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Power System Planning in Disparate Systems: Modeling Sustainability and Electricity Access

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POWER SYSTEM PLANNING IN DISPARATE SYSTEMS: MODELING SUSTAINABILITY AND ELECTRICITY ACCESS

A Dissertation Presented

by

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DEDICATION

I dedicate this dissertation to my parents, my fiancé, the family members that kept me grounded, and the friends that kept me smiling along the way. The positive energy you all sent to me kept me going on this long road I call academia. Specifically, I would like to thank my mom (Tish) and dad (George) for showing me the value of education. I would also like to give a big shout out to my fiancé (Martin) who supported me through the thick and thin of this journey. Thank you for your support, and for not letting me give up on my dreams.

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ABSTRACT

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Electricity goals around the world tend to focus on increasing social benefit through one of two avenues: (1) increasing overall system sustainability or (2) increasing access to electricity. These goals guide the transition of the power system. In pursuit of these goals decision makers will need modeling tools that can inform decisions, in a way that is flexible enough to include a wide range of preferences and goals. It is clear that the future generation mix of the power system will change, but the most sustainable solution, will change based on a country's goals. This dissertation will explore the various options for power grid expansion in disparate electricity systems. We present three essays that focus on evaluating the sustainability of different electricity futures to allow decision makers to understand impacts and tradeoffs between various combinations of power generating technologies. The first two essays are focused on evaluating the sustainability of generation mixes for New England. In the first essay we take a multi-model approach, first determining the reliability of the system overall, then evaluating different generation portfolios based on seven sustainability criteria. In the second essay we expand this work by implementing pumped hydro storage into the model. The sustainability of the system with and without storage capabilities is presented and evaluated. The third essay focuses on the UN Sustainable Development Goals, and electricity access in developing countries. Here we present a model that can be used by decision makers in developing countries to determine the best method of grid expansion to meet electricity access goals subject to system and budget constraints.

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CHAPTER 1

ELECTRICITY IN DISPARATE SYSTEMS

1.1 MOTIVATION

Electricity goals around the world tend to focus on increasing social benefit through one of two things: (1) increasing overall system sustainability or (2) increasing access to electricity. These goals guide the transition of the power system. In pursuit of these goals, decision makers will need to ask the question of how to increase system sustainability while maintaining reliability. Thus, decision makers can benefit from modeling tools that can inform decisions, in a way that is flexible enough to include a wide range of preferences and goals.

The remainder of Chapter 1 lays the foundation of this dissertation. We begin in Section 1.2 by discussing the various objectives of this dissertation. Section 1.3 presents background information and challenges for power system planning in developed and developing countries. We follow with a discussion of multi-criteria decision analysis (MCDA) as it pertains to energy planning.

1.2. OBJECTIVES

In this dissertation we provide modeling tools that evaluate a region's electricity expansion plans in terms of sustainability, reliability, and equality. We implement these tools to explore various options for power grid expansion in both developed and developing countries.

In Chapters 2-4 we present three essays that focus on evaluating different power generation portfolios to allow decision makers to meet their objectives for their energy systems. When decision makers are deciding which generation technologies to incorporate into the power system there is a value in determining the sustainability of the overall system as opposed to evaluating the sustainability of each technology individually. Due to the interactions between different technologies, the sustainability of entire system will not be equivalent to summing the sustainability of the individual parts of the system.

The first two essays are focused on evaluating generation mixes for New England in terms of reliability and sustainability. In the first essay we present a method for determining the sustainability of the system overall. We then apply this method to evaluate different generation portfolios based on seven sustainability criteria. We take a multi-model approach, first determining the reliability of the system, then evaluating different reliable generation portfolios based on seven sustainability criteria. In the second essay we expand this work by implementing pumped hydro storage into our model. We then compare the sustainability of the system with and without storage capabilities.

The third essay is inspired by the UN Sustainable Development Goals, which we discuss further in background section 1.3. The focus of the third essay is energy access in developing countries. We present a model that can be used by decision makers in developing countries to determine the mix of centralized and decentralized generation to meet electricity access goals subject to system and budget constraints.

Chapter 5 concludes the dissertation with the synthesis and future work for how different regions can benefit from the power grid expansion tools that have been developed as a part of this research.

1.3. BACKGROUND

1.3.1 Power System Planning in New England

In this section, we describe the composition of the New England power system, and discuss literature related to reliability concerns and electricity markets. Developed countries, particularly the USA, typically have large established centralized grids. The power system is well developed and access to electricity is unlimited. In general, these systems are considered reliable, meaning they have less than a couple of hours of outage per year. When modeling grid expansion problems for developed countries, typically the objective has been to minimize the system costs subject to meeting a demand constraint. Currently many countries have sustainability goals, such as reducing their GHG emissions, linked with their energy targets. As the effects of climate change become more apparent sustainability will become a more pressing issue.

The rest of this subsection focuses on the power system composition, the reliability concerns around the natural gas pipeline, and the energy targets in New England.

1.3.1.1 Composition of the New England Portfolio

As of January 2017, the power system in New England consisted of 30.5 GW of installed generation capacity. The grid is composed of a mix of nuclear, oil, coal, natural gas, hydro, and renewable energy technologies including wind, solar, biomass, and others. The capacity is primarily made up of natural gas (45%) followed by oil (23%), while the largest portion of supplied energy came from natural gas (45%) followed by nuclear (30%). Figure 1 details the total system capacity and electricity contribution by generation type.

ISO-NE, the region’s power system operator, has announced that more than 4.2 GW of generation capacity will be retired between 2012 and 2020. In addition, 5.5 GW of coal and oil capacity are at risk for retirement, and there is uncertainty surrounding the region’s remaining 3.3 GW of nuclear capacity (ISO NE Regional Energy Outlook 2017). While retirement of coal and oil technologies may prove to have a positive benefit for environmental sustainability, this could impact the ability of the system to satisfy electricity needs. Historically, coal and nuclear were typically used to supply baseload electricity demand, while oil and gas were used to satisfy peak demand in New England. This has changed recently: low-priced Natural Gas now supplies much of the baseload as well. In New England retired coal and oil plants are typically replaced by natural gas generation capacity. In the summer, New England faces no constraint on its natural gas pipelines. Thus, most of the region’s baseload needs are supplied by low-cost Marcellus shale gas from Pennsylvania and West Virginia. In the winter months, however, heating needs claim a significant portion of the region's natural gas supply and may push the region up against pipeline constraints.

The summer and winter peak demands for 2010-2015 can be seen in Table 1 (ISO NE 2017). In 2015, the seasonal peak demand periods occurred in February (19562 MW) and July (24437 MW). Although the summer had a higher peak demand for electricity, the low winter temperatures mean that in the winter natural gas had lower availability to supply electricity demand due to heating sector needs, which get precedence.

Table 1: Seasonal Peak Demands

		Date	Day	Peak (MW)	Hour	Temp (°F)

2010	JUL	6	Tue	27102	15	95.4
	JAN	24	Mon	21053	19	8
2011	JUL	22	Fri	27707	15	98.6
	JAN	4	Wed	19905	18	24
2012	JUL	17	Tue	25880	17	93.1
	JAN	24	Thu	20887	19	14.7
2013	JUL	19	Fri	27379	17	94.7
	DEC	17	Tue	21448	18	15
2014	JUL	2	Wed	24443	15	88.5
	JAN	8	Thu	20556	18	19.5
2015	JUL	20	Mon	24437	17	89.4
	FEB	15	Mon	19562	18	17.5

New England sourced 44% of its electricity from natural gas in 2015 (ISO NE 2017). While natural gas produces less CO_2 emissions than coal and oil, the increasing heating sector dependence on natural gas could put the region at risk for a natural gas shortage. Natural Gas in New England is the most important fuel in both the electricity and heating sectors, providing challenges to the electricity sector. The amount of electricity that can be produced from NG is limited by two factors: the available NG generation capacity and the supply of NG itself. The supply of natural gas is determined by the pipeline capacity, and the amount of stored LNG. Figure 1 reports the capacity and energy supplied by fuel type in New England for 2015.

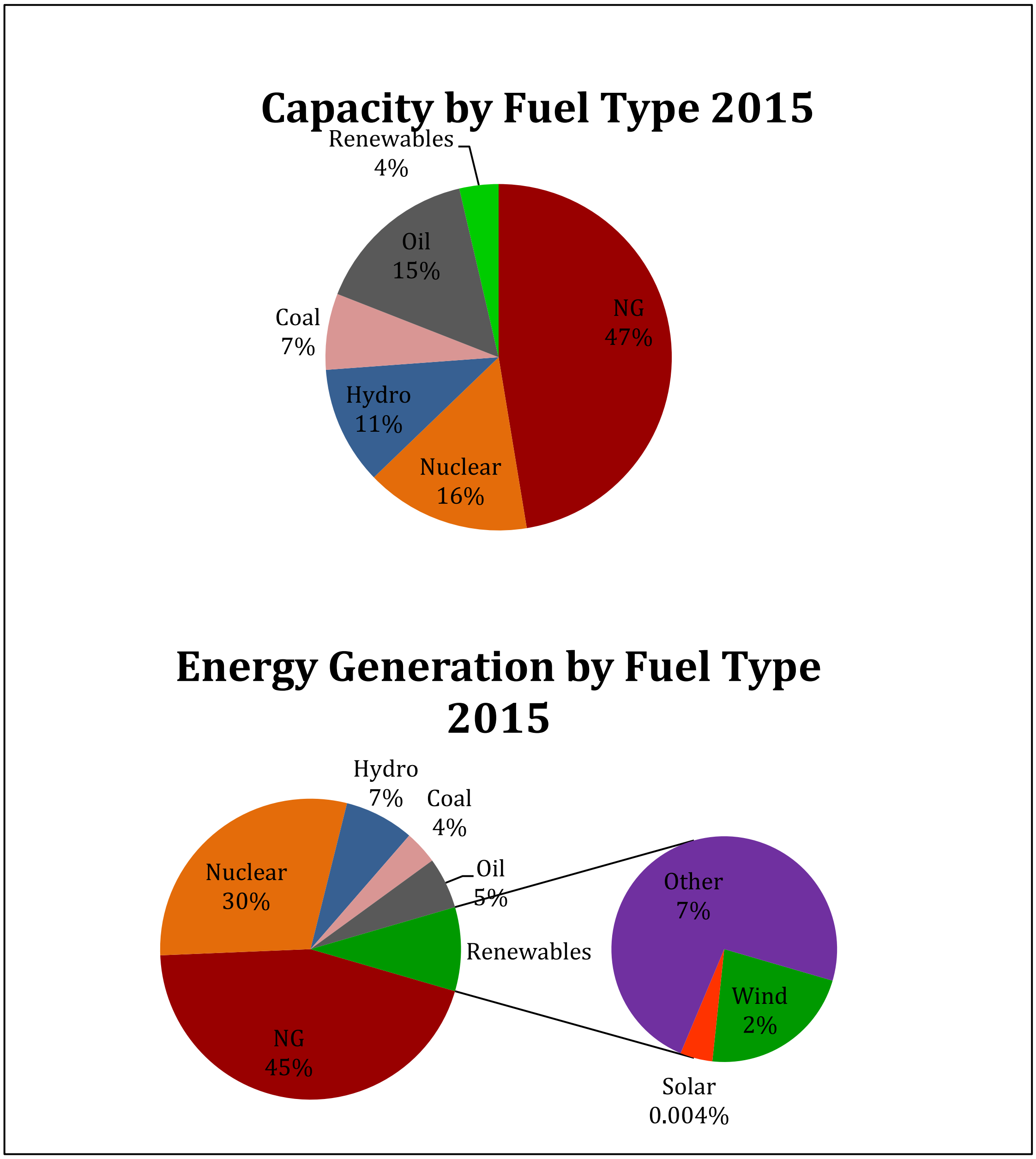

Figure 1: Capacity and generation by fuel type (ISO NE resource mix 2016; 2015 Annual Markets Report 2016). Note the Other in the Renewables Section is comprised of wood, methane, landfill gas, refuse, and steam.

1.3.1.2 Reliability in New England

When determining the reliability of a power system, studies vary in the metrics they use and the results. Reliability, like sustainability, has many different definitions and evaluation metrics. In this study we define reliability as the ability of the system to satisfy demand in every hour of a given time period.

For the purposes of our study we will define reliability as the ability of the portfolio of generation technologies to supply the amount of electricity demanded for every time period. We will assume that the demand for natural gas in the heating sector grows by 11% for winter months (December - March), and by -0.5% for summer months each year and the winter electricity demand increases by 6%, and the summer electricity demand increases by 11% over the 2015-2030-time span (ISO NE 2015).

A hot-button issue in New England right now is whether or not the region needs a new NG pipeline to maintain the reliability of the grid. In 2015 three separate reports were released evaluating the need for a Natural Gas pipeline in New England for 2030 (Knight and Stanton, 2016).

ICF International (2015) examined a specific pipeline proposal for New England, comparing the costs of building the pipeline to a future scenario with no pipeline. In this study the authors assumed the pipeline would be complete by November 2018, and supply an additional 1.3 billion cubic feet of gas per day. They found that the specific pipeline proposal would result in cost savings when compared to the no pipeline scenario. The analysis of this report focuses on New England. This report assumed demand for natural gas outside of the electricity sector grew by 2.7% each year between 2015 and

2018, and 1.3% each year for 2018 to 2035. In their study they assumed that future electricity sales, net of energy efficiency, would grow by 0.8% each year.

Hibbard and Aubuchon (2015) came to the opposite conclusion of ICF International (2015), stating that a future without the pipeline was the most cost effective. Similar to ICF International (2015) the analysis of this report focuses on New England. Hibbard and Aubuchon (2015) compared the costs of building a pipeline with alternative strategies to meet the energy demand. They found that a new pipeline is cost-effective in only two out of the scenarios they considered. In both of these scenarios, ISO-NE's winter reliability program is halted. This program includes a demand response component and incentives to oil and liquefied natural gas generators to secure fuel before the winter begins. The base case in this study reflected severe winter conditions indicating a high heating demand for natural gas. They found that in their base case there would not be a reliability deficiency in 2030 under the assumptions that there would be a continued decline in the long-term peak winter demand, and an increase in availability of non-gas generation resources. In their stressed system they modeled the increase in dependence on natural gas in the electricity sector. Under the stressed system the authors report that there would be a reliability deficiency by 2024. It was assumed that demand for heating from natural gas would grow by 1.4% each year for 2016 through 2030. In their study they estimated future energy efficiency levels for MA, which was not the focus of the other two studied mentioned above.

Stanton et al (2015) compared the costs of building a pipeline to alternate strategies, and found that a pipeline would be needed in all of their scenarios. In addition, they found that none of the scenarios they considered were complaint with MA's emission reduction goals. Stanton et al (2015) did not examine a scenario without a pipeline, which prevented a cost comparison from being made. One factor that could lead to different results is that the Stanton et al (2015) study was conducted prior to the winter of 2015, meaning is contains no data from this time period. In addition, they assumed and expansion of the pipeline in New England would be complete by 2017, and a new pipeline would only be built if demand for natural gas exceeded 95% of existing pipeline capacity in the peak hour. While this report modeled New England, the analysis was focused on Massachusetts. In their study they assumed that future electricity sales without energy efficiency would grow 1% each year, 0.1% per year with low energy efficiency, and -0.2% per year with high energy efficiency. The high energy efficiency is also considered the low demand scenario.

The varying assumptions and focuses of each of the studies mentioned above have produced different and conflicting results. The varying assumptions for heating demand increases and energy efficiency programs play into the level of reliability each study reports. In contrast to the studies mentioned above our study does not examine the viability of a specific pipeline proposal, and we do not evaluate the need for a pipeline on a cost basis. Instead we determine how pipeline limitations impact the ability of generation to meet the demand in New England. In addition, we determine how the sustainability of the overall system changes with and without a pipeline expansion.

1.3.1.3 Electricity Market

In the New England Electricity Market generators must place bids for the quantity and price of electricity they are willing to sell to the market. These bids can be based upon operation and maintenance costs for each of the generators. In particular the fuel cost will play a large role in the bid each generator submits to the market. Historical fuel costs and the LCOE of different technologies define the minimum amount each generator is willing to accept for electricity production. Benes and Augustin (2016) discuss the impact that inclusion of air pollution, social cost of carbon, and federal tax credits has on the reported LCOE per technology. Their analysis showed that existing Nuclear has the lowest LCOE, in all cases. This combined with the low fuel cost and the fact that New England does not plan to build any new nuclear facilities in the coming years indicates that Nuclear will bid the lowest in the New England electricity market.

While the LCOE metric is commonly used to compare electricity generation technologies, there is much criticism when LCOE is applied to variable renewables. This criticism stems from the fact that LCOE does not capture the time varying nature of renewable energy. For instance, if wind is able to contribute 50 MWh towards peak demand, this would be more valuable than if it contributed 50 MWh of energy during periods of low demand. Since LCOE does not include integration costs, and cannot determine economic efficiency (Ueckerdt et al. 2013). In addition, the LCOE metric is limited because the value of renewables changes with the penetration level. Ueckerdt et al. (2013) proposed the system LCOE metric for renewables, which is defined as the sum of marginal generation and marginal integration costs. While this metric is more robust than the traditional LCOE metric the integration costs are highly dependent on the location and size of the technology. In this research we find the Portfolio LCOE, which is the overall LCOE for the combined portfolio of technologies. The definition of this metric and supporting arguments is discussed in more detail in Section 2.2.4.3 after the

Portfolio LCOE calculation is introduced. Using historical fuel, capital, and marginal operation cost data the dispatch order was determined to be Nuclear, Onshore Wind and Solar, Offshore Wind, Natural Gas and Hydro, followed by Oil.

1.3.1.4 New England Energy Targets

There are many climate change policies in New England states that could help push renewable integration to the top of policy maker's agendas. The Regional Greenhouse Gas Initiative (RGGI) is the first mandatory, market-based program to reduce emissions of carbon dioxide (CO2) in the USA. The states participating in RGGI include Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont. As a part of the RGGI these states have established a regional cap on CO2 emissions from the power sector. Once the regional cap is set an auction for a limited number of tradable CO2 allowances is held in which fossil fuel-fired power plants 25 MW or greater in size, currently 164 facilities region-wide, need to secure allowances to cover their emissions. As of 2016 the auctions have produced $2.6 billion, which states reinvest in consumer benefit initiatives (RGGI Factsheet, 2017). Some of these initiatives can include energy efficiency, renewable energy, and greenhouse gas abatement programs.

In addition, some states have made energy targets that reinforce the goal of the power sector. In 2008 Massachusetts (MA) signed the Global Warming Solutions Act (GWSA) into law. The GWSA required the Executive Office of Energy and Environmental Affairs (EOEEA), and other state agencies, to set economy-wide greenhouse gas (GHG) emission reduction goals for MA aimed at reducing the 1990

GHG emission levels by 10-25% by the year 2020, and 80% by the year 2050 (EOEEA, 2017). In 2016 the Vermont Department of Public Service released the "2016 Comprehensive Energy Plan," which established two main goals for reducing GHG emissions from Vermont's energy use. The first is a 40% reduction of the 1990 GHG emissions level by the year 2030, and the second is an 80-90% reduction by the year 2050. The method proposed in the document was to reduce to energy use in 3 possible ways: (1) Improve the efficiency of demand-side thermal and electric units, primarily through from improvements in building shells which reduce the need for building heat; (2) Exchange combustion technologies for more efficient electric-powered technologies, such as electric vehicles; (3) Reduce source energy requirements of the electricity generation fleet through switching the state's electric power supply to solar, wind, and hydro resources (Vermont Dept of Public Service, 2016).

Policies such as these in New England will likely lead to higher levels of renewable energy integrated into the grid to meet their GHG emission reduction goals. Although NG produces fewer emissions than coal and oil, states will need a combination of technologies to reach their targets. In addition, intermittency and lack of dispatchability make it difficult to use wind and solar resources to offset the region's dependence on Natural Gas. Battery storage and hydro may offer support for wind and solar to become a bigger part of the generation mix in the future, if technology prices decrease.

1.3.2 Power System Planning in Sub-Saharan Africa

Developing countries face different challenges when faced with power grid planning. Specifically, the current grid is typically under-developed, with low penetration and low reliability. In the parts of the country where there is an established grid, access to electricity is limited. The system is often considered unreliable with a number of outages per day, and demand may be unknown. When modeling grid expansion problems for developing countries the issue is to maximize social benefit subject to a cost.

In support of increasing power system development and electricity access the UN has stated the targets from Goal 7 of the UN sustainable development goals driving this research are as follows (World Bank 2018b):

1. Considerably Increase the share of renewable energy in the global energy mix by 2030
2. Universal access to affordable, reliable, and modern energy services by 2030

While it is agreed upon that there should be a progression towards increased electricity access there are many avenues for providing universal access to electricity. options included a multitude of technology options, a debate between decentralized and centralized avenues, and configuration of transmission systems. Stakeholder preferences for these different systems will impact the rate of adoption of various technologies, rural versus urban electrification, investment in transmission and generation infrastructure, and the level of energy access equality in the country. The level of equality in terms of energy access across the country can have further implications on the level of well-being and human development that the country experiences.

1.3.2.1 Well-being and Electricity Access

We make two key assumptions in our model: that electricity access will lead to proportional electricity consumption, and that this in turn will lead to increased utility through improvements in the quality of life. Regarding the first assumption, there is evidence that demand for electricity tends to increase rapidly once access is provided for the first time, provided there is sufficient access to electrical appliances (Bezerra et al., 2017; Williams et al., 2017; Bridge et al., 2016; Campbell et al., 2003). We note here that the relationship between access and consumption will not be constant as access grows – there will be saturation in demand. Moreover, this assumption includes an implicit assumption that electricity demand is price inelastic. Nevertheless, we believe that this is a reasonable approximation in developing countries that currently have low levels of access.

Regarding our second assumption, there are two arguments for this. The first is that utility will depend on energy services and energy consumption is a good proxy for energy services. We note that utility is not directly over electricity consumption, but rather over the services that it provides, such as lighting. However, electricity consumption is a reasonable proxy for energy services. This will be moderated by energy efficiency: utility will be higher for the same amount of energy if appliances are more energy efficient. For a fixed level of energy efficiency, however, and in the absence of pure waste, utility will increase with electricity consumption.

The second argument is more controversial, but important. It is the idea that energy access in developing countries contributes to economic growth and quality of life. It is well established that there is a correlation between per capita energy consumption and well-being indicators, such as the Human Development Index (HDI), the Physical Quality of life Index, infant mortality, and life expectancy (Carvallo et al. 2017; Arto et al. 2016; Tezanos Vazquez and Summer, 2013; Alam et al. 1991; Goldemberg et al. 1985; Morris 1978). A socio-economic impact study by the World Bank correlated electricity access to significant educational achievement (World Bank, 2002). In addition to well-being indicators, there are a host of energy indicators for sustainable development that relate to equality and health, such as accessibility, energy resource risk, affordability, safety, and air quality (Kemmler and Spreng, 2007; Vera and Langlois, 2007). Alam et al. (1991) established a logarithmic relationship between quality of life and per capita electricity consumption.

Figure 1 illustrates how the HDI (HDI 2015) is related to per capita electricity consumption at the country level (OECD/IEA 2017) for the year 2014. Each data point represents a different country. The HDI is a composite statistic, developed by the UN, which measures achievement in three parts of human development: length and quality of life, education, and standard of living. The length and quality of life is determined through life expectancy at birth. The education indicator is derived from the mean number of years of schooling for adults aged 25 years or older, and the number of years of schooling a child is expected to receive once they enter school (Jahan 2016). Gross national income per capita is used to evaluate standard of living.

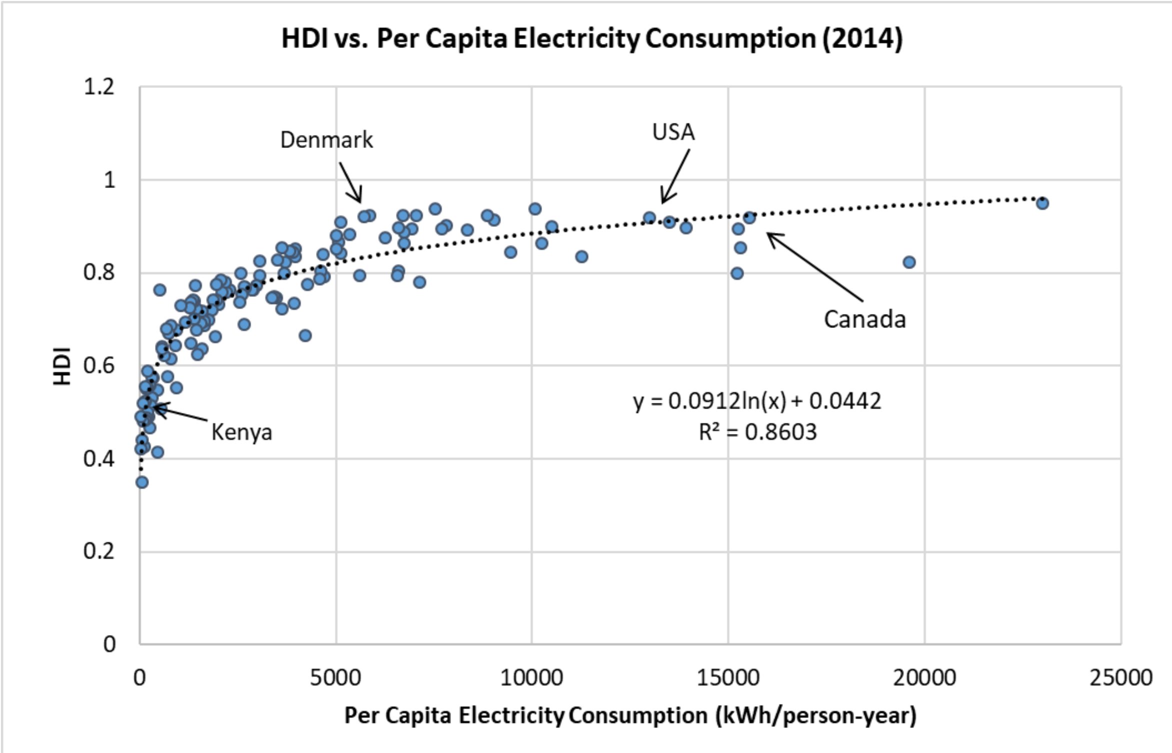

Figure 2: The HDI compared to Per-Capita Electricity Consumption

Figure 2 shows that there is a logarithmic relationship between HDI and 2014 per capita electricity consumption, confirming the relationship identified by Kanagawa and Nakata (2008) using 2002 data.

Although these links between energy consumption and well-being indicators are well-established, it is hard to determine the degree to which electrification causes increases in well-being, particularly for the economic development aspect of well-being (Best and Burke 2018). Along with the normal challenges of establishing causation, predicting the impact of electrification has other difficulties, such as challenges in the reliability for electric supply and the rate at which electric appliances are adopted (Lenz et al. 2017; Munyaneza et al. 2016). Parikh et al. (2015), however, found evidence in their study of slum residents in India that that providing infrastructure, including electricity, in Indian slums increases literacy, income, and health, particularly for women.

Finally, there is some indication that the benefits of additional units of electricity are not infinitely increasing. The saturation effect indicates that increased consumption at low levels has a positive correlation with a greater relative impact on socio-economic development, but this relationship may become less pronounced as the country becomes more developed and well-being is less dependent on energy consumption (Martinez and Ebenhack, 2008). In their paper Martinez and Ebenhack (2008) highlighted that the diminishing returns to HDI from increased per-capita energy consumption became stronger when major energy exporting nations, such as OPEC countries, were filtered out.

There is evidence that, in general, stakeholders care about equality in terms of electricity access due to rural electrification programs and the UN SDGs. We also recognize that the benefits of increased electricity consumption have decreasing returns to scale due to the initial development gains, and energy efficiency allowing regions to maintain the same level of development, under tighter energy consumption. Thus, we model utility as a function of electricity access, using an isoelastic utility function, also known as the constant relative risk aversion utility function.

In this dissertation, our specific focus is on the Liberian power system, discussed further in Chapter 4. While our work is generalizable, we use Liberia to highlight the implications of our analysis, the opportunity for increasing electricity access, and the equality implications of different pathways.

1.3.3 Multi-Criteria Decision Analysis in Energy Planning

Multi-criteria decision analysis (MCDA) is a tool that is used to evaluate multiple conflicting criteria in the decision-making process. Various stakeholders have a role in determining how the power grid will expand. Typical objectives are the security, reliability, and sustainability of the overall system. Some decision makers wish to include more renewables to the power system, while other are more focused on reliability of the overall system. MCDA has been used to rank different options for grid expansion, while taking into account various stakeholder preferences. MCDA has made a large contribution to the energy planning sector, so while we mention energy planning studies that use MCDA the following literature survey is by no means exhaustive.

