Cost	Fixed O&M Cost	Variable O&M Cost	Capacity Factor	Lead Time	Lifetime	Output Energy Coefficient (Electricity, Heat)
Wind	$2000/kW	$30/kW	$0.005/kWh	0.30	1	20	(1,0)
PV	$4000/kW	$10/kW	0	0.15	1	30	(1,0)

The price of RECs is estimated to be around 0.4 cents/kWh or $4/MWh between 2015 and 2020. Moreover, the prices are estimated to rise to 1.9 cents/kWh or $19/MWh between 2020 and 2030 (EIA, 2007). It is assumed that prices of RECs will stay at $19/MWh after 2030.

4.3.8 Emission Data

For the past few years, the major contributors to total greenhouse gas emissions have been combustion of natural gas on campus for heating purposes and purchased electricity (RIT, 2011). It should be noted that this thesis only includes emissions associated with on-campus fuel combustion and purchased energy. The average carbon footprint of one kWh of purchased electricity in NY State is about 0.226kg of CO2 equivalent (EPA, 2012). The average transmission losses in the eastern region is about six percent (EPA, 2012). As each purchased unit of electricity is associated with transmission losses, therefore, the overall carbon footprint of each unit of purchased electricity should also include transmission losses in the analysis. Therefore, total carbon footprint of one kWh of purchased electricity is equal to 0.240kg (1.06*0.226) of CO2 equivalent. The emission factor of natural gas is about 53kgs of CO2 equivalent/MMBtu.

4.3.9 Uncertainty in the Data

4.3.10 Energy Prices

The prices may not follow a specific or single price trajectory. There will be some variability and volatility in addition to uncertainties. The forecasts of electricity prices from the year 2010 to the year 2035 under various scenarios are presented in *Annual Energy Outlook-2012* published by Department of Energy. According to the forecasts, average growth in electricity prices in real dollars for the commercial sector in East-North-Central region will be between zero percent and 1.5 percent depending on a scenario (EIA, 2012a, 2012b). Therefore, to capture uncertainty in the electricity prices, it will be assumed that the annual electricity prices vary independently. The electricity prices for each year of the planning horizon will be randomly chosen from a range derived from best case scenario (low prices and zero escalation) and worst case scenario (high prices and high escalation as shown in table 9-1 (see appendix). Future natural gas prices can be modeled in the same way electricity prices are modeled. Prices of natural gas were very sensitive to the carbon tax. The average growth rate of natural gas prices varied from zero percent to 2.3 percent depending upon the scenario (EIA, 2012b). In order to capture uncertainty in the natural gas prices, it will be assumed that the annual natural gas prices will vary independently. The natural gas prices for each year of the planning horizon will be randomly chosen same way as electricity prices as shown in table 9-1 (see appendix).

4.3.11 Carbon Prices

"A carbon offset negates or neutralizes a ton of CO2e (carbon dioxide equivalent) emitted in one place by avoiding the release of a ton of CO2e elsewhere or absorbing / sequestering a ton of CO2e that would have otherwise remained in the atmosphere " (Taiyab, 2006). An entity (individual, government, companies, and colleges) can offset their carbon footprints by

purchasing offsets.

Despite uncertainties in government policies to reduce greenhouse gas emissions, it is very likely that there will be at least some costs on carbon emissions (Johnston et al., 2011). Therefore, long-term resource planning decisions should consider costs of carbon emissions. However, it is not possible to predict specific policies or scenarios that might happen in the future. (Johnston et al., 2011) reviewed existing literature and presented range of future carbon prices. According to projections made by (Johnston et al., 2011), lower bound of CO2 prices over the period 2015 to 2030 is expected to rise linearly from $.017/kg CO2 in 2020 to $0.033/kg CO2 in 2030. Higher bound on carbon prices expected to rise linearly from $0.017/kgCO2 in 2015 to $0.088/kg in 2030. The authors considered few extreme values as outliers and excluded from the projections because according to the authors, those values depended on various factors that may not occur in combinations.

This thesis will use carbon price information given in (Johnston et al., 2011) as shown in table 9-2 (see appendix) because the authors appropriately considered and analyzed various factors including legislative proposals in order to forecast carbon prices. It may be slightly different from (Johnston et al., 2011) due to conversion of units and rounding error. The uncertainties in the CO2 prices can be significant. Therefore, it becomes necessary to use a range of costs associated with emissions in the investment planning to develop robust plans. (Johnston et al., 2011) incorporated a number of government proposals on carbon emissions in addition to various carbon price estimates produced by many utilities and government organizations such as Environmental Protection Agency (EPA) and Energy Information Administration (EIA). Therefore, forecasts provided by the authors seem to be reliable and representative of realistic future prices on carbon emissions. However, low range of carbon prices is fixed at $15 in this

thesis, which is assumed to reflect the best case carbon prices scenario.

The authors forecasted carbon prices until year 2030 only. As planning horizon in this thesis spans up to 2034, it will be assumed that the price range after 2030 stays at its 2030 level throughout the remaining period. Carbon price for each year of the planning horizon will be randomly chosen from a low range and a high range estimates shown in table 4-5.

Chapter 5. Results

Our work analyzed effects of length of a planning period, emission trajectories, and the uncertainties in electricity, natural gas, and carbon prices may have on costs and decisions to achieve carbon neutrality. A methodology was developed and tested by developing energy plans for RIT. The optimization model was coded in AMPL and solved using GUROBI solver. The analysis was carried out in two parts. The first part focused on the effects of length of planning period and emission trajectory on cost and planning decisions. Based on the findings of the first part, Monte Carlo Simulation (section 5.2) was used in the second part to test the effects of uncertainties in electricity, natural gas, and carbon prices.

5.1 Results and Analysis for the First Part

5.1.1 Short Term Planning vs. Long Term Planning

The results for the first part are shown in table 5-1. When there are no annual emission constraints before the target date, the results indicate that the BAU energy system is going to be the least cost effective planning strategy (see energy plans 1, 5, 9, and 13 in the table). It implies that there is potential for improvements in existing energy system. The 20 year planning strategy (Master Plan) was the most cost effective planning strategy in all scenarios considered (see energy plans 4, 8, 12, and 16 in the table). Table 5-2 compares optimal energy plans obtained through a 20 year planning strategy in various cost scenarios. In scenario-A, a natural gas based CHP power plant with generating capacity of 6408kW was installed in the first year of the planning horizon. In subsequent years, additional generating capacity was added in order to meet the rising energy demand. In this scenario, natural gas was cheap. Therefore, instead of burning natural gas in the boilers to meet only heat demand and purchase all electricity from the grid, it

was cost effective to install a CHP power plant to produce heat and electricity simultaneously on campus.

