A Spatial Decision Support System for the Development of Multi-Source Renewable Energy Systems

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Abstract

This research involves the development of a comprehensive decision support system for energy planning through the increased use of renewable energy sources, while still considering the role of existing electricity generating facilities. This dissertation focuses on energy planning at the regional level, with the Greater Southern Appalachian Mountain region chosen for analysis due to the dependence on coal as the largest source of generation and the availability of wind and solar resources within the region.

The first stage of this planning utilizes a geographic information system (GIS) for the discovery of renewable energy sources. This GIS model analyzes not just the availability of wind and solar power based on resource strength, but also considers the geographic, topographic, regulatory, and other constraints that limit the use of these resources. The model determines potential wind and solar sites within the region based on these input constraints, and finally the model calculates the cost and generation characteristics for each site.

The results of the GIS model are then input into the second section of the model framework which utilizes a multi-objective linear programming (MOLP) model to determine the optimal mix of new renewable energy sources and existing fossil fuel facilities. In addition to the potential wind and solar resources discovered in the GIS, the MOLP model considers the implementation of solid wood waste biomass for co-fire at coal plants. The model consists of two competing objectives, the minimization of annual generation cost and the minimization of annual greenhouse gas emissions, subject to constraints on

electricity demand and capital investment, amongst others. The model uses the MiniMax function in order to find solutions that consider both of the objective functions.

The third major section of this dissertation analyzes three potential public policies – renewable portfolio standard, carbon tax, and renewable energy production tax credit - that have been used to foster increased renewable energy usage. These policies require minor modifications to the MOLP model for implementation. The results of these policy cases are then analyzed to determine the impact that these policies have on generation cost and pollution emissions within the region.

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Chapter 1: Introduction

Renewable energy development at the regional level can serve as a mechanism to reduce the environmental impacts of energy consumption, to improve the local economy, and to increase community participation in local environmental management (Cosmi, Macchiato et al. 2003; Khan, Chhetri et al. 2007). The need for renewable energy sources has been recognized as an essential component to the reduction of carbon emissions worldwide. The European Union has set projections for the percentage of all electricity being generated by renewable sources, and emerging nations with rural areas being newly electrified have focused on renewable energy in the planning process. The United States has not set nationwide goals for renewable energy implementation, though states such as California have been pushing for investment in renewable energy sources and setting renewable energy portfolio standards (Short, Blair et al. 2009).

One reason that renewable energy sources have failed to be implemented widely in the United States is cost. The cost of fossil fuel sources has remained low, while the costs associated with installing renewable energy technologies have been comparatively high. These trends have been reversing in recent years, as fluctuations in fossil fuel prices, including large spikes, have been met by decreasing prices in renewable energy technologies such as wind turbines and solar panels. While much discussion has focused on the creation of a national grid that can meet the nation's energy needs through the use of large-scale renewable energy source installations in strategic locations, the costs of the upgrades and expansions necessary for this idea are estimated to be enormous, and the technical hurdles to such a plan are still largely underexplored.

A great deal of research has been devoted to different techniques focused on improving renewable energy planning at the regional level. The majority of this research has focused on applications in developing nations such as India (Ramachandra 2009) or China (Xiaohua and Zhenmin

2002), and in countries in the European Union (Domínguez Bravo, García Casals et al. 2007). Developing nations often are studied because in many cases these electrification efforts are the first instances of electricity being placed in these regions and the use of renewable energy sources helps create sustainable communities. The EU has been the subject of much research because of regulations requiring an increase in renewable energy as a percentage of overall power supply. Though some research has been conducted on renewable energy sources in the United States, it has mainly focused on the exploration of potential energy sources, such as the work conducted at National Renewable Energy Laboratory (NREL) in Golden, Colorado (Short, Blair et al. 2009).

With this in mind, this research effort discusses the design and construction of a decision support system to help regions of the United States interested in exploring the use of renewable energy sources in conjunction with the existing electricity facilities and infrastructure. The electricity demand analyzed includes all end uses, both residential and commercial. Many regions will not have the financial resources or renewable energy potential to create a system that is entirely composed of renewable energy, but this decision support system will allow decision makers to explore the possibilities that exist within the region for increased renewable energy utilization.

A mathematical model has recently been developed by NREL (Short, Blair et al. 2009) that is focused on the national ability to use renewable energy sources. The research effort in this dissertation complements this existing work, but is built around a smaller-scale, the region. Analyzing a region independently allows more flexibility in determining the constraints of the model, as well as allowing for more detailed use of parameters in the system. The system provides an aggregate plan at the regional level, which can be decomposed into smaller areas, such as counties, for more detailed planning at the local level as the system is designed to be scalable.

This research utilizes a geographic information system (GIS) to provide visualization of potential renewable energy sources, allowing for the use of geographic, atmospheric, and regulatory characteristics to determine potential new large-scale, utility-grade installation sites. These potential wind or solar farm locations are determined through the use of criteria in the GIS model, and characteristics of these locations are utilized in cost and generation calculations. This information will then be incorporated into a multi-objective deterministic optimization model. The problem will be composed of two competing objectives, the minimization of greenhouse gas emissions and the minimization of annual generation costs, subject to constraints on generation, capital investment, and resource usage. The model itself is based on the 'environment-economic' model that has been utilized in previous research (Nakata, Kubo et al. 2005; King, Rughooputh et al. 2005; Wang and Singh 2007). These models have varied in implementation, but the general concept is that there are two competing objectives in renewable energy planning. One objective seeks to minimize environmental impact, or maximize renewable energy usage. These are each an example of the 'environment' portion of the model. The 'economic' part of the model is concerned with minimizing costs, either capital investment or operating costs, or optimizing another economic indicator, such as maximizing return on investment.

The long term goal for this research is to create an overall framework that could be applied to energy planning in regions other than just the one studied in this research. With this in mind the system has been designed so that it is easily adaptable to other regions, as well as being scalable to smaller areas, such as counties or communities. This will require a new set of layers in the GIS model representing the constraints and characteristics for that particular area. The optimization portions of the framework can remain intact, only requiring updated parameters due to the differences that will exist between regions. In addition, many of the parameters in the system, both for GIS modeling and mathematical optimization, are subject to user discretion. This allows the user to experiment with different scenarios and analyze the impact that changes to the parameters will have on the renewable energy source potential and the energy plan developed thereafter.

The final major section of this research analyzes three different public policies that have been used to increase electricity generation from renewable sources: renewable portfolio standard, carbon tax, and renewable energy production tax credit. These policies are implemented both individually and in different combinations to determine the most effective policy, if any, to increase renewable energy generation and to decrease greenhouse gas emissions without increasing cost too greatly.

The remainder of this dissertation is organized as follows: first is a literature review that establishes the background of existing research and open research problems, and that will be used in support of each of the primary research contributions in the proposed dissertation. This is followed by three individual sections which each discuss one of the main dissertation contributions: (1) a GIS framework for determining renewable energy source potentials, (2) a deterministic multi-objective optimization model for finding the best mix of renewable energy source projects to be implemented, and (3) an analysis of three different potential renewable energy policies and the impact of their implementation on renewable energy planning. The final chapter provides conclusions and potential future research directions.

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Chapter 2: Literature Review

Introduction

Renewable energy development at the regional level can serve as a mechanism to reduce the environmental impacts of energy consumption, to improve the local economy, and to increase community participation in local environmental management (Cosmi, Macchiato et al. 2003; Khan, Chhetri et al. 2007). Planning for the integration of renewable energy source into existing electricity systems has been conducted via two main approaches: the use of geographic information systems (GIS) for discovery of resource potential, and decision making techniques and mathematical programming for modeling and optimizing energy planning. In addition, the role of public policy in energy planning and encouraging the use of renewable sources is also explored in this research. The following sections provide more information regarding the previous research in these areas and how they relate to the research presented in the following chapters.

Geographic Information Systems

The use of geographic information systems (GIS) to determine renewable energy source potential has been quite extensive as GIS is an appropriate tool to use due to the nature of the problem. The suitability of renewable energy source deployment at specified locations is based on a variety of characteristics which express the fitness of a certain renewable energy source. First and foremost, a solar or wind farm location is constrained by the fact that this source is only exploitable where the resource is readily available and the development of a farm is permissible. While there may be good potential for wind at a certain location, if there are conservation restrictions on the area, or it is located close to a densely populated area, the ability to harness that resource is constrained and the potential resource cannot be utilized. It is not possible to move the availability of wind and solar resources to other areas which do not have such limitations or may be cheaper to access. The process of determining a suitable location for wind or solar farm usage is a very specific form of the site selection problem, in which one or more sites are selected for use based on a series of characteristics such as cost or distance. GIS for site selection has been used for many purposes, such as warehouse location (Vlachopoulou, Silleos et al. 2001), hazardous waste storage facilities (Jensen and Christensen 1986), and aquaculture (Ross, Mendoza Q.M et al. 1993). In these cases, GIS is the appropriate tool to utilize because it can synthesize these geographic and regulatory parameters that are important in the site selection process. The use of GIS for renewable energy site selection has also been explored previously at the local, regional, and national level (Short, Blair et al. 2009, Domínguez Bravo, García Casals et al. 2007, Biberacher, Gadocha et al. 2008, Voivontas, Assimacopoulos et al. 1998).

A variety of research has focused on the exploration of renewable energy sources through the use of GIS. However, these surveys have been fairly limited, focusing on only one possible source in many cases, with specific research devoted to solar (Muselli, Notton et al. 1999; Ramachandra 2007; Arán Carrión, Espín Estrella et al. 2008), wind (Himri, Rehman et al. 2008; Shamshad, Bawadi et al. 2003; Dutra and Szklo 2008; Voivontas, Assimacopoulos et al. 1998), and biomass (Perpiñá, Alfonso et al. 2009; Ayoub, Martins et al. 2007; Panichelli and Gnansounou 2008). In the few cases in which research has explored the potential for multiple resources (Dutra and Szklo 2008, Yue and Wang 2006, Domínguez Bravo, García Casals et al. 2007; Tegou, Polatidis et al. 2007; Schneider, Duic et al. 2007), the development of a map for each source was created independently of the other source, or sources, being explored. There has been no consideration of the interaction between the different energy options, and an optimal plan for utilization of these resources was not developed.

In addition, some previous research that has used GIS to this end was conducted on multiple software packages with specialized programs for each source (Belmonte, Núñez et al. 2008). This makes the idea of comparing one set of output to another set of output more difficult. In order to provide a user-friendly system that can be utilized to explore the renewable energy potential for multiple sources, there must be integration between the different outputs, or there should be one system to handle all of the analysis. This would provide the users with an ability to more easily examine the outputs for each resource and determine the potential for each source based on the criteria specified.

Research of renewable energy potential in the United States with the use of GIS has been less explored than in Asia or Europe, where many of the previous research efforts have been focused. The National Renewable Energy Laboratory (NREL), a laboratory run by the U.S. Department of Energy (DOE), has been working on developing maps of resource potential in the United States for more than a decade. A few papers have been published from this research, explaining the role of GIS in determining wind resource potential (Heimiller and Haymes 2001), as well as emphasizing the role of small-scale wind energy projects on federal land (Kandt, Brown et al. 2007). A new model, the Regional Energy Deployment System (ReEDS) has been developed to combine GIS source determination with mathematical programming (Short, Blair et al. 2009). The similarities and differences between that model and this research are discussed in the proceeding chapters.

Modeling

A variety of techniques have been used to analyze and model the generation and distribution of electricity. These methods have included multi-criteria decision making (Hobbs and Meier 1994; Afgan and Carvalho 2002; Hamalainen and Karjalainen 1992; Terrados, Almonacid et al. 2009), and use of the analytic hierarchy process (Xiaohua and Zhenmin 2002). However, some of the most effective methods for energy planning belong to the family of mathematical programming techniques.

The use of mathematical programming for energy planning, whether renewable sources have been included or not, has been considerable and has taken on a variety of approaches, such as linear programming seeking to minimize capital investment in new sources (Ashok 2007), to minimize costs of energy flows (Meier and Mubayi 1983; Cormio, Dicorato et al. 2003; Ramachandra 2009), or to maximize use of renewable energy (Iniyan and Sumathy 2000). More comprehensive models have been developed through the use of multi-objective linear programming (Schulz and Stehfest 1984, Borges and Antunes 2003; Subramanyan, Diwekar et al. 2004; Suganthi and Williams 2000) and goal programming (Ramanathan and Ganesh 1995; Deshmukh and Deshmukh 2009). The model developed in this research will be a mixed-integer, multi-objective optimization model based on the 'environmental-economic' approach, which has been used extensively (Nakata, Kubo et al. 2005; Wang and Singh 2007; King, Rughooputh et al. 2005). These models have varied in implementation, but the general concept is that there are two competing objectives in renewable energy planning. One objective seeks to minimize environmental impact, or maximize renewable energy usage. These are each examples of the 'environment' portion of the model. The 'economic' part of the model is concerned with minimizing costs, either capital investment or operating costs, or optimizing another economic indicator, such as maximizing return on investment.

The previous models have also had one flaw; none of them includes a direct connection to the location of the potential energy sources. These models have all been conducted independently of the research on identifying potential renewable energy sources using GIS. The models, when necessary, have simply contained estimates related to the potential renewable energy source, or sources. There is limited discussion of the origin of these numbers, and most often these are derived from other research and resources. These numbers may not reflect the reality of the situation, nor do they consider the location of these sources, which can impact the acceptability, costs, and timing of these resources on these models. There is a need to seamlessly combine the exploration of potential sources with the modeling capability to provide a comprehensive model of both potential and optimization of that potential.

Renewable Energy Policies

The final section of this research analyzes the impact that three different renewable energy policies would have on energy planning. These policies are a renewable portfolio standard (RPS), carbon tax, and renewable energy production tax credits. A RPS is a government regulation stating that a certain percentage of electricity generation must be derived from renewable sources. Worldwide there have been a few nations that have implemented a RPS, such as the United Kingdom, Belgium, and Italy (Lauber 2004). While there have been a few RPS bills proposed in the United States none of them have been enacted at this point (Nogee, Deyette et al. 2007). To date, RPS in the U.S. has been based on state regulations. There are currently 25 states that have a mandatory RPS in place. Each of these regulations differs with respect to the generation targets, the timeline, the sources considered as renewable, whether or not existing facilities are eligible, and more (Wiser, Namovicz et al. 2007, Wiser 2008).

A carbon tax is a tax placed on the emissions of CO_2. These taxes are placed on the generation of electricity from fossil fuel sources, such as coal, that emit CO_2 through the combustion process. CO_2 is the leading greenhouse gas emitted through electricity generation, and is recognized as one of the leading causes of climate change (IPCC 2007). Carbon taxes are generally utilized to help increase the competitiveness of renewable energy sources in relation to traditional fossil fuel sources. The effects of carbon taxes on electricity generation have been studied previously (Goulder 1995, Hoel 1996), and a carbon tax included in the cost minimization function used by the Regional Energy Deployment System (ReEDS) model developed by the National Renewable Energy Laboratory (Short, Blair et al. 2009).

Government sponsored tax credits to reduce the cost of generation from renewable sources have been used in the United States previously (UCS 2009). However, these incentives are currently set to expire in 2012, which is a shorter time-frame than required for development of the projects found in this research. Therefore, these tax credits are not implemented in the model formulated in Chapter 4. Through these tax credits, the production of electricity from renewable sources is made more competitive with existing fossil fuel sources. The renewable energy production tax credit (REPTC) attempts to achieve the same outcome as the carbon tax, increasing renewable energy usage through more competitive costs compared with fossil fuel sources. Though these two policies attempt to achieve the same thing, they do so through different means. The carbon tax penalizes fossil fuel usage, while the REPTC rewards investment in renewable energy technologies.

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Chapter 3: GIS Exploration of Potential Renewable Energy Sources

Introduction

This research focuses on the creation of an integrated decision support system to analyze the availability of renewable energy sources within a region and to decide how to best allocate funds to utilize these resources. Through the use of this system, a user is able to determine the availability of resources within the region utilizing a geographic information system (GIS). This GIS module will provide the user with the ability to locate potential sites for wind and solar farm installations based on the geographic and regulatory characteristics of the region. The results of this geographic analysis are then exported to Microsoft Excel for cost and generation calculations to provide additional analysis. These calculations are then utilized in Chapter 4 of this research in a multi-objective linear programming problem that seeks to minimize generation costs while minimizing emissions of greenhouse gases within the region through the increased use of renewable energy sources.

The suitability of renewable energy source deployment at locations within the region will be based on a variety of characteristics, stored in data layers, which provide information about the fitness of a certain renewable energy source. First and foremost, a solar or wind farm location is constrained by the fact that this source is only exploitable where the resource is readily available and the development of a farm is permissible. While there may be good potential for wind at a certain location, if there are conservation restrictions on the area, or it is located close to a densely populated area, the ability to harness that resource is constrained and the potential resource cannot be utilized. It is not possible to move the availability of wind and solar resources to other areas which do not have such limitations or may be cheaper to access. The process of determining a suitable location for wind or solar farm usage is a very specific form of the site selection problem, in which one or more sites are selected for use based on a series of characteristics such as cost or distance. GIS for site selection has been used for many purposes, such as warehouse location (Vlachopoulou, Silleos et al. 2001), hazardous waste storage facilities (Jensen and Christensen 1986), and aquaculture (Ross, Mendoza Q.M et al. 1993). In these cases, GIS is the appropriate tool to utilize because it can synthesize the geographic and regulatory parameters that are important in the site selection process. The use of GIS for renewable energy site selection has also been explored previously at the local, regional, and national level (Short, Blair et al. 2009, Domínguez Bravo, García Casals et al. 2007, Biberacher, Gadocha et al. 2008, Voivontas, Assimacopoulos et al. 1998).

The parameters that are utilized in GIS models for the site selection process are defined as either factors or constraints. A factor is a parameter or characteristic that makes one location more desirable than another location, while a constraint is a parameter that eliminates a location from consideration even though the location may have many characteristics that would otherwise be advantageous. With respect to this model, many of the factors and constraints relevant to determining the potential at a given site are also utilized in the modeling portion of the research. For example, the current land use at a given location can act as a constraint and eliminate a potential location from further consideration in the GIS model, and the land use can also play a role in the capital investment cost associated with utilizing a location.

A variety of research has focused on the exploration of renewable energy sources through the use of GIS. However, these surveys have been fairly limited, focusing on only one possible source in many cases, with specific research devoted to solar (Muselli, Notton et al. 1999; Ramachandra 2007; Arán Carrión, Espín Estrella et al. 2008), wind (Himri, Rehman et al. 2008; Shamshad, Bawadi et al. 2003; Dutra and Szklo 2008; Voivontas, Assimacopoulos et al. 1998), and biomass (Perpiñá, Alfonso et al. 2009; Ayoub, Martins et al. 2007; Panichelli and Gnansounou 2008). In the few cases where research has explored the potential for multiple resources (Yue and Wang 2006, Domínguez Bravo, García Casals et al. 2007; Tegou, Polatidis et al. 2007; Schneider, Duic et al. 2007), the development of a map for each source was created independently of the other source, or sources, being explored. There has been no consideration of the interaction between the different energy options, and an optimal plan for utilization of these resources was not developed. In this research, the GIS portion will determine potential locations for wind and solar farm utilization. The GIS can also be used to display the results from Chapters 4 and 5, providing a final map of the chosen locations and tying the work of the modeling sections back to the GIS section.

In addition, some previous research that has used GIS to this end was conducted on multiple software packages with specialized programs for each source (Belmonte, Núñez et al. 2008). This makes the idea of comparing one set of output to another set of output more difficult. In order to provide a user-friendly system that can be utilized to explore the renewable energy potential for multiple sources, there must be integration between the different outputs, or there should be one system to handle all of the analysis. This would provide the users with an ability to more easily examine the outputs for each resource and determine the potential for each source based on the criteria specified.

Research of renewable energy potential in the United States with the use of GIS has been less explored than in Asia or Europe, where many of the previous research efforts have been focused. The National Renewable Energy Laboratory (NREL), a laboratory run by the U.S. Department of Energy (DOE), has been working on developing maps of resource potential in the United States for more than a decade. A few papers have been published from this research, explaining the role of GIS in determining wind resource potential (Heimiller and Haymes 2001), as well as emphasizing the role of small-scale wind energy projects on federal land (Kandt, Brown et al. 2007). A new model, the Regional Energy Deployment System (ReEDS) has been developed to combine GIS source determination with mathematical programming (Short, Blair et al. 2009). The similarities and differences between that model and this research are discussed later in this chapter and in Chapter 4.

This research creates a framework for the identification of multiple renewable energy sources. Three different sources of renewable energy are being analyzed in this model: wind, solar, and solid wood waste biomass. For wind and solar, large-scale, utility-grade installations were chosen as the basis for this work because of the efficiencies that can be achieved through the use of these technologies at this scale. Another reason this approach was chosen is because small-scale home installations of technologies require additional policy analyses to be integrated into the methodology, and the investment decision ultimately lies with the individual land owner. Although a great deal of renewable energy potential can be harnessed through these small-scale deployments, if the public is unwilling to make the investment in the technology then the energy plan developed will not be accurate. This is a future research direction which can be explored after the completion of this framework.

In addition to the use of GIS for large-scale, utility grade installations for wind and solar, a third form of renewable energy will be analyzed in this research: the incorporation of solid wood waste biomass sources as a replacement for coal at coal-fired facilities, a process known as co-firing. Co-firing biomass and coal at power plants designed for coal usage has been shown to decrease emissions substantially without impacting the generation capabilities of the plants. In addition, the cost to retrofit these facilities for co-fire is much less expensive than the creation of dedicated facilities for biomass generation or the creation of wind and solar farms. Therefore, co-firing is recognized as a short-term, cost-effective measure to help decrease greenhouse gas emissions (Caputo 2009; FEMP 2004; De and Assadi 2009; Robinson, Rhodes et al. 2003). The use of other biomass sources such as crops and landfill gases would require more expensive retrofitting of coal facilities, or the development of dedicated biomass facilities, and these sources are currently not analyzed in this model. In addition, the conversion of food crop land to fuel crop land is one that has seen some controversy, so this source is not considered in the model currently.

Region

The region chosen for this research is centered on the greater southern Appalachian Mountains. This region is comprised of large portions of North Carolina, Virginia, and West Virginia, as well as smaller segments of Kentucky and Tennessee. There are a total of 210 counties, or county-equivalents, in these five states and an estimated population of over 10 million residents within this region. Figure 1 shows the region under study.

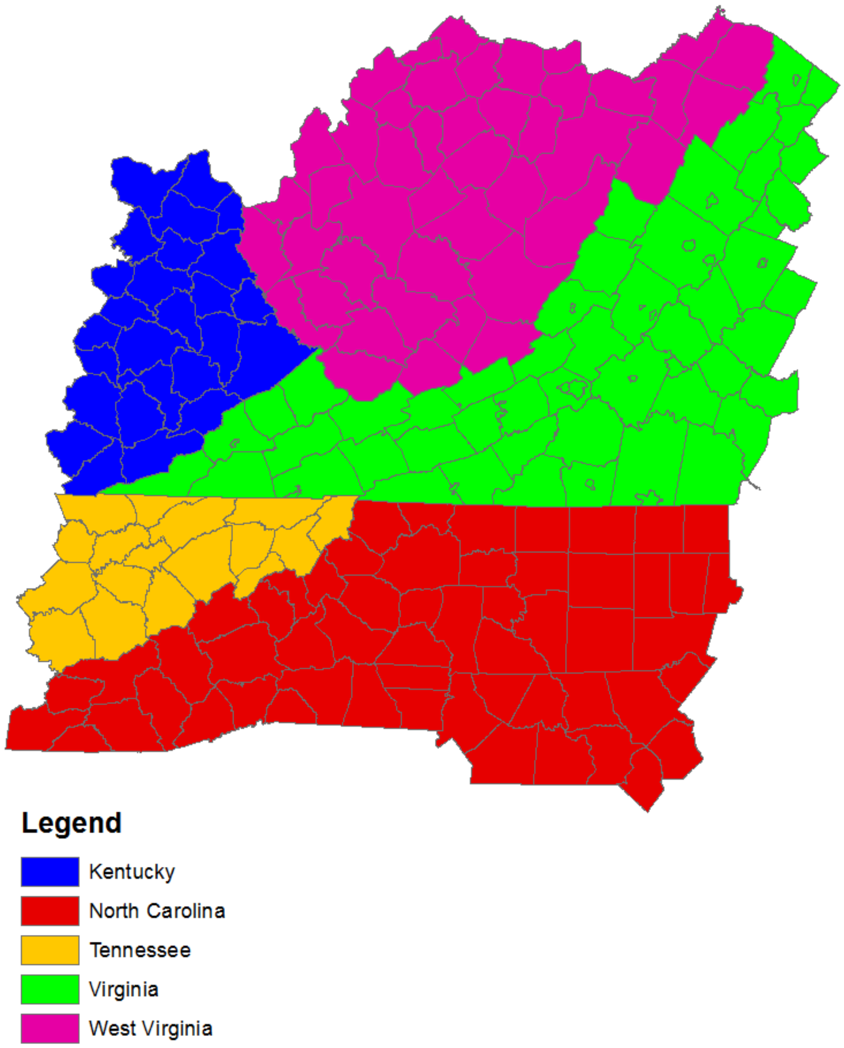

Figure 1: Greater Southern Appalachian Mountain Region used in this research

Baseline information for the region was determined from the 2007 U.S. Energy Information Administration report on electricity generation (EIA-861 2007). Currently there are 148 facilities in the region, generating a total of 198,474,165 MWh in the baseline year, though an unknown portion of the electricity generated is transmitted out of the region. Additionally, an unknown amount of electricity is imported into this region. This research will focus on meeting demand based on the amount currently generated within this region. Table 1 shows a breakdown of MWh generated by fuel source in this region, while Figure 2 displays the location of these facilities.

Source	Number of Facilities	MWh Generated	Percentage of Total Generation
Coal	31	165,721,345	83.50%
Nuclear	1	17,619,492	8.88%
Gas	13	6,449,095	3.25%
Water	69	4,981,292	2.51%
Co-Fire	4	2,188,456	1.10%
Biomass	3	1,026,986	0.52%
Oil	22	241,841	0.12%
Wind	1	167,588	0.08%
Landfill	4	78,071	0.04%

Table 1: Generation by Source within the Region

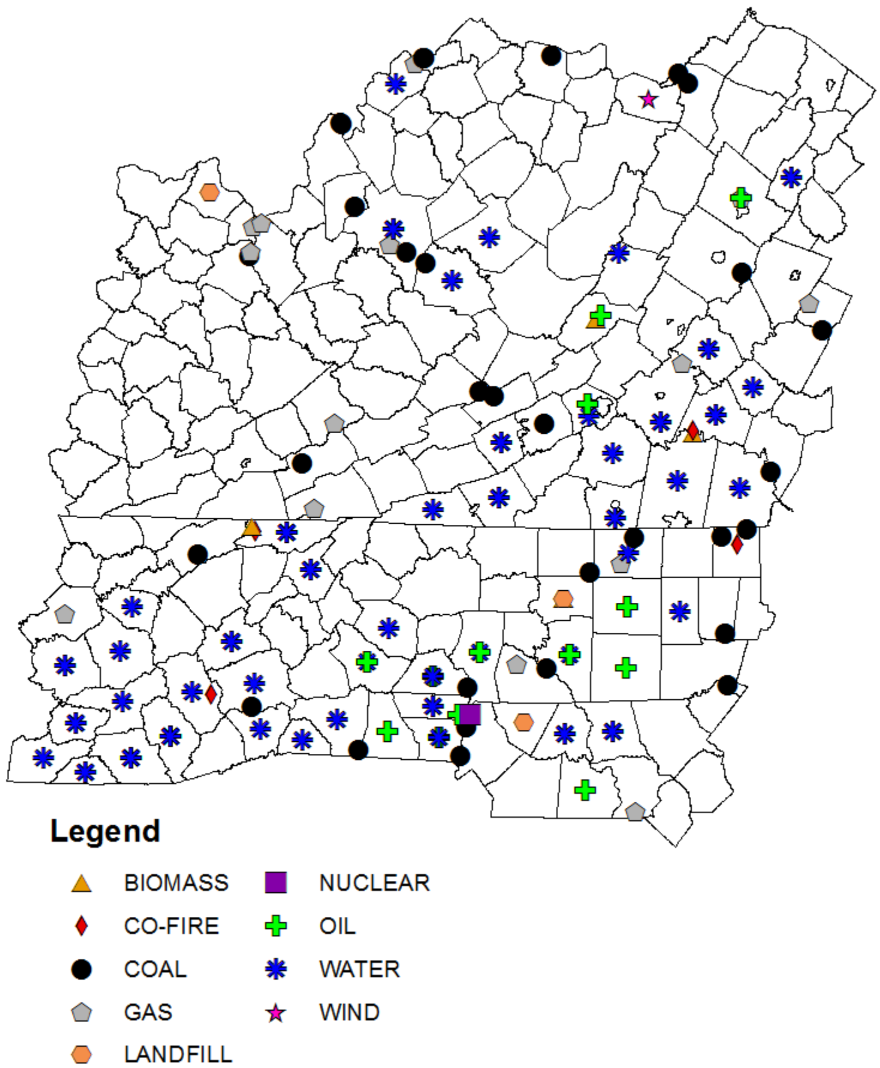

Figure 2: Electric Generation Facilities within the Region

This region was chosen for two main reasons. First, this region is dependent on coal as the primary fuel source for electricity generation, and the increased use of renewable energy sources, while scaling back the use of coal, would lead to substantial decreases in emissions of pollutants. The region is dominated by coal-powered generation plants, with 83.50% of total MWh being generated by coal-only plants. There are four plants in the region that are currently co-firing coal and biomass resources at levels ranging between 8.93% and 71.17% of generation from biomass sources. As these plants have already implemented a form of biomass co-fire, they were separated from the other coal plants within the region for the purposes of modeling. Therefore an additional 0.89% of total generation is derived from coal utilized at these plants currently co-firing coal and biomass. This gives an overall total of 84.39% of generation from coal, while nationwide coal is responsible for 48.2% (EIA 2010) of the electricity generation, so this region shows potential for substantial reduction in greenhouse gases through the use of renewable sources. The second major reason that this area was selected is that some of the best onshore wind power potential in the eastern United States is located within this region. In addition, this region is less densely populated than other areas in the eastern United States, allowing for the same amount of capital investment to provide for a greater percentage of renewable generation and reduced emissions than in other regions.

There are four categories of renewable sources currently being used within the region: water (hydroelectric), biomass, wind, and landfill gas. These four sources currently generate 3.15% of the total generation within the region, plus an additional 0.22% of co-fire generation estimated to be derived from biomass, for a total of 3.37%. Currently, only North Carolina has established a binding renewable portfolio standard (RPS), while Virginia has enacted a voluntary RPS (Wiser 2008). An RPS specifies the amount of generation that must be generated from renewable sources. Thus there is a need to explore many renewable options if the areas of those states within this region were to meet those standards. Though the region within this model does not contain any state in its entirety, the portions of the states within the region are substantial and the ability for any state to meet an RPS without increased renewable penetration within the region would be quite difficult. There are currently a small number of wind and solar farms that are being proposed for future use within this region, but these locations have not been approved at this time so they are not considered in the model.

Modeling Approach

The GIS analysis was conducted on ESRI's ArcMap 9.3.1 software (ESRI 2009). The geographic model utilized in this decision support system is a constraint-only model. All potential locations are chosen based solely on the criteria that would restrict their use. The use of factors, characteristics that describe the desirability of one location to another, is not explored in this model, though certain locations would be more desirable than others for a variety of reasons, such as wind potential or cost of connecting to the transmission grid. Factors are not being considered because each location is considered acceptable in the geographic model and the final process of site selection will be conducted by the mathematical modeling portion of the system. The use of a constraint-only model does have a disadvantage when compared to a mixed constraint-factor model. Through the use of constraints for criteria in site selection, locations that are just outside of the acceptable range for only one of the constraints will be eliminated from further consideration. Therefore this constraint-only model does not analyze any location that fails to meet all of the criteria specified. For example, if the constraint for maximum slope of a potential wind farm location is set at 20% then a location with a slope of 19.99% would be acceptable, while a site with a slope of 20.01% would be eliminated. Even though this constraint-only modeling approach is very conservative for site selection it was determined that this model and the criteria used in the constraints is consistent with previous research. In addition, the use of factors provides additional information regarding the fitness of potential sites which is not needed as the mathematical model would be used to determine the best mix of sources based on these characteristics.