Zakerinia and Torabi (2010) present a multi-objective model that can be used to obtain Pareto optimal solutions under cost, CO2 emission, energy consumption and reliability objectives, which can then be presented to the decision maker. They argue that using an MCDM approach in energy planning provides a more realistic long-term plan for power expansion planning, and allows the decision maker to consider the transmission network and geographical impacts to obtain a more realistic energy plan.

Sustainability has many definitions associated with it that change depending on the type of decision maker planning the electricity system. Even with varying definitions the goal of creating a sustainable energy system is seen across multiple literatures. However, like the definition of sustainability, the criteria for a sustainable energy system varies across the literatures (Streimikiene et al. 2012; Tstoutsos et al. 2009). Wang et al. (2009) reviewed the methods for selecting, weighting, evaluating and aggregating different sustainability criteria. In their review they covered roughly 29 sustainability criteria that have been used in the literature. Other papers have looked at the tradeoff between increasing the generation capacity specific technologies ranked against environmental and economic factors (Lee et al. 2009; Chaouachi et al. 2017). In addition, other studies have ranked renewable energy sources against each other (Kabak and Dağdeviren 2014).

Previous studies have used MCDA to investigate different technology options in systems with only one energy source (Scott et al. 2012). In addition, studies have used MCDA to aid decision makers when considering energy policies for expansion of the power system (Diakoulaki and Karangeli 2007; Fernando et al 2013). Maxim (2013) compared 14 technologies across 10 sustainability indicators in a global context, while Klein and Whalley (2015) compared 13 electricity options across eight decision-maker preference scenarios for the USA. Klein and Whalley (2015) evaluated sustainability of power plants using 7 individual metrics in 4 categories: economic sustainability, environmental sustainability, social sustainability and technical sustainability. Our study builds on this study, by considering sustainability of the entire system, rather than one technology at a time. This approach lends itself well to the power industry because the power grid is a complex structure which cannot rely on a singular power source.

In general, sustainable energy planning MCDA problems involves m alternatives evaluated according to n criteria, each with user defined weights. Our contribution to this realm of MCDA is a methodology for ranking a portfolio of technologies as opposed to ranking one generation option at a time. In other words, the different generation portfolios are the set of alternatives. This is done in the context of the ISO New England (ISONE) power system, and will be discussed further in section 2.1.

CHAPTER 2

ESSAY I: SUSTAINABILITY EVALUATION OF GENERATION PORTFOLIOS FOR THE NEW ENGLAND POWER SYSTEM

2.1 Abstract

Designing policies to achieve a more sustainable electricity system requires policy-makers to weigh different electricity futures against a wide range of societal, economic, environmental, and technical implications. There is controversy on multiple fronts, as no technology satisfies all the demands of sustainability. Moreover, electricity systems include combinations of interacting technologies, meaning it is not enough to analyze technologies individually. We present a methodology for evaluating the sustainability of a region's electric generation portfolio, using multi-criteria decision analysis. Our framework focuses on long-term capacity planning for resource adequacy and sustainability. Our New England case study pays close attention to regional controversies involving offshore wind, natural gas pipelines, and the retirement of nuclear plants. We evaluate a set of generation portfolios under nine illustrative stakeholder preference scenarios across seven sustainability metrics. We find that if stakeholders are against nuclear and put a high value on water conservation, then retiring oil and nuclear, while adding high levels of offshore wind backed up by natural gas and hydro scores the highest. However, if stakeholders are concerned about the full range of sustainability metrics, then the most sustainable solution is to add high amounts of offshore wind and increase nuclear, while eliminating oil.

2.2 Background and Motivation

Regions around the world have goals to increase the sustainability of their electricity systems, consistent with the World Bank Sustainable Development Goals and the Paris Climate Change Agreement (World Bank 2018b; UN 2014).. Sustainability, however, is multi-dimensional, making it difficult to evaluate; and the metrics used for evaluation of a sustainable energy system vary across the literature (Bhardwaj et al. 2019; Atabaki and Aryanpur 2018). Previous studies have used multi-criteria decision analysis (MCDA) approaches to evaluate the sustainability of generation technologies on an individual basis; some globally (Cartelle Barros et al. 2015; Hong et al. 2015; Maxim 2014), while others focus on specific regions, including the USA (Klein and Whalley 2015), Egypt (Shaaban and Scheffran 2017), Australia (Hong et al. 2014), Finland (Häyhä, Franzese, and Ulgiati 2011), Italy (Mahbub, Viesi, and Crema 2016), Jordan (Malkawi, Al-Nimr, and Azizi 2017), Taiwan (Lee and Chang 2018), Tunisia (Brand and Missaoui 2014), and Turkey (Atilgan and Azapagic 2016).. These analyses miss important interactions between technologies, especially when high levels of intermittent renewables are included. Here, we introduce a methodology for evaluating the system-level sustainability of a region's electricity generation portfolio, applying it to the New England power system. This method evaluates the sustainability of the system under multiple metrics, while simultaneously capturing the interactions between technologies. This provides policy makers with quantitative estimates for the tradeoffs between electricity system futures against multiple sustainability metrics.

New England has been a leader in moving toward a more sustainable electricity system in a number of ways. The New England-based Regional Greenhouse Gas

Initiative (RGGI) was the first mandatory, market-based program to reduce emissions of carbon dioxide (CO2) in the USA. The New England states participating in RGGI include Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont. All of the states in New England have Renewable Portfolio Standards, which require utilities to ensure that a percentage of the electricity they sell comes from renewable resources, with the aim of promoting domestic energy production to encourage economic growth through job creation, and diversification of energy resources (NCSL 2018)

Some states have additional energy targets as well. In 2008, Massachusetts signed the Global Warming Solutions Act (GWSA) into law. The GWSA required the Executive Office of Energy and Environmental Affairs, and other state agencies, to set economy-wide goals to reduce the 2020 greenhouse gas (GHG) emission levels by 10-25% below 1990 levels, and 2050 emissions by 80% (EOEEA 2017). In 2016 the Vermont Department of Public Service released the "2016 Comprehensive Energy Plan," with goals of a 40% and 80-90% reduction below 1990 GHG emissions level by 2030 and 2050, respectively. They specifically mention electrification of the transportation sector and moving toward solar, wind, and hydro resources (Vermont Dept of Public Service 2016). On the other hand, there is a push to reduce the cost of electricity. According to the EIA the average price of electricity for New England customers in 2018 was 20 cents per kWh, significantly higher than the USA average of 13.12 cents/ kWh (Hankey 2018).

Despite the large push for sustainability, the region has seen considerable debate over how to reach the goal of a sustainable power system. A recent transmission plan aimed at connecting Canadian Hydro to Massachusetts was voted down by New Hampshire at the last minute. There is continuing controversy about new Natural Gas pipelines: with the system operator of New England (ISO-NE) preferring new pipelines to preserve electricity security and reduce dependence on expensive imports of liquefied natural gas, but a number of different groups opposing the pipelines for environmental and safety reasons. In 2015 there were three separate reports released evaluating the need for a Natural Gas pipeline in New England (Knight and Stanton 2016), highlighting the debate over the natural gas pipeline and energy security concerns.

ISO-NE has reported that 2200 MW of oil, nuclear, and coal capacity will retire by May 2019, and an additional 5500 MW of coal and oil capacity is at risk of being retired in future years. Moreover, there is uncertainty surrounding New England's remaining 3300 MW of nuclear power (ISO NE 2017). In 2018 Connecticut put out a request for proposals in hopes of procuring up to 900,000 MWh/yr of renewable energy and associated Renewable Energy Certificates from offshore wind and other renewable energy sources. While recent legislation has carved out a mandate of 1600 MW of offshore wind in the next 8 years, the failed Cape Wind project, derailed by focused opposition on Cape Cod, hangs over this development.

In order to explore these issues, we analyze and evaluate the electricity system in terms of portfolios of generation technologies, rather than individual technologies one by one. This is important, because the impact of the electricity system as a whole may be quite different than the impacts of individual technologies considered alone. For example, the levelized cost of electricity (LCOE) of an individual technology does not capture the cost to serve the entire system’s demand; it is well-known to be a flawed metric when comparing the economic attractiveness of intermittent and conventional generation (Ueckerdt et al. 2013). Similarly, while individual intermittent technologies have low pollution and water consumption, their employment may nevertheless lead to significant emissions and water use from the conventional generation technologies used as backup (Gonzalez-Salazar, Kirsten, and Prchlik 2018; de Groot, Crijns-Graus, and Harmsen 2017).

In our analysis, we first require candidate portfolios to reliably satisfy the region's electricity demand. We then evaluate the portfolios under a mix of sustainability metrics, including societal, environmental, and economic factors (i.e. LCOE, land use, water consumption, jobs, fatalities, emissions). These metrics are evaluated considering the impact of both energy and capacity. This contrasts with the literature, which used lifecycle estimates for metrics, assuming typical energy use, based on historical capacity factors, for a given amount of capacity. At the system level, however, a fixed amount of capacity can produce varying amounts of energy, depending on the composition of the electricity portfolio. Our method provides a holistic picture, as we explicitly distinguish the sustainability impacts of installed capacity versus electricity produced.

Four papers examine sustainability and reliability for an overall system, using MCDA techniques in combination with an electricity model. Atabaki and Aryanpur (2018), Lo Prete et al. (2012) and Brand and Missaoui (2014) optimize for least-cost technology options, rather than using cost as just one component of sustainability. Atabaki and Aryanpur (2018) focused on comparing different optimization objectives and the resulting electricity systems. Lo Prete et al. (2012) focused on comparing the sustainability of micro-grids when combined with the current centralized grids in Europe. Brand and Missaoui (2014) focused on evaluation of electricity portfolio options for the Tunisian power system in terms of energy security, cost, socio-economic, and ecological criteria using a linear optimization model in combination with MCDA analysis. The fourth paper, Hong et al. (2014), evaluate generation portfolios using an MCDA framework to optimize portfolio mixes under a range of stakeholder preferences, with a focus on nuclear scenarios. This paper does not address the intermittency of resources in the system.

Some gaps in the literature remain. (1) There is a need to consider economic viability as just one sustainability criterion rather than the key objective. (2) Most systems globally are dominated by centralized power systems; thus, it is crucial to address these. (3) The set of social and environmental sustainability metrics in these papers is limited. (4) It is important to represent hourly, seasonal, and annual variation in resource availability and demand. (5) The impacts of generation technologies depend on both their capacity and their energy generation. Our analysis expands the literature through our careful attention to the role of capacity and energy in sustainability calculations, rather than using general lifecycle assessments.

Our specific contributions are two-fold. First, we emphasize that sustainability is a multi-dimensional measure reflecting tradeoffs between multiple metrics. Stakeholders may agree that both reducing costs and reducing GHG are important, but may differ in the importance they put on either. This framework provides the information that stakeholders need to start this conversation. This paper lays the foundation for future studies to assist stakeholders in fully understanding the trade-offs between sustainability categories when adding and retiring different technologies from their energy systems. The second contribution is to put the discussion surrounding sustainable electricity production into a system framework. This is crucial since electricity technologies interact in important ways. It is almost nonsense to discuss the sustainability, or even the cost, of individual technologies, without a system perspective. A region's ultimate performance depends on the overall system, the portfolio in which they find themselves.

The rest of the paper is organized as follows. Section 2 presents our integrated electricity and sustainability model. Section 3 presents the results of our New England case study. Section 4 concludes with some policy implications. The specific data used in our analysis can be found in Appendices A and B.

2.3 Methodology

We apply a two-step methodology to evaluate the sustainability of electricity generation portfolios (Figure 3). We define a *portfolio* to be the combination of power plants that satisfy a regions electricity demand. Candidate portfolios are defined in terms of installed generation capacity for each technology. The electricity model, in Section 2.1, calculates energy supplied by each technology, under the constraint that demand is satisfied for every hour over a period of 5 years. If demand is not satisfied, the generation portfolio is deemed unreliable, and more capacity is added into the system. The sustainability model, in Section 2.2, uses the capacity and energy contribution of each technology as inputs to evaluate a set of metrics for each portfolio. Using multi-criteria decision analysis (MCDA) the portfolios are ranked under multiple illustrative preference scenarios, which apply exogenously-defined sustainability metric scaling coefficients.

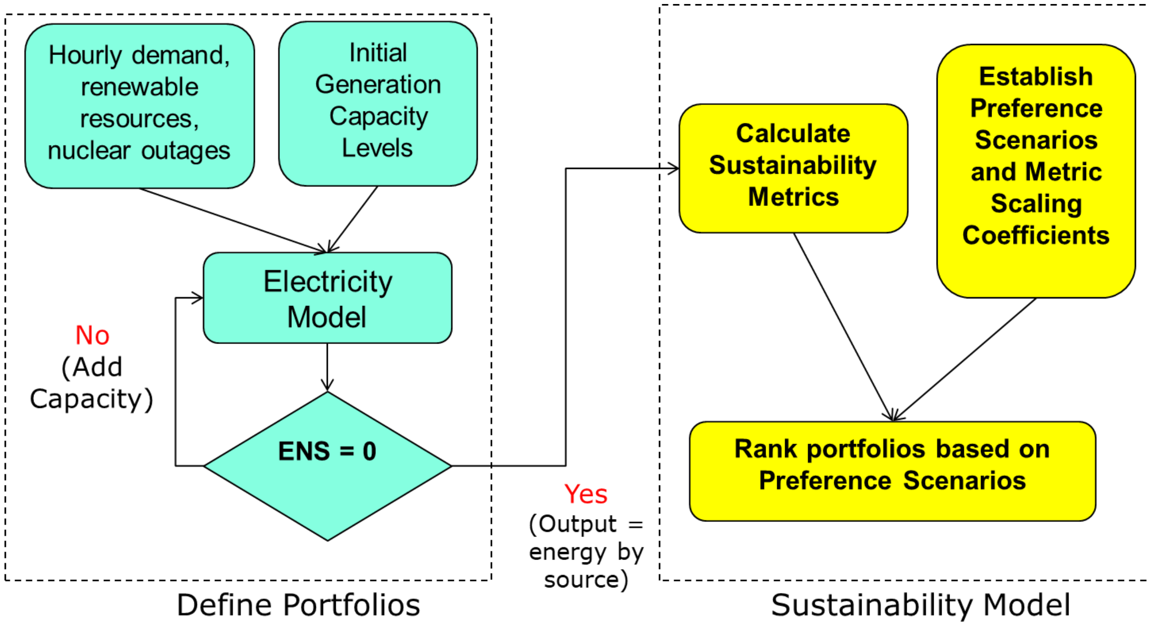

Figure 3: Flow Chart for Portfolio Evaluation

2.3.1. Electricity Model

The structure of our electricity system model is generalizable, but the specific model is inspired by the New England electricity system. We focus on generation capacity adequacy, assuring that there is never a mismatch of supply and demand. We define generation adequacy, as the "ability of the electric system to supply the aggregate electrical demand and energy requirements of customers at all times, taking into account scheduled outages and reasonably expected unscheduled outages of system elements" (T. Mount, A. J. Lamadrid, and S. Maneevitjit 2011). We note that in the ISO-NE market, generators are dispatched based on their bids and transmission constraints. We abstract from transmission constraints, leading us to find a lower bound on generation capacity requirements. The analysis includes commercially available technologies which currently contribute, and are projected to continue contributing, to the New England electricity generation mix. The 2015 electricity energy contribution by technology was as follows

(ISO NE 2017): Solar (0.9%), Wind (3.2%), Other Renewables (6.3%), Natural Gas (48%), Hydro (8.4%), Nuclear (31%), Oil (0.7%), Coal (1.6%). Coal was excluded from the model because currently ISO-NE projects that coal will make up 2% or less of its generation capacity by 2025. Storage is also excluded from this analysis. This is a first step in moving from a technology-by-technology calculation to a sustainability calculation for the entire electricity system. Future work includes understanding the role of storage, and integrating other components of the energy system (i.e. heating and natural gas pipelines).

The purpose of the electricity model is to estimate the amount of energy generated by each source. We do this using simple dispatching rules for the different technologies. Specifically, we mimic the typical merit-order found in the historical trends in New England. The flow chart in Figure 4 illustrates the rules governing the order in which generators are dispatched. Nuclear generation is allocated first, as nuclear typically bids very low, or even negative, to avoid having to power down. Next solar is allocated, followed by onshore wind. Again, these generators tend to bid zero. We allocate solar first because it is more decentralized, thus more difficult to "spill". If there is load remaining, this gets allocated to offshore wind. Next, remaining load is divided between natural gas and hydro, with 87.5% to natural gas and 12.5% to hydro. These percentages reflect the proportion of energy supplied by these technologies in 2015 in NE. If there is remaining demand, and if the natural gas pipeline is not operating at maximum capacity, then demand is allocated to natural gas first, followed by hydro, and finally to oil. Hydro is dispatched before oil because oil is expensive and typically only used to cover the demand peaks. If the natural gas pipeline is at maximum capacity, then oil is used to meet demand followed by hydro. In this case, oil is dispatched before hydro because we assume that if the pipeline is at capacity the heating demand is high, indicating low temperatures. During periods where the temperature is low, hydro-power generators usually keep the reservoir level higher to prevent the reservoir from freezing and protect fish populations. We do not separately consider electricity imports. Instead, our model defines the generation portfolio as the combination of power plants that will supply electricity to the New England region, eliminating the need to distinguish between imported and domestically generated electricity.

The outputs of the electricity model include the total energy supplied, the average power, and the capacity factor by each technology over the 5-year time period. The capacity factor for technology τ, CF_τ is calculated by dividing the total energy generated, E_τ, by the amount of energy technology τ would generate if it ran at full capacity, G_τ, for every hour, h, over 5 years, equation 1.

$$CF_\tau = \frac{E_\tau}{h * G_\tau} \qquad (1)$$

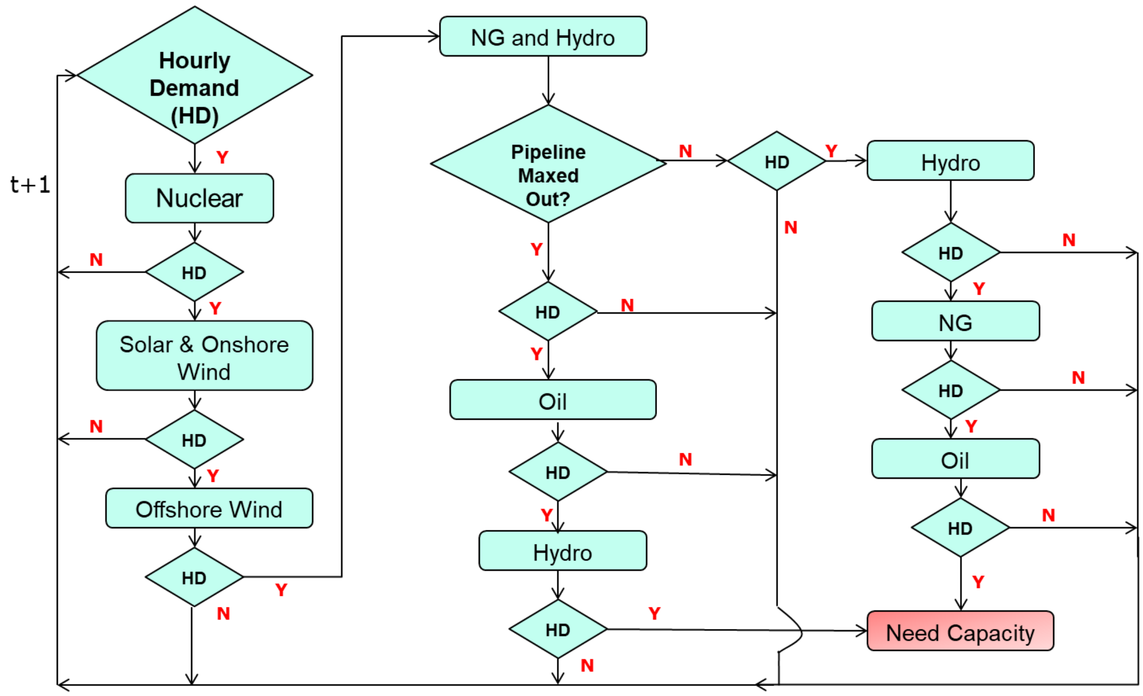

Figure 4: Merit-Order Dispatch Flow Chart for the Electricity Model.
Note: The diamonds containing HD are decision points where the model evaluates if there is any remaining hourly demand after a generation technology has been deployed

Each technology is dispatched up to its constraints. All technologies are limited by the overall capacity of the technology in the portfolio. Nuclear is limited by planned outages, which are based on previous data. Hourly data on solar radiation, onshore, and offshore wind speed (see Appendix A) are used to determine the maximum energy output based on the portfolio-specific capacity levels. Natural gas capacity is the minimum of installed generation capacity and pipeline capacity, as illustrated in equation 2.

$$NG_{i,t} = \min\left[G_{i,NG}, PL_t - D_{Heat,t}\right] \qquad (2)$$

Here $NG_{i,t}$ is the electricity available from natural gas generation in portfolio i at hour t; $G_{i,NG}$ is the generation capacity of natural gas in portfolio i; PL_t the pipeline capacity (power-equivalent in MWh); $D_{Heat,t}$ the heating demand for natural gas (power-equivalent in MWh) at hour t. The power-equivalent for both parameters is calculated using a power plant heat rate, or efficiency, of 10,408 Btu/kWh for a steam electric generator. This is a simplifying assumption: in reality the amount of fuel required to generate electricity varies by types of generators, power plant emission controls, and fuel quality. We convert the pipeline capacity, reported in fuel per day, to energy capacity per hour through tracking the natural gas used from the pipeline over a 24-hour time period. Once the fuel used has reached the maximum amount for that day, we set $PL_t = 0$, indicating no more natural gas power can be generated until the beginning of the next 24-hour time period.

We abstract from transmission (and its related complications such as Kirchhoff's laws), thus assuming that there is an unconstrained network, meaning necessary investments in transmission capacity have been made to ensure reliable supply of electricity to demand centers. When evaluating the reliability of a given portfolio, we use the electricity not supplied (ENS) metric, defined in equation 3, which is defined as the difference in available energy supply and the energy demand for a given hour t:

$$ENS_{t,i} = D_t - E_{t,i} \qquad (3)$$

where $ENS_{t,i}$ is the electricity not supplied at time t for portfolio i; E_{ti} is the electricity generated by portfolio i at time t; and D_t is the demand of electricity at time t. Let ENS_i be the maximum energy not supplied for portfolio i over the time period of the model:

$$ENS_i = \max_t \left(ENS_{ti} \right) \qquad (4)$$

If $ENS_i > 0$ the candidate portfolio i is considered unreliable and capacity is added.

2.3.2. Sustainability Model

Given the capacity and energy of each generation technology in a portfolio, we calculate the sustainability of the portfolio, using a multi-criteria decision analysis model, building on the work of Klein and Whalley (2015) and Maxim (2014). A key contribution of this paper is the division of each sustainability metric, seen in Table 2, into its fixed (per capacity) and variable (per energy) components. The ultimate measure of sustainability will be driven by stakeholder preferences over multiple metrics using the weighted sum method. To get at this, we consider a number of illustrative preference scenarios. In order to operationalize this, the preferences of stakeholders in New England would need to be elicited. In the rest of this section, we define our set of sustainability metrics, then discuss the calculations used to evaluate the sustainability of generation portfolios.

Table 2: List of the three types of sustainability and their metrics

Sustainability	Metric	Units
Economic Sustainability	Levelized Cost of Energy (LCOE)	\$/kWh
Environmental Sustainability	Life cycle greenhouse gas (GHG) emissions	Gram of CO_2 equivalent(gCO_2eq)/kWh
	Life cycle air pollution (SO_2, NO_X, PM)	Milligram(mg)/kWh
	Land use (on-site, direct, operational)	Square meters (m^2)/MWh
	Life cycle Water consumption (on-site, direct, operational)	Liters(L)/MWh
Social Sustainability	Fatalities	Fatalities/GWh
	Jobs	Full-time equivalent (FTE)/GWh
	Nuclear aversion	unitless

We discuss the calculations for individual sustainability metrics in Section 2.2.1, and how they are aggregated into portfolio metrics in Section 2.2.2.

2.3.2.1 Individual Sustainability Metrics

When analyzing portfolios rather than individual technologies, both generation capacity and energy consumption need to be considered. If a metric is proportional to capacity, such as direct land use, then using a lifecycle estimate of per energy land use will be misleading if a technology generates only a small amount of energy within a portfolio. Thus, we define a fixed and variable portion for each technology τ. Let $x_{ij\tau}$ be the value of metric j for technology τ in portfolio i; and let $F_{j\tau}$ and $V_{j\tau}$ represent the fixed value per unit of capacity and variable value per unit of electricity for metric j, respectively. The total value of the metric is as follows:

$$x_{ij\tau} = \frac{F_{j,\tau}}{hCF_{i\tau}} + V_{j,\tau} \qquad (5)$$

Where the capacity factor $CF_{i\tau}$ depends on the specific portfolio i and technology τ.

We assume that all technologies have a 30-year lifetime. This assumption accommodates the technologies that had multiple lifetime estimates in the literature, reduces general variability, and provides consistency across sustainability metrics. Below, we discuss each metric in turn, dividing them into categories depending on whether they have only a fixed amount, only a variable amount, or both. Table 2 lists key parameters and Table 3, variables.

Table 3: Parameters used to calculate the sustainability for various portfolios

Symbol	Description	Value	Units
T	Effective tax rate, includes state and federal taxes	39.2	%
h	hours in a 5-year period	8760*5	h
DR	Discount rate	4	%
N	Number of operational years	30	years

Table 4: Variables used to calculate the sustainability for various portfolios

Symbol	Description	Units
$LCOE_{i\tau}$	Levelized cost of electricity for technology τ in portfolio i	$/kWh
$C_{cap, \tau}$	Overnight capital cost	$/kW
D_{pv}	Depreciation, based on IRS Modified Accelerated Recovery System	%
$CF_{i\tau}$	Capacity factor of technology τ in portfolio i	%
$C_{O\&M,F}$	Fixed O&M cost	$/kW
$C_{O\&M,V}$	Variable O&M cost	$/kWh
$C_{Fuel, \tau}$	Fuel cost for fossil fuels, uranium	$/Btu
HR_{τ}	Heat rate: fossil fuels, uranium	Btu/kWh
CRF	Capital recovery factor	%
$E_{i\tau}$	Electricity generated by technology τ in portfolio i	kWh
$G_{i\tau}$	Installed Capacity of technology τ in portfolio i	kW

Combined Fixed and Variable Metrics: LCOE, Greenhouse gas (GHG) Emissions, Air Pollution Emissions, Water Consumption. These four metrics have both a fixed and variable component for most technologies. *LCOE* is an economic assessment of the discounted total cost to build and operate a power-generating asset over its lifetime divided by the total electricity output of the asset over that lifetime. Typically, LCOE is regarded as the average minimum price at which electricity must be sold in order to break-even over the lifetime of the project. We note that our LCOE will depend on how much electricity is generated in each specific portfolio.

We calculate LCOE for individual technologies as seen in equation 6 and 7. The fixed and variable LCOE components are:

$$F_{L\tau} = \frac{C_{cap,\tau} * CRF\left(1 - TD_{pv}\right)}{\left(1 - T\right)} + C_{O\&M,F} \qquad (6)$$

$$V_{L\tau} = C_{O\&M,V} + \left(C_{Fuel,\tau} * HR_{\tau}\right) \qquad (7)$$

All data for LCOE comes from Klein and Whalley (2015) except the portfolio-specific capacity factors, $CF_{i\tau}$, which are derived from the electricity model.

Water consumption is defined as the portion of water withdrawn from the environment and not directly returned to the 'immediate water environment' (Meldrum et al. 2013). Water consumption includes both a fixed amount (equation 8) from construction and installation, and a variable amount (equation 9), comprised of water used in the fuel cycle and operations of the plant.

$$F_{W\tau} = \frac{W_{P\tau}}{G_{\tau} N_{\tau}} \qquad (8)$$

$$V_{W\tau} = W_{\varphi\tau} * f_{\tau} + W_{O\tau} \qquad (9)$$

$W_{P\tau}$ is the lifecycle water consumption for the construction and installation of the power plant equipment. $W_{\varphi\tau}$ is the water consumption due to the fuel cycle per unit of fuel. This is key in thermal power plants where drilling and mining the fuel source uses significant amounts of water. Here f_{τ} is the amount of fuel per unit of electricity used by technology τ; this value was sourced from the literature (Meldrum et al. 2013). $W_{O\tau}$ is the ongoing variable water consumption from operations of the plant, such as cooling.

The source of *GHG* and *air pollution emissions* varies by technology. Emissions from fossil fuels depend most strongly on the operation of the plant, while solar and wind create emissions primarily through the production of their components. For natural gas and oil, we use a lifecycle estimate of GHG emissions and air pollution, since the amount of emissions created from construction are negligible compared to the lifetime emissions. On the other hand, we assume that for the renewable technologies and nuclear, emissions are wholly fixed. GHG emissions include upstream (i.e. manufacturing, construction, and mining), O&M, and downstream (i.e. decommission) CO_2, CH_4, and N_20 emissions. Air pollution is the sum of the total lifecycle emissions of SO_2, NO_X and PM.