Table 5-1 Scenario description and the cost of optimal solutions under various strategies and scenarios

Energy Plans	Emission trajectory	Cost Scenarios	Planning Strategy	Total discounted Cost (in millions of dollars)[10]
1	No Limit (NL)	Low and stable (A)	BAU_NL	$114
2			5_NL	$112
3			10_NL	$112
4			MP_NL	$106
5		Low, but increasing (B)	BAU_NL	$128
6			5_NL	$127
7			10_NL	$126
8			MP_NL	$115
9		High, but stable (C)	BAU_NL	$140
10			5_NL	$139
11			10_NL	$138
12			MP_NL	$122
13		High and increasing (D)	BAU_NL	$159
14			5_NL	$157
15			10_NL	$146
16			MP_NL	$124

This result also indicates that if prices of natural gas are low, a natural gas based CHP power plant can meet campus's partial heat and electricity requirement at lower costs than the current energy system (BAU) of the campus. No other energy alternative turned out to be cost effective in scenario (A).

In scenario B, gas, electricity, and carbon prices rose at a gradual rate from their present values. Rising electricity prices made wind energy economical as compared to grid electricity. Therefore, in this scenario, addition of natural gas based CHP and wind turbines in the energy

[10] Values were rounded off to nearest integers.

system were the most cost effective investment decisions. Although this optimal energy plan requires high initial capital investment, it also saves future expenses on electricity, natural gas, and carbon credits as compared to BAU planning strategy.

Table 5-2[11] New capacities to be installed under MP_NL year planning strategy in various scenarios

	Scenario A	Scenario B		Scenario C			Scenario D		
	CHP NG	CHP NG	Wind	CHP NG	Wind	CHP B	CHP B	Wind	Boiler B
2015	6408	5823	15188	x	24323	2778	2929	23870	x
2016	32	174	x	x	x	174	174	0	x
2017	32	177	x	x	x	177	177	0	x
2018	32	180	x	180	x	x	16	0	x
2019	33	183	x	183	x	x	16	490	x
2020	33	33	x	33	x	x	17	499	x
2021	33	33	x	33	x	x	17	507	x
2022	33	33	x	33	x	x	17	516	x
2023	x	33	x	33	x	x	17	525	x
2024	x	33	x	33	x	x	17	534	x
2025	x	34	x	x	x	x	17	x	x
2026	x	34	x	x	x	x	17	x	x
2027	x	x	x	x	x	x	x	x	50
2028	x	x	x	x	x	x	x	x	50
2029	x	x	x	x	x	x	x	x	50
2030	x	x	x	x	x	x	x	x	50

In scenario C and D, high energy and carbon prices have made biomass based CHP power plant cheaper than natural gas based energy generation. Also, due to higher electricity prices, wind energy also became cheaper than purchased electricity. These two optimal solutions suggest that the biomass based CHP and wind turbines may become cost effective in certain high energy prices scenarios.

[11] In all tables 'x' implies no capacity was installed. If any year is not listed in the table, it means that no new capacity of any alternative was installed in that year.

It can be inferred from the above analyses that the high gas, electricity prices, and carbon prices increase the share of renewable energy in the energy system. BAU planning strategy is heavily dependent on natural gas and purchased electricity. Therefore, rising gas and electricity prices also increase the costs to purchase not only the energy, but carbon credits to neutralize emissions associated with it. Based on the results shown in table 5-1, it is clear that 20 year planning strategy performs better than BAU planning strategy.

Furthermore, a 10 year planning strategy performed only slightly better than BAU planning strategy (see table 5-1) except in scenario D, in which it performed considerably better. A 10 year planning strategy focuses on values of parameters for a period of 10 years only. Therefore, over a planning horizon of 20 years, decision makers have to develop two plans sequentially, one for each ten-year period. The first plan is developed at the beginning of year 2015. Subsequently, the second plan, which depends on the decisions made in the first plan, is made at the beginning of year 2025. In other words, this planning strategy will choose the solution which is the least cost solution during those ten years period only. Optimal capacity additions through a 10 year planning strategy in various scenarios are presented in table 5-3. In scenario A, the 10 year planning approach produced energy system similar to the BAU approach. No new power plants were installed. Five year and 10 year approaches were cheaper than BAU only because the BAU planning strategy bought RECs equivalent to 15 percent of its electricity.

In scenario B, during the second phase of the planning (from year 2025), natural gas based CHP generating units became cost effective even for a period of less than 10 years. The main reason for this outcome was that it was cheaper to produce electricity from CHP unit than purchase from grid. In scenario C, the results were no different than BAU planning strategy because producing electricity from natural gas based CHP generators was more expensive than purchasing

electricity from the grid. In scenario D, during both phases of the planning, new power plants were installed. High natural gas, electricity, and carbon prices made biomass based CHP generating cost effective for a period of ten years.

Table 5-3 New capacities to be installed under 10_NL year planning strategy in various scenarios

	Scenario A	Scenario B	Scenario C	Scenario D		
		CHP NG		CHP NG	Boiler B	CHP B
2015	x	x	x	6408	x	x
2016	x	x	x	x	x	x
2017	x	x	x	x	x	x
2018	x	x	x	x	x	x
2019	x	x	x	x	x	x
2020	x	x	x	x	x	x
2021	x	x	x	x	x	x
2022	x	x	x	x	x	x
2023	x	x	x	x	x	x
2024	x	x	x	x	x	x
2025	x	6736	x	x	x	3414
2026	x	34	x	x	x	17
2027	x	x	x	x	50	x
2028	x	x	x	x	50	x
2029	x	x	x	x	50	x
2030	x	x	x	x	50	x

The main conclusion that can be drawn from above results is that integrating multiple short-term energy plans each of which has its own short-term objectives to meet a long-term goal may be sub-optimal. Developing an energy plan to meet a long-term goal with interim objectives can be much more cost effective. These observations were consistent even in worst case cost scenarios. The 10 year planning strategy was only slightly better than BAU planning approach under many scenarios. Focusing on a period of only ten years to develop an energy plan produced sub-optimal energy plans as compared to 20 year planning approach, which produced the most cost effective energy plans in every scenario. Therefore, length of planning period is an important

decision factor in developing an optimal energy plan. It should also be noted that most of the installation of the alternatives needed to done within the first two or three years of the planning horizon. Therefore, decision makers may have to take these decisions at the beginning of the planning period.

5.1.2 Effects Investment Constraints

The energy plan developed by assuming the best-case scenario required small capital investments, but it was heavily dependent on purchased electricity, natural gas, and carbon prices; therefore, it was riskier than expensive energy plans. Energy plans developed for the worst-case scenario (Scenarios C and D) had a higher share of renewable energy as compared to the energy plan design for best-case scenario, which not only reduced overall emissions, but also the risks associated with the energy and carbon prices.

Scenario C was chosen for the analysis because optimal energy plan developed under this scenario required large capital investments. It should be noted that both energy plans developed under scenarios C &D were similar. Therefore, choosing either of these scenarios would produce similar results. The results are shown in table 5-4.