The GIS portion of the system is focused solely on determining which sites could be utilized for a certain renewable energy source; the GIS model is not utilized to determine which sites would be best in relation to the other sites in the model. Characteristics of these potential sites, such as resource potential, are calculated through the use of the GIS. These values can then be utilized in the mathematical model to determine the most effective mix of sites given the objectives of the model. The GIS component of the system is essential for determining the potential sources of renewable energy, but does not have the capability to solve complex mathematical programming problems such as the multi-objective optimization model developed in Chapter 4. Therefore, the use of a separate program for optimizing the resource mix in addition to the GIS is critical to solving the problem, but the use of GIS is necessary for accurate discovery of renewable energy sources. The two parts of the program work in conjunction with one another. It would not be possible to achieve the same results while only using one component of the system.

The model being implemented throughout this system is for planning on an aggregate level. This system seeks to provide a big picture view of renewable energy source potential within a region, and is scalable for both larger and smaller areas than the region being analyzed. NREL has previously conducted research on the use of various renewable energy sources at the national level, including the recently developed ReEDS model (Short, Blair et al. 2009), which analyzes geographic information and contains a mathematical programming component. The differences between this model and ReEDS are many with respect to the GIS component of the research. First, ReEDS focuses on the utilization of wind resources for electricity generation at a national level. As the model focuses at the national level for resource discovery, the characteristics used in the model are broadly defined and are conservative estimates in many cases, ruling out potential locations more readily than previous research models. This means that many potential resources are eliminated from consideration by the model due to the conditions specified. Second, the development of solar photovoltaic farms is not currently implemented in ReEDS, but is mentioned as a future capability of the model. Instead, ReEDS analyzes only concentrated solar power (CSP), which is not cost effective outside of the Southwestern United States. Third, the research model developed here allows for the implementation of biomass co-fire at existing coal facilities, which is not fully explored in ReEDS. Further differences between ReEDS and this research in relation to the mathematical programming model will be discussed in Chapter 4.

Focusing on the greater southern Appalachian Mountain region allows for the precise discovery of resources based on constraints appropriate for this region. For example, this allows for the development of wind and solar farm locations in this region to be a priority of the model independent of other regions which may contain better resources or may be more cost-effective than this region. The regional approach utilized in this model still uses generalized characteristics and is intended to provide an overview or aggregate level plan which requires further inquiry and more detailed exploration of potential locations before being used for implementation. Each of the three renewable energy sources being considered in this region was modeled independently within the GIS. The following sections discuss the modeling approach for each of the respective sources.

Biomass

The estimate for the amount of biomass available within the region was derived from a dataset created by NREL (NREL-GIS 2003). The data is maintained at the county level, and more accurate location information of the biomass sources is not provided. While other datasets have been created for portions of the region, the NREL dataset provides the most complete dataset for the entire region, even though it lacks detailed locations for the sources. However, for planning at this scale, the dataset provides a good estimation of resource availability.

The NREL data contains eight possible sources of biomass, and the only sources considered in this study are those derived from solid wood waste which can be utilized in a coal-biomass co-fire scenario. The sources utilized in this model include urban wood waste, primary and secondary mill residue, and forest residue. These sources allow for the cheapest and easiest utilization of biomass resources within the region, as wood waste can be used for co-fire with coal with minimal disruption to the generation process and minimal investment (Caputo 2009; FEMP 2004; Robinson, Rhodes et al.

2003). Other biomass sources such as crops, manure, and landfill gases are not utilized as these sources generally require the construction of a new electricity generating system for effective use. Each county, or county-equivalent, has solid wood waste biomass currently available.

The geographic modeling of biomass utilization is minimal. The locations of the coal plants are derived from the U.S. Environmental Protection Agency's eGrid data set (EPA 2008). The centroid of each county is calculated in ArcMap, which can then be used to provide an estimate of distances between the biomass resources and the coal plants at which the sources can be co-fired. This estimate of distance is sufficient as more detailed location information for the biomass sources is not known. This data is exported for use in the mathematical model and no further geographic processing of this data is required. The amount of wood waste biomass resource available in tons for each county is shown in Figure 3, along with the location of the 31 coal plants that can be utilized for co-fire in the model.

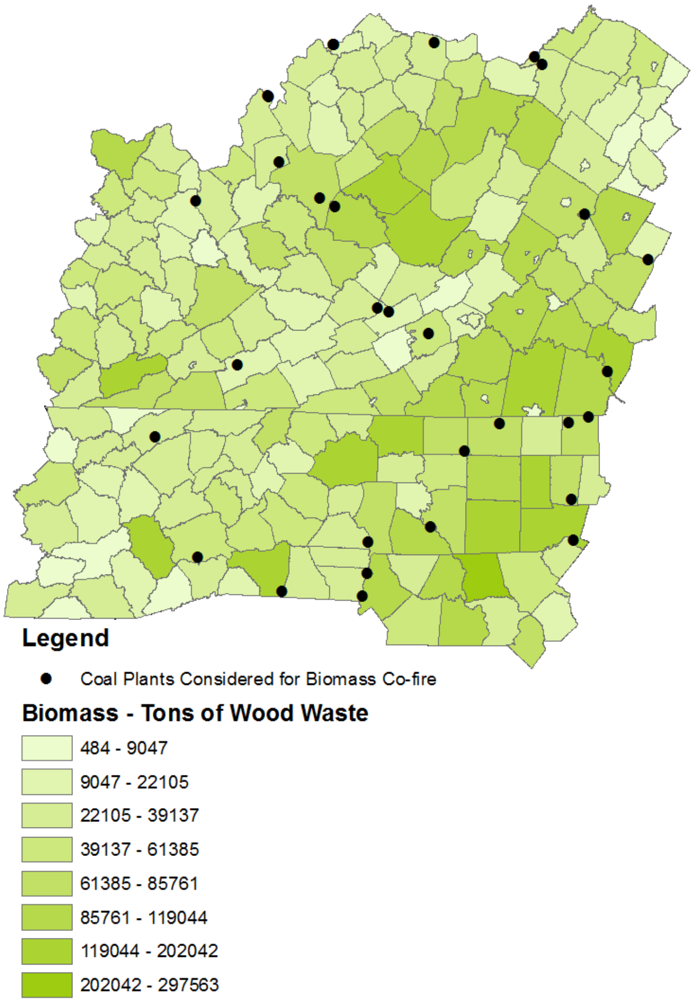

Figure 3: Wood Waste Biomass Availability for Each County & the Coal Plants available for Co-Fire Implementation

Solar

The exploitation of potential solar resources in this model is being analyzed for large-scale, utility solar farm installations. Solar is a renewable energy source that can be efficiently utilized in extreme distributed generation scenarios, allowing end-users to create their own electricity and sell any additional generation to the grid. Although wind turbines can also be installed for home use, many of the regulations on height within residential areas limit the effectiveness of their use, and the implementation of policies and research on their use is more limited than home solar generation. The implementation of end-use solar generation requires property owners to invest in the necessary technologies on their own accord. Utility companies and local governments have created incentive mechanisms such as feed-in tariffs and net-metering to encourage such investments. However, the willingness of property owners to invest in such technologies is largely unknown and estimation of urban land that can realistically be utilized for this level of generation are not fully explored at this time. This model of decentralized electricity generation has been effectively implemented in several countries, particularly Germany (Gaertner 2001), as well as a few localities in the United States (Rolland 2008). However, this approach requires too many assumptions for effective aggregate planning at this time, therefore it is not analyzed in this model but is a potential future research direction that would require modifications to the GIS model.

Solar insolation is a measure of the solar radiation received on the Earth's surface. This value is used in the calculation of potential solar generation, and the greater the value of insolation present at a given location, the greater the potential for electricity generation (NREL-GIS 2003). The NREL data provides estimates for $kWh/m^2/day$ for each month of the year, as well as an annual average. The amount of solar insolation within the chosen region ranges from 4194.1 – 5006.5 $kWh/m^2/day$ annually (Figure 4). The data is provided at an approximate resolution of 10km in vector format, and is synthesized from a variety of atmospheric and satellite data sources. There is no constraint placed on the NREL data within this model. All values of solar insolation are classified as "good" according to the NREL dataset and therefore can be used for potential solar farm locations.

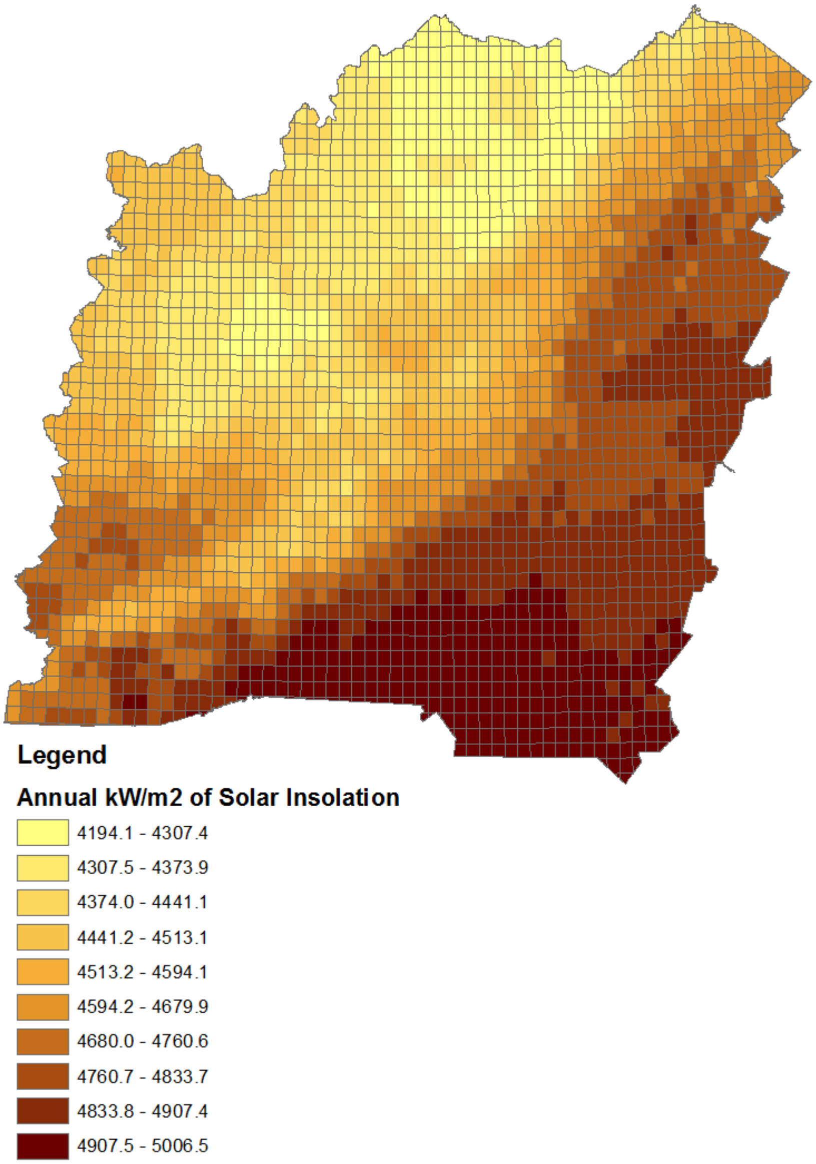

Figure 4: Solar Insolation ratings for the Region

The National Elevation Dataset (NED), created by the U.S. Geological Survey (USGS), provides elevation information which is utilized in the calculation of two different values which serve as criteria in our GIS model (USGS-NED 2004). The data is provided in raster format with cell size of 30m, the value of the cell represents the elevation which can be used to calculate slope and aspect with ArcMap. The first value, slope, is a measure of the steepness of a surface. Though steep slopes can be utilized on home installations, flatter surfaces are desirable for solar farms. The second value, aspect, is the direction in which a slope faces. Aspects of southern exposure are more desirable than slopes facing other directions for harnessing solar power because this region is in the northern hemisphere. The combination of slope and aspect are utilized as constraints defining potential solar farm installations. This combination is the first set of criteria in the model, and these criteria were derived and adapted from previous research (Arán Carrión, Espín Estrella et al. 2008, Domínguez Bravo, García Casals et al. 2007). Areas with a slope of less than 2.5% are acceptable with any aspect. Because of the relatively flat surface that a slope of 2.5% or less represents, southern exposure is not required as the solar panels can be tilted to the south with no impact on potential. The next set of criteria was applied to find areas with slopes of 2.5% to 15% which have south-facing aspects (112.5°-247.5°). Locations meeting this combination of slope and aspect are good locations for solar farms due to the southern exposure, while not being too steep. Any location with a slope greater than 15%, regardless of the exposure, is considered undesirable for solar farm development. These two sets of criteria are then added together to provide a new data layer of potential locations based on slope and aspect. Any 30m cell in the region that has a slope of 0-2.5% is assigned a value of 1, any cell with a slope of 2.5-15% that also has a southern exposure is assigned a value of 1, and all other cells are assigned value of 0.

The next criterion applied in the determination of potential solar farm locations is the current land use. This data was obtained from the National Land Cover Dataset (NLCD), another product of the USGS (USGS-NLCD 2001). Table 2 provides a list of NLCD data types, as well as the percentage of land within the region composed of each land cover. One criticism of solar farms is that these installations take up large areas of land that can be utilized in other ways, and the potential for electricity generation is less economically beneficial than other potential uses of the land. Unlike wind farms, which can be placed on agricultural land without substantially decreasing the amount of productive land, solar farm installations require the majority of land to be utilized solely for these installations. As a result, the only NLCD classification considered as permissible in this model is barren land. This is land that NLCD describes as "barren areas of bedrock, desert pavement, scarps, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits and other accumulations of earthen material. Generally, vegetation accounts for less than 15% of total cover" (USGS-NLCD 2001). All other NLCD classifications are not potential land uses in the model currently as these lands can be utilized in more productive manners. Only cells with a value of 31 (barren land) in the NLCD layer are assigned a new value of 1, and all other NLCD values are replaced with the value of 0. This constraint greatly limits the amount of land available for solar farm development, as only 0.41% of the region is composed of barren land. This constraint could be relaxed to allow other land uses in future research or at the discretion of the user.

NLCD Value	Description	Percentage of Region
41	Deciduous Forest	59.76%
81	Pasture/Hay	15.41%
42	Evergreen Forest	6.05%
21	Developed, Open Space	5.79%
71	Grassland	3.26%
43	Mixed Forest	3.01%
22	Developed, Low Intensity	1.98%
82	Cultivated Crops	1.08%
11	Open Water	1.01%
52	Scrub/Shrub	0.85%
23	Developed, Medium Intensity	0.60%
90	Woody Wetlands	0.57%
31	Barren Land	0.41%
24	Developed, High Intensity	0.19%
95	Emergent Herbaceous Wetlands	0.03%

Table 2: NLCD Classification and Percentage of Land within Region

The final criterion in solar farm siting is based on land use restrictions. The Protected Areas Database of the United States (USGS-PADUS 2009) contains information that classifies land as private or government-owned, as well as providing information regarding conversation restrictions. Any area that is restricted due to conservation is constrained in this model, meaning that the land is not permissible for solar farm development even if other characteristics of the land make it a desirable location. All other private and public land is permissible for use in this model. This data is provided by USGS in vector format. This data was converted to raster format with cell size of 30m to correspond to the other raster datasets. The use of buffers, or restricted zones between features in the region and potential solar farm locations, is not considered in this model. Political issues related to solar farm development close to farm land, urban land, or conservations areas are minimal in comparison to wind farms due mainly to the visibility, noise, and impact on wildlife associated with wind turbines and buffers have not been used in previous solar farm siting research.

Any area that does not meet the criteria in one of these three sets (slope and aspect, land use, conservation restriction) is assigned a value of 0 in the model, while the allowable areas are assigned a value of 1. These three sets of constraints are then multiplied together to provide the final map of possible solar farm locations. In this constraint-only model, any area that does not meet all three of these criteria is not considered a potential location. For example, an area may have a desirable slope and aspect combination and be located on barren land, but if that land is restricted due to conservation reasons then it cannot be considered any further.

Each cell that receives a final value of 1 is considered a potential solar farm location. However, each cell is of size 30m, which is not useful measure in final site selection as there are millions of cells in the GIS model. The final raster dataset was then converted to polygons using the features in ArcMap. This allows cells of the same value to be grouped together and larger polygons are then created. Following this conversion, there were 54,935 polygons present in the model, 53,774 of which had a value of 1. In order to narrow down the potential locations, the area of each polygon was calculated. The values ranged from 0.14 to 325.5 acres, and only locations that were greater than 10 acres are considered any further as the cost of preparing land and connecting to the grid would not be worthwhile for smaller areas. This limited the number of potential locations to 477. Larger areas are capable of installing greater capacity of generating technologies thus achieving lower generation costs per kWh due to some of the fixed costs being spread over greater levels of generation. However, the size of the locations is not the only factor in determining generation potential as smaller areas with greater values for solar insolation may be capable of generating more electricity than larger areas with lower values for solar insolation. Due to the tradeoff between these different characteristics, a factor-based model is not explored, instead focusing on the use of GIS for determining these characteristics which are used later in cost and generation calculations.

To determine the characteristics of these polygons, the “Zonal Statistics” feature of ArcMap was used to calculate the average value for the slope, aspect, and solar insolation within each polygon. This information is then exported to text files which can be imported into Microsoft Excel, at which point values for cost and resource potential at these locations can then be analyzed. Additionally, these characteristics will serve as inputs to the mathematical model described in Chapter 4.

Wind

The wind resource potential dataset was created by NREL, and was synthesized from numerous meteorological, satellite, and ground cover datasets (NREL-GIS 2003). This wind data is provided in vector format, with a wind power class value assigned to each polygon in the dataset. The values in the dataset range from 0 (“poor”) to 7 (“superb”), and each wind power class has a corresponding wind speed density range (in terms of watts per square meter of wind turbine sweep). NREL considers any location with a wind power class of 3 or greater to be considered acceptable for wind farm usage. Table 3 shows the percentage of land within the region being modeled that belongs to each of the seven wind power classes. Without any further restrictions, only 2.38% of the land located within this region would be suitable for development of wind farms, and a map of this potential is presented in Figure 5. For use in the model, the data was converted from vector format to raster format with a cell size of 30m. Each location with a wind power class of 1 or 2 was assigned a value of 0 in the raster, while the remaining wind power classes were converted to a value of 1 in the raster dataset. Although converting the NREL values to 0 or 1 results in the loss of exact wind power class in each cell, the final stages of the GIS model will recover this information for use in the mathematical model, thus a factor-based approach is not needed.

NREL Wind Power Class	Wind Speed Density (W/m^2)	Percentage of Land in Region
1	0 – 200	92.83%
2	200 – 300	4.79%
3	300 – 400	1.36%
4	400 – 500	0.52%
5	500 – 600	0.24%
6	600 – 800	0.18%
7	>800	0.08%

Table 3: Percentage of Land within the Region by NREL Wind Power Class

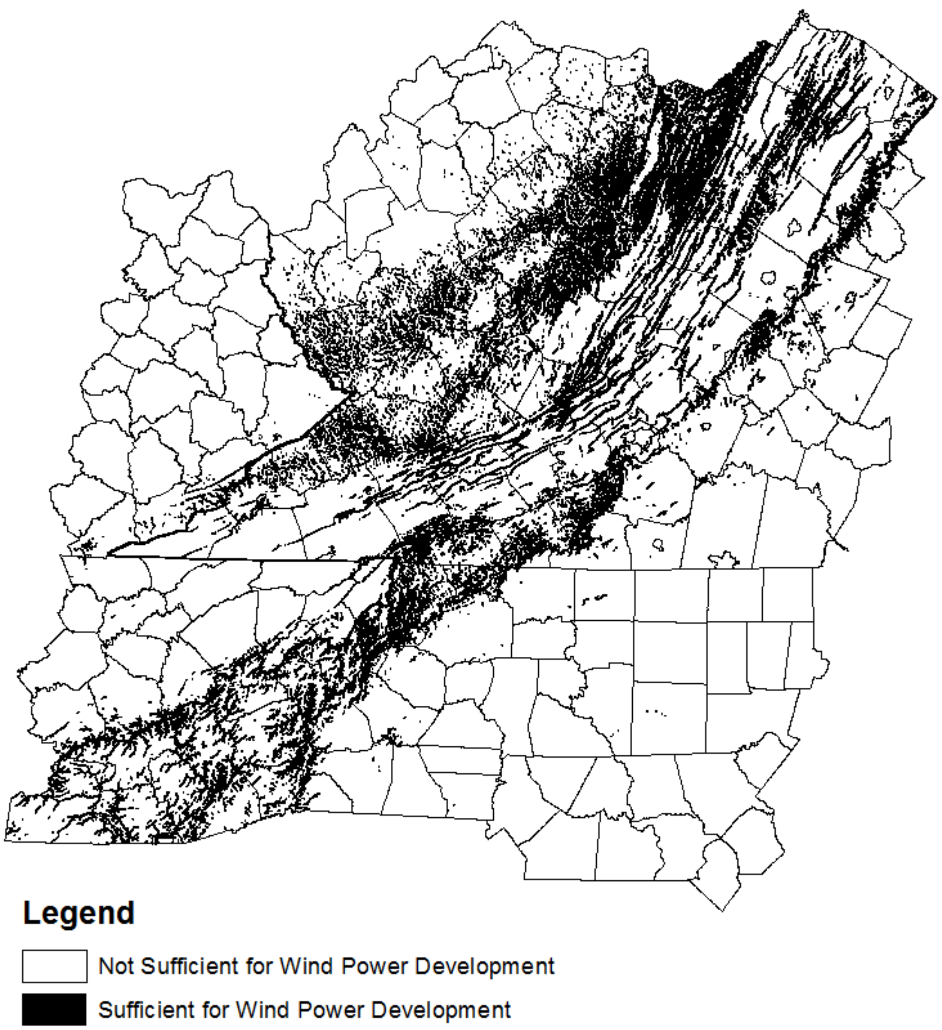

Figure 5: Wind Power Levels within the Region

The wind farm siting model utilizes many of the same datasets as the solar farm model. The NED values were used to calculate slope, and locations with a slope of 20% or greater were considered undesirable for wind farm siting due to difficulties with installation and the stability of turbines installed at greater slopes (Short, Blair et al. 2009).

The NLCD classifications that are permissible in the wind farm model include barren land, the three forest types, scrub/shrub, grassland, pasture/hay, and crop land. Because of the fact that wind farms can be sited on land currently used for agriculture without completely eliminating the productivity of the land, as well as providing another source of income for landowners, the number of NLCD classifications is greater than in the solar scenario. The availability of wind power in this region is highly connected with the location of forest land within this region. A total of 68.82% of the region is composed one of the three forest classifications, while 92.5% of the land with an NREL Wind Power Class value of 3 or greater is located on forest land. This makes the ability to utilize forest land for wind power development a necessity in this model. This is another area where the ReEDS differs from this model. Nationally the areas of greatest onshore wind power are located within regions with low levels of forest cover, such as the Great Plains or Southwest. As a result, this model removes some of the additional restrictions placed on forest land use in ReEDS in order to take greater advantage of the wind resources present within the region. A new raster dataset was created with a value of 1 for the acceptable land uses, and a value of 0 was assigned to all other land uses, which includes the four classes of developed land, water, and wetlands. The same conservation raster dataset created for the solar model is utilized in determining which cells represent land that cannot be used, as the restrictions on land use due to conservation and wildlife management are unchanged.

The site selection process for wind farms has additional constraints that were not present in the solar farm model. Many of these constraints are due to the visible nature of wind farms, the noise generated by these facilities, the impact that turbines can have on urban land uses and airports, as well as the fact that wind farms can interfere with conservation efforts particularly with respect to wildlife. These additional constraints result in the creation of buffers, or distances required between the location of specified land use or conservation area and the location of a wind farm. Table 4 summarizes the buffer distances utilized in the wind farm siting model. A new raster layer was created for each of these buffer constraints. These constraints are based on NREL's ReEDS model (Short, Blair et al. 2009) and previous studies on wind farm development (Shamshad, Bawadi et al. 2003; Domínguez Bravo, García Casals et al. 2007; Tegou, Polatidis et al. 2007).

Restriction	Data Source	Buffer Distance
Developed, Open Space	NLCD	500m
Water and Wetlands	NLCD	500m
Conservation Areas	PAD-US	1000m
Developed, Low/Medium/High Intensity	NLCD	2000m
Airports	USGS	2000m

Table 4: Buffers Utilized in the Wind Farm Siting Model

These buffer constraints are implemented using conservative estimates of distances because many of these buffering distances are subject to local regulations, rather than state or federal regulations, and can vary within a region of this size. Additionally, many localities have not established firm regulations for these buffers or do not make the information readily available. However, in order to provide an aggregate level view of the wind potential within the region, these conservative values were chosen. The buffer restrictions in the ReEDS model are even more conservative, using only one value (3 kilometers) for all exclusions except water. Utilizing the NREL buffer conditions, over 99.995% of all land within the region was eliminated from consideration. When this constraint was combined with the additional constraints on slope and wind power class, there was no land left for implementation of wind farms within the region. Therefore, a new set of restrictions was used in this model reflect the more common use of buffers in previous research. The use of a smaller buffer for "Developed, Open Space" land uses versus "Developed, Low/Medium/High Intensity" land uses reflects the fact that many of the land uses classified in the former category are roads, which are desirable to be in close proximity to a potential location.

Even though these buffer values were scaled back in comparison to the ReEDS model, they remain very conservative. In fact, the one working wind farm within this region is located on land that is constrained using these buffers in the GIS model, and a few of the other potential wind farm locations being discussed in the region do not meet the constraints present in this model. Therefore, it is recommended that more detailed planning be carried out at the local level to determine actual potential with respect to local regulations, as well as receiving input from community members which can help increase the social acceptance of wind farms.

These nine constraint layers (wind power class, slope, land use, conservation, and the five buffers) were then multiplied together to create a final raster layer representing the constrained cells. Similar to the solar model, the raster layer was converted to polygon features representing potential locations for wind farms. A total of 28,360 possible good wind farm locations were found using these constraints. The area for each location was calculated, and any area of 120 acres or more was considered a potential location, resulting in the final 203 polygons. Estimates for the amount of land required for a wind turbine vary greatly and is largely dependent on the shape and terrain of the land. A value of 40 acres per turbine was determined to be the minimum amount necessary for this model, and any location that cannot accommodate at least three wind turbines under that requirement is not being considered for further exploration (NYSERDA 2007).

The “Zonal Statistics” feature of Arc was utilized to calculate the average wind power class, average slope, and percentage of forest land for each polygon. This data was exported to text files for use in the cost and generation calculations, as well as the mathematical modeling portion of the system.

Additional Analysis of Potential Sites

One of the major costs of setting up new wind and solar farms is the expense associated with construction of new transmission lines that must be built from the location of the facility to existing grid structures. The lack of transmission capacity for new projects has been one of the major hurdles that projects have needed to overcome and siting of new transmission lines can be a costly and contentious process (Vajjhala and Fischbeck 2007, Vajjhala 2006). GIS data for transmission lines and other grid infrastructure is not made available publicly, with the exception of one data set for high voltage transmission lines created by the Federal Emergency Management Agency (FEMA) in 1984. This dataset does not contain changes to the transmission infrastructure since that date, and it does not include any substation, transformers, or other necessary transmission details. The potential problems with using this dataset can be seen in the fact that generation facilities built since the creation of this dataset do not have transmission lines running to them, and in some cases the nearest transmission lines are more than 10 miles away. The age of the dataset means that any information garnered from the use of this dataset will not be up to date with the latest information, and can result in overestimations for cost.

To determine possible connection points, therefore, an analysis of all transmission line starting and end points was run, and any point that was found to be the intersection of three or more lines was considered a possible connection point for new transmission lines. Intersections of only two lines were not considered because of the nature of the dataset, in which an intersection of two lines in many cases represents a change in direction between line segments. As the transmission line dataset is both outdated and contains incomplete information, the estimates for construction costs of new transmission lines are considered to be very rough and assist only with planning at the aggregate level; more detailed information would be required for full exploration of a potential location. The centroid for each potential wind or solar farm location was computed, and a distance function was used to find the shortest straight-line distance between the centroid and the possible connection points. A more sophisticated function could be created to compute distance between the potential wind and solar locations and the existing grid infrastructure, including the consideration of obstacles associated with transmission line creation, the capacity of the current lines, and other detailed information that is currently unavailable in this model, as new data sets are made available or existing data sets are updated.

Finally, this model analyzed the relationship between the possible wind farm locations and the possible solar farm locations. Much of the previous research has not analyzed the potential interactions between sources at the same location and has considered all amounts of resource potential to be valid, overestimating the total potential for an area in the process. In this region there was no overlap present between the two sets of locations. One of the main reasons for the lack of overlap is that all of the solar farms are being placed on barren land, while only 0.15% of the land being used for wind farms is placed on barren land. If there was the possibility that a location could be utilized for either a wind farm or a solar farm, this information would need to be known so that the mathematical model would not be able to assign more than one renewable energy farm site to the land.

Results

Rather than provide a ranking of potential of locations, or use a factor-based model to determine the suitability of each location, the results of this GIS-based model will be combined with information for the current electricity generating facilities within the region to determine the optimal mix of resources. These cost and generation values will be analyzed through the use of a multi-objective linear program outlined in the next chapter. However, the results of the GIS model can be used to compute some basic information about the availability of renewable energy sources within the region.

There are four biomass-only facilities and four biomass/coal co-fire plants currently in the region. These facilities use either black liquor, the liquid that is created during the conversion of wood into pulp, or solid wood waste as the biomass fuel source. It is assumed that the current use of solid wood waste at two facilities in the region is being drawn from sources other than those described in the NREL dataset, which specifies 9,571,545 tons of estimated solid wood waste found within the region. A total of 67,174,951 tons of coal was used at the 31 coal plants within the region in the baseline year (EIA-861 2007). At an efficiency level of 61% for a ton of biomass compared to a ton of coal (FEMP 2004), if all biomass wood waste in the region were utilized for co-firing at coal plants, it would represent the replacement of 8.7% of the coal used within the region. Estimates for capital investment cost required to retrofit coal plants for biomass co-fire vary greatly, but in this model it is estimated to cost $100/kW of installed co-fire capacity (FEMP 2004, Caputo 2009). The actual capital investment cost required for full utilization of these resources depends on the distribution of the biomass among the coal plants in the region, as well as the efficiencies of those plants. However, a rough estimate can be computed based on the installed capacity of 18,961,046 kW at the 31 coal plants within this region (EIA-861 2007). If 8.7% of that capacity were dedicated to biomass co-fire, that would represent an estimated capital investment cost of $164,961,100. Though the use of biomass is considered a short-term solution to pollution problems, the implementation of co-fire at these coal plants is a cheaper solution than the creation of new biomass dedicated facilities within the region. Even though these co-fire plants are still emitting greenhouse gases due to the use of coal, the co-fire will result in a significant reduction in greenhouse gas emissions as one ton of biomass wood waste is estimated to represent a 100% reduction in CO_2 and SO_2 versus one ton of coal, and a reduction of 15% in NO_X emissions (FEMP 2004). Table 5 shows the breakdown of emissions within the region due to coal and other sources.

	Emissions from Coal Plants	Emissions from Other Facilities	Total Emissions
CO_2	163,055,697	2,504,204	165,559,901
SO_2	859,587	1,524	861,110
NO_X	253,350	1,500	254,951

Table 5: Tons of Emissions of Greenhouse Gases within the Region

The parameters that are utilized in the cost and generation calculations associated with biomass/coal co-fire (Table 6), wind (Table 7), and solar (Table 8) are displayed on the next page. This data is compiled from a variety of sources: academic research, government analysis, and non-profit reports[1]. The creation of new wind or solar farms within the region represents a long-term solution to the problems associated with the pollution, eliminating all greenhouse gas emissions during the electricity generation process. The life-cycle of these technologies, and the pollutants associated with activities such as manufacturing and transportation, are not explored in this model but represent a potential future research direction.

