ABSTRACT


This study explores the effect of adding 1,644 MW of solar photovoltaic electricity generators to the Duke Energy Carolinas (DEC) and Duke Energy Progress (DEP) electric grid. It focuses on how the operation and emissions of traditional fossil fueled electric generators will change as a result of the addition of the intermittent renewable energy sources to the grid. Previous studies have established that greenhouse gas emissions will be reduced, and fossil fuel generation will decrease. However, most studies have been focused on maximum solar PV penetration levels for specific areas, or how much intermittent energy generation can be handled in one area before grid operations can no longer meet North American Electric Reliability Corporation standards. Therefore, effect on emissions has been a secondary objective and not well defined.

The amount of solar generation that was simulated was chosen based on the Duke Energy interconnection queue. The interest of this study was to determine the effect of adding all of the proposed solar PV facilities in the queue to the grid. The amount of generation to be added was determined based on an analysis of the February 2016 queue which determined the generators most likely to be added within the next year or two. This resulted in 438 proposed facilities with a combined nameplate capacity of 1,644 MW.

To simulate the electricity generation from these plants, a performance model was required. The National Renewable Energy Laboratory’s PVWatts (version 5) tool was used for the model. The modeling was performed with 2014, 30-minute solar radiation data downloaded from the National Solar Radiation Database. Overall, the facilities were projected to produce 2,355,906 MWh with a peak power of 1,465 MW. This represents a capacity factor of 16.17% and an energy penetration of 2.11%.

Three different analyses were performed; two based on the Environmental Protection Agency’s (EPA) Emissions & Generation Resource Integrated Database (eGRID) and one based on EPA’s Avoided Emissions and Generation Tool. eGRID results included emissions
reductions by weight for CO₂, SO₂, CH₄, NOₓ. AVERT included the same greenhouse gas emissions reductions (except CH₄) and changes in heat input and heat rate for fossil fueled generators.

The eGRID analysis used average, or baseline, emissions rates and non-baseload specific emissions rates. The baseline rates estimated annual emissions reductions of about 2% for all pollutants. The non-baseload rates revealed more variable reductions: 4.8% for NOₓ, 6.1% for SO₂, 2.5% for CO₂ and 2.5% for CH₄. The difference in results was analyzed and the non-baseload results were interpreted as a reduction maximum, while the baseline results were treated as an order of magnitude check.

Using AVERT several simulations were performed, the ones of interest for this study were North Carolina (NC) and the Southeast (SE). It was estimated that the proposed PV generators would result in 2,337,400 MWh of fossil fueled generation being displaced. The resulting change in emissions was 3.9% for SO₂, 3.5% for NOₓ and 3.2% for CO₂. It was found that the overall heat rate for NC decreased as a result of the PV integration. The region became more efficient, possibly a result of decreasing the number of partially loaded fossil fuel generators. The SE region did not show much of a change in heat rates, but, emissions were still reduced.
The Effect of Adding Solar Photovoltaic Electricity Generators to the Duke Energy Service Area in North Carolina on the Emissions of Fossil Fueled Generators

by
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A thesis submitted to the Graduate Faculty of North Carolina State University in partial fulfillment of the requirements for the Degree of Master of Science

Mechanical Engineering
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2016

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Dr. Alexei Saveliev
DEDICATION

This thesis is dedicated to my family and friends. It is also dedicated to Dwight Schrute – “Bears. Beets. Battlestar Galactica.”
BIOGRAPHY

James E. Turner was the third child born to Jim and Sue Turner in Charlotte, NC. Around 2003 his family relocated to Wesley Chapel, NC. In high school he developed an interest in the environment and renewable energy, thanks to his AP Environmental Science class. In 2011, James graduated high school and enrolled at North Carolina State University where he studied Mechanical Engineering.

James was awarded the opportunity to be a part of the Goodnight Scholars Program. This quickly became a community that James strived to give back to. During his time as an undergraduate, James helped develop the Goodnight Scholars Program as a part of the Goodnight Scholars Executive Council, and an Alternative Service Break trip leader.

During his sophomore year at NCSU, James enrolled in Basic Rock Climbing. The instructor, Scott Schneider, encouraged him to pursue a minor in Outdoor Leadership. Three years later, after completing the program, James strives to continue his involvement with the Outdoor Leadership program, assisting with trips and PE classes. James is an avid climber and has a resting heart rate of 23 beats per minute. The scientists who study him say his heart can pump jet fuel up into an airplane.

In May 2015 James graduated from NCSU with a Bachelor in Science in Mechanical Engineering and a minor in Outdoor Leadership. Following graduation James set out on a western road, settling in Pinedale, WY to work for the United States Forest Service as a Wilderness Ranger. James returned to Raleigh, NC in August to pursue a Master’s of Science in Mechanical Engineering degree. During his graduate career he worked for the Industrial Assessment Center as a research assistant.
ACKNOWLEDGEMENTS

I would like to acknowledge and thank the several people that supported me during the process of researching and writing this report. First, I would like to thank my family for encouraging me to pursue my master’s degree and providing the motivation to follow through with it. I have doubted my choice to pursue a graduate degree on several occasions and they have always been there to talk to and support me, no matter what choice I may make.

Additionally, I would like to acknowledge several other people who have had a great influence on my life. Catherine McCloskey, my high school environmental science teacher pushed me to discover and pursue my academic passions. Scott Schneider was just a physical education teacher when we first met, but over my years at NCSU, he has become a good friend. I can always count on him to encourage me to explore all of the possibilities and pursue things that I would not otherwise think possible. Erin Doran, roommate and friend, began her graduate program at the same time and provided me an outlet where I could express the doubt in my life choices (and know that she felt the same way). The staff of the Goodnight Scholars Program (Jen Foster, Jason Perry, and Allison Medlin), granted me numerous leadership and development opportunities which have helped me grow as a leader and individual.

Finally, I would like to thank each of my committee members for their guidance throughout this process. Dr. Stephen Terry has been an awesome advisor throughout this project providing academic support and encouragement. The opportunities that he afforded me by letting me join the Industrial Assessment Center have been influential on my career path, interests and technical experience. I would also like to thank Dr. Andre Mazzoleni and Dr. Alexi Saveliev for serving on my graduate advisory committee. I greatly appreciate your participation in this project.
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1 INTRODUCTION

1.1 Overview of the United States’ Electric Grid Operations

In the United States the infrastructure used to produce, transmit and distribute electricity is often referred to as “the grid,” but what does the grid actually do? This section will provide a brief overview of how the generation, transmission and distribution of the grid work together to get power to your home, office, or industrial plant. At the highest level, Figure 1 represents how electricity is moved throughout the grid.

Figure 1. High-level overview of electrical grid operations [1].

In summary, alternating current (AC) electricity is generated at a power plant, often owned by a utility company, and then stepped up via transformer to high voltage (155,000 – 765,000 V) to be transmitted long distances. Before the electricity reaches point-of-use, it goes through a substation to lower the voltage to 7,200 V (standard line voltage). This substation represents the divide of the transmission grid and the distribution grid. From here electricity is distributed to customers. Commercial and industrial customers typically use an on-site transformer or substation to lower the voltage to the required service voltage. In the case of residential customers, the electricity flows through another substation, and then another transformer before entering the home at 120/240V [1].
One of the major challenges that utility companies face is balancing electricity supply and demand. The demand for electricity fluctuates throughout the day, as illustrated by Figure 2.

Regional hourly actual and forecast demand

![Figure 2. Electricity demand for Carolinas region, 3/2-3/4/2016 [2].](image)

Figure 2 was produced using the Energy Information Administration’s real-time grid data application.

There is no single entity that owns or operates the grid. The grid in the continental U.S. and Canada (minus Alaska and Quebec) is divided into three interconnections, Western, Eastern and Texas. These interconnections represent many local grids that have linked together in order to provide greater reliability to their customers. The U.S. and Canada interconnections are shown in Figure 3. Furthermore, the interconnections are subdivided into regional organizations, Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs), shown in Figure 3.
Finally, the regions are broken down once more into balancing authorities (BA’s). It is the ultimate responsibility of these entities to create resource plans and maintain load-balance (supply and demand). Duke Energy Carolinas is an example of one balancing authority in North Carolina.

In order to balance loads in their area Duke Energy uses sophisticated energy modeling, historical data and analytics to predict what the demand for the next day will be in their area. Then, they determine which generators they should commit to produce the power, based on how much it will cost to run the generators. However, no two days are ever the same, thus the BA’s predictions are never 100% accurate and changes must be made to generating capacity throughout the day, down to a second-to-second basis. Generally, there is a large constant load which can be accurately predicted, this is the baseload. The baseload is served by the largest generators in the area, like nuclear and coal plants, which function most efficiently at full load and are harder to turn-down. The variable load is generated by intermediate and peaking units, usually gas or oil-fired turbines and hydro-electric plants. Throughout the day as the actual load on the grid varies, the balancing authority takes various actions to maintain frequency and match the demand [4]. The BA has several different reserves that they can implement to restore balance in the event of under-generation. These actions range from bringing new generation on-line, adjusting (or ramping) individual unit
outputs, and accepting power flow from other BA’s. Similarly, to correct over-generation events, the BA can allow power to flow into other BA’s (if they require additional power), load-shed through demand response, or ramp down generators. Figure 4 represents the time scale of different BA actions.

![Figure 4. Balancing Authority Responses [4].](image)

Some various other terms that are useful to know when discussing BA responses and electrical grid stabilization:

- **Spinning reserves** – generating capability that can be governed by automatic generation control (AGC). Used for grid regulation and responds in a range from seconds to 5 minutes [4].
- **Non-spinning reserves** – generating capacity that is able to come online within 30 minutes of being called upon [4].
- **Ramp rate** – the speed at which a generator can alter its output [4].

This background information provides a foundation for the rest of this report which will explore how intermittent renewable energy resources, like solar PV, effect fossil fueled electric generators.
1.2 Renewable Energy in North Carolina

When you flip the light switch in your house and the lights come on, where does that electricity come from? According to 2015 data from the Energy Information Administration, shown in Figure 5, in North Carolina (NC) that electricity was most likely to have been generated by a nuclear power plant [5].

![Electric Power Net Generation by Primary Energy Source in 2015](chart.png)

**Figure 5. Electric Power Net Generation by Primary Energy Source**

Despite predominately using nuclear fuel for power generation, it is evident that North Carolina is also heavily dependent on fossil fuels for electricity generation. Over the last decade, there has been a great deal of research performed on the topic of climate change. The Intergovernmental Panel on Climate Change (IPCC) has concluded that the probability that human activities have contributed to climate change over the last 250 years is greater than 90%. They also concluded that human produced greenhouse gases, like carbon dioxide, methane and nitrous oxides have influenced the greenhouse effect creating a rise in global temperatures [6]. It is indisputable that burning fossil fuels produces greenhouse gases, and since the IPCC believes that greenhouse gases may be contributing to climate change, many people argue that society needs to move away from traditional, fossil fuel based electricity generation towards more renewable resources. However, climate change is a highly debated topic among scientists, policymakers, and the public. Outside of climate change, there are other reasons that renewable energy sources should be implemented. Fossil fuels take
millions of years to be formed through geological processes, in comparison to humanity’s existence, they are a finite resource. Thus, in order to conserve fossil fuels for use in the future, alternative energy sources should be considered. In 1978, Congress passed the Public Utilities Regulatory Policies Act (PURPA) as part of the National Energy Act. This bill served several purposes including to reduce demand on fossil fuels and to create a market for power from non-utility power producers. The act established guidelines for Qualifying Facilities, or QFs, which are power generating facilities that utilities can purchase power from. In North Carolina, all QFs under 5 MW can receive a 15 year fixed price contract from a utility company for the power they generate. The utilities are required to purchase power from any generators less than 5 MW. This act laid the groundwork to get to where we are today with non-utility owned generating resources (like cogeneration and solar PV plants) and power purchase agreements. [7].

In 2007, North Carolina’s state legislature established a Renewable Energy and Efficiency Portfolio Standard (REPS). This law requires investor-owned utilities to meet 12.5% of their 2020 energy needs with renewable energy sources and the implementation of energy efficiency measures by the year 2021. Municipal utilities and electric cooperatives must utilize 10% renewables by 2018 [8].

The two main alternative energy sources receiving attention from commercial electric utilities in North Carolina are wind turbines and solar PV. These generation methods utilize sophisticated engineering to harness the energy from the sun and wind. The main advantage of these electricity sources is that they do not directly contribute to any fossil fuel use while generating electricity. However, no energy source is perfect, solar and wind not excluded. One of the major drawbacks of solar and wind energy is intermittent generation. Intermittent generation arises from the technology and from nature itself. The sun does not shine at night and solar panels depend on direct irradiation to generate electricity, therefore they cannot generate power at night. During the day, there are events, such as weather fronts and patches of clouds that adversely affect the amount of direct solar irradiation that reaches a solar panel, lowering the generation output of panels and altering their output instantaneously. Wind power encounters similar problems in that wind speed is variable with weather, and without a set schedule like the sun, it is can be less predictable than solar. The intermittency
of solar is often very rapid, if a cloud passes over, output changes quickly; conversely, large changes in wind power occur more slowly [9].

One of the main requirements of electric utility companies is to provide reliable energy to its users, intermittent generation sources make this a challenge when they are connected to the electric grid because the utility company has to be able to compensate for any deficit or surplus energy on the grid. If a solar farm is producing energy and a group of clouds pass over it for fifteen minutes, its output will decrease and the utility company will have to compensate for this deficit by supplying power from another generation source immediately. Utilities can compensate for these variabilities in various ways, but they all currently rely on a fossil fuel energy source. According to a study performed by the National Renewable Energy Laboratory, wind and solar power generators connected to the electric grid can cause coal or natural gas fired plants to cycle (turn on, or off) and ramp more frequently in order to follow the generation load from the variable renewable sources. This adjustment often leads to an increase in wear-and-tear on the units. Additionally, there is a decrease in efficiency of the fossil fuel generators since most of these power plants are designed to operate at full-load and exhibit a lower thermal efficiency when they are not operated at full load [9].

1.3 Project Objective
Over the last few years there has been a push for products and services to become more “sustainable,” in order to reduce their carbon footprint and impact on climate change. Electric utilities have been no different. With 39% of energy consumption in the United States being for electricity generation [10], there is a demand for electricity generation to evolve and reduce its greenhouse gas footprint. As mentioned previously, several states, including NC, have implemented plans to reduce GHG emissions from power generation through the implementation of renewable energy sources. Some renewable energy sources, like solar and wind, are variable generators. Adding these resources to the electric grid reduces the amount of fossil fuel generation needed, but not at an exact one-to-one ratio. If a 1 megawatt nameplate solar plant is added to the grid, that does not mean that a 1 MW fossil fuel generator can be removed from the grid, because the solar plant will not produce 1 MW continuously and reliably like the fossil fuel generator. The resulting implication is that there
is not a one-to-one correlation between the amount of variable renewable energy added and the amount of GHG emissions reduced.

Due to numerous tax credits, grants, loans and various other incentive programs available through federal, state and local governments, solar PV has taken off. North Carolina dominates utility-scale (greater than 1 MW) solar. Owning close to 11% of the nearly 10,000 MW of solar PV generation in the United States, North Carolina is consistently ranked in the top 10 states for solar electricity capacity. The North Carolina REPS requires that 0.2% of its total electric power sold to retail customers must come from solar energy [11]. Given the rapid growth of solar PV in North Carolina and the motivation behind the growth, it is desired to determine the effect that adding solar PV to the North Carolina electric grid will actually have on GHG emissions from electricity generation.

This project aims to determine the effect that adding solar PV to the North Carolina electric grid will have on the GHG emissions directly associated with burning fossil fuels for electricity generation. It is expected that GHG emissions will decrease since the adding solar PV to grid will decrease the amount of fossil fuel generation required. However, the interest of this project is to determine the effect that solar PV’s variability has on other generating sources, their efficiency and GHG emissions.

There are various types of utility companies in the United States. In North Carolina there are three investor owned utilities (IOUs), 32 electric membership corporations, and 76 municipality-owned electric utilities. The majority of North Carolina is serviced by Duke Energy, an IOU, which is comprised of Duke Energy Carolinas (DEC) and Duke Energy Progress (DEP). The Energy Information Administration’s online dictionary defines an Investor Owned Utilities as a “privately-owned electric utility whose stock is publicly traded. It is rate regulated and authorized to achieve an allowed rate of return.”

A general map of Duke’s service area is shown below in Figure 2. Note that the Duke service area does not encompass 100% of the area shown because there are municipality-owned and cooperative utility companies which occupy some portions of the state.
Figure 6. Duke Energy Service Area

Because Duke Energy provides the majority of the electricity generation for the state, this project will focus on their service area within NC. It will look at the February 2016 interconnection queue, which was the most up-to-date queue at the start of this study. The interconnection queue is a database of proposed generation projects that builders would like to connect to Duke’s transmission and/or distribution infrastructure. These projects can utilize any generation source, this project will focus on the current solar PV projects that are in the interconnection queue. The ultimate goal of the project is to determine what the effect of adding this specific amount of solar PV capacity to the electric grid would be on the traditional generators. In particular, the effect on GHG emissions is of interest. It is desired to know how much GHG (CO₂, SO₂, NOₓ and CH₄) emissions would change with the introduction of this new solar capacity, and what the cause of the change was.
There have been many studies done on how variable renewable energy sources affect electric grid reliability.

2.1 Impacts of Wind and Solar on Fossil-Fueled Generators, Lew and Brinkman

Of these studies, several are relevant to this research project. Lew and Brinkman presented a paper at the IEEE Power and Energy Society General Meeting about the “Impacts of Wind and Solar on Fossil-Fueled Generators” in July 2012 [12].

Lew and Brinkman recognized that regional integration studies have proved that variable generating renewable energy sources, like wind and solar, cause fossil fuel generators to cycle on and off, as well as ramp down to partial load more frequently. They were interested in determining the cost and emissions impacts of ramping and cycling fossil-fueled resources in order to improve the assessments of wind and solar impacts on the electric grid. The study performed a top-down and bottom-up analysis of plants and reported data for the energy production simulation. The paper reports results for start-up costs, equivalent forced outage rates (EFOR), baseload variable operations and maintenance (VOM) and ramping costs. They found that on and off cycling of small subcritical coal plants (35-299 MW) and cold starts of generators have the largest impact on cost. It was also reported that “ramping costs [are] relatively small, especially when units are ramped at normal ramp rates” [12].