Table 5-4[12] New capacities to be installed under annual investment limits

	Energy Plan C5			Energy Plan C2
	CHP NG	Wind	CHP B	CHP_NG
2015	2500	x	x	1000
2016	2500	x	x	1000
2017	1472	1028	x	1000
2018	32	2468	x	1000
2019	33	2467	x	1000
2020	33	x	x	1000
2021	33	x	x	603
2022	33	x	x	33
2023	33	x	x	33
2024	33	x	x	33
2025	x	x	x	x
2026	x	x	x	x
2027	x	x	x	x
2028	x	x	x	x
2029	x	x	x	x
2030	x	x	x	x
Total Cost	$130 million dollars			$133 million dollars
Total Investment Cost	$21 million dollars			$11 million dollars

The main observations are the differences not only in total cost and investment cost, but also in mix of alternatives in the energy plans. The energy plan shown in table 5-2, with no capital constraints has total cost of 122 million dollars and total investment cost of 62 million dollars. Energy plans C2 (with 2 million dollars annual investment limit) and C5 (with 5 million dollar annual investment limit) require lower total capital investment, but have higher total cost. The main observation is the composition of alternative mix. Plans with investment limits do not propose any investment CHP_B technology, but rather choose CHP_NG because it is cheaper to

[12] In all tables 'x' implies no capacity was installed. If any year is not listed in the table, it means that no new capacity of any alternative was installed in that year.

install. Share of wind also reduced as compared to the plan described in table 5-2 under scenario C. Similar observations were made for energy plans developed under scenario B with investment limits.

Impact of investment limit on costs was intuitive, but its impact on alternative mix was much more pronounced. It should be noted all these plans were analyzed for 20-year planning period. These observations are important especially for those decision makers who want to make gradual investments to have more flexibility in future decisions. In this way, decision makers may take corrective actions if conditions change. For example, instead of adding large capacity of wind energy, only small capacity of wind energy was added. If in future electricity prices stay low, this may turn out be right decision. If electricity prices rise further, more wind can be added. However, there is a trade-off. Limiting capital expenditure in early decisions may also reduce their ability to switch to different alternative mix that is more cost effective. For example, in above results, natural gas based CHP was chosen over biomass based CHP. If in future, if prices of gas rise or prices of biomass fall drastically, it may not be feasible to install biomass based CHP technologies in future because system already has natural gas based CHP.

Apart from length of planning period and investment limits strategy such as interim emission targets or share of renewable energy by adding more constraints in order to limit the dependency on various external factors such as electricity, natural gas, and carbon prices can be important too. Adding more constraints may increase the cost of an energy plan, but it can also help reduce the risks. In the next section, the effects of various emission constraints on an energy plan are discussed.

5.1.3 Effects of Planned Emission Reduction

The effects of planned emission reduction on energy plans are presented in this section. Suppose, based on the results described in previous section, the decision makers choose to develop an energy plan through 20-year planning strategy with no investment limits. One of the main problems in developing an energy plan is choosing appropriate values of energy and carbon prices under uncertainties, which decision makers cannot control. Therefore, one of the ways to design an energy system is assuming a worst-case scenario, which would require huge capital investments as described in previous section. Another approach is to design the system by assuming best-case scenario, and then, control certain decision factors by imposing additional constraints that can limit the overall risks associated with uncertainties in energy and carbon prices. For example, decision makers might consider adding a constraint that ensures a minimum percentage of energy production from renewable energy. A similar constraint can be limits on annual emissions.

As the main focus of this analysis was to reduce emissions rather than increase the share of renewable energy, the effects of limits on annual emissions were analyzed. It should be noted that higher share of renewable energy also implies decrease in emissions. However, reducing emissions may not necessarily imply higher share of renewable energy because emissions can also be neutralized through carbon offset and RECs.

In the previous sections (5.1.1 and 5.1.2), it was assumed that the annual emission would follow 'NL' emission trajectory. However, in this section, it was assumed that total emissions would be reduced gradually to zero by year 2030 as shown in figure 4-4. This analysis was done under a best-case scenario only. The rational for doing so was to develop an energy plan for best-case scenario and analyze the effects of certain control factors (constraints) on the energy plans to

meet the needs of the decision makers. Another reason was that that in the worst-case/high cost scenario, energy plan had higher share of renewable energy because it became more economical, which reduced emissions without any constraints; so any emission limits did not have any effect.

MP_PR planning strategy, which represents 20 year energy plan (master plan) with gradual emission reduction, was analyzed and compared with MP_NL planning strategy. The upper limit on combined contribution of carbon offsets and RECs to meet the emission targets was up to 100 percent of the annual carbon footprint respectively. The total cost of each strategy is presented in table 5-5.

Table 5-5 Scenario description and the cost of optimal solutions under various strategies and scenarios

Energy Plans	Emission trajectory	Cost Scenarios	Planning Strategy	Total discounted Cost (in millions of dollars)[13]
1	No Limit	Low and stable (A)	MP_NL	$106
2	Planned Reduction		MP_PR	$109

The energy plan developed through MP_PR strategy cost more than the plan developed through MP_NL strategy. By imposing annual emission restrictions, extra money had to be spent to buy carbon and energy credits every year. This was the main reason for the higher cost of MP_PR strategy. The cost and new capacity installed through MP_PR strategy are shown table 5-6.

[13] Values were rounded off to nearest integers.

Table 5-6 New capacities to be installed under MP_PR strategy

Year	Scenario A
	CHP NG
2015	6408
2016	32
2017	32
2018	32
2019	33
2020	33
2021	33
2022	33
2023	x
2024	x
2025	x
2026	x

The optimal energy obtained through the MP_PR planning strategy was compared with the results obtained through the MP_NL planning strategy shown in table 5-1 and 5-2. There was no difference in the installation of new capacities of any alternative. However, due to emission restrictions in MP_PR strategy, the emission targets were met through purchase of carbon offsets, which only increased the total cost. One conclusion that can be drawn is that annual emission limits or emission trajectory may not be an important part of planning strategies as long as carbon offset is allowed to meet 100 percent of the emission targets. Also, buying carbon offsets to reduce emissions still exposes optimal energy plans to uncertainties in carbon prices. The next section extends the analysis by controlling the purchase of carbon offset and RECs.

5.1.4 Effects of Limiting Contribution of Carbon Offsets and RECs

Limiting the contribution of carbon offsets and RECs to meet emission target will increase the share of renewable energy alternatives in an energy system. A higher share of renewable

energy in an energy system can also make the annual cost of the system less sensitive to the uncertainties in electricity, natural gas, and carbon prices. However, a higher share of renewable energy requires large capital investment. Therefore, controlling the share of carbon offsets and RECs can be important because it affects both risks and capital costs of an energy plan.

Five different levels of percentage limits were considered in this part of the analysis. Percentage limit on the total share of offsets and RECs in meeting emission targets was the main decision factor. In each case, the effects of the various upper limits on the annual contribution of carbon offsets and RECs towards emissions reduction were analyzed on a 20 year planning strategy as shown in table 5-7. The baseline emissions were the emissions at the beginning of the planning horizon i.e. 2015 (see figure 4-4).

