Using a Modified SAFE Model to Evaluate the Overall Sustainability of Three of the Largest Investor-Owned Utility Companies in the United States: NextEra Energy Inc., Duke Energy Corporation, and Exelon Corporation

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Contents

1. Abstract

The sustainability of three of the largest investor-owned utility companies operating within the United States—NextEra Energy Inc., Duke Energy Corporation, and Exelon Corporation—was evaluated using a modified Sustainability Assessment and Fuzzy Evaluation (SAFE) model (Figure 1-1). All three corporations generate, transmit, and distribute electric energy to consumers in the contiguous United States.

The SAFE model computes an overall sustainability measure for each company based on environmental, human, and financial indicators. The sustainability assessment considers the operation of each corporation during the time period from 2014-2018. The data was collected largely from annual performance reports, sustainability reports, and financial documents from each company's website. Supplemental data sources were used when corporation websites and reports were not sufficicent.

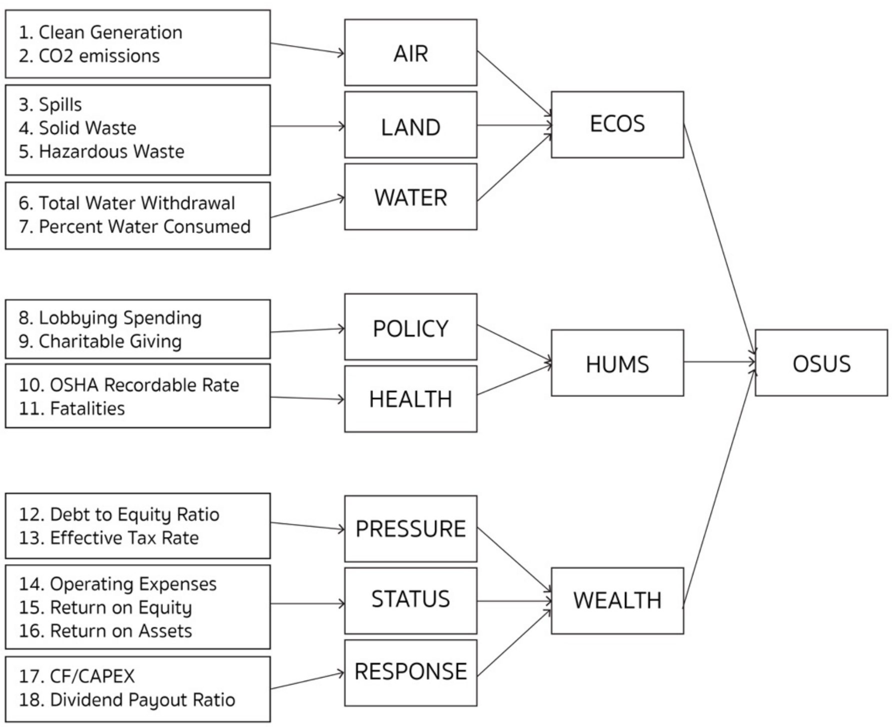

Figure 1-1: Overview of SAFE Model

The results of the analysis concluded the highest sustainability to be associated with Exelon for the period of analysis. The overall sustainability of Duke Energy was found to be consistently the lowest during the period 2014-2018, but was observed to be consistently improving (Figure 1-2). The overall sustainability of NextEra Energy was found to have changed the least over the period of analysis.

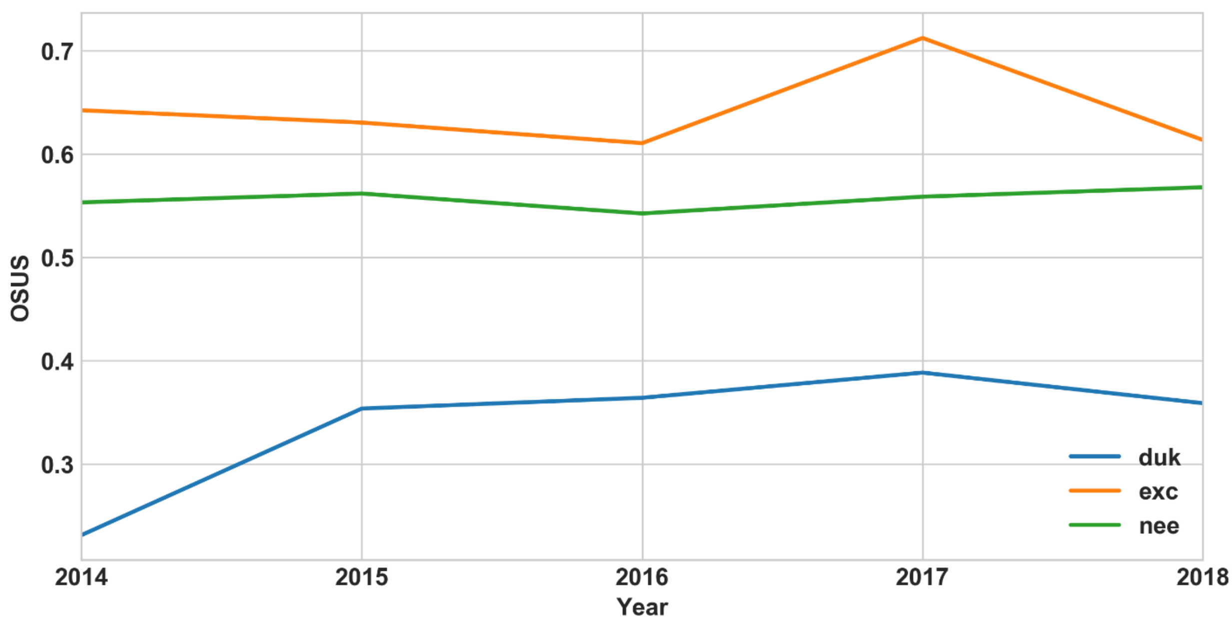

Figure 1-2: Graph of crisp values of overall sustainability calculated from the modified SAFE model

2. Introduction

This report evaluates the overall sustainability of three of the largest investor-owned utility companies in the United States: NextEra Energy Inc., Duke Energy Corporation, and Exelon Corporation. These investor-owned corporations were selected based on the annual generation from fossil fuel, nuclear, and renewable facilities in 2017. The three corporations under evaluation made up 15.19% of the total annual generation for all of the power produced in the United States in 2017 [1]. Southern Company was omitted from the report because of a lack of data available for the LAND impacts indicator within the SAFE model – in the future, it can be added by implementing more advanced missing data techniques.

Rank	Owner	Ownership Type	Total Generation 2017 *(MWh)*
1	Duke	investor-owned corp.	221,410,729
2	Exelon	investor-owned corp.	194,728,907
3	Southern	investor-owned corp.	192,499,694
4	NextEra Energy	investor-owned corp.	185,145,296
5	Tennessee Valley Authority	federal power authority	134,068,968
6	Entergy	investor-owned corp.	121,658,052
7	Dynegy	investor-owned corp.	117,330,383
8	Berkshire Hathaway Energy	privately held corp.	113,269,201
9	Dominion	investor-owned corp.	102,153,095
10	AEP	investor-owned corp.	101,966,086

Table 2-1: Top 10 largest power producers in the United States in 2017

This sustainability report limits the scope of utility companies to investor-owned utilities (IOUs). IOUs are electricity and natural gas providers that are privately owned by shareholders. The largest of these corporations operate assets across the United States. In contrast, publicly owned utilities (POUs) are owned and operated by local governmental bodies and therefore are subject to local public control and often have a relatively limited service area. The difference in operation between IOUs and POUs is significant when considering not only the ownership of the entity but also the structure, management, the determination and regulation of rates, the mission of the entity, financing, power generation, net revenue and heterogeneity [2]. In 2017, approximately 3,000 utilities were operating in the United States, of which investor-owned utilities (IOUs) collectively served over 71% of the customers [3].

The three corporations under analysis, NextEra Energy, Duke Energy, and Exelon represent a variety of efforts in the transition to renewable energies and the reduction of emissions. Two of the companies included within the analysis, NextEra Energy and Duke Energy have recently announced emissions reduction plans. In June 2019, NextEra Energy announced its plan to reduce emissions by 40% from 2005 levels by 2025 and in September 2019, Duke Energy announced its plan to reach net-zero by 2050 [4]. These two emissions plans are part of a larger effort of energy utility companies to decarbonize their electricity generation by transitioning to zero-carbon sources of electricity.

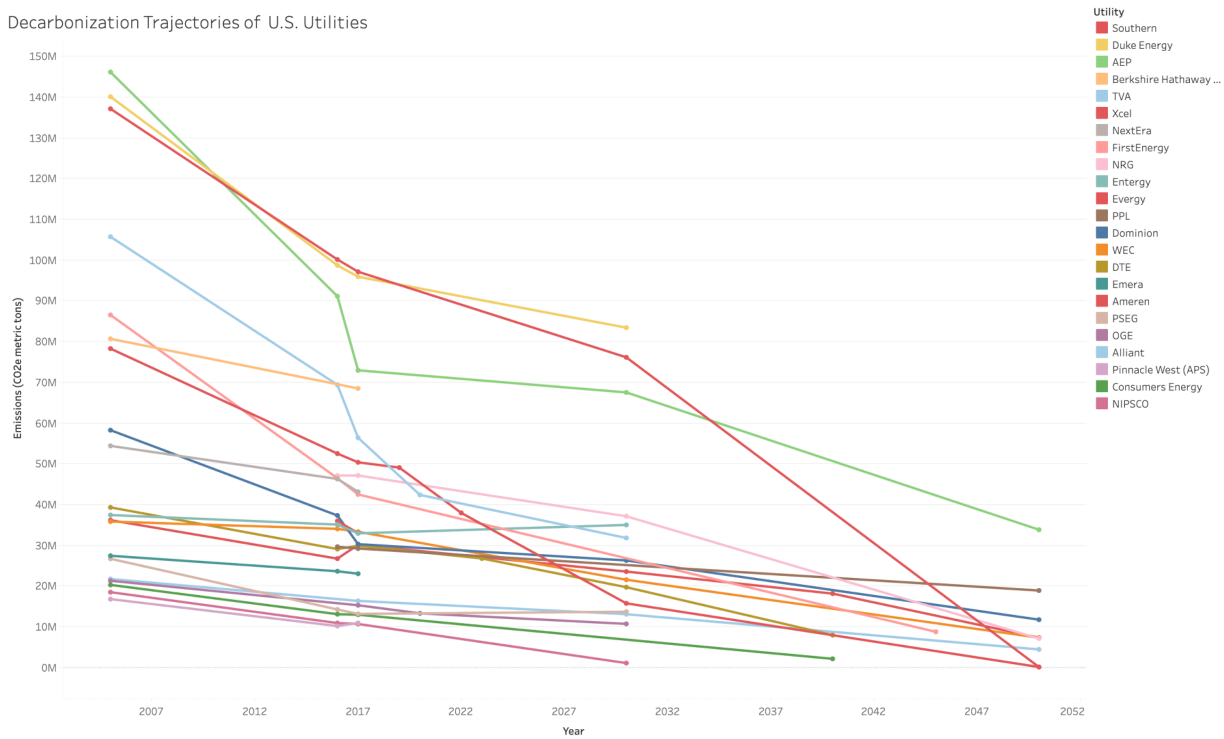

Table 2-2: Predicted decarbonization pathways of a selection of the largest investor-owned utilities in the United States according to their proposed emissions plans [5]