Fixed Metrics: Land Use, Jobs, and Nuclear Aversion. Land use by power plants is a concern due to the direct and indirect impacts on the environment. We use the maximum life cycle land use of power plants presented in Klein and Whalley (2015), which is defined as an upper bound on the amount of land that will be used in each power plant. We assume that land use is a fixed metric for all cases. This is clearly the case for renewables since the size of the plant impacts the amount of raw materials that will need to be mined for the plant (indirect land use) and the amount of land needed to house the facilities (direct land use). This assumption is less justified for fuel-based technologies because an increase in demand for fuel will increase impacts on land. Thus, assuming land use is wholly fixed lends itself towards over- (under-) estimating the amount of land needed for fossil fuel and nuclear plants when they produce a small (large) amount of electricity. However, due to limited information regarding the amount of land used in the drilling process, and radioactive waste storage requirements, we assume that land use is entirely fixed, shown in equation 10.

$$F_{U\tau} = \frac{A_{i\tau}}{G_{i\tau} N_{\tau}} \qquad (10)$$

where the subscript U stands for land use, A is the total land area covered by the plant in m^2.

We assume that *jobs* are proportional to capacity and not electricity because, other than mining, the majority of jobs are generated through construction of the power plant, and there are no mining or drilling activities in New England. Moreover, even the operations of most power plants are fixed rather than variable. To estimate jobs created in the New England States we use the Jobs and Economic Development Impact (JEDI) models. The JEDI models estimate the number of annual and construction jobs for a given technology at a specified capacity level. The reported number of construction and annual jobs is converted to a per MW value using the JEDI-specified capacity level, G_τ, and equation 11.

$$F_{J\tau} = \frac{J_c * \frac{TC_\tau}{N_\tau} + J_a}{G_\tau} \quad (11)$$

where J_c is annual construction jobs; TC is the period of construction; and J_a is annual operation jobs. The resulting total metric, J_τ measures the direct (construction and operation), indirect, and induced full time equivalent (FTE) jobs per MW. Indirect jobs are related to building the plant, and occur in supporting industries, such as plant materials, and financing. Induced jobs are created through reinvestment and spending of earnings at local establishments. The data for the job calculation is discussed further in Appendix B.

Nuclear Aversion. While nuclear generation is a low emission technology, many stakeholders are averse to adding nuclear to the generation fleet for a variety of reasons, including safety, proliferation, and the long-term environmental impacts of radioactive waste. Thus, in order to represent this preference and analyze the impact of nuclear aversion on the sustainability of the portfolios, we define a metric representing aversion to nuclear. Nuclear technology is assigned a value of 1 per unit of capacity; all other technologies, a value of 0.

Variable Metrics: Fatalities. The evidence is not clear on the proportion of fatalities that occur during construction versus during operation (in developed countries). Thus, consistent with the Intergovernmental Panel on Climate Change (IPCC) (IPCC 2012), we assume fatalities are wholly variable, and source values from Klein and Whalley (2015).

2.3.2.2 Portfolio-level metrics of Sustainability

To calculate a metric for a portfolio, we take the weighted average of the technology-specific metrics, scaling by the proportion of electricity generated by each technology in the portfolio:

$$x_{ij} = \sum_{\tau} x_{ij\tau} \frac{E_{i\tau}}{E_i} \qquad (12)$$

where x_{ij} is the aggregated value of metric j for portfolio i. See Appendix C for more details regarding the aggregation.

In order to create a single value function combining all metrics, we normalize each criterion to be on a scale of 0 to 1, where 1 is best, using value normalization presented in Appendix D (Maxim 2014; Klein and Whalley 2015). This normalization is performed using the minimum and maximum values of the portfolio metric scores across a broad group of 35 portfolios. We note that our illustrative preference scenarios must be interpreted with these extreme values in mind. See Table E1 in Appendix E for these values. In general, if a new generation portfolio is defined that scores outside of the bounds of the original minimum and maximum values, then it would require a new preference elicitation (Keeny 1992; McLean 1995).

A preference scenario represents a possible stakeholder weighting across the metrics. In this analysis we use a linear additive value function with linear individual value functions to calculate the sustainability score of various portfolios. In the absence of formal preference elicitations, we assume that sustainability metrics are mutually utility and additive independent for all stakeholders (Keeny 1992). Thus, the scaling coefficient w_j can be interpreted as a stakeholder's preference for moving from the worst to the best value for metric j, relative to all the other metrics. The aggregate score for a portfolio, y_i, is the weighted sum of the normalized metrics. Section 4.3 presents the illustrative preference scenarios we consider. Data sources are discussed in Appendix B. Many papers have multiple estimates for each of the technology specific metrics. For the initial portfolio comparison, we use the median values of technology specific values sourced from the literature, and then present a sensitivity analysis, of minimum and maximum values found in the literature in Section 2.4.

2.4 Results and Discussion

We investigate how generation capacity investments impact electricity contributions and the sustainability of different electricity futures. The methodology is generalizable, but this case study focuses on New England. We provide insights into how policy makers can plan for a more sustainable power system in 2035 and beyond, and illustrate the policy implications of using a portfolio analysis in sustainability debates as opposed to individual technology comparisons. We start by describing the generation portfolios we evaluate and discuss how capacity relates to energy in different portfolios. Then we discuss the results of the sustainability model, including a discussion of sensitivity to key parameters, and end with a discussion of the role of nuclear aversion.

2.4.1. Candidate Portfolios

We evaluate a set of 15 candidate portfolios that vary in terms of capacity in oil, offshore wind, nuclear, natural gas, and hydro (where increases in hydro reflect transmission projects connecting Canadian hydro to New England). These candidate portfolios reflect a number of the discussions and arguments in New England today, as discussed in the introduction. The 15 portfolios, described in Table 5 and Figure 5, were culled from a larger set of 35, to highlight these key questions and controversies. Each portfolio has the minimum possible excess generation capacity needed to ensure reliability. Here we provide a discussion of how the portfolios relate to specific questions; and how the composition of the portfolio impacts the energy contribution of specific technologies.

- **Base Case.** Portfolio 0 reflects ISO-NE's current projections for generation capacity for 2035 and is provided for comparison.
- **Decreasing Nuclear.** Portfolios 1 - 3 reflect different ways to achieve a power system where nuclear generation is retired. These portfolios vary by the levels of offshore wind, natural gas, and oil, with portfolios 1 and 2 completely retiring oil, and adding combinations of wind, natural gas, and hydro; and portfolio 3 maintaining oil and offshore wind at their base levels, while increasing natural gas and hydro to meet demand.
- **Increasing Nuclear.** While nuclear is currently out of favor due to low gas prices and public opinion, some activists and analysts consider it an important technology

for addressing climate change. Thus, we consider four portfolios with nuclear increased above the base case: Portfolio 4 replaces oil with nuclear; Portfolio 5 replaces a combination of natural gas and oil; and Portfolios 9 and 10 use nuclear to support high levels of offshore wind.

- **Increasing Offshore Wind.** We investigate five scenarios with higher offshore wind, to investigate how the generation capacity used to balance offshore wind impacts system sustainability. In Portfolios 6 and 7 we maintain base case values for all other technologies, except oil, which is reduced, and add medium and high levels of offshore wind, respectively. Portfolios 8-10 have high levels of offshore wind and no oil capacity; they have elevated levels of hydro (Portfolio 8), nuclear (Portfolio 9), and a combination of nuclear and natural gas (Portfolio 10). Portfolios 2 and 3, introduced above, are also relevant, having medium and high offshore wind in a system with no nuclear. In addition to the above-mentioned portfolios we tested a portfolio in which there was high offshore wind, no oil capacity, and increased levels of natural gas capacity. This portfolio received similar sustainability scores to Portfolio 6 in all categories, leading us to exclude this portfolio from our analysis.
- **Tradeoffs between natural gas and Hydro.** Given the prominence of arguments around natural gas pipelines and transmission to Canadian Hydro, we include four portfolios to investigate the tradeoffs between hydro and natural gas, as both can provide flexibility. Portfolios 11 and 12 follow the base case, but tradeoff between the level of natural gas and hydro. Portfolio 11 has a higher level of natural gas, while Portfolio 12 has a higher level of hydro. Along similar lines, Portfolios 13 and 14 replace oil capacity with either natural gas or hydro.

Table 5: Description of Portfolios[1]

Portfolio	Capacity (GW)							Description
	Solar	Onshore Wind	Offshore Wind	Natural Gas (NG)	Hydro	Oil	Nuclear	
0	0.3	0.2	1.6	18.8	3.3	6	3.5	No Nuclear and Oil, High Offshore Wind, NG and Hydro
1	0.3	0.2	9	22.8	8.3	0	0	No Nuclear and Oil, Medium Offshore Wind, High NG and Hydro
2	0.3	0.2	4	24.8	7.3	0	0	No Nuclear, Medium NG and Hydro
3	0.3	0.2	1.6	20.5	4.3	6	0	No Nuclear
4	0.3	0.2	1.6	18.8	3.3	0	9.5	High Nuclear, No Oil
5	0.3	0.2	1.6	17	3.3	4	7	High Offshore Wind, Low Oil
6	0.3	0.2	10	18.8	3.3	4.8	3.5	Medium Offshore Wind, Reduced Oil
7	0.3	0.2	4	18.8	3.3	5	3.5	High Offshore Wind, Reduced Oil, High Hydro
8	0.3	0.2	10	18.8	9.3	0	3.5	High Offshore Wind, No Oil, High Nuclear
9	0.3	0.2	10	18.8	3.3	0	9.2	High Offshore Wind, No Oil, High Nuclear and NG
10	0.3	0.2	10	22.8	3.3	0	7	No Oil, High Offshore Wind, Nuclear, NG, and Hydro
11	0.3	0.2	1.6	24.75	1.3	0	3.5	High NG, Low Hydro
12	0.3	0.2	1.6	14.75	9.3	3	3.5	Low NG, High Hydro
13	0.3	0.2	1.6	24.75	3.3	0	3.5	No Oil, High NG
14	0.3	0.2	1.6	18.75	9.3	0	3.5	No Oil, High Hydro

[1] Note that high indicates that the generation capacity is larger than base case levels, and low indicates the generation capacity is below base case levels. The colors represent the portfolios aimed at answering the different questions in our analysis. Orange: decreasing nuclear; Pink: increasing nuclear; Green: increasing offshore wind; Blue: tradeoffs between natural gas (NG) and hydro

The results of the electricity model are presented in Figure 5, showing the energy contribution from each technology resulting from the portfolios. We highlight a few points: first, oil results in a capacity factor of less than 1% in all portfolios, because it is dispatched last to cover peak demand. Nevertheless, the capacity is required in order to meet demand on certain days. We note that the model does not consider minimum generation requirements of thermal generation; if it did, the contribution from oil might be slightly larger. Second, Figure 2.3 highlights that the energy contribution of each technology depends not only on the capacity of that technology, but the composition of the portfolio. For example, Portfolios 5 and 7 have similar capacities for hydro, but the average energy is 9.9 and 12.2 GW, respectively. Third, we note that natural gas plays a prominent role in energy, with over 42% electricity contribution in all portfolios, except 4, 9 and 10, which have high levels of nuclear. The sustainability model uses these results to rank the portfolios under various stakeholder preference scenarios, discussed in Sections 2.4.1 – 2.4.3.

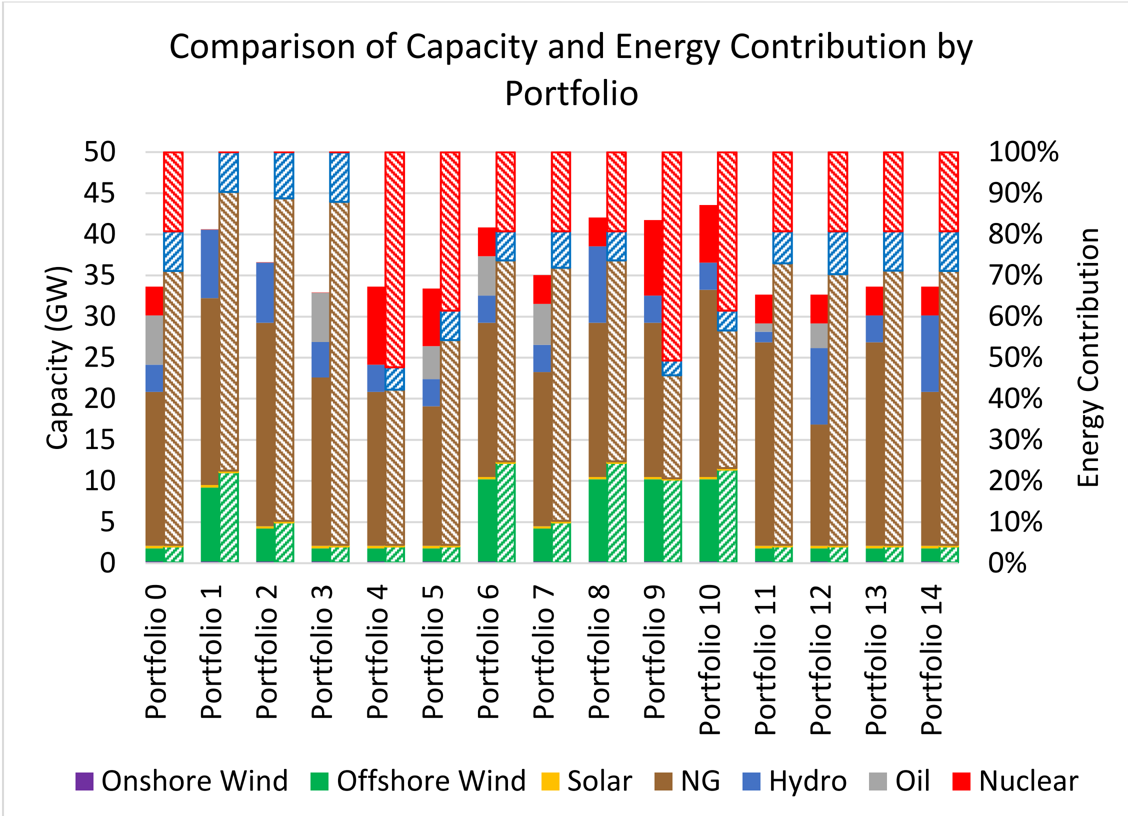

Figure 5: Comparison of Capacity and Energy Contribution of the portfolios. Solid bars represent capacity, measured on the left axis; striped bars represent energy, measured as a percentage of the portfolio on the right axis.

2.4.2. Sustainability Results under Equal Scaling coefficients

In this section we present the results of the sustainability evaluation under the preference scenario where all metrics have equal scaling coefficients. We focus on the base values for all data, as sensitivity analysis shows that results are quite robust to the full range of data (see Appendix B). We consider two sets of metrics: one includes nuclear aversion, the other does not. Under equal scaling coefficients, the role of each metric is clear in its contribution to the overall sustainability score.

Figure 6 shows the portfolios ranked in terms of their relative sustainability scores excluding nuclear aversion. The striped portion of the bars shows the additional impact on the sustainability score when nuclear aversion is included. A longer bar indicates a higher sustainability ranking; for example, a longer portion for cost is synonymous with a lower cost. The first key finding is that the top ranked portfolio does not change with the addition of nuclear aversion – either way, high offshore wind supported by high levels of nuclear ranks best under equal scaling coefficients. These two technologies play a prominent role in general: among the top five portfolios, four have high offshore wind and three have high levels of nuclear. This implies that retiring nuclear completely may not be consistent with sustainability when all metrics are given the same scaling coefficient. This is due to its large energy contribution of low-emission electricity. We delve further into the role of nuclear aversion in section 2.4.2.

Portfolio 9 scores well in all categories except cost and water consumption, which is due to the high cost of offshore wind and the large water consumption of nuclear. The portfolio that contrasts with this one is Portfolio 12 (ranked 8th), which has base level nuclear and some oil capacity, scoring well on cost and water, but poorly on GHG and air pollution emissions.

Comparing the top two portfolios highlights the role of offshore wind in combination with nuclear. Both Portfolios 9 and 4 have high nuclear and no oil, but Portfolio 9 has six times the amount of offshore wind compared to Portfolio 4. Portfolio 4, with slightly more nuclear, is less robust to preferences, falling to 5th when nuclear aversion is included.

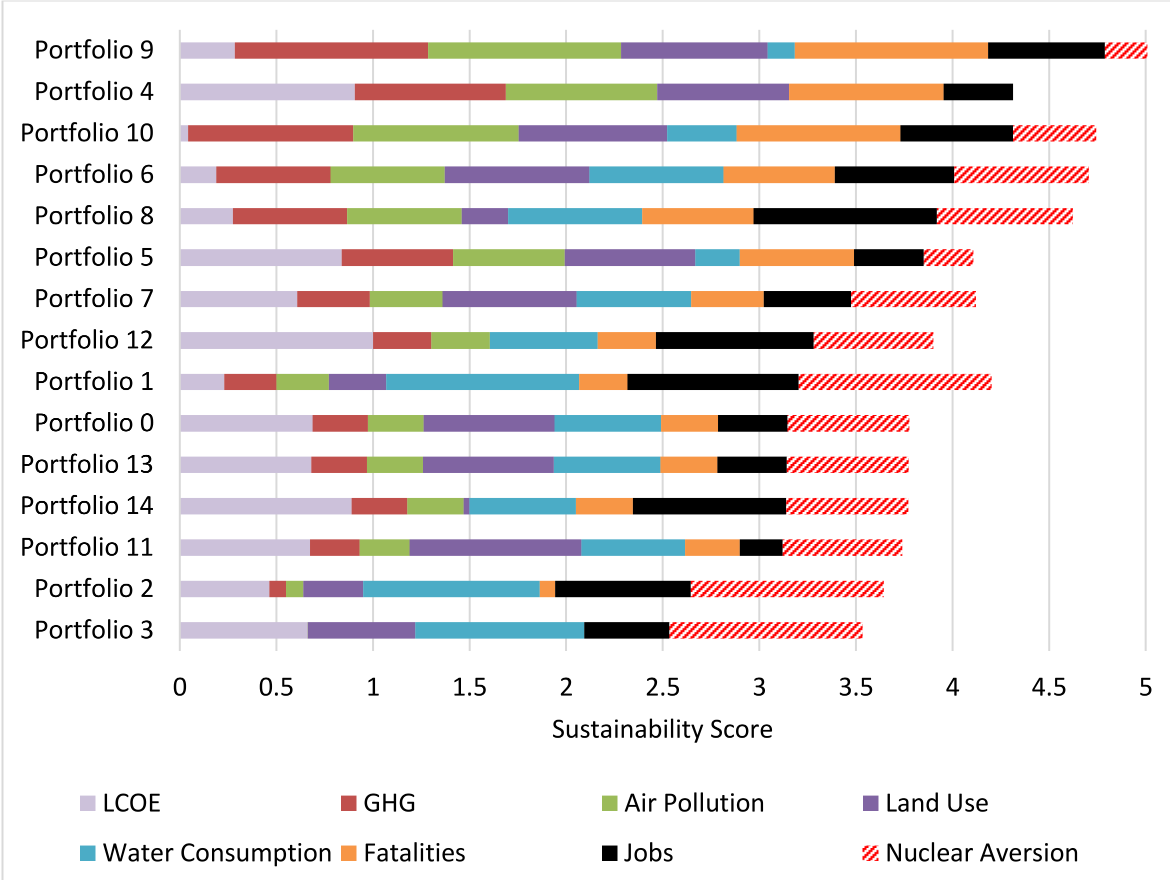

Figure 6: Comparison of the generation portfolios under the equal scaling coefficients preference scenario

The results under the equal scaling coefficients are very robust to uncertainty in the data. Under a sensitivity analysis for a wide range of input parameters, including and excluding nuclear aversion, we found that only nuclear capital costs and natural gas air pollution emissions made any significant difference in overall sustainability rankings. Portfolio 9 remains the highest ranked under the equal scaling preference scenario for all of the input parameters tested when nuclear aversion is not included. When accounting for nuclear aversion, we see a change in the highest ranked portfolio when the nuclear capital cost is greater than \$7680/kW (103% increase from base assumptions), or when natural gas air pollution emissions are below 505 mg/kWh (49% decrease from base assumptions). If either of these conditions is satisfied, Portfolio 6 (which keeps base level nuclear and slightly reduced oil) becomes the top ranked portfolio.

To develop more intuition into the results, Figure 7 presents a scatter plot matrix, illustrating tradeoffs between pairs of metrics for each portfolio. Each point within a square represents one of the 15 portfolios, with the red solid point highlighting Portfolio 9. A score of one indicates that the portfolio scored the best in that category. This shows that some metrics are clearly correlated with one another, for example nuclear aversion and water; or GHG, air pollution, and fatalities. There is no tradeoff required between the metrics that are positively correlated. For example, if stakeholders only care about avoiding nuclear and minimizing water consumption, then there is only one non-dominated portfolio, Portfolio 1, in which all of the oil and nuclear capacity is retired. The metrics can be organized into five groups, with tradeoffs between the groups: (1) nuclear aversion and water consumption; (2) GHG, air pollution, and fatalities; (3) land use; (4) LCOE; (5) jobs. It is only when we combine metrics from these five groups that we see tradeoffs resulting in Pareto frontiers. From the figure we see that group 1 is negatively correlated with group 2, meaning that stakeholders will be required to think carefully about these tradeoffs: saving water and avoiding nuclear comes at a cost of higher GHG, pollution, and fatalities.

These results are driven by the specific set of technologies considered; in this case primarily by nuclear, natural gas, hydro, and offshore wind. The negative correlation between groups 1 and 2 is driven mostly by nuclear, which is good on emissions and fatalities, but bad on water and general concerns about nuclear waste and safety. Hydro scores the worst on land use but very high on jobs.

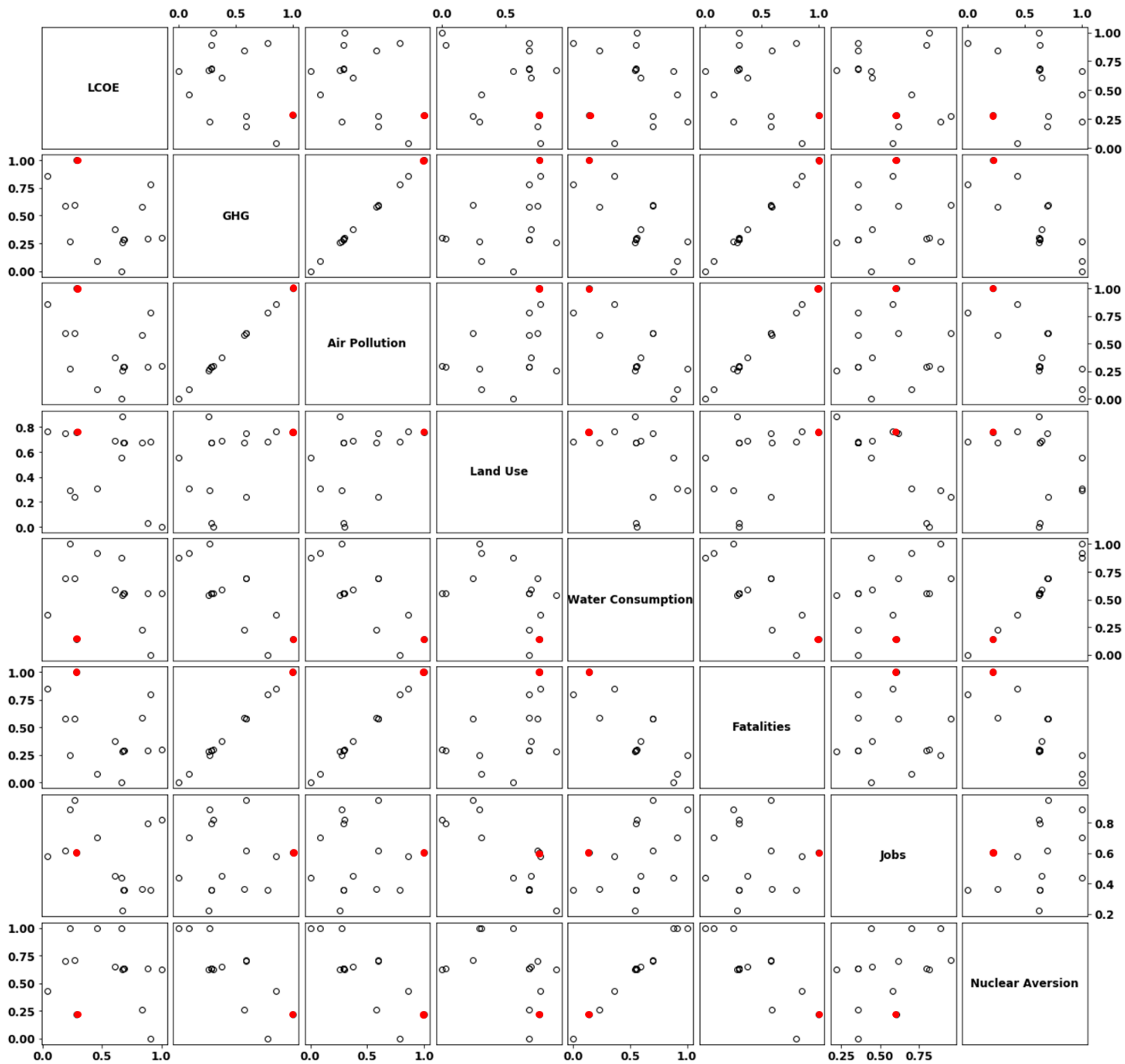

Figure 7: Scatterplot matrix comparing the various sustainability metrics for generation portfolios. Each point represents a portfolio and shows the normalized score under pairs of metrics. The red solid point signifies Portfolio 9.

2.4.3. Sustainability Results under various Stakeholder Preferences

We further analyze the portfolios across nine possible stakeholder preferences, presented in Table 6, to illustrate how preferences impact which electricity systems are ranked as most sustainable. The scaling coefficients (i.e. the relative importance of moving from the worst to best value on each criterion) are created using the method sourced from Klein and Whalley (2015), and meant to be purely illustrative of different types of stakeholders. Aversion to nuclear is excluded from this section.

Table 6: Scaling Coefficients for Illustrative Preference Scenarios[2]

Preference Scenarios	LCOE	GHG	Air Pollution	Land	Water	Fatalities	Jobs
Equal	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Climate Change	0.02	**0.90**	0.02	0.02	0.02	0.02	0.02
Climate Change-economy	**0.45**	**0.45**	0.02	0.02	0.02	0.02	0.02
Economic	**0.90**	0.02	0.02	0.02	0.02	0.02	0.02
Environmental	0.03	**0.23**	**0.23**	**0.23**	**0.23**	0.03	0.03
Jobs	0.02	0.02	0.02	0.02	0.02	0.02	**0.9**
Jobs-climate change-economy	**0.30**	**0.30**	0.03	0.03	0.03	0.03	**0.30**
Jobs-economy	**0.45**	0.02	0.02	0.02	0.02	0.02	**0.45**
Socio-economic	**0.23**	0.03	**0.23**	0.03	0.03	**0.23**	**0.23**

[2] Note the bold values signify the highest weighted metrics in that preference scenario

First, we note that eight of the 15 portfolios are dominated by another portfolio across preference scenarios. A portfolio is dominated if another portfolio ranks higher under all of the preference scenarios. A portfolio is non-dominated if no other portfolio dominates it. Table 7 shows the rankings of the non-dominated set of portfolios under each preference scenario. Portfolio 9 dominates Portfolios 6 and 10, while Portfolio 4 dominates Portfolios 0, 3, 5, 11, and 13. This illustrates the importance of retiring oil in electricity systems: portfolios with no oil and high nuclear dominate those with base or low levels of oil. This is largely due to savings on pollution and GHG emissions. Portfolio 8 dominates Portfolio 1, indicating that increasing natural gas to offset retired nuclear plants may not be the best way to support high levels of offshore wind. We note, however, that Portfolio 1 becomes non-dominated upon just a 7% increase in nuclear capital costs over base assumptions. Overall, using base assumptions, four of the six portfolios including high natural gas are dominated by portfolios with increased nuclear, due to the savings on emissions and fatalities.

Of note is how the energy diversity of the portfolios impacts the sustainability rankings. There are four unique portfolios that are ranked first in at least one of the preference scenarios, all of which contain nuclear. Three of these four portfolios completely retire oil. Thus, full electricity diversity may not be required for sustainability. All but two of the non-dominated portfolios contain nuclear, with these two generally ranked low resulting from high GHG and air pollution emissions. Portfolio 12, which ranks highest on the economy, is the most diversified; Portfolio 9, which ranks first most often, is one of the more diversified portfolios, except for excluding oil.