In order to analyze the emissions impacts the researchers compiled measured emissions from almost every generating plant in the United States. The emissions dataset was procured from the United States Environmental Protection Agency’s continuous emissions monitors (CEM). The data included hourly reports of NO\textsubscript{x}, SO\textsubscript{2}, CO\textsubscript{2}, fuel input and generation from 2008. The study broke down generators into four categories: coal-fired, gas-fired combined cycle (CC), gas-fired combustion turbine (CT), and gas-fired steam. Ultimately, the study found that emissions from ramping were insignificant when compared to start up and part-load operation, therefore the results are not reported. After curve fitting the emissions and generating data, graphs illustrating the effect of part-load and start-up emissions were created, as seen in Figure 7.
In Figure 7, it is seen that CT’s are least efficient at partial loading (they have the highest heat rate) while CC’s are most efficient (lowest heat rate). Although, CC and CT units have the highest decrease in thermal efficiency when operating at partial load. This graph can also be used to find CO₂ output using the carbon content of the fuel. Analyzing the NOₓ figure, it is clear that coal and gas steam units are the least desirable in terms of NOₓ emissions regardless of loading. Gas steam units exhibit the largest variation in NOₓ emissions with percent load while coal, CC and CT units have relatively constant NOₓ emissions. While NOₓ and CO₂ emissions from the study are reliable, the SO₂ emissions are less so. When analyzing SO₂ emissions data, over half of the dataset was eliminated due to bad curve fits.
The remaining data found that coal (natural gas has very low sulfur content and thus very low SO$_2$ emissions) emissions rose with percent load when SO$_2$ controls were in place and declined with percent load without SO$_2$ controls.

In addition to emissions from partial loading of fossil fueled generators, the emissions during generator start up were investigated. The startup emissions were quantified in terms of heat input per megawatt capacity, and pounds per megawatt. The results from the study are shown in Table 1 [12].

### Table 1: Startup Emissions per Megawatt Capacity

<table>
<thead>
<tr>
<th></th>
<th>Heat Input (MMBTU/MW)</th>
<th>NO$_x$ (lbs/MW)</th>
<th>SO$_2$ (lbs/MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal (all)</td>
<td>11.4</td>
<td>2.51</td>
<td>3.90</td>
</tr>
<tr>
<td>Gas CC</td>
<td>2.4</td>
<td>0.83</td>
<td>n/a</td>
</tr>
<tr>
<td>Gas CT</td>
<td>3.8</td>
<td>0.59</td>
<td>n/a</td>
</tr>
<tr>
<td>Gas Steam</td>
<td>9.3</td>
<td>-0.03</td>
<td>n/a</td>
</tr>
</tbody>
</table>

The paper notes that most coal units are started with either oil or natural gas, and thus the heat input should be contributed to the appropriate fuel in order to calculate the CO$_2$ emissions. An example was given: during the startup period of a coal plant, it will emit 2.51 lbs/MW of NO$_x$, the equivalent of the coal plant running for 0.98 hours at full load. There was insufficient data to breakdown startup emissions by type (i.e. cold, warm, and hot start).

The conclusion of this study stated that the impacts of cycling and ramping fossil fueled generators are significant enough to necessitate accounting for them in integration studies, however, they are “modest” compared to the overall effect of replacing fossil fueled generators with variable renewable generation. The authors also noted that future integration studies can now incorporate the cost of wear and tear on fossil fueled generators, leading to a more accurate prediction of the real impacts of solar and wind on the grid. They predict that the incorporation of these costs will lead to less cycling and ramping occurring in the models, lowering the predicted limit of renewables penetration [12].
2.2 Duke Energy Photovoltaic Integration Study: Carolinas Service Areas, PNNL


PNNL, along with experts from Power Costs, Inc. (PCI), Clean Power Research (CPR), Alstom and Duke Energy completed a study to determine the impact that solar PV has on ancillary generation services, generation production cost, and transmission and distribution systems. Due to the relatively short length of the study, the team decided it would not focus on dynamic system characteristics such as frequency response, and transient stability. This study was undertaken because of the rapid increase of PV integration that is occurring in the Duke Energy service area. With the establishment of North Carolina REPS, the number of PV projects started to rise. When state tax credits were introduced for PV facilities, growth increased again, and it was even further promoted by the falling price of PV panels. Duke realized that PV growth may exceed what was dictated by North Carolina REPS, prompting them to initiate an impact study to help guide the development of future infrastructure, resource and operations plans. They were interested in quantifying the impact of high-PV penetration rates.

To complete the research, the investigators modeled three scenarios: compliance with State Bill 3 (SB3, which established the North Carolina REPS), modest increase over SB3, and rapid penetration of PV. Their models ranged from 2% of peak production to 20% over 8 years (2014-2022). For each of the scenarios, energy production costs, system variability and reserve requirements were analyzed. The model that was ultimately implemented used new modeling capabilities to model PV variability up to 1-minute intervals. The resources that were modeled included generators, pumped-storage, demand-response and long-term contracts, comparing these the model values to Duke’s latest integrated resource plan. The main assumptions that were used in this model included “PV installations, future load growth, resource mix, and fuel prices” [13].
The findings of the integration study were as expected. The study found that the variation in net load increases with PV penetration. The system net load was defined as the difference between the load and PV production. In fact, they found that at the highest penetration levels modeled, 20% of peak load (6,800 MW), “system day-ahead (DA) planning reserve requirements (contingency reserve excluded) increase 30 percent compared to the values without PV (reference cases), and regulation reserve requirements increase 140 percent” [13]. Further, it was found that Duke’s system was able to accommodate the high levels of PV penetration while complying with the standards for reliability set by the North American Electric Reliability Corporation. Total system production cost decreases (if PV implementation cost is neglected) with increasing levels of PV penetration, however, the unit cost of conventional generators increases due to cycling. After analysis, the team determined that the higher the penetration level, the higher the integration cost. Integration cost is the additional costs imposed on Duke Energy when a new generator is added to the grid. The cost results from the need of additional reserves and cycling of other generators. With 2% penetration the integration cost of PV was $1.43/MWh, while it was $9.82/MWh at 20% penetration. This study did not take into account the effect of wear and tear due to the additional ramping of regulation reserves.

Overall, this study looked at the effect of different levels of solar PV penetration. The study found that Duke’s system is capable of handling up to 20% penetration (6,800 MW) in 2022. This is based on Duke’s current infrastructure and their planned upgrades based on their integrated resource plan. The study’s mid-level penetration ranged from about 2.5% to 11% of peak load. They suggest that, based on Duke’s interconnection queue, this level is closest to what actual penetration may be, modeling 1,322 MW_{AC} connected in 2016, about 3.9%. At mid-penetration levels in 2016, day-ahead planning reserves increased slightly from the base scenario, while regulation reserves did not appear to be affected.

2.3 Residential Solar PV Systems in the Carolinas: Opportunities and Outcomes, Alqahtani

In January 2016, Alqahtani published a paper in Environmental Science and Technology loosely based on the masters research of Kyra Holt [14]. Holt’s thesis is also of interest, providing additional details, titled “Limits and Economic Effects of Distributed PV
Generation in North and South Carolina.” Both Alqahtani and Holt looked at the effect of high solar PV penetration within the DEC and DEP service areas. Similar to the PNNL study, the authors were interested in determining if a balancing authority, like DEC and DEP could handle the variability of solar PV that arises with high penetration. They chose the Duke Energy North Carolina area because the high generating capacity of must-run base load facilities, like nuclear plants. Alqahtani modeled a generating system with 49% of total system capacity being generated by nuclear plants, based on Duke Energy’s Integrated Resource Plan (IRP) for 2015 [14]. The remaining generating capacity was based on Duke’s 2015 IRP as well. The system was simulated with hourly demand data from 2005, to correspond with the available solar irradiance data.

Alqahtani’s study found that the maximum level of PV penetration is 5.3% of electric load, or 6,510 MW. Holt used a model with slightly different parameters (generation mix based on an older IRP) came to a similar conclusion, which is a 5.7% maximum. In both cases the limit was attributed to the inflexibility of nuclear power plants. The limit was defined as the point at which net-demand fell below the power production of base-loaded nuclear plants. It occurred in spring, when energy demand is low and PV production is high. It is at this point that over- and under-generation (imbalance) events began to occur, which were highly penalized at $10,000 /MWh in the model. At 5.3% penetration, 7 events occurred, at 9% 122 occurred. Modeling the nuclear resources as flexible, less than 3 imbalance events occurred.

In the United States nuclear generation is considered an inflexible resource (their output cannot be changed to follow changes in load). Thus, it was concluded that 5.3% was the penetration limit [14].

Note that the penetration levels listed in Alqahtani’s paper are significantly less than those in the PNNL study, however, the absolute generation levels in megawatts are not that different. For example, 6,800 MW in the PNNL paper is 20% penetration, while Alqahtani lists 6,510 MW as 5.3%. This suggests a difference in penetration calculations, PNNL probably based penetration on MW and nameplate capacity while Alqahtani used generation and MWh.

It is worth noting that load following with nuclear power plants is possible and in European countries with high nuclear penetration, it is currently implemented. Countries such as
Germany and France load-follow between 50% and 100% of a plant’s rated power with ramping of 3-5% (of rated power) per minute [15]. The merit of ramping nuclear power plants is debated among operators and engineers due to the thermal stresses it can induce on the plant’s core components. However, there are alternative ways to adjust the electrical output of a nuclear power plant aside from ramping. Steam from the reactor can be diverted from the turbines at one or various points along the path to electricity generation, or the part of the electricity can be diverted. Misenheimer and Terry suggest that diverting some electricity from the generator to power chillers coupled with a chilled water storage tank could provide a buffer for renewable energy intermittency, acting as a thermal sink during reactor transients [16].

The limits presented by Alqahtani’s paper are similar to those from the PNNL study if generation capacity (MW) is considered, although not exactly the same. There are a few reasons this small difference may have occurred. The PNNL study had access to one minute solar irradiance data from 2012, while Alqahtani used one hour solar irradiance data from 2005. One hour data tends to exhibit more variability than one minute data. With data that overestimates solar variability, there will be a corresponding increase in the variability of PV production, making it harder for the modeled system to maintain stability. This ultimately leads to an underestimation of the PV penetration limit, Holt noted this [17]. However, there are other factors that likely contributed to the variation in results. It is interesting that the PNNL study only accounted for 26% nuclear generation, half of what Alqahtani modeled, and still came to nearly the same conclusion because Alqahtani found that nuclear generation was the limiting factor. Other reasons for the variation could have resulted from data discrepancies, PNNL modeled a representative 1-kW PV system for each zip code in the Duke service area and then scaled up the time-series results to projected PV installation capacity. This is compared to Alqahtani, who used modeled 4-kW systems using 10km-by-10km hourly irradiance data; then validated the results using PVWatts. The models also had different prescribed operating conditions. PNNL was able to model demand response while Alqahtani mentions that his results present “what may be an upper limit of PV penetration in the absence of energy storage and demand response” [14]. Demand response is a current practice at Duke Energy. Additionally, PNNL modeled the system to allow for exporting energy at uneconomical prices (including negative prices), which would have a positive
effect on the predicted PV penetration rate. This is different from Alqahtani whose model economically penalized imbalance events. Although negative energy prices may seem confusing, they do occur in the market. For example, in 2011 in the Pacific Northwest U.S., there were 80 instances of negative spot prices. A negative spot price indicates that the seller pays the buyer to take power, rather than the buyer paying the seller. This occurs when there is more energy supplied then there is demanded and the producer does not, or cannot adjust energy generation levels [18].

The differences between Alqahtani and PNNL’s studies are vast. In this literature review it is suggested that they both have merits as long as the parameters and operating conditions of the models are considered before using one or the other to draw a final conclusion.
3 METHODS

3.1 Overview
As mentioned in the Project Objective, the goal here is to model the effect that adding new solar PV to the electric grid will have on fossil fueled generators’ emissions in the Duke Energy and Progress service areas in North Carolina. In order to accomplish this goal, it is necessary to know how generators on the grid really interact with one another in order to achieve stability.

The overall method for accomplishing the project goal is outlines below.

1. Collect data on the proposed solar PV plants in the DEC and DEP service areas.
2. Model the performance of these proposed plants using PVWatts and actual solar radiation data to create a forecast.
3. Use Emissions & Generation Resource Integrated Database (eGRID) to develop estimated emissions reduction.
4. Use the Avoided Emissions and Generation Tool (AVERT) to develop estimated emissions reduction for the Southeast AVERT Region.
5. Use AVERT to develop a North Carolina region and estimate emissions reduction.
6. Analyze and compare the results from the AVERT simulations and those from eGRID.

The following sections provide more details about each of the steps listed here.

3.2 Data Collection
In order to provide a realistic analysis, the most recent real world data was utilized. Utility companies are required to report operating data to the Federal and State government to prove compliance with regulations. However, due to the intensive nature of data collection, reporting and publishing, the most recent data available is from 2014. In this report, the most recent solar radiation data (from 2014) will be used. Additionally, the most recent eGRID data will be used, the dataset was published in 2015, and the data it contains is from 2012.
3.3 PV Plants

3.3.1 Proposed Facilities

The North Carolina Utilities Commission (NCUC) is the governing body of regulated utilities in the state of North Carolina. They establish requirements, state and local ordinances, electrical permitting, and regulations for all utility service providers, like DEP and DEC. These standards are establish under Docket E-100, Sub 101. Customers who intend to connect a nonutility-owned electrical generator to the grid in North Carolina must prove that they can adhere to all standards set forth by the NCUC [19]. To ensure that prospective generation projects can meet these requirements most utilities have set up an interconnection process which all projects must go through. The interconnection process involves several steps that require submitting documentation for review to the utility. Duke Energy keeps track of the projects that have been submitted in their “interconnection queue.” The queue is available to the public and it provides details about the project’s operational status, capacity, energy source, and the name of the substation which it will be connected to.

As established in the Project Objective, this study will focus on the February 2016 interconnection queue for DEP and DEC. In that queue, there were 851 solar projects for DEP and 515 for DEC, representing 93.8% and 91.7% of the queues’ projects respectively. In order to avoid modeling 1,366 solar PV plants, further filtering of the queue was done based on operational status and capacity. First, the plants were filtered by size, for DEC all of the plants that were less than 50 kW were removed, for DEP anything less than 100 kW was removed from the dataset. These removals represent about 0.1% of the total proposed solar generating capacity for both companies. The removal of these small plants from the dataset can be justified since they make up such a small portion of the proposed capacity, they will have much less of an effect on grid stability than the larger plants.

The queue also lists a number of plants which have recently been connected to the grid as well as some projects which have been cancelled. The connected and cancelled projects were filtered out. Additionally, a few more were filtered out because they had just begun the process and DEC/DEP are still waiting for the first documents following the interconnection application. The projects in the beginning stages of interconnection, before major documentation has been submitted, are not considered because these are the projects which
are most likely to be cancelled. After all of the filtering, the interconnection queues had been trimmed down to 115 PV plants for DEC and 323 for DEP. The capacity for these plants are 338.7 MW and 1,324.7 MW, respectively. This brings the total proposed generation to 1,663.4 MW, or about 4.8% of DEC and DEP’s combined generating nameplate capacity. The current nameplate capacity of all generating assets for DEC/DEP, according to 2012 eGRID data is 32,791.4 MW. In 2012, DEC had about 35.6 MW of Solar PV generating capacity and DEP had 48.2 MW [20]. Currently, in 2015, DEC has a solar PV capacity of 480 MW, and DEP has a capacity of 485 MW. The PV plants modeled represent a 175% increase in solar PV capacity over current capacity.

3.3.2 Modeling

In order to keep the modeling of the proposed PV plants simple and easy to work with, NREL’s System Adviser Model (SAM) was utilized. SAM was chosen for its ability to handle different types of models, and its user interface. The program not only has a graphical user interface, it can also exchange data with Microsoft Excel, perform stochastic models, and allows for the writing and execution of scripts to automate the modeling process.

SAM is has several modules built in to in order to evaluate the performance and finances of various renewable energy technologies like solar PV, concentrated solar power (CSP) and wind. Inside of SAM the PVWatts5 performance module was used. A financial model was not utilized. PVWatts5 was chosen over the detailed PV module because of the numerous unknown characteristics of the proposed plants. NREL recommends only using the detailed module when you have detailed information about the equipment which is going to be used for the project (inverter, PV module, etc.). The detailed PV module utilizes separate models for the inverter and module, making details about those components more critical to the model results. The PVWatts5 module is much more general in its simulations. It uses simple inputs such as nameplate capacity, array orientation, mounting type and system losses to simulate the system. NREL recommends this type of model for preliminary system evaluations, or instances in which a reasonable estimate of electrical output will suffice [21]. Alqahanti’s paper verified their PV simulation results using PVWatts and they found less than 0.5% difference between the PVWatts output and the calculation intensive analysis that
they performed. Therefore, it is reasonable to assume that using the PVWatts module in SAM is more than adequate.

### 3.3.2.1 Weather Files

The first input that SAM needs when defining a new project is a weather file for the location of the generator. This project will use a 2014 National Solar Radiation Database (NSRDB) file for each location. NSRDB files are location dependent, therefore, a location for each of the proposed solar plants needs to be established. As mentioned earlier, the only location specific identifier on the interconnection queue is the substation that the plant will be connected to. This presented somewhat of a challenge because substation locations are considered NERC critical infrastructure, and thus their locations are proprietary information.

Figure 8 provides an example of the data obtained from the public interconnection queue, this is a snapshot of a file that was created to analyze the queue data.

<table>
<thead>
<tr>
<th>Queue Number</th>
<th>Operational Status</th>
<th>Capacity</th>
<th>Feeder Number</th>
<th>Substation Name</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Alternate Identifier</th>
</tr>
</thead>
<tbody>
<tr>
<td>CHKLIST-0711</td>
<td>Pending</td>
<td>100</td>
<td>904206</td>
<td>Randolph Ave Ret 2405</td>
<td>36.098483</td>
<td>-79.827108</td>
<td>Greensboro</td>
</tr>
<tr>
<td>CHKLIST-0713</td>
<td>Pending</td>
<td>150</td>
<td>9252412</td>
<td>Denny Rd Ret 2412</td>
<td>36.275677</td>
<td>-80.356865</td>
<td>King</td>
</tr>
<tr>
<td>CHKLIST-0944</td>
<td>Under Construction</td>
<td>1996.4</td>
<td>1524302</td>
<td>Riverstone Ret 1202</td>
<td>35.432883</td>
<td>-82.507430</td>
<td>Fletcher</td>
</tr>
<tr>
<td>CHKLIST-0883</td>
<td>Under Construction</td>
<td>3000</td>
<td>11151201</td>
<td>Saxapahaw Ret 1201</td>
<td>35.960751</td>
<td>-79.316168</td>
<td></td>
</tr>
<tr>
<td>CHKLIST-0954</td>
<td>Under Construction</td>
<td>3000</td>
<td>11181203</td>
<td>Pleasant Grove Ret 1203</td>
<td>35.121895</td>
<td>-79.346913</td>
<td>Green Level</td>
</tr>
<tr>
<td>CHKLIST-10045</td>
<td>Fast Track Study</td>
<td>350.24</td>
<td>1162401</td>
<td>Park Rd Ret 2401</td>
<td>35.208707</td>
<td>-80.830739</td>
<td>Charlotte</td>
</tr>
<tr>
<td>CHKLIST-10047</td>
<td>Fast Track Study</td>
<td>1000</td>
<td>1191204</td>
<td>Remount Rd Ret 1264</td>
<td>35.208707</td>
<td>-80.830739</td>
<td>Charlotte</td>
</tr>
<tr>
<td>CHKLIST-10108</td>
<td>Under Construction</td>
<td>280</td>
<td>11252408</td>
<td>St Marks Ret 2408</td>
<td>35.405780</td>
<td>-80.574023</td>
<td>Huntersville</td>
</tr>
</tbody>
</table>

![Figure 8. Examples of Interconnection Queue Information. Green represents DEC, Blue represents DEP.](image)

The first five columns are data that is straight from the queue, the last three were obtained from data analysis. As seen in the figure, some of the substation names are descriptive enough to make an educated guess about where the station is located. For example, “Aberdeen 115kV,” this is obviously named for the town in which is presides, Aberdeen,
NC. However, other substations, like “Randolph Ave Ret 2406,” is harder to decipher a location from.