In the last two years, an increased number of energy utility corporations in the United States have begun to provide their investors with annual environmental, social, and governance (ESG) reports. ESG reports reflect a more thorough and diverse analysis of the sustainability of a corporation and their rise in popularity indicates a shift in how consumers and their buying decisions are taken into consideration by corporations [6]. The Edison Electric Institute (an association representing investor-owned utility corporations in the United States) reports that “more than 90% of the US investor-owned electric power industry is currently using the ESG/Sustainability Template to report information to investors” [7].

The three corporations under analysis serve different regions of the United States, use diverse approaches to emissions reduction, and represent three very different energy mixes. In 2017, the largest percentage of NextEra Energy’s generation was natural gas (46.9%), the largest percentages of Duke Energy’s generation were nuclear (33.4%) and coal (33.2%), and the largest percentage of Exelon’s generation was nuclear (85.2%) [1].

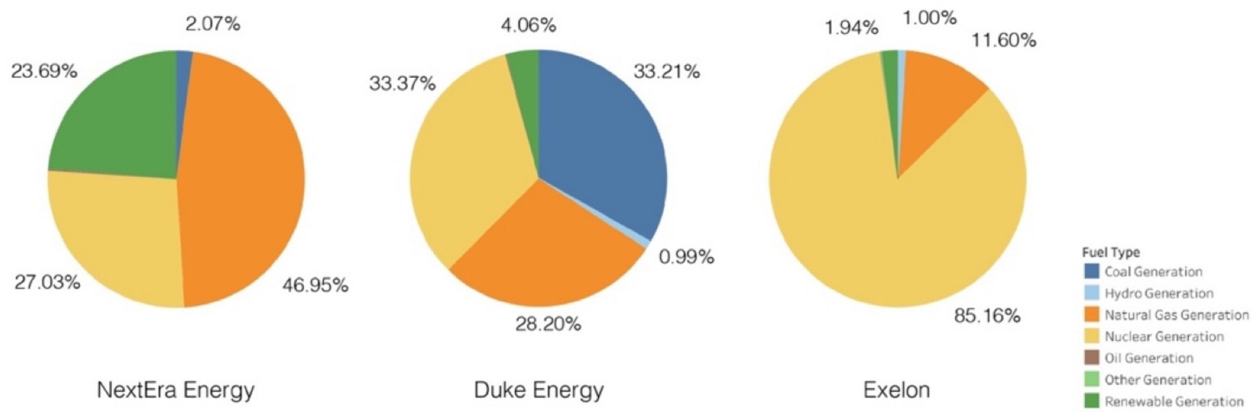

Figure 2-1: Annual Generation by Fuel Type for NextEra Energy, Duke Energy and Exelon in 2017

NextEra Energy Inc. is the largest utility company in the United States by market capitalization and includes subsidiaries that provide services in the generation, transmission, selling, and distribution of electric energy. The largest subsidiary of NextEra Energy—Florida Power & Light—has an estimated 10 million customers and is the third-largest electric utility company in the United States [8]. NextEra Energy provides services in 36 states, with the majority of its services in Florida. Relative to the other major IOU's studied, a significant percentage of NextEra Energy's energy mix (23% in 2017) comes from renewable sources (Figure 2-1). Duke Energy is a utility company headquartered in North Carolina that serves 7.7 million customers across six states [9]. In addition to electricity services, Duke Energy provides natural gas to 1.6 million customers in five states and operates wind and solar power facilities in 14 states. Historically, coal and nuclear generation have made up significant portions of their generation mix. In 2017, each constituted about a third of the total energy generated (Figure 2-1). Exelon Corporation is one of the largest electric utilities in the United States by revenue and is one of the largest operators of nuclear power plants in the United States. Exelon is headquartered in Illinois and provides services to 10 million customers in 6 states on the East Coast [10].

The energy utility sector is one of the largest economic sectors targeted for decarbonization. Therefore, it is important to try and quantify the sustainability trends of major companies within the sector over the last five years. The scope of analysis focused on IOUs because they serve the largest portion of the population of the United States and because many of them are considered to be leading the industry in efforts to decarbonize and report the sustainability of their corporations more holistically. This analysis aims to develop a model that evaluates the overall sustainability of each IOU corporation holistically in order to determine a more holistic set of metrics for evaluating sustainability beyond the generation mix.

3. Model Description

The model used in the sustainability assessment of NextEra Energy, Duke Energy, and Exelon was a SAFE model in which the overall sustainability (OSUS) was determined from the impacts of three primary indicators. The three primary indicators included within the model were: ecosystem and environmental impacts (ECOS), impacts on people and society (HUMS), and financial health and economic impacts (WEALTH). Each of these primary indicators was constructed from a series of secondary indicators. The traditional SAFE model includes three secondary indicators corresponding to each of the primary indicators.

The SAFE model was originally developed to assess the sustainability of countries using only the ECOS and HUMS primary indicators. The modified SAFE model assesses the sustainability of a corporation using WEALTH as a third primary indicator instead of as a secondary indicator informing HUMS. The addition of the WEALTH indicator allows for the model to more accurately assess the sustainability of the corporation.

The secondary indicators recommended for ECOS are impacts on air resources and the atmosphere (AIR), impacts on land and land resources (LAND), and impacts on water and water resources (WATER). The secondary indicators for HUMS are impacts of a company's policies on customers, employees, and citizens (POLICY), impacts on human health of customers, employees and citizens (HEALTH), and a company's contributions to research, education, and training (KNOW). The model used in this analysis contains only the secondary indicators POLICY and HEALTH in the evaluation of the HUMS primary indicator—this was necessary because of insufficient data for the KNOW indicators such as employee training and research and development expenditures. The secondary indicators recommended for the financial health and economic impacts indicator are indicators currently changing the economics of a company (PRESSURE), the current financial health of a company (STATUS), and indicators that a company is pursuing changes in response to financial pressures (RESPONSE).

Basic indicators are used to evaluate each of the previously listed secondary indicators. Each basic indicator is an annual value collected from a variety of sources including annual performance reports, sustainability reports, and financial documents. Once the data is collected, each indicator is made intensive and normalized. The methodology for building the SAFE model and evaluating the sustainability of a corporation is outlined in the remainder of the section. A summary of the basic indicators chosen for the sustainability assessment of NextEra Energy, Duke Energy, and Exelon is included below. The 18 basic indicators included were identical for the three companies under analysis (Table 3-1).

Primary Indicators	Secondary Indicators	Basic Indicators
ECOS	AIR	1. Clean Generation
		2. CO_2 Emissions
	LAND	3. Spills
		4. Solid Waste (non-hazardous)
		5. Hazardous Waste
	WATER	6. Total Water Withdrawal
		7. Percent of Water Consumed
HUMS	POLICY	8. Lobbying Spending
		9. Charitable Giving
	HEALTH	10. OSHA Recordable Rate (TCIR)
		11. Fatalities
WEALTH	PRESSURE	12. Debt to Equity Ratio
		13. Effective Tax Rate
		14. Operating Expenses
	STATUS	15. Return on Equity
		16. Return on Assets
	RESPONSE	17. CF/CAPEX
		18. Dividend Payout Ratio

Table 3-1: Summary of basic indicators in the modified SAFE model

A. Basic Indicators & Data Collection

1. Clean Generation *(% generated)*

Utility companies can generate electricity from renewable, nuclear, or fossil fuel sources. Those that generate energy from 'clean' low-carbon sources pollute the air less per unit of energy generated than those who use higher carbon fuels. The 'Clean Generation' indicator quantifies the percentage of the total energy generated by a utility that came from coal during a particular year. Utility companies are facing increasing pressure to transition their energy mix to cleaner sources like natural gas, renewables, and nuclear. Coal is considered the 'dirtiest' fuel source, and coal power powerplants are being retired across the country. Since the indicator is inversely correlated with how clean a utility's energy mix is, the normalization curve is a line that indicates that lower values are better than higher values. The indicator differentiates itself from CO_2 emissions because it is also a leading indicator of future air impacts.

2. CO_2 Emissions *(tons/MWh)*

The 'CO_2 Emissions' indicator measures the amount of carbon dioxide a utility emits into the atmosphere per unit of energy generated. It is computed by taking the total tons of CO_2 produced and divided by the total amount of electrical energy generated. The intensive indicator measures a utility's air impact independently from how much energy it produces for its customers. Larger utilitiy corporations produce higher total emissions than smaller corporations as a result of the larger annual generation. Although CO_2 is not the only gas that is produced during fuel combustion, it can be used as an approximation for total greenhouse gas emissions. The normalization curve for the indicator is a decreasing line which indicates that lower values are better.

3. Spills *(spills/Wh)*

Oil spills caused within utility companies are very different than those caused by oil tankers or offshore drilling. Utility companies use oil to fill cavities in transformer boxes and electrical transmission line infrastructure for cooling purposes. When accidents happen, oil and other harmful liquids can damage land resources. Each company's reported annual number of 'recordable' spills was divided by total generation to obtain an indicator that is independent of the size of the utility. Units of Wh was used instead of GWh to reduce the computational and storage intensity of the model.