We note here that none of the 15 portfolios are dominated across all individual metrics. This shows the importance of understanding how stakeholders value the combination of sustainability metrics and the relative tradeoffs, as opposed to evaluating metrics individually. For example, we found that some of the portfolios that scored well in water consumption were dominated across the preference scenarios. This is because all of the preference scenarios we considered combined water consumption with other environmental metrics, meaning that high scores in water consumption were drowned out by low scores in land-use and air pollution. This highlights the value of taking a portfolio approach, and the importance of eliciting preferences of stakeholders regarding the relative importance of environmental sustainability metrics.

Our paper differs from previous papers, as it takes a system approach, considering the entire portfolio. The question in Maxim (2014) and Klein and Whalley 2015 was which individual technology is most sustainable. But, we find here that combinations of technologies are often more sustainable than portfolios heavily weighted toward any one. For example, both Maxim (2014) and Klein and Whalley 2015 identified nuclear as the most sustainable technology (among the technologies evaluated in our paper) under equal scaling coefficients; and Klein and Whalley (2015) find that nuclear nearly dominates offshore wind, being better under all scenarios except environmental (Klein and Whalley 2015; Maxim 2014).In contrast, our analysis finds that a combination of nuclear and offshore wind outscores portfolios with a focus on one or the other. For example, Portfolio 9 has less nuclear and more offshore wind than portfolio 4, yet is preferred under more than half of the preference scenarios. Portfolio 4 only outranks portfolio 9 when the economic sustainability criteria is given a weight of 0.3 or higher, indicating that cost needs to be a high priority on the stakeholder's agenda to justify increasing nuclear at the expense of offshore wind.

Table 7: Sustainability Ranking under nine preference scenarios for Non-Dominated Portfolios[3]

		Equal	CC	CC-EC	EC	EV	JB	JB-CC-EC	JB-EC	SC
\	Portfolio 9	1	1	2	6	1	4	3	7	1
\	Portfolio 4	2	2	1	2	2	7	1	2	2
\	Portfolio 8	3	3	5	7	3	1	4	3	3
	Portfolio 7	4	4	4	4	4	5	5	5	5
	Portfolio 12	5	5	3	1	7	2	2	1	4
X	Portfolio 2	6	6	7	5	6	3	6	4	6
/	Portfolio 3	7	7	6	3	5	6	7	6	7

[3] Dark blue indicates the best sustainability ranking (i.e. a ranking of 1), red the worst. A bold portfolio name indicates that the portfolio contains all technologies. An X indicates both nuclear and oil were retired; \ signifies only oil is completely retired; / signifies only nuclear is fully retired. CC = climate Change; EC = Economy; EV = environmental; JB = Jobs; SC = socioeconomic

2.4.4. The role of aversion to nuclear power

Policy makers may have an aversion to nuclear power, whether from direct concerns about waste, safety, or proliferation, or indirectly based on political pressure. This impacts the sustainability of portfolios, as seen from Figure 8. In analyzing the equal scaling and climate change preference scenarios, we see each has a key break point, where Portfolio 1, which was dominated prior to the inclusion of nuclear aversion, begins to outrank Portfolio 9. If the scaling coefficient for nuclear aversion is high enough, it is desirable to retire nuclear and oil and support high offshore wind with increasing levels of natural gas. Under equal scaling this happens at a coefficient of 0.2; for climate change preferences, at a coefficient of about 0.35.

To put this in perspective, consider a situation in which all metrics have equal scaling coefficients except nuclear aversion. If we hold the value of all other metrics constant, we can look at the implied tradeoff between nuclear aversion and LCOE. If the scaling coefficient on nuclear aversion is 0.2 then the stakeholder would be willing to increase the LCOE from $0.12/kWh to $0.16/kWh in return for reducing nuclear from 9.5 GW to zero. If the scaling coefficient on nuclear aversion was 0.35, then that stakeholder would be willing to increase the LCOE up to $0.22/kWh in return for the same reduction in nuclear.

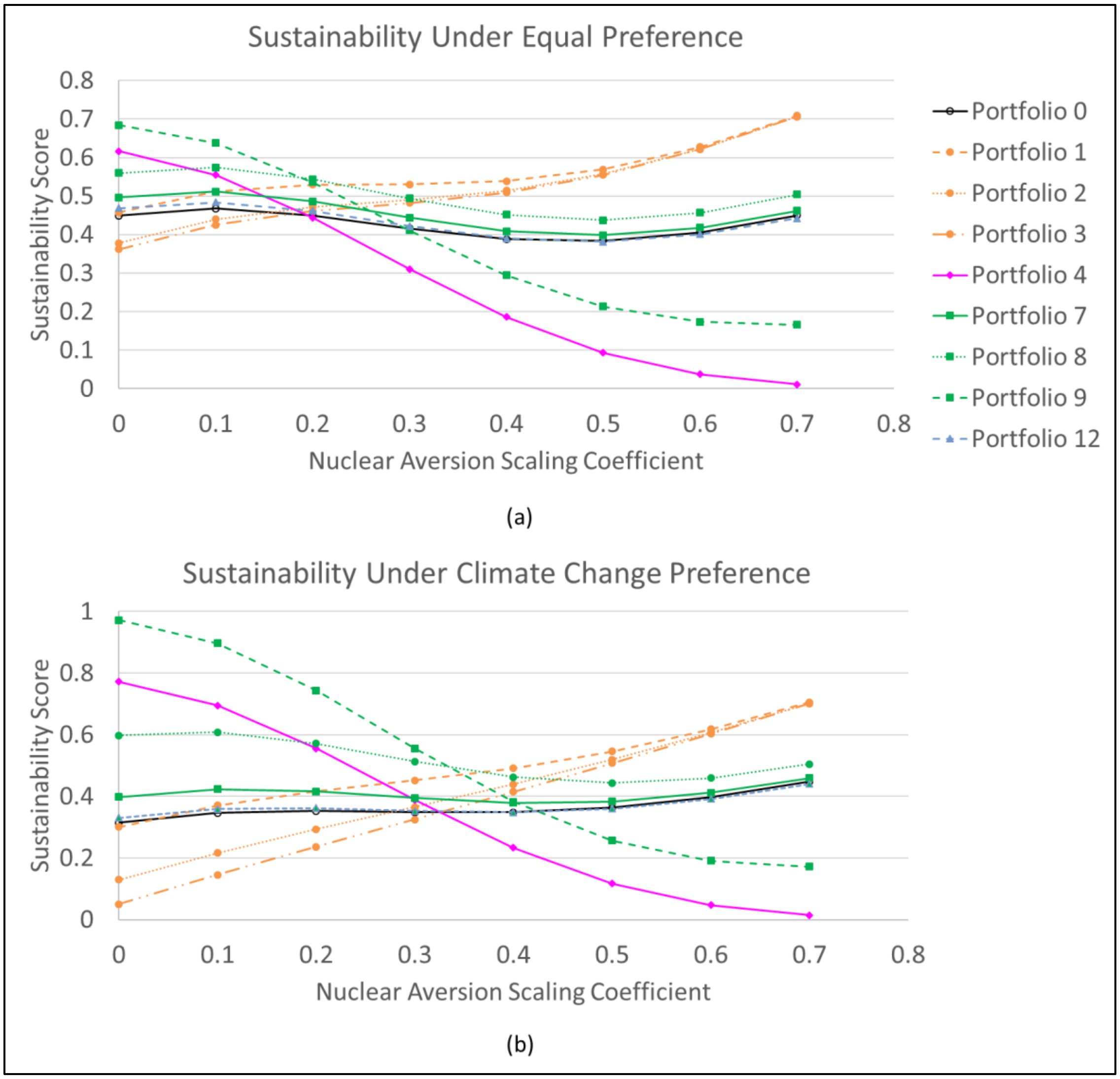

Figure 8: Sensitivity analysis of the impact of nuclear aversion under preference scenarios (a) Equal Scaling Coefficients (b) Climate Change

2.5 Conclusions

We evaluated electricity generation portfolios across economic, social, and environmental sustainability metrics, using an electricity model to investigate the system-level interactions between technologies, particularly between renewables, flexible generation (i.e. natural gas, hydro, and oil), and less flexible generation (i.e. nuclear). We provided analysis using nine illustrative stakeholder preference scenarios for the New England power system. This work identified a few good portfolios among a large group. The smaller group highlights the importance of trade-offs between costs, GHG and air pollution emissions, water consumption, and nuclear aversion. We emphasize that sustainability is multi-dimensional, and so must reflect tradeoffs between multiple metrics. Stakeholders may agree that reducing both costs and GHG emissions are important, but may differ in the importance they put on either.

For the technologies considered in this study we find that the metrics can be organized into five groups that have tradeoffs between them: (1) nuclear aversion, and water consumption; (2) GHG, pollution, and fatalities; (3) land use; (4) LCOE; (5) jobs. If stakeholders only consider category two then replacing all oil capacity with nuclear is a dominant choice. On the other hand, if stakeholders were only concerned about water consumption and avoiding nuclear power, then the ideal choice would be to retire all oil and nuclear capacity and include a high level of offshore wind backed up by natural gas and hydro. Finally, if stakeholders are concerned about the full range of sustainability metrics, then the most sustainable solution may be to support high offshore wind with nuclear and keep a largely diversified portfolio, while retiring oil. Understanding these trade-offs are key to policy and electricity decision makers progressing toward a more sustainable power system.

From this work, it is clear that there are many paths towards a more sustainable future. Determining that path will involve a careful discussion among stakeholders to understand societal preferences regarding the three pillars of sustainability and towards the special concerns around nuclear power. The results presented here indicate that in the transition to a high renewable future, retiring oil makes sense, but retiring existing nuclear capacity is less obvious. While maintaining the current level of nuclear is consistent with sustainability, there is a high cost to retiring nuclear entirely, especially in terms of GHG, and air pollution. On the other hand, our system analysis indicates that there is no single most sustainable technology, with a combination of offshore wind and nuclear outscoring portfolios heavy in only one. Finally, while natural gas is likely to remain an important part of the New England electricity system, it is not the only gateway to renewables.

We note that this is a first step toward integrating MCDA with an electricity system approach. The key contribution of this work is to move beyond simple lifecycle assessment, incorporating a deeper understanding of the roles capacity investments and subsequent energy contributions play in the sustainability evaluation of an electricity system. Disentangling the fixed and variable contributions for each sustainability metric and using portfolio-specific capacity factors is essential to understanding the role investments and retirements of various generation capacities play in enhancing a regions' overall sustainability. Future work will include adding storage options, electric vehicles, and a larger integration of other aspects of the energy system such as the heating sector and natural gas pipelines.

The framework introduced in this paper takes a systems and sustainability approach to capacity planning. The results can inform regional discussions about the future of the power system by highlighting the sustainability tradeoffs between generation capacity mixes. These tradeoffs include balancing electricity costs, different types of environmental impacts, job creation, worker safety, and public acceptance of infrastructure and generation, while maintaining reliability. Understanding these tradeoffs can help steer electricity systems toward a sustainable future and inspire new directions for investment and research.

CHAPTER 3

ESSAY II: VALUING SYSTEM FLEXIBILITY THROUGH ADDING PUMPED HYDRO ENERGY STORAGE IN THE NEW ENGLAND ELECTRICITY SYSTEM

3.1 Abstract

As energy transition pushes the world towards low-carbon or high renewable economies, the share of renewables supplying electricity continues to increase. Due to their intermittent nature, as the share of renewables increases so does the demand for flexible power systems. Pumped hydro energy storage (PHES) is one method of enhancing power system flexibility due to its ability to regulate power output from renewables, acting as a supplier and consumer, and enhance overall system sustainability through enhancing the capacity factor of renewables and being a low emission technology. In this paper we determine the value of PHES using multi-criteria decision analysis and the three pillars of sustainability (i.e. social, environmental, and economical). We rank the various low carbon generation portfolios (i.e. the mix of PHES, wind, solar, natural gas, nuclear, and oil) under nine-illustrative preference scenarios. In this work we find that using PHES to support renewables proves beneficial for the New England Power System, and that as PHES capacity is increased the offshore wind energy contribution is increased by at least 14%, and led to a 3-10% reduction in usage of fossil fuel plants. This indicates that the optimal strategy to enhance flexibility and sustainability of power systems may be to add storage to the system due to its ability to reduce GHG emissions and support renewables.

3.2 Background and Motivation

Currently many power systems around the world are shifting away from fossil fuel burning plants and integrating a larger number of renewables to their power system (World Bank, 2018; UN, 2018). With increasing amounts of distributed and variable generation being connected to the power system there have been concerns regarding voltage fluctuations, reverse power flow, and grid instability (Nock and Baker 2017; Passey et al. 2011). Enhancing overall system flexibility is one method of accommodating high penetration of variable renewables, while moving to low-carbon systems. Previous studies have discussed how system flexibility can be increased through existing power plants (Kopiske, Spieker, and Tsatsaronis 2017), demand response, renewable energy control methods (Nock and Baker, 2017; Nock et al., 2014), and storage (Das et al., 2015, Carton and Olabi 2010). Including storage will impact the shape of the demand profile by increasing electricity demand while it is charging, and reducing electricity demand while it is discharging. Inclusion of storage has the potential to enhance power systems through increased demand and supply flexibility, reduced wind farm curtailment, higher system efficiency, reduced need for backup power and excess generation capacity, reduced transmission losses, ensured security of supply, black start capabilities, and lower system emissions (McKenna et al., 2017, Carton and Olabi 2010; Deane, Ó Gallachóir, and McKeogh 2010).

Other papers have used multi-criteria decision analysis to rank generation portfolios in terms of their sustainability discussed how the composition of a portfolio of generation technologies impacts overall system sustainability (Nock and Baker 2019; Brand 2014; Lo Prete et al. 2012), but have not included a look into the system flexibility. Our contribution is to bring these two threads in the literature together, evaluating the impact that inclusion of storage has on overall system sustainability. We focus on pumped hydro energy storage (PHES) as the method for increasing system flexibility. PHES stores electricity through using it to pump water up to a reservoir, where it is held as potential energy. This water can then be released through a tunnel with a turbine housed in it, to a lower reservoir. As the water passes over the turbine the potential energy is then converted back into electrical energy.

When evaluating sustainability of a generation portfolio (i.e. the combination of power plants used to satisfy a region's electricity demand) there are many factors that can conflict with each other. Here we evaluate sustainability impacts using multi-criteria decision analysis (MCDA) to accommodates the conflicting metrics. This paper is the first to take an MCDA to valuing system flexibility from a broader sustainability perspective. In this work we define sustainability using economical, societal, and environmental factors. Seven sustainability metrics (i.e. system cost, emissions, land-use, jobs, safety, and water consumption), are evaluated under nine illustrative decision maker preference scenarios to illuminate sustainability trade-offs stakeholders would make between different electricity portfolios.

Here we use New England as a backdrop due to the region being a leader in energy transition towards more sustainable electricity systems. The system operator of New England, ISO-NE, has reported that a significant portion of their generation capacity is set to retire. As it stands 2200 MW of oil, nuclear, and coal capacity will retire by May 2019, and an additional 5500 MW of coal and oil plant capacity could be retired in the coming years. It has been reported that there is also uncertainty regarding the fate of NE's remaining 3300 MW of nuclear capacity (Nock and Baker 2018; ISO-NE 2015). A recent transmission plan aimed at connecting Canadian Hydro to Massachusetts was voted down by New Hampshire at the last minute, while controversy surrounds NG pipeline proposals, with ISO-NE expressing concern about electricity security, and a number of different groups opposing the pipelines for environmental and safety reasons. With the large controversies surrounding generation technologies, storage and renewables are one method of keeping New England on a path of increasing system sustainability, while maintaining system reliability.

Through our work we show how the size of a PHES plant and offshore wind penetration impact the level of wind farm curtailment, and the energy contribution of other generators and overall system sustainability.

The rest of the paper is organized as follows. Section 3.3 details the PHES model formulation, and presents the data used to model the PHES facility in the New England Power System. Section 3.4 reviews the results and analysis, and Section 3.5 presents some conclusions and policy implications.

3.3 Methodology

In this section we detail how we estimate the supply and demand of electricity from PHES capacity. Storage has both a power capacity and an energy capacity. The power capacity of PHES is determined by the difference in reservoir heights, and turbine equipment; energy is determined by the volume of the upper reservoir in combination with the difference in reservoir heights. These values will vary based on the specific characteristics of the PHES plant. For this study, we focus on a single measure to define the plant, the power capacity; and scale energy from that value. We use a specific plant in New England, the Northfield Mountain Pumped Storage Facility to model the PHES facility. We scale both power and energy linearly. This can be interpreted as building multiples of the Northfield plant. For example, if we consider an installed capacity that is twice the installed capacity of Northfield, our model will act as if there are two Northfield plants.

Our methodology builds on of the work presented in Nock and Baker (2019), who evaluated the sustainability of electricity portfolios through using loosely coupled electricity and sustainability models. We expand their work by adding PHES capacity into the electricity and sustainability models. Section 2.1 provides a brief introduction to the electricity model from Nock and Baker (2019) and details the methodology for including PHES into the larger model.

Here we provide a brief overview of how PHES works in practice. PHES plant operators use electricity prices to decide when to store water or generate electricity. When the price is low, electricity is consumed from the grid and used to pump water from the lower reservoir to the upper reservoir, effectively storing electricity as potential energy. During peak prices the stored water is used to generate electricity, which is sold back to the grid for a profit. The PHES operators will also consider opportunity costs which involve comparing the price of electricity with the opportunity cost of generating in future periods.

At every given hour in any reliable electricity system there is excess generation capacity available. This excess capacity depends on electricity demand, availability of wind and sun resources, and installed capacity levels. Excess generation capacity is defined on an hourly basis, as the potential power that could be generated at a particular hour over and above the demand at that hour. Our model abstracts from prices, thus we use demand and excess generation as a proxy for electricity prices.

We make this modeling choice because there is an uncertainty around future electricity prices due to changes in fuel prices, and the composition of future electricity portfolios. For example, the cost of a 100% renewable power system will be different from a grid with a large portion of natural gas plants. By using demand and excess generation as a proxy for electricity prices we can capture the PHES operator's habits within our simulation. In an electricity market the PHES operator would not have a perfect prediction for prices, but would need to determine whether to generate or supply electricity based on historical trends, and price projections based on demand and generation make-up of the grid.

The remainder of the section is organized as follows: In section 3.3.1 we overview the New England Electricity model and how PHES is incorporated. The operation rules, which determine when the plant will be scheduled to store and generate electricity, based on demand, water level in the reservoir, and the amount of excess generation capacity. Section 3.3.2 explains how we calculate the amount of power the PHES plant consumes or generates every hour, based on the excess generation capacity and the amount of water in the reservoir. Section 3.3.3 details the sustainability calculation for PHES which builds upon Nock and Baker (2019). Finally, Section 3.3.4 presents metrics for evaluating the impact PHES has on other generation facilities.

3.3.1 PHES within the New England Electricity model

The New England Electricity model is originally presented and discussed in more detail in Nock and Baker (2019). Nock and Baker (2019) simulated and electricity market using a merit-order dispatch based on historical generator costs. This original model without PHES dispatches generators to supply electricity to the grid based on historical prices and trends, similar to Figure 1, without the PHES node. Installed generation capacity levels are defined for each generation type. Nuclear generation is allocated first due to the lack of flexibility and this generation tending to bid zero or negative. This is followed by solar and onshore wind, due to these generators tending to bid zero. If there is remaining electricity demand, then offshore wind is allocated. Next, the remaining electricity demand is divided between natural gas and hydro. If there is remaining demand, and if the natural gas pipeline is not operating at maximum capacity, then demand is allocated to natural gas, followed by hydro, and finally to oil. If the natural gas pipeline is at maximum capacity, then oil is used to meet demand followed by hydro. The model does not separately consider electricity imports from neighboring regions. Instead, it defines the generation portfolio as the combination of power plants that will supply electricity to the New England region. We expand the methodology of the previous paper by incorporating PHES into the dispatch order, presented in Figure 9.

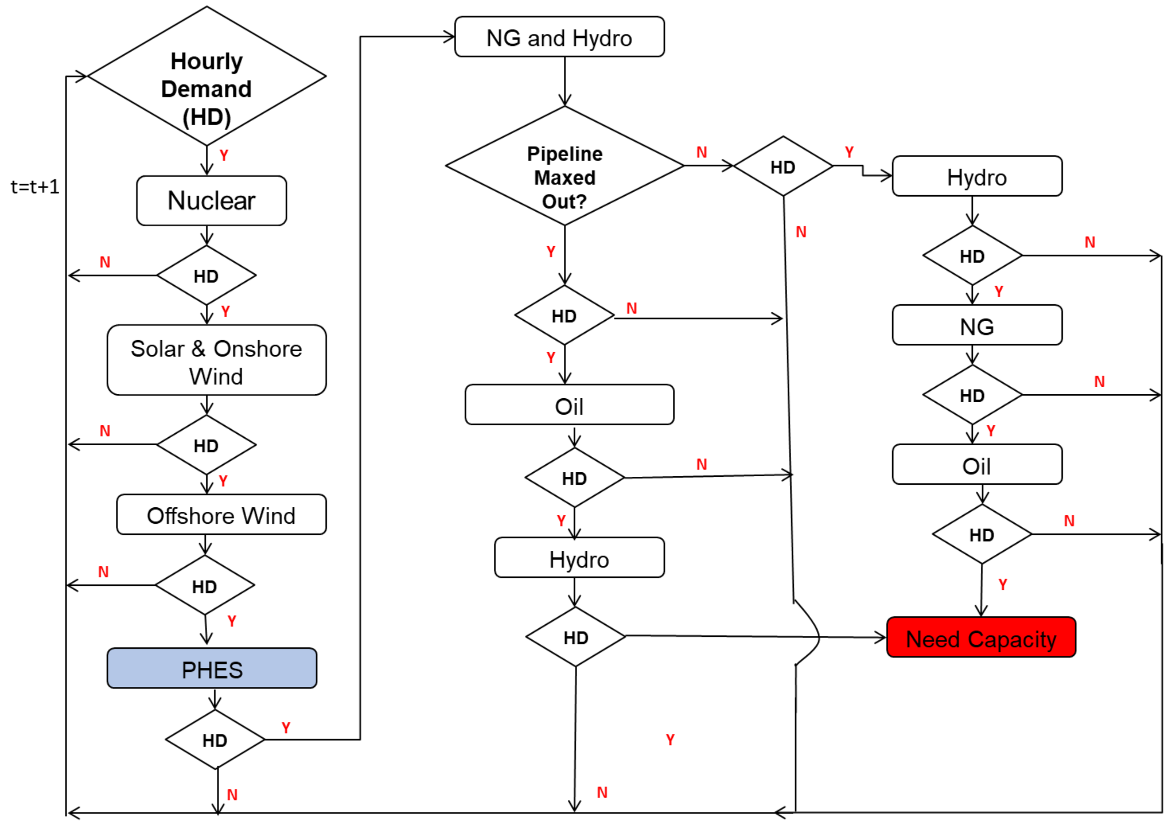

Figure 9: Flow Diagram for the flexible New England Electricity Model. Here HD is the hourly demand, and NG is natural gas.

In the model in this paper, the installed capacity of PHES is defined along with oil, nuclear, natural gas, solar, onshore wind, offshore wind, and traditional hydro. We simulate an energy market over a 5-year period. The PHES plant is dispatched according to a set of operation rules, using available generation capacity as a proxy for prices, illustrated in Figure 2. We use the energy not supplied (ENS) metric to ensure overall system reliability. After a portfolio is tested in the system if any of the demand is not met by the installed generation capacity over the 5-year time period (i.e. ENS > 0) then the portfolio is deemed unreliable, and we iterate by adding more capacity. Once a reliable generation portfolio has been established, the output statistics of the model include the energy contribution and portfolio specific capacity factor (CF) per technology. The installed capacity, energy contribution, and capacity factors are then fed into a sustainability model.

Within the PHES node the facility goes through a series of calculations and operation decisions, seen in Figure 10. The blue dashed line represents the PHES facility. There are two key operation decision points. The first is an hourly decision on whether the facility will pump water (to store electricity), use stored water to generate electricity, or do nothing. This decision depends on the level of excess generation capacity in the system, available renewable energy (RE), and the water level in the reservoir. The second key operational decision is how much to pump or generate. This depends on the amount of demand, amount of excess capacity, available renewable generation, and level of water in reservoir. Following the PHES decisions, the HD and reservoir level is updated and the model continues moving through the dispatch order.

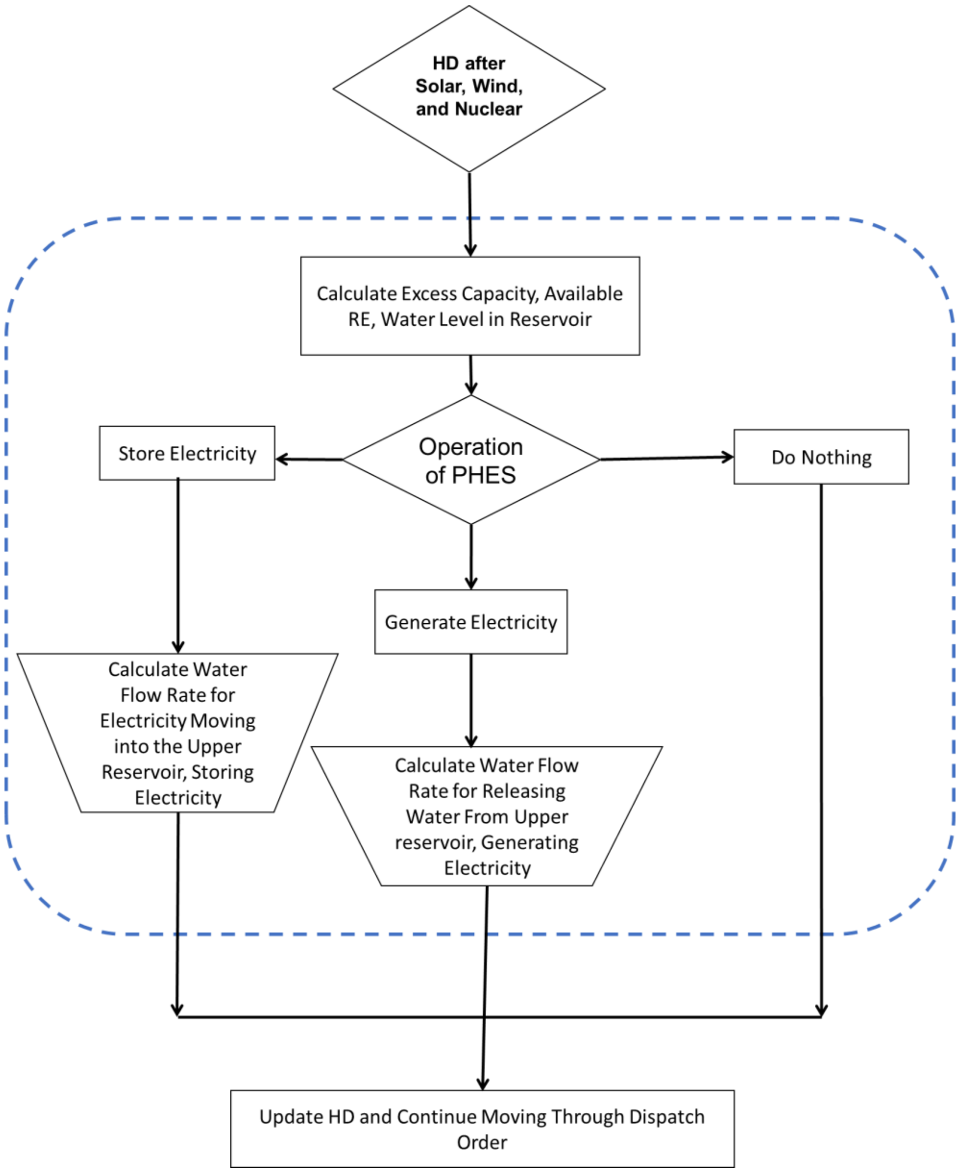

Figure 10: Flow Diagram for the PHES Facility

Operation Rules. In this section we define the operational rules used to determine the electricity generation and storage schedule for the PHES facility. Table 8 and Table 9 present the variables and parameters that will be used throughout this paper.