[1] A: Short, Blair et al. 2009, B: Sims, Rogner et al. 2003, C: Komar 2009, D: EIA 2010, E: FEMP 2004, F: Caputo 2009, G: MIT 2007, H: NYSERDA 2007, I: Roth and Ambs 2004, J: Porter 2002, K: ArboristSite 2006

Parameter	Value	Source[1]
Maximum Cofire % (Energy Basis) =	10%	E, F
Efficiency of Ton/Biomass vs. Ton/Coal =	61%	E
Capital Cost of Cofire Retrofit (per kW) =	$100	E, F

Table 6: Parameters for Biomass & Coal Co-Fire Calculations

Parameter	Value	Source[1]
Cost of preparing Forest land ($/acre) =	$5,000	K
Capital Cost ($/kW) =	$1,570	A
Diameter of wind turbine blades (m) =	50	H
Spacing between Turbines (# of Diameters) =	8	H
Electricity conversion factor (%) =	25%	I
Fixed O&M ($/kW year) =	$10.95	A
Variable O&M ($/MWh) =	$5.19	A
Slope Penalty (% of Capital Cost/Degree of Slope) =	2.5%	A
Cost of New Transmission Lines ($/mile) =	$2,000,000	C

Table 7: Parameters for Wind Farm Calculations

Parameter	Value	Source[1]
Capital Cost ($/kW) =	$3,480	A
Derate Factor (%) =	77%	I
Fixed O&M ($/kW year) =	$22.00	A
Variable O&M ($/MWh) =	$0.00	A
Expected Plant Life (years) =	30	I
Converstion Factor (%) =	12.5%	I
Cost of New Transmission Lines ($/mile) =	$2,000,000	C

Table 8: Parameters for Solar Farm Calculations

Generation Type	Average $/kWh	Source[1]
Biomass	$0.05200	B
Coal	$0.02000	D
Co-fire	$0.03000	B, D
Gas	$0.06993	D
Landfill	$0.05200	D
Nuclear	$0.02116	D
Oil	$0.03567	D
Water	$0.00967	D
Wind	$0.06993	B

Table 9: Estimated Cost per kWh by Source

Based on the constraints specified in the GIS model, there is an estimated maximum capacity of 77.85 mW from wind power that can be installed in this region. This capacity is capable of an estimated 6,437,656 MWh of annual generation and Figure 6 shows the estimated annual MWh generation at each location. This generation represents 3.24% of baseline generation, which is just shy of the current amount of renewable generation that exists within the region. Installing the full capacity would require an estimated total capital investment cost of approximately $11.59 billion, and an average generation cost of $0.1337/kWh. Figure 7 displays the estimated cost per kWh generated at each potential site. Compared with estimated average cost of generation by other sources, this average is not competitive. However, there are a number of potential sites within the region that are capable of generating each kWh at a cost that is lower than the sources listed in Table 9. The potential wind sites in the region are located mainly in the upper western portion of Virginia and the bordering region in West Virginia. Though there a few other sites located in Virginia, while there are no potential wind generation sites in Kentucky, North Carolina, or Tennessee. In the portions of Kentucky and Tennessee within this region, the lack of wind sites is mainly due to the insufficient wind speeds. In North Carolina, though the majority of the state within this region lacks sufficient wind power potential, there are areas in the western portion of the state that contain sufficient wind speeds. These areas were not determined to be potential locations in this model due to the series of constraints or minimum size requirements for potential site locations, showing again that a localized analysis can lead to different results than the aggregate plan determined by this model.

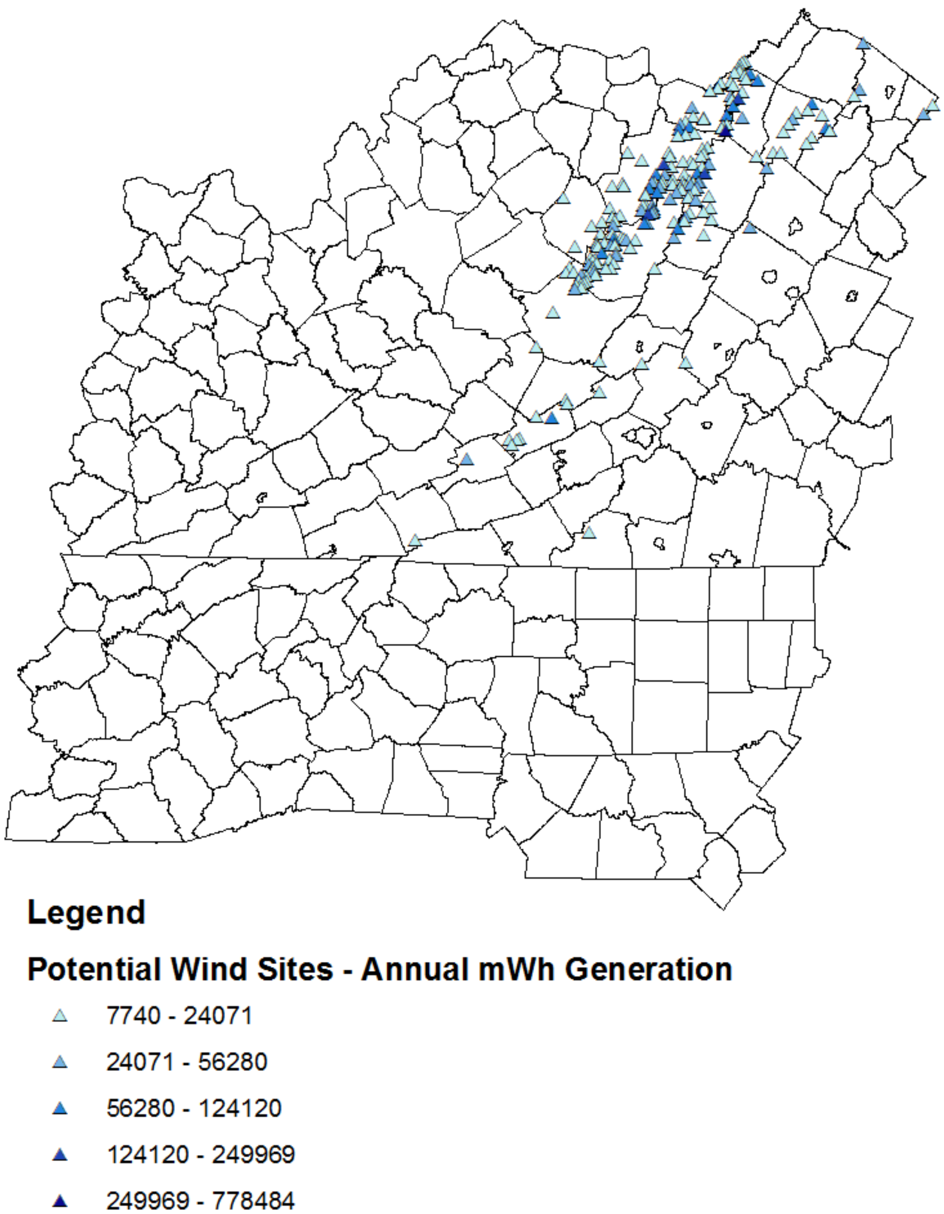

Figure 6: Estimated Annual MWh Generation at Potential Wind Farm Sites in the Region

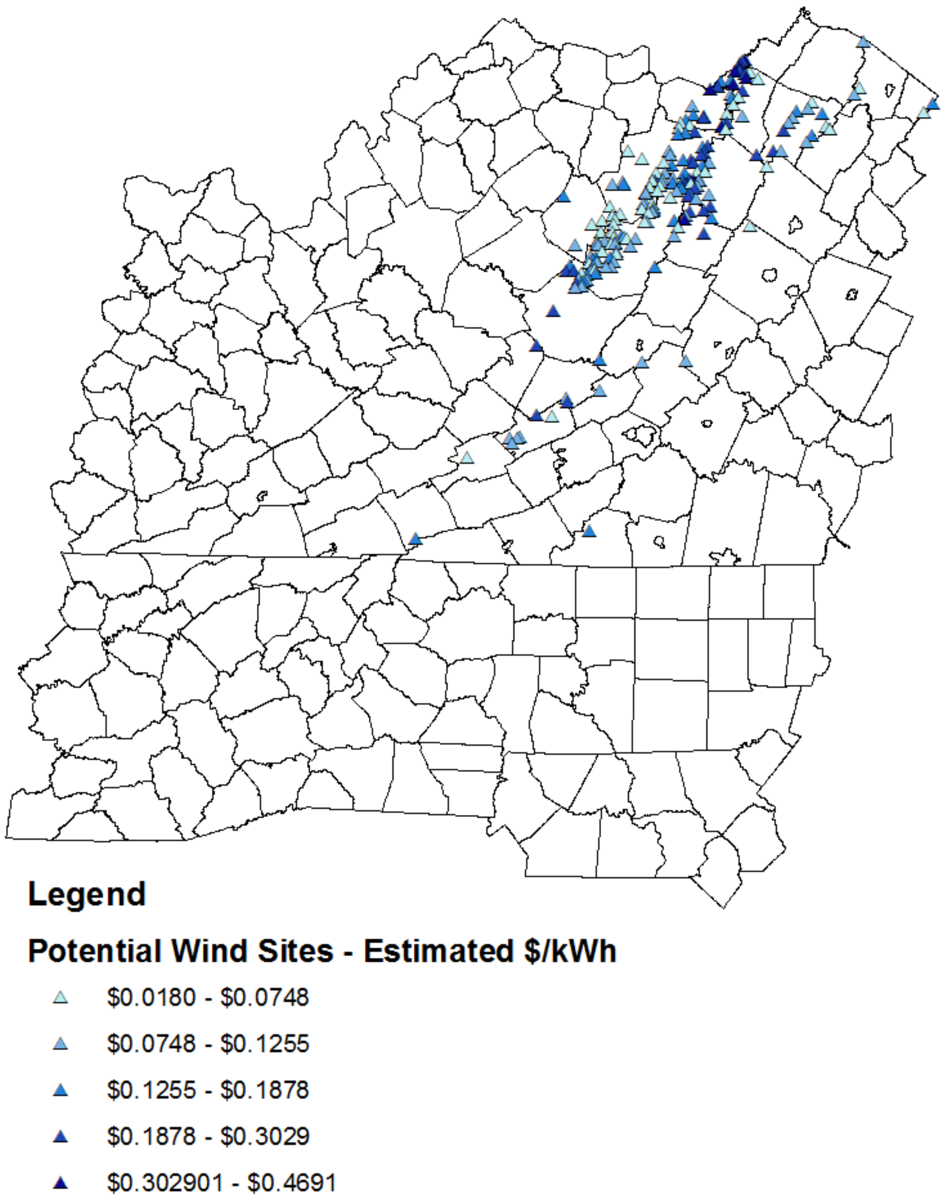

Figure 7: Estimated $/kWh Generated at Potential Wind Farm Sites in the Region

The results of the GIS model provide a maximum solar capacity of 672.66 mW that can be installed given the current set of constraints. This capacity represents an estimated 5,892,546 MWh of annual production. The estimated annual MWh generation for each potential site is displayed in Figure 8. The estimated generation from solar could replace 2.97% of baseline generation. The capacity of solar is greater than the capacity of wind, but due to the fact that solar resources can only be harnessed for shorter portions of the day, the expected annual generation is lower than that of the wind resources. Installing the full capacity of solar resources within this model would require an estimated total capital investment of over $17.3 billion, and an average generation cost of $0.1446/kWh. The expected $/kWh for each location is displayed in Figure 9. Though the average cost is not competitive with the cost estimates for other sources, there are many locations in the regions that have a competitive cost per kWh generated.

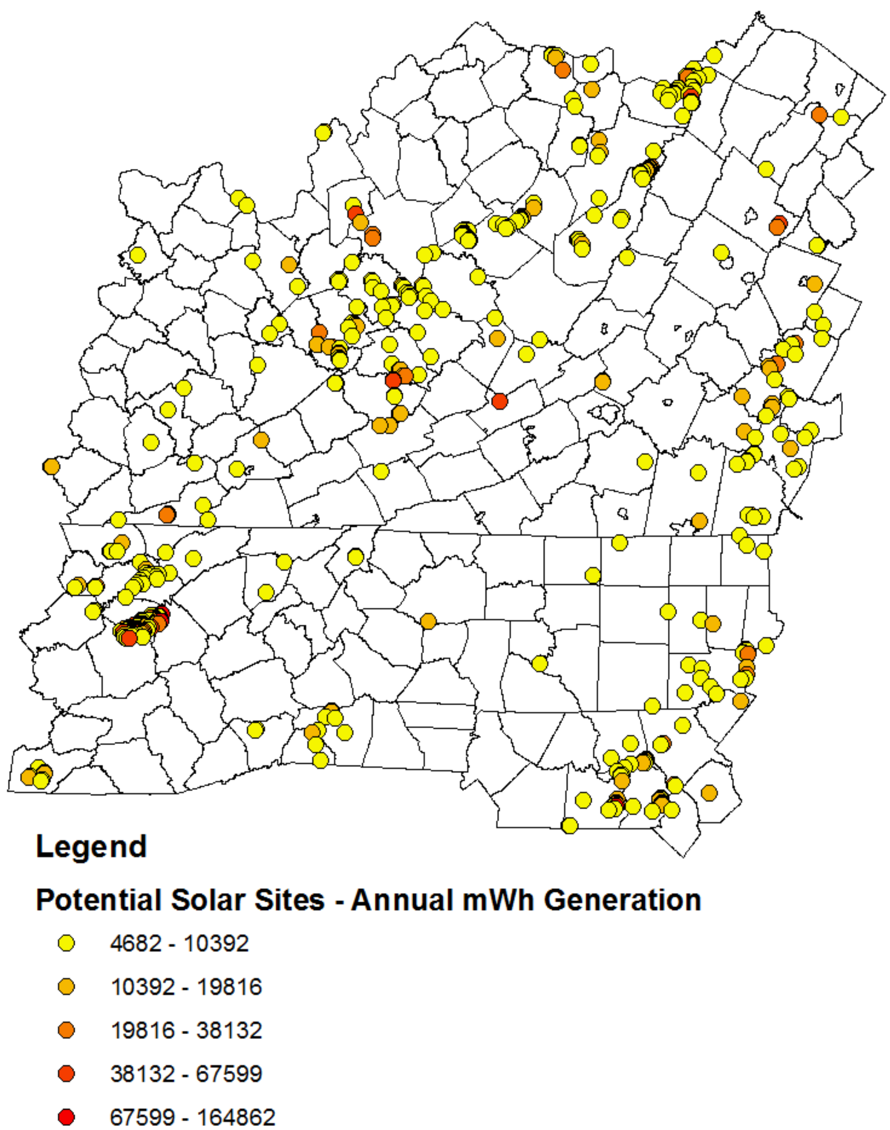

Figure 8: Estimated Annual MWh Generation at Potential Solar Farm Sites in the Region

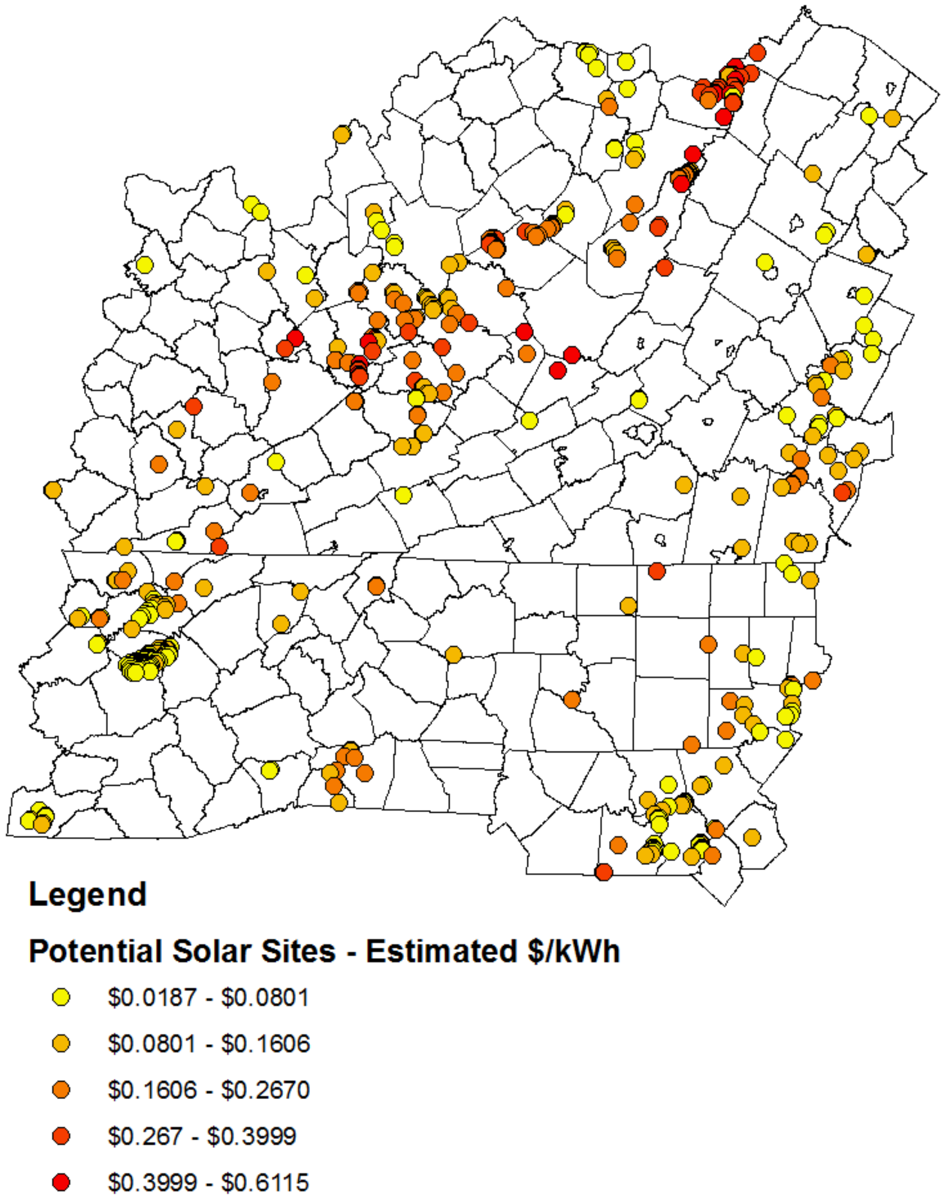

Figure 9: Estimated $/kWh Generated at Potential Solar Farm Sites in the Region

If full implementation of all potential renewable sources discovered in the GIS model were realized, the estimated total capital investment required would be over $29.05 billion. The use of biomass, solar, and wind resources are estimated to replace a total of 14.9% of baseline generation, which combined with the 3.25% of generation currently derived from renewable sources, would result in 18.2% of baseline generation from renewable sources. As no one source presents a substantial, long-term solution to increased renewable energy generation in this region, the results of this model show the need to explore multiple sources of renewable energy to meet goals for greenhouse gas emission reduction and increased energy independence.

Extensions

The mathematical model discussed in Chapter 4 will determine a mix of existing fossil fuel sources and new renewable energy facilities within the region using a multi-objective linear program that seeks to minimize both the annual generation costs and annual greenhouse gas emissions, subject to a set of constraints related to generation requirements and capital investment allocation. The required $29.05 billion for complete investment in renewable sources determined by the GIS model is probably too large an amount for investment at one time, so the constraint on capital investment presented in Chapter 4 will allow for the model to determine the best mix of renewable energy sources given a limit on capital investment.

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Chapter 4: Multi-Objective Optimization

Introduction

Utilization of renewable energy resources is recognized as a means to reduce emissions of greenhouse gases that are associated with fossil fuels. There are a number of additional benefits to be derived from the use of renewable energy instead of fossil fuels: energy independence, stability of energy prices, and socio-economic benefits for the areas where these resources are utilized. Even though these benefits exist when using renewable energy sources, the capital investment costs associated with implementing the technologies required to realize these resources has been a significant barrier to increased use. A variety of techniques have been used to analyze and model the generation and distribution of electricity. These methods have included multi-criteria decision making (Hobbs and Meier 1994; Afgan and Carvalho 2002; Hamalainen and Karjalainen 1992; Terrados, Almonacid et al. 2009) and use of the analytic hierarchy process (Xiaohua and Zhenmin 2002). However, some of the most effective methods for energy planning belong to the family of mathematical programming techniques.

The use of mathematical programming for energy planning, whether renewable sources have been included or not, has been considerable and has taken on a variety of approaches, such as linear programming seeking to minimize capital investment in new sources (Ashok 2007), to minimize costs of energy flows (Meier and Mubayi 1983; Cormio, Dicorato et al. 2003; Ramachandra 2009), or to maximize use of renewable energy (Iniyan and Sumathy 2000). More comprehensive models have been developed through the use of multi-objective linear programming (Schulz and Stehfest 1984, Borges and Antunes 2003; Subramanyan, Diwekar et al. 2004; Suganthi and Williams 2000) and goal programming (Ramanathan and Ganesh 1995; Deshmukh and Deshmukh 2009). The model developed in this chapter will be a mixed-integer, multi-objective optimization model based on the 'environmental-economic' approach, which has been used extensively (Nakata, Kubo et al. 2005; Wang and Singh 2007; King, Rughooputh et al. 2005). This approach is based on conflicting objectives related to environmental and economic objectives in a multi-objective model. This model will be discussed in further detail later in the chapter.

The previous models have also had one flaw; none of them includes a direct connection to the location of the potential energy sources. These models have all been conducted independently of the research on identifying potential renewable energy sources using GIS. The models, when necessary, have simply contained estimates related to the potential renewable energy source, or sources. There is limited discussion of the origin of these numbers, and most often these are derived from other research and resources. These numbers may not reflect the reality of the situation, nor do they consider the location of these sources, which can impact the acceptability, costs, and timing of these resources on these models. There is a need to seamlessly combine the exploration of potential sources with the modeling capability to provide a comprehensive model of both potential and optimization of that potential.

The region being analyzed in this study is the greater southern Appalachian Mountain region, comprised of portions of Kentucky, North Carolina, Tennessee, Virginia, and West Virginia (Figure 10). This region was selected for two major reasons: first, the region is home to some of the best on-shore wind potential in the Eastern United States; and second, the region is heavily dependent on the use of coal for generation of electricity. The use of coal at coal-only plants and coal/biomass co-fire facilities is responsible for 84.39% of electricity generation (Table 10) in the region, while nationwide coal generates only 48.2% of all electricity (EIA 2010). This presents a great opportunity for the penetration of renewable energy sources from wind, solar, and biomass. Currently, only 3.37% of generation in this region is from renewable sources.

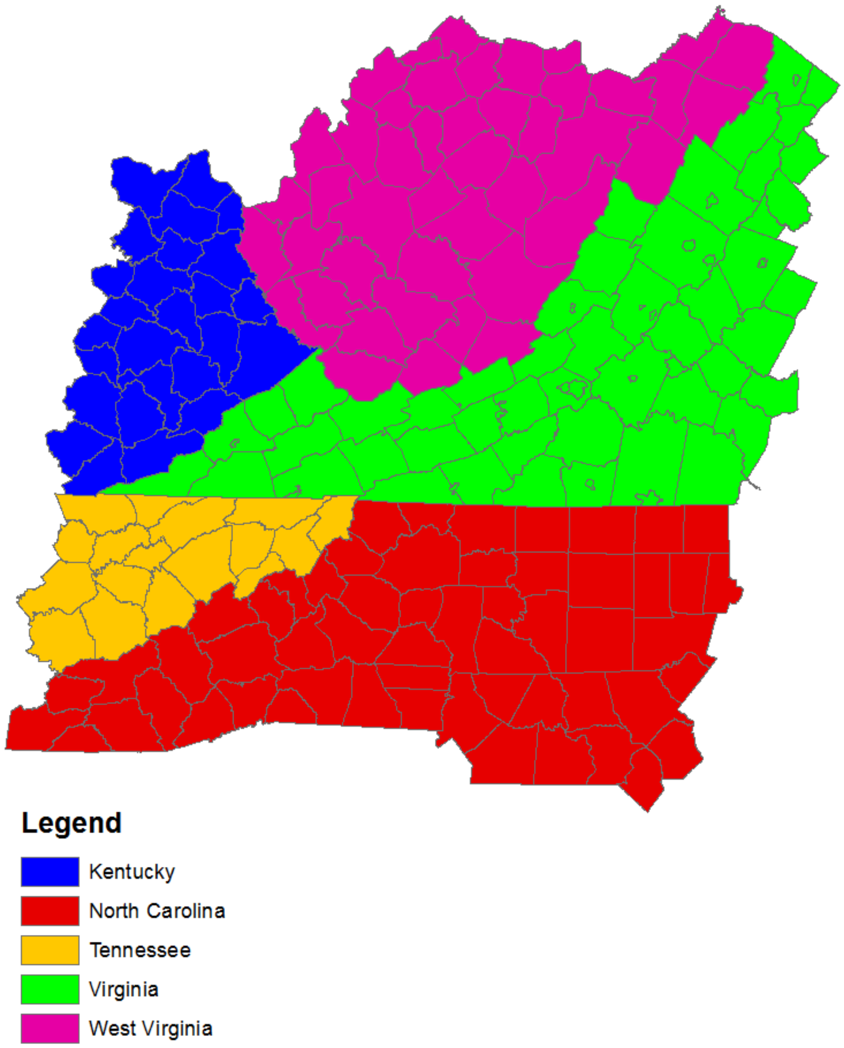

Figure 10: Greater Southern Appalachian Mountain Region

Source	Number of Facilities	MWh Generated	Percentage of Total Generation
Coal	31	165,721,345	83.50%
Nuclear	1	17,619,492	8.88%
Gas	13	6,449,095	3.25%
Water	69	4,981,292	2.51%
Co-Fire	4	2,188,456	1.10%
Biomass	3	1,026,986	0.52%
Oil	22	241,841	0.12%
Wind	1	167,588	0.08%
Landfill	4	78,071	0.04%

Table 10: Generation by Source within Region

In Chapter 3, the use of a geographic information system (GIS) model was employed to determine the potential locations for wind and solar farm sites based on a set of constraints derived from geographic and atmospheric conditions, as well as constraints based on the development of these sources due to land use, conservation, and other regulations. There were a total of 203 potential wind farm sites and 477 potential solar farm sites within the region based on the current constraints (Figure 11), representing the potential to replace 3.24% and 2.97% of baseline generation requirements respectively. The characteristics of each potential location, as calculated by the GIS, serve as inputs and parameters into the multi-objective optimization model in this chapter, which will be used to find the best locations to utilize. These derived characteristics include the resource potential, area, land uses, slope, aspect, and new transmission line requirements. This information will be utilized in the mathematical model to determine costs and generation potential for the locations. The use of mathematical modeling allows for the relationships between potential sites to be explored more fully than in a factor-based model, as each location has different power generation capabilities and costs associated with it.

In addition to wind and solar, the optimization model will explore the possibility of biomass co-fire at existing coal plants in the region. Biomass co-fire is recognized as a cost-effective way to reduce emissions and increase renewable energy generation (Robinson, Rhodes et al. 2003; Caputo 2009). The region currently has an estimated 9,571,545 tons of solid wood waste within the region (NREL-GIS 2003) which can be utilized for co-fire at coal plants. In the baseline generation data 67,174,951 tons of coal were utilized (EIA-861 2007), and solid wood waste biomass is estimated to have an efficiency of 61% per ton in comparison to a ton of coal (FEMP 2004). Therefore, approximately 8.7% of the coal utilized in this region could be replaced with this biomass type through co-fire at existing coal plants.

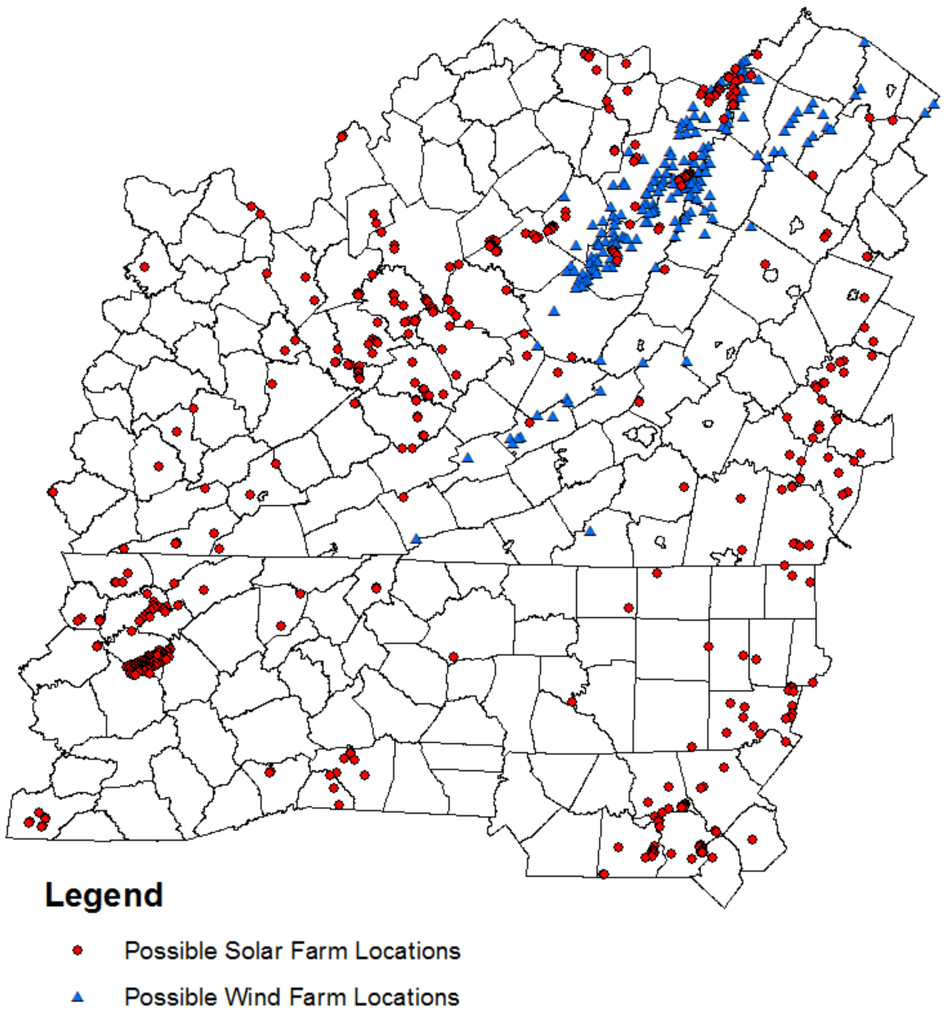

Figure 11: Potential Wind and Solar Farm Sites within the Region

The model developed in this chapter is based on the 'environmental-economic' model (Nakata, Kubo et al. 2005, Wang and Singh 2007, King, Rughooputh et al. 2005), seeking to simultaneously minimize environmental impact and minimize overall energy generation costs while meeting constraints on generation. This model provides the ability to work towards meeting the two major goals that are present in renewable energy planning. However, there are many additional objectives that could be examined in future research, such as the impact on employment and social acceptance.

The model will examine the environmental objective in terms of seeking to minimize total emissions of CO_2, SO_2, and NO_X within the region. The model does not allow for the creation of new fossil fuel power plants to meet increases in future electricity demand, as this demand must be met through renewable sources to help reduce pollutant emissions. The model does allow for the conversion of existing coal plants to biomass and coal co-fire facilities, subject to some constraints. Additionally, the model allows for a decrease in generation at existing coal plants, as well as the other existing electric generation facilities within the region, again subject to certain constraints. Through the integration of new solar and wind farms, as well as the ability to decrease capacity at existing plants and incorporate biomass into coal plants, the model will try to meet anticipated growth in electricity demand through the increased use of renewable energy sources.

However, the actions that lead to decreased emissions come at a cost. Therefore, another objective will be considered, that of minimizing annual system operating costs. The annual costs for new solar or wind farms include the amortized value of the capital investment costs, plus additional annual operating and maintenance costs. The cost for the existing non-coal facilities in the region are based on an average cost per kWh generated. The cost for coal plants is comprised of the cost per tons of biomass wood waste material and the cost per ton of coal, as well as annualized capital investment costs for the retrofit of coal plants for biomass co-fire if selected for such implementation, and an additional cost associated with each MWh produced throughout the year that covers labor, operating expenses, and other costs not directly accounted for in the model. The co-firing of biomass and coal at existing coal plants is recognized as one of the most cost-effective methods for integrating renewable energy sources into an existing system (FEMP 2004, Caputo 2009). Though this does not solve the long-term problems associated with coal-fired electricity generation, this is an acceptable short-term measure which can help reduce pollution emissions without requiring large sums of capital investment funds. Additionally, there is a small transportation charge assigned to each ton of biomass on a per mile basis to deter transporting large quantities of biomass over long distances.

The model shares many of the same features of the Regional Energy Deployment System (ReEDS) model developed by the National Renewable Energy Laboratory (NREL), part of the U.S.

Department of Energy (Short, Blair et al. 2009). Some of the input parameters and calculations related to cost were derived or adapted from the ReEDS model. However, the model in this research differs from the ReEDS formulation in a number of key ways. First, the ReEDS model has only a single objective function related to cost, while the model described in this research features two objective functions, one for cost and one for emissions. Second, this model features a constraint for capital investment, seeking to achieve the best results possible subject to a limit on capital investment spending. Third, this model allows for the creation of photovoltaic solar farm installations and the implementation of biomass/coal co-fire, neither of which are currently implemented in the ReEDS model. Finally, this model allows for costly or heavily polluting plants to be closed in order to minimize the objective functions. There are many other minor differences between the two models, but these main differences, in addition to the focus on the regional rather than national level, provide distinctions between the two models.