Table 5-7 Share of carbon offsets and RECs as a percentage of baseline carbon emissions

Level	Baseline Emissions (kgs of CO2 equivalent)	Percentage Limit	Maximum contribution of offsets and RECs allowed (kgs of CO2 equivalent)
1 (baseline)	36514698	100%	36514698
2	36514698	75%	27386023
3	36514698	50%	18257349
4	36514698	25%	9128674
5	36514698	0%	0

The model was run for every combination of the percentage limit level and emission trajectory. The total cost of each energy plan is presented in table 5-8. Comparing these results with the results shown in table 5-4, it can be observed that limiting the total share of carbon offsets and RECs increased the total cost of energy plans irrespective of the emission trajectory followed. The main reason for the higher costs was the installation of various renewable energy alternatives to the energy system as shown in tables 5-9, 5-10, and 5-11.

Table 5-8 Scenario description and the cost of optimal solutions under various levels of the percentage limits

Energy Plan	Emission trajectory	Cost Scenarios	Planning Strategy	Total discounted Cost (in millions of dollars)[14]
1	No Limit (NL)	Low and stable (A)	MP_NL_100%	$108
2			MP_NL_75%	$110
3			MP_NL_50%	$112
4			MP_NL_25%	$116
5			MP_NL_0%	$120
6	Planner Reduction (PR)	Low and stable (A)	MP_PR_100%	$110
7			MP_PR_75%	$112
8			MP_PR_50%	$114
9			MP_PR_25%	$117
10			MP_PR_0%	$120

Unlike the findings in the previous section, it was observed that the emission trajectories also influenced the results when the limits were imposed, though impact for modest. Comparing the effects of different emission trajectories, planned emission trajectory (PR, see energy plans 6-10) proved to be costlier than NL emission trajectory (see energy plans 1-5). When the total contribution of offsets and RECs was 100 percent (100% limit), emission trajectory had modest influence on the total cost and optimal energy plan as shown in tables 5-8 and 5-9. One of reasons was as because of the limit, wind energy was introduced in into the mix at the beginning, which reduced total emissions even below 'PR' requirements.

[14] Values were rounded off to nearest integers.

Table 5-9 New capacities to be installed under MP_NL_100% and MP_PR_100% year planning strategy

Year	Energy Plan 1			Energy Plan 6			
	CHP NG	Wind	Boiler_B	CHP NG	CHP_B	Wind	Boiler_B
2015	6408	13434	x	6173	0	14139	x
2016	32	x	x	79	95	x	x
2017	32	x	x	x	16	x	x
2018	32	x	x	x	16	x	x
2019	x	x	x	x	16	x	x
2020	x	x	x	x	x	x	x
2021	x	x	x	x	x	x	x
2022	x	x	x	x	x	x	x
2023	x	x	x	x	x	x	x
2024	x	x	x	x	x	x	x
2025	x	x	x	x	x	x	x
2026	x	x	x	x	x	x	x
2027	x	x	x	x	x	x	x
2028	x	x	x	x	x	x	x
2029	x	x	1250	x	x	x	442
2030	x	x	239	x	x	x	239
2031	x	x	242	x	x	x	242
2032	x	x	245	x	x	x	245

When the total contribution of offsets and RECs was zero (0% limit), emission trajectory had only small influence on the total cost and optimal energy plan as shown in tables 5-8 and 5-11 because 100 percent of the energy demand had to be met through renewable energy. Therefore, emission limits didn’t affect planning decision much.

The main difference in this energy plan from previous energy plan was that biomass based CHP was favored over natural gas based CHP alternative. In order to be a cost effective energy plan, large capacity of wind energy had to be installed in the first year of the planning period. This influence became more pronounced as the limits were reduced to smaller values (100 percent in

table 5-8 to zero percent in table 5-10), where share of energy produced from CHP_NG declined to zero in order to meet emission target.

Table 5-10 New capacities to be installed under MP_NL_50% and MP_PR_50% year planning strategy

Year	Energy Plan 3			Energy Plan 8			
	CHP NG	Wind	Boiler_B	CHP NG	CHP_B	Wind	Boiler_B
2015	6276	13830	x	3916	274	20089	x
2016	164	x	x	79	174	x	x
2017	32	x	x	x	177	x	x
2018	32	x	x	x	180	x	x
2019	x	x	x	x	183	x	x
2020	x	x	x	x	186	x	x
2021	x	x	x	x	189	x	x
2022	x	x	x	x	17	x	x
2023	x	x	x	x	x	x	x
2024	x	x	x	x	x	x	x
2025	x	x	x	x	x	x	x
2026	x	x	x	x	x	x	x
2027	x	x	x	x	x	x	x
2028	x	x	x	x	x	x	1037
2029	x	x	9488	x	x	x	1470
2030	x	x	239	x	x	x	239
2031	x	x	242	x	x	x	242
2032	x	x	245	x	x	x	245

One conclusion that can be drawn from above results is emission trajectory may or may not be an important part of planning strategy. Imposing percentage limit on the contribution of carbon offsets and RECs seems to play more important role than choosing an emission trajectory. By choosing an appropriate contribution limit, decision makers can increase share of renewable energy in the energy system, which can also reduce the exposure to the fuel and electricity purchase.

Table 5-11 New capacities to be installed under MP_NL_0% and MP_PR_0% year planning strategy

Year	Energy Plan 5			Energy Plan 10		
	CHP_B	Wind	Boiler_B	CHP_B	Wind	Boiler_B
2015	0	32144	x	x	32144	x
2016	0	514	x	174	514	x
2017	177	523	x	177	x	x
2018	180	x	x	180	x	x
2019	183	x	x	183	x	x
2020	186	x	x	186	x	x
2021	189	x	x	189	x	x
2022	192	x	x	192	x	x
2023	195	x	x	195	x	x
2024	198	x	x	198	x	x
2025	201	x	x	201	x	x
2026	204	x	x	204	x	x
2027	207	x	x	207	x	369
2028	211	x	x	287	x	699
2029	825	x	973	541	x	x
2030	17	x	x	17	x	x
2031	18	x	x	18	x	x
2032	18	x	x	225	x	x

As most of the capital investments to develop energy plans are irreversible and the most of decisions must be made at the beginning of planning horizon, it becomes necessary to analyze trade-offs between costs and risks associated with the investments. A university's decision makers are unable to either know or control what the future energy and carbon prices are going to be when developing an energy plan.

5.2 Part II: Uncertainty Analysis

Monte-carlo simulation (MCS) experiments were conducted on some of the energy plans (technology mix) developed through the strategies discussed in section 5.1. Each energy plan represented certain technology mix and an implementation schedule. The main purpose was to find an energy plan that would be satisfactory in many realizations of uncertain parameters rather than remain optimal in just one scenario. The analysis first focused on uncertainties only in electricity, natural gas, and carbon prices. Then it was extended to included uncertainties in other parameters such as biomass prices and discount rate.

The energy plans that were analyzed are shown in the table 5-11. The simulation for each energy plan was performed by running the deterministic model for 500 trials. For every trial, the values of the decision variables for the energy plan, obtained through deterministic analysis under a particular cost scenario, were fixed. Then, for each trial, a single set of the values of uncertain parameters was chosen from their respective distributions and the model was run. The value of objective function (total present cost) was recorded for each trial. After 500 trials, the distribution of the objective function was obtained and mean and standard deviation of the distribution were calculated.