4. Non-Hazardous Solid Waste *(tons/Wh)*

Non-hazardous solid waste is an annual measurement in total tons of a variety of industrial wastes. Some examples of non-hazardous solid wastes that are included in this measurement are construction waste streams, non-hazardous waste generated from plant operations, and various recyclable wastes [11]. The quantity of solid waste is collected internally often from solid waste manifest information recorded when energy is generated. The solid waste data is recorded and publicized in part to describe a utility's recycling and reuse practices. To intensify the measurement of the raw tons of annual solid waste, it was divided by the annual energy generation (MWh). This value was then converted from tons/MWh to tons/Wh to reduce the computational and storage intensity of the model.

5. Hazardous Waste *(tons/Wh)*

Hazardous waste (tons) is usually recorded internally in annual sustainability reports. Each phase of the electric utility process produces some type of waste and affects the environment. The quantity of hazardous waste produced relied heavily on the scale of the process, the geographic location, and the type of energy produced. To make the value intensive, the annual hazardous waste in tons was divided by the annual energy generated. Then it was converted from tons/MWh to tons/Wh to reduce the computational and storage intensity of the model.

6. Total Water Withdrawal *(gallons/MWh)*

The 'total water withdrawn' indicator measures the amount of water used per unit of energy generated. The less water a utility withdraws from the environment to provide the energy the better. Consequently, the normalization curve follows the 'lower is better' relationship. Most utilities reported this indicator in their sustainability reports.

7. Percent Water Consumed *(% of withdrawn water)*

The percent of water consumed in the electricity production and delivery process is defined by the World Resources Institute (WRI) as the total portion of water that is withdrawn and not returned to the original water source [12]. Consequently, the normalization curve followed a 'lower is better' relationship. The basic indicator indicates how effective a utility is at treating and returning water to its source. The companies reported this indicator in their sustainability reports.

8. Lobbying Spending *(% of revenue)*

Lobby spending was calculated by dividing the total amount of money spent on lobbying by total annual revenue. The lobbying could be spent in support or opposition to a political figure or policy. Although lobbying spending could ultimately result in financial benefits, it reflects negatively on a company's policies. Consequently, the normalization curve for this indicator follows the 'lower is better' behavior.

9. Charitable Giving *(% of revenue)*

The charitable giving indicator is calculated by dividing the amount of money spent on charitable activities by the total annual revenue. The amount of charitable giving was collected from the annual sustainability reports while revenue was collected from financial statements. Charitable giving was selected as a policy indicator because it measures the positive impact the utility has on local communities. The normalization curve for this indicator was a line that indicated 'higher is better'.

10. OSHA Total Case Incident Rate *(incidents/100 workers)*

The OSHA Total Case Incident Rate (TCIR) indicates the number of employees that have been involved in a recordable accident or injury in a given year. The metric is useful for comparing employee safety across different industries. This standardized and intensive measurement of safety is measured per 100 employees and is computed using a statistically significant sample size. In normalizing the data for the OSHA TCIR indicator, the curve will follow the lower is better behavior [13].

11. Fatalities *(% of workforce * 100)*

Recorded fatalities were collected from internal annual reports and through the OSHA establishment database. Companies often do not include fatalities related to contracted work. Fatality data was collected for each year and then calculated as a percent of the total workforce for a given year to create an intensive indicator. In normalizing the data for the fatality's indicator, the line follows the 'lower is better' relationship.

12. Debt to Equity Ratio *(unitless)*

The debt to equity ratio is calculated by dividing total debts by total equity. The indicator provides a measure of how financially leveraged a utility is. The indicator was selected as a pressure on wealth because a higher ratio indicates risk and increasing pressure to pay back debt investors. At the same time, utilities need to use debt to fund their capital-intensive operations and achieve higher growth than would be possible without debt financing. Consequently, the normalization curve for the indicator follows the 'middle is better' behavior [14].

13. Effective Tax Rate *(% of income)*

The effective tax rate is calculated by dividing total taxes by total earnings using values from the income statement. The indicator was selected for the pressure on wealth since a higher tax rate will reduce the earnings that utility can use for growth and meeting investor expected returns. Consequently, a line that indicates 'lower is better' was used for the normalization curve for this indicator.

14. Operating Expenses *($/MWh)*
The operating expense indicator measures the cost of obtaining electricity per unit of energy. The indicator is calculated by dividing the annual operating costs spent on fuel and electricity purchases (income statement) by the total amount of energy served. A utility can generate electricity on its own or buy it from another utility or independent power producer. Higher fuel and electricity costs can strain on margin, which is the difference between the selling price of electricity and the cost to acquire it. Consequently, the normalization curve for the indicator was a line that indicates that lower operating expenses are better.

15. Return on Equity *(%)*
The return on equity indicator measures how well a utility is at increasing the value of its equity, which is particularly important for investor-owned utilities. It is calculated by dividing the annual net income by the total equity. Return on equity is similar to return on assets, discussed next, but a higher value is not strictly better than a lower one: higher return on equity could signal unsustainable growth—therefore the normalization curve is a triangle which indicates 'middle is better'. Similarly, a below-average return on equity could mean the company is not making enough earnings to benefit equity investors [15].

16. Return on Assets *(%)*
The return on assets indicator measures how well a utility is at utilizing its assets, such as generators and transmission lines, to generate income. Return on assets is calculated by dividing annual income by total assets, which can be acquired from a company's income statement and balance sheet respectively. A higher return on assets indicates that a company effectively used its resources to bring in income that can be used to fund company growth or dispersed to debt or equity investors. Consequently, the normalization curve for this indicator is a line that indicates that 'higher is better'. Since it indicates an ability to pay both types of investors, our model considers return on assets as a strong status indicator for investor-owned utilities [16].

17. CF/CAPEX *(unitless)*
CF/CAPEX is a ratio of total annual operating cash flow to total capital expenditures. Capital expenditures for utilities include investments in new power plants and maintenance work on transmission lines. A high CF/CAPEX ratio indicates that a company is bringing in enough money to fund the investments necessary to continually provide service to customers. The ratio was selected as an indicator for wealth response because a high value can indicate the company is poised for future growth with their existing investments bringing in significant cash flow compared to the ones they are making for the future. Consequently, a line that indicates that 'higher is better' was used as the normalization curve for this indicator [17].

18. Dividend Payout Ratio *(%)*
The dividend payout ratio is a measure of dividend payments made to shareholders as a percentage of total annual earnings. An investor-owned utility the organization must retain enough money to support its growth while also provide returns for investors. Consequently, the dividend payout ratio has a triangular normalization curve that reflects the balance that is needed between the two goals. The indicator was selected for a response to wealth challenges because a high value may indicate that too much money is being returned to investors and this may stunt the future growth

of the company. Conversely, a low value may indicate the company will have a harder time raising money from equity investors in the future. The ratio was converted to a percent reduce the computational and storage intensity of the model. [18].

B. Normalization

The normalization for each basic indicator was done statistically using 15 datapoints (three companies over five years). The 15 data points served as the domain of discourse and the critical values were based on maximum, minimum, and mean values of the domain of discourse. The normalization functions used were strictly increasing lines, strictly decreasing lines, or triangles. A statistical approach was taken to determine the values in order to allow for the model to be improved continuously as more companies and yearly data was added to the indicator database. Efforts to find industry-wide reports and values for the vast majority of the indicators were unsuccessful, therefore it was determined that a statistical approach would be the most accurate approach. An example for each primary indicator ECOS, HUMS, and WEALTH, is included below which outlines the normalization process. The associated normalization curves for each basic indicator can be found in Appendix II.

C. Linguistic Variables

The WMS linguistic variable was used to fuzzify the crisp basic indicator values in the SAFE model. The WMS linguistic variable is comprised of three fuzzy sets, each corresponding to a peak value — weak (W) corresponding to the peak value of 0, medium (M) corresponding to the peak value of 0.7, and strong (S) corresponding to the peak value of 1.

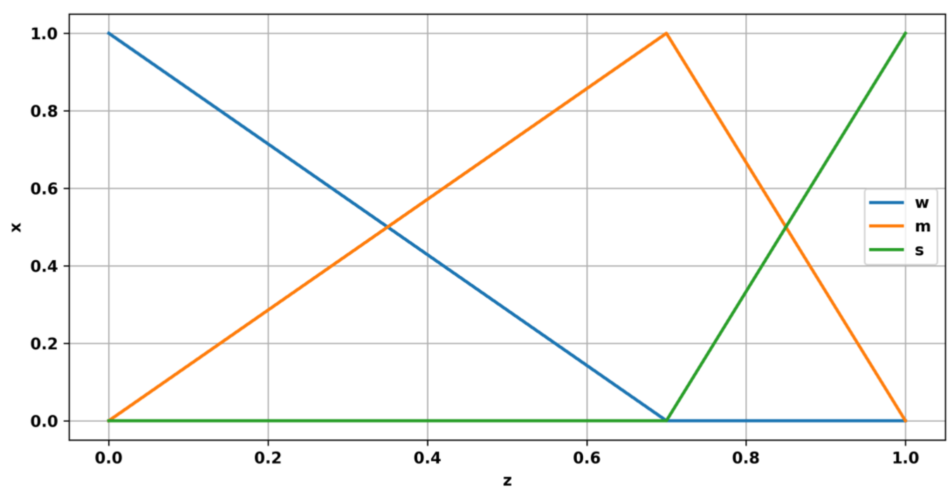

Figure 3-1: WMS Linguistic Variable (z the domain of discourse)

The VBBAGVG linguistic variable was used for the secondary and primary indicators in the model (Figure 3-2). It is comprised of five fuzzy sets, each of which has a membership function with critical values 0.25 apart.