Table 8: PHES Model Variables

Variable	Description	Units
P_t	PHES Output Power	MW
Q_t	PHES Flow Rate	$m^3/_s$
H_t	Hydraulic Head	m
HD_t	Hourly demand	MW
W_t	Reservoir Water Level	m
V_t	PHES Volume of Water Stored	m^3
V_p	Volume of Water Added/Removed	m^3
P_h	PHES Adjusted Output Power	MW
s_t	Number of Seconds Plant Runs in an Hour	s
X_t	Excess Capacity	MW
x_t	Available Generation	MW
$x_{i,m}$	potential generation for technology m in portfolio i	
d_t	Demand	MWh
$\overline{X}_t$	Running Average of Excess Capacity	MW
$NRE_{g,t}$	Total Nuclear and Renewable Energy Generation Available at time t	MW
$NRE_{d,t}$	Total Nuclear and Renewable Energy Dispatched at time t	MW
β	Installed Capacity Gain Factor	*scalar*

Table 9: PHES Model Parameters

Parameter	Description	Value	Units
G_c	PHES Generation Capacity	Varies	MW
G_o	Base PHES Generation Capacity	1150	MW
Q_m	Maximum Flow Rate	Varies	$m^3/_s$
ρ	Density of water	1000	$kg/_{m^3}$
g	Acceleration of Gravity	9.8	$m/_{s^2}$
η	PHES Efficiency	0.82	%
TSC	PHES Total Storage Capacity	Varies	m^3
α	Smoothing Factor for Running Average	0.05	$scalar$
T_G	Generating Threshold	5	%
T_P	Pumping Threshold	5	%
W_{max}	Maximum Water Level	305	m
W_{min}	Minimum Water Level	286	m

Operation Decision. The decision on whether to pump, generate, or wait depends on the amount of excess capacity and the water in the reservoir. If potential capacity is much larger than demand and if the reservoir is not full, then the decision is to pump. If demand is high compared to potential capacity and there is water in the reservoir, the decision is to generate. We model this through two sets of conditions.

PHES will pump if condition 13a, and at least one of 14a and 15a holds:

$$W_t < W_{max} \quad (13a)$$

$$NRE_G - NRE_D > 0 \quad (14a)$$

$$X_t < \overline{X_t} * (1 - T_P) \quad (15a)$$

PHES will generate electricity if all conditions 13b, 14b, 15b, and 16 hold:

$$W_t > W_{min} \quad (13b)$$

$NRE_G - NRE_D = 0$ (14b)

$X_t > \overline{X_t} * (1 + T_G)$ (15b)

$HD_t > 0$ (16)

Equations 13a and b check whether the reservoir is full or empty. Equations 14 a and b are checking for excess capacity for nuclear, wind, and solar. If there is excess capacity, then the plant should pump, as these technologies are assumed to bid zero.

The excess generation capacity, X_t, is defined as the amount of potential generation power left after allocating the grid demand for the current hour, not including PHES. If the excess capacity is negative this signifies that without PHES there is a shortage of supply. When the value of excess capacity is negative PHES would be signaled to generate electricity provided that the reservoir water level is above the minimum threshold.

$$X_t = x_t - d_t \quad (17)$$

$$x_t = \sum_{m=1}^{M} x_{i.m} \quad (18)$$

The excess generation capacity can be thought of as the amount of additional power that can be produced by all generation technologies within the portfolio after demand has been satisfied, at time t. This metric is used to determine periods of high and low net demand. The supply is the available generation, x_t, and the demand is the total load on the grid, d_t. Available generation, defined in equation (18), is the sum of the potential generation, $x_{i,m}$, for technologies $m \epsilon M$ in portfolio i, where M is the set of technologies. In others words, it is the maximum amount of energy that can supplied by the generators in portfolio i at time t. This value depends on the capacity of generator m, its availability, and in the case of wind and solar, the resource available. When there is a high excess capacity - the demand is low, and the available generation is high - the price of electricity should be relatively low. This is when a PHES operator would decide to pump water into the upper reservoir. When the excess capacity is low, the PHES operator would start generating power because the demand is high, and the available generation is low, indicating the higher cost marginal generators would be operating at this time.

Equations 11a and b are checking whether excess capacity X_t is "low" or "high". We do this using a running average of the excess capacity, equation 19. The parameters T_P and T_G are the thresholds are used to determine when the excess capacity is low and high, respectively. When the excess capacity goes below the generating threshold, T_G, provided the other necessary constraints hold, the PHES plant starts generating power. Similarly, when the excess capacity goes above the pumping threshold, T_P, and the other necessary constraints hold, the PHES plant starts pumping, and storing, water. As an example, if the generating threshold is set to 6%, then any time the excess capacity is 6% greater than the running average, the PHES plant starts generating power to sell to the grid. These constraints are discussed in more detail in the following subsections.

$$\bar{X}_t = \alpha X_t + (1 - \alpha)\bar{X}_{t-1} \qquad (19)$$

Peaks and Valleys in the level of excess generation capacity are the primary mechanism for predicting periods of high and low electricity prices, and simulating the PHES operator's behavior. We focus on the short-term fluctuations are used as a proxy from electricity prices in a real-time electricity market, which would be more influenced by short term price fluctuations. Detection of peaks and valleys in the daily variation of excess generation, and keeping track of long-term trends of the available capacity is accomplished through a running average. The running average (equation 19) uses earlier data points along with new data to calculate an average. $\bar{X}_t$ is the running average at time t, and $\bar{X}_{t-1}$ is the running average from the previous hour, t-1. The smoothing factor, α, determines the weighting the function gives to historical versus new data and is in the range $0 < \alpha < 1$.

Finally, equation 14 signifies that PHES cannot will only generate electricity when there is demand left to be satisfied.

If neither of these cases holds, for example the water level is between the min and the max and there is no excess nuclear and renewable capacity, but the overall excess capacity is not above the generation threshold then the PHES facility will enter the do-nothing mode. This signifies that the PHES operator expects the opportunity cost of operating PHES in a later time frame is higher than the value of operating the PHES in the current hour.

3.3.2 Level of Storage or Generation Calculation

Following the operation decision, the PHES will continue pumping, storing, or being idle until one of the conditions no longer holds. While in the generation and storage phase the PHES facility must decide the amount of electricity the PHES plant generates or consumes at time *t*, and subsequently the amount of water stored.

The power output P_t, of the PHES generator at time *t* is defined by the potential energy stored in the water (equation 20) and is measured in Watts. This is the standard PHES equation. As a constraint of the system, the power output of the PHES plant cannot exceed the maximum generation capacity, G_c, equation 21.

$$P_t = Q_t \rho g H_t \eta \qquad (20)$$

$$P_t \leq G_c \qquad (21)$$

The variables and parameters in equations 20 and 21 are defined in Tables 1 and 2. The hydraulic head, H_t, is measured as the height between the water levels in the upper and lower reservoirs; this depends on the amount of water in the upper reservoir. The flow rate, Q_t, depends on amount of surplus energy available or demand to be filled. The rest of this section details the flow rate and water level calculations, as well as the method for scaling PHES output capacity. Next, we discuss how the water flow rate is determined for each hour, and how the water level in the reservoir changes with the flow rate. Once the flow rate and water level are known, the output power is scaled to the installed generation capacity.

Flow Rate Calculation. Due to operator decisions in response to the state of the grid, the water flow rate, measured in $m^3/_s$, can be altered hourly to control the amount of power being generated by the PHES plant. For example, the maximum generation capacity at time *t* could be 1000 MW, but the grid may only have 500 MW of demand left to be filled. In this instance, the flow rate is reduced to scale the power output down to 500 MW. **T**he maximum capacity of the PHES facility, Q_m, is presented in equation 22.

$$Q_t \leq Q_m \qquad (22)$$

The flow rate determines the amount of water being added to or removed from the upper reservoir. The flow rate at time t affects the volume of water stored in the reservoir instantaneously.

The volume of water pumped to the upper reservoir during one hour of operation is calculated using equation 23. The flow rate is multiplied by the number of seconds, t_o, that the PHES plant operates to find the volume of water added to the reservoir.

$$V_p = Q_t * t_o \quad (23)$$

This volume is then used to calculate the new water level in the reservoir, which is relevant because this changes the hydraulic head and impacts the amount of power the PHES facility can generate at time t.

Water level Calculation. The volume of stored water in the upper reservoir determines the water level at time *t*. The water level changes when the reservoir is pumping or generating because the volume of water stored will increase and decrease respectively. In this section we explain how the water level is calculated for the reservoir.

When the water level is at its minimum, the storage in the reservoir is considered to be at zero volume. The range of acceptable water levels is specified in equation 6. As the PHES plant pumps water into the reservoir, the volume of water being pumped is added to V_t, the effective volume of water stored, and is dependent upon the flow rate as shown in equation 24.

$$W_{min} \leq W_t \leq W_{max} \quad (24)$$

PHES reservoirs are typically based on available geologic features, so are nonuniform and not a standard geometric shape. Thus, the correlation between storage and water level is unique to every PHES reservoir. The reservoir used in this project is based on the Northfield Pumped Hydro Storage Project located in Massachusetts. The specifications for this facility are discussed in section 3. Using information from

Northfield, we relate the effective volume of stored water to the water level in the upper reservoir and then translate volume of water stored in the reservoir into a water level incrementation.

We generalize our methodology to model any size PHES plant using a gain factor β, in equation 25, which is defined as the ratio between the installed capacity of PHES generation, G_c, and the output capacity of the original reservoir, G_o.

$$\beta = \frac{G_c}{G_o} \quad (25)$$

Using the hydraulic head and the flow rate, the PHES plant output power or consumption can be calculated using equation 2. The power calculated is then multiplied by the gain, β to obtain the scaled output of the PHES plant.

3.3.3 Sustainability Calculation

In this section we present the methodology for calculating the sustainability of a power system. The methodology for calculating the sustainability of a generation portfolio is originally presented and discussed in more detail in Nock and Baker (2019). Here we will highlight the overall methodology, and highlight the changes from Nock and Baker (2019) for incorporation of the PHES facility.

We consider a set of sustainability metrics, including levelized cost of electricity (LCOE), life-cycle greenhouse gas (GHG) emissions, life cycle air pollution (SO_2, NO_x, PM), land use, life cycle water consumption, fatalities, and jobs. Note, we use the LCOE of the system, not of individual technologies. The total value of sustainability metric j depends on both the energy and installed capacity of the technology being evaluated, as defined in equation 26. Let $x_{ij\tau}$ be the value of metric j for technology τ in portfolio i; and let $F_{j\tau}$ and $V_{j\tau}$ represent the fixed value per unit of capacity and variable value per unit of electricity for metric j, respectively.

$$x_{ij\tau} = \frac{F_{j,\tau}}{hCF_{i\tau}} + V_{j,\tau} \qquad (26)$$

The capacity factor $CF_{i\tau}$ depends on the specific portfolio i, technology τ.

In each simulation there are two demand levels due to PHES acting as a consumer. The first demand level, d_1, is the demand prior to the addition of PHES, and reflects the actual demand delivered to the consumer. The second demand level, d_2, is the total electricity demand after PHES is allowed to act as a consumer. We use a scaling metric, equation 27, to capture the true change in sustainability metrics based on the addition of PHES.

Let $x_{ij\tau}$ be the value of metric j on a per kwh basis following the addition of PHES. We define $x_{ij\tau}$* as the value of metric j for the kWh that were delivered to the consumer, where

$$x^*_{ij\tau} = x_{ij\tau}\left(\frac{d_2}{d_1}\right) \qquad (27)$$

Here we discuss how each metric is related to PHES. For details regarding the metrics for all other technologies, refer to Nock and Baker (2019). The sustainability of PHES facilities will depend on the operation of the pumped hydro storage facility and the location of this facility. In our study the PHES facility was modeled based on the Northfield Mountain pumped storage station in New England, which uses a river as the lower reservoir. This differs from closed-loop PHES facilities which use a lake as the lower reservoir. Since PHES is very similar to hydro, except for land-use. Due to the river playing a large impact in the water consumption and operation of the pumped hydro storage facility we assume that all of the sustainability metrics, except costs and land use, will be comparable to a hydro facility. Costs will differ from traditional hydro due to the extra costs in the pumping infrastructure.

Land use by generation facilities is a concern for stakeholders due to the direct and indirect impacts on the environment. Land-use in a PHES facility differs due to the need for an upper reservoir and the change in the landscape to accommodate the pumping infrastructure. The maximum life cycle land use of generation facilities is defined as an upper bound on the amount of land that will be used in each power plant (Nock and Baker 2019; Klein and Whalley 2015). We assume that land use is wholly fixed for PHES generation facilities. This assumption holds because the size of the plant impacts the amount of raw materials that will need to be supplied for construction of the plant (indirect land use) and the amount of land needed to house the facilities and reservoirs (direct land use).

3.3.4 PHES Impact on Other Generators

Adding PHES to an electricity system will have an impact on the energy contribution from other generators due to its ability to load shift, increase overall system demand, and act as both a consumer and supplier. Due to the location in the dispatch order it is expected that PHES will increase the energy contribution of renewable generation. This is because, in cases where some renewable energy is not used because of low demand, it will now be used to pump. On the other hand, PHES will have a different impact on hydro, oil, and NG based on the way PHES changes the demand profile. We evaluate the impact on renewable and fossil fuel generation using the change in capacity factor of each technology.

3.3.5 Data

In this section we present the data used in the New England Electricity model and the sustainability model. We present information regarding the PHES facility calculations. For all other data refer to Nock and Baker (2019).

Electricity Data. The modeled reservoir for the PHES facility is based on information gathered from the Northfield Mountain Pumped Hydro Storage Project, located in New England. The Northfield project is the largest pumped hydro storage plant in New England and the second largest power plant in the state. The Connecticut River is used as the lower reservoir and the 320-acre upper reservoir is located on top of Northfield Mountain, located 240 meters above the top river. A tailrace connects the two bodies of water and water is pumped up using four large turbines. The power output is calculated based on the Northfield facility, which has a nameplate capacity of G_o = 1150 MW, and is scaled to the installed generation capacity.

For the Northfield reservoir, the minimum water level is 285.9 meters, and the maximum is 305 meters. This allows the water level in the reservoir to fluctuate in a 19.1-meter range giving a total storage capacity (TSC) of $1.519\ million\ \mathrm{m}^3$ of usable generating volume. The Northfield Relicensing website (Gomez and Sullivan Engineers 2017) provided information relating the height of the water level in the reservoir to the volume stored. Using a simple regression model on this data, we estimated the following polynomial relating the TSC volume in millions, Vt, with reservoir water level, W_t (Gomez and Sullivan Engineers 2017).

$$V_t = 1293 - 9.5 * W_t + 0.0174 * W_t^2 \quad (28)$$

Here W_t is the water level and V_t is the effective volume of water stored. The current volume of water stored can be calculated using equation 28. The volume of water to be added to the reservoir when pumping is calculated using equation 23 and summed with the effective volume of water stored.

If the water level reaches the minimum or maximum threshold in the middle of the hour, the PHES plant stops its current operation. In general, the amount of power used or generated is calculated using equation 29 where s_t is the number of seconds the plant operated for the current hour and P_h is the adjusted power output. The adjusted output is the amount of power generated or consumed if the plant stops operating in the middle of the current hour.

$$P_h = \frac{s_t}{3600} * P_t \quad (29)$$

Sustainability Data. Information regarding the land use of PHES was gathered from the Northfield Relicensing website (Gomez and Sullivan Engineers 2017). Here the direct Land Use is calculated as the total area of Northfield divided by the nameplate capacity of the PHES facility. This assumption leads us to source the information for the sustainability calculations of PHES facilities from reports detailing the sustainability of traditional hydro facilities (Nock and Baker 2019; Meldrum et al. 2013; Macknick et al. 2011; Klein and Whalley 2015).

The land use of the PHES model was taken from the Center for Land Use Interruption (Center for Land Use Interpretation 2019). The area of the reservoir encompassed 320-acres or $1.295 * 10^6\ m^2$. This corresponds to a land use of 1,132 $\frac{m^2}{MW}$.

Costs will differ from traditional hydro due to the extra costs in the pumping infrastructure. This is accounted for by estimating PHES capital costs from Barbour et al. (2016) and Deane et al. (2010), and assuming the variable costs will be similar to the traditional hydro facility (Nock and Baker 2019; Klein and Whalley 2015). Deane et al (2010) found that PHES capital costs ranged from 625 $/kW to 2,886 $/kW, while a more recent study reported that the capital costs of PHES ranged from 2000 – 4300 $/kW (Barbour et al. 2016). Here we assume the capital cost of PHES facilities to be 2800 $/kW due to the limited space in the New England region meaning land costs could be at a premium.

3.4 Results and Discussion

Here we detail the results of the how storage capacity investments impact energy contributions and sustainability ratings, in order to provide insights into how New England can plan for a more sustainable power system in 2035 and beyond.

In general, there are two types of impacts that adding storage can have on the system. The first is short-run impacts which result from simply adding PHES to the currently existing power system. Short-run impacts include changes in capacity factors of other technologies, and impacts in overall system sustainability. Long-run impacts include changes in the composition of the generation portfolio, reflected in the overall capacity needs of the electricity system. For example, one long-run impact could be the ability to retire nuclear power plants. In this dissertation we will focus on the short-run sustainability impacts of increasing system flexibility via PHES, and leave the exploration of long-term impacts as an opportunity for future work.

We start by describing how adding PHES to Portfolios 0, 1, 4, and 9 from Chapter 2 impacts the energy contribution from other generators. These portfolios were chosen to illustrate the value of increasing system flexibility in the top two sustainable portfolios from Chapter 2, a third portfolio in which future oil and nuclear are completely reduced, and the base case. We follow this by discussing the sustainability impacts of adding PHES to the aforementioned portfolios.

Energy Impacts. For the initial comparison 5,000 MW of PHES was added to Portfolios 0, 1, 4, and 9 from Chapter 2. In all scenarios, upon the addition of 5,000 MW of PHES capacity there was an increase of more than 10% in the energy contribution from onshore wind, and no change in the contribution from solar and nuclear due to these technologies going first in the dispatch order. Table 10 illustrates the changes to the energy contribution for the demand and all other technologies. A positive value indicates that a 5,000 MW addition of PHES increased the energy contribution of that technology. Here we see that in all cases the electricity demand increased by 6% or more. Due to the PHES facility directly consuming electricity from renewables the energy contribution from offshore wind increased in all cases, with a high of 62% in the base case. On the other hand, the energy contribution from NG, hydro and oil always decreased or remained unchanged. The largest decrease in NG and Hydro came from the high offshore wind and nuclear scenario, Portfolio 9.

Table 10: Change in Energy Contribution after addition of 5,000 MW of PHES

	Demand	Offshore Wind	NG	Hydro	Oil
Portfolio 0 - Base	8%	62%	-3%	-3%	-27%
Portfolio 1 – No Oil or Nuclear	7%	29%	-8%	-8%	0%
Portfolio 4 – High Nuclear	8%	56%	-5%	-5%	0%
Portfolio 9 – High Offshore Wind and Nuclear	6%	14%	-10%	-10%	0%

Sustainability Impacts. Figure 11 illustrates the sustainability impacts from adding PHES to Portfolios 0, 1, and 9 from Chapter 2. A longer bar indicates a higher sustainability ranking. We find that, under the equal weight scenario, adding PHES to the system leads to higher sustainability in every portfolio. This signifies that even with the additional costs associated with adding storage to the New England power system it could be beneficial to add in storage due to the addition of jobs, reduced water consumption, and savings in GHG and air pollution for the region. These results are robust to the inclusion of nuclear aversion, highlighted by the red striped bar.

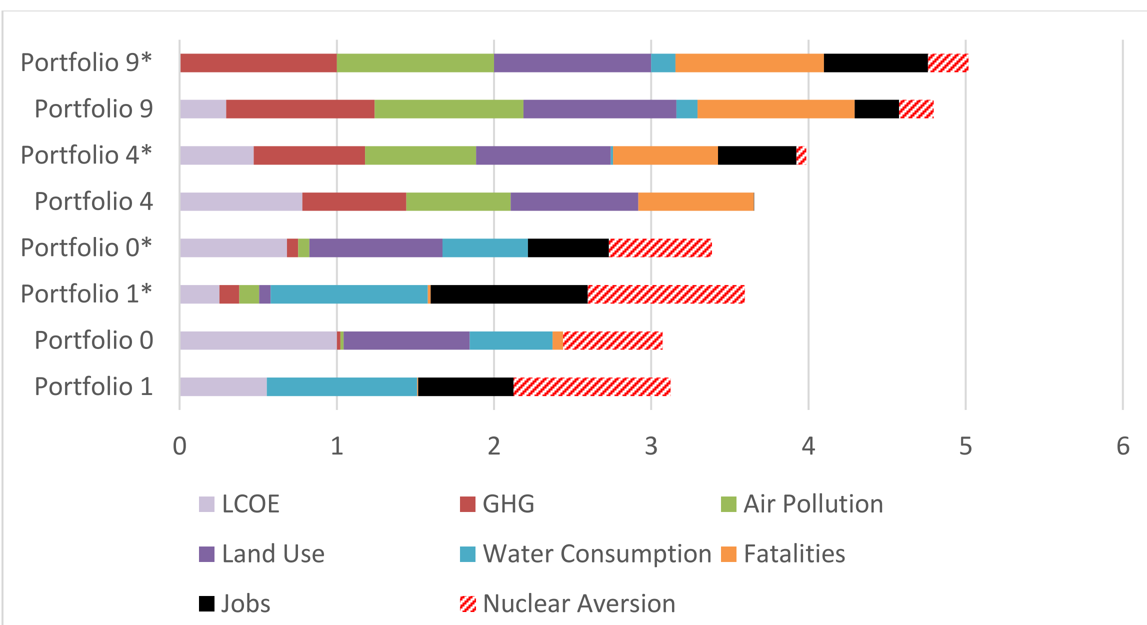

Figure 11: Normalized sustainability scores for portfolios with and without PHES. The (*) attached to the portfolio name indicates portfolios which have an additional 5,000 MW of PHES.

In Figure 12 we see how adding PHES to the system impacts normalized sustainability scores for each of the sustainability criterion. A positive value indicates that a 5,000 MW addition of PHES benefited the system in that sustainably category. In general, we find that adding PHES to the system increases system costs and fatalities, while reducing GHG, air pollution, land use and water consumption and increasing jobs. The higher sustainability rankings in terms of GHG and air pollution result from the reduction in energy contribution from NG and oil in all portfolios after the inclusion of PHES.

In general, we find that with the inclusion of PHES there is an increase in LCOE (reduced sustainability) and jobs (increased sustainability). This trend depends on our assumptions regarding the regarding the base values for each technology. Since we focus on short-term sustainability here and do not reduce the capacity of any other technologies after the inclusion of PHES this causes the economic sustainability to fall. The large increase in jobs sustainability rating has to do with our assumptions regarding the job intensity of offshore wind. We assume that offshore wind energy is more than twice as job intensive than NG and oil on a per GW basis. This means that as the energy contribution from offshore wind increases the social sustainability rating from jobs will increase.

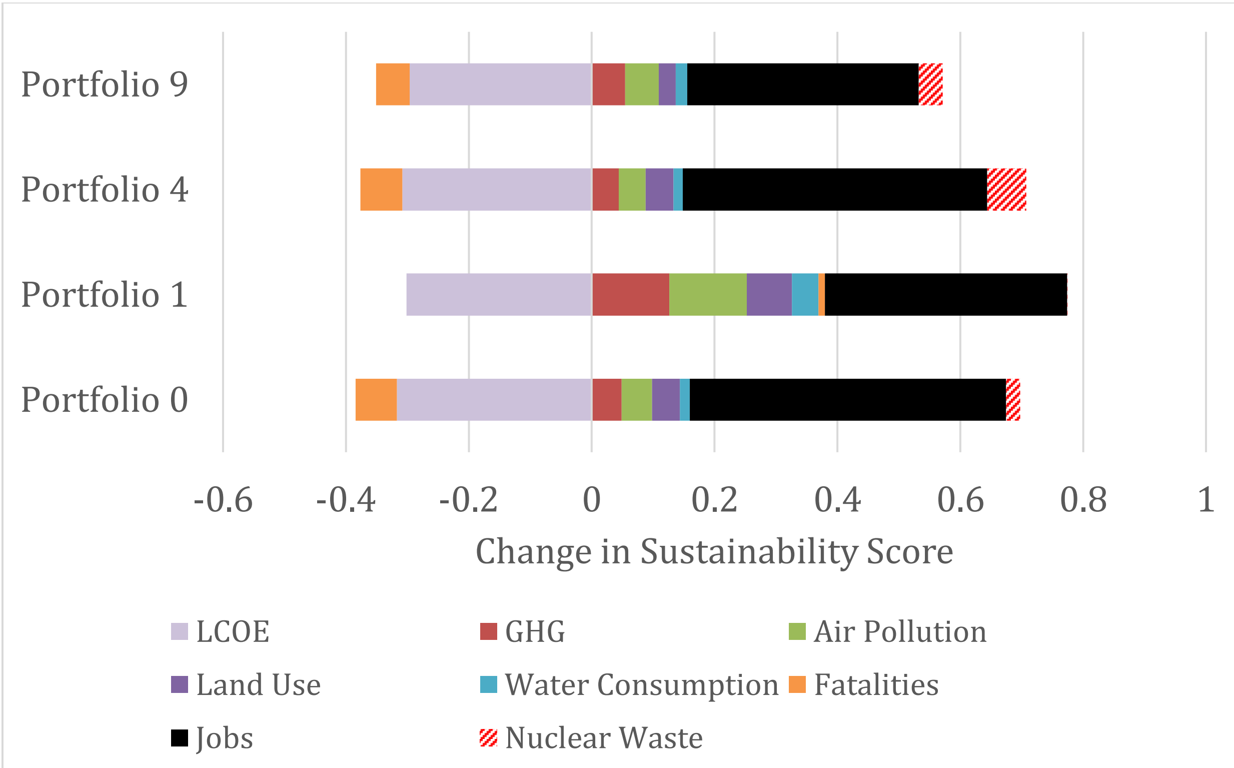

Figure 12: Changes in the portfolio sustainability scores following the addition of 5,000 MW of PHES

3.5 Conclusions

Here we have presented a model that highlighted the role of increasing system flexibility for a region's power system. This research highlights the role storage can play for power systems. From the case study of the New England power system we have found that adding 5,000 MW of storage (to a 33 – 42 GW system) would significantly increase jobs in the region, and have a positive impact on reducing GHG, air pollution, and water consumption for the key portfolios tested in this section. While this was applied to the New England Power System this work has wide applications for stakeholders who wish to understand the role adding storage to their power system plays in sustainability advancements.

Future work involves investigating long-term sustainability impacts in terms of the structural changes that can be made to the systems regarding retirement of generation facilities after addition of PHES, and testing a wider range of portfolios.

From our work we found that increasing system flexibility, using PHES, can reduce the energy contribution from fossil fuel technologies, while raising the energy contribution of offshore wind. It is clear that increasing the flexibility of the system by simply adding storage capacity for the grid increases costs, but the savings in GHG emissions, water consumption, and air pollution mean this could be a worthwhile endeavor for power systems.

CHAPTER 4

ESSAY III: CHANGING THE POLICY PARADIGM USING A BENEFIT MAXIMIZATION APPROACH TO ELECTRICITY PLANNING IN DEVELOPING COUNTRIES

4.1 Abstract

Access to electricity can lead to enhanced education, business, and healthcare opportunities. Governments in emerging economies are often faced with the challenge of increasing access to electricity within budgets set by foreign aid and resource allocations. This paper develops a methodology for finding the optimal expansion of a power system under the objective of maximizing social benefit, with an emphasis on the balance between centralized and distributed renewable generation, and the transmission system layout. This is in contrast to traditional models, which minimize the cost of providing a high level of service and reliability, while also satisfying a projected electricity demand. We formulate the problem as a utility-maximization mixed integer program and apply it to Liberia. We find that a high preference for equality between rural and urban areas often leads to lower overall electricity generation, greater investment in transmission infrastructure, and wider adoption of residential solar; indifference to equality leads to the development of urban areas first. This methodology can inform decision makers about the various pathways to maximize electricity access in their respective countries.

4.2 Background and Motivation

Over 600 million people in sub-Saharan Africa do not have access to electricity (World Energy Outlook 2018). In 2012, only 35% of the people in Sub-Saharan Africa had access to electricity (United Nations 2018). Several studies have shown that access to electricity can provide a number of socio-economic benefits, including enhanced education, business, and healthcare opportunities (Parikh et al. 2015; Kirubi et al. 2009). A socio-economic impact study by the World Bank found a significant link between electricity access and educational achievement (World Bank 2002).

The United Nations (UN) has further cemented the interrelationship between equality, electricity access, and well-being through their Sustainable Development Goals (SDGs). Goal 7 of the UN SDGs focuses on providing access to affordable, reliable, sustainable, and modern energy for all. The metrics used to evaluate this goal include energy intensity (energy consumption per unit of GDP), renewable energy shares in total final energy consumption, proportion of the population with primary reliance on clean fuels and technologies for cooking, and proportion of the population with access to electricity by region (United Nations 2018). In addition to well-being indicators, there are a host of energy indicators for sustainable development that relate to equality and health, such as accessibility, energy resource risk, affordability, safety, and air quality (Kemmler and Spreng 2007; Vera and Langlois 2007). This focus on universal electrification goals highlights the need for a holistic electricity planning approach that considers not just cost and access but also equality in the level of access.