Decision Variables

The first set of decision variables in the model determines whether or not to develop a potential wind or solar farm location. It is assumed for each location that the full capacity of the location will be utilized based on parameters derived from the GIS, the parameters of the mathematical model, and the user inputs. Less than full utilization is considered less cost effective, as the capital investment costs associated with preparing a selected location, especially costs associated with new transmission requirements, is being divided over lower levels of capacity, which in turn increase the cost of generating electricity at that location. These decision variables are binary and represent the selection of a location by the model.

$$W_i = \begin{cases} 1 \; if \; a \; wind \; farm \; is \; to \; be \; placed \; at \; location \; i \; for \; i = 1, \dots, N_i \\ 0 \; otherwise \end{cases}$$

where N_i = the number of possible wind farm locations

$$S_j = \begin{cases} 1 \; if \; a \; solar \; farm \; is \; to \; be \; placed \; at \; location \; j \; for \; j = 1, \dots, N_j \\ 0 \; otherwise \end{cases}$$

where N_j = the number of possible solar farm locations

The next decision variable represents the amount of biomass transported from county *y* to coal-plant *p*. These are non-integer variables specifying the tons of biomass being transported, and each of these variables has a corresponding distance parameter associated with it, estimating the miles between the county and the plant which is utilized later in the model.

B_{yp} = tons of biomass transported between county *y* and coal plant *p*

for $y = 1,\ldots, N_y$ where N_y = the number of counties in the region

and $p = 1,\ldots, N_p$ where N_p = the number of coal plants in the region

The next set of decision variables determines the capacity utilization of an existing electricity generating plant. These variables are non-integer, with a maximum value of 1, representing full capacity utilization in terms of generation in the baseline year, which is not necessarily the full capacity of the plant, and a minimum value of 0, which represents the closure of an existing facility. These decision variables apply to all electricity generating facilities in the region, regardless of fuel source being utilized. This includes all coal, oil, gas, nuclear, and hydro facilities found within the region, as well as existing wind farm facilities and dedicated biomass plants. These variables will allow the model to scale back electricity generation at facilities that generate larger amounts of pollution or are more costly to operate, even to the point of closing an existing facility.

U_q = capacity utilization of existing non-coal electricity generation facility *q* relative to baseline levels

for $q = 1,\ldots, N_q$ where N_q = the number of existing non-coal facilities in the region

G_p = capacity utilization of existing coal electricity generation facility *p* relative to baseline levels

for $p = 1,\ldots, N_p$ where N_p = the number of existing coal plants in the region

The value for the electricity generation decision variables represents a percentage of baseline generation levels being utilized in the model. A constraint must be placed on these variables with a maximum value of 1, representing 100% use of the facility.

$$G_p, U_q \leq 1$$

Additionally, all non-binary decision variables have a non-negativity constraint.

$$B_{yp}, G_p, U_q \geq 0$$

Objectives

The two competing objectives in this model are the desire to minimize the annual cost of generating electricity and minimize total emissions of three greenhouse gases (CO_2, SO_2, NO_X), while satisfying the electricity generation requirements, as well as constraints on capital investment and resource utilization outlined later in the model.

Objective 1: minimize cost

The first objective of the model is the minimization of annual generation costs within the region. The model utilized here does not include some costs incurred in the ReEDS model, such as penalties for excessive renewable energy growth and a carbon tax, but does include new costs associated with the use of biomass and coal, as well as the costs associated with the existing electricity generating facilities in the region.

The first two components of this calculation are for the cost of producing wind and solar power. Though there are no fuel costs for wind or solar power, the costs of capital investment are amortized over a user-specified number of years. An annual fixed cost for each potential site represents operating and maintenance costs relative to the kW capacity installed. This fixed O&M cost reflects the costs associated with insurance, property taxes, and site maintenance. The final cost for wind and solar is the variable operating and maintenance cost, and this value is based on the actual MWh generated annually. In this model that MWh generation will remain constant, as the model is deterministic and does not consider the variability of the generation potential at each location. These variable expenses include the turbine warranties, labor costs, and royalties paid to land owners. The model was originally formulated to include costs for leasing land from both public and private owners in terms of $/acre, though this has been excluded from the model due to the inclusion of royalty costs accounted for in the variable expenses. This three-part cost structure is based on the function used in the NREL ReEDS model (Short, Blair et al. 2009).

Parameters associated with operating a wind farm:

C_i^{vw}= annualized capital investment of wind farm location *i*

C^{kwm} = annual operating and maintenance costs per installed kW of wind capacity

K_i^w = kW capacity at wind farm location *i*

C^{mwm} = annual operating and maintenance costs per MWh of wind generation

M_i^w = expected annual MWh generation at wind farm *i*

Parameters associated with operating a solar farm:

C_j^{vs} = annualized capital investment of solar farm location *j*

C^{ksm} = annual operating and maintenance costs per installed kW of solar capacity

K_j^s = kW capacity at solar farm location *j*

C^{msm} = annual operating and maintenance costs per MWh of solar generation

M_j^s =expected annual MWh generation at solar farm *j*

Coal-fired plants being considered for biomass co-fire have a few sources of cost in the calculation. One cost is the amortized cost of the capital investment for co-fire retrofit at each facility selected for biomass implementation. Other costs include the cost per ton of coal and cost per ton of biomass utilized at the plant. There is an additional cost per MWh of generation at each plant which represents labor, plant operating costs, and other costs not directly accounted for elsewhere in the model. Finally, there is a cost associated with transporting a ton of biomass for one mile. The distance between each county and each coal plant is estimated, and this cost penalty is utilized to encourage consumption of biomass closest to where the fuels are located to minimize transportation of biomass within the region.

C_p^{vc} = annualized capital investment for co-fire retrofit at coal plant *p*

C^{tc} = cost per ton of coal

C^{tb} = cost per ton of biomass

C^{tbd} = cost of transporting one ton of biomass one mile

D_{yp} = estimated distance between county *y* and coal plant *p*

C^{ac} = additional cost per MWh generated at a coal plant, including labor, operating, etc.

M_p^c = MWh generated at coal plant *p* in baseline year

T_p = tons of coal used at coal plant *p* in baseline year

The costs for electricity generation at each existing non-coal facility are estimated on the basis of annual MWh generated. The model does not utilize direct fuel costs, but is based on a cost for each non-coal fuel type that includes fuel costs, plant operating costs, labor, and more. These costs are assumed constant throughout the region and are based on fuel type.

C_q^{mn} = cost per MWh generated at non-coal facility q

M_q^n = MWh generated at non-coal facility q in baseline year

An additional parameter is also introduced in this equation, representing the efficiency of biomass versus coal, which is derived from previous research (FEMP 2004).

F = percentage efficiency of one ton of biomass versus one ton of coal, assumed constant for all plants in the region

The objective function for annual electricity generation costs is therefore given by:

$$\begin{aligned} Min \sum_{i=1}^{N_i} W_i\left(C_i^{vw} + C^{kwm}K_i^w + C^{mwm}M_i^w\right) + \sum_{j=1}^{N_j} S_j\left(C_j^{vs} + C^{ksm}K_j^s + C^{msm}M_j^s\right) \\ + \sum_{p=1}^{N_p} \left\{ \left(C_p^{vc} + C^{ac}G_pM_p^c + C^{tc}G_pT_p\right) \right. \\ \left. + \sum_{y=1}^{N_y} \left(C^{tb}B_{yp} + C^{tbd}B_{yp}D_{yp} - C^{tc}B_{yp}F\right) \right\} + \sum_{q=1}^{N_q} C_q^{mn}M_q^nU_q \end{aligned} \tag{1}$$

Objective 2: minimize emissions

The second objective, minimizing emissions, uses data from the U.S. Department of Energy (EIA-861 2007) on MWh production and the amount of emissions for each gas at the plant. The emissions data used in the model are taken from the U.S. Environmental Protection Agency's eGRID report (EPA 2008) and are calculated for each plant in the model as each plant has different rates of emission based on a variety of factors, such as the age and efficiency of the plant. The model assumes a linear relationship between the amount of electricity generated at a facility and the amount of emissions, based on previous research (Robinson, Rhodes et al. 2003). The calculation for emissions at coal plants, whether the plant is coal only or coal-biomass co-fire, is based on tons of input, while the calculation of emissions at all existing non-coal facilities is based on the MWh generated in the baseline year and the capacity utilization decision variable.

In this second equation, three sets of parameters are used to represent the emissions of greenhouse gases associated with electricity generation. For each set of parameters, there is one parameter for each of three greenhouse gases. The first set of parameters is for coal generating facilities, and each parameter is defined as the tons of emissions per ton of coal burned

E_p^{co-p} = tons of CO_2 emissions per ton of coal used at plant p

E_p^{so-p} = tons of SO_2 emissions per ton of coal used at plant p

E_p^{no-p} = tons of NO_X emissions per ton of coal used at plant p

The next set of parameters is for the emissions of greenhouse gases based on each ton of biomass co-fired in an existing coal plant. The numbers used in the model are constant for each ton of biomass used in the model, regardless of the plant, based on previous research and pilot programs (Robinson, Rhodes et al. 2003, FEMP 2004, Caputo 2009).

E_p^{co-b} = tons of CO_2 emissions per ton of biomass used at plant p

E_p^{so-b} = tons of SO_2 emissions per ton of biomass used at plant p

E_p^{no-b} = tons of NO_X emissions per ton of biomass used at plant p

The value for each of these parameters is calculated as one minus the reduction in emissions per ton of biomass. For example, if the user input is 15% reduction in NO_X emissions versus one ton of coal, then the value of E_p^{no-b} for each plant would be 85% of the rate of emissions for one ton of coal at that coal plant.

The final set of emission parameters used in this equation represents the non-coal generating electricity facilities in the region. These numbers are represented as a rate of emissions per MWh generated at the facility.

E_q^{co-q} = tons of CO_2 emissions per MWh generated at non-coal facility q

E_q^{so-q} = tons of SO_2 emissions per MWh generated at non-coal facility q

E_q^{no-q} = tons of NO_X emissions per MWh generated at non-coal facility q

The objective function for total greenhouse gas emissions is thus given by:

$$Min \sum_{p=1}^{N_p} \left\{ \left(\left[E_p^{co-p} + E_p^{so-p} + E_p^{no-p} \right] G_p T_p \right) \right.$$
$$\left. - \sum_{y=1}^{N_y} \left(\left[E_p^{co-p} + E_p^{so-p} + E_p^{no-p} \right] B_{yp} F + \left[E_p^{co-b} + E_p^{so-b} + E_p^{no-b} \right] B_{yp} \right) \right\} \tag{2}$$
$$+ \sum_{q=1}^{N_q} \left[E_q^{co-q} + E_q^{so-q} + E_q^{no-q} \right] M_q^n U_q$$

Constraints

The first constraint is on the tons of biomass available within each county. The total tons of biomass transported from county *y* to all plants must be less than or equal to the tons of biomass available within the county, defined as B_y^{avail}.

$$\sum_{p=1}^{N_p} B_{yp} \leq B_y^{avail} \tag{3}$$

The second constraint is on the maximum amount of biomass to be co-fired at each plant. The amount of biomass cannot exceed a specified percentage of total fuel generation without requiring major modifications to the plant (FEMP 2004; Caputo 2009). As each ton of biomass does not generate as much electricity as a ton of coal, the constraint is based on the amount of electricity generated through the use of biomass, not a percentage of total tonnage consumed at the plant. The parameter X = percentage of total fuel generating tons that can be derived from biomass is introduced in this equation.

$$\sum_{y=1}^{N_y} B_{yp}F \leq G_p T_p X \tag{4}$$

The third constraint is that the total amount of electricity generation, in terms of MWh/year, must meet or exceed total demand for electricity within the region. Electricity generation planning requires estimating electricity consumption for future time periods. In this model, the user can determine the amount of electricity needed based on a growth factor, defined as H, that is multiplied by the baseline MWh generated within the region, defined in the model as M^{base}. This allows the user to have some flexibility in planning and does not lock them into a model that only plans for a certain number of years in the future.

$$\sum_{i=1}^{N_i} M_i^w W_i + \sum_{j=1}^{N_j} M_j^s S_j + \sum_{p=1}^{N_p} M_p^c G_p + \sum_{q=1}^{N_q} M_q^n U_q \geq M^{base}(1+H) \tag{5}$$

The fourth constraint is for the total amount of capital investment allowed in the model. Many of the previous models have sought only to minimize total electricity generation costs without considering the amount of money that is available for capital investment at the time. Therefore many models may produce results that prescribe increased levels of wind and solar electricity generation, but the up-front capital investment funds may not be sufficient to meet the levels of new wind and solar capacity. Adding this constraint will allow the user to experiment with different capital investment levels to determine the mix of resources given the constraint on these funds and analyze different investment scenarios.

While the capital cost of installing solar is based solely on the amount of capacity installed, wind farm locations carry some additional costs. The first additional cost is due to the fact that wind farms can be installed on forest land which requires clearing, while solar farms were not permitted on forest land in the GIS model. The second additional cost for wind farm development is a penalty on the average slope at a wind farm location. Mild slopes can be beneficial to the development of a solar farm location, but these slopes require additional land preparation and installation costs for wind turbines. The capital investment costs associated with kW of capacity for wind and solar include all equipment, basic installation, and interconnection fees and are assumed linear, as is the installation cost per degree of slope. This approach to calculating costs has been used in previous models (Roth and Ambs 2004; Short, Blair et al. 2009).

C^{kw} = cost of installing one kW of wind capacity

C^{af} = cost of clearing one acre of forest land for wind farm installation

A_i^f = acres of forested land at wind farm location *i*

C^l = cost per degree of slope at wind farm location

L_i = average degree of slope at wind farm location *i*

C^{ks} = cost of installing one kW of solar capacity

C^{kb} = cost of retrofitting a coal-fired plant for biomass co-fire per kW of capacity

K_p^c = overall kW capacity at coal plant *p*

M_p^{tc} = MWh generated per ton of coal in baseline year at plant *p*

V = total amount of capital investment available

Thus the constraint on capital investment is as follows:

$$\sum_{i=1}^{N_i} K_i^w\left(C^{kw} + C^{af}A_i^f + C^l L_i\right) + \sum_{j=1}^{N_j} C^{ks}K_j^s + \sum_{p=1}^{N_p}\left[C^{kb}\left(\frac{K_p^c}{M_p^c}\right)M_p^{tc}\sum_{y=1}^{N_y} B_{yp}F\right] \leq V \qquad (6)$$

Parameters

The calculations for cost and generation require a number of parameters that are specific to the source being analyzed, biomass/coal co-fire (Table 11), wind (Table 12), solar (Table 13), and existing non-coal facility generation (Table 14), and many of these parameters are subject to variability. For example, the cost of a ton of coal has fluctuated greatly in the past few years, and the average cost per ton increased more than 20% between 2007 and 2008 (EIA 2010). Due to the changing cost structure of traditional fossil-fuel sources, the model does not provide fixed values for these cost coefficients, instead allowing the user to test out different scenarios with different costs to see how these changes impact the mix of sources utilized within the region being analyzed. Costs vary greatly between regions of the United States and by allowing for user-specified costs, the system can be transferrable to other regions of the United States or even other countries.

The user is allowed to define the costs and sizing for wind turbines and solar panels. These technologies have been experiencing a rapid decrease in cost, making them more competitive with traditional fuel sources than in the past. The variety of wind turbine and solar panel technologies has been increasing over the last few years as well. This model does not lock the user into one type of technology, instead it allows for different inputs to the model, such as turbine size and cost, to be altered by the user to test the impact that different technologies would have on the model.

The parameters used in this iteration of the model are culled from various government agencies, academic reports, and non-profit organizations[2]. In some cases, such as the maximum amount of biomass

[2] A: Short, Blair et al. 2009, B: Sims, Rogner et al. 2003, C: Komar 2009, D: EIA 2010, E: FEMP 2004, F: Caputo 2009, G: MIT 2007, H: NYSERDA 2007, I: Roth and Ambs 2004, J: Porter 2002, K: ArboristSite 2006

that can be co-fired at a coal plant and the cost of retrofitting a coal plant for co-fire capabilities, the estimates provided by these sources vary greatly and an average or most often cited value was used as an estimate for this model.

Parameter	Value	Source[2]
Maximum Cofire % (Energy Basis) =	10%	E, F
Efficiency of Ton/Biomass vs. Ton/Coal =	61%	E
Cost of Biomass Transport (ton/mile) =	$0.25	J
Cost of Biomass ($/ton) =	$40	D
Cost of Coal ($/ton) =	$55	D
Capital Cost of Cofire Retrofit (per kW) =	$100	E, F
NOx Reduction for Biomass % =	15%	F
SO2 Reduction for Biomass % =	100%	F
CO2 Reduction for Biomass % =	100%	F
Additional Cost Per MWh Generated at Coal Plant =	$7.50	G

Table 11: Parameters for Biomass & Coal Co-Fire

Parameter	Value	Source[2]
Cost of preparing Forest land ($/acre) =	$5,000	K
Capital Cost ($/kW) =	$1,570	A
Diameter of wind turbine blades (m) =	50	H
Spacing between Turbines (# of Diameters) =	8	H
Electricity conversion factor (%) =	25%	I
Fixed O&M ($/kW year) =	$10.95	A
Variable O&M ($/MWh) =	$5.19	A
Slope Penalty (% of Capital Cost/Degree of Slope) =	2.5%	A
Cost of New Transmission Lines ($/mile) =	$2,000,000	C

Table 12: Parameters for Wind Farm Calculations

Parameter	Value	Source[2]
Capital Cost ($/kW) =	$3,480	A
Derate Factor (%) =	77%	I
Fixed O&M ($/kW year) =	$22.00	A
Variable O&M ($/MWh) =	$0.00	A
Expected Plant Life (years) =	30	I
Converstion Factor (%) =	12.5%	I
Cost of New Transmission Lines ($/mile) =	$2,000,000	C

Table 13: Parameters for Solar Farm Calculations

Cost of Electricity Generation by Source ($/kWh)	Value	Source[2]
Biomass =	$0.05200	B
Co-fire =	$0.03000	B, D
Gas =	$0.06993	D
Landfill =	$0.05200	B
Nuclear =	$0.02116	D
Oil =	$0.03567	D
Water =	$0.00967	D
Wind =	$0.06993	D

Table 14: Parameters for Non-Coal Facility Generation

As the model is scaled to smaller regions, or the level of detail available to the user increases, more accurate and site specific information can be used for the parameters. Though the values of the parameters may change, the model remains functional and does not require changes to be made.

Even though some of the parameters defined in these tables require values that accurately describe the reality of the area being studied, some of these parameters, such as turbine size which can be altered by the user to reflect different technologies being considered for the region, are more flexible and open to user alteration. Two additional inputs (Table 15) in the model must be derived solely from the user. Both of these inputs provide the model with values that determine the right hand side of two of the constraints. First is the value of increased generation required in the model, defined as H, in relation to the baseline generation level. By allowing the user to specify this value, the model does not force the user into a single scenario, permitting the use to experiment with different values representing different time horizons or growth circumstances. According to the Energy Information Administration (EIA), part of the United States Department of Energy, electricity consumption in the United States decreased 1.6% in 2008 and 3.9% in 2009, the two years since the data used for this baseline scenario was reported (EIA 2010). The value of 2.5% does not represent a long time-horizon, but given that the model currently only has 6.2% of baseline levels that can be generated through new wind and solar potential determined in the GIS portion, pushing the value too much higher would require a substantial increase in capital investment or the model would be required to select all possible sites to meet higher growth values. Over the past ten years, the average growth in demand was 0.75%, and 2.5% would represent approximately 3 years of growth, which is generally not a long enough time-frame to complete the development of these wind and solar farms. However, the demand values used in the model reflect generation in the baseline year and are not representative of the full capacity of these facilities. Therefore, any demand fluctuations between the planning stage and the full implementation of the plan are assumed to be met by existing resources. Finally, as more investment capital is made available in the model, the ability to meet growth in electricity demand through renewable energy sources increases.

The second user input specifies the maximum amount of capital investment allotted to the model. This is a unique and very important constraint in this model, providing the ability to determine the best mix of current and future resources given a limit on investment. The estimated capital investment required for meeting all co-fire, wind, and solar development is $29.05 billion. The value of $10 billion was chosen, representing a value that is approximately one-third of the maximum total capital investment.

Parameter	**Values Defined for the Current Model**
Increase in MWh over Baseline Levels	2.5%
Max Amount of Capital Investment	$10,000,000,000

Table 15: User-Defined Parameters for the Model

Results

Utilizing the parameters specified in the previous section, the mixed-integer multi-objective optimization problem was run on the Frontline System Risk Solver Platform in Microsoft Excel (FSI 2008), on a Pentium 4, 3.2 GHz machine with Microsoft Windows XP. The model for this region consists of 7,370 decision variables and 8,197 constraints. Given the size of this model, the computing time was relatively small, as each of the five scenarios analyzed in this section where solved in less than four minutes. As this model is composed of two competing objectives, the approach to solving this problem utilizes a technique that provides non-dominated, Pareto optimal solutions (Ragsdale 2008). The model is first run for each of the two objectives individually to determine target solutions which will be utilized in the creation of a new single objective function.

Minimize Costs

The first objective function, minimizing annual generation costs, was solved first without explicitly taking emissions into consideration. Solving for the cost function alone produced an optimal annual generation cost of $6,067,506,773. This minimized cost is an increase from the estimated baseline cost of only 1.2%, and is due to the increased demand present in the model. The total emissions associated with this optimal cost solution were 166,168,723 tons, a decrease from the baseline scenario (166,675,862) due to the closure of a few existing facilities. The model meets the exact amount of demand specified by the generation constraint, but uses only $5,756,432,379 of the $10 billion allotted for capital investment.

Under this cost minimization scenario, the implementation of biomass co-fire at coal plants is not utilized (Table 16). Although the use of co-fire can be generally beneficial in decreasing emissions, the increased costs associated with its implementation do not provide extra capacity for generation and only lead to increased cost per unit of power generated at coal plants. Therefore, the lack of co-fire implementation in this scenario makes sense.

BIOMASS/COAL CO-FIRE RESULTS	
Number of Plants Using Biomass =	0
Total Tons of Biomass =	0.00
% of Biomass Utilization =	0.00%
Total MWh Produced at Coal Plants =	165,721,345
% Utilization versus 2007 Levels =	100.00%
MWh from Biomass =	0.00
% of Overall MWh from Biomass =	0.00%
# of Plants at Full Capacity =	31
# of Plants Shutdown =	0
Total Cost of Generation =	$4,937,512,519
Total Cofire Capital Investment =	$0.00
% of Overall Capital Investment =	0.00%
Total Emissions (tons) =	164,043,590
Reduction in Emissions over Baseline =	0.00%

Table 16: Biomass/Coal Co-Fire Results for Minimize Cost Objective

Of the 203 possible wind locations in the model, 47 are chosen for development when seeking to minimize overall generation costs (Table 17). These sites have an installed capacity of 18,582 kW, capable of generating an estimated 3,725,546 MWh of electricity annually, and representing 1.83% of total generation in this scenario. The capital investment cost for these sites is $2,629,587,746, or 45.68% of the investment capital utilized. The average cost of generating electricity from these 47 sites is $0.0347, a decrease from the average of all possible sites due to only the most cost effective sites being selected.

WIND RESULTS	
Number of Locations Selected =	47
Total kW Capacity Installed =	18,582
Total Capital Investment =	$2,629,587,747
% of Overall Capital Investment =	45.68%
Annual Generation Cost =	$129,176,026
Annual MWh Generated =	3,725,546
% of Overall Generation =	1.83%
Average Cost per kWh =	$0.0347

Table 17: Wind Farm Results for Minimize Cost Objective

The annual MWh generated from solar energy are estimated to be 3,045,307 through the development of 144 of the 403 possible locations in the model (Table 18). This represents 1.5% of the overall generation in this scenario. The capital investment required for these installations is $3,126,844,633, or 54.32% of the total capital investment in this scenario. The average cost per kWh produced is $0.0367, again reflecting the selection of the most cost-effective. Figure 12 shows the locations selected for wind and solar farm development by the model.

SOLAR RESULTS	
Number of Locations Selected =	144
Total kW Capacity Installed =	347,638
Total Capital Investment =	$3,126,844,633
% of Overall Capital Investment =	54.32%
Annual Generation Cost =	$111,876,186
Annual MWh Generated =	3,045,307
% of Overall Generation =	1.50%
Average Cost per kWh =	$0.0367

Table 18: Solar Farm Results Results for Minimize Cost Objective

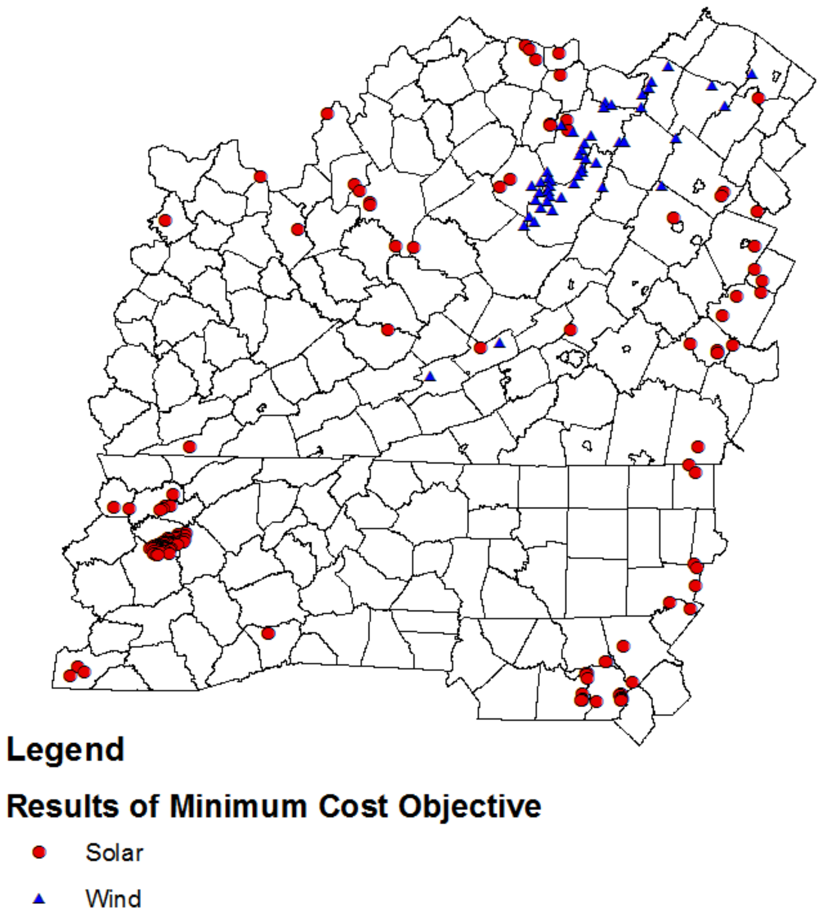

Figure 12: Wind and Solar Farm Sites Selected by the Minimize Cost Objective

Nearly all of the non-coal facilities in the region are utilized at full capacity (Table 19). Four of the gas facilities are shutdown, while another operates at 53% capacity. Additionally, the one wind farm currently deployed in the region is shut down as well. This is due to the higher estimated cost for this wind farm than the wind farms discovered in the GIS model. This is due to two reasons: first, the current wind farm has been in operation for a number of years already and was built using more costly and less efficient technology; and second, the cost estimate utilized in this model is derived from an average across all installations operating in the United States. The actual cost at this wind farm location may be lower, or higher, than this estimated value, reflecting the need for more detailed information that is not readily available and therefore supports the idea that this model should be used for aggregate planning within the region. As more detailed information is made available the plan provided by the model becomes more accurate, and the model can be utilized with new parameters without requiring adjustments to the formulation.

The use of renewable energy sources in this scenario is 6.53%, representing a slight increase over the previous 3.37% in baseline generation, which is due mostly to the increase in demand over the baseline generation requirements.

NON-COAL FACILITIES RESULTS				
	# at Full Capacity	**Total MWh**	**Total Emissions (tons)**	**Annual Cost**
Biomass	3	1,026,986	14,226	$53,403,274
Co-Fire	4	2,188,456	277,946	$65,653,666
Gas	8	4,807,684	1,792,902	$336,201,316
Landfill	4	78,071	423	$4,059,692
Nuclear	1	17,619,492	0	$372,828,451
Oil	22	241,841	40,018	$8,626,476
Water	69	4,981,292	0	$48,169,096
Wind	0	0	0	$0

Table 19: Non-Coal Facility Results for Minimize Cost Objective

Minimize Emissions

Minimizing emissions, without explicitly considering costs, was the second objective for which the model was solved. Solving for this objective minimized emissions of greenhouse gases from the baseline scenario to a total of 147,458,417 tons, a reduction of over 19 million tons or 11.46%. This value for total emissions is the lowest value that can be achieved in this model given the current results of the GIS model, the constraint on capital investment availability, and the anticipated growth in demand. This reduction in total greenhouse gas emissions came at an annual generation cost of $6,676,682,693, an increase of 12.16% over the estimated baseline cost. The model produces the exact amount of MWh required, but a total capital investment cost of $9,999,596,747 is required to meet this generation while providing reduction in emissions.

Coal remains the dominant source of electricity in the region, even when attempting to minimize emissions. 28 of the 31 coal plants continue operating at full baseline capacity, two plants are scaled back, and one plant is shut down completely. However, the use of renewable energy increases greatly through minimizing this objective. 21 of the 31 coal plants implement some amount of biomass co-fire, utilizing the entire amount of biomass available within the region, and 7.15% of the total MWh generated in the region is through the use of biomass co-fired at coal plants (Table 20). The total capital investment cost for this biomass co-fire capability is $168,709,212, only 1.69% of the total capital investment. The use of biomass leads to a reduction in 11.62% of the emissions from coal plants over baseline levels.

BIOMASS/COAL CO-FIRE RESULTS	
Number of Plants Using Biomass =	21
Total Tons of Biomass =	9,571,546
% of Biomass Utilization =	100.00%
Total MWh Produced at Coal Plants =	162,062,126
% Utilization versus Baseline Levels =	97.79%
MWh from Biomass =	14,547,801
% of Overall Generation from Biomass =	7.15%
Number of Plants at Full Capacity =	28
Number of Plants Shutdown =	1
Total Cost of Generation =	$5,258,173,458
Total Cofire Capital Investment =	$168,709,212
% of Overall Capital Investment =	1.69%
Total Emissions =	144,988,441
Reduction in Emissions over Baseline =	11.62%

Table 20: Biomass/Coal Co-Fire Results from the Minimize Emissions Objective

Out of the 203 possible wind locations determined in the GIS model, 102 are selected by the model in the minimizing emissions scenario, with an estimated 40,509 kW of capacity installed, and an estimated 4,995,853 MWh of annual generation; 2.46% of the generation requirements in the model (Table 21). The capital investment required to meet this wind generation is $5,287,303,155, or 52.88% of the total capital investment, and the sites averaged $0.0488/kWh generated. This represents a very competitive value within the region and is a substantial decrease from the average cost of $0.1337 for all potential wind sites in the model.

WIND RESULTS	
Number of Locations Selected =	102
Total kW Capacity Installed =	40,509
Total Capital Investment =	$5,287,303,155
% of Overall Capital Investment =	52.88%
Annual Generation Cost =	$243,665,421
Annual MWh Generated =	4,995,853
% of Overall Generation =	2.46%
Average Cost per kWh =	$0.0488

Table 21: Wind Farm Results Results from the Minimize Emissions Objective

In terms of solar generation, 194 of the possible 407 sites are selected (Table 22). These sites represent an installed capacity of 415,970 kW and are estimated to produce 3,643,894 MWh annually, or 1.79% of the total generation requirement. The capital investment required for these installations is $4,543,584,380, 45.44% of the total capital investment, and an average cost of $0.0441 per kWh. The average cost for all locations in the model is $0.1446, so the model has again selected the most cost effective sites. Figure 13 shows the wind and solar sites selected by the model in this scenario.