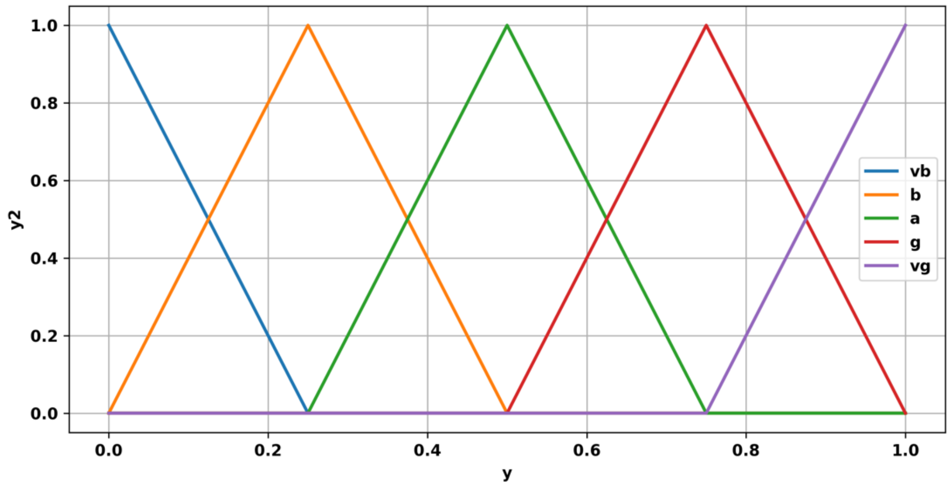

Figure 3-2: VBBAGVG Linguistic Variable

The ELVLLFLIFHHVHEH linguistic variable was used for the OSUS indicator in the SAFE model, including for defuzzification (Figure 3-3). It is comprised of five fuzzy sets, each of which has a membership function with critical values 0.125 apart.

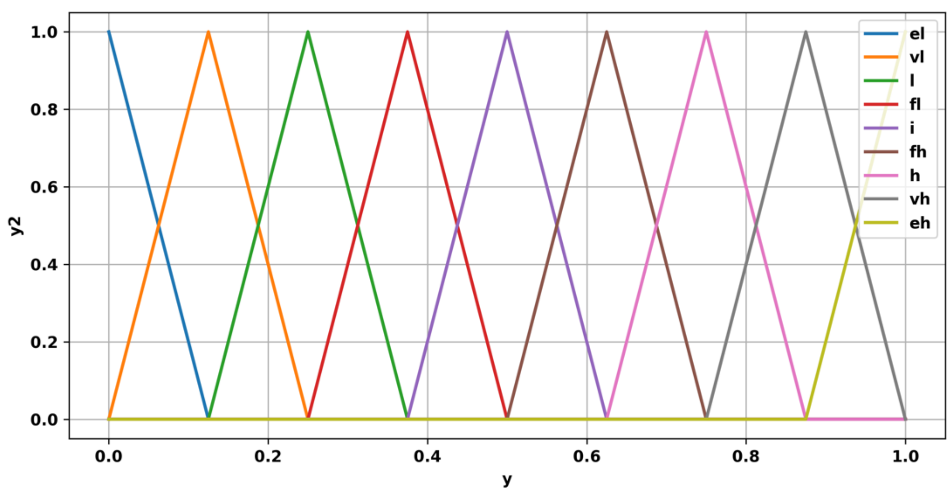

Figure 3-3: ELVLLFLIFHHVHEH Linguistic Variable

D. Basic Indicator Sample Calculations

The procedure for calculating the fuzzy and crisp values of one basic indicator is outlined below by three examples, one from each of the primary indicators used in the SAFE model.

1. *Example 1: CO_2 Emissions*

Primary Indicator: ECOS
Secondary Indicator: AIR
Basic Indicator: CO_2 Emissions

Company	Year	Raw Value *(tons)* [11]	Normalization Value *(MWh)* [11]
NextEra Energy	2018	42,097,424	193,086,226

The intensive CO_2 emissions are calculated by dividing the total annual emissions (reported in tons) by the annual generation of the corporation (reported in MWh).

$$CO_2 \text{ Emissions (Intensive)} = \frac{42{,}097{,}424 \text{ tons}}{193{,}086{,}226 \text{ MWh}} = 0.2180 \text{ tons/MWh}$$

The intensive value calculated for CO_2 emissions was normalized using the lower is better methodology. The domain of discourse was constructed using the maximum and minimum value across all years and companies. The minimum value set where the normalization curve is equal to 1 and the maximum set where it is 0.

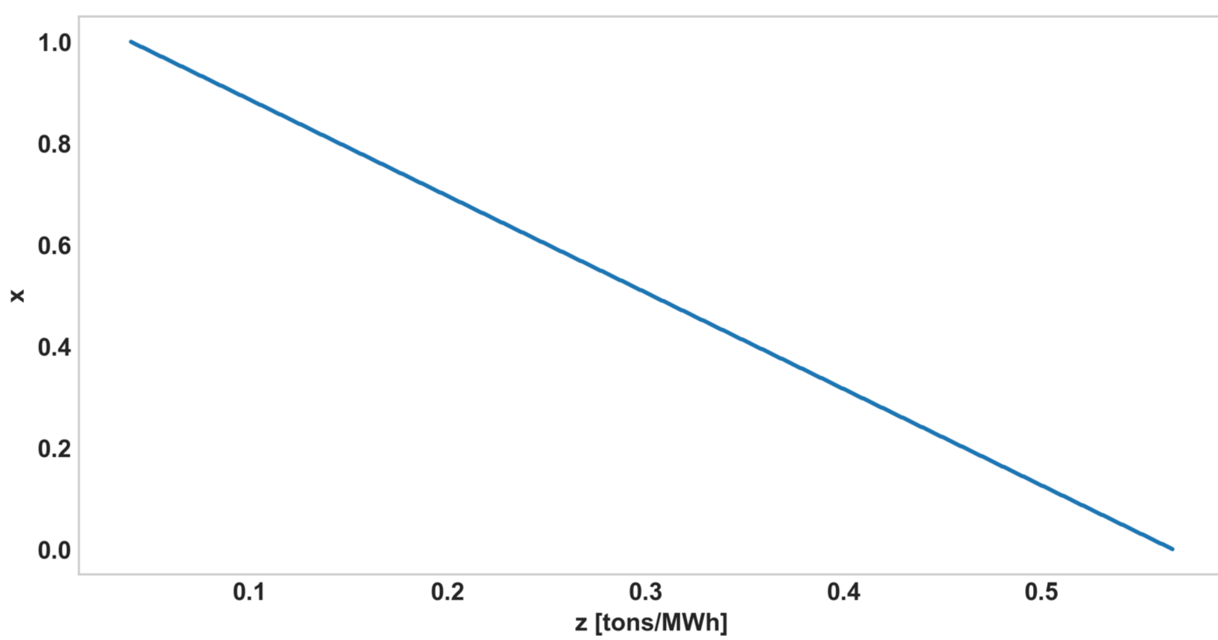

Figure 3-4: Normalization Curve for CO_2 Emissions Data

The normalized value for NextEra Energy in 2018 is determined to be 0.662. Then, the fuzzy value for the given data point is determined by the membership functions of the WMS linguistic variables. The basic indicator CO_2 emissions for NextEra Energy in 2018 is determined to be W(0.054) and M(0.946).

2. *Example 2: Charitable Giving*

Primary Indicator: HUMS
Secondary Indicator: POLICY
Basic Indicator: Charitable Giving

Company	Year	Raw Value *($)* [11]	Raw Value *($)* [11]
NextEra Energy	2018	13,755,679	16,700,000,000

Intensive value for charitable giving is calculated by dividing the total annual charitable donations (reported in dollars) by the annual operating revenue of the corporation (reported in dollars).

$$\text{Charitable Giving (Intensive)} = \frac{\$13{,}755{,}679}{\$16{,}700{,}000{,}000} * 100 = 8.237\ \%$$

The intensive value calculated for charitable giving was normalized using the higher is better methodology. The domain of discourse was constructed using the maximum and minimum value across all years and companies. The minimum value set where the normalization curve is equal to 1 and the maximum set where it is 0.

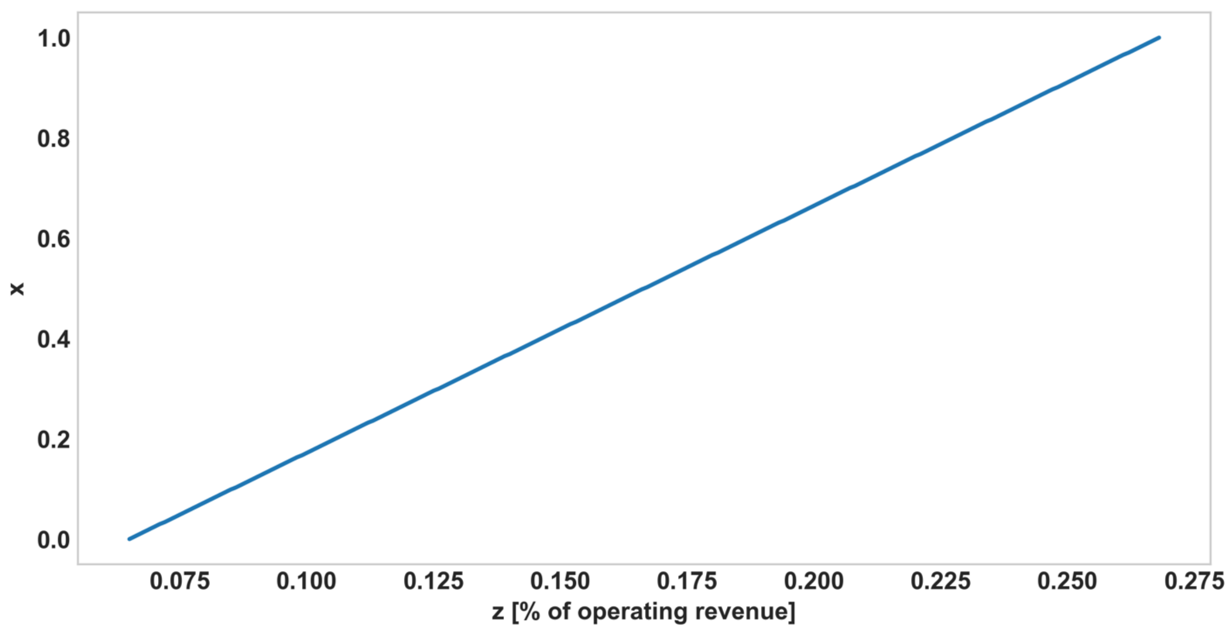

Figure 3-5: Normalization Curve for Charitable Giving Data

The normalized value for NextEra Energy in 2018 is found to be 0.084. Then, the fuzzy value for the given data point is determined by the membership functions of the WMS linguistic variables. NextEra Energy's basic indicator for charitable giving in 2018 is W(0.88) and M(0.12).