In order to find the substation locations, the queue was compared with a list of cities and towns in North Carolina and their geographic coordinates. After the initial matches were made, all of the remaining substations were located using manually associated “alternate identifiers,” show in Figure 8. The alternate identifiers were found using keywords from the substation names in a Google Maps search, then satellite view was used to look for substations in the area, if one was located, the location was recorded, otherwise other locations were checked. After all of the substations were associated with coordinates, they were plotted on a map to check if they were inside the DEC or DEP service area. There were a few stations which had been inaccurately located, so the location was corrected. The map with the locations plotted is shown in Figure 9.
Figure 9. Locations of proposed solar PV plants based on interconnection queue data
These locations are not exact, but they are generally in the correct area. More importantly, they are spread out over the generating area which will capture the differing weather conditions across the state during a specific time. Additionally, if exact coordinate locations were available for the PV plants the models would still not be 100% accurate because of the weather data. The NSRDB is only available at locations with weather stations that are capable of recording solar radiation data. The data used in our simulations are established for 4 km x 4 km blocks of land. The coordinates that were used to obtain weather files were limited to two decimal places. This gives a location within 1.11 km of the coordinates entered. With the locations of the PV plants specified, the 2014 NRSDB files were obtained from the NSRDB Application Programming Interface (API). A program was written in Python in order to automate the download process. The program code can be found in Appendix A: Python code for weather file download. Table 2 shows what the weather data looked like when it was output.

### Table 2: Example weather file output from NSRDB code

<table>
<thead>
<tr>
<th>Source</th>
<th>Location ID</th>
<th>City</th>
<th>State</th>
<th>Country</th>
<th>Lat.</th>
<th>Long.</th>
<th>Time Zone</th>
<th>Elevation</th>
<th>Local Time Zone</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSRDB</td>
<td>1055558</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>36.09</td>
<td>79.82</td>
<td>5</td>
<td>258</td>
<td>-5</td>
</tr>
<tr>
<td>Year</td>
<td>Month</td>
<td>Day</td>
<td>Hour</td>
<td>Minute</td>
<td>DHI W/m²</td>
<td>DNI W/m²</td>
<td>GHI W/m²</td>
<td>Solar Zenith Angle</td>
<td>Temp. °C</td>
</tr>
<tr>
<td>2014</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>166.024</td>
<td>-1.784</td>
</tr>
<tr>
<td>2014</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>166.820</td>
<td>-1.885</td>
</tr>
<tr>
<td>2014</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>164.625</td>
<td>-1.986</td>
</tr>
<tr>
<td>2014</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>160.426</td>
<td>-2.025</td>
</tr>
<tr>
<td>...</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2014</td>
<td>12</td>
<td>31</td>
<td>21</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>140.608</td>
<td>-0.308</td>
</tr>
<tr>
<td>2014</td>
<td>12</td>
<td>31</td>
<td>22</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>146.571</td>
<td>-0.715</td>
</tr>
<tr>
<td>2014</td>
<td>12</td>
<td>31</td>
<td>22</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>152.372</td>
<td>-1.057</td>
</tr>
<tr>
<td>2014</td>
<td>12</td>
<td>31</td>
<td>23</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>157.846</td>
<td>-1.399</td>
</tr>
<tr>
<td>2014</td>
<td>12</td>
<td>31</td>
<td>23</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>162.646</td>
<td>-1.591</td>
</tr>
</tbody>
</table>

### 3.3.2.2 SAM Simulation - NSRDB

Once weather files for the desired locations were obtained, code was written in Python to run simulations of the PV plants. The code was written to use the PVWatts5 simulation module
through System Advisor Model’s Software Development Kit (SDK) to simulate the electricity output and capacity factor based on input parameters and weather files. The detailed code can be found in Appendix B: Python code for PV plant simulation.

The input parameters used are the defaults from PVWatts. The system capacity was changed during each simulation to match the size of the plant for the location, most other parameters were held constant. The parameters used are shown below in Table 3.

**Table 3. Simulation Input Parameters**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Specific to PV Plant</th>
</tr>
</thead>
<tbody>
<tr>
<td>System Capacity</td>
<td></td>
</tr>
<tr>
<td>DC to AC Size Ratio</td>
<td>1.1</td>
</tr>
<tr>
<td>Tilt</td>
<td>25°, 50° and Latitude of plant</td>
</tr>
<tr>
<td>Azimuth</td>
<td>180°</td>
</tr>
<tr>
<td>Inverter Efficiency</td>
<td>96%</td>
</tr>
<tr>
<td>Losses</td>
<td>14.08%</td>
</tr>
<tr>
<td>Array Type</td>
<td>Fixed, open rack</td>
</tr>
<tr>
<td>Ground Coverage Ratio</td>
<td>0.4</td>
</tr>
</tbody>
</table>

The other parameters were held constant because of the variety in PV system design. There is no way to tell what the parameters of the proposed PV systems will be when they are built, therefore an assumption had to be made. For simplicity, the default values from PVWatts were assumed. The PVWatts documentation indicates that these are values are “appropriate for flat-plate photovoltaic systems with typical crystalline silicon or thin-film modules,” based on this description, the author believes that these values are also appropriate for this model [22].

The systems were simulated three times each at different tilt angles. The first simulation was at 25°, the default value in PVWatts, the second was 50°, two times the default and finally the simulation was done with the tilt angle equal to latitude. Looking at the simulation results, it was confirmed that a quick way to optimize a PV system is to set the tilt angle to the latitude. It is assumed that anyone who installs a PV system will, optimize their system to
some extent. By simply optimizing the tilt angle, we can conservatively account for this in our model.

At the end of each simulation, an output file is created with the specific parameters for the system, along with the generation output and capacity factor. Finally, the program puts together one output file with the AC power output of all of the systems combined. Table 4 shows the output of all of the systems modeled at different tilt angles.

**Table 4. AC Power Output of all Modeled PV Systems based on 2014 NSRDB Weather Files**

<table>
<thead>
<tr>
<th>Tilt Angle</th>
<th>25°</th>
<th>50°</th>
</tr>
</thead>
<tbody>
<tr>
<td>Latitude</td>
<td>1,474.80</td>
<td>1,483.63</td>
</tr>
<tr>
<td>Max AC Power (MW)</td>
<td>1,448.59</td>
<td>1,474.80</td>
</tr>
<tr>
<td>Total MWh</td>
<td>2,342,940</td>
<td>2,355,906</td>
</tr>
<tr>
<td>MWh Penetration</td>
<td>2.09%</td>
<td>2.11%</td>
</tr>
<tr>
<td>Capacity Factor</td>
<td>16.08%</td>
<td>16.17%</td>
</tr>
</tbody>
</table>

The solar PV penetration is the ratio of MWh generated by the modeled solar PV to the MWh of electricity generated by the power plants in NC and in the DEC/DEP control area in 2012 (111,962,013 MWh) [20].

Graphing the first three days of PV performance happens to provide an illustration of the erratic nature of PV electricity generation. It can be poor one day due to weather (January 2, 2014), and great the next (January 3, 2014). It can also vary significantly throughout the day.
In this paper we will consider the generation results from the second simulation. This is the simulation in which the PV panel’s tilt angle was set to that of the panel’s latitude location. The simulation results show that for the proposed 1,663.4 MW of PV facilities, the maximum AC power output was 1,474.8 MW, the total electricity output was 2,355,906 MWh and the capacity factor was 16.17%. This capacity factor can serve as a check to ensure that the model was executed accurately. The average capacity factor in North Carolina is between 15 and 20%. The capacity factor, as defined by the EIA, is “the ratio of the electrical energy produced by a generating unit for the period of time considered to the electrical energy that could have been produced at continuous full power operation during the same period” [5]. In this scenario, a capacity factor or 16% means that the generating facility on produces power 16% of the time, or about four hours per day.

3.4 Basic Modeling - eGRID

The Emissions & Generation Resource Integrated Database, or eGRID, was started in the 1990s. It was developed to serve as a preeminent source of data on the environmental attributes of almost all electric power generated in the United States. The database is updated every few years as new information becomes available, the most recent version, which we will use, was published in October 2015 and the data is from the 2012 calendar year. The
The database is comprehensive, listing characteristics and parameters of individual power plants including: state/county, owner/operator, emissions (annual and rates per unit of generation), resource type (gas, coal, solar, etc.), heat input and many more [20]. Most importantly for this project, eGRID provides a simple way to filter through thousands of electricity generators in the United States down to those only in North Carolina which are operated in Duke Energy Carolinas and Progress control areas.

eGRID tracks emissions rates for individual fuel sources (oil, gas, coal, etc.) and groups of sources (non-renewable, baseload units, etc.). With so much data available, it was necessary to determine which numbers were significant to this project and which were not. This issue was addressed by reviewing Susy Rothschild and Art Diem’s paper, “Total, Non-baseload, eGRID Subregion, State? Guidance on the Use of the eGRID Output Emission Rates” [23]. According to Rothschild and Diem, non-baseload emissions rates “were developed to provide an improvement over the fossil fuel output emission rates as an estimate of emissions reduction benefits from energy efficiency and clean energy projects” [23]. Therefore, the non-baseload emissions rates should be used to estimate avoided emissions due to renewable energy projects, and they can be used here to provide a rough estimate for expected reduction. These non-baseload rates have been meticulously developed to include plants that combust fuel, but have a capacity factor less than 0.8.

Additionally, eGRID data can be used to determine the current emissions rates and total annual emissions in the area of interest. These values will serve as a baseline to compare our results to and determine any improvements. These baseline emissions rates can also be used to provide a rough, order of magnitude estimate for the emissions reduction.

A more in-depth analysis of eGRID data and the results obtained using eGRID can be found in section 4.2.1 Emissions & Generation Resource Integrated Database (eGrid).

### 3.5 Intermediate Modeling - AVERT

The Avoided Emissions and Generation Tool (AVERT) was developed by the EPA to help states evaluate the expected impacts of proposed energy efficiency and renewable energy (EE/RE) policies and programs. The tool works by estimating displaced generation – the
generation that will not occur because of the improvements in energy efficiency and increased energy generation from renewable sources [24].

AVERT was intended to serve as an intermediate method for state air quality planners to use when quantifying the emissions impact of EE/RE programs. Basic methods, like multiplying non-baseload emissions rates by the avoided generation, can be too broad in the way that they quantify avoided emissions, as was discovered with the eGRID model (discussed later). Complex methods like Unit Commitment and Economic Dispatch models can be too costly or complicated for state planners to utilize. AVERT was intended to serve as a middle ground, and a “credible, free, user-friendly, and accessible tool” to quantify the displaced emissions of quantifies the sulfur dioxide (SO$_2$), nitrogen oxides (NO$_x$), and carbon dioxide (CO$_2$) [24].

AVERT is based entirely on public, historical data provided by the EPA. It is programmed to use statistical methods (Monte Carlo simulations) to analyze the historical operating characteristics of electric generators and predict future unit generation behaviors based on demand. In this way the program can designate certain generators as “must-run,” and determine forced and maintained outages. The program also maintains accurate representations of unit generation and emissions output capturing emissions rates during periods of high-load, start-up, seasonal changes, and decreasing heat rates. Although AVERT covers a lot of emissions and generation scenarios, it does have its limitations which designate it as an “intermediate” method. It cannot account for characteristics such as generator ramp rates, least-cost dispatch, changes in fuel economics, minimum down times and explicit relationships between generating units [24]. The results and limitations of this type of model are further discussed in section 4.2.2 Avoided Emissions and Generation Tool (AVERT).

3.6 Complex Modeling – Unit Commitment and Economic Dispatch

The most complex method for estimating emissions reductions from EE/RE involves gathering significant amounts of data and putting them together in a Unit Commitment and Economic Dispatch (UC-ED) model. These models allow users to develop an understanding of the interactions between electric load and generators on the power grid. Simply explained,
a UC-ED model schedules the dispatch of generating units based on the forecasted load and the cost to operate each of the available generators. It solves an optimization problem, to find the minimum operating cost while supplying enough electricity to meet demand. This is how most of the current research is being carried out, and this is also how generators are selected for dispatch in the real world [13] [14] [25]. This method will be presented at the end of the paper, as a topic for future work on the project.
4 DISCUSSION OF RESULTS

4.1 Baseline Emissions

In order to calculate emissions reductions, a baseline needs to be established, setting the foundation with data on current operations. Any predicted reductions in electric generation or emissions will be based on this data. This data is based on eGRID plant data from 2012. Filters were applied by state (NC) and power control areas (Duke Energy Carolinas and Duke Energy Progress). There are 153 electricity generating plants in this defined area. The total nameplate capacity for these plants is 32,791 MW and the annual generation was 111,962,013 MWh [20]. The peak demand for this area in 2012 was 32,666 MW according to FERC Form 714. The emissions data from this plants is perhaps the most relevant to the project and it is shown in Table 5.

Table 5. 2012 Emissions Data for all relevant generating plants in North Carolina

<table>
<thead>
<tr>
<th></th>
<th>Plant annual NO\textsubscript{x} emissions</th>
<th>Plant annual SO\textsubscript{2} emissions</th>
<th>Plant annual CO\textsubscript{2} emissions</th>
<th>Plant annual CH\textsubscript{4} emissions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output (tons)</td>
<td>46,471</td>
<td>58,353</td>
<td>60,342,671</td>
<td>1,272</td>
</tr>
<tr>
<td>Rate (lbs/MWh)</td>
<td>0.83</td>
<td>1.04</td>
<td>1077.91</td>
<td>0.0227</td>
</tr>
</tbody>
</table>

It is not surprising to see that CO\textsubscript{2} emissions rates are extremely high compared to other rates. This is simply because fossil fuels are primarily comprised of carbon and during the combustion process they combine with oxygen to form CO\textsubscript{2}. It is noteworthy to point out that compared to all of the eGRID subregions, North Carolina has one of the lowest CO\textsubscript{2} emissions rates at 1,077.91 lbs/MWh (although, it is not its own subregion). Comparatively, the CO\textsubscript{2} emissions rate for the United States was 1,136.53 lbs/MWh in 2012. This is explained by the area’s resource mix which is high in nuclear generation (about 50%).

The SO\textsubscript{2} and NO\textsubscript{x} emissions rates are also below average for the eGRID subregions and below the United States’ overall rate as well. The average NO\textsubscript{x} and SO\textsubscript{2} emissions rates for eGRID subregions were 1.41 lbs/MWh and 1.92 lbs/MWh, respectively. The United States’ emissions rates were 0.94 lbs/MWh and 1.89 lbs/MWh, respectively. High SO\textsubscript{2} and NO\textsubscript{x} rates are usually a sign of high levels of coal powered generation, as coal fuel has high sulfur and
nitrogen content as opposed to natural gas which is mostly comprised of CH₄. The takeaway here is that the emissions rates derived from eGRID are logical; there are no surprises based on the area’s resource generation mix.

4.2 Expected Results

Before formulating complex models and getting lost in the details, it is a good idea to do some preliminary calculations to set expectations. These calculations help establish limits for this problem. We wanted to know what results should set off red flags and indicate that the model may not be correct. In order to calculate an initial estimate of the emissions reduction associated with these new PV facilities, the EPA’s eGRID database was used. Then the Avoided Emissions and Generation Tool (AVERT) was used to confirm our initial findings. Finally, the data which was generated is used to come to a final conclusion regarding the effect of the new solar PV facilities on fossil fueled generators’ emissions.

4.2.1 Emissions & Generation Resource Integrated Database (eGrid)

EGRID data was used to formulate two estimates for emissions reductions. The first method was very basic, it used the baseline emissions data presented in the previous section. The second method was a slightly more complex, only considering the emissions rates of non-baseload generators in the reduction estimate.

The eGRID data that has been collected can be used to generate a conservative estimate of expected emissions reductions. One of the reasons that this is a conservative estimate is that eGRID does not account for transmission and distribution line losses. There are inherent inefficiencies associated with distributing electricity long distances at high voltage (and shorter distances at low voltage); therefore, more electricity must be produced than is demanded at any moment in time. Interestingly, the grid loss on the distribution side is higher than it is on the transmission side, since it is transmitted at a lower voltage. All of the PV facilities that have been modeled for this project are on the distribution side, which means if they are modeled to produce 2,355,906 MWh, a fossil fuel generator on the transmission side would have to produce more than 2,355,906 MWh to supply the same amount of energy to the grid. The grid loss will not be accounted for in this analysis since we are only interested in obtaining a rough, order of magnitude estimate. However, eGRID lists the grid loss factor. In the Eastern United States region the factor is 9.17% (2012) and it is 8.33% for the entire
country. Grid loss is significant when considering emissions reductions due to renewable sources that are connected to the distribution side of the grid, but it was not considered in this project.

4.2.1.1 Baseline Emissions Rates

The first reduction estimate was based solely on the known emissions rates for all of the generators in North Carolina, which is, the data presented in Section 4.1 Baseline Emissions. This method is the most basic which will be presented in this project. In order to calculate the emissions reductions from a specific amount electricity generated with solar PV, the emissions rate is multiplied by the amount of electricity generated by the solar PV. The underlying assumption with this method is that when a certain amount of electricity is generated using solar PV, then that amount of electricity does not need to be generated using fossil fuels. The introduction and literature review in this paper discusses the flaws with this assumption. However flawed this method may be, it represents the way that much of the general public views solar PV electricity generation (and all other renewable generation as well). This method will not only serve as a good discussion point after the results from all methods have been compiled, but it will also serve as a logical check for our problem. This method will provide a good “ballpark” number. It is expected that more complex solutions will yield results of the same magnitude, providing a way to judge the accuracy and completeness of more complex models.
The formula for calculating these reductions is simple.

\[ PER = \frac{ER \times AG}{C_1} \]

PER = Predicted Emissions Reduction (tons)

ER = Emissions Rate (lbs/MWh)

AG = Avoided Generation, 2,355,906 MWh

\( C_1 = \) Conversion Factor, 2,000 lbs/ton

The results are listed in Table 6.