This process was repeated for each of the nine energy plans. In table 5-11, Energy Plans 'EP2', 'EP3','EP6', and 'EP7' were obtained through strategy MP_NL_ (cost scenarios A, B, C, D), details of which are mentioned in table 5-2. For example, the optimal values of decision variables shown in table 5-2 for energy plan 'EP2' were fixed. Then, the simulation was performed for 500 trials. The mean and standard deviation of the objective function are shown in the table. All costs figures are in millions of dollars.

Table 5-12 Results of MCS [15]

		Cost distribution after MCS		
Energy Plans	Planning strategy and cost scenario used to find corresponding energy plan	Actual mean total discounted cost	Standard deviation	Total Capital Investment in the scenario
EP1	BAU_NL_A	$136.45	$2.28	$0
EP2	MP_NL_A	$125.6	$1.72	$12.4
EP3	MP_NL_B	$120.87	$1.33	$41.1
EP4	MP_NL_100%_A	$121.78	$1.34	$38
EP5	MP_PR_100%_A	$124.58	$1.29	$39.40
EP6	MP_NL_C	$121	$0.5	$61.9
EP7	MP_NL_D	$121.4	$0.47	$65.5
EP8	MP_NL_0%_A	$124.34	$0.61	$72
EP9	MP_PR_0%_A	$124.18	$0.59	$71.9

These experiments showed how an energy plan would perform under future uncertainties when designed for a particular cost scenario. The energy plan 'EP2' had an optimal cost of $106 million dollars under scenario A as shown in table 5-1. However, after MCS, the mean cost becomes $ 125.6 million dollars with standard deviation of $ 1.72 million dollars as shown in figure 5-2.

[15]All cost figures are in millions of dollars

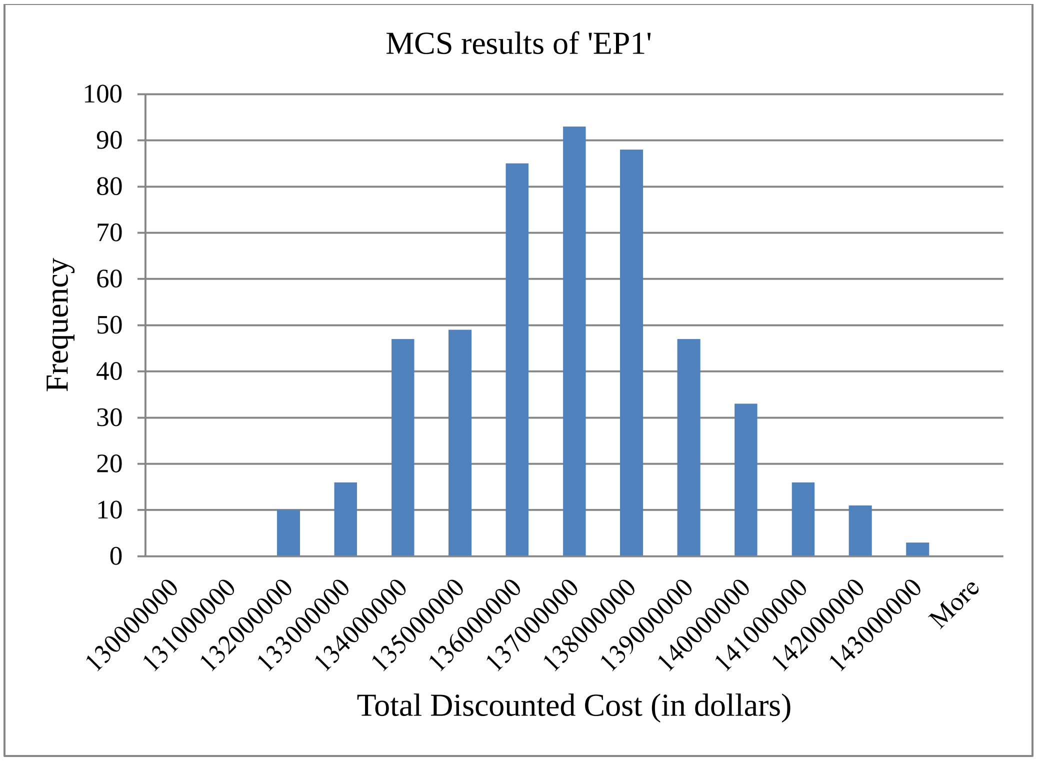

Figure 5-1 Cost distribution of energy plan EP1

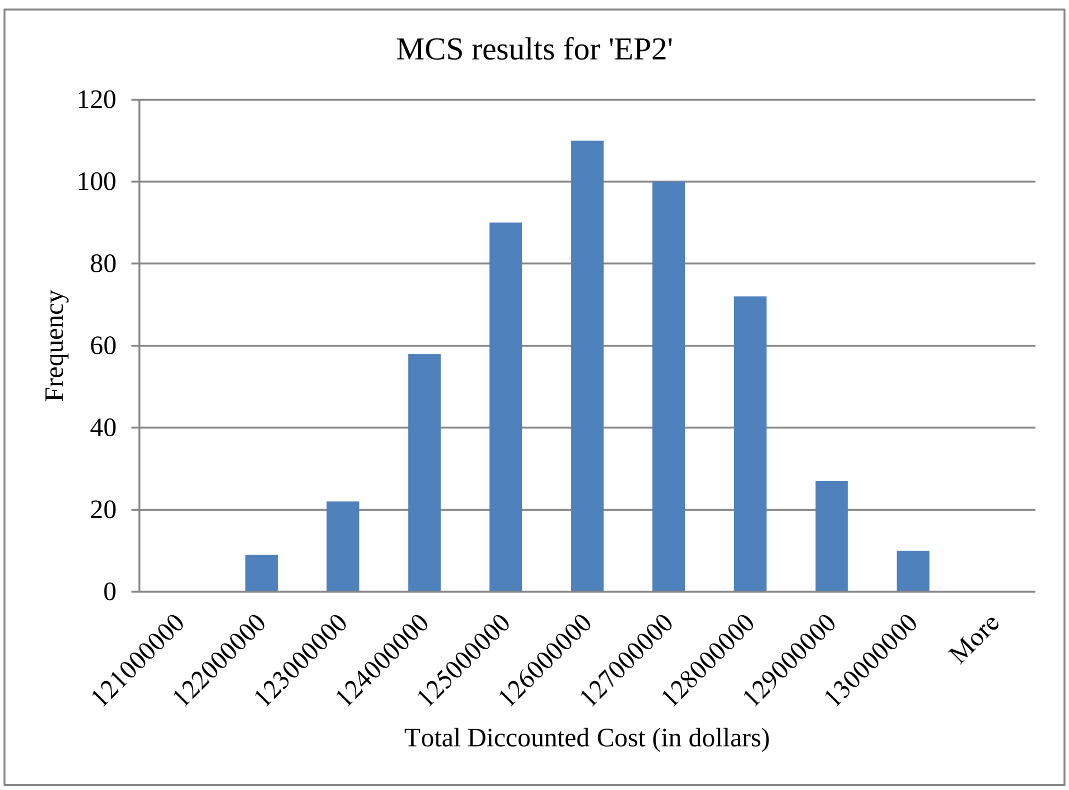

Figure 5-2 Cost distribution of energy plan EP2

It can be observed from above analyses is that the cost of some energy plans, such as ‘EP1’and ‘EP2’ developed through deterministic modeling using optimistic input data or constraints (best-case cost scenario, or small limit on share of carbon offsets) may underestimate the actual cost of the plan due to potential uncertainties. In other words, this approach will find energy plans with small capital investment, but higher operating expenses.