3. *Example 3: Dividend Payout Ratio*

Primary Indicator: WEALTH
Secondary Indicator: RESPONSE
Basic Indicator: Dividend Payout Ratio

Company	Year	Raw Value *(unitless)*[19]
NextEra Energy	2018	0.316511

Raw value for the dividend payout ratio is intensive, but before the value is normalized it is converted to a percentage.

Dividend Payout Ratio (Intensive) = 0.316511 * 100 = 31.6511%

The intensive value calculated for the dividend payout ratio was normalized using the middle is better methodology.

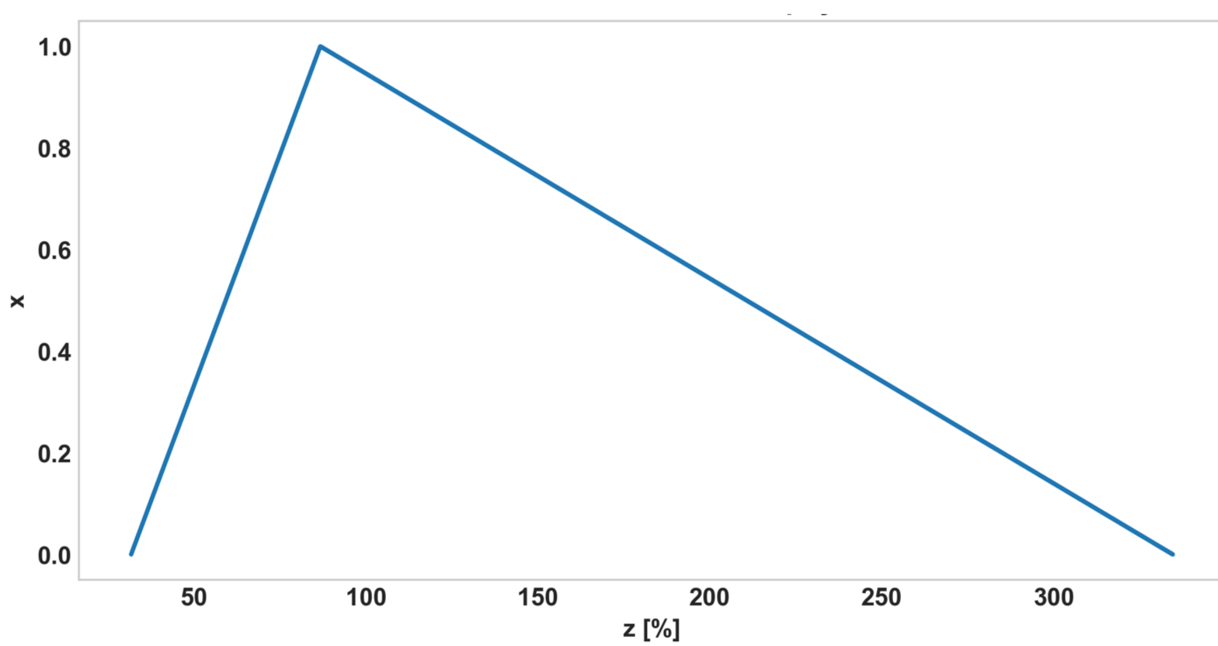

Figure 3-6: Normalization Curve for Dividend Payout Ratio

The normalized value for NextEra Energy in 2018 is found to be 0. Then, the fuzzy value for the given data point is determined by the membership functions of the WMS linguistic variables. The basic indicator for charitable giving in 2018 was W(1).

E. Secondary Indicator Sample Calculations

Fuzzy values of basic indicators are fed into an inference engine that uses a rule base (such as Table 3-2) to perform implication and compute the VBBAGVG values for the secondary indicators. Instead of constructing the rule base one by one, a linear mapping between WMS and VBBAGVG was created. A weighted average of the two basic WMS was calculated based on an assigned relative weight before it was passed through the linear map.

1. *Example 4: Air (*Continuation of Example 1)

Primary Indicator: ECOS
Secondary Indicator: AIR
Basic Indicators: Clean Generation and CO_2 Emissions

Company	Year	Basic Indicator	Raw Value *(%)* [11]
NextEra Energy	2018	Clean Generation	1.50

From Example 1 we saw that in 2018 NextEra Energy had CO_2 Emissions which where W(0.054) and M(0.946). Following the same methodology for the Clean Generation indicator with the lower is better normalization (Figure 3-7), it is determined that it has a normalized value of 0.965 which maps to M(0.117) and S(0.883).

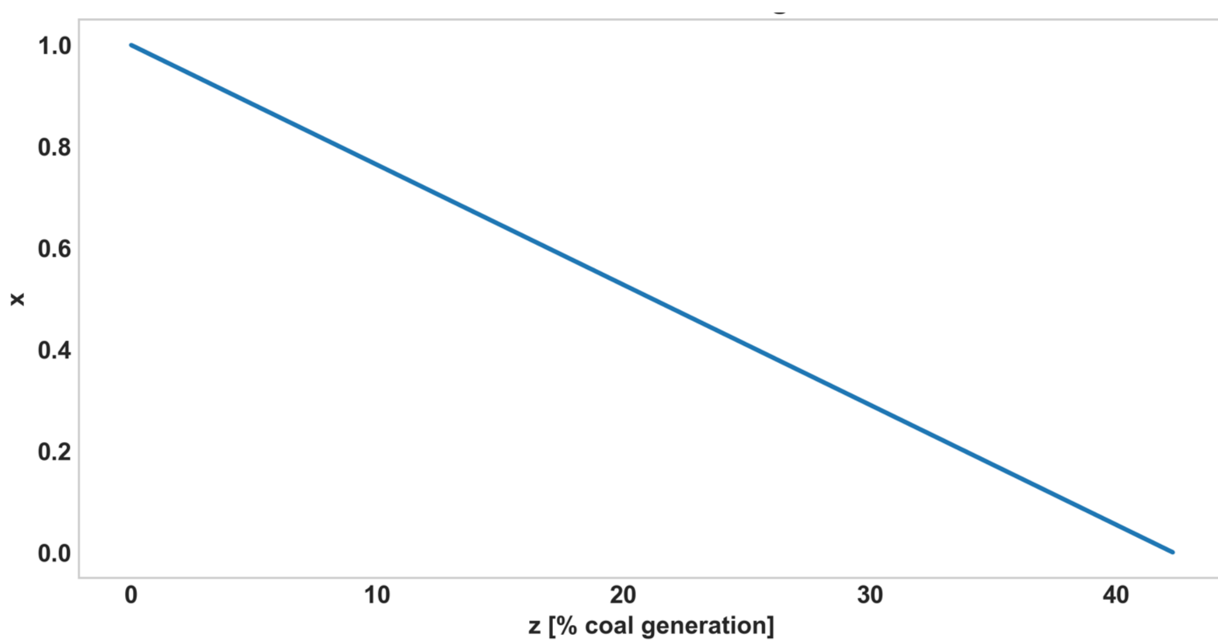

Figure 3-7: Normalization Curve for Clean Generation

Once the fuzzified values for the basic indicators are determined, the rule base used for inference is constructed. The linear map between WMS and VBBAGVG can be expressed as y = 2x - 1, where x is an element of [1,3] and y is an element of [1,5]. The integer in each set corresponds with the respective linguistic value. Based on our domain knowledge, relative weights of 1:2 were assigned between clean generation and CO_2 emissions to compute a weighted average. This value was then passed through the linear map. Rounding of the output to the nearest integer was performed to map the value to the closest VBAGVG value. This methodology did not build the rule bases either as optimistic or pessimistic and was used to avoid bias and inconsistency in the process of rule construction.

Weighted Average Calculation for Rule 6 (does not fire in this example):

$$M \rightarrow 2$$
$$S \rightarrow 3$$
$$\frac{\left(RW_{cg} * M + RW_{CO_2} * S\right)}{RW_{cg} + RW_{CO_2}} = \frac{(1 * 2 + 2 * 3)}{1 + 2} = 2.66$$
$$y = 2x - 1,\ x = 2.66$$
$$y = 4.33$$
$$y = 4.33 \rightarrow \text{round down to } 4$$
$$4 \rightarrow G$$

RW	1	2	
Rule	Clean Generation	CO_2 Emissions	AIR
1	W	W	VB
2	W	M	B
3	W	S	A
4	M	W	B
5	M	M	A
6	M	S	G
7	S	W	A
8	S	M	G
9	S	S	VG

Table 3-2: Example rule base for two indicator inputs

Once the rule base is constructed, we can proceed with our example seeing that rules: 4, 5, 7, 8, fire. By the Larsen Implication, we conclude:

IF Clean Generation IS M(0.117) AND CO_2 Emissions IS W(0.054) THEN AIR IS B(0.01)
IF Clean Generation IS M(0.117) AND CO_2 Emissions IS M(0.946) THEN AIR IS A(0.11)
IF Clean Generation IS S(0.883) AND CO_2 Emissions IS W(0.054) THEN AIR IS A(0.05)
IF Clean Generation IS S(0.883) AND CO_2 Emissions IS M(0.946) THEN AIR IS G(0.84)
AIR IS B(0.01) A(0.16) G(0.84)

This result matches the result calculated in the SAFE model in Table 3-3, which contains the results for all of NextEra's secondary indicators. To find the crisp value for AIR, each membership value is multiplied by the associated linguistic values' peak value and divided by the sum of those peak values.

$$\text{Crisp Value} = \frac{(0.01 * 0.25 + 0.16 * 0.5 + 0.84 * 0.75)}{0.25 + 0.5 + 0.75} = 0.48$$