Table 6. Predicted emissions reduction based on baseline emissions rates from eGRID 2012

<table>
<thead>
<tr>
<th>PER (tons)</th>
<th>Annual NO(_x) emissions</th>
<th>Annual SO(_2) emissions</th>
<th>Annual CO(_2) emissions</th>
<th>Annual CH(_4) emissions</th>
</tr>
</thead>
<tbody>
<tr>
<td>977.70</td>
<td>1,225.07</td>
<td>1,269,727</td>
<td>26.74</td>
<td></td>
</tr>
<tr>
<td>2.01%</td>
<td>1.93%</td>
<td>2.04%</td>
<td>1.95%</td>
<td></td>
</tr>
</tbody>
</table>

4.2.1.2 Non-baseload Emissions Rates

Using the previous 5 years of eGRID data (2005, 2007, 2009, 2010, 2012) two graphs were produced to show the trend of non-baseload unit emissions per unit of generation (lb/MWh or lb/GWh). Note that non-baseload emissions rates are only calculated for power control areas (PCAs). The DEC and DEP PCAs actually include 48 (out of 195) generators in South Carolina and Georgia. Despite this, the PCA non-baseload emissions rates were still used for estimates; since these are just baseline projections it is not imperative that they be exclusive to North Carolina. Figure 11 shows the non-baseload emissions rates for CH\(_4\), NO\(_x\), SO\(_2\), and CO\(_2\) trended over 5 years for Duke Energy Progress. Figure 11 shows the same trend for Duke Energy Carolinas.
Figure 11. Non-baseload emissions rates for CH$_4$, NO$_x$, SO$_2$, and CO$_2$ trended over 5 years for Duke Energy Carolinas and Progress

In Figure 11, there is a significant increase in DEP’s CH$_4$ emissions from 2010 to 2012. Examining the accompanying eGRID data, it was hypothesized that the rise came from an increase in natural gas generating units because natural gas is a main contributor to CH$_4$ emissions. Duke Energy Progress’s total nameplate capacity increased from 16,523 MW in 2010 to 21,505 MW in 2012. However, upon further investigation, total annual net generation actually decreased in the power control area. Without more detailed information, it is hard to say with certainty what caused the increase in the CH$_4$ emissions rate. Additionally, there is a chance that this is an outlier statistic, which is believed to be the case here, since the CH$_4$ emissions rate doubled over a two year period while net generation decreased. There would have had to have been a serious shift in the type of generating units or pollution control devices used to incur this type of change; evidence of this occurring in the data, specifically in the resource mix, is non-existent. The eGRID technical support document warns against outliers, therefore, it is assumed that this data point is a misrepresentation of CH$_4$ emissions rates in 2012 [26].
The emissions rates illustrated in Figure 11, however, follow the expected trend, they are relatively constant with a slight decreasing trend. The decreasing trend results from improved emissions reducing technologies and legislation passed throughout the years.

The emissions rates used to calculate the estimated reduction are a weighted average based on Power Control Authority (PCA), DEC or DEP, nameplate capacity. Note that these are different from the Baseline generation data. The difference arises from looking at individual plant data versus overall area data. The area includes states outside of NC, increasing overall generation numbers. PCA was used instead of plant data, which was used in the Baseline calculations, because it offers a pre-determined breakdown of baseload and non-baseload emissions and generation. Table 7 lists the values that were used to calculate the weight factors used to average the emissions rate.

**Table 7. Nameplate capacity and weight factors for estimated emissions reduction calculation**

<table>
<thead>
<tr>
<th></th>
<th>2012 Generation (MWh)</th>
<th>Weight Factor</th>
<th>2010 Generation (MWh)</th>
<th>Weight Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DEC</td>
<td>95,828,921</td>
<td>0.601</td>
<td>105,296,367</td>
<td>0.6115</td>
</tr>
<tr>
<td>DEP</td>
<td>63,852,150</td>
<td>0.399</td>
<td>66,905,518</td>
<td>0.3885</td>
</tr>
<tr>
<td>Total</td>
<td>159,681,071</td>
<td>1.000</td>
<td>172,201,885</td>
<td>1.000</td>
</tr>
</tbody>
</table>

After the weight factor was calculated using the nameplate capacities, the weighted emissions rates were found. Table 8 shows the emissions rates from the eGRID data.

**Table 8. Non-baseload emissions rates based on 2012 and 2010 eGRID data**

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>DEC (lb/MWh)</th>
<th>DEP (lb/MWh)</th>
<th>Weighted Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOx</td>
<td>2.28</td>
<td>1.58</td>
<td>2.00</td>
</tr>
<tr>
<td>SO2</td>
<td>4.54</td>
<td>1.41</td>
<td>3.29</td>
</tr>
<tr>
<td>CO2</td>
<td>1,840.55</td>
<td>1,927.94</td>
<td>1,875.50</td>
</tr>
<tr>
<td>CH4 (lb/GWh)*</td>
<td>34.67</td>
<td>23.12</td>
<td>30.18</td>
</tr>
</tbody>
</table>

*2010 Data was used due to potential reporting error in 2012 data*
With the weighted emissions rate, the predicted reduction in tons can be found simply.

\[ PER = \frac{WA \times AG}{C_1} \]

PER = Predicted Emissions Reduction (tons)

WA = Weighted Average Emissions Rate (lbs/MWh or lbs/GWh)

AG = Avoided Generation, 2,355,906 MWh

\[ C_1 = \text{Conversion Factor, 2,000 lbs/ton} \]

Table 9 shows the results from the calculations.

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Current Annual Emissions (tons)</th>
<th>Predicted Reduction (tons)</th>
<th>% Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO\textsubscript{x}</td>
<td>48,712</td>
<td>2,357</td>
<td>4.84%</td>
</tr>
<tr>
<td>SO\textsubscript{2}</td>
<td>63,460</td>
<td>3,871</td>
<td>6.10%</td>
</tr>
<tr>
<td>CO\textsubscript{2}</td>
<td>62,299,603</td>
<td>2,209,247</td>
<td>3.55%</td>
</tr>
<tr>
<td>CH\textsubscript{4}*</td>
<td>1,369</td>
<td>35.55</td>
<td>2.60%</td>
</tr>
</tbody>
</table>

*2010 Data was used due to potential reporting error in 2012 data

Based on eGRID non-baseload data, it is predicted that the proposed PV facilities will reduce CO\textsubscript{2} emissions by about 3.5%, NO\textsubscript{x} by 4.8% and, most notably, SO\textsubscript{2} emissions by 6.1%. Based on information in the introduction, natural gas generators are typically used for load following. Therefore, based on these results, it is predicted that natural gas generation would be reduced most significantly. Contrary to this hypothesis, the results from the eGRID calculations show high displacement of SO\textsubscript{2} and NO\textsubscript{x}. This suggests that mostly coal generation was displaced. The decrease in CH\textsubscript{4} emissions does indicate that there was a
reduction in natural gas generation, since natural gas combustion is the primary contributor to CH₄ emissions in electricity generation, according to average eGRID emissions data [20].

In order to confirm this theory, an investigation of how non-baseload generators are chosen was required. After referring to the eGRID technical support document; the high-level procedure for generating non-baseload emissions rates is as follows [26].

1. All units and prime movers that do not combust fuel (nuclear, hydro, wind, solar, and geothermal) are removed.
   a. Emissions rates are determined with unit or prime mover level data
2. Plants are assigned a weight factor based on amount of generation and emissions.
3. Units are divided into categories and assigned a baseload, non-baseload or semi-baseload based on capacity factor (CF).
   a. Non-baseload (factor = 1): CF < 0.2
   b. Semi-baseload (factor = -5/3*CF + 4/3): 0.2 < CF < 0.8
   c. Baseload (factor = 0): CF > 0.8
4. Finally, the total non-baseload generation and total non-baseload emissions are summed up for various levels of aggregation (state, power control authority, eGRID subregion, etc.)

Now, using this method it is possible to investigate eGRID data to determine if the coal displacement theory is correct. Analyzing unit data, there are 84 non-combustion based generating units (hydro, solar, nuclear, etc.) in the DEC/DEP power control area. There are 47 true non-baseload units (capacity factor greater than 0 and less than 0.2), six true baseload units (capacity factor greater than 0.8) and 37 units that are part baseload units. Now, consider the composition of the non-baseload units, illustrated in Figure 12.
The first thing noted was the high number of oil-fired units. These are have a capacity factor of 0.0027, so while they are true non-baseload units, they don’t contribute to the emissions reduction rates much. This is a result of step number two in the procedure listed above. The amount of non-baseload gas units is expected, as well as the number of semi-baseload biomass generators. The unexpected result, which supports the curtailed coal generation theory, is the number of non-baseload coal generators. Based on this analysis natural gas and coal generating units would be most affected by the increase in solar PV facilities, since these are considered typical peaking units.

To further confirm this theory, the average emissions rate for each type of generating unit can be analyzed. These rates are shown in Table 10.
Coal fired units have inherently higher NO\textsubscript{x} and SO\textsubscript{2} emissions when compared to natural gas and biomass fuels, as evidenced by the data shown above. Therefore, the coal generation displacement theory makes sense. Based on the eGRID non-baseload emissions calculation procedure, the oil emissions rates do not heavily factor into the emissions reduction rate, which is the only other logical explanation for the high NO\textsubscript{x} and SO\textsubscript{2} reductions.

This means that eGRID considers coal facilities to be non-baseload generators. This explains the disparity in the reduction estimates, coal contains higher concentrations of sulfur than natural gas, oil or biomass, resulting in coal-fired electric generators that have significantly higher SO\textsubscript{2} or NO\textsubscript{x} emissions rates.

This is an interesting finding because upon starting this project it was assumed that most coal generators were used for baseload generation, however, the data that has been found using eGRID suggests otherwise. It is important to note that this does not exclusively indicate that coal generators are being used to load follow, like natural gas units typically do. It could simply mean that the coal generators are being cycled frequently, or more likely, that they are being used as spinning reserves. In the case of spinning reserves, the generator runs constantly but does not produce any electricity, in case another generator unexpectedly turns off. A simple way to confirm or deny this notion is to look at the plant heat rates, how much heat is being used to generate one megawatt-hour of electricity (MMBTU/MWh). There are varying technologies in place in coal plants, but the historical average heat rate for coal plants is about 10.5 MMBTU/MWh according to an annual EIA report [27]. If the coal plants were being used as spinning reserves, they would have higher than normal heat rates as a result of combusting fuels (adding heat) and not producing electricity (MWh’s). This is

Table 10. Emissions rate for various types of generating units with capacity factors between 0 and 0.8 in the DEC/DEP Power Control Area (PCA)

<table>
<thead>
<tr>
<th>Fuel</th>
<th>NO\textsubscript{x} (lb/MWh)</th>
<th>SO\textsubscript{2} (lb/MWh)</th>
<th>CO\textsubscript{2} (lb/MWh)</th>
<th>CH\textsubscript{4} (lb/GWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal</td>
<td>2.90</td>
<td>8.56</td>
<td>2,523.59</td>
<td>49.99</td>
</tr>
<tr>
<td>Biomass</td>
<td>0.77</td>
<td>1.26</td>
<td>117.90</td>
<td>157.12</td>
</tr>
<tr>
<td>Gas</td>
<td>1.75</td>
<td>0.16</td>
<td>2,422.55</td>
<td>44.61</td>
</tr>
<tr>
<td>Oil</td>
<td>72.63</td>
<td>4.70</td>
<td>4,876.51</td>
<td>208.27</td>
</tr>
</tbody>
</table>

Coal fired units have inherently higher NO\textsubscript{x} and SO\textsubscript{2} emissions when compared to natural gas and biomass fuels, as evidenced by the data shown above. Therefore, the coal generation displacement theory makes sense. Based on the eGRID non-baseload emissions calculation procedure, the oil emissions rates do not heavily factor into the emissions reduction rate, which is the only other logical explanation for the high NO\textsubscript{x} and SO\textsubscript{2} reductions.

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evident in the eGRID data. There are several plants in North Carolina, and other locations, that show extreme heat rates indicating they are spinning reserve facilities. For example, the Cleveland County Generating Facility, a 736 MW gas generating facility, had a capacity factor of less than 0.1% and a heat rate of 166.7 MMBTU/MWh. This is significantly higher than the average heat rate for a gas-fired generating plant, 8.0 MMBTU/MWh [27]. The heat input to the plant was about 305 MMBTU and it generated about 1,800 MWh. This is not the case with the coal plants under investigation, the average heat rate for these plants is 11.24 MMBTU/MWh, slightly higher than the national average, but not enough of a difference to support the spinning reserve idea.

Further investigation revealed that the data used for analysis was the problem. Plant level data from eGRID was analyzed as opposed to generator data. Each plant in eGRID is made up of one or more generators, all of which may or may not be constantly running. However, because the generators are in place at the plant, they are considered in the name plate capacity, which is used to calculate the capacity factor. The most likely answer to this coal curtailment conundrum is that not all of the generators at coal plants are being run all of the time. This would result in a low capacity factor appearing for the generating plant, even if the generators that are running are fully loaded, and have higher individual capacity factors.

We investigated the generator level data for several of the plants to confirm this. The best examples are the Cliffside and G.G. Allen coal plants. According to plant level data Cliffside has a nameplate capacity of 1,480 MW and a capacity factor of 0.0911, G.G. Allen has a capacity of 1,155 MW and a capacity factor of 0.193. The generator level data reveals a different story, the Cliffside coal plant is actually comprised of seven generators and the G.G. Allen plant comprised of five individual generators. As shown in Table 11, none of the individual generators at the plants had the same capacity factor, they all ran for different amounts of time.
Table 11. Individual generator data from eGRID

<table>
<thead>
<tr>
<th>Plant name</th>
<th>Nameplate capacity (MW)</th>
<th>Capacity factor (%)</th>
<th>Annual net generation (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cliffside</td>
<td>40.00</td>
<td>0.00</td>
<td>0</td>
</tr>
<tr>
<td>Cliffside</td>
<td>40.00</td>
<td>0.00</td>
<td>0</td>
</tr>
<tr>
<td>Cliffside</td>
<td>65.00</td>
<td>0.00</td>
<td>0</td>
</tr>
<tr>
<td>Cliffside</td>
<td>65.00</td>
<td>0.00</td>
<td>0</td>
</tr>
<tr>
<td>Cliffside</td>
<td>570.90</td>
<td>22.88</td>
<td>1,144,368</td>
</tr>
<tr>
<td>Cliffside</td>
<td>909.50</td>
<td>0.47</td>
<td>37,401</td>
</tr>
<tr>
<td>Cliffside</td>
<td>800.00</td>
<td>0.00</td>
<td>0</td>
</tr>
<tr>
<td>G G Allen</td>
<td>165.00</td>
<td>6.92</td>
<td>100,069</td>
</tr>
<tr>
<td>G G Allen</td>
<td>165.00</td>
<td>5.41</td>
<td>78,152</td>
</tr>
<tr>
<td>G G Allen</td>
<td>275.00</td>
<td>25.17</td>
<td>606,229</td>
</tr>
<tr>
<td>G G Allen</td>
<td>275.00</td>
<td>32.27</td>
<td>777,282</td>
</tr>
<tr>
<td>G G Allen</td>
<td>275.00</td>
<td>16.06</td>
<td>386,992</td>
</tr>
</tbody>
</table>

When looking at the generator data it becomes clear that lower than expected capacity factors are a result of the independent operation of generators. A capacity factor based on weighted average (weighted by total generation output) would be more effective for these types of plants, rather than the plant nameplate capacity and generation output that eGRID uses. A weighted average calculation yields a capacity factor of 24.5% for G.G Allen and 22.2% for Cliffside. With these capacity factors the subsequent eGRID calculations for non-baseload emissions rates would have treated the coal plants differently, resulting in different emission rates.

Based on these findings it is expected that this mildly inaccurate representation of non-baseload plants will make the emissions reduction estimates in this section less conservative (over estimates). The estimates provided here will serve as a ceiling, it is expected that with more sophisticated modeling, the emissions reductions in SO₂, NOₓ, and CO₂ will be lower than that which was predicted using 2012 eGRID data.
4.2.1.3 Baseline versus Non-baseload Predictions

The two sets of emissions reductions that have been calculated so far represent very rough numbers. As discussed already, the baseline calculation will serve as an order of magnitude check, while the non-baseload calculation will serve as an upper limit for the problem. Table 12 shows the results of the basic methods for predicting emissions reductions.

Table 12. Comparison of basic predicted emissions reduction (PER) results

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>2012 Emissions, Tons</th>
<th>Baseline Method</th>
<th>Non-Baseload Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PER, Tons</td>
<td>% Reduction</td>
<td>PER, Tons</td>
</tr>
<tr>
<td>NOx</td>
<td>48,712</td>
<td>977.7</td>
<td>2.01%</td>
</tr>
<tr>
<td>SO2</td>
<td>63,460</td>
<td>1,225</td>
<td>1.93%</td>
</tr>
<tr>
<td>CO2</td>
<td>62,299,603</td>
<td>1,269,727</td>
<td>2.04%</td>
</tr>
<tr>
<td>CH4*</td>
<td>2,737,139</td>
<td>26.74</td>
<td>1.95%</td>
</tr>
</tbody>
</table>

Table 13 showcases one of the disparities of the two basic methods. The non-baseload method encompassed more generating units than the baseline method. The baseline method only captured the generators in North Carolina, while the non-baseload method capture all of the generators in the DEC/DEP power control area. This difference resulted in the same amount of fossil fueled generation being displaced, but a lower percent reduction overall.

Table 13. Differences in generation data and electricity generation reductions for the basic prediction methods

<table>
<thead>
<tr>
<th>Calculation Method</th>
<th>2012 Electricity Generation, MWh</th>
<th>Modeled PV Generation, MWh</th>
<th>Red. in Fossil Fuel Generation, MWh</th>
<th>% Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>111,962,013</td>
<td>2,355,905</td>
<td>2,355,905</td>
<td>2.10%</td>
</tr>
<tr>
<td>Non-Baseload</td>
<td>159,681,071</td>
<td>2,355,905</td>
<td>2,355,905</td>
<td>1.48%</td>
</tr>
</tbody>
</table>

It is noted that while the non-baseload method accounts for higher levels of electricity generation, this does not factor into the predicted emissions reduction. This can be explained by considering the reduction in fossil fueled generation, this value is the same for both methods since both methods assume that 1 MWh of PV generation can displace 1 MWh of fossil fueled generation.
The reason that the Predicted Emissions Reduction (PER) calculated using the Non-Baseload Emissions Rates (NBER) was so much higher than that calculated using the Baseline Emissions Rate (BER) can be explained simply. Once again, consider the types of generating units that make up the non-baseload fleet; they are all fossil fuel units. Now, consider that within the DEC and DEP power control areas, 58.9% and 41.9% of all electricity generation was provided by nuclear power plants, respectively. Considering that the main pollutant from nuclear power plants is water vapor (they do not emit any NO\textsubscript{x}, SO\textsubscript{2} or CO\textsubscript{2} [28]), these units drive the apparent emissions rates for other pollutants, like CO\textsubscript{2} and NO\textsubscript{x}, in the control area down. This is a result of the nuclear plants producing a lot of electricity (MWh) and not a lot of emissions (lbs). However, when only considering the fossil fueled, non-baseload units, the overall emissions rates are higher because all of the units produce pollutants. Realizing this, it is very logical that the PER found using the NBER is significantly higher than that found using the BER.