In this chapter we investigate the electrification strategy– including investments in centralized and decentralized generation and transmission infrastructure – that maximizes social benefit from the perspective of a central government or system planner, given equality preferences and budget constraints. We consider the mix between centralized and decentralized generation, the layout of the power system, and the choice of generation technologies, maximizing utility under different levels of equality preferences.

Electrification is considered essential for development due to areas without access being less developed than electrified regions (Kabir et al. 2017; World Bank 2002). Electrification can lead to improved businesses, clean sources for lighting, enhanced farm productivity, and convenience of house hold tasks, especially in rural areas. We build directly on the idea that increased electricity access leads to social benefits in this paper. We introduce the Maximize Energy Access (MEA) model, which determines the optimal power system expansion plan by maximizing a utility function that is based on electricity access and stakeholders' preferences towards equality. We model utility as a direct function of electricity access, measuring electricity access as potential per-capita electricity consumption at each node in the system, given the power system and the budget constraint. Here we focus on supply-side access, which is measured as the potential energy consumption. A key distinguishing factor between our methodology and previous literature is that we employ an opportunity-focused approach to electricity planning.

Traditionally, the problem of how to expand the power system in emerging economies has been addressed by setting goals for overall electricity access in a region or country, then choosing a plan that minimizes the cost of achieving the goal. The majority of energy planning studies have been conducted from this least-cost perspective (Afful-Dadzie et al. 2017; Carvallo et al. 2017; Abdul-Salam and Phimister 2016; Zeyringer et al. 2015; Levin and Thomas 2013; Modi et al. 2013; Deichmann et al. 2011; Kaundinya et al. 2009; Parshall et al. 2009). The least-cost approach focuses on minimizing the overall cost of expanding the power system, while satisfying a projected demand constraint. While this approach is common throughout the developed world, it presents unique challenges when applied in developing regions, where it is more difficult to forecast future electricity demand, particularly for populations who have not previously had access to electricity (Modi et al, 2013).

When striving to obtain social objectives there are also concerns regarding the choice between urban and rural electrification. Many stakeholders wish to ensure that rural communities also receive access to electricity. Some studies have focused on rural electrification specifically (Kabir et al. 2017; Feron 2016; Alfaro and Miller 2014; Poudel 2013), while others focus on the choice between grid expansion and decentralized options in developing countries (Zeyringer et al. 2015; Modi et al. 2013; Levin and Thomas 2012). Both sets of analyses use a least-cost perspective. In regions without an existing power system infrastructure, research has indicated that decentralized electricity systems are more economically viable than centralized grids (Flores et al. 2016; Levin and Thomas 2016; Hiremath et al. 2009). When stakeholders focus solely on increasing electricity consumption, they may disproportionately favor urban areas and increasing industrial production (Hiremath et al. 2009).

Even when least-cost analysis deems distributed generation as the more cost-effective option for initial grid integration, the local population may view a connection to a reliable centralized grid as the ultimate goal to provide the opportunity for increased future demand (Mehigan et al. 2018; Flores et al. 2016; Hiremath et al. 2009). In cases where the long-term, least-cost plan requires a highly coordinated effort with years or decades of sustained funding, delays in implementation can be common, leaving large quantities of demand unserved for extended periods of time (Levin and Thomas 2014). These delays can diminish consumer utility, and such cases raise the question of whether limited resources could have been allocated more efficiently to achieve targeted social objectives. Afful-Dadzie et al. (2017) explored the impact of funding uncertainties by analyzing the role that periodic budget constraints and demand uncertainty play in the generation expansion problem. We extend this analysis by focusing on the impacts of stakeholder preferences for electricity access equality on optimal transmission and generation infrastructure investments. In this work we do not use demand projections to determine the electrification pathway because our goal is to determine the most efficient way of increasing access to electricity under a social welfare objective.

While the studies mentioned above have analyzed electricity planning in developing countries, they have not explicitly included stakeholder preferences regarding equitable access to electricity in electricity system expansion. Ignoring stakeholder preferences implicitly ignores the political climate which can play a significant role in electricity investment and subsequent power system development in sub-Saharan Africa (Nock and Baker 2019; Trotter et al. 2017, Onyeji et al. 2012). There are numerous places where preferences for equality are implied (i.e. World Bank's energy tiers and rural electrification programs). This paper fills the gap in the current literature by being the *first to explicitly integrate a stakeholder preference towards equality* into an electricity planning optimization program, thus presenting a way to integrate political climate into electricity planning. Our contribution to the electricity system planning literature is to illuminate how stakeholders' preferences around equality in electricity access impact the design of the electricity system under budget constraints. This model is not intended to replace detailed analyses of electrification pathways for a country, and cannot be used as a stand-alone implementation tool. Instead it is intended to guide discussions between various electricity stakeholders (donor organizations, rural electrification agencies, and Ministries), and illustrate a framework for taking a benefit maximization approach to electricity planning.

We present a case study analysis of Liberia to demonstrate the MEA model. While we use Liberia as a backdrop, this approach has wider applications, and can support the discussion revolving around how to best expand a nation's power system. For example, in small-island nations, such as Puerto Rico, who need to rebuild their power systems after natural disasters, there is a need to consider equality preferences among donors and stakeholders. The configuration of a regional power system depends heavily on the underlying goals of the country, stakeholder preferences, and the technology options available for providing electricity services.

The remainder of the paper is organized as follows: Section 4.3 covers the methods and approaches used in the models; Section 4.4 details the case study assumptions and discusses the results. We conclude with some policy implications and general insights in Section 4.5.

4.3 Methodology

In section 4.3.1 we describe the model formulation, Section 4.3.2 details the methodology for the cost calculation, and section 4.3.3 discusses the measure of inequality used to evaluate the population's resulting access to electricity.

4.3.1 MEA Model Formulation

Designing an optimal power system is a complex spatial planning problem. The MEA model is formulated as a bottom-up techno-socio-economic mixed-integer program (MIP), maximizing consumer utility as a function of electricity consumption subject to physical constraints on network flow and budget constraints on the total cost of power system expansion and operation. The objective of our model is to maximize the consumer utility that is gained through electricity access, which we measure as the maximum available per capita electricity consumption. We use a nodal representation of the geographic population distribution and assume that the total consumer utility realized across an entire country is equal to the sum of the utility of each individual consumer. The model determines optimal investments in new generation and transmission infrastructure, as well as the optimal allocation of electricity consumption across each node. The overall flow of the model is presented in Figure 13.

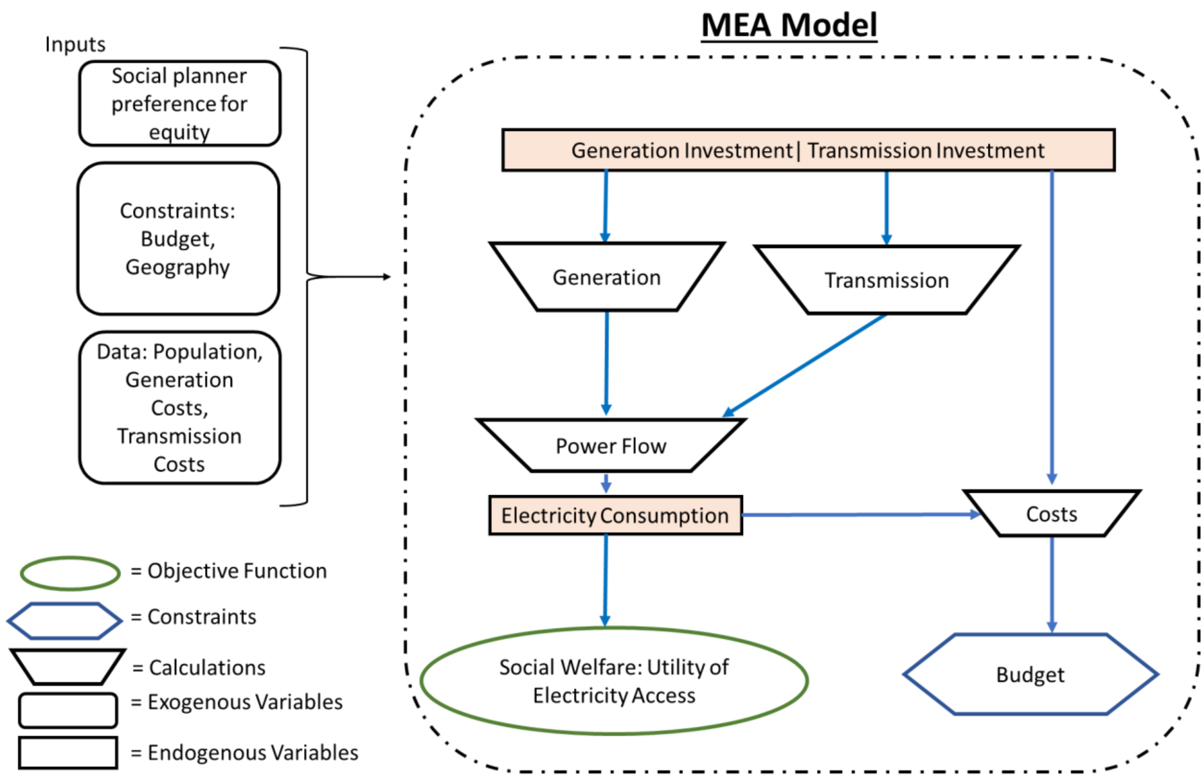

Figure 13: Flow of Information within the MEA model.

Similar to the studies from Parshall et al. (2009), Deichmann el at (2011), and Abdul-Salam and Phimister (2016) we determine the optimal power system for a static future year and therefore do not explicitly consider a temporal dimension in our analysis. We follow a methodology similar to Levin and Thomas (2012) in the power grid formulation, which uses a simplified network flow representation of electricity transmission rather than explicitly considering the direct or alternative current power flow equations that govern how electricity flows through a connected power system. Our model differs from cost minimization models through treating the cost minimization as a budget constraint. This leads this to be similar to a multi-objective optimization model where the second objective (i.e. cost minimization) has been constrained.

In this section, we first present the overall model formulation, then discuss the objective function (equation 30), budget constraint (equation 31), power flow constraints (equation 32), transmission constraints (equations 33-36), and generation constraints (equations 37-40). The variables and parameters used in the methodology can be found in Table 11 and Table 12.

Table 11: MEA Variables

Symbol	Description	Units
$e^L_{i,j}$ and $e^H_{i,j}$	Indicates if a low-voltage or high-voltage transmission line is constructed between nodes i and j	
$f_{i,j}$,	Average annual power flow from node i to node j	MWh
$F_{i,j}$	Peak electricity flow on edge (i, j)	MWh
$g_{i,k}$	Generation by technology k in node i,	MWh
$G_{i,k}$	Capacity of technology k installed at node i	MW
ρ_i	Per-capita energy consumption in node i	MWh/ppl
x_i	Electricity available at node i	MWh
$y_{i,k}$	Indicates if generation k was built at node i	

Table 12: MEA Parameters

Symbol	Description	Units
af_k	Availability factor of technology k	%
$C^{T,L}$ and $C^{T,H}$	Annualized costs per km for low voltage and high voltage transmission lines	\$/km-year
$C^F_{i,k}$	Annualized fixed cost (including capital and fixed operations and maintenance) for generation technology k in node i.	\$/kW-year
$C^V_{i,k}$	Variable cost (including fuel and variable operations and maintenance), for generation technology k in node i;	\$/kWh
$d_{i,j}$	Length of the transmission line needed to connect nodes i and j	km
γ	Ratio of peak power flow to average power flow	-
T^H, T^L	High and low transmission capacities	MW
$\mathbf{p}$	Vector of populations at each node i.	-
$\mathbf{p}_i$	Population at node i	ppl
$\mathbf{x}$	Vector of the electricity consumed (in MWh) at each node i	
E	Set of possible transmission edges	-
I	Set of nodes in the system	-
K_i	Set of Generation options in node i	-

The MEA model is formulated as follows:

Maximize

$$U(\mathbf{x},\mathbf{p}) = \sum_{i\in I} u(x_i, p_i) \tag{30}$$

Subject to

$$\sum_{(i,j)\in E}\left(C^{T,L} d_{i,j} * e^L_{i,j} + C^{T,H} d_{i,j} * e^H_{i,j}\right) + \sum_{i\in I,k\in K}(C_k{}^F G_{i,k} + C_k{}^V g_{i,k}) \le B \tag{31}$$

$$x_i \le g_i + \sum_{j\in N} f_{j,i} - \sum_{j\in N} f_{i,j} \quad \forall i \in I, (i,j) \in E \tag{32}$$

$$e_{i,j}^{L} + e_{j,i}^{L} + e_{i,j}^{H} + e_{j,i}^{H} \le 1 \ \ \forall (i,j) \in E \tag{33}$$

$$F_{i,j} = \gamma f_{i,j} \ \ \forall (i,j) \in E \tag{34}$$

$$F_{i,j} \le \left(T^{L} * e_{i,j}^{L} + T^{H} * e_{i,j}^{H} \right) \ \forall (i,j) \in E \tag{35}$$

$$F_{i,j} \ge -\left(T^{L} * e_{i,j}^{L} + T^{H} * e_{i,j}^{H} \right) \ \forall (i,j) \in E \tag{36}$$

$$g_i = \sum_{k \in K_i} g_{i,k} \ \ \forall i \in I, k \in K_i \tag{37}$$

$$g_{i,k} \le 8760 * af_k * G_{i,k} \ \ \forall i \in I, k \in K_i \tag{38}$$

$$G_{i,k} \ge m_k * y_{i,k} \ \ \forall i \in I, k \in K_i \tag{39}$$

$$G_{i,k} \le M_k * y_{i,k} \ \ \forall i \in I, k \in K_i \tag{40}$$

$$x_i, g_{i,k} \ge 0 \ \forall i \in I, k \in K_i \tag{41}$$

I is the set of nodes, and E is the set of possible connections between population nodes. The MEA model is implemented in Python using the Gurobi optimization solver. The non-linear objective function is approximated using a piecewise linear function. We do not consider electricity losses or theft.

Objective Function. In equation 30, U(**x,p**) is the overall utility of the country; **x** is a vector of the electricity available (in MWh) at each node i, and **p** is the vector of populations at each node i. I is the set of nodes in the system.

We assume that the utility at each node is a concave function of per capita electricity consumed at that node, scaled by the population of that node. In other words, consumers have decreasing marginal utility of electricity consumption. We use an isoelastic utility function as seen in equation 42.

$$u(x_i, p_i) = p_i \frac{\left(\left(\frac{x_i}{p_i}\right)^{1-\alpha} - 1\right)}{1-\alpha} = p_i \frac{(\rho_i^{1-\alpha} - 1)}{1-\alpha} \qquad (42)$$

where $\rho_i = \frac{x_i}{p_i}$ is the per-capita energy consumption in node i. The overall utility U is equivalent to the equal-weighted sum of all individual utilities. An exercise showing how the individual utilities can be aggregated into group utilities has been included in Appendix F.

Stakeholder preferences for equality are modeled through the equality parameter $\alpha \in [0,1)$, where a higher value of α represents a desire for more equality across the population. This is typically called an inequality aversion parameter in the economics literature (Atkinson et al 2009; Carlsson et al. 2005; Johansson-Stenman et al. 2002) when it is applied to income; we focus on inequality between electricity consumption. As α approaches zero, there is more emphasis placed on the total quantity of generation supplied in the system. As α approaches 1, the marginal utility of each additional unit of electricity supplied to a node approaches zero. As a result, the first unit of electricity consumption in a node provides far greater utility than an additional unit at higher consumption levels, meaning there is more emphasis placed on an equitable distribution of electricity, instead of the total quantity of countrywide consumption. We assume that within each node, there is equal per capita electricity consumption. Here the value of α represents the social planner’s preference for electricity equality between individuals.

The highest possible equality level occurs when each node gets the same *per-capita* energy.

Budget Constraint. The budget constraint, equation 31, accounts for the annual costs in the power sector, including all fixed and variable costs, of investment and operation over the lifetime of the facilities. We assume that existing generation and transmission infrastructure does not incur any capital costs.

The first summation accounts for the cost of building transmission lines. The set of edges, E, includes the possible connections between nodes for transmission edges. The binary variables, $e^L_{i,j}$ and $e^H_{i,j}$ are equal to one if a low-voltage or high-voltage transmission line is constructed between nodes i and j, and zero otherwise. The parameters $C^{T,L}$ and $C^{T,H}$ are the annualized costs per km for low voltage and high voltage transmission respectively; and $d_{i,j}$ is the length of the transmission edge needed to connect nodes i and j. The second summation accounts for the cost of constructing and operating generation technologies in all nodes. $C^F_{i,k}$ is the annualized fixed cost (including capital and fixed operations and maintenance), per kW for generation technology k in node I; note this factor will depend on the lifetime of the technology as well as the interest rate. These two parameters are discussed in more detail in section 4.3.2. $C^V_{i,k}$ is the variable cost (including fuel and variable operations and maintenance) of generating one kWh, for generation technology k in node i; B is the annual development and operations budget, assumed to be set by a social planner. This does not include the cost to connect individual households. To keep estimates consistent, we do not include balance of system costs for decentralized solar home systems. Thus, we are excluding household connection costs for both centralized and decentralized generation. G_{ik} is the installed capacity of technology k at node i; and $g_{i,k}$ is the annual electricity generated by technology k in node i.

Power Flow Constraints. Equation 32 provides the power balance constraint for each node, ensuring that electricity consumption at each node (x_i), does not exceed the sum of energy generated at that node (g_i) and the net transmission flow into the node ($f_{i,j}$–$f_{j.i}$). Average annual power flow from node i to node j is represented as $f_{i,j}$, ; and is positive if power flows from i to j, and negative otherwise. This constraint ensures that power flow is balanced at each node. Figure 14 illustrates the power flow constraints. Here node 1 contains a power plant that generates g_1 units of electricity. Node 1 consumes x_1 units of electricity and sends the remaining g_1-f_{12} units of electricity to Node 2. Node 2 consumes x_2 and the remaining, f_{12}-x_2 is sent to node 3. The total electricity consumed by the nodes is $x_1+x_2+x_3$, which equals the total electricity generated by the power plant, g_1. Here T_{ij} is the capacity of transmission edge ij.

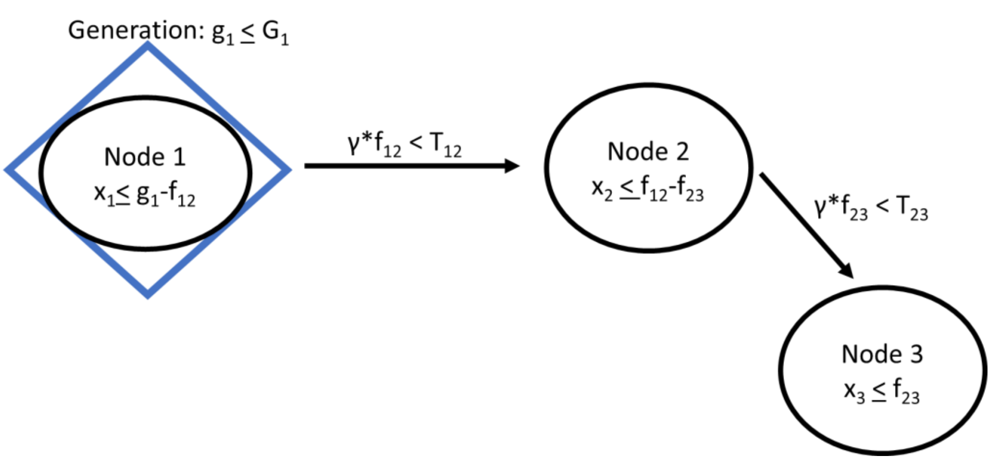

Figure 14: Power flow example

Transmission Constraints. A positive flow on $e_{i,j}$ means that electricity is transmitted from node i to node j, while a negative flow means electricity is transmitted from node j to node i. T^H and T^L are the transmission capacities of high-voltage and low-voltage transmission edges, respectively, in MW. The constraint defined in equation (33) ensures that there is at most one transmission line connecting any two nodes.

Power flow along transmission edges will vary through time, with the instantaneous flow being sometimes higher and sometimes lower than the average flow. The factor γ is the ratio of peak flow to average flow, and is the mechanism used to account for reliability of the centralized transmission system. The relationship between peak flow, F_{ij}, and average flow is presented in equation 34. Constraints 35 and 36 dictates that the peak flow on edge (i, j) must be less than or equal to the transmission capacity on that edge.

Generation Constraints. Equations 37 and 38 establish the relationship between annual generation and installed capacity. Total annual electricity generation in node i, g_i, is made up of the generation by all technologies $k \in K_i$ installed at node i. Annual generation $g_{i,k}$ by technology k in node i, cannot exceed the capacity, $G_{i,k}$, of technology k installed at node i, multiplied by the hours in a year and the availability factor, af_k, of technology k.

The binary variable $y_{i,k}$ indicates whether or not new generation capacity k is built at node i. Equation 39 enforces a minimum bound on capacity, as some types of generation are inefficient below a certain level. Equation 40 similarly enforces an upper bound on installed capacity.

Other Constraints. Equation 41 is the set of non-negativity constraints.

We made a simplifying assumption that per capita electricity consumption is constant within each individual node, although we recognize this is often not the case due to wealth disparities. In our model, we do not account for interconnections between countries, which would impact the amount of per capita consumption in nodes connected to the centralized power system. In addition, we consider potential consumption as opposed to actual consumption, which allows us to determine the social benefit of increased electricity access. We do not investigate the impact of electricity prices in this model, instead we focus on the cost of building the system from a social planner's perspective. There is no stochasticity considered in this model, but the reliability of the centralized power system is captured through the peak factor, and the reliability of generation supply is captured through the availability factor for generation sources. We leave the impact of stochastic outages as future work.

4.3.2 Methodology for Cost Calculation

We determine the annualized capital and operating costs incurred by each technology as outlined in equations 43 and 44.

$$C_k^F = C_{cap,k} * CRF + C_{O\&M,k}^F \tag{43}$$

$$C_k^V = C_{O\&M,k}^V + \left(C_{Fuel,k} * HR_k \right) \tag{44}$$

Where the subscript k refers to the technology type. The parameters are defined in Table 12. C_k^F is the annual cost incurred each year from capital and fixed O&M. The capital costs include interest during construction, project development costs, and upfront financing costs. When this is multiplied by the total installed capacity of the plant this represents the annual costs incurred from building the power plant k. C_k^V represents the cost of generating one kWh per year for the plant. When this is multiplied by the annual generation g_{ik} in equation 38 it provides the annual value of the cost of generating g_{ik} units of energy per year for the plant.

The capital recovery factor (CRF) is a function of the lifetime of the generation plant, η, and discount rate, r, as defined in equation 17.

$$CRF = \frac{r}{1 - \left(1 + r\right)^{-\eta}} \tag{45}$$

Here we use a discount rate of r = 12%, consistent with the rate used in the economic analysis of investment operations in Africa by USAID and the African Development Bank (Baurzhan and Jenkins 2017). We note that countries that have limited capital resources are likely to have a higher discount rate due to the higher economic opportunity costs of funds.

4.3.3 Methodology for Evaluating Equality

An important contribution of this paper is the role of equality preferences in power system planning. To evaluate equality impacts on the development of power systems, we employ the Gini coefficient. The Gini coefficient is a measure of inequality in society and is defined as the mean of absolute differences between all pairs of individuals for some measure, such as income, or in our case, electricity consumption. Here the Gini coefficient represents the electricity consumption gap within a given population and is defined using equation 46:

$$Gini = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} n_i n_j \left|\rho_i - \rho_j\right|}{2\left(\sum_{i=1}^{N} n_i\right)\left(\sum_{i=1}^{N} n_i \rho_i\right)} \tag{46}$$

where ρ is the per-capita electricity consumption in a node, and n is the total population at each node i. The indices i and j represent the population nodes. When the Gini coefficient is zero, there is perfect equality; when the Gini coefficient reaches its theoretical maximum of 1, all value accrues to a single individual, with all others having zero.

4.3.4 Contrast with least cost methodology

In this subsection we provide details regarding how our benefit maximization methodology differs from the least cost methodology. First, we address the role of costs in a different way. In least cost, the costs are a part of the objective function; in the MEA model, the least cost objective function has been converted into a constraint. The value of the MEA model is that we can explicitly derive solutions for a wide range of budgets. The budget limitation of least cost method has been noted before by Afful-Dazie et al. (2017) who considered stochastic demand and budget constraints, over a multi-year planning horizon. Similar to our study the authors investigate generation investment under varying budget constraints. Here we diverge from their work by incorporating equality preferences.

Another contrast is the importance of demand projections in the least cost methodology. The demand is set as a constraint. Thus, there is flexibility in how the electricity is delivered, but not in the amount and location of the electricity delivered. Thus, the MEA provides an alternative analysis, in which under different assumptions a different total amount and location of electricity is available.

Related to this, the projections of electricity demand exogenously determine the level of equality of access in a country. It is possible that equality preferences, say between rural and urban users, are implicitly reflected in the projections, with rural users often assumed to demand far less electricity. Our model, in contrast, explicitly considers preferences over equality and how these impact outcomes.

4.4 Results and Discussion

We now present a case study analysis of the Liberian power system to demonstrate the capabilities of the MEA model and examine how the optimal system configuration is influenced by different choices of the equality parameter, the budget, and other key parameters. We start this section with a brief overview of the Liberian power sector, and then we delve into the model assumptions pertaining to the case study. As a note this case study is meant to provide an illustration of how equality preferences impact power system development, and prior to implementation a more detailed spatial analysis would need to be conducted.

Liberia lies in West Africa along the Atlantic coast and, as of 2017, has a population of roughly 4.7 million people. USAID reports that there is 126 MW of centralized installed capacity in Liberia, the majority of which is the Bushrod Island oil power plant (38 MW) and the Mt. Coffee hydro facility (88 MW). The Mt. Coffee hydro plant, however, is currently only operating at a 22MW capacity. Only 5% of the country, and less than 7% of the capital city, Monrovia, has access to electricity (USAID, 2018). Currently, generation expansion projects are being pursued in Liberia to increase electricity access through constructing additional centralized oil generation, reconstructing the hydroelectric facility at Mt. Coffee, and developing interconnections to the West African Power Pool (Alfaro et al. 2017; Modi et al. 2013).

In this case study, both renewable and non-renewable technologies are considered for expansion of the Liberian power system. We assume a 15-node system in Liberia, based on the smallest division of the aggregated settlement population data from the Gridded Population of the World Data Set (CIESIN 2016). The 15 nodes represent the 15 counties in Liberia. Due to the limited spatial resolution for a detailed electricity systems development plan a higher spatial resolution is recommended. Figure 15 illustrates how the population is distributed between nodes in the country. Most of the population resides in the northern portion of the country, with a large majority residing in the capital of Monrovia, located in Montserrado county.

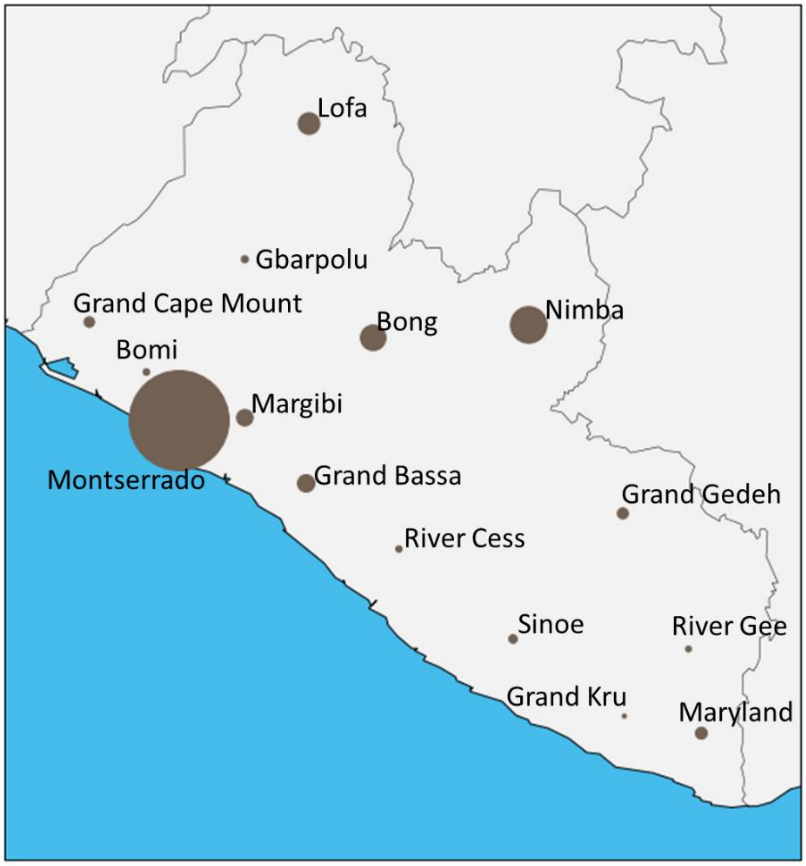

Figure 15: Liberia Population Density

After a 14-year civil war, which ended in 2003, the hydropower plant at Mt. Coffee and the entire transmission and distribution network had been completely destroyed (Africa Energy Unit 2011). While there have been many efforts to rebuild the power system, electricity access in Liberia is still extremely limited for much of the population. Due to the limited existing electricity infrastructure in Liberia, we demonstrate the model by assuming that there are only two pre-existing generation facilities, a 38 MW heavy fuel oil plant and a 22 MW hydro plant near Monrovia, and no pre-existing transmission capacity in the country. Thus, this paper aims to analyze how the power system could be rebuilt to maximize the benefits of electricity access under several different formulations of the social objective function, and can have wider applications to countries looking to rebuild systems after a disaster. The model is also applicable in regions with more developed electricity infrastructures, provided that data on the existing generation and transmission infrastructure are available. This analysis provides general insights into the role prioritizing equitable electricity access plays in expansion of the power system.