On the other hand, energy plans from ‘EP6’ to ‘EP9’ developed through deterministic models using pessimistic input data or constraints (worst-case cost, or no offsets allowed) may overestimate the actual costs. In other words, this approach will find energy plans that have huge investment costs, but low operating expenses.

One of the advantages of using MCS is that it can assist decision makers in finding a set of energy plans that have desirable total mean cost and variability associated with it. Using deterministic model, decision makers can only find costs of an energy plan under different cost scenarios. Application of MCS can provide insights into the cost distribution of an energy plan. For example, the cost of ‘EP1’ varied from \$109 to \$159 million dollars from best-case (A) to worst-case (D) cost scenario. However, in MCS, the mean cost of the energy plan was \$136.34 million dollars with standard deviation of \$2.28 million dollars. The distribution of cost is shown in figure 5-1.

However, all energy plans showed very little variability in their cost distributions. One of the reasons of small variability could be that the narrow range of uncertainties in electricity, natural gas, and carbon prices were explored. In addition to that, no correlation among uncertain parameters was considered. Therefore, for each energy plan, though year to year variability could be significant, but adding all those annual variability to calculate total cost might reduce the

impact of inter-annual variability. For energy plans such as ‘EP1’ and ‘EP2’ hat were largely dependent on purchased energy, another reason for low variability could be using higher discount rate, which could have underestimated the amount of future costs as costs associated with emission restrictions didn’t come into effect until 2031.

Chapter 6. Discussion and Conclusion

Our work tried to demonstrate the importance of mathematical models in decision making process related to energy investments in universities. Through the application of mathematical models certain relevant research questions were explored and addressed. Questions such as the importance of length of planning period, investment constraints, limiting share of carbon offsets and RECs in meeting emissions targets, and the effects of uncertainties in natural gas, electricity, and carbon prices were explored. A methodology was developed and tested by developing energy plans for RIT. The analysis was carried out in two parts. The first part focused on analyzing the effects of length of planning period and emission trajectory on cost and planning decisions. Based on the findings of the first part, Monte Carlo Simulation was used in the second part to test the effects of uncertainties in electricity, natural gas, and carbon prices, biomass, and discount rate.

Based on the findings, it can be concluded that developing a long-term plan is much better planning strategy than a planning strategy that integrates multiple short-term plans irrespective of the future costs scenarios. It is also clear from the results that most of the investments in every plan were made within the first few years when no constraints on investments were imposed. These findings show that many important decisions that will affect the future goals should be made very early in the planning period in order to develop cost-effective energy plans.

Moreover, making more gradual investments increased overall costs of an energy plan. This approach was intended to provide decision makers an opportunity to change some parts of an energy plan as range of uncertainties become narrower in the future. For example, if growth in energy demand or energy prices didn't turn out to be as predicted, huge capital investments made at the beginning would be underutilized. However, when decision makers preferred to make

gradual investments by imposing constraints on annual investment limits, optimal energy plans for various investments limits were very different in their respective alternative mixes from the beginning of the planning period. These experiments demonstrate that making gradual investments may not always provide desired flexibility in future decisions because some of the critical decisions should be made at the beginning of the planning period irrespective of investment limits. Therefore, switching to different alternative mixes (transition from one energy plan to another) over time may not be always possible even if more resources and better data become available in future.

Furthermore, uncertainty analysis was carried out to assist decision makers in making better decisions under uncertainty. It showed that natural gas, electricity, and carbon prices had little impact on total cost variability of an energy plan. One of the main reasons for small variability was the assumption that the all uncertain parameters varied independently throughout the entire planning period. Therefore, over multi-year period, the overall effect of annual variability on total cost was very small. However, if there was a correlation among uncertain parameters, then it might have introduced much larger variability. Other reasons include focusing on limited number of uncertain parameters. Uncertainties in capital costs of wind and solar, prices of biomass, and discount rate were excluded from the analyses. As many energy plans had higher share of renewable energy, uncertainties associated with these alternatives should also be explored. Discount rate also affect the contribution of future cost streams. Choosing a higher discount rate may underestimate future expenditures and may lead to development of poor energy plans. On the other hand, choosing low discount rate might overestimate future cost streams.

This study does not generalize the experimental results to the planning of energy investments made by all universities, but it rather looks for an opportunity to suggest an optimization based methodology that could be used to enrich and improve decision making process related to energy planning on college campuses.

Chapter 7. Future Work

There were several limitations to this work, which can be addressed in future research. One of the weaknesses of this approach was its focus on yearly energy data only, which may lead to poor system design in real life applications. For example, focusing on annual data neglects the hourly, daily, or seasonal variations in energy consumption pattern of the campus such as high heat demand in winter and high electricity demand in summer. CHP alternatives produce both heat and electricity usually in constant ratio whenever they are running. If a system is designed based on annual energy data and has major share of CHP energy alternatives, it may produce large quantities of heat in summer, and/or electricity in winter causing waste of energy, which may be not desirable. In addition, intermittent energy sources such as wind and solar may generate electricity when it is not required, thus also causing waste of energy. In addition to that, cost modeling of purchased electricity may be more complex in reality, which our work ignores. For example, electricity prices are expensive during the day; therefore, PV system may get extra incentive over other technologies in cost analysis.

Findings of this work also suggested that the most of the decisions must be made in the first few years of the planning period. Also, the trade-offs involved in making gradual investments for over few large investments were also discussed. Waiting for more data on energy demand, capital costs of renewable energy alternatives and, energy prices can give decision makers more flexibility. However, it is also possible that due to the lost opportunities at the beginning the transition from one energy plan to another energy plan using better information overtime may become much more expensive. Once an energy plan is developed, the costs and decisions required to transition from it to another energy plan were not included in this work. Proposing an approach for such transition can be an interesting extension of this work.

Uncertainty analysis in this work tried to address some of these difficulties associated with talking early decisions through the application of MCS. Limiting the scope of uncertainties to prices of natural gas, electricity, and carbon prices without assuming any correlation among uncertain parameters did not introduce much variability in total cost. Including uncertainties in other parameters such as capital costs of renewable energy and discount rate may improve results of uncertainty analysis and increase the scope of conclusions of this thesis. Also, developing an approach to find appropriate weight for present and future cost streams may be an important value addition.