It is also noteworthy that although the eGRID 2012 CH\textsubscript{4} emissions rates were discounted as erroneous in the NBER calculation (2010 was used instead), in the BER calculations 2012 data is sufficient. This is because the emissions rate was calculated using plant data rather than power control area data. Additionally, it was calculated by simply dividing the amount of CH\textsubscript{4} emissions (lbs) by the electricity generated (MWh). Comparing the CH\textsubscript{4} emissions to historical data, the rate presented in the BER section does not raise any red flags to indicate that it may be erroneous, therefore, it is assumed that it is adequate for an order of magnitude calculation.

### 4.2.2 Avoided Emissions and Generation Tool (AVERT)

As discussed previously, AVERT is a tool used to estimate the amount of emissions that would be replaced by new Energy Efficiency and Renewable Energy measures (EERE). In order to model the displaced emissions there are two key inputs: model location and EERE data. Model location can have a large impact on the model for a few reason. One reason that location is important is because electricity demand varies widely across the country, mostly due to differences in weather. Additionally, grid infrastructure can have an impact on electricity balancing and grid stability as well. Some Regional Transmission Organizations
(RTOs) or balancing authorities (BAs) may have the infrastructure in place to allow an adequate amount of electricity to flow between BAs during a fluctuation in demand, while others have to rely more heavily on altering their generators output. This is a result of transmission constraints, the physical power lines connecting BAs and RTOs around the country can restrict the amount of electricity flow between areas. Due to the wide variation of electricity demand across the country and grid infrastructure, AVERT has divided the country into multiple regions. These regions are shown in Figure 13.

![Figure 13. Map of AVERT Regions [24]](image)

These regions were developed with much thought and research. They accurately reflect where electricity in a region is generated and, thus, where emissions displacements will occur. The area of interest for this project is North Carolina, therefore our models will be mostly focused on the Southeast (SE) region.

The Energy Efficiency and Renewable Energy (EERE) program characteristics are important as well. The underlying algorithms of AVERT require hourly profiles for any EERE programs that are to be modeled. Users can enter their own hourly data for an EERE program or they can choose from several options built into AVERT to create an estimated profile. Figure 14 shows the EERE profile input screen. This screen shows some of the options
available to those who do not already have hourly data for their EERE program. The solar and wind impact profiles are calculated based on proxy renewable energy profiles developed for each region. The Utility and Rooftop PV proxies were created using hourly capacity factors obtained from PVWatts (v1). The wind proxies were also created using hourly capacity factors, these were developed from annual 6-hour datasets [24].

Figure 14. Screenshot of AVERT, showing the input screen for EERE profiles

When modeling grid operations with AVERT, a few different approaches were taken using different regions and different EERE programs. The scenarios are listed below.

1. Southeast region modeled using the AVERT utility scale PV renewable energy proxy.
   a. 1,644 MW of PV, and 2,775,800 MWh
2. Southeast region modeled using the PV simulation data from section 3.3.2 Modeling.
   a. 1,644 MW of PV, and 2,355,905 MWh
3. Southeast region modeled with 18,000 MW of utility scale PV (data from renewable energy proxy).
   a. 18,000 MW of PV and 30,416,800 MWh
4. A modified region which only included North Carolina generators and the modeled PV data
   a. 1,644 MW and 2,355,905 MWh
Further discussion of the results is presented after the results from each model.

### 4.2.2.1 Southeast Region Model

The first model that was executed was intended to gain a sense of the overall program, how it works, the outputs, and to get familiarized with the program. For this, the Southeast region was chosen. The EERE program which was modeled was a 1,644 MW utility scale capacity. This is the same capacity that was modeled using PVWatts for all of the proposed facilities in NC. The result of the EERE program was a 2,775,800 MWh reduction in fossil fuel generation, a 0.37% reduction. The Southeast region has a fossil fuel capacity of about 452,000 MW. The results of the model are shown in Table 14.

**Table 14. Southeast region, 1,644 MW modeled using utility scale proxy**

<table>
<thead>
<tr>
<th></th>
<th>Original</th>
<th>Post-EERE</th>
<th>Impacts</th>
<th>% Red.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation (MWh)</td>
<td>742,905,700</td>
<td>740,129,900</td>
<td>-2,775,800</td>
<td>0.37%</td>
</tr>
<tr>
<td>Total Emissions</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SO₂ (lbs)</td>
<td>1,706,727,000</td>
<td>1,700,161,600</td>
<td>-6,565,400</td>
<td>0.38%</td>
</tr>
<tr>
<td>NOₓ (lbs)</td>
<td>824,156,000</td>
<td>820,974,200</td>
<td>-3,181,800</td>
<td>0.39%</td>
</tr>
<tr>
<td>CO₂ (tons)</td>
<td>563,671,400</td>
<td>561,714,700</td>
<td>-1,956,700</td>
<td>0.35%</td>
</tr>
<tr>
<td>Emission Rates</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SO₂ (lbs/MWh)</td>
<td>2.297</td>
<td>2.297</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NOₓ (lbs/MWh)</td>
<td>1.109</td>
<td>1.109</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CO₂ (tons/MWh)</td>
<td>0.759</td>
<td>0.759</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The Southeast region, by generation (MWh) is about seven times as large as the North Carolina area explored in the basic models. This explains why the percent reduction is so much smaller than what was seen previously. The regional generation increased by the proposed but PV generation did not.

For this model, the AVERT renewable energy proxy was used. This is why the generation impact shown in Table 14, 2,775,800 MWh, is different than what was modeled earlier, 2,355,905 MWh. The difference between these is rather large at 419,895 MWh, or 16% of what our PV model estimated. This is a direct result of the RE proxy that AVERT employs. This proxy uses hourly capacity factors estimated by PVWatts over the entire region. Given this less detailed method of PV modeling and considering that not all of the Southeast has the
same capacity factor as North Carolina, it is not surprising that there is a difference between the PV generations calculated by AVERT and that shown in section 3.3.2.2.

![Figure 15. Top 10 days for solar PV generators](image)

Continuing on with the results from this model, the displacement data for the top ten days is easily examined with the tool’s interface. The figure shows that in some cases more fossil fuel generation was displaced than was expected based on the PV model, and at other times, less fossil fuel generation can be displaced than expected.

The final output that was examined for this run was the signal-to-noise diagnostic shown in Figure 16.
This figure is a scatterplot of every hour of the year modeled, it shows “calculated total generation reduction in each hour (y-axis) against user-input EE/RE load reduction in each hour (x-axis).” In an ideal scenario, AVERT would perfectly match unit generation reduction to the amount requested by the user’s EERE load profile. If generation reduction is well-matched to the EERE load reduction, the graph will show a relatively straight, clustered line. If the line shows significant scatter, this signifies that the generation reduction does not capture the EERE load reduction well. The R² value can be used to evaluate the EERE/reduction match. A high R² value signifies a good match (greater than 0.9), a 1 MWh reduction through EERE programs will results in a 1 MWh reduction of fossil fuel generators. A low R² value suggests that the EERE program is insufficiently sized to produce the desired effect (a 1:1 generation reduction). For example, “a value of 0.7 indicates that AVERT has only correctly captured 70 percent of the EE/RE required by the user (i.e., noise
accounts for 30 percent of the observed variability.” In this example, with an $R^2$ value of 0.98, there is a high correlation, the modeled EERE program has produced the desired effect and been simulated accurately [24].

4.2.2.2 Southeast Region – PV Model Comparison

In order to gain an understanding of how AVERT’s renewable energy proxies work, the same model was run again, except this time the hourly PV data generated from our PVWatts model was used. The results of the model are shown in Table 15.

**Table 15. Southeast region, 1,644 MW modeled using PVWatts**

<table>
<thead>
<tr>
<th></th>
<th>Original</th>
<th>Post-EERE</th>
<th>Impacts</th>
<th>% Red.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation (MWh)</td>
<td>742,905,700</td>
<td>740,561,200</td>
<td>-2,344,500</td>
<td>0.32%</td>
</tr>
<tr>
<td>Total Emissions</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SO$_2$ (lbs)</td>
<td>1,706,727,000</td>
<td>1,701,168,500</td>
<td>-5,558,600</td>
<td>0.33%</td>
</tr>
<tr>
<td>NO$_x$ (lbs)</td>
<td>824,156,000</td>
<td>821,456,900</td>
<td>-2,699,100</td>
<td>0.33%</td>
</tr>
<tr>
<td>CO$_2$ (tons)</td>
<td>563,671,400</td>
<td>562,014,500</td>
<td>-1,656,900</td>
<td>0.29%</td>
</tr>
<tr>
<td>Emission Rates</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SO$_2$ (lbs/MWh)</td>
<td>2.297</td>
<td>2.297</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NO$_x$ (lbs/MWh)</td>
<td>1.109</td>
<td>1.109</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CO$_2$ (tons/MWh)</td>
<td>0.759</td>
<td>0.759</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

When comparing PV models, emphasis should be on the generation impact and % Red. from Table 15. The PVWatts model, shown above, estimated a 2,344,500 MWh reduction in fossil fuel generation. The AVERT utility scale proxy estimated a reduction of 2,775,800 MWh. This is a large difference in MWh, about 431,000 MWh, however, in this model the difference is insignificant. The percent reduction in generation and emissions is less than 0.05%.

The conclusion here is that PV generation profiles need to be consistent among models with smaller simulation regions. In large simulation regions, such as the Southeast, the difference is lost in the noise of other generators. The result is an insignificant difference in the estimated impact of the EERE program. In smaller regions, such as North Carolina, a difference of 431,000 MWh would have a significant effect on the estimated emissions reduction.
The other results from this model do not show anything substantially different from the first model. The $R^2$ value is 1.00. The top ten peak days are different, but that is to be expected with different PV simulation data, and the magnitude of differences between displaced and expected displaced generation are within 200 MWh of each other.

Note that the difference between generation from the PVWatts model in Section 3.3.2.2, 2,355,905 MWh, and the generation impact shown in Table 15. Southeast region, 1,644 MW modeled using PVWatts is due to rounding. AVERT rounds manual EERE profiles to the nearest integer value. Additionally, if the signal-to-noise diagnostic is not near 1, then the generation impact will be less than the total PV generation.

**4.2.2.3 Southeast Region Scale Up**

Before attempting to create a model of the North Carolina grid, another Southeast simulation was performed. In this model, the PV penetration in the Southeast was scaled up to that which was modeled for North Carolina, about 2.11% (Table 4. AC Power Output of all Modeled PV Systems based on 2014 NSRDB Weather Files), or about 4% of the fossil fuel load. This resulted in about 18,000 MW of solar PV since the region has a capacity of about 475,000 MW, as programmed in AVERT. The results are shown in Table 16.

| Table 16. Southeast region, 18,000 MW modeled using utility scale proxy |
|-----------------------------------------------|-----------------|-----------------|-----------------|-----------------|
| Generation (MWh)                             | Original        | Post-EERE       | Impacts         | % Red.          |
|                                               | 742,905,700     | 727,694,800     | -30,416,800     | 4.09%           |
| Total Emissions                               |                 |                 |                 |                 |
| SO₂ (lbs)                                     | 1,706,727,000   | 1,635,235,700   | -71,491,300     | 4.19%           |
| NOₓ (lbs)                                     | 824,156,000     | 789,984,200     | -34,171,800     | 4.15%           |
| CO₂ (tons)                                    | 563,671,400     | 542,369,700     | -21,301,700     | 3.78%           |
| Emission Rates                                |                 |                 |                 |                 |
| SO₂ (lbs/MWh)                                 | 2.297           | 2.295           |                 |                 |
| NOₓ (lbs/MWh)                                 | 1.109           | 1.109           |                 |                 |
| CO₂ (tons/MWh)                                | 0.759           | 0.761           |                 |                 |

The original emissions rates for the Southeast region can be compared to those for the North Carolina region to get a sense of how these results may apply to the North Carolina region.
<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Southeast</th>
<th>North Carolina</th>
<th>% Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO\textsubscript{x} (lb/MWh)</td>
<td>1.11</td>
<td>0.83</td>
<td>29%</td>
</tr>
<tr>
<td>SO\textsubscript{2} (lb/MWh)</td>
<td>2.27</td>
<td>1.04</td>
<td>74%</td>
</tr>
<tr>
<td>CO\textsubscript{2} (lb/MWh)</td>
<td>1,518</td>
<td>1,078</td>
<td>34%</td>
</tr>
</tbody>
</table>

The emissions rates, as discussed previously, can offer some insight into the types of generators being used in a region, for example, high SO\textsubscript{2} emissions signify more coal generation. In this comparison it is noted that with such large differences in emissions rates, there might not be much correlation between the emissions reductions in the Southeast and North Carolina, as hoped. This will be explored further in section 4.2.2.5 Emissions Reductions from EERE Programs in the AVERT Southeast Region Compared to the User-Created North Carolina Region.

To further analyze the data from the resulting model, Figure 17 provides a graphical representation. This is an interesting graphic because it illustrates the coincidence between the peak output of solar PV and the peak electrical demand. The pre-EERE line shows the cyclical, hourly fossil fuel load before the solar PV generation was considered. The post-EERE line shows the fossil fuel load after the solar PV generation was considered. The yellow area between the two lines illustrates the displaced generation resulting from the EERE program. This week was chosen because it contains the five highest days of generation displacement for the simulated year. The top five days were August 1\textsuperscript{st}-5\textsuperscript{th}. During these days 900,900 MWh of fossil fuel generation, 1,189 tons of NO\textsubscript{x}, 629 tons of SO\textsubscript{2} and 654,900 tons of CO\textsubscript{2} were avoided.

Figure 18 illustrates the generation impact on individual generating units.
Fossil-fuel load, pre- and post-EERE, in Week of 8/1

Figure 17. Fossil fuel load displacement for the week of August 1, 2012
Figure 18. Hourly displacement from each generating unit for the week of August 1, 2012
Figure 18 is a little hard to comprehend at first glance. The graph along the bottom, “Total Fossil-fuel Load (MW),” shows the pre-EERE load. The yellow line, “Total Change in Generation (MW),” depicts the amount of generation that has been avoided due to the EERE program. The alignment of these peaks coincides with the displaced load in Figure 17.

The other part of this graph is the shading, which depicts the changes to individual electric generators. The shading is made up of stacked, gradated bar plots. For every hour during the week there is one bar, which is one of many shades of blue, for each active generator. If the plot is below the x-axis, the generator’s output was decreased due to the EERE program. The total contribution of all generators adds to the total change in generation.

The shade of the bar, ranging from dark to light blue, signifies the capacity factor of the generators, with dark blue areas representing high capacity factor baseload units, and the light areas representing low capacity factor, peaking units. One trend that was noticed was that mostly baseload units were displaced in the early hours of PV generations and mostly peaking units were displaced during the peak of the change in generation. This can be explained by looking at the total fossil fuel load graph in the lower part of the figure.

In the early hours that the PV starts generating electricity (where the yellow line moves from zero), more baseload units are displaced. Examining these hours on the fossil fuel load graph, you can see that the PV generation starts when the fossil fuel load is beginning to rise out of its cyclic trough. This represents a summer morning when utility customers begin to wake up and use more electricity, increasing demand. This period in the load cycle is actually the time that baseload units were designed for, mostly serving the “baseload,” or the load which is generally constant. It appears that the PV is beginning to generate enough electricity to offset some of the power coming from baseload units, rather than peaking units, almost immediately when they start generating power. However, as the day continues, as the demand for electricity begins increasing across the region, the PV generation begins to displace more peaking units. This makes a lot of sense because according to how most electric grids operate now, as the demand begins to rise throughout the day, following its predicted cycle, more peaking units are brought online to serve this cyclic load that is above the baseload. This is why the number of displaced baseload units steadily decrease throughout the day and the number of displaced peaking units increase.
The other phenomena that occurs in the figure is an positive change in generation. It was unexpected that there would be increases in generation. However, after consulting the AVERT user manual, a quick explanation was found. The manual describes increases in generation as a result of maintenance outages in the base year data, this is how AVERT accounts for forced outage rates [24]. The outage of one generating unit would result in a decrease in generation for that unit, and an increase in generation for another unit, and a corresponding plot above the x-axis.

The previous figures and analysis have been for the PV’s top performing summer week. Now, a winter month will be analyzed. Winter months are interesting because a typical winter day usually has two demand peaks, one in the morning and one at night. This is usually explained by utility customers waking up early in the morning, turning up the heaters in their homes and then leaving, as the hours of the day move on, the temperature outside gets warmer and the heaters don’t have to work as hard. When the customers return home in the evening, it gets dark early so customers turn on more lights, and the temperature begins to go down again so they turn the heat up. This cycle of activity creates a unique demand profile, illustrated in Figure 19.
It is interesting that on February 1st and 2nd, 2012, the electric demand is fairly constant for a long period of time during the day. As a result of this, mostly baseload generators are displaced by the PV generation. This makes sense because, as discussed in the introduction of this paper, utilities often use day-ahead planning based on historical data to predict the next day’s load, and schedule generators. If the utilities could accurately predict a constant demand on days such as February 1st and 2nd, they would be more likely to schedule a baseload generator(s) to ramp up to that generating level to supply the load since these are usually the most efficient generators. Considering that this model does not take into account predicted generation from EERE programs, it makes sense that baseload generators would be displaced when electric demand is relatively constant. Although, this could lead to an over
estimate of emissions reduction, because in reality, utilities will account for predicted
generation from EERE programs when they are scheduling generators in the day-ahead
market.

On some days, like February 3rd, 4th, 6th and 7th, a decrease in demand sometimes occurs
between demand peaks. This creates a trough between the two peaks rather than a flat line
constant demand. When a decrease occurs between two peaks more peaking generating units
are displaced. This is a result of the utility effectively using scheduling to serve the peak
demand loads with low capacity factor units, designed for ramping capacity up and down
easily. As the demand begins to decrease and PV generation increases, the need for peaking
units decreases more quickly that it would if there were no PV generation. Additionally, as
demand decreases to the point at which the peaking units are shut down, PV generation
continues to stay high, forcing a change in output of some baseload generators. This explains
why, even though some peaking generators are displaced, there is still a high number of
baseload units which have generation that is displaced.