SOLAR RESULTS	
Number of Locations Selected =	194
Total kW Capacity Installed =	415,970
Total Capital Investment =	$4,543,584,380
% of Overall Capital Investment =	45.44%
Annual Generation Cost =	$160,604,146
Annual MWh Generated =	3,643,894
% of Overall Generation =	1.79%
Average Cost per kWh =	$0.0441

Table 22: Solar Farm Results Results from the Minimize Emissions Objective

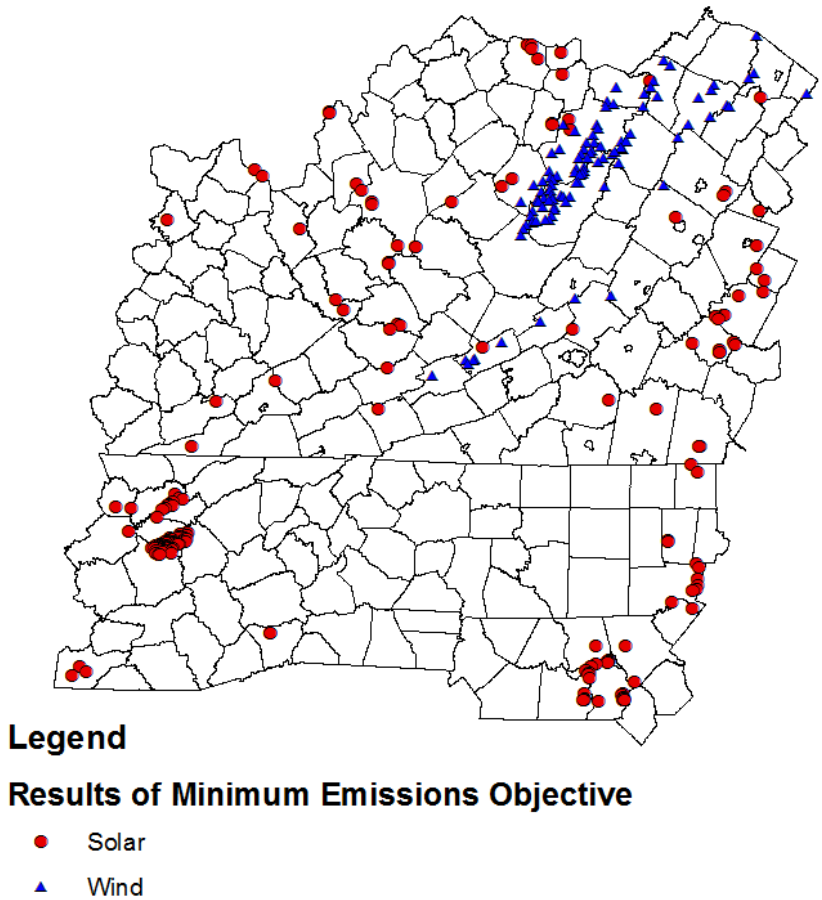

Figure 13: Wind and Solar Farm Sites Selected by the Minimize Emissions Objective

As for the non-coal facilities currently operating in the region, all biomass, co-fire, landfill, nuclear, water, and wind facilities continue operating at full capacity (Table 23). Two of the 13 gas facilities and 17 of the 22 oil facilities were shut down in this model. Even though a large number of oil facilities were shut down, they were the least productive facilities in the region, as the MWh produced through oil decreased only 1.2% over the baseline levels, and the two gas facilities shut down only resulted in a decrease of 0.24% in generation.

NON-COAL FACILITIES RESULTS				
	# at Full Capacity	Total MWh	Total Emissions (tons)	Annual Cost
Biomass	3	1,026,986	14,226	$53,403,274
Co-Fire	4	2,188,456	277,946	$65,653,666
Gas	11	6,433,348	2,144,518	$449,884,034
Landfill	4	78,071	42	$4,059,692
Nuclear	1	17,619,492	0	$372,828,451
Oil	5	238,913	33,244	$8,522,027
Water	69	4,981,292	0	$48,169,096
Wind	1	167,588	0	$11,719,429

Table 23: Non-Coal Facility Results from the Minimize Emissions Objective

Through the increased use of renewable sources, particularly the implementation of biomass co-fire at existing coal plants, a significant decrease in emissions was achieved, 11.46% over baseline emissions. The total amount of generation from renewable resources increased from 3.25% to 14.68% within the region. Over half of this increase was due to the implementation of biomass-coal co-fire, and this reduction came at a fraction of the overall investment cost, showing the cost effectiveness of co-fire as means to help reduce emissions.

MiniMax - Equal Weight Results

The results of the two previous scenarios, minimizing costs and minimizing emissions, are utilized in this scenario. The values achieved for the objective function in each of those scenarios provide target values for the model. The level of emissions achieved in this combined model cannot be lower than the value achieved when minimizing emissions was the sole objective function, while the overall cost achieved when minimizing cost cannot be bettered given the same set of inputs and constraints. The previously achieved minimum values thus serve as target values in this new scenario.

In this combined formulation of the model, a new value is created that is used as a decision variable, the right hand side of a new constraint, and the objective function. This value, Q, becomes the new objective function, which the model seeks to minimize through changing the value as a new decision variable. Finally, Q becomes the right hand side of a new set of constraints. These new constraints compare the total emissions and total cost values to their respective target values, and the percentage deviation from the target value is calculated. The user also inputs a weight for each of these two objectives, specifying the importance of each objective function. The percentage deviation is multiplied by the weight to provide a weighted deviation value. This value must be less than or equal to *Q*, thereby minimizing the maximum deviation between the two objectives. This approach is called the MiniMax function, and it provides Pareto optimal solutions (Ragsdale 2008). For this current scenario, the value of the weight for each objective function is set to 1, representing equal importance between the objectives.

The objective function results of this scenario are displayed in Table 24. The total emissions found in this scenario are 151,225,781.50, an increase of 2.55% over the minimum value previously achieved. The cost function experienced an identical 2.55% increase over the target value, for a total of $6,222,523,403.55. Thus the model found a point between the two objective functions whereby both objective function values were the same percentage deviation from the target values. This scenario utilized a total of $7,210,400,939.33 of the maximum $10 billion of capital investment funds.

Objective:	**Value**	**Target Value**	**Deviation**	**Weight**	**Weighted Dev.**
Minimize Emissions	151,225,781.50	147,458,417.44	2.55%	1	2.55%
Minimize Cost	$6,222,523,403.55	$6,067,506,773.45	2.55%	1	2.55%

Table 24: Objective Function Results of the MiniMax – Equal Weight Function

The use of biomass under the MiniMax function is 94.31% of the total available amount (Table 25Retrofitting the 26 coal plants selected for biomass co-fire costs $155,035,698, only 2.15% of the total capital investment in this scenario. This biomass co-fire represents 6.67% of the generation requirements, again showing the cost effectiveness of co-fire as a means of emissions reduction. Through the increased use of biomass at these facilities, emissions from coal plants are reduced 8.79% over baseline levels. Additionally, no coal plants are shutdown under this scenario, though one plant is scaled back to 5.76% while the remaining plants operate at full capacity relative to baseline levels.

BIOMASS/COAL CO-FIRE RESULTS	
# of Plants Using =	26
Total Tons of Biomass =	9,026,856
% of Biomass Utilization =	94.31%
Total MWh Produced at Coal Plants =	165,216,776
% Utilization versus 2007 Levels =	99.70%
MWh from Biomass =	13,563,131
% of MWh from Biomass =	6.67%
# of Plants at Full Capacity =	30
# of Plants Shutdown =	0
Total Cost of Generation =	$5,053,541,086
Total Cofire Capital Investment =	$155,035,698
% of Overall Capital Investment =	2.15%
Total Emissions =	149,724,398
Reduction in Emissions over Baseline =	8.80%

Table 25: Biomass/Coal Co-Fire Results from the MiniMax – Equal Weight Function

The use of wind in this model is implemented at 60 of the possible 203 locations (Table 26). The installed wind capacity is 23,586 kW, and is capable of generating an estimated 4,138,576.37 MWh annually, which is 2.03% of the total generation in the region. Installing this wind capacity requires $3,343,079,446 of investment capital, or 46.36% of the total funds required in this scenario, and costs an estimated $0.0388 per kWh generated.

WIND RESULTS	
Number of Locations Selected =	60
Total kW Capacity Installed =	23,586
Total Capital Investment =	$3,343,079,446
% of Overall Capital Investment =	46.36%
Annual Generation Cost =	$160,375,610
Annual MWh Generated =	4,138,576
% of Overall Generation =	2.03%
Average Cost per kWh =	$0.0388

Table 26: Wind Farm Results from the MiniMax – Equal Weight Function

The use of solar in this scenario is developed at 165 of the possible 477 locations for a total capacity of 378,451 kW (Table 27). The cost of this development is $3,712,285,795, representing

51.49% of the total capital investment. The annual generation of electricity from solar farms is estimated at 3,315,238 MWh, 1.63% of total generation, at an average cost of $0.0398 per kWh. Figure 14 displays the wind and solar farm sites utilized under this scenario.

SOLAR RESULTS	
Number of Locations Selected =	165
Total kW Capacity Installed =	378,451
Total Capital Investment =	$3,712,285,795
% of Overall Capital Investment =	51.49%
Annual Generation Cost =	$132,068,800
Annual MWh Generated =	3,315,238
% of Overall Generation =	1.63%
Average Cost per kWh =	$0.0398

Table 27: Solar Farm Results from the MiniMax – Equal Weight Function

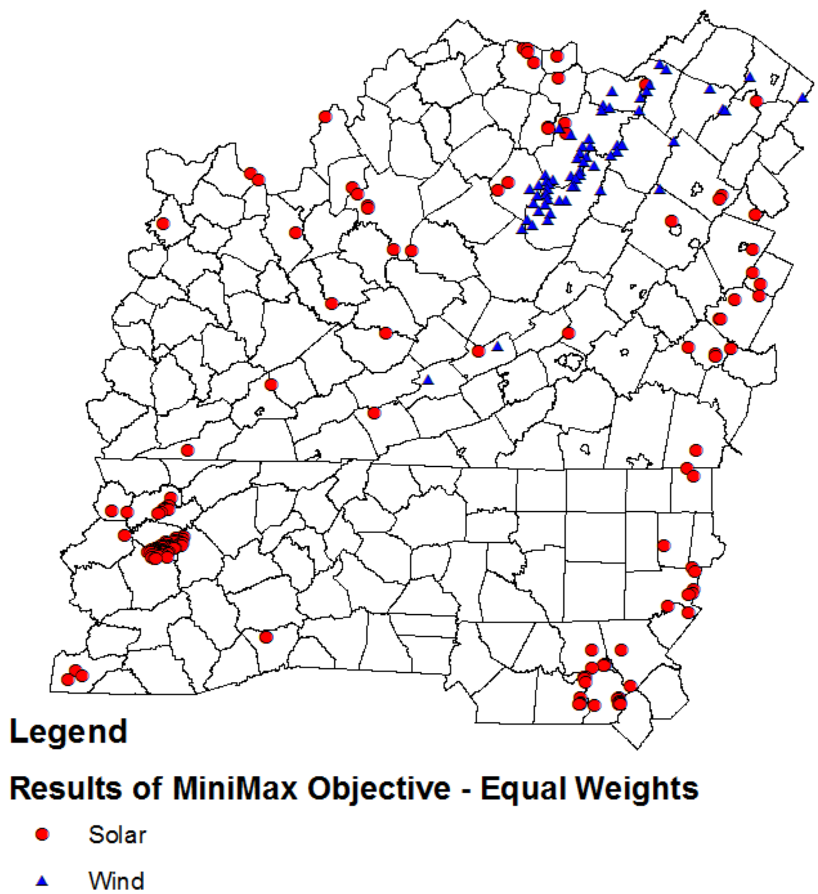

Figure 14: Wind and Solar Farm Sites Selected by the MiniMax – Equal Weight Function

The baseline generation levels of the biomass, co-fire, landfill, nuclear, water, and wind facilities are fully realized in this scenario, while a number of gas or oil plants are scaled back in generation or shutdown completely (Table 28). This reflects the higher cost for these fossil fuels in comparison to coal. While coal causes the most emissions, some of these emissions can be reduced through the use of biomass co-fire, while oil and gas do not have the same opportunity in this model.

NON-COAL FACILITIES RESULTS				
	# at Full Capacity	**Total MWh**	**Total Emissions (tons)**	**Annual Cost**
Biomass	3	1,026,986	14,226	$53,403,274
Co-Fire	4	2,188,456	277,946	$65,653,666
Gas	8	4,463,773	1,174,518	$312,151,652
Landfill	4	78,071	42	$4,059,692
Nuclear	1	17,619,492	0	$372,828,451
Oil	7	239,771	34,651	$8,552,649
Water	69	4,981,292	0	$48,169,096
Wind	1	167,588	0	$11,719,429

Table 28: Non-Coal Facility Results from the MiniMax – Equal Weight Function

The use of renewable energy sources in this scenario represents 13.61% of total generation, a dramatic increase over the baseline scenario generation of 3.37%, or the minimized cost scenario generation of 6.53%. This percentage is a decrease from the minimized emissions scenario (14.68%). This decrease is to be expected, but the decreased value is closer to the maximum percentage than it is to the baseline percentage, meaning that the model has greatly increased the use of renewable energy resources in the region over the baseline scenario. In addition, the model was able to find a balance between the total emissions and total generation costs while only utilizing 72.1% of the capital investment available.

MiniMax - Cost Weighted Results

In order to see the effects that different weights would have on the outcome of the model, two additional scenarios utilizing the MiniMax function were analyzed. The first of these scenarios placed a weight of 2 on the minimizing cost objective function, while retaining a value of 1 for the weight of minimizing emissions. This means that the cost function is twice as important as the emissions function, and therefore the percentage deviation from the target value for annual generation cost should be smaller than the emissions deviation from its target value. The objective function results of this scenario are displayed in Table 29. In this scenario, the deviation from the minimized target cost value is 1.92%, while the emissions value is 3.84% greater than its target value. Thus the percentage deviation for the cost function was half the deviation of the emissions function, reflecting the importance of the weight assigned to the cost function. This scenario utilized $6,758,730,480 of the $10 billion available in the capital investment constraint.

Objective:	Value	Target Value	Deviation	Weight	Weighted Dev.
Minimize Emissions	153,123,113.03	147,458,417.44	3.84%	1	3.84%
Minimize Cost	$6,184,050.065.66	$6,067,506,773.45	1.92%	2	3.84%

Table 29: Objective Function Results of the MiniMax – Cost Weighted Function

The use of biomass co-fire was reduced from 94.31% in the equally weighted MiniMax function to a value of 85.07% (Table 30), which is still far greater than in the scenario that sought only to minimize cost. The retrofitting of 26 coal facilities chosen for co-fire represents only 2.07% of the capital investment requirement, while reducing the emissions at coal plants by 7.49% over the baseline levels. All of the coal plants are utilized at full baseline levels.

BIOMASS/COAL CO-FIRE RESULTS	
# of Plants Using =	26
Total Tons of Biomass =	8,142,322
% of Biomass Utilization =	85.07%
Total MWh Produced at Coal Plants =	165,721,345
% Utilization versus 2007 Levels =	100.00%
MWh from Biomass =	12,218,802
% of MWh from Biomass =	6.01%
# of Plants at Full Capacity =	31
# of Plants Shutdown =	0
Total Cost of Generation =	$5,052,613,097
Total Cofire Capital Investment =	$139,882,261
% of Overall Capital Investment =	2.07%
Total Emissions =	151,752,766
Reduction in Emissions =	7.49%

Table 30: Biomass/Coal Co-Fire Results from the MiniMax – Cost Weighted Function

The use of wind in this scenario accounts for 1.95% of the total generation within the region (Table 31). 54 of the 203 possible wind sites are selected for use in this scenario, with a total capital investment cost of $3,019,351,857, or 44.67% of the total capital investment, while the average cost per kWh generated is $0.0369.

WIND RESULTS	
Number of Locations Selected =	54
Total kW Capacity Installed =	21,355
Total Capital Investment =	$3,019,351,857
% of Overall Capital Investment =	44.67%
Annual Generation Cost =	$146,290,547
Annual MWh Generated =	3,962,185
% of Overall Generation =	1.95%
Average Cost per kWh =	$0.0369

Table 31: Wind Farm Results from the MiniMax – Cost Weighted Function

Solar farm installations account for 1.61% of the MWh generated in the region on an annual basis through the use of 159 of the 477 possible sites (Table 32). Capital investment costs for these sites are estimated to be $3,599,496,362, or 53.26% of the total capital investment. The cost per kWh generated from these solar sites is estimated to be $0.0392. Figure 15 shows the wind and solar farm sites selected by the model.

SOLAR RESULTS	
Number of Locations Selected =	159
Total kW Capacity Installed =	372,840
Total Capital Investment =	$3,599,496,362
% of Overall Capital Investment =	53.26%
Annual Generation Cost =	$128,185,695
Annual MWh Generated =	3,266,080
% of Overall Generation =	1.61%
Average Cost per kWh =	$0.0392

Table 32: Solar Farm Results from the MiniMax – Cost Weighted Function

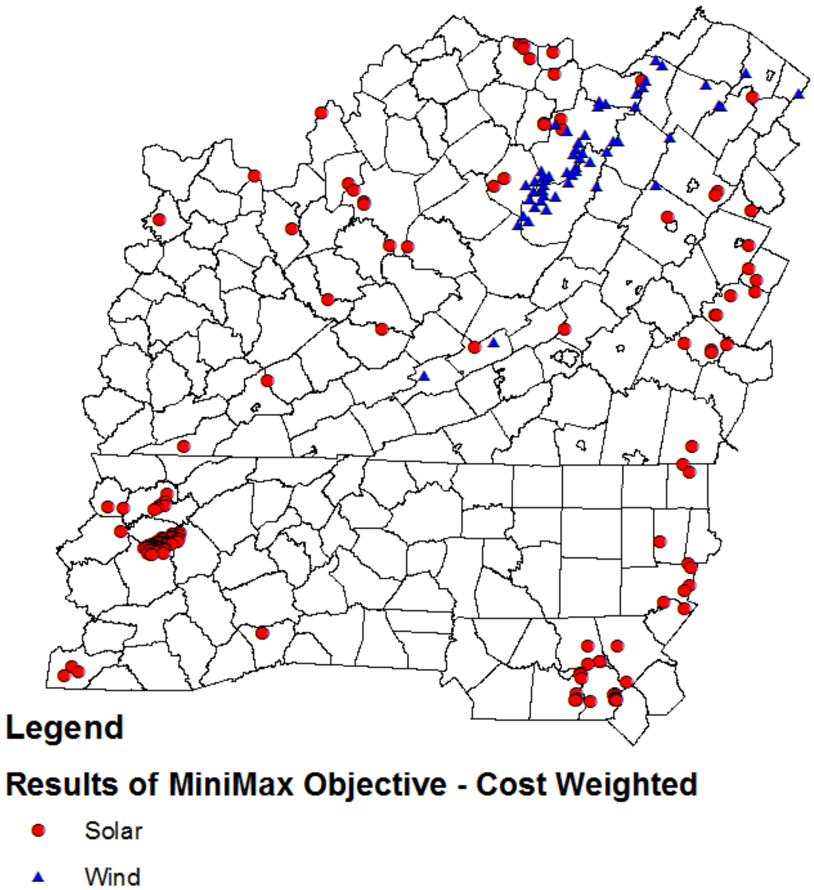

Figure 15: Wind and Solar Farm Sites Selected by the MiniMax – Cost Weighted Function

The majority of non-coal facilities are fully operational under this scenario (Table 33). Four of the thirteen gas facilities are shutdown, while another operates at 11% of baseline capacity. In addition, ten of the twenty-two oil facilities are shutdown. Again, this reflects the higher costs associated with gas and oil facilities.

NON-COAL FACILITIES RESULTS				
	# at Full Capacity	Total MWh	Total Emissions (tons)	Annual Cost
Biomass	3	1,026,986	14,226	$53,403,274
Co-Fire	4	2,188,456	277,946	$65,653,666
Gas	8	4,182,846	1,039,285	$292,506,422
Landfill	4	78,071	42	$4,059,692
Nuclear	1	17,619,492	0	$372,828,451
Oil	12	241,679	38,848	$8,620,697
Water	69	4,981,292	0	$48,169,096
Wind	1	167,588	0	$11,719,429

Table 33: Non-Coal Facility Results from the MiniMax – Cost Weighted Function

The use of renewable energy sources in this scenario accounts for 12.84% of total generation. This represents a decrease in renewable generation of less than one percent from the equally weighted MiniMax scenario, but is still nearly three times greater than the current percentage, as well nearly double the percentage found in the minimizing cost scenario. Thus the scenario represents a substantial increase in renewable energy usage even while emphasizing the importance of cost in relation to emissions.

MiniMax - Emissions Weighted Results

The second MiniMax scenario represents the opposite weighting of the previous scenario, placing two times the emphasis on minimizing emissions in comparison to minimizing cost. The percentage deviation for minimizing emissions was 1.65% greater than the target value, while the percentage deviation for minimizing cost was 3.31% more than the minimum value found in the model. This scenario resulted in the use of $8,751,573,629 of the possible $10 billion in capital investment available. The objective function results are displayed in Table 34.

Objective:	Value	Target Value	Deviation	Weight	Weighted Dev.
Minimize Emissions	149,897,547.52	147,458,417.44	1.65%	2	3.31%
Minimize Cost	$6,268,233,711.41	$6,067,506,773.45	3.31%	1	3.31%

Table 34: Objective Function Results of the MiniMax – Emissions Weighted Function

Biomass co-fire is implemented at 25 of the 31 plants in the region, while three plants are completely shut down and another is utilized at 26% of baseline capacity (Table 35). The implementation of biomass co-fire accounts for 7.06% of all MWh generated, and all of the available biomass within the region is used for co-fire. Through the implementation of biomass co-fire and the closure or scaling back of plants, total tons of emissions from these coal plants decreases by 9.42% over baseline levels. The cost of retrofitting these plants for biomass co-fire is 1.88% of the total capital investment cost in this scenario, $164,279,132.

BIOMASS/COAL CO-FIRE RESULTS	
# of Plants Using =	25
Total Tons of Biomass =	9,571,546
% of Biomass Utilization =	100.00%
Total MWh Produced at Coal Plants =	164,931,531
% Utilization versus 2007 Levels =	99.52%
MWh from Biomass =	14,370,064
% of MWh from Biomass =	7.06%
# of Plants at Full Capacity =	28
# of Plants Shutdown =	1
Total Cost of Generation =	$5,067,764,242
Total Cofire Capital Investment =	$164,279,132
% of Overall Capital Investment =	1.88%
Total Emissions =	148,584,496
Reduction in Emissions =	9.42%

Table 35: Biomass/Coal Co-Fire Results from the MiniMax – Emissions Weighted Function

The use of wind power in this scenario accounts for 2.2% of all MWh generated (Table 36). To accomplish this level of generation, 73 of the possible 203 sites are selected for development, at a total cost of $4,029,617,726, or 46.04% of total capital investment. The average cost per kWh generated is estimated at $0.0424, an increase over the average found in the cost minimization weighted MiniMax scenario due to the selection of additional sites with higher costs than those utilized previously.

WIND RESULTS	
Number of Locations Selected =	73
Total kW Capacity Installed =	29,042.53
Total Capital Investment =	$4,029,617,726.74
% of Overall Capital Investment =	46.04%
Annual Generation Cost =	$190,029,406.76
Annual MWh Generated =	4,478,990.32
% of Overall Generation =	2.20%
Average Cost per kWh =	$0.0424

Table 36: Wind Farm Results from the MiniMax – Emissions Weighted Function

Out of the 477 possible solar farm sites in the model, 195 are selected in this scenario (Table 37). These sites total 52.08% of the total capital investment, or $4,557,676,771. These sites are responsible for generating 1.79% of the total MWh requirements for this region, at an average cost of $0.0441 per kWh. Figure 16 displays the wind and solar farm sites chosen by the model.

SOLAR RESULTS	
Number of Locations Selected =	195
Total kW Capacity Installed =	416,579.61
Total Capital Investment =	$4,557,676,771.12
% of Overall Capital Investment =	52.08%
Annual Generation Cost =	$161,087,310.37
Annual MWh Generated =	3,649,237.35
% of Overall Generation =	1.79%
Average Cost per kWh =	$0.0441

Table 37: Solar Farm Results from the MiniMax – Emissions Weighted Function

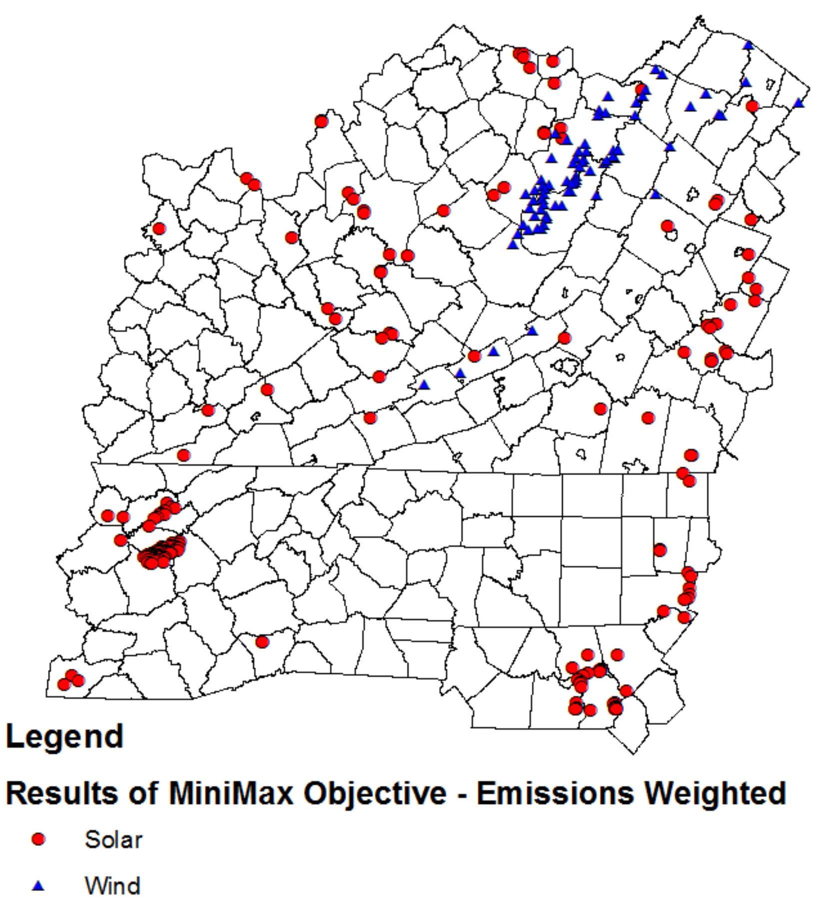

Figure 16: Wind and Solar Farm Sites Selected by the MiniMax – Emissions Weighted Function

The non-coal generation facilities within the region operate at the same level as in the previous scenario, except for the closure of seven additional oil facilities, leaving only five of the twenty-two oil facilities operational (Table 38). In addition, the gas facility that was operating at 11% when the MiniMax function was weighted to minimize cost is reduced down to 7% of baseline capacity. The remainder of the non-coal facilities in the region operate at 100% of baseline generation levels. Total generation from renewable sources is 14.34%, the second highest value achieved in the five different scenarios, trailing only the results of the minimized emissions objective function scenario.

NON-COAL FACILITIES RESULTS				
	# at Full Capacity	Total MWh	Total Emissions	Annual Cost
Biomass	3	1,026,986	14,226	$53,403,274
Co-Fire	4	2,188,456	277,946	$65,653,666
Gas	8	4,075,463	987,593	$284,997,118
Landfill	4	78,071	42	$4,059,692
Nuclear	1	17,619,492	0	$372,828,451
Oil	5	238,913	33,244	$8,522,027
Water	69	4,981,292	0	$48,169,096
Wind	1	167,588	0	$11,719,429

Table 38: Non-Coal Facility Results from the MiniMax – Emissions Weighted Function

Conclusions

The results of the five different scenarios show the impact that the two opposing objective functions have on one another. Results of these five scenarios are summarized in Table 39. The first objective function, minimizing annual operating costs, was able to provide the 2.5% increase in demand for annual electricity generation while increasing costs only 1.92% over estimated baseline generation costs. The model was able to decrease emissions by 0.3% over the baseline levels as well. This represented a good starting point, as the increase in cost was less than the increase in demand, and emissions decreased, even if only by a fraction of one percent. This scenario also resulted in the increase of renewable energy from 3.37% in the baseline to 6.53%. This increase in renewable sources consisted only of new sites for wind and solar farms. The model failed to implement any of the potential biomass co-fire at coal plants due to the increased cost associated with this process, which can greatly reduce emissions but fails to create new generation capacity. In addition, this scenario utilized only 57.56% of the potential $10 billion in capital investment.

The second scenario, minimizing emissions within the region, reduced the total tons of emissions by 11.53% over baseline levels, even while increasing generation by 2.5%. The achievement of this objective comes at a cost that is 10% greater than the target value achieved when solved for the minimizing cost function. The use of renewable energy sources is increased greatly, representing 14.68% of total generation in the region. In order to achieve this increase in renewable sources and the decrease in emissions, over 99.99% of the possible capital investment is utilized in this scenario.

Based on the target values achieved when solving for each of the two objective functions independently, a new variation on the objective function was created to solve the problem. This objective function utilizes the MiniMax function, minimizing the maximum deviation of an objective function from its target value. Through the implementation of this methodology, a new scenario was created with the two objective functions assigned an equal weight which is then multiplied by the deviation from the target value. This function resulted in a 2.55% deviation from each of the objective target values. This scenario generated 13.61% of all generation from renewable sources while utilizing 72.10% of the investment capital.

The final two scenarios placed twice as much weight on one of the two objective function deviations. The minimized cost objective function was weighted twice as heavily as the emissions function, resulting in a 1.92% deviation from the cost target and a 3.84% deviation from the emissions target. This scenario utilized 67.59% of the capital investment available, while generating 12.84% of MWh from renewable sources. The weights were reversed in the final scenario, with minimizing emissions being twice as important as minimizing costs. This resulted in a deviation of 1.65% from the target emissions value, and a deviation of 3.31% from the target cost value. This scenario increased renewable generation to 14.34% while using 87.52% of the capital investment funds.

	Minimize Cost	Minimize Emissions	MiniMax – Equal Weight	MiniMax – Cost Weighted	MiniMax – Emissions Weighted
Total Cost	$6,067,506,773	$6,676,682,693	$6,222,523,404	$6,184,050,066	$6,268,233,711
Deviation from Target Cost	0.00%	10.04%	2.55%	1.92%	3.31%
Total Emissions (tons)	166,168,723	147,458,417	151,225,782	153,123,113	149,897,548
Deviation from Target Emissions	12.69%	0.00%	2.55%	3.84%	1.65%
Renewable Generation	6.53%	14.68%	13.61%	12.84%	14.34%
Capital Investment Utilization	57.56%	99.99%	72.10%	67.59%	87.52%

Table 39: Summary of Scenario Results

These results are in line with the expectations for this model, as the lower cost scenarios result in more tons of emissions being generated, along with lower levels of renewable energy penetration and capital investment utilization. The inverse relationship is also present in the model, illustrating the trade-off between the two objective functions. Figure 17 presents the efficient frontier for the five optimization scenarios analyzed with this model. Point 1 on the graph represents the results of the Minimize Emissions scenario and Point 5 is the Minimize Cost scenario. These points represent the target values for the respective objective functions and form the extreme points of the efficient frontier. The use of the MiniMax function to provide non-dominated, Pareto optimal solutions (Points 2, 3, and 4) that lie on the efficient frontier between the two extreme solutions. These points are just three of many non-dominated Pareto optimal solution points along the efficient frontier.