4.4.1 Liberian Case Study Assumptions and Data

We consider three types of centralized generation (i.e. utility scale solar, oil, and hydro), and one type of decentralized generation, solar home systems (SHS). Decentralized solar costs are based on data from Liberia power sector analysis by Modi et al. (2013) and global solar PV costs from IRENA (2018). SHS costs include the cost of some battery storage, which enables operation at night and increases the availability factor. We assume that SHS can be built at any node. We exclude wind power from the generation options due to the low wind resource in the country (Alfaro and Miller 2014). While we focus on SHS, we note that small diesel generators can be modeled in the same way and are a substitute for SHS; thus, we account for this technology indirectly in our sensitivity analysis of SHS costs.

We include the option to build up to eight large centralized generation plants, with possible locations listed in Table 13. The Montserrado, Margibi, and Maryland locations are chosen based on Liberia's existing plans for increasing electricity access in the country, and the Nimba, Bong, and Grand Bassa locations are chosen based on Liberia's peak demand projections (Modi et al. 2013). In two nodes, the most logical choice is hydro due to the location near rivers; in three nodes the choice is oil; and in the remaining node we allow for the choice between hydro and oil. We also model the one existing oil plant in Margibi. We assume that the minimum capacity for hydro is 20 MW and for oil is 30 MW. The current plant at Margibi has 38MW.

Table 13: Centralized Generation Options

Location	**Fuel**
Bong	Hydro
Gbarpolu	Solar
Grand Bassa	Oil
Grand Gedeh	Solar
Lofa	Hydro
Margibi	Oil (existing)
	Oil
Maryland	Hydro
	Oil
Montserrado	Hydro (existing)
	Hydro
Nimba	Oil
Sinoe	Solar
River Cess	Solar

To limit the computation space of the model, the set **E** is limited to the transmission edges that connect each node i with its four closest nodes.

Cost Data. The cost assumptions for generation and transmission are based on a power expansion report for Liberia (Modi et al 2013), a literature survey for generation and transmission costs in Sub-Saharan Africa; and models that evaluate electricity planning options for Liberia (Alfaro and Miller 2014; Levin and Thomas 2013), the World

(IRENA 2018; Lazard 2017), and the USA (Klein and Whalley 2015). All costs are presented in United States Dollars (USD). Oil fuel costs are sourced from the Liberian Ministry of Commerce & Industry (2018), who reported that the price of fuel oil was 781.75 USD per metric ton in July 2018 (equivalent to 16.93 USD/MMBtu in 2016). Capital and operations and maintenance costs are assumed to be similar to the median values of coal plants (Lazard 2017). The technical and economic assumptions for the calculation are summarized in Table 14

Table 14: Parameters used to calculate costs of generation technologies

Symbol	Description	Technology, k	Value	Units	Source
r	Discount rate	-	12	%	Baurzhan and Jenkins 2017
h	Hours in a year	-	8760	hr	
y_k	Number of operational years	Hydro	30	Years	Narayan et al. 2018; Lazard 2017; Uddin et al. 2017; IRENA 2016; Modi et al 2013
		Diesel	20		
		Oil	40		
		Solar	20		
		SHS (solar panel)	20		
		SHS (battery)	5		
af_k	Availability factor	Hydro	81	%	DOE 2018; IRENA 2018; World Bank 2016; EIA 2015
		Diesel	90		
		Oil	75		
		Solar	30		
		SHS	26		
$C_{cap,k}$	Total capital cost	Hydro	2652	$/kW	IRENA 2018; Lazard 2017; Modi et al 2013 Kost et al. 2013; Modi et al 2013
		Oil	1033		
		Solar	2600		
		SHS (solar panel)	470		
		SHS (battery)	1491		
$C^F_{O\&M,k}$	Fixed Operations & Maintenance cost	Hydro	22	$/kW-yr	Baurzhan and Jenkins 2017; Lazard 2017;
		Oil	15		
		Solar	14		

		SHS	16		Ommontuemhen, Bredenhann, and Bedwei 2017; Klein and Whalley 2015; Kost et al. 2013; Modi et al 2013
$C^{V}_{O\&M,k}$	Variable Operations & Maintenance cost (excluding fuel)	Hydro	0	$/kWh	Baurzhan and Jenkins, 2017; Lazard 2017; Ommontuemhen, Bredenhann, and Bedwei 2017; Klein and Whalley 2015; Kost et al. 2013
		Oil	0.004		
		Solar	0.007		
		SHS	0		
$C_{Fuel,k}$	Fuel cost: fossil fuels	Oil	9.09	$/Mbtu	Nock and Baker 2019; Omontuemhen et al. 2017
HR_k	Heat rate: fossil fuels	Oil	10687	Btu/kWh	Nock and Baker 2019

For hydropower, IRENA (2018) provides the total capital cost, defined as all of the costs of developing a project including interest during construction, project development costs, and upfront financing costs. Operating costs are sourced from Lazard (2017) and Klein and Whalley (2015). Costs for SHS were sourced from Modi et al. (2013); then were projected to 2016 costs using a simple regression analysis from the weighted average of global solar PV costs from IRENA (2018). We assume that SHS capital costs will fall at a rate similar to the costs of solar PV, but that the balance of systems costs has stayed the same. Taking into account the 20-year lifetime of the solar panel and the 5-year lifetime of the battery this leads us to an annualized per-unit cost of the SHS to be 798 $/kW. This is equivalent to a present value per-unit cost of 6,647 $/kW when assuming a 12% discount rate and a 20-year time frame.

We analyze a range of annual budgets to evaluate how the system expansion plans change under increased investment. Liberia has a GDP of $2 billion USD. Thus, we focus attention on the following annual budgets: $10 million (equivalent to 0.5% of GDP); 50 million (equivalent to 2.5% of GDP); $130 million (equivalent to the 1.1 billion USD present value estimated by Modi et al. (2013) to be necessary for power system expansion, and near the continental average at 5% of GDP); and $200 million to show a very high budget range indicating what could happen with a large foreign aid investment. As a note the 1.1 billion projected by Modi et al. (2013) included grid construction and household connection costs, but did not include the costs for power generation and high voltage transmission lines. The annualized budget is calculated from the present value estimated by Modi et al. (2013) using a discount rate of 12% and a loan term of 30 years. For example, an annual budget of 100 million would correspond to a present value budget of $806 million.

We source transmission cost estimates from (Levin and Thomas 2012) who performed a literature review of transmission line costs. We operate under the assumption that medium and low voltage transmission lines (<66 kV) cost $90,000/km, and high voltage transmission lines (230 – 66 kV) cost $200,000/km. We assume the capacities of the transmission lines are 60 MW for medium and low voltage and 100 MW for high voltage transmission lines.

For the base equality preference, we assume that α is equal to 0.86, as this is the best fit of the well-known relationship between the country per-capita electricity, and HDI (HDI 2015; OECD/IEA 2017), as described in Section 1.3.2.1. We further assume that peak annual load in the system is 1.7 times greater than average load. (i.e. γ=1.7). This is based on Rwanda's peak-average power demand ratio (Levin and Thomas 2014).

4.4.2. Liberian Case Study: Results

In this section we first detail how power system development is impacted by the budget. We then conduct a sensitivity analysis of two key parameters, stakeholder equality preferences and residential solar capital costs, to better understand how the power system development plan is influenced by changes in these parameters.

Impacts of the budget. We start by presenting results using base assumptions that equality preference α is equal to 0.86; and that SHS present value per-unit cost is 6,647 $/kW. The resultant optimal expansion plans for various budgets are presented in the maps in Figure 16, and the nodal information in Table 15. These maps illustrate how the optimal electricity expansion plan changes under increasing budgets. On the maps the $\bar{\rho}$ represents the average per-capita electricity consumption in the country, and the gini value signifies the level of equality in the country, with a lower value indicating more equal.

Here we see that investment in large centralized hydro generation and small utility solar is the primary means of increasing the level of energy access in the country. Of interest is that the existing oil plant is not used at any budget, indicating that due to the high variable costs of oil it may be more beneficial to expand the Mt. Coffee hydro facility near the capital city to provide initial electricity access. This result is consistent with Modi et al. (2013), who suggest the Mt. Coffee Hydro Facility is rebuilt and expanded. Similarly, SHS are only used in the low budget scenarios since they are more modular.

The maps reveal two distinct power systems in the north and south of the country, signifying that due to the sparse population in the middle of the country it may be ideal to develop two separate power systems, as opposed to one large completely connected system. This result is consistent with Modi et al. (2013) who suggest stand-alone and off-grid systems for the less dense areas in the middle of the region. From Table 15 we see that Montserrado always receives the highest level of investment due to the high population density.

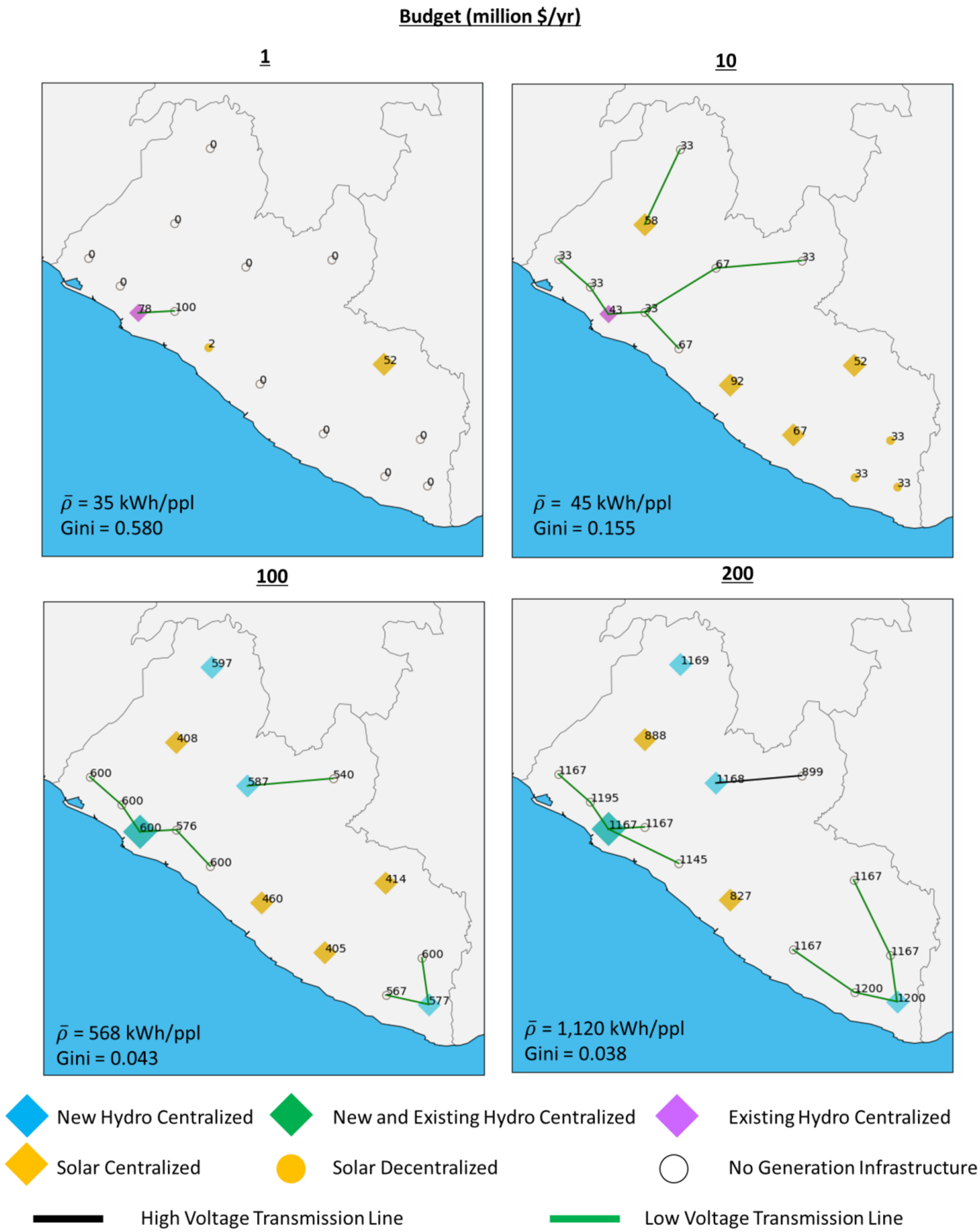

Figure 16: Maps under various budgets

Table 15: Nodal information for Power system expansion under various budgets

Location (i)	B = 1 million, Gini = 0.580, $\bar{\rho}$ = 35 kWh/ppl			B = 10 million, Gini = 0.155, $\bar{\rho}$ = 45 kWh/ppl			B = 100 million, Gini = 0.043, $\bar{\rho}$ = 568 kWh/ppl		
	Centralized Capacity (MW)	Decentralized Capacity (MW)	ρ_i (kWh/ppl)	Centralized Capacity (MW)	Decentralized Capacity (MW)	ρ_i (kWh/ppl)	Centralized Capacity (MW)	Decentralized Capacity (MW)	ρ_i (kWh/ppl)
Bomi	-	-	-	-	-	33.34	-	-	600.10
Bong	-	-	-	-	-	66.68	62	-	586.65
Gbarpolu	-	-	-	2	-	58.01	5	0.13	407.68
Grand Bassa	-	0.19	1.65	-	-	66.68	-	-	600.10
Grand Cape Mount	-	-	-	-	-	33.34	-	-	600.10
Grand Gedeh	-	-	51.72	1	-	51.72	8	-	413.72
Grand Kru	-	~0	-	-	0.9	33.34	-	-	566.76
Lofa	-	-	-	-	-	33.34	23	-	597.32
Margibi	-	-	100.02	-	-	33.34	-	-	576.09
Maryland	-	-	-	-	2.6	32.66	22	-	576.76
Montserrado	22	-	78.41	22	-	43.22	144	-	600.26
Nimba	-	-	-	-	-	33.34	-	-	539.70
River Cess	-	-	-	1	-	91.93	5	-	459.67
River Gee	-	-	-	-	1.3	33.34	-	-	600.10
Sinoe	-	-	-	1	-	67.44	6	-	404.66

Impacts of equality preferences. Here we present the role equality preferences play in the expansion plan for the power system. In Figure 13, we saw a steady increase in equality as the budget increases, signified by a lower gini, until we get to a medium-high budget (i.e. B > 50 million $/yr). Figure 17 provides more detail on this relationship and expands to other equality preferences. We see that equality is slightly non-monotonic in the budget, since the investment into centralized generation and transmission is lumpy. The lumpiness comes from investments in large centralized generation facilities that require a minimum investment to get started. First the model will choose to build a generation facility, and keep expanding that facility and transmission line connections until the budget is large enough to meet the minimum capital requirements for a second plant. At that point the optimal investment plan is to reduce the size of the first plant and transmission investment, and build the second power plant. In general, we find that the overall pattern is that equality generally increases with the budget, regardless of the equality preferences, but it is not everywhere monotonic.

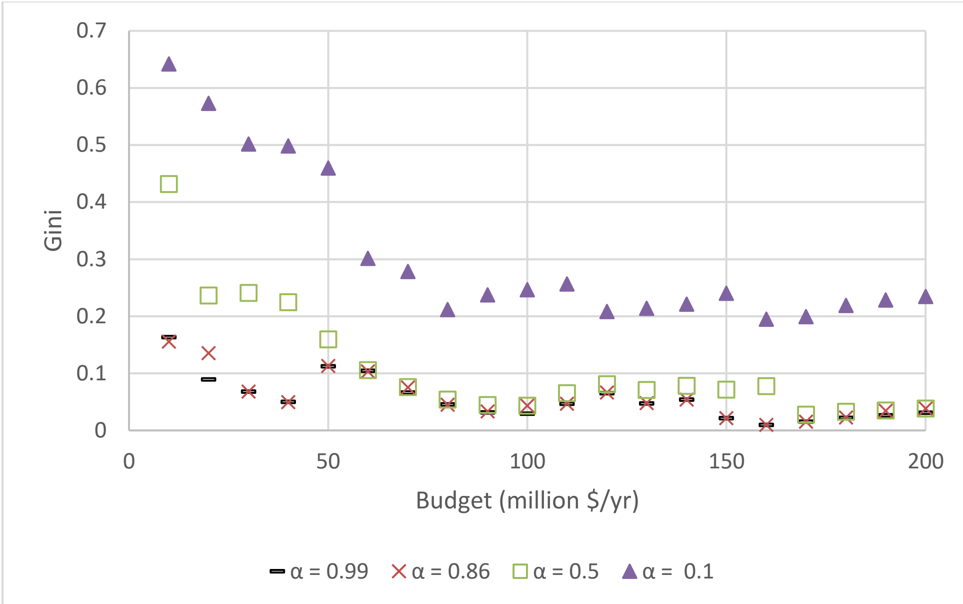

Figure 17: Impact of preferences and budget on equality

Figure 18 illustrates how the power expansion plan changes between the base and low equality preference. Here we see that the low equality preference places the most emphasis on increasing the total amount of power generation in the country, which results in using the existing oil plant near the capital city. If there is not a high emphasis on equality then the optimal expansion plan involves building much larger power plants near the capital city. With the high preference money gets redistributed from large power plants to transmission investments. This leads to less electricity overall and more access.

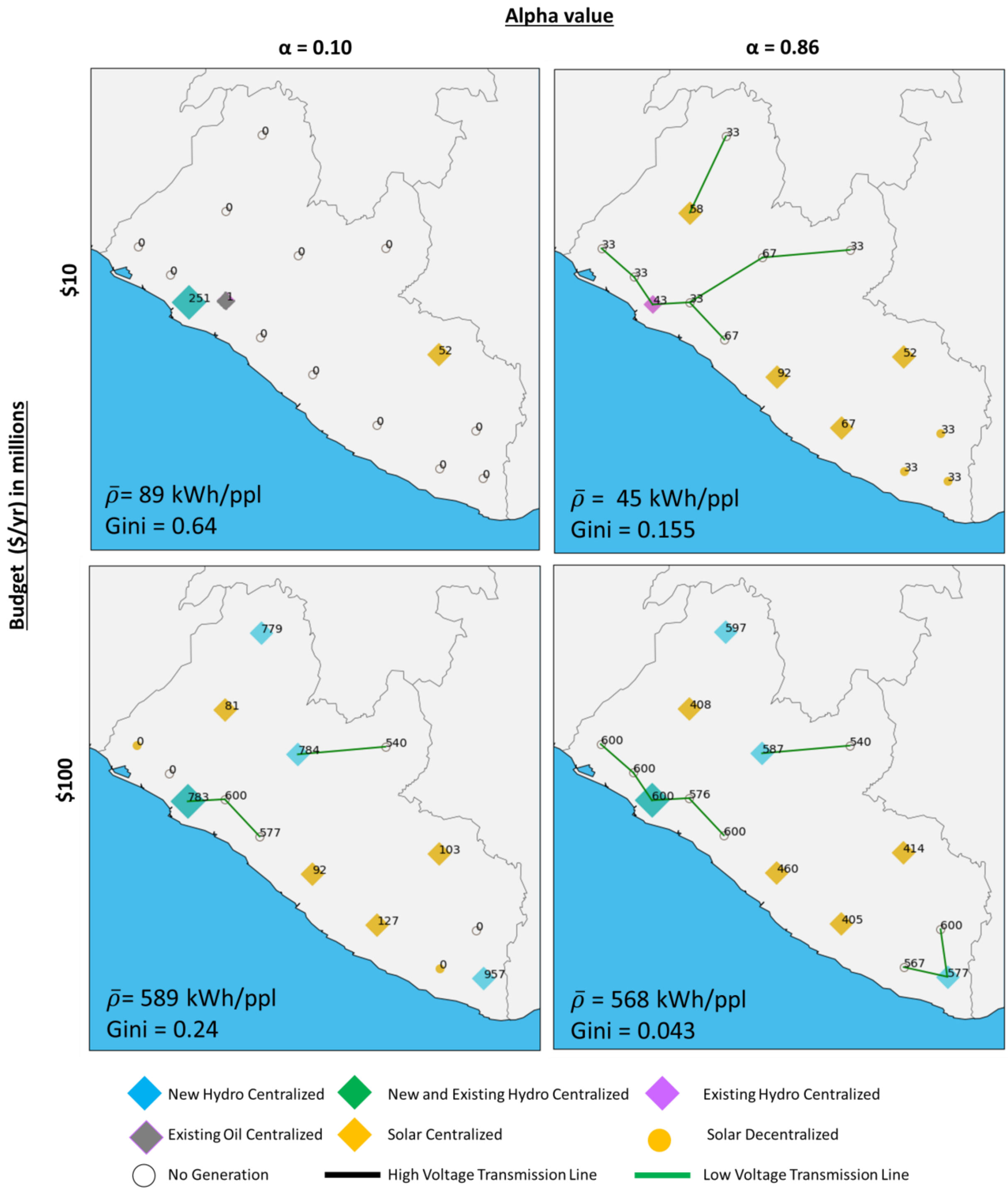

Figure 18: Power Expansion Maps under various equality preferences

In Figure 19 we see that the relationship between increasing budget and transmission investment depends somewhat on equality preferences. Mostly, as the budget increases, more is invested in transmission. At very low budgets and high preference for equality, this relationship can be non-monotonic. This is because there are trade-offs between investments in utility scale solar versus transmission investments for large hydro generation facilities.

At low equality preferences the optimal decision is often to leave a largely disconnected grid indicated by the gap in transmission line investment between the low and medium equality preferences. This gap gets larger as the budget increases.

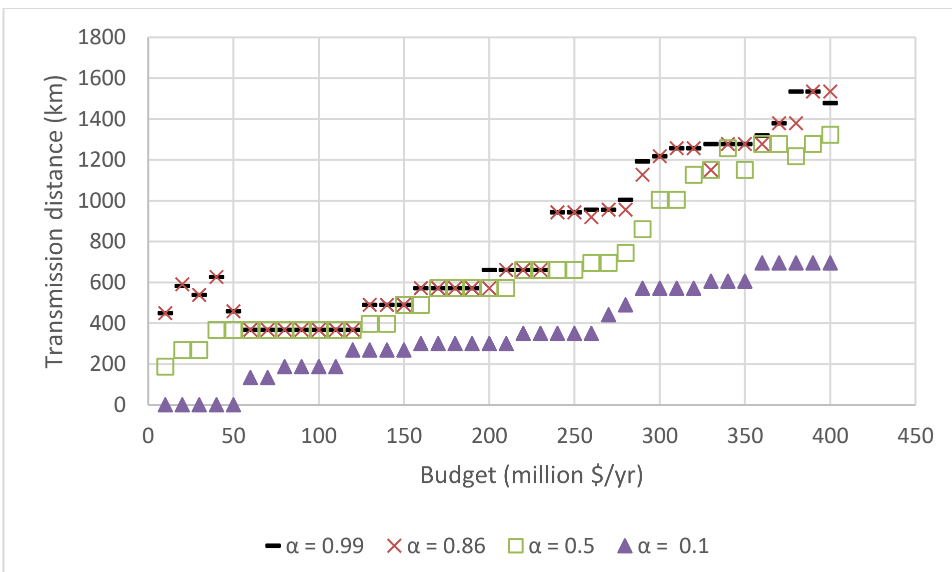

Figure 19: Transmission line investment as a function of the budget for various equality preferences.

While equality preferences have an impact on the level of transmission line investment, we find that these preferences have no significant impact on the level of SHS investment. At the base level SHS costs, the lower per-unit cost of hydro and utility solar generation causes the optimal investment strategy to never include more than 4.86 MW of SHS capacity for any of the equality preferences and budgets included in this study. We explore the impact of falling SHS costs in the next section.

Impacts of SHS capital costs. Here we present a sensitivity analysis for the impact of SHS capital cost under the base equality preference ($\alpha = 0.86$). Figure 20 indicates how the SHS capacity changes under varying budgets and SHS component capital costs. A 50% increase in solar panel or battery costs, from our base assumptions, results in the total SHS investment equating to approximately 0%. We see that falling SHS battery capital costs have the greatest impact on SHS adoption, compared to falling solar panel costs. Note that the only time we see the energy contribution of solar rise above 13% is for the 10-million-dollar budget for the 50% and 75% decrease in SHS battery costs. The 50% and 75% decrease in battery capital costs correspond to a present value of per-unit SHS costs being 3,625 and 2,115 $/kW respectively. While there is capital investment in SHS under falling battery costs, the energy contribution from this technology is often dwarfed by the energy contribution from centralized generation. The low use of modular SHS is consistent with Modi et al (2013) who proposed in their 30-year planning horizon that 90% of the population receive grid connectivity, and 10% receive access from stand-alone systems.

While the falling component costs impact the level of investment at low budgets, we see no change in the investment strategy for annual budgets greater than 50 million $/yr. For budgets greater than 50 million the primary investment strategy is to invest in a large centralized power system, composed of hydro and utility scale solar.

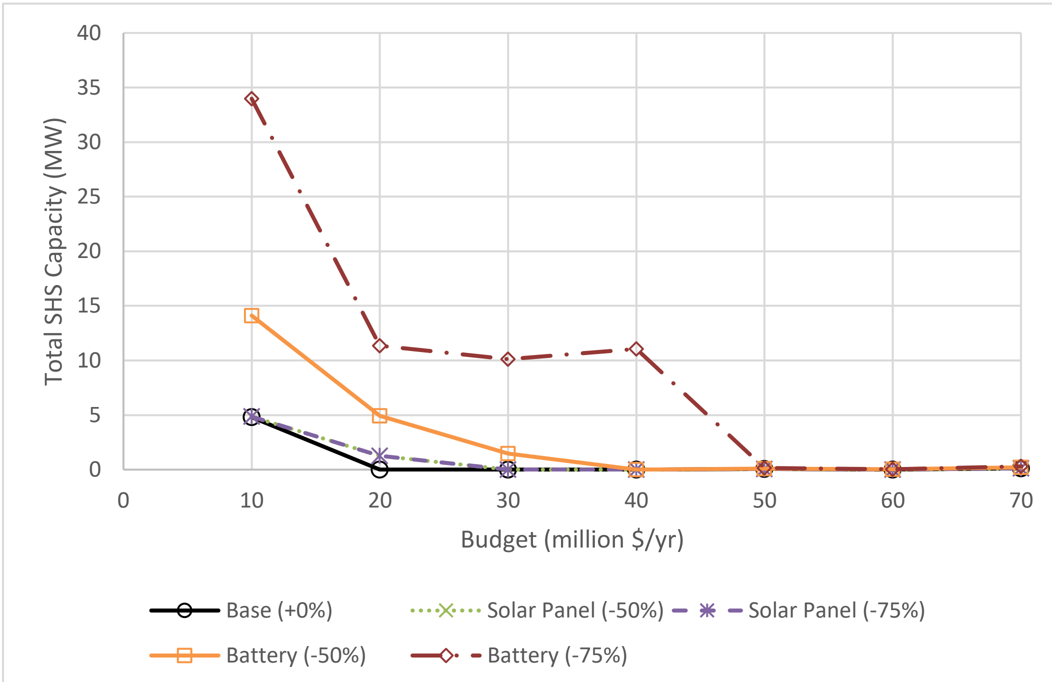

Figure 20: Impacts of SHS capital costs on Decentralized generation investment for various budgets.

We found that solar panel costs had no significant impact on SHS investment. Even with a 50% decrease in solar panel costs from base levels the SHS capacity investment never totals more than 5 MW, and the energy contribution is essentially zero for the base alpha. There was also only a 3% investment difference between the 50% and 75% solar panel decrease scenarios. Any increases in solar panel and battery costs results in the total SHS investment being less than 1 MW for the entire region. The equivalent mini-grid diesel per-unit costs occur when the SHS battery costs have fallen between 50% and 75%. Given Figure 20, we can say that even with lower cost diesel-mini grid systems, the primary investment strategy would still include a majority of centralized generation due to the added fuel costs for diesel systems.

A potential cause of the lack of SHS investment could be the resolution of the population dispersed around the country. A fruitful direction of future work would be to perform a similar analysis with a higher spatial resolution to understand how the investment in the distribution system would impact the trade-offs between investments in SHS in a centralized transmission system.