The analysis of the Southeast section may seem a little bit out of place given that this project
focuses on North Carolina and that it was found that there may not be much correlation
between the two regions based on current emissions rates. However, it is important to have
an understanding of how the larger region, which encompasses the DEC and DEP electric
grids, operates. Electric grids in the United States, as discussed previously, do not operate by
themselves. These grids are all interconnected, depending on one another to supply electricity
in times of deficit and take electricity in times of surplus. Therefore, it is necessary to have a
solid understanding of how that larger area would function with a similar EERE program. It
may offer some insight into an area that may otherwise have been lost. It also provided an
opportunity to familiarize ourselves with AVERTs capabilities and its limitations. Now that a
thorough understanding of how AVERT works has been established, an attempt can be made
to use it to analyze the impact of the proposed EERE program on the DEC and DEP service
areas in North Carolina.
4.2.2.4 Modified Region – North Carolina Only Generators

The final simulation that was done with AVERT was using it to simulate the North Carolina region. However, AVERT does not have regions that are broken down as far as states, therefore some of the tools provided with AVERT had to be used to create a new region.

AVERT is made up of three distinct components: main module, statistical module and the future year scenario template. The main module is the main graphical interface for the program, and what most users will interact with. The main module handles every analysis year, this is where users choose which region and year they would like to analyze. For each region and data year there is a Regional Data File, or RDF, that contains all the output from the statistical module needed to run a simulation.

The statistical module is MATLAB based, it performs analysis on historical data (generation, heat input, etc.) to produce the individual RDFs. The statistical module analyzes both plant data from eGRID and the EPA’s Clean Air Markets Division (CAMD’s) Air Market Program Data (AMPD) to predict the generation and emissions profile for a given year and region. The predefined regions in AVERT can be modified using the future year scenario template. The template allows users to simulate how a region will operate in a future year when the generators that provide the electricity have evolved or changed. For example, a user may wish to model the effects of retiring certain power plants, or changing emissions rates on a regions electricity generation and emissions output [24].

4.2.2.4.1 Modifying AVERT Regions

Using these components, a dedicated North Carolina region was developed within the program. First, the region had to be created, this required two main modifications, the region had to be programmed into all of the menus since it did not exist, and then it had to be defined by reassigning the generators to the appropriate region. In the main module, the “EnterRegionalData” sheet was edited to include a North Carolina region in the drop down menu. In the “EERE_Default” sheet, a North Carolina region needed to be defined for the EERE proxies; because the PV data that was modeled would be used rather than the proxy, Southeast region’s RE profile was copied and renamed. This was more of a formality to reduce the number of errors received when the program ran. At this point a North Carolina region has been established, however, it has no generating units with in it. To add generating
units, the future year scenario template needed to be edited, to assign generators to the region. Then the statistical module was run to simulate those units.

In the future year scenario template, an Excel workbook, each sheet was meticulously reviewed. Anywhere in the workbook where there were relations between state and region or region and generator, these were changed to assign all generators in North Carolina to the North Carolina region. Additionally, AVERT uses the most recent eGRID data available for the program year, when AVERT 2012 was developed, eGRID plant09 (2009 plant level data) was used. This data was updated as well, to include eGRID 2012 data, this way the results should be more closely aligned with the basic modeling that was done earlier in the project using eGRID. Now that the future year scenario template has been modified, the statistical model must be edited.

The statistical model was similar to the main module in that it was simple to edit. There are two MATLAB files which contain all of the variables for the statistical module, “AVERT_regionNames,” and “AVERT_CAMDAry_2012.” In the region names file, it was as simple as editing the two variables in the file to include a North Carolina region. In the CAMD array, a short MATLAB program was written (code shown in Appendix C: CAMD_Edits.m), to search through all of the facilities in the CAMD array and look for those located in North Carolina. Once the generators in NC were located, their regions were changed to NC. The CAMD array and region names were then saved and the statistical module was run. To test the alterations a small number of Monte Carlo runs were used for the first simulation of the NC region, as suggested by the AVERT user manual. Using 10 Monte Carlo runs and generation-only Monte Carlo runs, the statistical module was successfully executed with no errors, signifying that the inputs and outputs are correctly read.

Next, the output file from the statistical module, the Regional Data File, needed to be tested to ensure that it was written correctly with realistic data. The new NC RDF was loaded into the main module and executed with modeled PV data. Table 18 shows the results.
Table 18. North Carolina Region, 1,644 MW modeled using PVWatts

<table>
<thead>
<tr>
<th></th>
<th>R² = 1.00</th>
<th>Original</th>
<th>Post-EERE</th>
<th>Impacts</th>
<th>% Red</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation (MWh)</td>
<td></td>
<td>58,088,000</td>
<td>55,750,700</td>
<td>-2,337,400</td>
<td>4.02%</td>
</tr>
<tr>
<td>Total Emissions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SO₂ (lbs)</td>
<td>96,841,900</td>
<td>92,276,400</td>
<td>-4,565,500</td>
<td>4.71%</td>
<td></td>
</tr>
<tr>
<td>NOₓ (lbs)</td>
<td>69,655,100</td>
<td>66,360,600</td>
<td>-3,294,500</td>
<td>4.73%</td>
<td></td>
</tr>
<tr>
<td>CO₂ (tons)</td>
<td>47,005,800</td>
<td>45,103,200</td>
<td>-1,902,600</td>
<td>4.05%</td>
<td></td>
</tr>
<tr>
<td>Emission Rates</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SO₂ (lbs/MWh)</td>
<td>1.667</td>
<td>1.655</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NOₓ (lbs/MWh)</td>
<td>1.199</td>
<td>1.19</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CO₂ (tons/MWh)</td>
<td>0.809</td>
<td>0.809</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The results show that the modifications to the AVERT program was successful. The program was able to successfully calculate the emissions reduction associated with the implementation of a 1,644 MW solar PV system. The signal-to-noise diagnostic graph for this simulation revealed an R² value of 1, which also signifies that the modification was successful.

One point to note here is the generation that AVERT predicts for this region. The program is using eGRID 2012 plant level data to make predictions for future fossil fuel generator demand. When the RDF is loaded, 106 fossil fueled generators are loaded, this is very close to the 101 generators that were found by manually sorting the eGRID plant data file. However, when the main module is executed, only 58,088,000 MWh are generated, this is significantly different from the 71,063,034 MWh that are recorded in eGRID for the 101 fossil fueled generators. This was discrepancy was dismissed when the Southeast region’s simulated generation was compared to eGRID data. The Southeast model’s simulated 742,905,700 MWh of generation while eGRID data records 778,932,000 MWh. Therefore, the discrepancy between data direct from eGRID and the output from the statistical module is likely due to how the statistical model carries out simulations. The AVERT User Manual states that the sum of all unit generation may not add up to the expected fossil generation because there is no constraint forcing the output of all the generating units to equal the size of the load bin [24]. We will not delve any further into the details of statistical model we will just recognize that there is a slight discrepancy and accept it. It is worth nothing this
difference because in larger regions, which AVERT is designed for, the magnitude of the difference is small compared to the generation of the whole region. In smaller regions, like North Carolina, the scale of the difference is more significant. Based on the results which are presented in the next section, this discrepancy does not appear to have any influence on how the program simulates the implementation of EERE programs and the resulting emissions reductions.

4.2.2.4.2 North Carolina Region Results

The results from the North Carolina simulation at shown again in Table 19.

<table>
<thead>
<tr>
<th></th>
<th>Original</th>
<th>Post-EERE</th>
<th>Impacts</th>
<th>% Red.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Generation (MWh)</strong></td>
<td>58,088,000</td>
<td>55,750,700</td>
<td>-2,337,400</td>
<td>4.02%</td>
</tr>
<tr>
<td><strong>Emissions</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SO₂ (lbs)</td>
<td>96,841,900</td>
<td>92,276,400</td>
<td>-4,565,500</td>
<td>4.71%</td>
</tr>
<tr>
<td>NOₓ (lbs)</td>
<td>69,655,100</td>
<td>66,360,600</td>
<td>-3,294,500</td>
<td>4.73%</td>
</tr>
<tr>
<td>CO₂ (tons)</td>
<td>47,005,800</td>
<td>45,103,200</td>
<td>-1,902,600</td>
<td>4.05%</td>
</tr>
<tr>
<td><strong>Emission Rates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SO₂ (lbs/MWh)</td>
<td>1.667</td>
<td>1.655</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NOₓ (lbs/MWh)</td>
<td>1.199</td>
<td>1.19</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CO₂ (tons/MWh)</td>
<td>0.809</td>
<td>0.809</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This table details the magnitude of the reduction as compared to the parameters of the model. The model represents a 4.1% PV penetration, but, this model only considers fossil fuel generation, therefore the overall emissions and generation reductions are much smaller. The simulation’s signal-to-noise diagnostic curve is shown in Figure 20 with an R² value of 1, the
model’s EERE program was adequately sized to produce a mostly 1:1 reduction in fossil fuel electricity generation.

**Reduction in Total Unit Generation Relative to EERE Load Reduction (MW) for All Hours, R²=1.00**

![Diagram showing reduction in total unit generation relative to EERE load reduction](image)

**Figure 20. Signal to noise diagnostic curve for NC region**

According to 2012 eGRID data, which includes generation from the entire DEC and DEP generation area, there was 111,962,013 MWh generated. Using this data, along with the baseline emissions data presented in Table 5, a new set of results was generated, it is shown in Table 20.
Table 20. AVERT Predicted generation and emissions impacts for the DEC and DEP region

<table>
<thead>
<tr>
<th></th>
<th>Original</th>
<th>Post-EERE</th>
<th>Impacts</th>
<th>% Red.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Generation (MWh)</strong></td>
<td>111,962,013</td>
<td>109,624,613</td>
<td>-2,337,400</td>
<td>2.09%</td>
</tr>
<tr>
<td><strong>Emission Rates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>SO₂ (lbs/MWh)</strong></td>
<td>1.04</td>
<td>1.023</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>NOₓ (lbs/MWh)</strong></td>
<td>0.83</td>
<td>0.845</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>CO₂ (tons/MWh)</strong></td>
<td>0.54</td>
<td>0.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>SO₂ (lbs)</strong></td>
<td>116,706,000</td>
<td>112,140,500</td>
<td>-4,565,500</td>
<td>3.91%</td>
</tr>
<tr>
<td><strong>NOₓ (lbs)</strong></td>
<td>92,941,480</td>
<td>92,612,030</td>
<td>-3,294,500</td>
<td>3.54%</td>
</tr>
<tr>
<td><strong>CO₂ (tons)</strong></td>
<td>60,342,671</td>
<td>58,440,071</td>
<td>-1,902,600</td>
<td>3.15%</td>
</tr>
</tbody>
</table>

This table shows the predicted emissions and generation reductions for the entire DEC and DEP area, including non-fossil generators. Notice that the emissions rates overall are much lower when non-fossil generators like nuclear and hydro power are considered.

AVERT predicted a 2,337,400 MWh reduction in fossil fueled electricity generation as a result of the EERE program. This is very close to the amount of solar electricity which was produced by the system, 2,355,906 MWh, less than 1% of the energy generated did not displace fossil fuels. This signifies that the simulated grid was able to handle the addition of 1,644 MW of PV and match the addition with a similar reduction. This reduction represents 4% of the fossil fuel generation, and 2.1% of the total generation. The penetration level was 2.11%, this is very close to a 1:1 reduction, as mentioned before. Now that we have results for the AVERT simulation, we can compare them to the results from the eGRID method that was used in Section 4.2.1.3. The results are shown side-by-side in Table 21.
Table 21. Comparison of eGRID and AVERT results

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Baseline Method</th>
<th>Non-Baseload Method</th>
<th>AVERT NC Region</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PER, Tons</td>
<td>% Reduction</td>
<td>PER, Tons</td>
</tr>
<tr>
<td>NO\textsubscript{x}</td>
<td>977.7</td>
<td>2.01%</td>
<td>2,357</td>
</tr>
<tr>
<td>SO\textsubscript{2}</td>
<td>1,225.07</td>
<td>1.93%</td>
<td>3,871</td>
</tr>
<tr>
<td>CO\textsubscript{2}</td>
<td>1,269,727</td>
<td>2.04%</td>
<td>2,209,247</td>
</tr>
<tr>
<td>CH\textsubscript{4}*</td>
<td>26.74</td>
<td>1.95%</td>
<td>35.55</td>
</tr>
</tbody>
</table>

Upon comparison, the AVERT results fall in between the Non-Baseload and Baseline predicted emissions reductions. This is another indication that the AVERT method was successful because the results fall within the previously establish bounds of the study. The AVERT results satisfy both of these conditions. We are unable to compare CH\textsubscript{4} emissions because AVERT does not account for this pollutant in its simulations.

Based on the analysis and comparison of the results from the AVERT method, these will be taken as the best estimate out of the three. This method is better than both eGRID methods because it accounts for many aspects which were previously unaccounted for like forced outages, actual displaced generation versus predicted displaced generation, and it captures variable emissions rates, to name a few advantages which increase accuracy.

4.2.2.5 Emissions Reductions from EERE Programs in the AVERT Southeast Region Compared to the User-Created North Carolina Region

One of the goals this project is to explore if the results found for North Carolina can be extrapolated to a larger geographic region. Comparing the AVERT Southeast region to the North Carolina region might provide some insight into this. First we will look at two similar simulations for the regions: 1,644 MW for NC and 18,000 MW for the Southeast. These simulations were chosen for comparison because they both represent about 4.1% of the fossil fuel load in AVERT.

Table 22 shows the comparison of emissions rates before and after the EERE program was implemented and simulated.
Table 22. AVERT region emissions rates comparison: Southeast vs. North Carolina

<table>
<thead>
<tr>
<th>Emission Rates</th>
<th>North Carolina</th>
<th></th>
<th></th>
<th>Southeast</th>
<th></th>
<th></th>
<th>Pre-EERE</th>
<th>Post-EERE</th>
<th>Pre-EERE</th>
<th>Post-EERE</th>
</tr>
</thead>
<tbody>
<tr>
<td>SO₂ (lbs/MWh)</td>
<td>1.667</td>
<td>1.655</td>
<td></td>
<td>2.297</td>
<td>2.295</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NOₓ (lbs/MWh)</td>
<td>1.199</td>
<td>1.190</td>
<td></td>
<td>1.109</td>
<td>1.109</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CO₂ (tons/MWh)</td>
<td>0.809</td>
<td>0.809</td>
<td></td>
<td>0.759</td>
<td>0.761</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notice that NOₓ and CO₂ emissions rates for both regions are fairly close, while the SO₂ rates are significantly different. The composition of fossil fuel generators for each region are shown below.
Figure 21. Fossil fuel generator breakdown by region

Note: The “other” fuel type is composed of biomass generators and a few coal generators as well. Results will be presented for this fuel category, but for the most part they will not be analyzed because of the mixed composition.

These figures were generated by analyzing the number of generators, not the amount electricity that they generate. It is logical to contribute the disparity between SO_2 emissions rates to the difference in oil fired electrical generators. On average fuel oil contains 2.9% sulfur while coal contains between 0.8 and 1% and natural gas only has trace amounts [29]. The resulting changes in emissions rates are nearly equivalent as well. Emissions rates for
SO$_2$ and NO$_x$ decrease or stay the same for both regions. Interestingly, CO$_2$ emissions rates in the Southeast region increase slightly, by about 0.002 tons/MWh.

It seems strange that emissions rates would increase, however, it is possible considering that the MWh’s being displaced from PV generation are causing fossil fuel plants to ramp down. When plants ramp down, they change their output and therefore the heat rate and efficiency can change as well, as discussed in the literature review. The following two tables show data regarding how displaced electricity generation was distributed among different types of generators, sorted by fuel sources.

**Table 23. Breakdown of changes in generation by fuel source (Southeast)**

<table>
<thead>
<tr>
<th></th>
<th>Pre-EERE Generation (MWh)</th>
<th>Post-EERE Generation (MWh)</th>
<th>% Reduction in Generation</th>
<th>Pre-EERE Penetration</th>
<th>Post-EERE Penetration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal</td>
<td>374,989,139</td>
<td>362,511,075</td>
<td>3.33%</td>
<td>50.48%</td>
<td>50.88%</td>
</tr>
<tr>
<td>Gas</td>
<td>354,485,950</td>
<td>337,682,762</td>
<td>4.74%</td>
<td>47.72%</td>
<td>47.40%</td>
</tr>
<tr>
<td>Oil</td>
<td>12,470,432</td>
<td>11,342,778</td>
<td>9.04%</td>
<td>1.68%</td>
<td>1.59%</td>
</tr>
<tr>
<td>Other</td>
<td>949,266</td>
<td>943,934</td>
<td>0.56%</td>
<td>0.13%</td>
<td>0.13%</td>
</tr>
<tr>
<td>Total</td>
<td>742,894,787</td>
<td>712,480,550</td>
<td>4.09%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In the Southeast, most of the displaced generation lowered the demand on oil-fired generators, they produced 9.04% less electricity than after the EERE was implemented than they did before. Natural gas generators also saw a decrease in the amount of generation required. Looking at the penetration levels for each fuel type, the Southeast’s fossil fuel load is primarily served by coal and gas-fired generators. Gas and oil-fired generators saw a slight decrease in the portion of the electrical demand that they had to supply, while coal-fired generators were responsible for slightly more electricity generation than other fuel types after the EERE was implemented. This is expected, since oil and gas generators are typically peaking and load-following units and they can be ramped up/down and cycled much more easily than coal-fired baseload units.

These results also help explain the trends of the emissions rates. The combustion of sulfur rich oil fuel was reduced, lowering the SO$_2$ emissions rate. According to the EIA, “coal
combustion emits almost twice as much carbon dioxide per unit of energy as does the combustion of natural gas,” therefore the increase in CO₂ emissions rate can be attributed to generation of more electricity using coal [30].

Table 24. Breakdown of changes in generation by fuel source (North Carolina)

<table>
<thead>
<tr>
<th>Fuel Source</th>
<th>Pre-EERE Generation (MWh)</th>
<th>Post-EERE Generation (MWh)</th>
<th>% Reduction in Generation</th>
<th>Pre-EERE Penetration</th>
<th>Post-EERE Penetration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal</td>
<td>40,233,727</td>
<td>38,626,731</td>
<td>3.99%</td>
<td>69.28%</td>
<td>69.30%</td>
</tr>
<tr>
<td>Gas</td>
<td>17,242,710</td>
<td>16,541,946</td>
<td>4.06%</td>
<td>29.69%</td>
<td>29.68%</td>
</tr>
<tr>
<td>Oil</td>
<td>188,448</td>
<td>162,030</td>
<td>14.02%</td>
<td>0.32%</td>
<td>0.29%</td>
</tr>
<tr>
<td>Other</td>
<td>410,193</td>
<td>409,886</td>
<td>0.08%</td>
<td>0.71%</td>
<td>0.74%</td>
</tr>
<tr>
<td>Total</td>
<td>58,075,078</td>
<td>55,740,593</td>
<td>4.02%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In North Carolina, the largest change in generation was seen with oil-fired generators; however, oil-fired generators accounted for less than one half of a percent of electricity generated in the region. Coal fired generation was curbed a little more in the NC region than the Southeast while natural gas generation was not decreased as much. Overall, a higher percentage of electricity generated came from coal while gas, oil and other fossil fuels provided less of the electricity that was generated. Note that there was no increase or change in CO₂ emissions rate in the NC region despite the coal penetration increasing as it did in the Southeast region. The magnitude of the increase serves as an explanation, 0.4% more generation came from coal in the Southeast compared to 0.02% more in North Carolina. Therefore, it is expected that there would be a more significant change in the Southeast region versus the North Carolina.