Chapter 8. Bibliography

Abbott, J. A. (2010). Notes From The Field On using Values Based Education To Engage Challenges and Opportunities of The American College and University Presidents'Climate Commitment.

ACUPCC. (2006). American College & University Presidents' Climate Commitment Text. Retrieved 1 December, 2011, from http://www.presidentsclimatecommitment.org

Awerbuch. (2000). Investing in photovoltaics: risk, accounting and the value of new technology. *Energy Policy, 28*(14), 1023-1035. doi: 10.1016/S0301-4215(00)00089-6

Awerbuch, S., & Berger, M. (2003). Applying portfolio theory to EU electricity planning and policy-making. *IEA/EET working paper*.

Cormio, C., Dicorato, M., Minoia, A., & Trovato, M. (2003). A regional energy planning methodology including renewable energy sources and environmental constraints. *Renewable and Sustainable Energy Reviews, 7*(2), 99-130. doi: 10.1016/s1364-0321(03)00004-2

Dicorato, M., Forte, G., & Trovato, M. (2008). Environmental-constrained energy planning using energy-efficiency and distributed-generation facilities. *Renewable Energy, 33*(6), 1297-1313. doi: http://dx.doi.org/10.1016/j.renene.2007.07.011

EIA. (2007). Impacts of a 15-Percent Renewable Portfolio Standard.

EIA. (2012a). EIA - Annual Energy Outlook 2012.

EIA. (2012b). Interactive Table Viewer. *Annual Energy Outlook-2012.* Retrieved 23 August, 2012, from http://www.eia.gov/oiaf/aeo/tablebrowser/

EIA. (2013). The State Energy Data System (SEDS):2011.

EPA. (2007). Biomass Combined Heat and Power Catalog of Technologies *U. S. Environmental Protection Agency Combined Heat and Power Partnership*.

EPA. (2008). Catalog of CHP Technologies *U.S. Environmental Protection Agency Combined Heat and Power Partnership*.

EPA. (2012). Generation Resource Integrated Database (E-GRID) *Year 2009 eGRID Subregion Output Emission Rates - Greenhouse Gases*.

ETSAP. (2010a). Technology Brief_Biomass for Heat and Power *Energy Supply Technologies-Electricity & Heat Production, Transmission and Distribution*.

ETSAP. (2010b). Technology Brief_Combined Heat and Power *Energy Supply Technologies- Electricity & Heat Production, Transmission and Distribution*.

Feretic, D., & Tomsic, Z. (2005). Probabilistic analysis of electrical energy costs comparing: production costs for gas, coal and nuclear power plants. *Energy Policy, 33*(1), 5-13. doi: 10.1016/s0301-4215(03)00184-8

Haq, Z. (2002). Biomass for Electricity Generation.

Hawkes, A. D. (2010, 25-29 July 2010). *Optimal selection of generators for a microgrid under uncertainty.* Paper presented at the Power and Energy Society General Meeting, 2010 IEEE.

Hobbs, B. F. (1995). Optimization methods for electric utility resource planning. *European Journal of Operational Research, 83*(1), 1-20. doi: 10.1016/0377-2217(94)00190-n

Jackson, J. (2008). *Energy Budgets at Risk (EBaR): a risk management approach to energy purchase and efficiency choices* (Vol. 422): Wiley.

Johnston, L., Hausman, E., Biewald, B., Wilson, R., & White, D. (2011). 2011 Carbon Dioxide Price Forecast. Cambridge, MA: Synapse Energy Economics.

Klein-Banai, C., & Theis, T. L. (2011). Quantitative analysis of factors affecting greenhouse gas emissions at institutions of higher education. *Journal of Cleaner Production*(0). doi: 10.1016/j.jclepro.2011.06.004

Levine, D. (2009). Degrees That Matter: Climate Change and the University – By Ann Rappaport and Sarah Hammond Creighton. *Review of Policy Research, 26*(4), 492-493. doi: 10.1111/j.1541-1338.2009.00400.x

Mavrotas, G., Demertzis, H., Meintani, A., & Diakoulaki, D. (2003). Energy planning in buildings under uncertainty in fuel costs: The case of a hotel unit in Greece. *Energy Conversion and Management, 44*(8), 1303-1321. doi: 10.1016/S0196-8904(02)00119-X

Mavrotas, G., Florios, K., & Vlachou, D. (2010). Energy planning of a hospital using Mathematical Programming and Monte Carlo simulation for dealing with uncertainty in the economic parameters. *Energy Conversion and Management, 51*(4), 722-731. doi: 10.1016/j.enconman.2009.10.029

Mirzaesmaeeli, H., Elkamel, A., Douglas, P. L., Croiset, E., & Gupta, M. (2010). A multi-period optimization model for energy planning with CO2 emission consideration. *Journal of Environmental Management, 91*(5), 1063-1070. doi: 10.1016/j.jenvman.2009.11.009

RIT. (2011). Climate Action Plan.

RIT. (2012a). Construction Projects. Retrieved April 13th, 2013, from http://www.rit.edu/fa/facilities/content/construction-projects

RIT. (2012b). Rochester Institute of Technology. *At A Glance.* Retrieved 5 February, 2013, from http://www.rit.edu/overview/

RIT. (2012c). Sustainability at RIT. Retrieved 5 February, 2013, from http://www.rit.edu/sustainability

RIT (2013). [Information on RIT's Energy System].

Rizzoa, G., & Savinob, G. (2012). *A Linear Programming model for the optimal assessment of Sustainable Energy Action Plans.* Paper presented at the International Conference on Efficiency, Cost, Optimization,Simulation, and Environmental Impact of Energy Systems, Perugia, Italy.

Roques, F. A., Newbery, D. M., & Nuttall, W. J. (2008). Fuel mix diversification incentives in liberalized electricity markets: A Mean–Variance Portfolio theory approach. *Energy Economics, 30*(4), 1831-1849. doi: 10.1016/j.eneco.2007.11.008

Sharp, L. (2002). Green campuses: the road from little victories to systemic transformation. *International Journal of Sustainability in Higher Education, 3*(2), 128-145.

Simpson, W. (2009). Cool Campus. *A How-To Guide for College and University Climate Action Planning, ed. Niles Barnes, Julian Dautremont-Smith, Toni Nelson, and Brittany Zwicker (Lexington: Association for the Advancement of Sustainability in Higher Education, 2009), 51*.

Spinney, P. J., & Watkins, G. C. (1996). Monte Carlo simulation techniques and electric utility resource decisions. *Energy Policy, 24*(2), 155-163.

Taiyab, N. (2006). *Exploring the market for voluntary carbon offsets*: Iied.

Tidball, R., Bluestein, J., Rodriguez, N., & Knoke, S. (2010). Cost and Performance Assumptions for Modeling Electricity Generation Technologies. *Contract, 303*, 275-3000.

UNEP. (2006). Scoping Study on Financial Risk Management Instruments for Renewable Energy Projects *United Nations Environment Program-Sustainable Energy Finance Initiative*. New York: United Nations.