NextEra Energy, Inc.						
	Year	VB	B	A	G	VG
AIR	2014	0	0.03	0.3	0.67	0
	2015	0	0.04	0.32	0.64	0
	2016	0	0.01	0.22	0.77	0
	2017	0	0.01	0.23	0.75	0
	2018	0	0.01	0.16	0.84	0
HEALTH	2014	0	0	0.22	0.78	0
	2015	0	0	0.53	0.47	0
	2016	0.32	0.52	0.17	0	0
	2017	0	0	0.01	0.99	0
	2018	0	0	0.09	0.91	0
LAND	2014	0	0	0.05	0.95	0
	2015	0	0	0.06	0.94	0
	2016	0	0	0.05	0.95	0
	2017	0	0	0	0	1
	2018	0	0	0.1	0.9	0
POLIC	2014	1	0	0	0	0
	2015	0	0.94	0	0.06	0
	2016	0	0.92	0.06	0.02	0
	2017	0.53	0.43	0.04	0	0
	2018	0.25	0.66	0.09	0	0
PRESSURE	2014	0	0	0.8	0.18	0.02
	2015	0	0	0.5	0.41	0.1
	2016	0	0	0.45	0.45	0.1
	2017	0	0	0.05	0.47	0.48
	2018	0	0	0.9	0.1	0
RESPONSE	2014	0	0.49	0.51	0	0
	2015	0.06	0.45	0.48	0	0
	2016	0.15	0.23	0.62	0	0
	2017	0.93	0	0.07	0	0
	2018	1	0	0	0	0
STATUS	2014	0.01	0.4	0.58	0	0
	2015	0	0.39	0.61	0	0
	2016	0	0.38	0.57	0.04	0
	2017	0	0.53	0.45	0.02	0
	2018	0	0	1	0	0
WATER	2014	0	0	0.14	0.86	0
	2015	0	0	1	0	0
	2016	0	0	0.03	0.96	0.01
	2017	0	0	0.05	0.94	0.01
	2018	0	0	0.03	0.96	0.01

Table 3-3: Summary of fuzzy secondary indicator values calculated for NextEra Energy Inc.

Table IV-1 and Table IV-2: Summary of secondary indicator values calculated for Exelon Corporation summarize the fuzzy secondary indicators for Duke Energy and Exelon can be found in Appendix IV: Fuzzy Secondary Indicator Values.

F. Primary Indicator Sample Calculation

1. *Example* 5: ECOS (Continuation of Example 4)

ECOS

The rule base for the primary indicators was created using the same method described in Example 4: Air (Continuation of Example 1 with the exeption of the mapping from secondary to primary linguistic variables is VBBAGVG to VBBAGVG. Consequently, the mapping equation is simply y = x. Table 3-4 summarizes the relative weighting of the ECOS indicators. AIR had the highest relative weight while WATER and LAND were weighted significantly less. For utility companies, the most significant environmental impact is emissions from electricity production – that is why AIR was weighed nine times higher than both LAND and WATER impacts.

AIR	LAND	WATER
9	1	1

Table 3-4: Assigned relative weights of secondary indicators within the ECOS indicator

Weighted Average Calculation for Rule 38 of Table V-1: ECOS Rule Base

	AIR	LAND	WATER	ECOS
38	B	A	A	B

Table 3-5: Rule 38 from ECOS Rule Base (Table V-1: ECOS Rule Base)

$$A \rightarrow 2$$
$$L \rightarrow 3$$
$$W \rightarrow 3$$

$$\frac{(RW_{air} * A + RW_{land} * L + RW_{water} * W)}{RW_{air} + RW_{land} + RW_{water}} = \frac{(4 * 2 + 2 * 3 + 1 * 3)}{4 + 2 + 1} = 2.4$$
$$y = x,\ x = 2.4$$
$$y = 2.4 \rightarrow \text{round down to } 2$$
$$2 \rightarrow B$$

Table 3-6 shows that 18 rules will fire from the rule base because there are 3 nonzero values for AIR, 2 nonzero values for LAND, and 3 nonzero values for WATER, 18 rules fire from the rule base: including 63 and 94.

	Year	VB	B	A	G	VG
AIR	2018	0	0.006	0.159	0.835	0
LAND	2018	0	0	0.103	0.897	0
WATER	2018	0	0	0.03	0.963	0.007

Table 3-6: NextEra Energy ECOS Secondary Indicators 2018

Using the Larsen Implication and summing the values of the same linguistic ECOS value, it can be calculated that the fuzzy values of ECOS fuzzy values are B(0.01) A(0.16) and G(0.84) in 2018 (Table 3-11). The associated crisp output is 0.48, calculated identically as Example 4: Air (Continuation of Example 1 except using the peak values of Figure 3-2: VBBAGVG Linguistic Variable.

HUMS

Table 3-7 summarizes the relative weighting of the HUMS indicator. For this model, the KNOW secondary indicator was removed due to a lack of data availability for basic indicators. Within the HUMS primary indicator, there were two secondary indicators with relative weights of 0.75 corresponding to POLIC and 2.5 corresponding to HEALTH. The two indicators were weighted almost identically, but with slight preference given to HEALTH. For the companies included within the model, the policies relating to lobbying spending and charitable giving (the basic indicators associated with POLIC) were determined to have slightly lower importance when considering the overall sustainability of the corporation. Lobbying has significant effects on the regulations and policies put in place that may have a significant impact on the future state of an investor-owned utility company but, were determined to be less of an indicator of sustainability than those included within the HEALTH indicator.

POLIC	HEALTH
0.75	2.5

Table 3-7: Assigned relative weights of secondary indicators within the HUMS indicator

Table V-2: HUMS Rule Base was constructed in the same fashion as Table V-1: ECOS Rule Base, described in the previous section, but with different weights associated with the new secondary indicators. Six rules fire from the rule base and the fuzzy values for HUMS are A(0.32) and G(0.68); the associated crisp value is 0.54 (Table 3-11).

	Year	VB	B	A	G	VG
HEALTH	2018	0	0	0.091	0.909	0
POLIC	2018	0.252	0.662	0.086	0	0

Table 3-8: NextEra Energy HUMS Secondary Indicators 2018

WEALTH

Table 3-9 summarizes the relative weights of the WEALTH secondary indicators. STATUS was weighed higher than the other secondary indicators because the profitability ratios contained within it would have the largest impact on the financial performance of a utility company. The RESPONSE indicator was weighed lower than the STATUS indicator to reduce variability caused by the cyclical nature of CF/CAPEX as utilities make large investments every few years. The PRESSURE indicator was weighted the least for the same reason, to reduce the variability caused by the cyclical nature of it's indicators.

STATUS	PRESSURE	RESPONSE
2.5	1	1.5

Table 3-9: NextEra Energy WEALTH Secondary Indicators 2018

Table V-3: WEALTH Rule Base was constructed in the same fashion as Table V-1: ECOS Rule Base, described in the previous section, but with different weights associated with the new secondary indicators. Four rules fire from the rule base and the fuzzy values for WEALTH are B(0.9) and A(0.1). The associated crisp output is 0.37.

	Year	VB	B	A	G	VG
STATUS	2018	0	0	1	0	0
RESPONSE	2018	1	0	0	0	0
PRESSURE	2018	0	0	0.9	0.1	0

Table 3-10: NextEra Energy WEALTH Secondary Indicators 2018

NextEra Energy Inc.						
	Year	VB	B	A	G	VG
ECOS	2014	0	0.04	0.3	0.67	0
	2015	0	0.04	0.32	0.64	0
	2016	0	0.01	0.22	0.77	0
	2017	0	0.01	0.23	0.75	0
	2018	0	0.01	0.16	0.84	0
HUMS	2014	0	0	1	0	0
	2015	0	0	0.53	0.47	0
	2016	0.31	0.52	0.17	0	0
	2017	0	0	0.54	0.46	0
	2018	0	0	0.32	0.68	0
WEALTH	2014	0	0.21	0.79	0	0
	2015	0	0.2	0.8	0	0
	2016	0	0.18	0.8	0.03	0
	2017	0	0.52	0.49	0	0
	2018	0	0.9	0.1	0	0

Table 3-11: Summary of fuzzy primary values calculated for NextEra Energy

Table VI-1 and Table VI-2 summarize the fuzzy primary indicator values calculated for Duke Energy and Exelon and can be found in Appendix VI: Fuzzy Primary Indicator Values.

4. Results

G. Overall Sustainability from 2014-2018

The results show NextEra and Exelon were consistently more sustainable than Duke Energy during 2014-2018. Duke has shown the most improvement over time, while the other two corporations remained relatively constant.

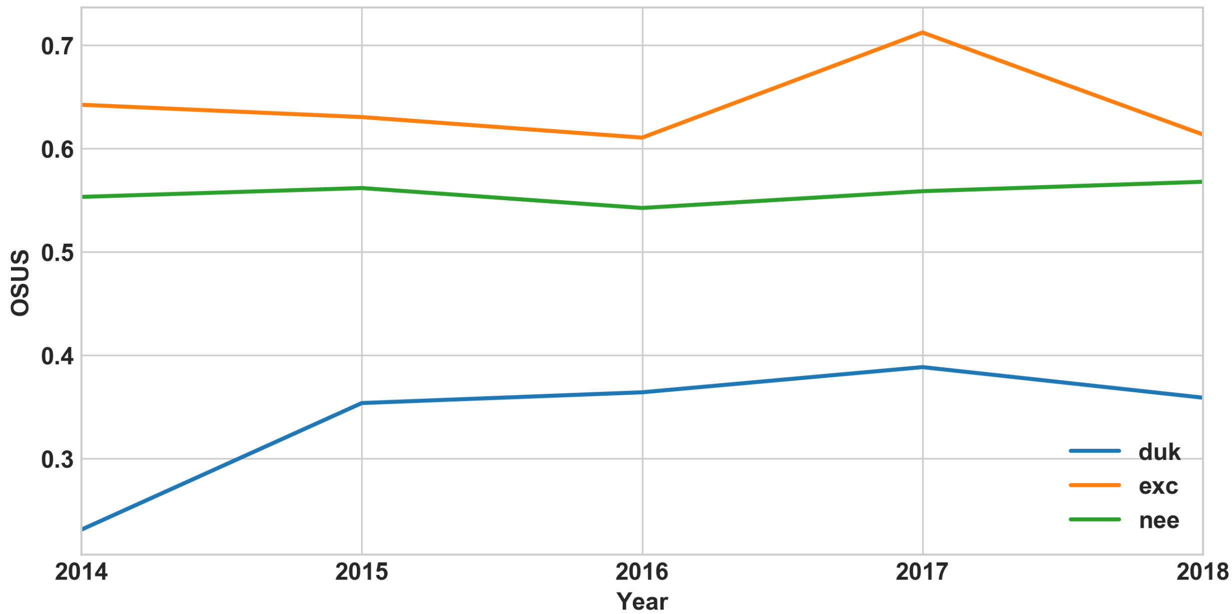

Figure 4-1: Graph of crisp values of overall sustainability calculated using the modified SAFE model