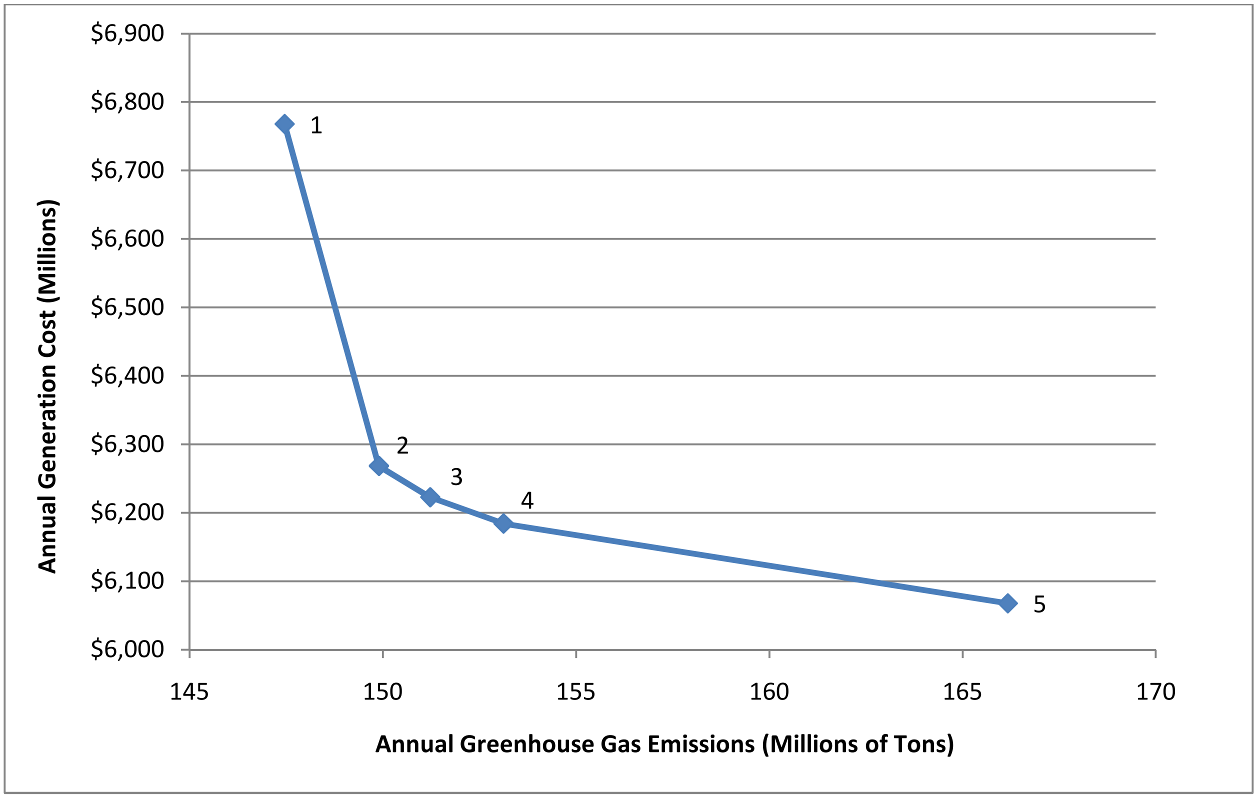

Figure 17: Efficient Frontier for Optimization Model Scenario Results[3]

Of the 203 possible wind farm sites, 47 were selected in all five scenarios, with an average cost of $0.0459/kWh. The model did not select 101 of the possible sites in any of the five scenarios, and these sites have an average cost of $0.1966 per kWh generated. As for the possible solar farm sites, 144 of the 477 were selected in each of the five scenarios. These sites average $0.0436 per kWh generated, as opposed to the $0.2075 for the 282 sites never selected in any iteration of the model. These results point to the fact that there are additional wind and solar farm installations possible within the region, the cost-effectiveness of many of these sites negates their possible benefits at this time. Unless the cost of renewable energy technologies continue to decrease, or more accurate assessments of the costs at these locations show a lower cost of generation, then many of the possibilities within this region should not be utilized due to the cost of generation in relation to other sites and sources in the region.

[3] Optimization Scenarios - 1: Minimize Emissions, 2: MiniMax – Emissions Weighted, 3: MiniMax – Equal Weight, 4: MiniMax – Cost Weighted, 5: Minimize Cost

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Chapter 5: Policy Scenario Analysis

Introduction

Planning for the integration of renewable energy sources into the existing electric generation system provides the ability to analyze the costs and the potential electricity generation associated with these resources and how they can play a role in meeting future energy demand. The costs associated with installing the technologies to exploit these renewable energy sources have been on the decline in recent years, while the cost of fossil fuels have been fluctuating with an overall increasing trend in the price of these resources (EIA 2010). These trends have made the utilization of renewable energy sources more competitive but many areas with renewable energy sources present are not moving to implement these sources in the near-future. Thus, the competitiveness of renewable sources versus fossil fuels on the basis of cost is not the only factor in determining whether to utilize renewable energy sources or not.

Many regions are extremely dependent on fossil fuels for generation of electricity, and these regions have been slower to integrate renewable energy sources into the existing infrastructure. This is true in the case of the greater southern Appalachian Mountain region (Figure 18), where 84.39% of the electricity generated in this region is derived from coal, including coal utilized at plants where biomass is co-fired with coal (Table 40). Nationwide only 48.2% of the electricity generated comes from coal (EIA 2010). The use of renewable energy sources in this region through wind, hydro, biomass, and landfill gas is 3.37% of total generation. Chapter 3 of this research utilized a geographic information system (GIS) model to discover the availability of potential wind and solar farm sites within the region using geographic, atmospheric, and regulatory constraints on the utilization of these sources. There were 203 possible wind farm sites and 477 potential solar farm locations found within the region based on the current constraints (Figure 19). If these sites were fully developed, an estimated 3.24% and 2.97% of baseline demand within the region could be met by wind and solar respectively.

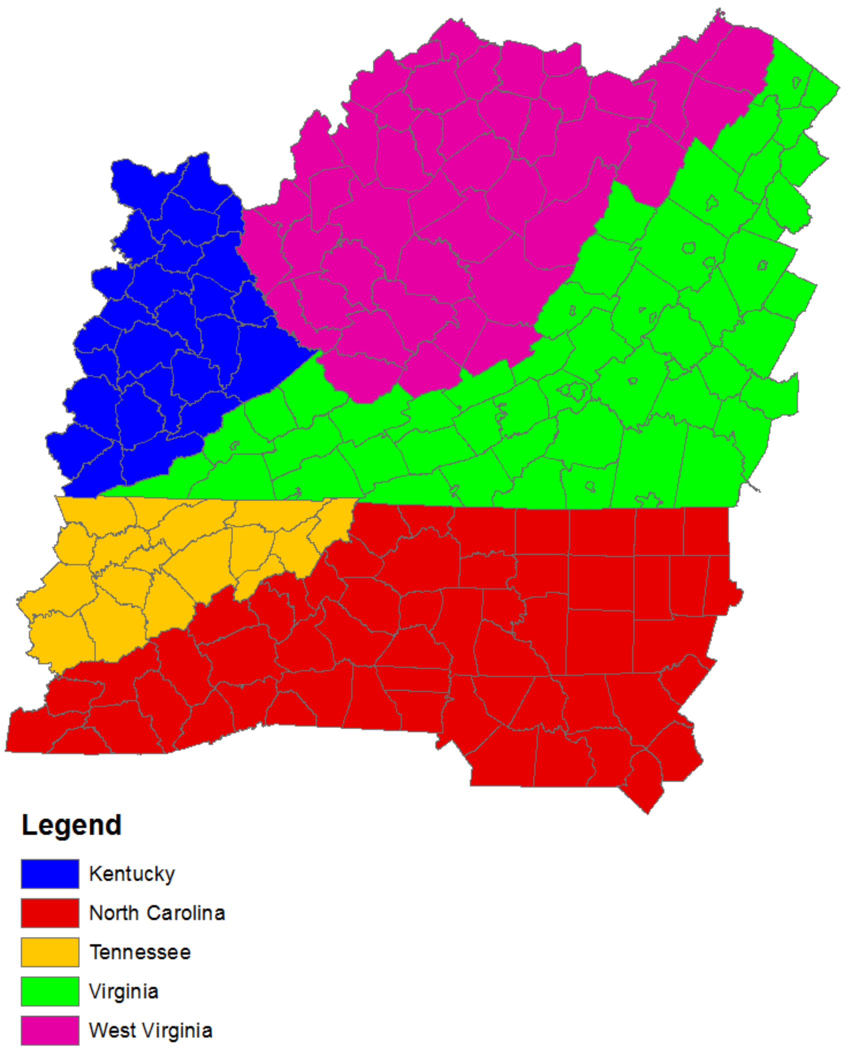

Figure 18: Greater Southern Appalachian Mountain Region

Source	Number of Facilities	MWh Generated	Percentage of Total Generation
Coal	31	165,721,345	83.50%
Nuclear	1	17,619,492	8.88%
Gas	13	6,449,095	3.25%
Water	69	4,981,292	2.51%
Co-Fire	4	2,188,456	1.10%
Biomass	3	1,026,986	0.52%
Oil	22	241,841	0.12%
Wind	1	167,588	0.08%

Table 40: Electricity Generation by Source in the Region

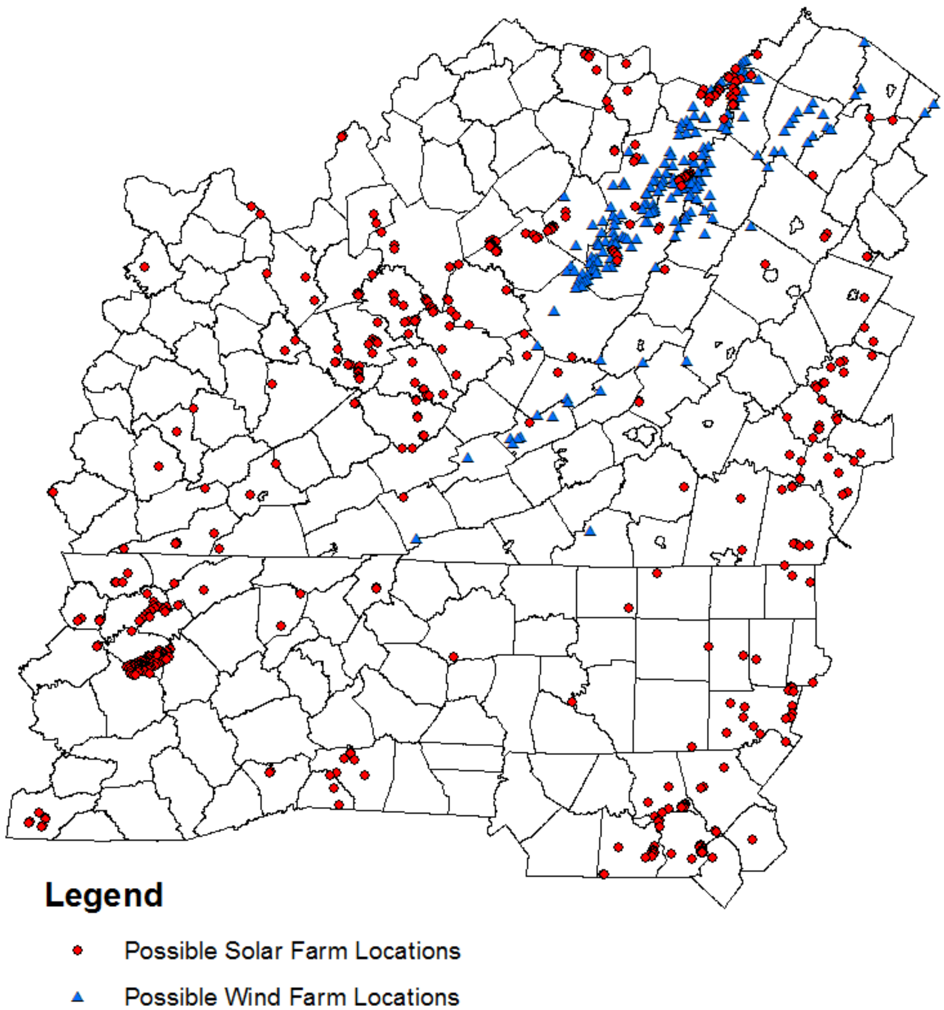

Figure 19: Potential Wind and Solar Farm Sites within the Region

In addition to the discovery of wind and solar farm sites through the use of GIS, the possibility of using biomass for co-fire in the region was also explored. There are an estimated 9.6 million tons of solid wood waste within the region (NREL-GIS 2003), while 67.2 million tons of coal were utilized in the baseline year at the 31 coal-only plants found within the region (EIA-861 2007). With an estimated efficiency of 61% for a ton of solid wood waste biomass versus a ton of coal for electricity generation (FEMP 2004), approximately 8.7% of the coal used within the region could be replaced with this biomass source representing 7.34% of total generation in the region. Therefore, an estimated 16.92% of current baseline generation could be met through the installation of wind, solar, and biomass co-fire, based on the current GIS model, in addition to existing renewable sources in the region.

The cost effectiveness of co-fire as a short-term solution to reducing greenhouse gas emissions has been shown (FEMP 2004, Caputo 2009, Robinson, Rhodes et al. 2003), yet the increased cost associated with retrofitting coal plants for this co-fire capability does not increase actual capacity at these plants. Therefore, implementation of this capability has not been widespread due to the increased cost per unit of electricity generated. Within this region, the 203 possible wind farm sites can produce electricity at an average cost of $0.1337/kWh, and the 477 potential solar farm sites average $0.1446/kWh. Though these averages are not competitive with the estimated cost of generation from other sources (Table 41), many of the potential sites are able to produce electricity at costs much below these averages.

Source	Average $/kWh	Reference
Biomass	$0.05200	Sims, Rogner et al. 2003
Coal	$0.02000	EIA 2010
Co-fire	$0.03000	Sims, Rogner et al. 2003, EIA 2010
Gas	$0.06993	EIA 2010
Landfill	$0.05200	EIA 2010
Nuclear	$0.02116	EIA 2010
Oil	$0.03567	EIA 2010
Water	$0.00967	EIA 2010
Wind	$0.06993	Sims, Rogner et al. 2003

Table 41: Estimated Cost of kWh Generation by Source

Using the information derived from the GIS model, a mixed-integer multi-objective programming model was formulated and implemented in Chapter 4. The model contained two objective functions, one which sought to minimize total greenhouse gas emissions in the region, while the other objective tried to minimize annual generation costs. These objectives were subject to constraints on electricity demand and biomass co-fire capability, as well as a limit on capital investment available for new renewable energy sources. The full model formulation is provided in Appendix A. The results of the five optimization scenarios are displayed in Table 42, and the efficient frontier is shown in Figure 20. The five scenarios utilized in the model were Minimize Cost, Minimize Emissions, MiniMax – Equal Weight, MiniMax – Cost Weighted, and MiniMax – Emissions Weighted. The first scenario, Minimize Cost, solves the model with the cost function being the only objective considered and the emissions objective function plays no role in the model solution, but is calculated for analysis purpose. The second scenario, Minimize Emissions, reverses the previous scenario, focusing solely on the total emissions while disregarding the role of the cost function in the optimal solution. These two scenarios provide target values for their respective objective function. For example, the cost achieved in the first scenario cannot be bettered given the current model formulation and parameters. As the model is formulated with two competing objective functions, the next three scenarios utilize the MiniMax function to find Pareto optimal solutions that consider the distance between the new values of the objective functions and their respective target values (Ragsdale 2008). The MiniMax function seeks to minimize the maximum deviation from a target value. In the third scenario, MiniMax – Equal Weight, the distance between the two target values are of equal importance. In the MiniMax – Cost Weighted scenario, the distance from the cost function is twice as important as the distance from the emissions function, so the solution is closer to the target cost than the target emissions. And finally, the MiniMax – Emissions Weighted scenario provides double importance for the emissions function over the cost function.

	Minimize Cost	Minimize Emissions	MiniMax – Equal Weight	MiniMax – Cost Weighted	MiniMax – Emissions Weighted
Total Cost	$6,067,506,773	$6,676,682,693	$6,222,523,404	$6,184,050,066	$6,268,233,711
Deviation from Target Cost	0.00%	10.04%	2.55%	1.92%	3.31%
Total Emissions (tons)	166,168,723	147,458,417	151,225,782	153,123,113	149,897,548
Deviation from Target Emissions	12.69%	0.00%	2.55%	3.84%	1.65%
Capital Investment Utilization	57.56%	99.99%	72.10%	67.59%	87.52%
Renewable Generation	6.53%	14.68%	13.61%	12.84%	14.34%
Generation from Wind	1.83%	2.46%	2.03%	1.95%	2.20%
Generation from Solar	1.50%	1.79%	1.63%	1.61%	1.79%
Generation from Biomass	0.00%	7.15%	6.67%	6.01%	7.06%
Generation from Coal	81.46%	72.51%	74.55%	75.45%	74.01%

Table 42: Results for the Original Case

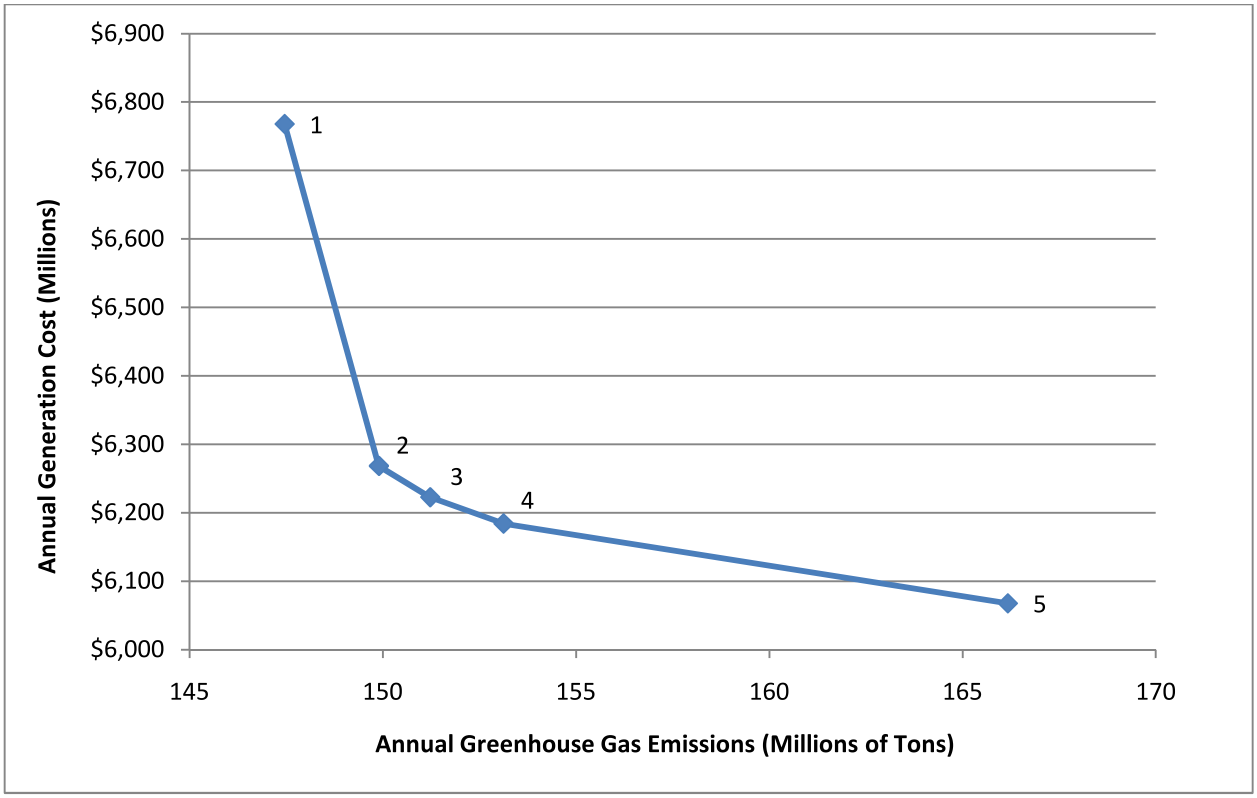

Figure 20: Efficient Frontier for Optimization Model Scenarios in the Original Case[4]

In one of these scenarios, Minimize Emissions, the utilization of existing and new renewable energy sources was 14.68%. This resulted from the model seeking to minimize emissions without respect to annual generation cost. When cost was the sole objective function being analyzed, the amount of renewable energy generation was 6.53% of total generation. In most cases, the lack of renewable energy usage has been due to cost being the sole, or main, driving force behind energy planning and these results support this idea. Therefore, an opportunity exists to increase the amount of renewable generation through public policy.

This chapter analyzes three different public policies that have been utilized to encourage investment in renewable energy sources: renewable portfolio standards, carbon tax, and tax credits for renewable generation. These policy alternatives are analyzed using the model developed in Chapter 4.

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[4] Optimization Scenarios - 1: Minimize Emissions, 2: MiniMax – Emissions Weighted, 3: MiniMax – Equal Weight, 4: MiniMax – Cost Weighted, 5: Minimize Cost

Each of these policies will require some modifications to the model, while the conceptual framework behind the model remains. Through the analysis of these three potential policies, it can be determined which policy, or mix of these potential policies, would most likely encourage development of renewable energy sources within the region.

Previous research papers have analyzed multiple renewable energy policies, such as those discussed in this chapter utilizing simulation models (Palmer and Burtraw 2005, Jorgenson and Wilcoxen 1993). Some of the previous mathematical programming models have included elements related to these ideas, such as the inclusion of a carbon tax (Short, Blair et al. 2009), but have not analyzed these policies in relation to a baseline scenario or other policies. The three policies analyzed in this chapter are not the only renewable energy policies that have been utilized previously, though they are among the most widely implemented. Additional policies such as cap-and-trade are not explored in this section but represent a potential future research direction.

Renewable Portfolio Standards

A renewable portfolio standard (RPS) is a government regulation stating that a certain percentage of electricity generation must be derived from renewable sources. Worldwide there have been a few nations that have implemented a RPS, such as the United Kingdom, Belgium, and Italy (Lauber 2004). While there have been a few federal RPS bills proposed in the United States, however, none of them have been enacted at this point (Nogee, Deyette et al. 2007). To date, RPS use in the U.S. has been based only on state regulations. There are currently 25 states that have a mandatory RPS in place. Each of these regulations differs with respect to the generation targets, the timeline, the sources considered as renewable, whether or not existing facilities are eligible, and other similar issues (Wiser, Namovicz et al. 2007, Wiser 2008).

Currently, in the greater southern Appalachian Mountain region only one state, North Carolina, has a mandatory RPS in place. The RPS for the state includes target values and timelines for different classes of producers: publicly owned (10% by 2018), and privately owned (12.5% by 2021). The state also includes a target value specifically for solar generation (0.2%). Virginia has enacted a non-binding RPS plan, specifying that 12% of generation by 2022 be derived from renewable sources. Each of these state plans includes variations that the other plan does not. For example, energy efficiency receives credit in NC, while wind and solar receive double credit in VA (Wiser 2008). At this time, Kentucky, Tennessee, and West Virginia have not implemented RPS laws.

In relation to this research, a region-wide RPS can be implemented in the model through an additional constraint to the model originally formulated in Chapter 4 (see Appendix A). This constraint will require that a minimum amount of generation be derived from renewable sources.

$$\sum_{i=1}^{N_i} M_i^w W_i H + \sum_{j=1}^{N_j} M_j^s S_j H + \sum_{y=1}^{N_y} M_p^{tc} B_{yp} F + \sum_{q=1}^{N_q} M_q^n U_q^{ws} H + \sum_{q=1}^{N_q} M_q^n U_q^r \geq Z\left(\sum_{i=1}^{N_i} M_i^w W_i + \sum_{j=1}^{N_j} M_j^s S_j + \sum_{p=1}^{N_p} M_p^c G_p + \sum_{q=1}^{N_q} M_q^n U_q\right) \quad (7)$$

This new constraint uses many of the previously defined parameters and decision variables (Appendix A), but also requires the use of two new parameters, as well as two related set of decision variables which are within the domain of a previously defined decision variable, as follows:

Z = the percentage of total generation derived from renewable sources (RPS)

H = credit multiplier for wind and solar generation

$$U_q^{ws} = \begin{cases} U_q, & \text{for all existing wind or solar facilities} \\ 0, & \text{otherwise} \end{cases}$$

$$U_q^r = \begin{cases} U_q, & \text{for all existing renewable facilities, except wind or solar} \\ 0, & \text{otherwise} \end{cases}$$

Equation 7 thus compares the amount of energy generated from new wind and solar sites, biomass co-fire locations, and existing renewable sources, against that generated from all sources. The sum of the renewable generation must be equal or greater than the percentage of total generation defined in the RPS. The credit multiplier, *H*, is used to provided additional credit for wind and solar generation, such as the credit in place in the Virginia RPS, including existing wind or solar facilities. Therefore when *H* is greater than one, the sum of renewable generation on the left-hand side of the constraint is greater than the actual generation total. Increasing the value of *H* while holding the value of *Z* constant makes it easier to achieve the RPS but reduces the actual amount of renewable generation in the model.

Carbon Tax

The second type of policy being considered is a carbon tax, or a tax placed on the emissions of CO_2. These taxes are placed on the generation of electricity from fossil fuel sources, such as coal, that emit CO_2 through the combustion process. CO_2 is the leading greenhouse gas emitted through electricity generation, and is recognized as one of the leading causes of climate change (IPCC 2007). Carbon taxes are generally implemented to help increase the competitiveness of renewable energy sources in relation to traditional fossil fuel sources. The effects of carbon taxes on electricity generation have been studied previously (Goulder 1995, Hoel 1996), and are included in the cost minimization function used by the Regional Energy Deployment System (ReEDS) model developed by the National Renewable Energy Laboratory (NREL) (Short, Blair et al. 2009).

The model developed in Appendix A, the original case, did not contain a carbon tax in cost calculations. This is due to the fact that a carbon tax has not been placed into law in the U.S. The implementation of a carbon tax is one that is largely unexplored in the United States, with the exception of a tax in place in Boulder, CO (Kelly 2006). Though these taxes have been implemented in other countries, the amounts levied and the implementations of the tax have varied with respect to fuel sources and end-users, amongst other differences.

In this model, the carbon tax is implemented in one of the more basic yet fairest forms, a tax assessed directly on the emission of CO_2 at the source. This will require only a minor change to the cost minimization objective function formulated in Appendix A, while the rest of the model will remain unchanged. This new calculation includes a carbon tax placed on CO_2 emissions due to the use of fossil fuel sources such as coal, oil, and gas. This includes the use of coal and biomass in co-fire implementations. Though the current parameters of this model specify a 100% reduction in carbon emissions when replacing a ton of coal with a ton of biomass, if this value were to decrease then emissions from biomass would need to be taxed and this new equation can handle a change in this parameter. Thus the new cost objective function becomes:

$$\begin{aligned} Min \sum_{i=1}^{N_i} W_i\left(C_i^{vw} + C^{kwm}K_i^w + C^{mwm}M_i^w\right) + \sum_{j=1}^{N_j} S_j\left(C_j^{vs} + C^{ksm}K_j^s + C^{msm}M_j^s\right) \\ + \sum_{p=1}^{N_p}\Bigg\{\left(C_p^{vc} + C^{ac}G_pM_p^c + C^{tc}G_pT_p + C^{CO2}E_p^{co-p}G_pT_p\right) \\ + \sum_{y=1}^{N_y}\Big(C^{tb}B_{yp} + C^{tbd}B_{yp}D_{yp} - C^{tc}B_{yp}F - C^{CO2}E_p^{co-p}B_{yp}F \\ + C^{CO2}E_p^{co-b}B_{yp}\Big)\Bigg\} + \sum_{q=1}^{N_q}\left(C_q^{mn}M_q^nU_q + C^{CO2}E_q^{co-q}M_q^nU_q\right) \end{aligned} \tag{8}$$

where the new parameter C^{CO2} = carbon tax, per ton of carbon dioxide emitted, is added to the function for all sources of generation except wind and solar.

Renewable Energy Production Tax Credit

Government sponsored tax credits to reduce the cost of generation from renewable sources have been used in the United States previously (UCS 2009). However, these incentives are currently set to expire in 2012, which is a shorter time-frame than required for development of the projects found in the previous results. Therefore, these tax credits were not implemented in the model formulated in Chapter 4. Through these tax credits, the production of electricity from renewable sources is made more competitive with existing fossil fuel sources. The renewable energy production tax credit (REPTC) attempts to achieve the same outcome as the carbon tax, increasing renewable energy usage through more competitive costs compared with fossil fuel sources. Though these two policies attempt to achieve the same thing, they do so through different means. The carbon tax penalizes fossil fuel usage, while the REPTC rewards investment in renewable energy technologies.

For implementation of this credit in the model, incentives will be placed into the annual generation cost objective function (Appendix A) to reduce the cost of generation for renewable energy sources. This credit will only be applied to wind and solar generation: other forms of renewable generation, such as hydro and biomass, are not eligible for this credit under current guidelines. In addition, this credit will be applied to any existing wind or solar facilities, as well as new installations credited in this model. This will reduce the overall generation costs within the region, while providing the incentive for more generation from renewable sources. Thus the new cost objective function becomes:

$$\begin{aligned} Min \sum_{i=1}^{N_i} W_i\left(C_i^{vw} + C^{kwm}K_i^w + [C^{mwm} - D]M_i^w\right) + \sum_{j=1}^{N_j} S_j\left(C_j^{vs} + C^{ksm}K_j^s + [C^{msm} - D]M_j^s\right) \\ + \sum_{p=1}^{N_p} \left\{ \left(C_p^{vc} + C^{ac}G_pM_p^c + C^{tc}G_pT_p\right) \right. \\ \left. + \sum_{y=1}^{N_y} \left(C^{tb}B_{yp} + C^{tbd}B_{yp}D_{yp} - C^{tc}B_{yp}F\right) \right\} + \sum_{q=1}^{N_q} C_q^{mn}M_q^nU_q - DM_q^nU_q^{ws} \end{aligned} \tag{9}$$

This updated objective function requires a new parameter and a new set of decision variables:

D = renewable energy production credit per MWh generated from wind or solar

$$U_q^{ws} = \begin{cases} U_q, & \text{for all existing wind or solar facilities} \\ 0, & \text{otherwise} \end{cases}$$

Policy Analysis Results

The policies analyzed in this section are assumed to be implemented at the national level or across all states within the region, as the region under study contains no state in its entirety and the implementation of a statewide policy would not affect the other states in the region. Though the implementation of a nationwide, or statewide, RPS would not require every area within a state to achieve the RPS goal, it is assumed that this region must be in line with the RPS. Therefore this policy analysis section is being used as a tool to provide insight into the impact that these possible policies would have on the selection of potential new renewable energy sources within this region. Additionally, though some generalizations can be made regarding these policies, the results of these policies would vary in other regions containing a different mix of existing sources and potential renewable sources.

Individual Renewable Energy Policy Analysis Cases

The first subsection of policy analysis focuses on individually analyzing each of the three potential renewable energy policies outlined in the previous section. There are thus four cases in this subsection (Table 43), as the RPS is analyzed in two different forms: one version calculates the actual renewable generation percentage while the second version applies double credit for generation from wind and solar. These four cases are analyzed with respect to the results of the model outlined previously in this chapter, which is referred to as the original case in the proceeding discussion.

Case	Policy
1	Renewable Portfolio Standard (RPS)
2	Renewable Portfolio Standard with Double Credit for Wind & Solar Generation (RPS w/ DC)
3	Carbon Tax (CT)
4	Renewable Energy Production Tax Credit (REPTC)

Table 43: Individual Renewable Energy Policy Cases

Case 1: 15% Renewable Portfolio Standard

The first policy chosen for analysis was a 15% renewable portfolio standard (RPS), with credit for renewable generation in place for wind, solar, hydroelectric, biomass-only facilities, as well as the biomass generation at co-fire plants. Though the latter source is generally not included in RPS calculations due to the majority of generation still relying on coal, the dependence on coal within this region makes the use of biomass co-fire much more important when attempting to increase renewable generation and decrease emissions of greenhouse gases. Additionally, non-co-fire renewable sources, such as hydroelectric and biomass, within the region currently account for only 3.15% of total baseline generation. The results of the GIS model provide 3.24% of baseline generation from potential wind farm sites and 2.97% of baseline generation from potential solar farm sites given the current constraints and parameters of the model. Thus a total of 9.36% of baseline generation could be generated from non-co-fire renewable energy sources in the current model. Installing the full capacity of potential wind and solar farms in the region is estimated to cost $28.9 billion, with an average cost of $0.1337/kWh of wind and $0.1446/kWh of solar. The total capital investment required for these installations could be prohibitive, thus the inclusion of a capital investment constraint in the linear programming model. In addition, the average cost per kWh of these installations is almost twice as much as the estimated highest cost per kWh for all sources in the model. Therefore achieving the maximum amount of non-co-fire generation would require a substantial increase in operating costs which is not desirable. Finally, if there is any expected growth in electricity demand within this region, the percentage of renewable generation will decrease in relation to this anticipated growth.

Given the parameters of the current model, the greatest percentage of renewable generation achieved in the original case was 14.68% in the minimized emissions scenario, while a minimum percentage of 6.53% was found in the minimized cost scenario. Each of the three MiniMax scenarios in the original case generated 12.84% or more of all electricity from renewable sources. Based on this result, along with the considerations outlined above, a value of 15% was chosen for the RPS in this first case. This value is greater than the mandatory RPS in place in North Carolina (Wiser 2008), and represents an aggressive policy to increase renewable generation. All generation is credited at actual value, so the value of H is one in this case and the use of the credit multiplier will be explored in the next case. Achieving the 14.68% renewable generation value in the original case required the use of 99.99% of the maximum $10 billion in capital investment, therefore the maximum capital investment must be increased to achieve renewable generation values of 15% or greater. In this case, the value of capital investment was increased to $15 billion, while all other parameters utilized in Chapter 4 are held constant.