Vithayasrichareon, P., MacGill, I., & Fushuan, W. (2009, 27-30 Sept. 2009). *Monte-Carlo optimization framework for assessing electricity generation portfolios.* Paper presented at the Power Engineering Conference, 2009. AUPEC 2009. Australasian Universities.

WBDG. (2012). Biomass for Heat. from http://www.wbdg.org/resources/biomassheat.php

Winston, W. L., & Goldberg, J. B. (1994). Operations research: applications and algorithms.

Zakerinia, M., & Torabi, S. A. (2010, 27-29 Sept. 2010). *Multiobjective power expansion planning in the planning horizon.* Paper presented at the Innovative Technologies for an Efficient and Reliable Electricity Supply (CITRES), 2010 IEEE Conference on.

Chapter 9. Appendices

Table 9-1 Representation of Uncertainties in Electricity and Natural gas Prices

Year	Lower Limit ($/kWh)	Upper Limit ($/kWh)	Lower Limit ($/MMBtu)	Upper Limit ($/MMBtu)
2015	0.080	0.097	6	8.00
2016	0.080	0.098	6	8.10
2017	0.080	0.100	6	8.19
2018	0.080	0.101	6	8.29
2019	0.080	0.103	6	8.39
2020	0.080	0.104	6	8.49
2021	0.080	0.106	6	8.59
2022	0.080	0.108	6	8.70
2023	0.080	0.109	6	8.80
2024	0.080	0.111	6	8.91
2025	0.080	0.113	6	9.01
2026	0.080	0.114	6	9.12
2027	0.080	0.116	6	9.23
2028	0.080	0.118	6	9.34
2029	0.080	0.119	6	9.45
2030	0.080	0.121	6	9.57
2031	0.080	0.123	6	9.68
2032	0.080	0.125	6	9.80
2033	0.080	0.127	6	9.92
2034	0.080	0.129	6	10.04

Table 9-2 Range of Carbon Prices

Year	Lower Limit ($/1000kgs of CO2)	Upper Limit ($/1000kgs CO2)
2015	15	25
2016	15	26
2017	15	28
2018	15	29
2019	15	30
2020	15	32
2021	15	34
2022	15	35
2023	15	37
2024	15	39
2025	15	41
2026	15	43
2027	15	45
2028	15	47
2029	15	49
2030	15	52
2031	15	55
2032	15	57
2033	15	60
2034	15	63

Table 9-3 the Historical Energy Consumption of RIT (source: (RIT, 2013))

Year	Electricity (kWh)	Natural Gas (MMBtu)	Heat Requirement (MMBtu)
1998	50,704,402	368,419	294735
1999	54,812,386	375,772	300618
2000	57,472,726	394,824	315859
2001	56,690,249	419,173	335338
2002	65,141,173	402,995	322396
2003	69,627,153	483,013	386410
2004	73,349,367	474,562	379650
2005	75,761,995	483,628	386902
2006	79,001,732	469,243	375394
2007	78,623,684	478,734	382987
2008	79,891,094	470,133	376106
2009	80,156,863	421,298	337038
2010	79,162,445	339,666	271733
2011	79,510,608	361,363	289090
2012	79,295,000	307,821	246257
Average Annual Growth	3.24%	-1.28%	-1.28%

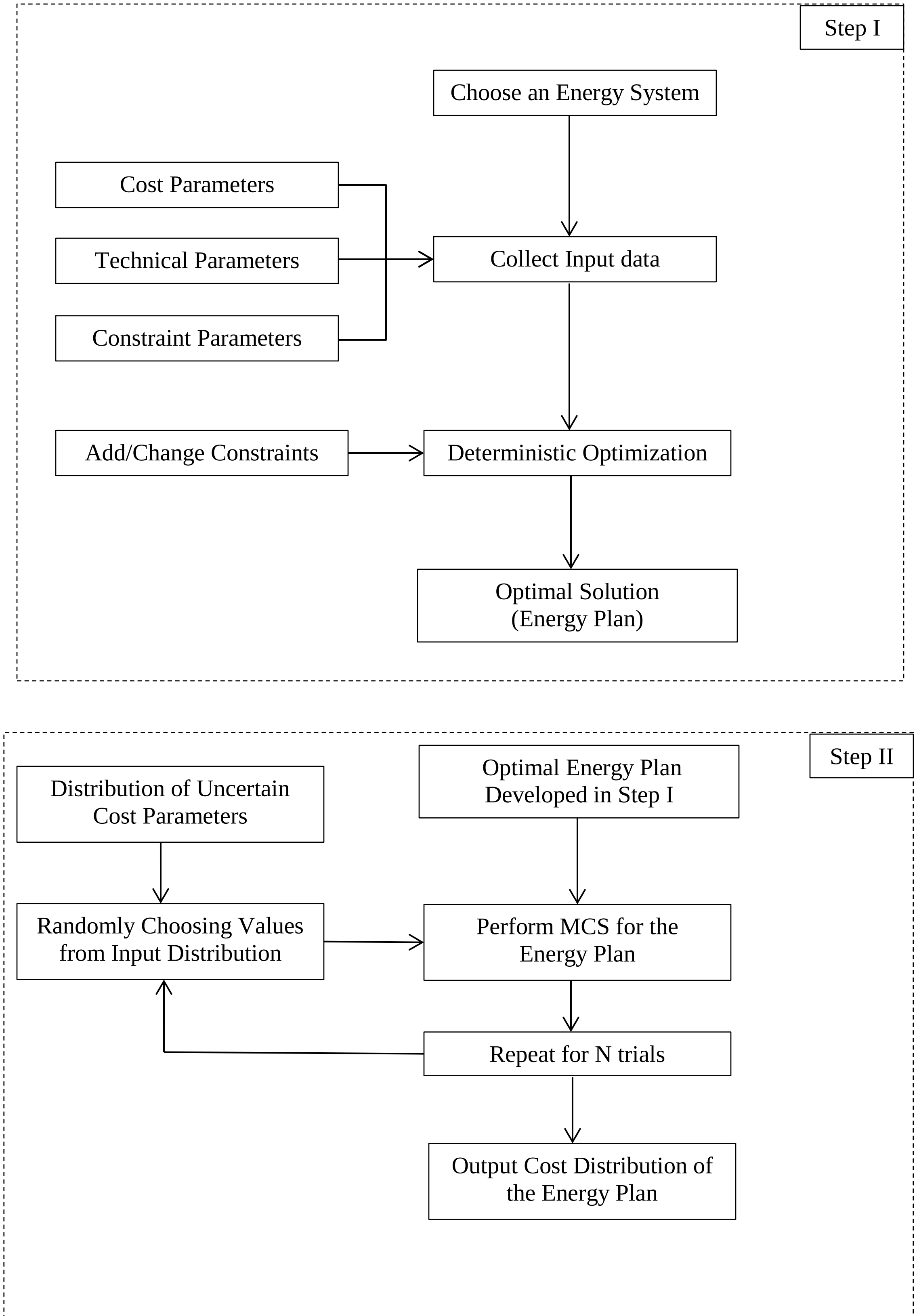

Figure 9-1 Flow Chart of Methodology