NextEra Energy had the most consistent overall sustainability over time. Based on the results, the financials of NextEra Energy appeared to have the most significant impact on overall sustainability of the corporation (Table 3-11). NextEra Energy has grown significantly over the past few years and have been making large investments in renewable (Table 3-11). Table 3-3 shows that the RESPONSE indicator has a trend to lower values. Upon further investigation into trends in the Raw Data, it appears as though the CF/CAPEX and Dividend Payouts indicators have decreased in value over time. As a result of the large capital investments NextEra is making, the corporation is achieving a lower CF/CAPEX, while simultaneously cutting back on the amount dividends they disperse. The sensitivity analysis (Figure 4-2) reveals that NextEra could benefit its overall sustainability significantly by focusing on improving its dividend payout ratio. It is likely NextEra Energy will do this as they start reaping the rewards of their renewable energy investments over time. These renewable energy investments will have low operational costs compared to fuel-based power plants. Outside of the company's weath indicators, NextEra's policies and impact on ecosystems appear to be improving over time.

Similarly, Exelon's financials appear to be reducing the overall sustainability of the corporation. This can be concluded from the fact that the HUMS and ECOS indicators have been relatively stable and high (Table VI-2). The results indicate that the financial PRESSURE and RESPONSE indicators have been decreasing over time. The results indicate an uptick in overall sustainability in the year 2017. This was likely caused by a sudden and short-lived improvement in performance of the PRESSURE indicator driven by a negative effective tax rate for that year (Raw Data). According to the sensitivity analysis, Exelon should focus on improving its return on assets and return on equity (Figure 4-2).

Though Duke has the 'dirtiest' energy mix from the three energy utility corporations studied, they have been improving over the period of analysis— coal made up 42% of their energy generation in 2014, and by 2018, it fell to about 30%. According to the sensitivity analysis, Duke can improve its sustainability the most by improving their clean generation (Figure 4-2). Meanwhile, Duke has seen significant improvement in the HUMS indicator, largely as a result of the HEALTH indicator and the decreasing injury rates. Financial PRESSURE and RESPONSE have also added to the company's improving overall sustainability. The regression between the years of 2017 and 2018 can be traced to an increased injury rate and increased fatalities within the HEALTH indicator and a worse performance in return on assets within the STATUS indicator.

H. Sensitivity Analysis

A sensitivity analysis was conducted to find the most impactful basic indicators for each company's overall sustainability for the year 2018. The analysis was conducted by perturbing one basic indicator at a time, capturing the change in OSUS, computing a sensitivity factor, then finally ranking the indicator for each company from high to low. Figure 4-2 shows the rank of each basic indicator for each company and the average rank across the three companies. The results depict a range in results for each individual company. The average rank, shown below in yellow, provides a view of which indicators generally have the highest and lowest indication of OSUS. The indicators that were determined to have the most importance were Return on Equity and CO_2 Emissions. Higher confidence can be placed in the average rank as more companies are added to the model.

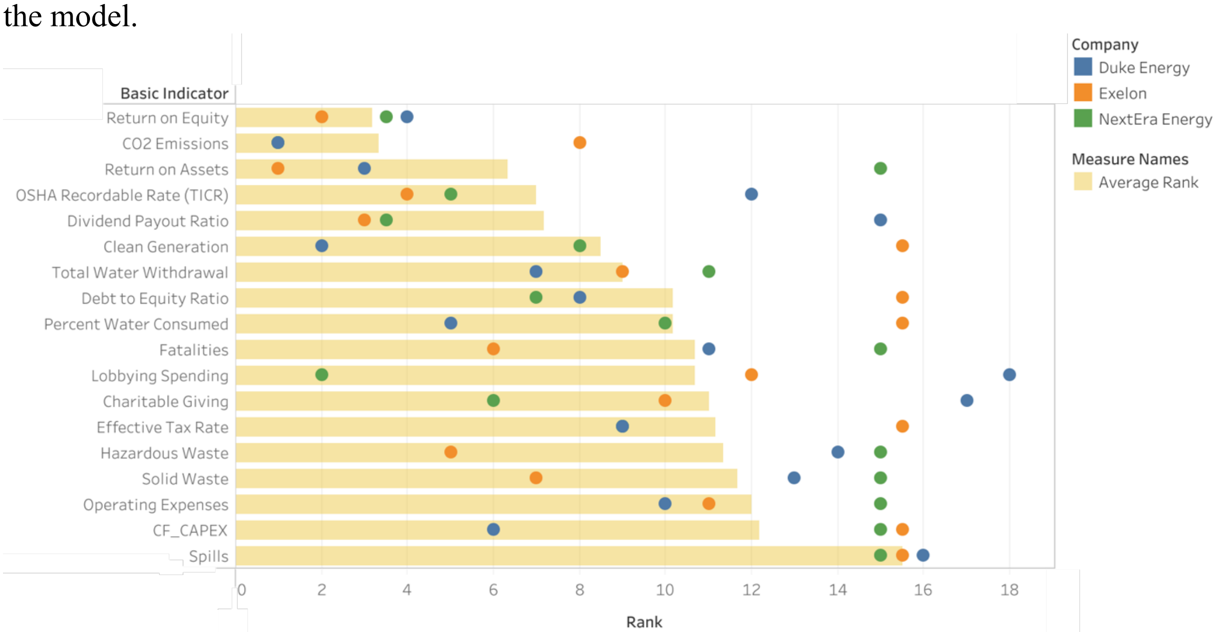

Figure 4-2:Rank of Basic Indicators in terms of their impact on OSUS in 2018 (Note: NextEra Energy overlaps with Duke Energy for both CO_2 emissions, and effective tax rate)

While return on equity (ROE) is the most straightforward way for ‘any’ utility to impact its overall sustainability, the spills indicator is consistently ranked as the least impactful. Notably, the majority of the basic indicators show high variability in rank between companies—this means that each company needs to prioritize different indicators to affect its overall sustainability. This result is expected considering each company differs in size, management, geographic area, energy mix, and many other factors. Priority could mean preventing a decrease and/or striving to achieve an improvement. For example, although NextEra and Duke are most affected by CO_2 Emissions, this isn’t the case for Exelon since the indicator ranks 8th most impactful. This result appears to be accurate considering that the vast majority of Exelon’s energy mix is nuclear power, a low carbon intensity source of energy. Instead, Exelon would be more successful in impacting its overall sustainability by prioritizing return on assets.

Appendix I: Raw Data

Note: NextEra Energy Inc is abbreviated as NEE, Duke Energy Corporation is abbreviated as DUK, and Exelon Corporation is abbreviated as EXC.

Primary Indicator	Secondary Indicator	Basic Indicator	Company	Year	Raw Value	Raw Value Units	Intensive Values	Intensive Value Units	Source
ECOS	AIR	Clean Generation	NEE	2014	2.50	% coal generation	2.50	% coal generation	NextEra Energy, By The Numbers [11]
ECOS	AIR	Clean Generation	NEE	2015	2.70	% coal generation	2.70	% coal generation	
ECOS	AIR	Clean Generation	NEE	2016	2.20	% coal generation	2.20	% coal generation	
ECOS	AIR	Clean Generation	NEE	2017	2.40	% coal generation	2.40	% coal generation	
ECOS	AIR	Clean Generation	NEE	2018	1.50	% coal generation	1.50	% coal generation	
ECOS	AIR	Clean Generation	DUK	2014	42.30	% coal generation	42.30	% coal generation	MJ Bradley, Emissions Benchmarking [1]
ECOS	AIR	Clean Generation	DUK	2015	35.20	% coal generation	35.20	% coal generation	
ECOS	AIR	Clean Generation	DUK	2016	33.70	% coal generation	33.70	% coal generation	
ECOS	AIR	Clean Generation	DUK	2017	33.20	% coal generation	33.20	% coal generation	
ECOS	AIR	Clean Generation	DUK	2018	30.30	% coal generation	30.30	% coal generation	2018 Annual Report [20]
ECOS	AIR	Clean Generation	EXC	2014	0.10	% coal generation	0.10	% coal generation	MJ Bradley, Emissions Benchmarking [1]
ECOS	AIR	Clean Generation	EXC	2015	0.10	% coal generation	0.10	% coal generation	
ECOS	AIR	Clean Generation	EXC	2016	0.10	% coal generation	0.10	% coal generation	
ECOS	AIR	Clean Generation	EXC	2017	0.00	% coal generation	0.00	% coal generation	
ECOS	AIR	Clean Generation	EXC	2018	0.00	% coal generation	0	% coal generation	Exelon Generation [21]
ECOS	AIR	CO_2 Emissions	NEE	2014	48573857.00	tons	0.260698873	tons/MWh	MJ Bradley, Emissions Benchmarking [1]
ECOS	AIR	CO_2 Emissions	NEE	2015	52793763.00	tons	0.265666941	tons/MWh	
ECOS	AIR	CO_2 Emissions	NEE	2016	43199657.00	tons	0.223051069	tons/MWh	