The changes in emissions rates and fuel source penetration have been explored, now the actual impacts in terms of pounds of pollutants will be shown. The results from both simulations can be seen side-by-side in Table 25.
Table 25. AVERT region emissions reduction comparison: Southeast vs. North Carolina

<table>
<thead>
<tr>
<th></th>
<th>North Carolina</th>
<th></th>
<th>Southeast</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Penetration</td>
<td>% Red.</td>
<td>Penetration</td>
<td>% Red.</td>
</tr>
<tr>
<td>Generation (MWh)</td>
<td>4.06%</td>
<td>-2,337,400</td>
<td>4.02%</td>
<td>-30,416,800</td>
</tr>
<tr>
<td>Impacts SO(\text{\textsubscript{2}}) (lbs)</td>
<td>4.71%</td>
<td>-4,565,500</td>
<td>4.71%</td>
<td>-71,491,300</td>
</tr>
<tr>
<td>Impacts NO(\text{\textsubscript{x}}) (lbs)</td>
<td>4.73%</td>
<td>-3,294,500</td>
<td>4.73%</td>
<td>-34,171,800</td>
</tr>
<tr>
<td>Impacts CO(\text{\textsubscript{2}}) (tons)</td>
<td>4.05%</td>
<td>-1,902,600</td>
<td>4.05%</td>
<td>-21,301,700</td>
</tr>
</tbody>
</table>

In both regions there is a slight difference between the level of penetration and percent reduction in generation. This confirms that there is not a 1:1 correlation between PV generation added to the grid and fossil fuel generation removed from the grid. However, it is close to a 1:1 correlation at this level of PV penetration. The Southeast region did show a closer correlation between penetration and generation reduction, likely because it was a larger geographic area. The larger area that the region covers, the more individual plants there are (about 10 times as many in this case). These individual plants can be operated in conjunction with one another to increase the avoided fossil fuel generation.

Comparing both regions, North Carolina shows slightly higher levels of emissions reductions than the Southeast region even though it was simulated at a slightly lower penetration level (4.06% versus 4.11%). One possible explanation for this is a difference in generator start-ups. Figure 22 shows the hourly generation displacement for North Carolina and the Southeast for the week of August 1st.
Figure 22. Hourly generation displacement for NC and SE regions
As discussed previously, the blue shading above the x-axis represents an increase in generation due to generator forced outages (maintenance, etc.). Based on the analysis of this figure in Section 4.2.2.3, it is reasonable to assume that anytime there is an increase in generation shown in the figure, there is an associated generator start up. It is clear in the figure that the Southeast experiences much higher levels generation increases and generator start-ups than North Carolina. Lew and Brinkman found that the largest impacts on fossil fuel generator emissions and costs are from cycling units on and off, especially starting up from a cold start [12]. Therefore, since the Southeast has more start-ups and generation increases, this could explain why the North Carolina region shows higher emissions reduction. Because North Carolina has less start-ups, they will see higher emissions reductions since the generators emissions rates will not be penalized from cold starts.

Another explanation could be the types of generators that were displaced when PV was added to the grid. AVERT does not output, or make accessible through hidden worksheets, the pre- or post-EERE heat inputs for individual generators. However, the heat input reduction can be accessed within the program. Table 26 shows the heat input reduction, by fuel type, for NC and the SE.

<table>
<thead>
<tr>
<th>Fuel Source</th>
<th>Heat Reduction, by fuel type</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>North Carolina</td>
</tr>
<tr>
<td>Coal</td>
<td>MMBTU</td>
</tr>
<tr>
<td>Coal</td>
<td>14,259,887</td>
</tr>
<tr>
<td>Gas</td>
<td>7,106,711</td>
</tr>
<tr>
<td>Oil</td>
<td>325,603</td>
</tr>
<tr>
<td>Other</td>
<td>3,841</td>
</tr>
<tr>
<td></td>
<td>21,696,042</td>
</tr>
</tbody>
</table>

It is known from Lew and Brinkman’s paper that average heat rate and emissions increase for fossil fuel generators as the generating load on the unit decreases. Therefore, if an increase in generator heat rate can be illustrated with data, then the increase in emissions can explained
using results from the model. In order to determine the effect the EERE program had on generator heat rates, only the heat rates from the time period when the PV was generating electricity were looked at. When the PV facilities were not generating electricity, there was no effect on fossil fuel generator heat rates in either region which was simulated.

The change in heat rate associated with each hour and generation level is shown in Figure 23.

**Figure 23. Change in heat rate for AVERT regions at each hour of PV generation**

The change in heat rate was calculated by dividing the total change in heat input for one hour by the corresponding change in generation for that hour. Therefore, this heat rate represents an average for the area. The graph illustrates a tighter grouping of data points in the SE. There are also less outliers in the Southeast region compared to NC. This is likely due to the generator population. North Carolina has about 10% of the generators that the Southeast region has, therefore extreme changes in heat rate for individual generators (calculated inside of the AVERT code) are likely to have a greater effect on the change in the overall region.

The same logic can be applied to the interpretation of the graph. The more generators that there are in an area which is implementing an EERE program, the less fluctuation in
generator heat rate can be expected. When there are more generators in an area, the system operators have more flexibility when it comes to resource dispatch, that is, which generators should run at any given time to meet the system demand. This greater flexibility comes from being able to choose the most efficient units to run. For example, natural gas generating plants are usually made up of many small gas turbine units, so if the demand decreases enough to turn off any individual units, the heat rate for that plant will not change. The fluctuation of positive and negative changes of the heat rate also illustrates the effect of the intermittency of the solar resource. The figures below illustrate how the heat rate can increase or decrease as a result of the intermittency of solar.

![Graph](image-url)
When solar PV behaves as expected with no intermittency it can be planned for and, by dispatching the optimal resources, it can even improve the heat rate (efficiency) of the overall grid. This is illustrated in the first figure, with the smooth bell-shaped PV generation curve and the lower post-EERE heat rate. When solar PV behaves less predictably, as shown in the second graph, it can be more difficult for the grid to make adjustments and handle. The pre- and post-EERE heat rates illustrate this, as the change in heat rate for some hours is positive and others it is negative. The overall heat rate for the regions can provide more insight about how the EERE program affected fossil fuel generators.

According to the AVERT results the pre-EERE heat rate for all NC fossil fuel generators was 8.936 MMBTU/MWh and the post-EERE value was 8.931 MMTBU/MWh. This is a slight decrease in heat rate after the EERE program was implemented. For the Southeast, the pre-EERE value was 9.108 MMBTU/MWh and the post-EERE value was 9.113 MMBTU/MWh, a slight increase in heat rate. With such small changes (less than 10 BTU/kWh) in pre- and post-EERE heat rates, it is difficult to draw conclusions based solely on these values.
The avoided heat rate can be calculated by analyzing the heat rates for the regions. The avoided heat rate (AHR) refers to the ratio of the amount of heat removed from the region versus the amount of generation removed in a region, as a result of an EERE program.

\[
AHR \left( \frac{\text{MMBTU}}{\text{MWh}} \right) = \frac{\text{Change in Regional Heat Input (MMBTU)}}{\text{Avoided Fossil Fuel Generation (MWh)}}
\]

The AHR can be seen as a measure of how the efficiency of a region’s fossil fuel generators changes as a result of an EERE. It should be compared to the pre-EERE heat rate of a region. It is best explained with an example. Consider NC, which has an AHR of 9.282 MMTBU/MWh and a pre-EERE heat rate of 8.936 MMBTU/MWh. It takes 8.936 MMBTU of heat from fossil fuels to generate 1 MWh of electricity for the region. If the region could operate at this efficiency level all of the time, no matter what the electrical demand was, when 8.936 MMBTU of fuel was not fired, there would be a 1 MWh reduction in electricity generation. However, the laws of thermodynamics are such that electrical generators are designed to operate most efficiently at their full load (or another designated value), and the efficiency decreases as load decreases. Therefore, when the load changes in a region the efficiency will change as well, unless they can dispatch different generators to match the load efficiently and maintain optimal efficiency. Considering a region, like NC, that has an AHR which is higher than the pre-EERE heat rate, this can be interpreted to mean that inefficient generators were removed from the generating pool as a result of the EERE. In the case of NC, when 9.282 MMTBU of heat was not fired, 1 MWh of generation was avoided. This is higher than the pre-EERE value because during that time, some generators were running at less than optimal load, thus when they were turned off, the efficiency of the region increased. Another explanation would be if a generator’s output was increased to its optimal load as a result of another generator being turned off, thus increasing its efficiency. This could happen as a result of a change in generator dispatch. Therefore, in the case of the North Carolina region, the addition of PV generators resulted in the removal of inefficient generators from the generating pool, increasing emissions reductions.
The Southeast region did not show as much of an improvement. The region has an AHR of 9.109 MMBTU/MWh and a pre-EERE heat rate of 9.108 MMBTU/MWh. These are essentially the same, meaning the region’s efficiency is not effected as much by the EERE, although it still benefits from the reduced emissions and fossil fuel generation. This is contributed to the fact that the region has many more generators, with the heat rate increasing on some generators, and decreasing for others, when they are added together to get the heat rate for the region, there could be a lot of noise which cancels out the individual generator heat rate changes.

Although the change in regional heat rate was small, the analysis provided using AHR does affirms the difference.

4.3 Future Growth

The tremendous growth in solar PV in NC was mentioned in the introduction, much of this is contributed to the generous tax incentives offered by state and federal government. The state government’s 35% tax credit expired in 2016 and was not renewed by legislature [31]. The end of state tax incentives is sure to bring about a slowdown of solar PV growth in NC. The research that has been presented here, in combination with the research of other’s in the area of maximum solar PV penetration levels in the state, begs the question of when NC might hit the penetration limit. This project examined a penetration level of 4.06% in NC. Alqahtani’s findings suggest that there is a penetration limit of 5.3%, and not far off from that study, PNNL found a limit of about 7% [14] [13]. Using information from Duke’s interconnection queues, an estimate of how long it might take to reach these levels of penetration can be formulated.

The most current interconnection queues that are available are from mid-August 2016. These queues can be compared to those used in this study, published in February 2016. The two queues can be compared for changes in operating status, project cancellations and new project additions. Upon combining both the February and August queues, several observations were made. First, there were 1,475 projects listed in the combined queue. This combined queue included all of the PV projects proposed to both DEC and DEP. There were 223 projects which had not had a status change in seven months (note: 26 are under
construction), 152 projects which were added and 25 which were removed between February and August, and finally 1,075 projects which moved forward in the interconnection process. There was a net change of 127 projects added to the queue, for a total proposed addition of 533 MW of capacity. However, there were 35 projects which were under consideration for connection in February that have since been canceled by Duke or withdrawn by the customer. The majority were withdrawn by customers. The capacity of these generators would have been 111 MW.

Now, consider the projects which are still in the interconnection process with Duke – a total of 1,075. Some of these have been cancelled in the recent months, however, they are still included in the data. It is important to include the cancelled and withdrawn projects in the analysis because a cancellation rate should also be addressed in the prediction which will be formed.

![Figure 25. Breakdown of changes made to projects in the Duke interconnection queue between February and August 2016](image)

Figure 25 provides a more in depth, and graphical explanation of the changes that occurred in the interconnection queues between February and August. It represents the projects that were listed in both the February and August queues. There was an increase in projects connected
to the grid (61 projects with a capacity of 140 MW), and an increase in the number of projects canceled, most of which were somewhere in the pending consideration phase.

Table 27 summarizes the data relevant to developing the estimated time to PV saturation in NC.

**Table 27. Data used for estimated time to PV saturation**

<table>
<thead>
<tr>
<th>Status</th>
<th>Number of Projects</th>
<th>Capacity of Projects (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Completed</td>
<td>61</td>
<td>140</td>
</tr>
<tr>
<td>Added</td>
<td>152</td>
<td>623</td>
</tr>
<tr>
<td>Removed</td>
<td>-35</td>
<td>-111</td>
</tr>
<tr>
<td>Cancelled</td>
<td>-25</td>
<td>-91</td>
</tr>
<tr>
<td>Net Total</td>
<td>153</td>
<td>561</td>
</tr>
</tbody>
</table>

From the table, it appears that the current completion rate, based on queue data, is about 561 MW every seven months, or 80 MW/month. Additionally, the average project size is about 3.67 MW. The project size was confirmed by averaging all of the project capacities from the combined queue. The estimated PV installation rate was checked against historical data. According to the Solar Energy Industries Association (SEIA), North Carolina installed 1,140 MW of electric capacity in 2015, this is about 95 MW/month. Additionally, the SEIA predicts 3,479 MW to be installed in NC within the next 5 years, which would require an installation rate of about 58 MW/month [32]. Based on this data, it appears that the installation rate calculated from the interconnection queue is fairly accurate. The average over the next five years is likely lower than the current installation rate because as the grid nears the maximum penetration level, Duke Energy is likely going to require much more stringent requirements for grid connection in order to maintain grid reliability and stability.

Using 80 MW/month, and Alqahtani’s 6,510 MW maximum penetration level, NC will reach its PV saturation point in 6.75 years. According to the PNNL findings, NC will reach its saturation level, 6,800 MW, in 7.1 years. Interestingly, if the SEIA growth estimate does not take into account the PV projects which were looked at in this study, NC will reach its maximum penetration level (6,510 MW) in about five years. Although five or seven years
seems like a long time, it is not for a utility company. Duke Energy’s integrated resource plans look at a generation forecasts for up to 10 years ahead. It is important that the effects of adding PV to the grid at these rates be considered now as pressure is ever increasing for utilities to add renewable energy sources to the grid. In addition, the cost of PV is still declining as more and more installations are completed around the world, and the technology advances. As installation costs continue to fall, it is going to be easier to finance these PV projects and more people will want to install PV for profit, or for personal gain. There will be a battle between the utility companies, who have to evaluate, approve, and provide the infrastructure for PV projects, and those who want to install them everywhere. It is important to remember how complex the process of balancing electric loads and grid stability is, and to be realistic when evaluating the economics and physical effects of new renewable energy projects. Although there are many positive effects of renewable energy, like the reduction in greenhouse gas emissions detailed in this study, there is also an integration challenge which includes changing how utilities operate. Without a change in operating procedures, the efficiency of generators will decline and fossil fuels will not be used efficiently. This study detailed how the conventional fossil fuel generators, which power the grid today, will have to change to accommodate new intermittent resources, like solar PV. This study showed that it is possible to maintain generator efficiency when intermittent resources are added, but not without a change in how conventional generators operate.
5 CONCLUSION

This project has built on previous studies. Rather than analyzing the effect of increasing PV penetration in nondescript percentage values on the DEC and DEP grid, it investigated the effect of adding PV generators in the areas which are likely to begin generation in the next year or two. Proposed PV generation facilities were chosen based on size and operational status in the DEC and DEP interconnection queue. Because the queue is updated up to two times per month, a snapshot had to be chosen, this study used the queue published at the end of February 2016.

The latest 30-minute solar radiation data was downloaded from the National Solar Radiation Database; this was for the 2014 calendar year. A performance model was then created for the PV facilities using the National Renewable Energy Laboratory’s PVWatts (version 5) tool. There were 438 solar PV facilities which were modeled, simulating 1,644 MW of generating capacity added to the grid. Three different emissions reduction models were used in the study, two based on eGRID data (non-baseload and baseline emissions rates), and one using the EPA’s Avoided Emissions and Generation Tool. Using AVERT, two different regional simulations were developed, one for the entire Southeast region, and the other specifically for North Carolina.

The data generated shows that using eGRID data for different regions can be useful for establishing boundaries for a more in-depth study. However, any calculations made using eGRID should be taken lightly because they incorporate a large amount of data and, most importantly, assume an equal reduction in generation across all units. This method does not account for some generators being affected more than other by the addition of an intermittent renewable resource like solar PV.

Data from AVERT was much more useful in terms of providing insight into how fossil fuel generators are actually effected when intermittent renewable resource, like solar PV, is added to the grid. Several simulations were created, and two were analyzed in depth. The effect of adding the proposed 438 PV generators from the DEC and DEP interconnection queues was examined in the North Carolina region. For comparison, a simulation was run with the same level of penetration for the entire Southeast AVERT region, this was about 18,000 MW of
solar PV. The results for the NC region showed that with the 2.11% PV penetration which was modeled, one could expect a corresponding 2.09% decreased in fossil fuel generation, or about 2,337,400 MWh reduction. Additionally, SO$_2$ and NO$_x$ emissions would decrease by 3.91% and 3.54% respectively, while CO$_2$ emissions decreased by 3.15%. The Southeast region showed similar results in terms of the magnitude of reduction.

Aside from emissions rates, emissions and generations reductions, the heat rate, types of generators displaced and generator efficiency were examined. In NC, it was found that the overall heat rate for the region decreased as a result of the PV integration. The NC region became more efficient, likely as a result of decreasing the number of partially loaded fossil fuel generators. This also explains why the emissions reductions were slightly higher in the region when compared to the Southeast. Note that the changes in heat rate before and after the EERE program implementation are negligible, the study has simply provided an explanation as to why they change at all. In the Southeast region, there is virtually no effect on the region’s heat rate as a result of the EERE program. This signifies that the region was able to absorb the variability of the PV generation without running more generators at part load, however, it was not able to select a more efficient group of generators to meet the demand.

Increasing pressure is being applied to utilities companies every day to become more efficient, implement more “green energy” and lower their environmental impact. Additionally, the North Carolina Renewable Energy and Efficiency Portfolio Standard (REPS) has placed a legally deadline of DEC and DEP to increase the efficiency and renewable energy generation. This study filled a void of a mid-level implementation study of actual proposed generators in the DEC and DEP area, not just incremental penetration levels. The study serves to provide an engineering analysis of what the implementation of new PV facility means for the efficiency of fossil fuel generators and emissions, as well as to bring to light some of the behind the scenes work that is required to make renewable energy work with the current grid. It is important to research and educate the public on the real effect of these solar facilities, not just the effects that are advertised by the contractors and staunch renewable energy advocates.
6 FUTURE WORK

The next step that should be taken with this project is to develop a more complex energy model for the DEC and DEP service areas. Once this is done, a base case for the area could be developed and compared to other energy models which have been developed for the area. Then, a more in-depth analysis could be performed on the effect of adding these PV generators to the grid. Additionally, other proposed renewable energy generators could be added to the model, like wind generators. The most interesting part of this project is how dynamic the parameters are. There are new proposed renewable energy projects being brought to utility companies every day, and it is important for independent parties to provide some validation for the claims being made by both project owners and the utility companies. With a sophisticated energy model, researchers could investigate how the proposed generators might affect grid stability, emissions rates, and the operation of other generators. Additionally, future models may be able to use more variable solar radiation data to capture the true intermittency of solar PV, rather than the distribution and variation provided by 30-minute average data points.