Future work involves taking one node and expanding it to look closer at impacts of population density on investment in centralized vs decentralized infrastructure.

Overall Trends. In Table 16 we present some overall findings of this analysis. In general, we found that transmission investment increased with budget and equality preferences, but decreased with falling solar costs. SHS investment fell with budget increases, and rose with decreasing component costs. Interestingly, the equality rating in the country had no clear relationship with SHS costs. One reason is that under the very high equality preference, there is more emphasis placed on the distribution of electricity, as opposed to the quantity, which would lead to SHS and transmission lines being substitutes.

Table 16: Overall trends in model outputs

	With budget increase	With equality preference increase	With SHS cost decrease
Transmission	↑	↑	↓
SHS installations	↓	↷	↑
Equality (gini)	↑	↑	↷
Total Electricity	↑	↓	↑
# people with access	↑	↑	↷

Discount Rate Sensitivity. In our analysis we used a discount rate of r = 12%. At higher discount rates (20%) we see less overall power generation, but similar power system configurations. At a lower discount rate (2% and 4%) we see less investment in solar of both scales, and more investment in transmission lines. At lower discount rates, we see more exports from the power plant near the capital city, and more installations of high voltage transmission lines.

Limitations of MEA model. While this model provided electrification plans for the Liberian transmission system, we discuss some limitations and their possible implications. Due to computation constraints in the model each node was restricted to building transmissions lines to the four closest nodes only. A potential concern from limiting the number of possible connections could be that we will not see very long North-South electricity connections. However, we note that our results do not change when each node is allowed to link to its eight closest nodes. Our model results in a hub and spoke design of the power system, which is similar to what we see in practice. Also, long cross-country transmission lines are generally not cost effective due to transmission line losses, and costs of transmission infrastructure.

Another limitation is the low spatial resolution of our model and the aggregation of the population into 15 nodes. Because the population is aggregated into 15 nodes, we were unable to model the distribution system. The distribution system will require more transmission line construction, which may lead to less investment in centralized infrastructure in the rural communities. Aggregating the population into 15 nodes cause the model to miss the extra costs in transmission line distance for connecting to households at the distribution level. The low spatial resolution could be the reason we see a favoritism towards centralized generation. By using a low spatial resolution, the population density is lost which could be the main driver of the model favoring more centralized generation.

Results are also limited due to limited data on the cost of building generation and transmission in Liberia and other African Countries.

Comparison with Least Cost Methodology. The least cost methodology starts with demand projections. Thus, the results of these models are highly sensitive to the projections, which are known to be highly uncertain for populations that have not previously had access to electricity (Modi et al, 2013). Our method and the least cost method would coincide if (1) the average annual demand projections by county were the same as our electricity availability allocations; (2) the equality preference happened to coincide with the demand projection; and (3) the available budget was approximately equal to the calculated least cost.

Similar to the results of Afful-Dazie et al (2017) we find that at very low budgets oil and coal plants are not attractive due to their high upfront capital costs. In our specific study, we find that some of our results coincide with Modi et al. (2013), while others provide new insights not available from Modi et al.

When comparing with Modi et al. (2013), who looked at expansion plans for Liberia, we found similar trends in our results for the high equality preference case. In general, there are two distinct centralized grids, in terms of large transmission lines, in the north and south, indicating this is a robust solution. Although we did not include demand in our model, we found that cities are consistently given a higher proportion of total electricity.

In contrast our model starts with equality preferences and a social welfare function, which lends itself towards taking a more opportunistic approach to electricity planning. Our model illustrates how preferences influence the design of the power system under similar budgets. Our model provides a tool for investigating how stakeholder preferences impact the design of the power system. In least cost planning preferences for equality may be indirectly expressed through electricity demand projections, with rural users often assumed to demand far less electricity compared to their urban counterparts. Our model takes a different approach by considering preferences over equality and how these impact outcomes.

4.5 Conclusions

The focus of this chapter was incorporating stakeholder preferences into the electricity planning literature. Here we analyzed how investment in power system infrastructure is impacted by changes in stakeholder equality preferences, level of investment, and generation costs. This work provides a tool for decision makers to understand how their preferences towards equality would impact the overall electricity expansion plan in the country. This work is the first to explicitly integrate stakeholder preferences towards equality into energy planning modelling, and has wide applications for countries looking to expand access to electricity, or rebuild systems after a disaster. From the results we can see that medium to high preferences for equality lead to a more interconnected power system. Under high equality preferences, investments in transmission infrastructure are made in lieu of building additional centralized generation capacity, as long as the budget is high enough. Under lower equality preferences, the system is more fragmented, with less transmission, more investment in large power plants near larger cities, and a higher average electricity consumption for the country.

As solar costs fall there is more investment in decentralized generation, but for high annual budgets the electrification strategy nevertheless centers primarily around investments in centralized generation. Decentralized generation investments come at a cost of investment in transmission lines. Changing the stakeholder's equality preferences significantly impacts the level of electricity access provided to different parts of the country. We would expect these observations to hold in other low-income countries. The specific results will depend on the existing infrastructure; this would likely cause the results to rely even more heavily on transmission as the primary means for electrification.

Future work involves modeling this generation expansion plan as a progression through time as opposed to a single static year, and a higher geographic resolution. Prior to implementation of this modeling framework into country we recommend obtaining updated data on generation costs, and a higher spatial resolution to capture the population distribution. This work has been the first to explicitly integrate a stakeholder preference towards equality into the electricity modeling literature, thus opening the doors to a greater understanding of how political uncertainty regarding equality preferences would impact the optimal power system development, and providing a more holistic approach to electricity planning. While the preferences here are illustrative this work is an important step in understanding the role political climate and stakeholder preferences play in energy expansion. A fruitful direction of research would be to elicit stakeholder preferences and integrate this into the modelling framework, and incorporate a wider range of electrification objectives.

From this work policy makers, with limited power system budgets, who prioritize the percent of the population with electricity access rather than the amount of demand served can gain insights into how changing preferences towards electricity inequality will impact overall allocation of resources within the country. From our work it is clear that electricity expansion under stakeholders who have a strong commitment towards equality and a target of increasing electricity access in a country will benefit from more interconnected power systems and expedited electrification of the entire country. While there is no perfect solution to reaching universal access to electricity under varying stakeholder preferences, sound investments in electricity infrastructure will assist developing countries in reaching their goals.

CHAPTER 5

SYNTHESIS AND CONCLUSIONS

This dissertation provides decision makers with some tools to assess different configurations of their power systems in terms of their overarching objectives. The results indicate that there are many paths for New England and developing countries to meet their electricity goals. As the budgets and decision maker preferences vary there will be different pathways to reach electricity targets, leading to a need for preference elicitation to properly understand the trade-offs decision makers are willing to make between electricity futures.

This work highlights the need for stakeholder-informed modeling solutions. In Chapters 2 and 4 we highlighted the role that stakeholder preferences play in the design of power systems. Ignoring stakeholder preferences implicitly ignores the political and societal factors that lead to enhanced sustainability, adoption of new technologies, and successful expansion of electricity access. Chapter 2 highlighted the trade-offs stakeholders would make between different electricity futures. If stakeholders were only concerned about water consumption and avoiding nuclear power, then the ideal choice would be to retire all oil and nuclear capacity and include a high level of offshore wind backed up by natural gas and hydro. On the other hand, if stakeholders are concerned about the full range of sustainability metrics, then the most sustainable solution may be to support high offshore wind with nuclear and keep a largely diversified portfolio, while retiring oil.

In Chapter 4 we turned our focus to developing countries and found that as a stakeholder preference for equality, in terms of access to electricity, decreases there is less investment in transmission line infrastructure leading to a plateau in equality improvements. That being said, regardless of the equality preference the strategy is to start the development of the power grid by placing the first power generation near the large cities, followed by attention to less dense areas.

The models created in this dissertation will provide insights for power system stakeholder regarding how sustainability of the system changes with baseload capacity assumptions, and how the layout of power systems changes with preferences towards equality and electricity access goals.

In Chapter 3 we found that PHES can play an important role in increasing the energy contribution from offshore wind energy, but could reduce the overall contribution from NG and traditional hydro. Simply adding PHES to the New England electricity system will lead to higher costs, and lower CO2 emissions provided that there are proper market mechanisms to allow the PHES facility to participate in energy arbitrage. Even with the addition of storage, high offshore wind supported by high nuclear may be ideal for stakeholders who are concerned about the full range of sustainability metrics included in Chapter 2. This work highlights the role large scale storage has to play in advancing New England towards a more sustainable energy future.

In conclusion we find that there are many opportunities to enhance the social benefits derived from power systems. This can be through reducing the CO2 and air pollution emissions through increased use of low emission technologies, and through a more equitable design of the power system in developing countries.

APPENDIX A

NEW ENGLAND ELECTRICITY MODEL DATA

A1 Electricity Demand and Generation Capacities

Demand projections were generated using information from ISO-NE (Anonymous 2015), projecting an 11% and 6% increase in summer and winter peak demand respectively, under the mean expected weather forecast. These were then used to project demand to 2035 for the set of historical data from 2011 to 2015. The current generation mix for New England was gathered from ISO-NE (ISO NE 2017). These projected increases can reflect increased electrification, and electric vehicle deployment. The demand projections we use were generated using information from ISO NE (2015 CELT Report, 2015).

A2 Data on individual Electricity Generation Technologies

Natural Gas. The natural gas monthly consumption data for the electricity and heating sectors in New England is derived from monthly consumption data from EIA (EIA 2017b). We assumed that natural gas deliveries to residential, commercial, and industrial customers were for heating, while deliveries to electric power customers were for electricity. The overall pipeline capacity for New England was estimated using information provided by the EIA (EIA 2015). We assume a power plant heat rate of 10,408 Btu/kWh for a steam electric generator; and the fuel heat content is 1,029,000 Btu per 1 Mcf. We present a snapshot of the NG deliveries for 2014 and 2015. Historically in New England priority has been given to residential and commercial heating customers. Therefore, we assume that the heating sector gets allocated natural gas first. Liquefied natural gas is not included in our model.

Onshore Wind. Onshore wind speed data was gathered from the National Climatic Data Center (NCDC 2017), and focused on three sites in the New England region: Western Massachusetts, the Boston Airport, and Lower Eastern Massachusetts. Onshore wind turbines were assumed to be 5 MW turbines, with rotor disk area of 12,469 m^2 and hub height of 90 meters. The cut-in and cut-out wind speeds are 3 and 25 m/s, respectively. This data was extrapolated to hub height using equation A1:

$$U_{hh} = U_m \left(\frac{z_{hh}}{z_m} \right)^{\beta} \quad \text{(A1)}$$

where U_{hh} is the wind speed at hub height, U_m is the measured wind speed, z_{hh} is the elevation at hub height, z_m is the elevation of the measured wind speed, and β is the wind shear coefficient. We assume the onshore wind shear coefficient, β, to be 0.15. Onshore wind speed data collected from Logan Airport was recorded at an elevation of 14 meters above sea level; for other locations, at 7 meters above sea level.

Offshore Wind. The offshore wind energy power calculation is based off of the General Electric 6 MW offshore wind turbine (GE Renewable Energy 2017), with a rotor diameter of 150 m, blade length of 73.5m, rotor swept area of 17,860m^2, and hub height of 100m. We assume the offshore wind shear coefficient, β, to be 0.1, and extrapolate the wind speed to a hub height of 150m using equation 14. We assume the same cut-in and cut-out wind speeds as onshore wind.
The offshore wind speed data was gathered from the National Data Buoy Center (NOAA 2017) located at Buzzards Bay, 26 nautical miles away from Block Island, the first offshore wind farm site in the USA. The anemometer height of the buoy at Buzzards Bay is 24.8 meters above sea level.

Solar. Solar radiation data was gathered from the National Solar Radiation Database through NREL (NREL 2016). This data was gathered from two sites: Western Massachusetts and Lower Eastern Massachusetts. We assume each solar farm is at least 1 MW in capacity; that the panels used have a 3/4 performance ratio and 15% yield; and that a 1 MW solar farm spans an area of 9290.34 m^2.

Nuclear, Hydro and Oil. Nuclear current capacity and retirement projections were gathered from ISO-NE (ISO-NE 2017), and the Nuclear Regulatory Commission (USNRC 2018). Nuclear outage data was obtained from the EIA (EIA 2016b). Information regarding the current capacity of hydro and oil was gathered from ISO-NE reports (ISO-NE 2017).

APPENDIX B

NEW ENGLAND SUSTAINABILITY MODEL DATA

In this section we discuss the data used to calculate the sustainability metrics.

B1 LCOE

Data on capital cost, depreciation, operation and maintenance (O&M) costs, fuel cost and heat rate came from (Klein and Whalley 2015), using a 5.37% inflation rate for conversion of 2011 to 2015 costs, with the exception of the natural gas fuel cost (EIA 2018a), the oil fuel cost (Statista 2018), and oil heat rate (EIA 2017). Other oil plant parameters are set equal to natural gas plant parameters. The data used to calculate the LCOE for each technology is in Table B1.

Table B1: Data used to calculate LCOE for each of the considered technologies

Technology	Capital Cost (C_{Cap}) $/kW	Depreciation (D_{pv}) %	Fixed O&M Cost ($C_{o\&m,f}$) $/kW	Variable O&M Cost ($C_{o\&m,v}$)$/kWh	Fuel Cost (C_{fuel})$/Btu	Heat Rate (HR) Btu/kWh
Hydro	2636.4	54%	36.8795	0.0063	0	0
Offshore Wind	3337	83%	116.9607	0.033	0	0
Onshore Wind	1940	83%	35.8258	0.011	0	0
Nuclear	3785	59%	150.6791	0.019	5.00E-07	10350
PV	4511	83%	13.69	0.0074	0	0
Natural Gas	1032	54%	284.499	0.037	2.96E-06	6645
Oil	1032	54%	216	0.037	8.09E-6	10687

B2 Other Sustainability Metrics

Table B2 summarizes the fixed and variable values for all sustainability metrics. For most technologies and metrics, the values were based on data from Klein and Whalley (2015). Oil, which was not analyzed in Klein and Whalley (2015), is assumed to have the same values as natural gas, except where noted. Here we highlight cases where data was not sourced from Klein and Whalley (2015).

Life cycle GHG emissions. The life-cycle GHG emissions per technology were presented as harmonized values (Klein and Whalley 2015) and thus not able to be separated into their fixed and variable components. Here we assume the GHG emissions are more proportional with the operation for natural gas and oil making it a variable metric, and with capacity for all other technologies. Although we assume the GHG emissions are primarily variable metrics since these are life-cycle estimates the emissions produced from building the power plant are included in the values. If there is a natural gas plant that is built and produces less energy than predicted this will lead to an under estimation of the emissions from the natural gas plant. The GHG value for oil was calculated by taking the 2009 total CO_2, CH_4, and N_2O emissions for oil power in the USA, and dividing this by the total amount of electricity produced by oil for 2009 in USA (EIA 2011).

Life cycle air pollution. Similar to GHG emissions it is assumed that the life-cycle air pollution emissions are more proportional with the operation for NG and Oil making it a variable metric, and with capacity for all other technologies. The value for oil was determined using the 2015 Massachusetts SO_2 and NO_X oil emissions, as determined by the EIA, and the 2014 Massachusetts PM emissions, using data from the United States Environmental Protection Agency (EPA 2018). The air pollution is taken as the sum of SO_2, NO_X, and PM emissions in mg per kilowatt-hour.

Water consumption. Data for water consumption for wind, solar, nuclear, and natural gas were sourced from (Meldrum et al. 2013), while information for hydroelectric water consumption was sourced from (Macknick et al. 2011). This information was then converted into fixed and variable components, with fixed water consumption being the water used in plant construction and manufacturing electrical components, and variable water use being the water used in the fuel cycle and plant operations.
For solar, values from (Meldrum et al. 2013) were converted to L/MW under the assumption of a CF of 22%. Nuclear and hydro fixed water consumption for construction are assumed to be the same as natural gas on a per-capacity basis. For hydroelectric, we do not consider the water flowing through the turbines and back into the river as consumptive. For hydro water consumption from evaporation, we use 0.208 L of fresh water per MWh (Torcellini, Long, and Judkoff 2003). Oil and natural gas plants are assumed to have similar water consumption for operation, except for the water used in hydraulic fracturing for natural gas.

Jobs. All job estimations, except nuclear and solar PV, were calculated using the JEDI model for the New England States (NREL 2016a). JEDI estimates the number of construction and annual jobs for a power plant using employment multipliers to represent FTE jobs per dollar spent in each economic sector. Thus, power plants with a high upfront capital or O&M cost will result in higher employment estimates. The JEDI model does not reflect the economic impact of increases or decreases in electricity rates resulting from new electricity infrastructure, local economic development losses associated with displacement of local resources, or the displacement of some economic activity resulting from investment in certain electricity projects. JEDI models were unavailable for nuclear and solar PV so values were sourced from Klein and Whalley (2015).

Construction times, N in equation 11, are sourced from Lazard (Lazard 2017) for all technologies except natural gas (NREL 2016a) and hydro (Klein and Whalley 2015).

Nuclear plants are assumed to create the same number of jobs as natural gas plants per unit of capacity. This assumption is consistent with median job estimates for nuclear and natural gas in Klein and Whalley (2015). The onshore and offshore wind FTE jobs were estimated for 2.3 MW and 6MW turbines, respectively. The JEDI model assumes 0% of the natural gas fuel is produced locally in NE, meaning the local share would be zero for drilling operations, and the revenue generated by fuel sales. For onshore and offshore wind, the local share for turbine equipment (i.e. blades, towers, etc) is zero due to these components being constructed outside of the region, meaning that a large portion of the jobs created by additional plant capacity would be outside of NE. Our estimates are in the bottom quartile of (Klein and Whalley 2015), implying a possible over-estimation of the jobs created by solar. There is, however, a significant amount of solar manufacturing in NE. Moreover, all portfolios contain the same level of solar capacity.

Table B2: Sustainability Metric Input Data ("Var" refers to the variable portion)[4]

Tech	LCOE		Life Cycle GHG		Air pollution emissions		Land use	Water Consumption		Fatalities	Jobs	Nuclear Aversion
	Fixed ($/kW)	Var ($/kWh)	Fixed (gCO2eq/kW)	Var (gCO2eq/kWh)	Fixed (mg/kW)	Var (mg/kWh)	Fixed (m^2/MW)	Fixed (L/MW)	Var (L/MWh)	Var (Fatalities / PWh)	Fixed (FTE/MW)	Fixed
Hydro	234	0.0063	53	-	419	-	190,606	16,587	0.208	5.80	1.91	0
Offshore wind	331	0.0326	41	-	362	-	31	3,660	0.13	1.70	1.39	0
Onshore wind	160	0.0105	39	-	345	-	3,950	11,048	2.02	0.52	0.36	0
Nuclear	427	0.024	95	-	1,671	-	1,024	16,587	2,415	0.92	0.48	1
Solar PV	303	0.0074	92	-	1,528	-	1,561	72,952	0	0.13	2.32	0
Natural gas	362	0.0056	-	449	-	988	2,308	16,587	815	9.40	0.48	0
Oil	362	0.117	-	752	-	2,668	2,308	16,587	795	9.40	0.48	0

[4] Note: all fixed values are annualized. The dash indicates that the life-cycle data was not able to be separated into separate fixed and variable components.

B3 Sustainability Metrics for Sensitivity Analysis

The sensitivity analysis input parameters are presented in Table B3.

Table B3: Sensitivity Analysis Input Parameters

Sustainability Category	Input Parameter	Technology	Minimum Value	Base Value	Maximum Value	Source
Economic	Capital Cost (\$/kW)	Offshore Wind	2333	3337	6629	(Klein and Whalley 2015)
		Nuclear	2858	3785	8286	(Klein and Whalley 2015)
		Natural Gas	910	1032	2578	(Klein and Whalley 2015)
	Fixed O&M costs	Offshore Wind	74	116.96	212	(Klein and Whalley 2015)
	Fuel Cost (\$/MMBtu)	Natural Gas	1.3	2.96	23.8	(International Monetary Fund 2017; World Bank 2018a; EIA 2018)
Environmental	Variable Water Consumption (L/MWh)	Nuclear	378	2415	2725	(Meldrum et al. 2013)
		Natural Gas	15	815	4,883	(Meldrum et al. 2013)
	Life cycle greenhouse gas emissions	Hydro (gCO2eq/kW)	7.62	53.35	1257.5	(Klein and Whalley 2015)
		Nuclear (gCO2eq/kW)	31.54	94.61	867.24	(Klein and Whalley 2015)
		Natural Gas (gCO2eq/kWh)	307	449	682	(Klein and Whalley 2015)
	Air Pollution Emission	Hydro (mg/kW)	91.4544	419.17	746.8776	(Klein and Whalley 2015)
		Nuclear (mg/kW)	157.68	1671.4	3185.136	(Klein and Whalley 2015)
		Natural Gas (mg/kWh)	119	988	1857	(Klein and Whalley 2015)

Social	Fatalities/GWh	Hydro	3.30E-07	5.80E-06	2.20E-05	(Klein and Whalley 2015)
		Nuclear	7.40E-07	9.20E-07	1.20E-06	(Klein and Whalley 2015)
		Natural Gas	8.30E-06	9.40E-06	2.10E-05	(Klein and Whalley 2015)
		Offshore Wind	1.10E-06	1.70E-06	3.30E-06	(Klein and Whalley 2015)

APPENDIX C

CALCULATING PORTFOLIO METRICS

The sustainability score, x_{ij}, of portfolio i for metric j can be defined as the sum of the total levelized fixed value of the portfolio and the total variable value of the portfolio:

$$x_{ij} = \frac{\sum_{\tau} F_{j\tau} G_{i\tau}}{E_i} + \frac{\sum_{\tau} V_{j\tau} E_{i\tau}}{E_i} \qquad \text{(C1)}$$

where $G_{i\tau}$ and $E_{i\tau}$ are the capacity and the average annual electricity for technology τ in portfolio i. Note that we can rewrite the equation (C1) for the individual metrics $x_{ij\tau}$ as follows:

$$x_{ij\tau} = \frac{F_{j\tau}}{hCF_{i\tau}} + V_{j\tau} = \frac{F_{j\tau} G_{i\tau}}{E_{i\tau}} + V_{j\tau} \qquad \text{(C2)}$$

The quantity on the left is derived by using the definition of CF and rearranging terms. Thus, combining equations (C1) and (C2), we show that the portfolio metric can be calculated the individual metrics.

APPENDIX D

SUSTAINABILITY SCORE USING AN ADDITIVE VALUE FUNCTION

Our MCDA involves the following steps: (1) identify sustainability metrics and a set of candidate portfolios reflecting a range of possible electricity futures; (2) assemble the metrics data for each portfolio in a comparable format; (3) compute the raw MCDA scores; (4) rank the portfolios under illustrative preference scenarios, which reflect the relative importance of each sustainability criterion. In order to combine the different metrics j, each metric is normalized using equations (D1) and (D2), resulting in each criterion being measured on a scale between 0 and 1. A measure of 1 and 0 reflect the best and worst calculated value of that metric across all portfolios being considered, respectively.

$$z_{ij} = \frac{x_{ij} - x_{\min}}{x_{\max} - x_{\min}}\text{, where } x_{\max} \text{ is preferred} \qquad \text{(D1)}$$

$$z_{ij} = \frac{x_{\max} - x_{ij}}{x_{\max} - x_{\min}}\text{, where } x_{\min} \text{ is preferred} \qquad \text{(D2)}$$

Here x_{ij} is the raw score of portfolio i for metric j, z_{ij} is the normalized score of portfolio i for metric j. Equation 14 is used where a higher value is most desirable (i.e. jobs). Equation 15 is used for where lower value is most desirable (i.e. GHG, water consumption, LCOE).

Let a vector of metric scaling coefficients represent a preference scenario, with the scaling coefficient on metric j, w_j. $\sum_{j=1}^{m} w_j = 1$. Using matrix notation, the metric scaling coefficients, w_j, and normalized scores of portfolio i for metric j, z_{ij}, are converted to weighted scores, y_i, for each portfolio. Note each row of the Z matrix represents the portfolios, and the columns represent the metrics. We do sensitivity analysis over a number of different vectors of preference scaling coefficients representing a variety of potential stakeholder scenarios.

$$\begin{bmatrix} w_1, & w_2, & \cdots, & w_m \end{bmatrix} \times \begin{bmatrix} z_{11} & \cdots & z_{1I} \\ \vdots & \ddots & \vdots \\ z_{m1} & \cdots & z_{mI} \end{bmatrix} = \begin{bmatrix} y_{1,} & y_{2,} & \cdots, & y_I \end{bmatrix} \qquad \text{(D3)}$$

In equation D3 above *m* is the number of metric and *I* is the number of portfolios. When combined the normalized scores result in a rank order from highest y_i (most preferable) to the lowest y_i (least preferable) for the set of portfolios.

APPENDIX E

MINIMUM AND MAXIMUM METRIC VALUES

The minimum and maximum values for each of the metric across all of the portfolios are presented in Table E1. These represent the extreme values for the 35 portfolios originally tested in our system, using median values for all parameters. These values effect the interpretation of the meaning of the scaling coefficients.

Table E1: Minimum and Maximum Portfolio Metric Values

	Minimum	Maximum
LCOE ($/kWh)	0.12	0.15
GHG (gCO_2eq/kWh)	113	375
Air Pollution (mg/kWh)	248	828
Land-Use (m^2/MW)	3713	54,477
Water Consumption (L/MWh)	557	1576
Fatalities/ GWh	3.37E-06	8.62E-06
Jobs (FTE/MW)	0.46	1.03
Nuclear Aversion	2.3E-05	0.28

APPENDIX F

UTILITY AGGREGATION

Here we briefly show that, under the assumption that power is allocated equally within each node, the utility of individuals is able to be aggregated into a group utility function for each node, n_i, in the set of nodes I. U(x, p) is equivalent to the sum of individual utilities. We start by claiming Theorem 1:

Theorem 1: $U\left(p_i, n_i\right) = \sum_{i} \sum_{n_i} \rho_i^{\alpha}$ (F1)

Note that using this functional form the sum of the utility at each node is equal to the sum of the utility of each individual. Here we state this proposition mathematically, assuming a two-node system, n1 and n2, with N individuals, where each individual has the same equity parameter α the equation above becomes.

$$\sum_{i=1}^{2} u(x_i, p_i) = u(x_1, p_1) + u(x_2, p_2) = p_1 \times \left(\frac{x_1}{p_1(1-\alpha)}\right)^{1-\alpha} + p_2 \times \left(\frac{x_2}{p_2(1-\alpha)}\right)^{1-\alpha} = \frac{p_1 * \rho_1^{1-\alpha} + p_2 * \rho_2^{1-\alpha}}{1-\alpha}$$

(F2)

From equation F2 above we can see that the total utility of the system is the sum of the utility in each node. Now we will show that the utility of node i is the sum of the individual utilities of the consumers in node i. Assuming V individuals in node i, and separating the individuals in node i two groups, [1,2,..., v] and [v+1, v+2,.., V], the equation above becomes.

$$\sum_{i=1}^{V} u(x_i, V) = \sum_{i=1}^{v} u(x_i, v) + \sum_{i=v+1}^{V} u(x_i, V) \qquad \text{(F3)}$$

Using substitution we obtain:

$$\sum_{i=1}^{V} \frac{\rho_i^{1-\alpha}}{1-\alpha} = \sum_{i=1}^{v} \frac{\rho_i^{1-\alpha}}{1-\alpha} + \sum_{i=v+1}^{V} \frac{\rho_i^{1-\alpha}}{1-\alpha} \qquad \text{(F4)}$$

Expanding the right side of the equation produces:

$$\sum_{i=1}^{v} \frac{\rho_i^{1-\alpha}}{1-\alpha} + \sum_{i=v+1}^{V} \frac{\rho_i^{1-\alpha}}{1-\alpha} = \frac{\rho_1^{1-\alpha} + \cdots + \rho_v^{1-\alpha} + \rho_{v+1}^{1-\alpha} + \cdots + \rho_V^{1-\alpha}}{1-\alpha} \qquad \text{(F5)}$$

Assuming each person in node i consumes the same amount of energy we have

$$\rho_1 = \cdots = \rho_v = \rho_{v+1} = \cdots = \rho_V = \rho \qquad \text{(F6)}$$

Thus

$$\frac{\rho_1^{1-\alpha} + \cdots + \rho_v^{1-\alpha} + \rho_{v+1}^{1-\alpha} + \cdots + \rho_V^{1-\alpha}}{1-\alpha} = \frac{v * \rho^{1-\alpha} + (V-v)\rho^{1-\alpha}}{1-\alpha} = V \frac{\rho^{1-\alpha}}{1-\alpha}$$

(F7)

Therefore, we can conclude that the individual utility preferences are able to be aggregated into a group utility function for each node, $_i$, in the set of nodes I.

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