The results of the 15% RPS with $15 billion in capital investment are displayed in Table 44. There are some new characteristics present in these results compared to the original results. The most interesting result found in this case is with regard to the use of capital investment. In the original case, the lowest use of capital investment was found in the Minimized Cost scenario and the greatest use was found in the Minimized Emissions scenario. In this case, the greatest use of capital investment still occurs in the Minimized Emissions scenario (99.99%), which results in the largest percentage of renewable generation (15.44%). However, the least utilization of capital investment is found in the MiniMax – Equal Weight scenario (80.01%). Thus the Minimized Cost scenario achieves a lower annual generation cost through the use of more capital investment (81.42%) than the MiniMax scenario. Through the use of the RPS constraint, the way in which capital investment is utilized is more complex than in the original case.

With respect to the utilization of the different sources, there are a few points of interest. First, the utilization of biomass is 100% in all five scenarios while in the original case the use of biomass was 100% in only two of the scenarios and was 0% in one scenario. Though the use of biomass is 100% in all scenarios, the generation from biomass varies between 7.11% and 7.15% depending on the actual distribution of biomass between coal plants and the efficiency of the plants selected for co-fire. This result is not surprising as biomass co-fire is included in the achievement of the RPS and is the cheapest implementation of new renewable generation in this model. In addition, the utilization of coal plants varies between the five scenarios, with the lowest generation (71.75%) achieved in the Minimize

Emissions scenario, and the greatest generation from coal is found in the Minimize Cost scenario (74.35%), again explaining the role of cost in energy planning and why this region has remained coal-dependent.

	Minimize Cost	Minimize Emissions	MiniMax – Equal Weight	MiniMax – Cost Weighted	MiniMax – Emissions Weighted
Total Cost	$6,294,000,289	$6,783,829,952	$6,391,778,783	$6,356,554,841	$6,430,779,997
Deviation from Target Cost	0.00%	7.78%	1.55%	0.99%	2.17%
Change from Original Case	3.73%	1.60%	2.72%	2.79%	2.59%
Total Emissions (tons)	151,057,152	145,659,841	147,922,695	148,555,198	147,242,564
Deviation from Target Emissions	3.71%	0.00%	1.55%	1.99%	1.09%
Change from Original Case	-9.09%	-1.22%	-2.27%	-2.98%	-1.77%
Capital Investment Utilization	81.42%	99.99%	80.01%	81.58%	81.34%
Renewable Generation	15.00%	15.44%	15.00%	15.00%	15.00%
Generation from Wind	2.52%	2.84%	2.50%	2.54%	2.52%
Generation from Solar	2.08%	2.17%	2.07%	2.07%	2.08%
Generation from Biomass	7.11%	7.15%	7.15%	7.11%	7.11%
Generation from Coal	74.35%	71.75%	72.97%	73.40%	72.51%

Table 44: Results for Case 1

For the existing non-coal facilities, all biomass, co-fire, landfill, nuclear, water, and wind facilities are utilized at full capacity in all five scenarios, while the gas and oil facilities are subject to variation in utilization. The use of oil-based facilities varies, but the difference in total generation is less than 0.001% between the five scenarios. The use of gas facilities has a greater range of generation values, accounting for only 1.00% of total generation in the Minimize Cost scenario and 3.16% in the Minimize Emissions scenario. When focused solely on minimizing the cost function, gas is utilized at the lowest levels because the cost of gas is higher than the cost of other fossil fuel sources and some of the potential wind and solar sites. In the Minimize Emissions scenario, the use of coal is scaled back due to the emissions associated with this source, while the more expensive but less polluting gas plants are used at full capacity. The use of wind and solar sites is fairly constant in the five scenarios, except for the Minimize Emissions scenario where the use of wind and solar is maximized subject to the capital investment constraint.

The results of this case are similar to the results of the original case (results of Chapter 4), with minor variation in the use of capital investment and the generation derived from these new renewable sites due to the implementation of the 15% RPS. The use of capital investment is around 80% in the four scenarios that achieve 15% exactly, thus showing the need for greater capital investment funds if an RPS is implemented with respect to this region.

The sensitivity of the 15% RPS value was analyzed to provide context for this choice of renewable generation requirement. A smaller RPS value, 12.5%, was utilized and the results were in line with the results found in this case. The increase in cost and decrease in emissions over the original case were smaller than when the RPS was set to 15%. A larger value for the RPS was not explored for this case due to the fact that installing every potential new wind and solar site, along with complete biomass utilization, only results in 16.49% renewable generation, and would require over $29 billion in capital investment.

In addition, the sensitivity of the capital investment constraint was explored as well. As the maximum capital investment is increased from $15 billion, the amount of renewable generation is increased, especially in the Minimize Emissions scenario wherein the cost is not considered, and results in additional reductions in emissions. However, the substantially larger generation costs associated with the wind and solar sites selected, as much as \$0.47/kWh and \$0.61/kWh respectively, make these investments less desirable in the MiniMax scenarios as the impact on emissions is much less than the impact on cost. The MiniMax scenarios are considered preferable to the other two scenarios as only the MiniMax function utilizes both of the competing objectives and thus provide optimality as opposed to considering the objectives independent of one another. Therefore, the use of more than \$15 billion in capital investment in this scenario is not necessary as amounts greater than this amount are not utilized extensively, and increased capital investment increases annual generation costs more rapidly than the associated decrease in emissions, which is not a desirable outcome .

Case 2: 15% Renewable Portfolio Standard with Double Credit

In the previous case achieving the 15% RPS required the use of more than the original capital investment constraint and was increased to \$15 billion. However, Case 1 did not provide any additional credit for wind and solar generation, which is found in some RPS guidelines, such as the voluntary RPS in Virginia (Wiser 2008). This second case provides double credit for wind and solar generation to achieve the 15% RPS, so the value of H in the constraint is set at 2. Through the use of double credit, 15% can be achieved given the original \$10 billion capital investment constraint.

The results of this case (Table 45) are very interesting when compared to Case 1 due to the double credit for wind and solar installations. First, the only scenario to achieve the minimum amount of required renewable generation is the Minimize Cost scenario, while all other scenarios achieve a credited amount of renewable generation that is 17.35% or greater. However, to achieve this minimum amount of renewable generation requires the use of 83.43% of the capital investment, while in two of the other scenarios the amount of renewable generation is greater while utilizing less of the capital investment. This is due to the distribution of capital investment among the three potential renewable energy sources, and the amount of generation derived from these sources.

	Minimize Cost	Minimize Emissions	MiniMax – Equal Weight	MiniMax – Cost Weighted	MiniMax – Emissions Weighted
Total Cost	$6,138,408,424	$6,644,367,702	$6,254,029,356	$6,219,397,899	$6,295,802,273
Deviation from Target Cost	0.00%	8.24%	1.88%	1.32%	2.56%
Change from Original Case	1.17%	-0.48%	0.51%	0.57%	0.44%
Total Emissions (tons)	158,127,227	147,458,417	150,235,893	151,349,517	149,348,895
Deviation from Target Emissions	7.24%	0.00%	1.88%	2.64%	1.28%
Change from Original Case	-4.84%	0.00%	-0.67%	-1.16%	-0.37%
Capital Investment Utilization	83.43%	99.99%	80.76%	72.10%	92.51%
Credited Renewable Generation	15.00%	19.01%	18.13%	17.35%	18.64%
Actual Renewable Generation	10.99%	14.68%	14.19%	13.61%	14.46%
Generation from Wind	2.17%	2.46%	2.13%	2.03%	2.26%
Generation from Solar	1.76%	1.79%	1.72%	1.63%	1.83%
Generation from Biomass	3.78%	7.15%	7.05%	6.66%	7.08%
Generation from Coal	77.68%	72.51%	74.14%	74.61%	73.66%

Table 45: Results for Case 2

In the Minimize Cost scenario, only 53.12% of the biomass is being utilized, while wind and solar are implemented at the third highest levels of the five scenarios, resulting in more capital investment used to achieve lower levels of renewable generation. In this case, the shift from biomass co-fire to wind and solar is due to the double credit provided for wind and solar. The model is selecting wind and solar sites that provide additional generation credit at a cost that is cheaper than fully implementing biomass co-fire. In the second least costly scenario, MiniMax-Cost Weighted, the use of capital investment decreases to 72.10% while increasing credited renewable generation to 17.35%.

The use of wind and solar varies greater among the non-Minimize Emissions scenarios than in the previous case, while the Minimize Emissions scenario provides the greatest amount of wind and solar generation. This result is to be expected and is in line with the previous results. The use of coal and gas varies among the five scenarios. Again the highest level of coal generation and lowest gas generation occurs in the Minimize Cost scenario, while the opposite is present in the Minimize Emissions scenario.

Overall, the use of double credit for wind and solar in an RPS policy increases the complexity of the model results. Some of the results were not expected based on the previous case and the original results, and the relationships between the constraints and objective functions is not as straightforward, increasing the complexity of the decision making process. Though the use of double credit artificially inflates the percentage of renewable generation, the actual amount of renewable generation in four of the five scenarios greatly increases over the original case. The only scenario that does not have increased renewable generation is the Minimize Emissions scenario because the amount of renewable generation is maxed out given the capital investment constraint. Coinciding with increased renewable generation, these four scenarios also reduce emissions when compared to the original case. Therefore the use of this policy does what is intended – increase renewable generation without increasing costs of fossil fuel sources or providing government incentives.

Again, the sensitivity of the 15% RPS with double credit was analyzed utilizing the values of 12.5% and 17.5%. In the previous case, only 16.49% renewable generation could be achieved, but through the use of double credit for wind and solar, the 17.5% RPS value was achievable. The results were in line with expectations based on the 15% RPS, with the lower RPS value achieving a smaller increase in cost and a smaller decrease in emissions and the larger RPS resulting in greater changes to the cost and emissions values on average.

Case 3: $14 Carbon Tax

Although the use of a carbon tax is present in the objective function in the ReEDS model (Short, Blair et al. 2009), there is no value provided for this parameter. Therefore, the derivation of the carbon tax value used in this model is based on a review of marginal damage costs due to carbon emissions (Tol 2005), wherein 103 estimates were analyzed. The median value of these studies was $14/ton, while the average value was $93/ton due to outliers in the distribution. Although the marginal damage cost of carbon is not the same as a carbon tax, this number provides a good estimate that can be used in this model. Furthermore, in the original case the Minimize Cost scenario provides the cheapest cost, but has the greatest amount of carbon emissions. For the other four scenarios, the average increase in cost versus one ton of carbon reduction is $16.13. However, the Minimize Emissions scenario decreases carbon emissions greatly but at a higher cost, $32.72 per ton of carbon, while in the three MiniMax scenarios the average is $10.60. Again, these carbon reduction costs are not the same as a carbon tax, but the numbers are in line with the $14 median value found in previous research, providing further validity for this value. The new cost function in Equation 8 is utilized with the value of C^{CO2} set to $14 and all other parameters are held constant.

The results of running the carbon tax scenario (Table 46) show that the renewable generation is greater in every scenario, except for Minimize Emissions, than in the original case. The renewable generation is already maximized in that scenario and cannot increase due to the capital investment constraint. Even though the level of renewable generation increases in the other scenarios, the cost is much greater than in previous cases due to the carbon-heavy nature of current generation within the region. The minimum cost achieved in this case is 36.8% greater than the minimum cost in the original case. This cost is also much greater than the minimum costs achieved in Case 1 and Case 2. The average increase in annual generation cost with this policy is 34.16%, while the average reduction in emissions is only 3.01%. Though the implementation of a carbon tax will impact the cost of generation in any region, the reliance on coal in this region means that the impact will be far greater in this region than in other areas of the United States. And given the amount of available renewable resources compared to the baseline generation from coal, the reduction in emissions is not as great as the increased cost.

	Minimize Cost	**Minimize Emissions**	**MiniMax – Equal Weight**	**MiniMax – Cost Weighted**	**MiniMax – Emissions Weighted**
Total Cost	$8,300,467,583	$8,700,037,238	$8,377,453,863	$8,356,120,915	$8,396,702,770
Deviation from Target Cost	0.00%	4.81%	0.93%	0.67%	1.16%
Change from Original Case	36.80%	30.30%	34.63%	35.12%	33.96%
Total Emissions (tons)	154,623,941	147,458,417	148,826,084	149,435,789	148,313,230
Deviation from Target Emissions	4.86%	0.00%	0.93%	1.34%	0.58%
Change from Original Case	-6.95%	0.00%	-1.69%	-2.41%	-1.06%
Capital Investment Utilization	58.84%	99.99%	78.91%	79.04%	88.54%
Renewable Generation	12.10%	14.68%	14.18%	14.18%	14.38%
Generation from Wind	1.83%	2.46%	2.11%	2.11%	2.22%
Generation from Solar	1.50%	1.79%	1.70%	1.70%	1.80%
Generation from Biomass	5.49%	7.15%	7.08%	7.08%	7.08%
Generation from Coal	75.98%	72.51%	73.08%	73.52%	72.86%

Table 46: Results for Case 3

The biggest source of carbon emissions in the region is due to generation from coal, and though the amount of generation from coal, and the associated emissions, decreases in comparison to the original case, the values are not as low as those obtained in Case 1 (15% RPS). However, the values in Case 1 were achieved by including an increase in capital investment availability. Therefore, the use of a $14 carbon tax reduces emissions by 6.95% over the original case in the Minimize Cost scenario, and this reduction comes at an increased cost of 36.8%. An unexpected result in this scenario is that biomass is not fully utilized, meaning that it is cheaper for some plants to pay the carbon tax than to implement co-fire when cost is the only consideration. In the Minimize Emissions scenario, the level of emissions cannot be reduced over the level achieved in the original case due to full utilization of capital investment. Therefore, the use of the carbon tax does reduce the amount of emissions in the region in four of the five scenarios, but if minimizing emissions is the main goal of the model one of the other policies can achieve the same results in emissions reduction at a much lower cost, and implementing no policy at all can achieve the same level of emissions by utilizing the results of the Minimize Emissions scenario in the original case.

Once again, a series of alternative values were used to analyze the sensitivity of the carbon tax value. Given the flexibility of the carbon tax price in comparison to the RPS values, a wider range of values were analyzed for sensitivity. Four additional values were selected for analysis, two values were smaller than $14/ton ($10 and $12) and two values were larger ($16 and $18). The efficient frontiers for the five carbon tax values are shown in Figure 21. As the carbon tax is increased, the annual generation cost increases while the total tons of greenhouse gas emissions decreases.

The percentage change in cost for each scenario remained fairly constant across the five carbon tax values, with the greatest increase occurring in the Minimize Cost scenario and the smallest increase occurring in the Minimize Emissions scenario, and the three MiniMax scenario changes falling in between these extremes. Each increase in $2 in the carbon tax increased cost fairly evenly; there were no wild swings found across the carbon tax values. However, the change in emissions was proportionally smaller as the carbon tax increased. This is due to the fact that the level of emissions does not decrease in the Minimize Emissions scenarios, as the values achieved in the original case cannot be improved upon without an increase in capital investment.

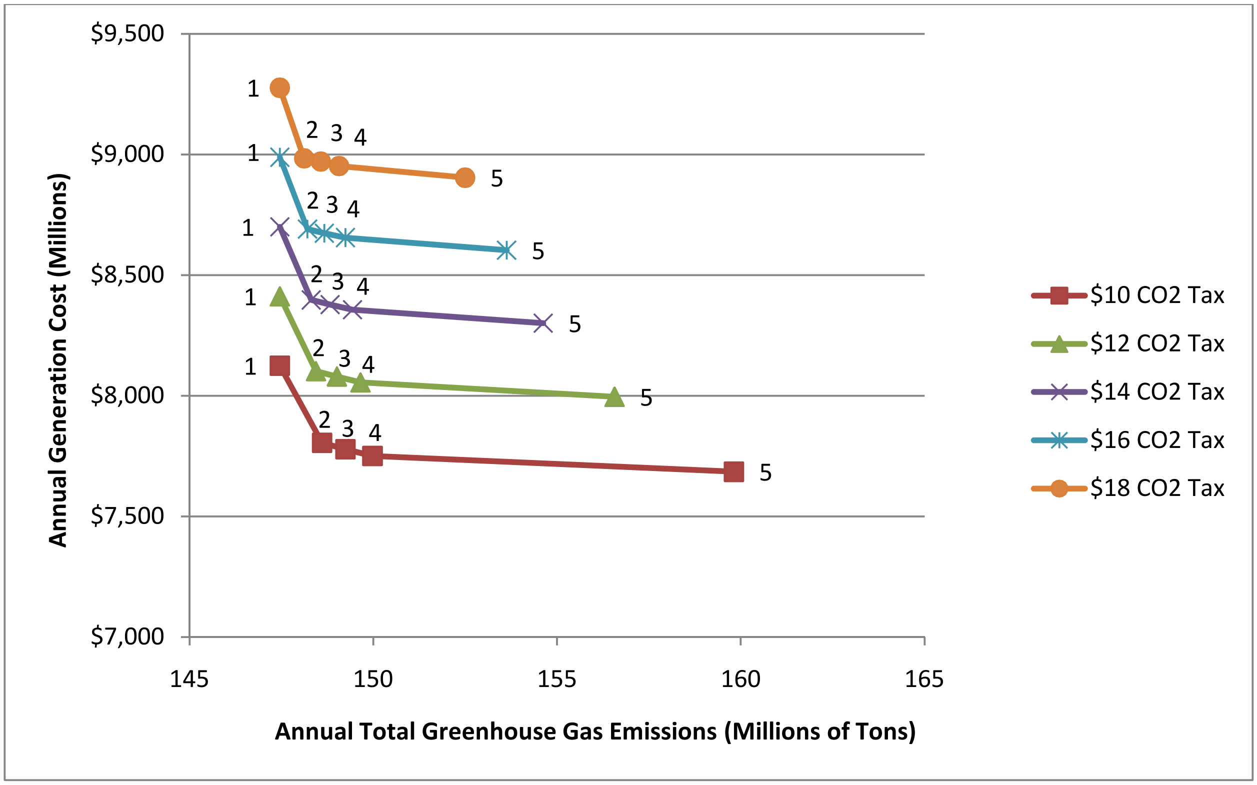

Figure 21: Efficient Frontiers for Carbon Tax Values[5]

Case 4: $19 Renewable Energy Production Tax Credit

Government incentives to encourage the use of renewable energy have taken many forms, most commonly through tax credits for investment or production. In the ReEDS model (Short, Blair et al. 2009), a production tax credit of $19/MWh is utilized for wind, while an investment tax credit is used for concentrated solar power (CSP). The ReEDS model does not explore the use of solar PV, the solar technology utilized in this model. The production tax credit in ReEDS originally expired at the end of 2009, but has since been extended into 2012. In the original case, as given above, the use of this

[5] Optimization Scenarios - 1: Minimize Emissions, 2: MiniMax – Emissions Weighted, 3: MiniMax – Equal Weight, 4: MiniMax – Cost Weighted, 5: Minimize Cost

renewable energy production tax credit (REPTC) was not explored. Case 4 will thus implement the $19/MWh credit applied to both wind and solar. This case uses the new annual generation cost function specified in Equation 9, with the value of D set to $19/MWh while all other parameters are held constant.

	Minimize Cost	**Minimize Emissions**	**MiniMax – Equal Weight**	**MiniMax – Cost Weighted**	**MiniMax – Emissions Weighted**
Total Cost	$5,924,636,540	$6,517,137,766	$6,077,910,819	$6,041,575,110	$6,118,994,024
Deviation from Target Cost	0.00%	10.00%	2.59%	1.97%	3.28%
Change from Original Case	-2.35%	-2.39%	-2.32%	-2.30%	-2.38%
Total Emissions (tons)	165,875,374	147,458,417	151,273,265	153,279,391	149,877,101
Deviation from Target Emissions	12.49%	0.00%	2.59%	3.95%	1.64%
Change from Original Case	-0.18%	0.00%	0.01%	0.10%	-0.01%
Capital Investment Utilization	81.01%	99.99%	89.78%	86.50%	94.00%
Renewable Generation	7.18%	14.68%	13.87%	13.02%	14.44%
Generation from Wind	2.15%	2.46%	2.23%	2.19%	2.26%
Generation from Solar	1.74%	1.79%	1.81%	1.79%	1.86%
Generation from Biomass	0.00%	7.15%	6.54%	5.76%	7.04%
Generation from Coal	81.46%	72.51%	74.74%	75.70%	74.07%

Table 47: Results for Case 4

This case results in lower generation costs for all five scenarios (Table 47), which is to be expected. In addition, this reduction in annual generation cost makes some of the wind and solar sites more competitive than in the original case, resulting in more capital investment being utilized and increased renewable generation in all of the non-Minimize Emissions scenarios. Even with the increased use of renewable energy sources, the total emissions increase in two of the three MiniMax cases. This increase is due to the lower target cost found in the Minimize Cost scenario with the REPTC in place. This lower target value changes the relationship between the deviations from both target values. Though the increase in emissions in these two scenarios is minimal (0.01% and 0.10%), this was an unexpected result.

As in the original case, the Minimize Cost scenario has no biomass utilization, and thus provides the highest percentage of generation from coal in this case. The use of biomass in the three MiniMax scenarios is lower than in the original case due to the lower cost for wind and solar due to the REPTC. Thus these sources become more cost-effective than the implementation of biomass co-fire at some coal plants. If the money is available for tax credit implementation within this region, the impact of this policy would result in lower costs but could actually increase emissions depending on the mix of generation sources selected.

Similar to the carbon tax, four additional values for the REPTC were analyzed to explore the sensitivity of this parameter. The efficient frontier for the optimization results (Figure 22) shows a nearly constant decrease in cost for each of the five values across the five optimization scenarios. As the REPTC value is increased from \$15 to \$23, the resulting change in annual generation cost remains similar, approximately 0.27% for each increase of \$2, ranging from 2.08% up to 3.15%.

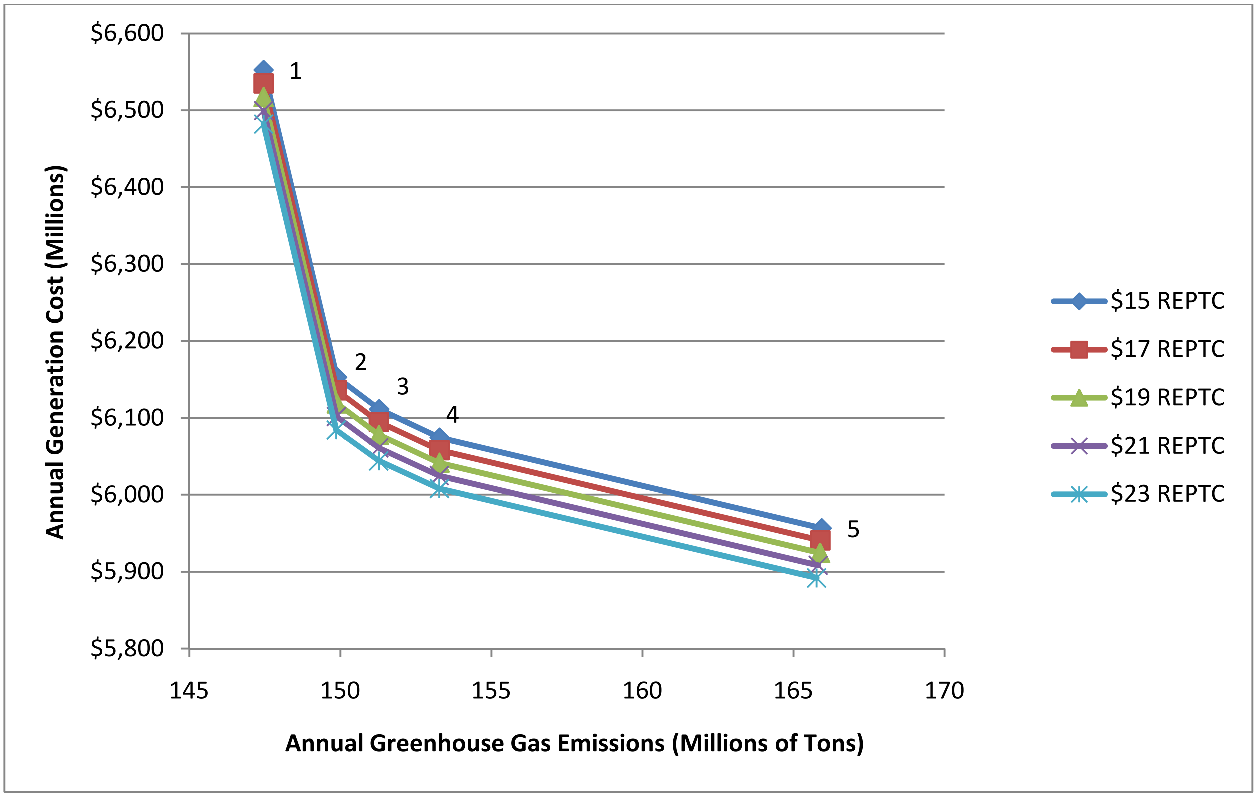

Figure 22: Efficient Frontiers for REPTC Values[6]

The percentage changes in emissions experienced less fluctuation than the cost changes. In the Minimize Cost scenario, as emissions only decrease by an additional 0.10% over the original case as the REPTC is increased from $15 to $23. In the Minimize Emissions scenario the level of emissions achieved is constant and cannot be improved due to the capital investment constraint. With respect to the three MiniMax scenarios, the values within each scenario only vary by 0.01% across the five different REPTC values, showing very little impact that this increased value has on emissions reduction, and in fact the emissions are increased in MiniMax-Equal Weight and MiniMax-Cost Weighted scenarios for every value of REPTC due to the decreased cost found in the Minimize Cost scenario and the impact that this value has on the deviations achieved in the MiniMax scenarios.

[6] Optimization Scenarios - 1: Minimize Emissions, 2: MiniMax – Emissions Weighted, 3: MiniMax – Equal Weight, 4: MiniMax – Cost Weighted, 5: Minimize Cost

Combined Renewable Energy Policy Analysis Cases

The next four policy analysis cases (Table 48) use the previous policies and parameters in combination with one another. In the first two cases, the carbon tax will be used in conjunction with one of the two RPS cases, while the final two cases will look at the REPTC when utilized with the RPS cases. The utilization of a carbon tax and REPTC in one case is not analyzed as these policies attempt to achieve the same thing, increased cost-effectiveness of renewable energy, through different means and thus would be less effective when used together, especially given the much larger increases found through use of the carbon tax than the savings achieved when using the REPTC policy.

Case	Policy One	Policy Two
5	Carbon Tax	Renewable Energy Portfolio Standard
6	Carbon Tax	Renewable Energy Portfolio Standard w/ Double Credit
7	Renewable Energy Prod. Tax Credit	Renewable Energy Portfolio Standard
8	Renewable Energy Prod. Tax Credit	Renewable Energy Portfolio Standard w/ Double Credit

Table 48: Combined Renewable Energy Policy Cases

Case 5: $14 Carbon Tax & 15% Renewable Portfolio Standard

This case is the first of four cases to combine two of the previous standalone policies. The use of the $14 carbon tax outlined in Case 3 is combined with the 15% RPS outlined in Case 1, with single credit for wind and solar generation and the available amount capital investment raised to $15 billion.

The results (Table 49) are in line with the previous cases wherein these policies were implemented individually. The cost of generation is greatly increased, by an average of 35.58% over the five scenarios. Because of the RPS constraint this average increase is greater than the increase when utilizing a standalone carbon tax. The total tons of emissions are reduced by 3.84% on average, with the largest decrease corresponding to the Minimize Cost scenario. Even though carbon emissions are being taxed, the use of fossil fuels is still cheaper than some of the potential wind and solar sites as capital investment is not fully utilized in all non-Minimize Emissions scenarios. Biomass is fully utilized in all five scenarios, increasing in the Minimize Cost scenario when compared to the carbon-tax only case. The generation from coal is reduced over the original case, as well as the carbon tax-only case, and the amount of wind and solar is increased in all non-Minimize Emissions scenarios in comparison to the original case.

	Minimize Cost	**Minimize Emissions**	**MiniMax – Equal Weight**	**MiniMax – Cost Weighted**	**MiniMax – Emissions Weighted**
Total Cost	$8,386,653,323	$8,785,505,365	$8,466,668,934	$8,445,088,618	$8,491,052,342
Deviation from Target Cost	0.00%	4.76%	0.95%	0.70%	1.24%
Change from Original Case	38.22%	31.58%	36.06%	36.56%	35.46%
Total Emissions (tons)	150,494,753	145,659,842	147,049,557	147,689,656	146,566,446
Deviation from Target Emissions	3.32%	0.00%	0.95%	1.39%	0.62%
Change from Original Case	-9.43%	-1.22%	-2.78%	-3.55%	-2.22%
Capital Investment Utilization	81.16%	99.99%	82.34%	81.20%	86.09%
Renewable Generation	15.00%	15.44%	15.00%	15.00%	15.10%
Generation from Wind	2.51%	2.84%	2.55%	2.51%	2.59%
Generation from Solar	2.09%	2.17%	2.08%	2.09%	2.12%
Generation from Biomass	7.12%	7.15%	7.09%	7.12%	7.10%
Generation from Coal	74.34%	71.75%	72.38%	72.76%	72.09%

Table 49: Results for Case 5

Case 6: $14 Carbon Tax & 15% Renewable Portfolio Standard with Double Credit

This case combines the carbon tax from Case 3 with the RPS specifications from Case 2, with results shown in Table 50. The use of the carbon tax increases the cost of generation by an average of

34.08%, while emissions are decreased in all non-Minimize Emissions scenarios by an average of 3.01%., which is less than in Case 5 due to the double credit. The use of the RPS does result in a slightly lower increase in average generation cost when compared to Case 3, but does not reduce emissions further.

	Minimize Cost	Minimize Emissions	MiniMax – Equal Weight	MiniMax – Cost Weighted	MiniMax – Emissions Weighted
Total Cost	$8,300,467,583	$8,671,175,078	$8,377,454,430	$8,356,122,793	$8,396,727,060
Deviation from Target Cost	0.00%	4.47%	0.93%	0.67%	1.16%
Change from Original Case	36.80%	29.87%	34.63%	35.12%	33.96%
Total Emissions (tons)	154,623,941	147,458,417	148,826,094	149,435,855	148,313,446
Deviation from Target Emissions	4.86%	0.00%	0.93%	1.34%	0.58%
Change from Original Case	-6.95%	0.00%	-1.61%	-2.41%	-1.06%
Capital Investment Utilization	58.84%	99.99%	78.91%	79.04%	87.90%
Credited Renewable Generation	15.51%	19.01%	18.07%	18.08%	18.46%
Actual Renewable Generation	12.18%	14.68%	14.26%	14.26%	14.46%
Generation from Wind	1.83%	2.46%	2.11%	2.11%	2.20%
Generation from Solar	1.50%	1.79%	1.70%	1.70%	1.80%
Generation from Biomass	5.49%	7.15%	7.08%	7.08%	7.09%
Generation from Coal	75.98%	72.51%	73.08%	73.53%	72.85%

Table 50: Results for Case 6

The amount of renewable generation increases in three of the scenarios when compared to the standalone implementation of double credit RPS in Case 2 due to the increased cost of fossil fuel generation. In terms of capital investment utilization, the amount is held steady in four of the five scenarios when compared to Case 3, but is decreased in two scenarios and increased in one scenario when compared to Case 2. This decrease is the result of increased biomass utilization due to the carbon tax. In terms of generation in this case, the utilization of biomass is the same as in the previous carbon tax-only scenario. Again, the carbon tax and double credit for wind and solar still means that at some coal plants it is cheaper to pay the carbon tax than to implement biomass co-fire given the current parameters. Generation from coal, gas, wind, and solar is in line with previous results.

Case 7: $19 Renewable Energy Production Tax Credit & 15% Renewable Portfolio Standard

This case explores the combined use of the REPTC outlined in Case 4 and the RPS specifications from Case 1. The results of this case are shown in Table 51. Lower costs are found in three of the scenarios when compared to the original case, even with the additional constraint placed on renewable generation. The only scenario which has an increased cost is the Minimize Cost scenario, but this increase is less than one percent and is due to the low level of renewable generation found in this scenario in the original case. Additionally, the total emissions decrease in all scenarios due to the increase in renewable generation to meet the RPS constraint.

Biomass is fully utilized in all of the scenarios except for Minimize Cost, which decreases from 100% when compared to Case 1. This decrease is the result of the REPTC for wind and solar, making biomass less cost-effective at some coal plants when compared to potential renewable sites. The generation from coal is decreased from the original case, but is in line with the previous cases using these policies. Gas utilization is at the lowest level in the Minimize Cost scenario due to the REPTC lowering the cost of wind and solar generation and the increased renewable generation required to meet the RPS constraint.