The complex modeling method that was proposed earlier in this paper, a unit commitment and economic dispatch model, would be a good place to start for future work. PHORUM, a UC-ED developed for the PJM RTO, could be modified to work as a UC-ED for the DEC and DEP service area.

6.1.1 PJM Hourly Open-source Reduced-form Unit-commitment Model (PHORUM)

In 2014, Roger Lueken and Jay Apt created a reduced-form UC-ED to simulate the PJM regional transmission organization (RTO). The model is called PJM Hourly Open-source Reduced-form Unit-commitment Model, or PHORUM. This model uses mixed integer linear programming to find the least-cost generators which will meet the load at each hour subject to generator and transmission constraints. It optimizes each day using a 48 hour window, then it moves forward 24 hours and optimizes the next 48 hour window, repeating until it has simulated 8,760 hours (1 year). PHORUM requires many RTO-specific inputs, mostly characterized as hourly data or generator data. After the model has been used to create a base case, showing how the grid is currently operating, variables can be changed to explore different areas like the effect of generator changes on emissions. [25].
Even with other researchers’ work on UC-ED models, a great deal of work is still required to create and utilize one. There are many commercially available models for use in industry, however, they are not utilized in research because of the cost of licensing. It proved difficult to find an appropriate, open-source model that could be used to use for this project. Therefore, PHORUM was chosen as a versatile model that could be modified to simulate the Duke Energy and Progress grids. We are able to modify this UC-ED model for PJM because dispatch and commitment optimization methods do not change much from RTO to RTO.

In order to utilize PHORUM for this project, a significant amount of data collection would be required to define the grid’s generators and load. Leuken used 13 different sources to collect information such as generator heat rate, capacity, ramp rate, and CO₂ emission rate. He utilized another six resources to define the hourly data such as load, transmission capacity and reserve requirements. In order to modify PHORUM, almost all of this data that Leuken collected for PJM needs to be collected for DEP and DEC. Table 28 lists all of the data elements required for the Duke PHORUM model, and the sources from which the information could be obtained.
Table 28. PHORUM Data Sources

<table>
<thead>
<tr>
<th>Data Element</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Generator Data</strong></td>
<td></td>
</tr>
<tr>
<td>Plant Type</td>
<td>[33]</td>
</tr>
<tr>
<td>State &amp; County</td>
<td>[33]</td>
</tr>
<tr>
<td>Heat Rate (BTU/kWh)</td>
<td>[33]</td>
</tr>
<tr>
<td>Fuel</td>
<td>[33]</td>
</tr>
<tr>
<td>Capacity (MW) (Summer &amp; Winter)</td>
<td>[34]</td>
</tr>
<tr>
<td>Variable O&amp;M Cost ($/MWh)</td>
<td>[35]</td>
</tr>
<tr>
<td>Monthly Fuel Price: Jan-Dec 2014 ($/MMBTU)</td>
<td>[36] [37]</td>
</tr>
<tr>
<td>Ramp Rate (MW/h)</td>
<td></td>
</tr>
<tr>
<td>Min uptime &amp; downtime (h)</td>
<td></td>
</tr>
<tr>
<td>Startup cost adder ($)</td>
<td></td>
</tr>
<tr>
<td>Minimum generation (% of maximum generation)</td>
<td></td>
</tr>
<tr>
<td>Monthly equivalent availability factor: Jan-Dec 2014</td>
<td></td>
</tr>
<tr>
<td>Stack height (ft)</td>
<td></td>
</tr>
<tr>
<td>CO₂ emission rate (lb/MMBTU)</td>
<td>[20]</td>
</tr>
<tr>
<td>NOₓ &amp; SO₂ emission rates (lb/MMBTU)</td>
<td>[20]</td>
</tr>
<tr>
<td><strong>Hourly Data</strong></td>
<td></td>
</tr>
<tr>
<td>Load</td>
<td>[38]</td>
</tr>
<tr>
<td>Imports/Exports (MW)</td>
<td></td>
</tr>
<tr>
<td>Zonal locational marginal prices (LMPs) ($/MWh)</td>
<td></td>
</tr>
<tr>
<td>Transmission capacity (MW)</td>
<td></td>
</tr>
<tr>
<td>Wind generation (MW)</td>
<td></td>
</tr>
<tr>
<td>Reserve requirement (MW)</td>
<td></td>
</tr>
</tbody>
</table>

More information on the model can be found in the appendix to Leuken’s paper “The effects of bulk electricity storage on the PJM market.” Both the paper and the appendix discuss the model and its parameters in depth.

After the model is updated for the DEC and DEP service area, a base case can be produced, to check the accuracy of the model as well to create a model with which to compare the PV results to. Then the model should be updated to include the proposed solar PV plants. The model results could then be analyzed and compared to results found in other studies and this one. A more in-depth analysis of AVERT could be completed once it was know how its predictions compared to those from more sophisticated technologies. This would provide an unbiased evaluation of the program as a tool for use by the public and policy makes.
The drawback of PHORUM is that it requires the use of the General Algebraic Modeling System (GAMS), which costs about $1,200 for an academic license. Additionally, an optimization solver, like IBM’s CPLEX, is required to run the code. However, PHORUM would be one of the simplest methods since the code for the model is open-source, that means a new model would not need to be developed from scratch.
7 REFERENCES


[27] Energy Information Administration, "Average Operating Heat Rate for Selected Energy Sources, 2004-2014".


APPENDIX
Appendix A: Python code for weather file download

# This code accesses the National Solar Radiation Database's (NRSDB) Application Programming Interface (API) in order to download weather files for a specific year and location pulled from an input file. The output files are csv's which contain hour or half-hour weather data for the specified location. The code is looped over a large number of locations pulled from a csv file.

import pandas as pd
import os, time

# A timer is used to track the computation time of the program
start = time.time()

# load Locations.csv which contains the locations and capacity of PV sites to be modeled.
# Store in dataframe df_locations
df_locations = pd.read_csv('C://Users//jeturne6//OneDrive//Research//Locations//Locations.csv')

# Count the number of sites in the CSV
i = len(df_locations.index)

# Inside of the following for loop, various pieces of data about a single PV site are called from df_locations. The lat and lon for this location, along with some other data, is used to go to the NSRDB API and pull weather data for the specified location/year. Once the weather file is downloaded, all of the data will be used to calculate the output of the PV site in another program. The weather information is saved to a dataframe, df, and then written to a csv file with the naming convention Utility_Queue_Number, year-interval.csv.

for x in range (0,i):

    # Declare all variables as strings. Spaces must be replaced with '+', i.e., change 'John Smith' to 'John+Smith'.

    # Define Utility and Queue_Num as two identifiers for the PV site that is currently being simulated, they are pulled from df_locations
    Utility = df_locations.get_value(x,0,takeable="true")
    Queue_Num = df_locations.get_value(x,1,takeable="true")

    # Define the lat, lon of the location from df_locations
    lat = df_locations.get_value(x,7,takeable="true")
    lon = df_locations.get_value(x,8,takeable="true")

# A timer is used to track the computation time of the program
end = time.time()

time_taken = end - start
# Enter NRSDB API key here to access data
api_key = 'JzBed1zaNpzTgmjIwUcz5M2bjgqDYqKK2WDnfpOh'
# Set the attributes to extract (e.g., dhi, ghi, etc.), separated by commas.
attributes = 'ghi,dhi,dni,wind_speed_10m_nwp,surface_air_temperature_nwp,solar_zenith_angle'
# Choose year of data
year = '2014'
# Set leap year to true or false. True will return leap day data if present, false will not.
leap_year = 'false'
# Set time interval in minutes, i.e., '30' is half hour intervals. Valid intervals are 30 & 60.
interval = '30'
# Specify Coordinated Universal Time (UTC), 'true' will use UTC, 'false' will use the local
time zone of the data.
# NOTE: In order to use the NSRDB data in SAM, you must specify UTC as 'false'. SAM
# requires the data to be in the local time zone.
utc = 'false'
# Your full name, use '+' instead of spaces.
your_name = 'James+Turner'
# Your reason for using the NSRDB.
reason_for_use = 'Research'
# Your affiliation
your_affiliation = 'NCSU'
# Your email address
your_email = 'jeturne6@ncsu.edu'
# Please join our mailing list so we can keep you up-to-date on new developments.
mailing_list = 'false'
# Declare url string
url = 'http://developer.nrel.gov/api/solar/nsrdb_0512_download.csv?wkt=POINT({lon}%20{lat})&names={year}&leap_day={leap}&interval={interval}&utc={utc}&full_name={name}&email={email}&affiliation={affiliation}&mailing_list={mailing_list}&reason={reason}&api_key={api}&attributes={attr}'.format(year=year, lat=lat, leap=leap_year, interval=interval, utc=utc, name=your_name, email=your_email, mailing_list=mailing_list, affiliation=your_affiliation, reason=reason_for_use, api=api_key, attr=attributes)
# Return all lines of csv to get data:
df = pd.read_csv(url)
# Write the weather data to a csv:
os.chdir('C://Users//jeturne6//Desktop//Research//Weather Files')
df.to_csv(Utility+' '+Queue_Num+ ', ' + year + '-' + interval + '.csv')

#output the amount of time it took to simulate
time = time.time() - start
if time <60:
    print "Elapsed Time", time, " seconds"
elif time >= 60 and time < 3600:
    print "Elapsed Time", time/60, " minutes"
else:
    print "Elapsed Time", time/3600, " hours"
Appendix B: Python code for PV plant simulation

# This code uses the System Advisor Model (SAM) Software Development Kit (SDK) to simulate the electricity output of any PV system with a defined capacity and location. 
# Simulation is done using the PVWatts module, and is looped over a large selection of PV sites. The output files are csv's which contain hour or half-hour generation data based on the weather file that was called and retrieved from the National Solar Radiation Database (NRSDB).

import pandas as pd
import numpy as np
import os, site, time

# A timer is used to track the computation time of the program
start = time.time()

# Set simulation interval 30 or 60 minutes, must correspond to the weather data's interval
interval = '30'
# Set simulation year, must match the weather data's year
year = '2014'

# Load Locations.csv which contains the locations and capacity of PV sites to be modeled. Store in dataframe df_locations
df_locations = pd.read_csv('C://Users//jetur//OneDrive//Research//Locations//Locations.csv')

# Count the number of sites in the CSV/DataFrame
i = len(df_locations.index)

# Set the total generation, total capacity, and total MWh for all of the PV sites to zero at the start of the program.
df_total_generation = 0
total_capacity = 0
total_MWh = 0

# Inside of the following for loop, various pieces of data about a single PV site are called from df_locations. The lat and lon for this location, along with some other data, is used to weather data for the specified location/year that has already been downloaded. The weather data is then used to calculate the output of the PV site using the PVWatts5 module called from the System Advisor Model (SAM) Software Development Kit (SDK). After the simulation is done, the following generating characteristics are loaded from the results: AC MWh, dc kWh, and capacity factor. This information is all written to the datafram df. A new dataframe is then created, df_parameters in which the PV site's parameter's are recorded such as system capacity and location. Then the simulation results and parameters are combined to create on dataframe, df_out which is then written to a csv file with the
for x in range (185,i):

    # Define Utility and Queue_Num as two identifiers for the PV site that is currently being
    # simulated, they are values pulled from df_locations
    Utility = df_locations.get_value(x,0,takeable="true")
    Queue_Num = df_locations.get_value(x,1,takeable="true")

    # Set system capacity in MW. The Capacity in df_locations is in kW, it is called and then
    # divided by 1000 to get system capacity in MW
    system_capacitykW= df_locations.get_value(x,3,takeable="true")
    system_capacity = system_capacitykW/1000

    # Open weather file that was previously downloaded using Weather.py, read only the first
    # row, store in dataframe, df_loc
    os.chdir('C://Users//jetur//OneDrive//Research//Locations//Weather Files')
    df_loc = pd.read_csv(Utility+' '+Queue_Num+', '+year+'-'+interval+'.csv',nrows=1)

    # Get lat, lon, timezone and elevation from weather file
    lat = df_loc.get_value(0,6,takeable="true")
    lon= df_loc.get_value(0,7,takeable="true")
    timezone = df_loc.get_value(0,8,takeable="true")
    elevation = df_loc.get_value(0,9,takeable="true")

    # Read the rest of the weather file, store in dataframe, df. The usecols parameter avoids
    # loading in blank columns
    df = pd.read_csv(Utility+Queue_Num+', '+year+'-'+interval+'.'+csv',skiprows=2,usecols=range(6,12))

    # Set the time index in the pandas dataframe:
    periods=525600/int(interval)
    df = df.set_index(pd.date_range('1/1/{yr}'.format(yr=year), freq=interval+'Min',
    periods=periods))

    # This is where the SDK module is called and used to simulate the PV site
    # Use site.addsitedir() to set the path to the SAM SDK API. Set path to the python
    # directory.
    site.addsitedir('C://Users//jetur//OneDrive//Research//SAM//SDK//languages//python')
    import ssca
    ssc = sscaapi.PySSC()
# Resource inputs for SAM model:

```python
wfd = ssc.data_create()
ssc.data_set_number(wfd, 'lat', lat)
ssc.data_set_number(wfd, 'lon', lon)
ssc.data_set_number(wfd, 'tz', timezone)
ssc.data_set_number(wfd, 'elev', elevation)
ssc.data_set_array(wfd, 'year', df.index.year)
ssc.data_set_array(wfd, 'month', df.index.month)
ssc.data_set_array(wfd, 'day', df.index.day)
ssc.data_set_array(wfd, 'hour', df.index.hour)
ssc.data_set_array(wfd, 'minute', df.index.minute)
ssc.data_set_array(wfd, 'dn', df['DNI'])
ssc.data_set_array(wfd, 'df', df['DHI'])
ssc.data_set_array(wfd, 'wspd', df['Wind Speed'])
ssc.data_set_array(wfd, 'tdry', df['Temperature'])
```

# Create SAM compliant object
```
# Create SAM compliant object
dat = ssc.data_create()
ssc.data_set_table(dat, 'solar_resource_data', wfd)
ssc.data_free(wfd)
```

# Specify the system Configuration
```
ssc.data_set_number(dat, 'system_capacity', system_capacity)
# Set DC/AC ratio (or power ratio). See
# https://sam.nrel.gov/sites/default/files/content/virtual_conf_july_2013/07-sam-virtual-
# conference-2013-woodcock.pdf
ssc.data_set_number(dat, 'dc_ac_ratio', 1.1)
# Set tilt of system in degrees
ssc.data_set_number(dat, 'tilt', 25)
# Set azimuth angle (in degrees) from north (0 degrees)
ssc.data_set_number(dat, 'azimuth', 180)
# Set the inverter efficency
ssc.data_set_number(dat, 'inv_eff', 96)
# Set the system losses, in percent
ssc.data_set_number(dat, 'losses', 14.0757)
# Specify fixed tilt system (1=true, 0=false)
ssc.data_set_number(dat, 'array_type', 0)
# Set ground coverage ratio
ssc.data_set_number(dat, 'gcr', 0.4)
# Set constant loss adjustment
ssc.data_set_number(dat, 'adjust:constant', 0)
```

# Execute and put generation results back into dataframe
```
mod = ssc.module_create('pvwattsv5')
ssc.module_exec(mod, dat)
df['AC MW'] = np.array(ssc.data_get_array(dat, 'gen'))
```
\[ df['DC kW'] = \text{np.array}(ssc.data\_get\_array(dat, 'dc')) \]

# Free the memory
ssc.data\_free(dat)
ssc.module\_free(mod)

# Calculate the total energy generated by the PV site in megawatt-hours:
if periods != 8760:
    MWh = df['AC MW'].sum() / 2
else:
    MWh = df['AC MW'].sum()

# Find the capacity factor for the plant. Divide sum of generation by the number of periods
# times the system size
capacity\_factor = df['AC MW'].sum() / (periods * system\_capacity)

# Create two arrays, d holds data, index holds data's headers
d = ['Queue\_Num', 'lat', 'lon', 'interval', 'system\_capacity kW', 'MWh', 'capacity\_factor']
index = ['Queue\_Num', 'lat', 'lon', 'interval', 'system capacity kW', 'generation MWh', 'capacity factor']

# Create a new dataframe, df\_parameters, which has data from d and headers of index,
# then transpose it so that it is a 2x7 df
df\_parameters = pd.DataFrame(d, index=index).T
# Concatenate df\_parameters and df in a new dataframe, df\_out, so that they can be
# written in one csv.
# This allows the parameters of each PV site to be written in the generation file for easy ID
df\_out = pd.concat([df\_parameters, df], axis=1, join='outer')
# Change directory to desired saving location
os.chdir('C://Users//jetur//OneDrive//Research//Locations//2014 Sims')
# Write df\_out to a csv that is named after the PV site's utility company and queue number
df\_out.to\_csv(path\_or\_buf= Utility+'\ '+Queue\_Num+'.csv', sep=':', na\_repr='",
float\_format=\text{None}, columns=\text{None}, header=True, index=True, index\_label=\text{None},
mode='w', encoding=\text{None}, compression=\text{None}, quoting=\text{None}, quotechar=",
line\_terminator='\n', chunksize=\text{None}, tupleize\_cols=\text{False}, date\_format=\text{None},
doublequote=True, escapechar=\text{None}, decimal=\text{'.}"

# Add all of the generation data to a dataframe, df\_total\_generation, so that at the end of
# the for loop we have a file with a year's worth of generation data for all of the PV sites
# combined
df\_total\_generation = df['AC MW'] + df\_total\_generation
# Calculate the combined capacity of PV sites modeled
total\_capacity = system\_capacity + total\_capacity
# Calculate the combined MWh of PV sites modeled
total\_MWh = MWh + total\_MWh
# Calculate overall capacity factor for all sites simulated
overall_capacity_factor = df_total_generation.sum() / (total_capacity * periods)
print 'The combined capacity factor for all of the PV Sites simulated is: ', overall_capacity_factor
# Write the df_total_generation to csv file
df_total_generation.to_csv(year+' Total Generation Load.csv')

# Output the amount of time it took to simulate
time = time.time() - start
if time <60:
    print "Elapsed Time", time, " seconds"
elif time >=60 and time <3600:
    print "Elapsed Time", time/60, " minutes"
else:
    print "Elapsed Time", time/3600, " hours"
Appendix C: CAMD_Edits.m

%Add a North Carolina region to the CSIRegionNames and CSIRegions_LUT
%variables
CSIRegionsNames{11}='North Carolina';CSIRegions_LUT{11}='NC';

%This loop looks through the entire FacilityStruc array, and any entries
%in the array with a state location of NC, will have the CSIRegion changed
%to NC and the CSIRegionIX entry changed to 11
for i=1:FacIDIndex
    QqQ=strcmp(FacilityStruc(i).State,'NC');
    if QqQ==1
        FacilityStruc(i).CSIRegion='NC';
        FacilityStruc(i).CSIRegionIX=11;
    end
    i=i+1;
end