	Minimize Cost	Minimize Emissions	MiniMax – Equal Weight	MiniMax – Cost Weighted	MiniMax – Emissions Weighted
Total Cost	$6,122,947,494	$6,598,206,294	$6,219,426,695	$6,184,080,479	$6,258,460,368
Deviation from Target Cost	0.00%	7.76%	1.58%	1.00%	2.21%
Change from Original Case	0.91%	-1.18%	-0.05%	0.00%	-0.16%
Total Emissions (tons)	150,869,842	145,659,842	147,955,002	148,568,448	147,271,711
Deviation from Target Emissions	3.58%	0.00%	1.58%	2.00%	1.11%
Change from Original Case	-9.21%	-1.22%	-2.18%	-2.97%	-1.75%
Capital Investment Utilization	85.70%	99.99%	81.96%	80.59%	82.05%
Renewable Generation	15.00%	15.44%	15.00%	15.00%	15.00%
Generation from Wind	2.59%	2.84%	2.54%	2.51%	2.53%
Generation from Solar	2.12%	2.17%	2.08%	2.07%	2.09%
Generation from Biomass	7.01%	7.15%	7.10%	7.13%	7.10%
Generation from Coal	74.45%	71.75%	73.01%	73.45%	72.55%

Table 51: Results for Case 7

Case 8: $19 Renewable Energy Production Tax Credit & 15% Renewable Portfolio Standard with Double Credit

The final case explores the use of the $19 REPTC (Case 4) and the 15% RPS with double credit (Case 2). The results of this combined policy are displayed in Table 52. The combination of these two policies results in lower generation costs and lower emissions compared to the original case, but the changes are not as large as those seen in Case 7, due to double credit for wind and solar generation.

	Minimize Cost	Minimize Emissions	MiniMax – Equal Weight	MiniMax – Cost Weighted	MiniMax – Emissions Weighted
Total Cost	$5,980,787,958	$6,488,275,606	$6,100,338,553	$6,067,846,260	$6,138,777,976
Deviation from Target Cost	0.00%	8.49%	2.00%	1.46%	2.64%
Change from Original Case	-1.43%	-2.82%	-1.96%	-1.88%	-2.07%
Total Emissions (tons)	159,105,262	147,458,417	150,405,728	151,750,823	149,405,940
Deviation from Target Emissions	7.90%	0.00%	2.00%	2.91%	1.32%
Change from Original Case	-4.25%	0.00%	-0.56%	-0.90%	-0.33%
Capital Investment Utilization	99.99%	99.99%	92.77%	89.31%	99.92%
Credited Renewable Generation	15.00%	19.01%	18.38%	17.93%	18.91%
Actual Renewable Generation	10.75%	14.68%	14.28%	13.90%	14.67%
Generation from Wind	2.34%	2.46%	2.26%	2.22%	2.33%
Generation from Solar	1.91%	1.79%	1.84%	1.81%	1.90%
Generation from Biomass	3.13%	7.15%	6.81%	6.50%	7.07%
Generation from Coal	78.33%	72.51%	74.34%	74.94%	73.78%

Table 52: Results for Case 8

The use of double credit again results in an unusual pattern for capital investment utilization, 99.99% in both the Minimize Cost and Minimize Emissions scenarios, while the utilization in the three MiniMax scenarios is lower. This is similar to the results found in Case 2, and is the result of double credit towards the RPS constraint for wind and solar. The fluctuations in these values are more extreme in this case because wind and solar also receive the REPTC.

Conclusions

This chapter analyzed three different base policies that have been utilized to increase renewable generation. One of these policies, the renewable portfolio standard, was analyzed in two variations, and several of the policies were then analyzed in different combinations. The only policies that were not analyzed in combination with one another were the carbon tax and the renewable generation production tax credit. These policies were not combined as they both try to achieve the same thing, making renewable sources more cost-effective by either increasing cost of fossil fuels or decreasing cost of wind and solar. Therefore, these two cost-altering policies were only combined with the RPS constraint and not used in conjunction with one another.

Minimizing cost vs. minimizing emissions

Of the two conflicting objectives, minimizing cost and minimizing emissions, only the cost function is altered through the use of the carbon tax and REPTC policies, which increase and decrease the minimum annual generation cost respectively. Though the RPS policy does not alter the cost function, this additional constraint placed on renewable generation does increase the minimum annual generation cost. As the emissions function is not altered in any of these cases, the minimum possible level of emissions (147.5 million tons) is never decreased over the original case when subject to the same parameters. The only cases where the minimum level of emissions is reduced are those with the increased availability of capital investment in the policies specifying 15% RPS with no double credit (Cases 1, 5, and 7). As a result, if decreasing emissions is considered the sole objective, then the use of any of these policies would not alter the mix of sources that result in the lowest possible level of emissions. Similarly, if cost was the only objective under consideration, then the RPS and carbon tax policies would always result in a higher cost, while the REPTC would always result in a lower cost. Thus the importance of analyzing both of these objectives in relation to one another can be observed from these results.

The efficient frontiers for the original case and for the eight policy cases analyzed are shown in Figure 23. In the following sections, we discuss these results in more detail by focusing on the relative behavior exhibited within each of the three policy types: RPS, carbon tax, and REPTC.

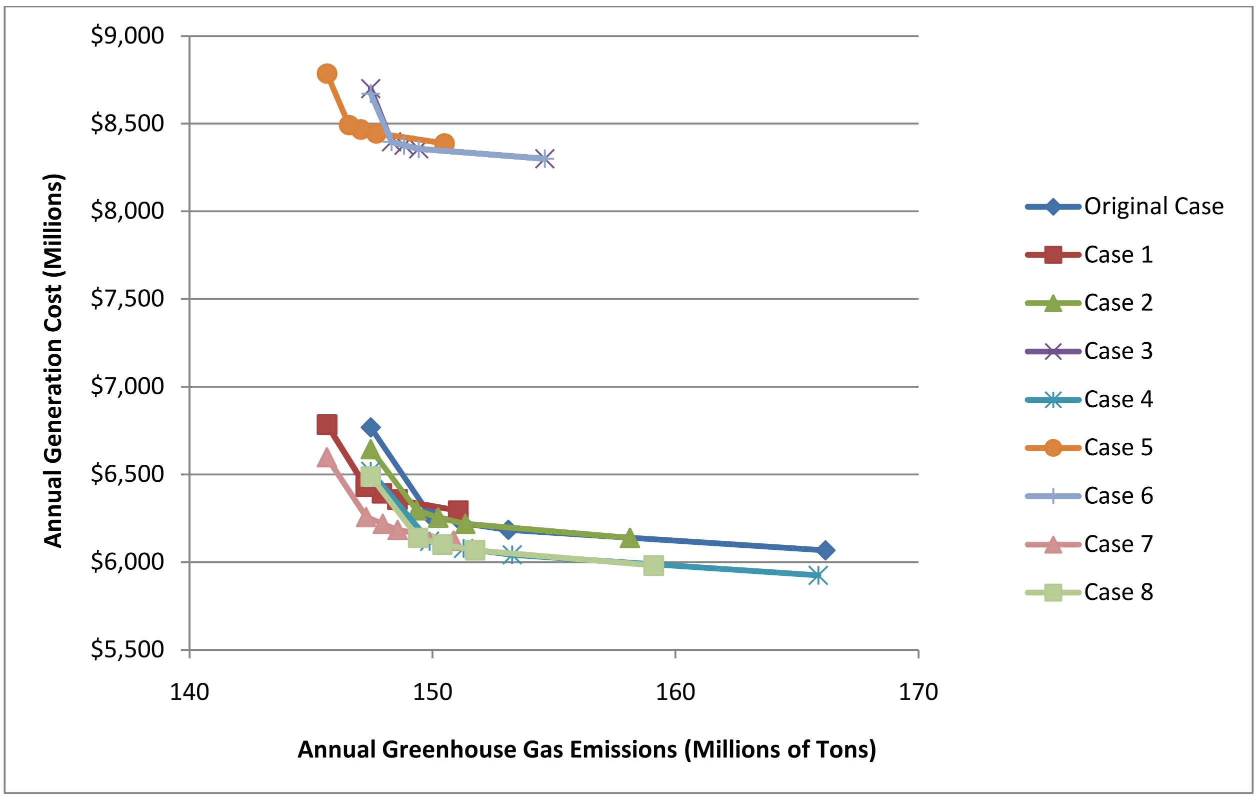

Figure 23: Efficient Frontiers for Original Case and Policy Cases

RPS

The use of a stand-alone RPS is explored in two different versions (Figure 24). The first version, represented in Case 1, implements a single-credit 15% RPS through an increase in capital investment from $10 billion to $15 billion. This case results in the largest average increase in cost (2.9%) for any non-carbon tax case. However, this scenario does result in the second best average decrease in emissions (3.47%). The second version of the RPS, Case 2, utilizes double credit for wind and solar generation in achieving the 15% RPS and does not require additional capital investment over the original case. This case results in a smaller average increase in annual generation cost (0.44%) and a smaller average decrease in emissions (1.76%), though the ratio of cost increase to emissions decrease is better for this case. Therefore, the use of the 15% RPS with double credit for wind and solar would be the most economically efficient way to decrease emissions, especially if additional funds were not available to increase capital investment or implement a REPTC. This case provides a cost-effective way to decrease emissions over the original case without requiring the government to provide tax credits or requiring energy companies to secure more sources of funding.

If an increase in capital investment is made available, then this will result in increased renewable generation and decreased emissions. But this increase is only cost-effective up to a certain point in this region, as some of the potential wind and solar sites are not cost-effective, reducing emissions by a much smaller percentage than the associated increase in cost from using these more expensive sites. Most of these sites are less cost-effective due to their size, with the fixed costs being spread over less generation.

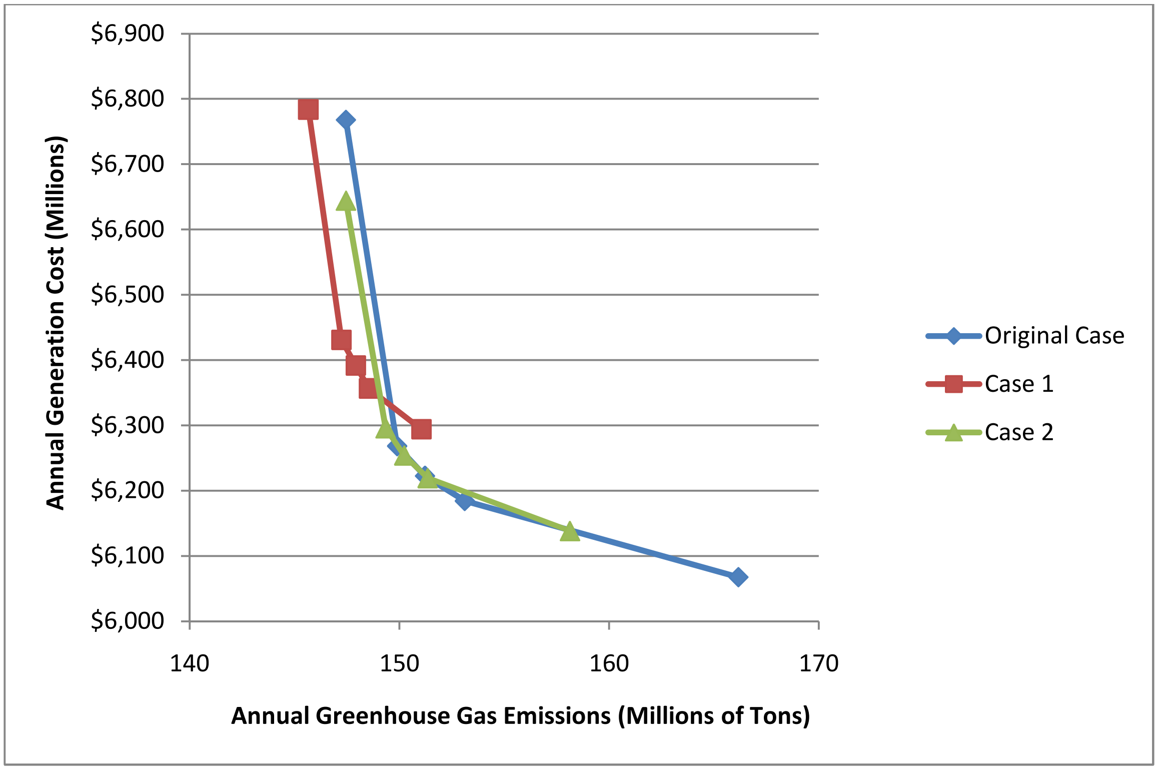

Figure 24: Efficient Frontiers for RPS-only Cases

Carbon Tax

The use of the carbon tax in Cases 3, 5, and 6 results in large increases in annual generation cost for each scenario (Figure 25). Given that the greater Southern Appalachian region is so heavily dependent on fossil fuel sources, particularly coal, the implementation of a carbon tax could be economically crippling to the region unless these increased tax revenues were being offset with cuts to tax revenue from other sources. Even though the use of the carbon tax in combination with an RPS constraint (Case 5) does result in the largest decreases in total emissions, there are other scenarios that reduce emissions nearly as much without having such a large impact on cost (see Figure 23). The other reason that a carbon tax would be unadvisable within this region is the small percentage of electricity that can be generated from renewable sources in relation to the dominance of carbon-based sources. Given the current constraints of the GIS model, only 3.24% and 2.97% of baseline demand within the region could be met by wind and solar respectively. However, many of the potential wind and solar sites have associated generation costs that are as high as \$0.47/kWh of wind and \$0.61/kWh of solar, which is extremely expensive and uncompetitive. Therefore, only a small percentage of generation can be effectively replaced with new wind and solar resources. Even in the cases that utilize the carbon tax, the minimum amount of coal generation possible is 71.75% and that comes through the increased availability of capital investment. Therefore, unless a greater percentage of coal generation can be replaced with renewable sources, whether through relaxing the constraints of the GIS model or through the exploration of distributed generation with small-scale installations, the use of a carbon tax has less benefit than the other policies. The three carbon tax cases do not provide substantially greater reductions in emissions than the other policy cases, but result in much higher generation costs due to the dependence on coal as the primary source of generation in the region.

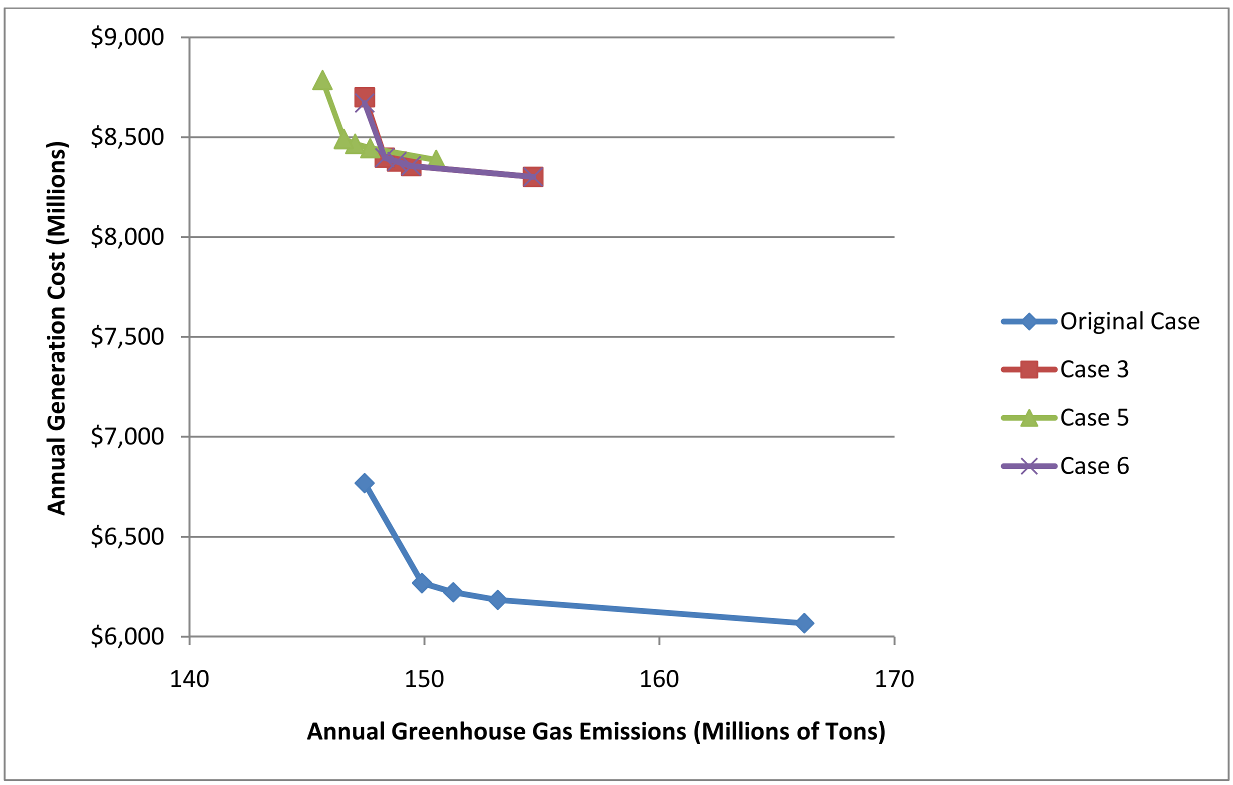

Figure 25: Efficient Frontiers for Carbon Tax Cases

REPTC

The use of the REPTC results in lower costs when utilizing the same amount of capital investment as in the base case (Cases 4 and 8), while in the case where capital investment is increased to meet the RPS requirement (Case 7) the cost increases in one scenario while decreasing in three of the other scenarios (Figure 26). The use of the REPTC as a standalone policy (Case 4) does result in lower emissions for two of the five scenarios, while increasing emissions in two of the others. However, these increases and decreases are the smallest changes experienced across all eight cases. Therefore, the use of the REPTC as a standalone policy would not be recommended, as the policy can achieve a greater impact when combined with an RPS (Cases 7 and 8). Case 7 relies on more capital investment availability, which may not be feasible at this time. However, this increase in capital investment does decrease costs slightly in three of the scenarios and results in the third best average decrease in emissions over the MiniMax scenarios. Case 8, which does not rely on more capital investment, has the second greatest decrease in average annual generation cost along with a modest reduction in emissions. The use of the REPTC represents the opposite approach to a carbon tax, decreasing the cost of renewable generation, and therefore requires the tax credits made available to be offset with budget cuts or tax increases in other areas. If the availability of REPTC funds is there, then Case 8, which utilizes a 15% RPS with double credit for wind and solar, would be the most effective use of these funds.

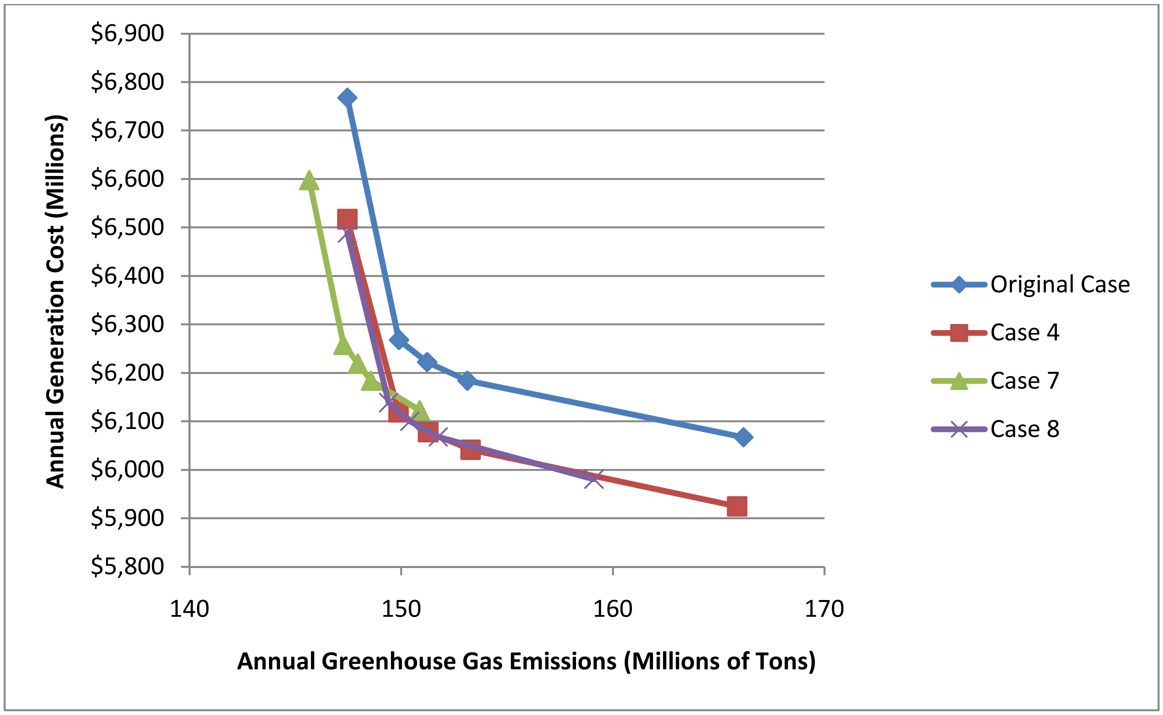

Figure 26: Efficient Frontiers for REPTC Cases

Summary

The model utilized in this research is composed of two competing objectives: the minimization of annual generation costs and the minimization of annual greenhouse gas emissions. As seen in the results of the original model and the eight policy cases above, the target values achieved when solving for one of the objectives independently of the other are in opposition with one another. It is not possible to achieve both the minimum cost and minimum emissions with the same mix of energy sources. Through the use of the MiniMax function, the model can be solved in a manner that considers both of the objectives. However, there are an infinite number of solutions that lie on the efficient frontier between the two target values. Through the use of weighting, a preference can be expressed for one objective in relation to the other objective, and a solution on the efficient frontier is then identified for that weighting scenario. There were three MiniMax weighting scenarios utilized in this research, one in which the objectives were equally weighted, one in which the emissions objective was twice as important as the cost objective, and a scenario in which the cost objective was twice as important as the emissions objective. Determining the weights for the objective functions is a subjective process, and these three scenarios analyzed in this research represent only a fraction of the possible weighting schemes.

If one wanted to focus specifically on one of the five weighting scenarios, the MiniMax – Cost Weighted would be the best choice due to two reasons. First, the decision to invest in new technologies and energy infrastructure is often very dependent on the costs involved and this is the only scenario in which the cost objective was considered more important than the emissions objective, while still considering the emissions function. The policy cases all involve some degree of government involvement, and it is reasonable to assume that minimizing cost would be of upmost importance to users of this system. The second reason is that the target value for the cost function ($6,067,506,773) in the original case is a magnitude of more than 40 times greater than the target value for the emissions objective (147,458,417). As the cost function will also produce values much greater than the emissions function, any percentage deviation for the cost function represents a larger absolute increase over the target cost than absolute change for the same deviation in the emissions function.

The results of this policy analysis section provide some insight into potential government legislation to increase renewable generation. These results should not be extrapolated to the entire country or other regions due to the intensely carbon-based generation within this region. As a result of the dependence on coal in the region, the use of a carbon tax is the least advisable of the policies considered and can result in cost increases of 30% or more. If government funds are available for tax credits, then the use of these credits in conjunction with an RPS, especially one in which double credit is provided for wind and solar generation, can provide better results than the use of these tax credits on their own. Finally, of the policies considered, the use of an RPS is the most cost effective way to cut down on emissions while moderately impacting the generation costs. If a government policy were implemented in this region, this would be the most advisable choice given the current availability of wind and solar resources and the dependence on fossil fuels, particularly coal.

Appendix A: Model Formulation

Decision Variables

$$W_i = \begin{cases} 1 \; if \; a \; wind \; farm \; is \; to \; be \; placed \; at \; location \; i \; for \; i = 1, \dots, N_i \\ 0 \; otherwise \end{cases}$$

where N_i = the number of possible wind farm locations

$$S_j = \begin{cases} 1 \; if \; a \; solar \; farm \; is \; to \; be \; placed \; at \; location \; j \; for \; j = 1, \dots, N_j \\ 0 \; otherwise \end{cases}$$

where N_s = the number of possible solar farm locations

B_{yp} = tons of biomass transported between county *y* and coal plant *p*

for y = 1,…, N_y where N_y = the number of counties in the region

and p = 1,…, N_p where N_p = the number of coal plants in the region

U_q = capacity utilization of existing non-coal electricity generation facility *q* relative to baseline levels

for q = 1,…, N_q where N_q = the number of existing non-coal facilities in the region

G_p = capacity utilization of existing coal electricity generation facility *p* relative to baseline levels

for p = 1,…, N_p where N_p = the number of existing coal plants in the region

$G_p, U_q \leq 1$

$B_{yp}, G_p, U_q \geq 0$

Objectives

Parameters associated with operating a wind farm:

C_i^{vw}= annualized capital investment of wind farm location *i*

C^{kwm} = annual operating and maintenance costs per installed kW of wind capacity

K_i^w = kW capacity at wind farm location *i*

C^{mwm} = annual operating and maintenance costs per MWh of wind generation

M_i^w = expected annual MWh generation at wind farm *i*

Parameters associated with operating a solar farm:

C_j^{vw} = annualized capital investment of solar farm location *j*

C^{ksm} = annual operating and maintenance costs per installed kW of solar capacity

K_j^s = kW capacity at solar farm location *j*

C^{msm} = annual operating and maintenance costs per MWh of solar generation

M_j^s =expected annual MWh generation at solar farm *j*

Parameters associated with operating a coal or co-fire plant:

C_p^{vc} = annualized capital investment for co-fire retrofit at coal plant *p*

C^{tc} = cost per ton of coal

C^{tb} = cost per ton of biomass

C^{tbd} = cost of transporting one ton of biomass one mile

D_{yp} = estimated distance between county y and coal plant p

C^{ac} = additional cost per MWh generated at a coal plant, including labor, operating, etc.

M_p^c = MWh generated at coal plant p in baseline year

T_p = tons of coal used at coal plant p in baseline year

F = percentage efficiency of one ton of biomass versus one ton of coal, assumed constant for all plants in the region

Parameters associate with operating an existing non-coal facility:

C_q^{mn} = cost per MWh generated at non-coal facility q

M_q^n = MWh generated at non-coal facility q in baseline year

<u>The objective function for annual electricity generation costs:</u>

$$Min \sum_{i=1}^{N_i} W_i\left(C_i^{vw} + C^{kwm}K_i^w + C^{mwm}M_i^w\right) + \sum_{j=1}^{N_j} S_j\left(C_j^{vs} + C^{ksm}K_j^s + C^{msm}M_j^s\right)$$

$$+ \sum_{p=1}^{N_p}\left\{\left(C_p^{vc} + C^{ac}G_pM_p^c + C^{tc}G_pT_p\right)\right.$$

$$\left. + \sum_{y=1}^{N_y}\left(C^{tb}B_{yp} + C^{tbd}B_{yp}D_{yp} - C^{tc}B_{yp}F\right)\right\} + \sum_{q=1}^{N_q} C_q^{mn}M_q^nU_q$$

Parameters associated with emissions:

E_p^{co-p} = tons of CO_2 emissions per ton of coal used at plant p

E_p^{so-p} = tons of SO_2 emissions per ton of coal used at plant p

E_p^{no-p} = tons of NO_X emissions per ton of coal used at plant p

E_p^{co-b} = tons of CO_2 emissions per ton of biomass used at plant p

E_p^{so-b} = tons of SO_2 emissions per ton of biomass used at plant p

E_p^{no-b} = tons of NO_X emissions per ton of biomass used at plant p

E_q^{co-q} = tons of CO_2 emissions per MWh generated at non-coal facility q

E_q^{so-q} = tons of SO_2 emissions per MWh generated at non-coal facility q

E_q^{no-q} = tons of NO_X emissions per MWh generated at non-coal facility q

<u>The objective function for total greenhouse gas emissions:</u>

$$Min \sum_{p=1}^{N_p} \left\{ \left(\left[E_p^{co-p} + E_p^{so-p} + E_p^{no-p} \right] G_p T_p \right) \right.$$
$$\left. - \sum_{y=1}^{N_y} \left(\left[E_p^{co-p} + E_p^{so-p} + E_p^{no-p} \right] B_{yp} F + \left[E_p^{co-b} + E_p^{so-b} + E_p^{no-b} \right] B_{yp} \right) \right\}$$
$$+ \sum_{q=1}^{N_q} \left[E_q^{co-q} + E_q^{so-q} + E_q^{no-q} \right] M_q^n U_q$$

Constraints

Biomass utilization within each county:

$$\sum_{p=1}^{N_p} B_{yp} \leq B_y^{avail}$$

where B_y^{avail} = tons of biomass available within county *y*

Maximum amount of biomass that can be co-fired at each coal plant:

$$\sum_{y=1}^{N_y} B_{yp}F \leq G_p T_p X$$

where X = percentage of total fuel generating tons that can be derived from biomass

Electricity Generation:

$$\sum_{i=1}^{N_i} M_i^w W_i + \sum_{j=1}^{N_j} M_j^s S_j + \sum_{p=1}^{N_p} M_p^c G_p + \sum_{q=1}^{N_q} M_q^n U_q \geq M^{base}(1+H)$$

where M^{base} = electricity generation (MWh) within region in baseline year

H= growth factor

Capital Investment:

$$\sum_{i=1}^{N_i} K_i^w \left(C^{kw} + C^{af} A_i^f + C^l L_i\right) + \sum_{j=1}^{N_j} C^{ks} K_j^s + \sum_{p=1}^{N_p} \left[C^{kb} \left(\frac{K_p^c}{M_p^c}\right) M_p^{tc} \sum_{y=1}^{N_y} B_{yp} F \right] \leq V$$

where C^{kw} = cost of installing one kW of wind capacity

C^{af} = cost of clearing one acre of forest land for wind farm installation

A_i^f = acres of forested land at wind farm location i

C^l = cost per degree of slope at wind farm location

L_i = average degree of slope at wind farm location i

C^{ks} = cost of installing one kW of solar capacity

C^{kb} = cost of retrofitting a coal-fired plant for biomass co-fire per kW of capacity

K_p^c = overall kW capacity at coal plant p

M_p^{tc} = MWh generated per ton of coal in baseline year at plant p

V = total amount of capital investment available

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Chapter 6: Conclusions

This research creates the framework for an integrated system to assist in renewable energy planning at the community or regional level. Through the use of GIS, the discovery of renewable energy source potential is achieved, with the additional benefit of visualization which improves the community participation and ultimately the public acceptance of the new energy plan. Even through the use of conservative constraints, 203 potential wind farm locations and 477 potential solar farm locations were discovered.

The second portion of the research develops a comprehensive model which can be used to better determine the mix of energy sources available within the region. Through the combination of the GIS-derived potential for renewable energy and the modeling portion of the system, the research provides a direct link between each stage of the planning process that has been underutilized or missing from previous work. Five different scenarios were run for the multi-objective optimization model. Each scenario increased renewable energy usage, some scenarios much more so than others, along with decreasing emissions while only increasing generation costs slightly.

In the final section of this research, three possible energy policies are explored independently and in various combinations to determine the impact they would have on the use of renewable energy. The use of a renewable portfolio standard (RPS) was determined to be the most cost-effective way to increase renewable energy usage. The carbon tax increased generation costs immensely while providing comparatively little impact on emissions. A final policy, a tax credit for renewable energy production, was found to be ineffective on its own, and can actually result in increased emissions, but can be effective when used with an RPS.

There are many possible future research directions for this research. One possibility that could be explored is the extreme distributed generation of solar energy generation. This would require estimates of the number of home and land owners that would be willing to install solar panels on their property. This model of generation is highly successful in many countries, particularly in Germany, and has been receiving limited exposure in the United States. Effective implementation of this generation requires a government policy to help attract interested parties. The two most popular methods, feed-in tariffs and net metering, could be explored to determine if either of these policies would be more successful. This generation could even be explored as a replacement for solar farms.

A second future research direction would involve eliciting input from the public to help determine the social acceptance of renewable energy planning, particularly in relation to wind farm siting. Having the public involved in the selection of more acceptable renewable energy locations can add another parameter or constraint to the model. The more accepting the public is of a new installation, the more successful those projects have been, as many projects have stalled due to public opposition.

Finally, there are a number of socio-economic benefits that can be derived from the implementation of renewable energy technologies within a community, making the communities more economically sustainable, as well as more environmentally sustainable. Adding a parameter related to job creation would help provide another look at the role these projects play within the region or community. There was an additional objective present in this proposal at one time related to job creation. This was removed due to insufficient details on the results of previous renewable energy projects. As this research progresses and more information is made available, this job creation objective, or similar socio-economic objectives, could be added to the mathematical model to widen the scope of the problem.

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