ECOS	AIR	CO_2 Emissions	NEE	2017	42194852.00	tons	0.223064346	tons/MWh	
ECOS	AIR	CO_2 Emissions	NEE	2018	42097424.00	tons	0.218023962	tons/MWh	NextEra Energy, By The Numbers [11]
ECOS	AIR	CO_2 Emissions	DUK	2014	138347641.00	tons	0.565915404	tons/MWh	MJ Bradley, Emissions Benchmarking [1]
ECOS	AIR	CO_2 Emissions	DUK	2015	107913913.00	tons	0.493390666	tons/MWh	
ECOS	AIR	CO_2 Emissions	DUK	2016	106376761.00	tons	0.485107331	tons/MWh	
ECOS	AIR	CO_2 Emissions	DUK	2017	104619272.00	tons	0.460316143	tons/MWh	
ECOS	AIR	CO_2 Emissions	DUK	2018	105000000.00	tons	0.450396349	tons/MWh	2018 Annual Report [22]
ECOS	AIR	CO_2 Emissions	EXC	2014	7138620.00	tons	0.040111155	tons/MWh	MJ Bradley, Emissions Benchmarking [1]
ECOS	AIR	CO_2 Emissions	EXC	2015	7397355.00	tons	0.041088898	tons/MWh	
ECOS	AIR	CO_2 Emissions	EXC	2016	9836775.00	tons	0.052643732	tons/MWh	
ECOS	AIR	CO_2 Emissions	EXC	2017	10394551.00	tons	0.053379599	tons/MWh	
ECOS	AIR	CO_2 Emissions	EXC	2018	9700000.00	tons	0.049942335	tons/MWh	2018 Annual Report [23]
ECOS	LAND	Spills	NEE	2014	0.00	# reportable spills	0	spills/Wh	NextEra Energy, By The Numbers [11]
ECOS	LAND	Spills	NEE	2015	2.00	# reportable spills	0.010064331	spills/Wh	
ECOS	LAND	Spills	NEE	2016	0.00	# reportable spills	0	spills/Wh	
ECOS	LAND	Spills	NEE	2017	1.00	# reportable spills	0.00528653	spills/Wh	
ECOS	LAND	Spills	NEE	2018	0.00	# reportable spills	0	spills/Wh	
ECOS	LAND	Spills	DUK	2014	26.00	# reportable spills	0.106353823	spills/Wh	Sus Report, 2014 [24]
ECOS	LAND	Spills	DUK	2015	23.00	# reportable spills	0.105157759	spills/Wh	Sus Report, 2015 [25]
ECOS	LAND	Spills	DUK	2016	23.00	# reportable spills	0.104886335	spills/Wh	Sus Report, 2016 [26]
ECOS	LAND	Spills	DUK	2017	18.00	# reportable spills	0.079198511	spills/Wh	Sus Report, 2017 [27]
ECOS	LAND	Spills	DUK	2018	28.00	# reportable spills	0.120105693	spills/Wh	Sus Report, 2018 [22]
ECOS	LAND	Spills	EXC	2014	592.00	# reportable spills	3.326385769	spills/Wh	Sustainability Report, 2018 [23]
ECOS	LAND	Spills	EXC	2015	726.00	# reportable spills	4.032595444	spills/Wh	
ECOS	LAND	Spills	EXC	2016	777.00	# reportable spills	4.158291688	spills/Wh	
ECOS	LAND	Spills	EXC	2017	746.00	# reportable spills	3.830966919	spills/Wh	
ECOS	LAND	Spills	EXC	2018	805.00	# reportable spills	4.144698904	spills/Wh	
ECOS	LAND	Solid Waste	NEE	2014	n/a	tons	479.4049442	tons/Wh	Average of 2017-2018
ECOS	LAND	Solid Waste	NEE	2015	n/a	tons	479.4049442	tons/Wh	
ECOS	LAND	Solid Waste	NEE	2016	n/a	tons	479.4049442	tons/Wh	
ECOS	LAND	Solid Waste	NEE	2017	37207.50	tons	196.698561	tons/Wh	NextEra Energy, By The Numbers [11]
ECOS	LAND	Solid Waste	NEE	2018	147153.20	tons	762.1113274	tons/Wh	
ECOS	LAND	Solid Waste	DUK	2014	n/a	tons	448.2971676	tons/Wh	Average of 2015-2018
ECOS	LAND	Solid Waste	DUK	2015	88000.00	tons	402.342732	tons/Wh	Sustainability Report, 2018 [28]
ECOS	LAND	Solid Waste	DUK	2016	102000.00	tons	465.1480949	tons/Wh	
ECOS	LAND	Solid Waste	DUK	2017	109000.00	tons	479.5909837	tons/Wh	
ECOS	LAND	Solid Waste	DUK	2018	104000.00	tons	446.1068598	tons/Wh	

ECOS	LAND	Solid Waste	EXC	2014	n/a	tons	531.8047795	tons/Wh	Average 2016-2018
ECOS	LAND	Solid Waste	EXC	2015	n/a	tons	531.8047795	tons/Wh	
ECOS	LAND	Solid Waste	EXC	2016	104000.00	tons	556.5795825	tons/Wh	Sustainability Report, 2018 [23]
ECOS	LAND	Solid Waste	EXC	2017	90000.00	tons	462.1809955	tons/Wh	
ECOS	LAND	Solid Waste	EXC	2018	112000.00	tons	576.6537606	tons/Wh	
ECOS	LAND	Hazardous Waste	NEE	2017	105.20	tons	0.556142945	tons/Wh	NextEra Energy, By The Numbers [11]
ECOS	LAND	Hazardous Waste	NEE	2018	222.20	tons	1.150781206	tons/Wh	
ECOS	LAND	Hazardous Waste	DUK	2015	317.00	tons	1.44934825	tons/Wh	Sustainability Report, 2018 [28]
ECOS	LAND	Hazardous Waste	DUK	2016	1195.00	tons	5.449529152	tons/Wh	
ECOS	LAND	Hazardous Waste	DUK	2017	126.00	tons	0.554389577	tons/Wh	
ECOS	LAND	Hazardous Waste	DUK	2018	281.00	tons	1.205346419	tons/Wh	
ECOS	LAND	Hazardous Waste	EXC	2016	3668.00	tons	19.63013374	tons/Wh	Sustainability Report Template [29]
ECOS	LAND	Hazardous Waste	EXC	2017	854.00	tons	4.385584113	tons/Wh	
ECOS	LAND	Hazardous Waste	EXC	2018	1460.00	tons	7.517093665	tons/Wh	
ECOS	WATER	Tot Water Withdr	NEE	2014	1752000000000	gallons	9.403091585	gallons/Wh	NextEra Energy, By The Numbers [11]
ECOS	WATER	Tot Water Withdr	NEE	2015	1857000000000	gallons	9.344730913	gallons/Wh	
ECOS	WATER	Tot Water Withdr	NEE	2016	1960000000000	gallons	10.11998998	gallons/Wh	
ECOS	WATER	Tot Water Withdr	NEE	2017	2025000000000	gallons	10.70522303	gallons/Wh	
ECOS	WATER	Tot Water Withdr	NEE	2018	5799000000000	gallons	23.72099302	gallons/Wh	
ECOS	WATER	Tot Water Withdr	DUK	2014	6250000000000	gallons	28.57547812	gallons/Wh	Sus Report, 2014 [24]
ECOS	WATER	Tot Water Withdr	DUK	2015	5341000000000	gallons	24.35643113	gallons/Wh	Sus Report, 2015 [25]
ECOS	WATER	Tot Water Withdr	DUK	2016	5293000000000	gallons	23.28876217	gallons/Wh	Sus Report, 2016 [26]
ECOS	WATER	Tot Water Withdr	DUK	2017	4991000000000	gallons	21.40883978	gallons/Wh	Sus Report, 2017 [27]
ECOS	WATER	Tot Water Withdr	DUK	2018	1960000000000	gallons	10.15090533	gallons/Wh	Sus Report, 2018 [22]
ECOS	WATER	Tot Water Withdr	EXC	2014	13849574000000	gallons	77.81930044	gallons/Wh	Corporate Sustainability Report, 2015-2018 Interactive [30]
ECOS	WATER	Tot Water Withdr	EXC	2015	13440737000000	gallons	74.65710025	gallons/Wh	
ECOS	WATER	Tot Water Withdr	EXC	2016	13456099000000	gallons	72.01336503	gallons/Wh	
ECOS	WATER	Tot Water Withdr	EXC	2017	15833678000000	gallons	81.31138957	gallons/Wh	
ECOS	WATER	Tot Water Withdr	EXC	2018	18986062000000	gallons	97.75342903	gallons/Wh	
ECOS	WATER	% Water Consum	NEE	2014	1.60	%	1.60	%	NextEra Energy, By The Numbers [11]
ECOS	WATER	% Water Consum	NEE	2015	2.20	%	2.20	%	
ECOS	WATER	% Water Consum	NEE	2016	1.50	%	1.50	%	
ECOS	WATER	% Water Consum	NEE	2017	1.50	%	1.50	%	
ECOS	WATER	% Water Consum	NEE	2018	1.50	%	1.50	%	
ECOS	WATER	% Water Consum	DUK	2014	1.60	%	1.60	%	Sus Report, 2014 [24]
ECOS	WATER	% Water Consum	DUK	2015	1.26	%	1.26	%	Sus Report, 2015 [25]

ECOS	WATER	% Water Consum	DUK	2016	1.39	%	1.39	%	Sus Report, 2016 [26]
ECOS	WATER	% Water Consum	DUK	2017	1.34	%	1.34	%	Sus Report, 2017 [27]
ECOS	WATER	% Water Consum	DUK	2018	1.68	%	1.68	%	Sus Report, 2018 [22]
ECOS	WATER	% Water Consum	EXC	2014	1.69	%	1.69	%	Corporate Sustainability Report, 2015-2018 Interactive [30]
ECOS	WATER	% Water Consum	EXC	2015	1.86	%	1.86	%	
ECOS	WATER	% Water Consum	EXC	2016	1.74	%	1.74	%	
ECOS	WATER	% Water Consum	EXC	2017	1.40	%	1.40	%	
ECOS	WATER	% Water Consum	EXC	2018	1.20	%	1.20	%	
HUMS	POLICY	Lobbying Spend	NEE	2014	4790000	$ expenditures	0.028176471	% operating revenue	Open Secrets [31]
HUMS	POLICY	Lobbying Spend	NEE	2015	2410000	$ expenditures	0.013771429	% operating revenue	
HUMS	POLICY	Lobbying Spend	NEE	2016	2810000	$ expenditures	0.017453416	% operating revenue	
HUMS	POLICY	Lobbying Spend	NEE	2017	4090000	$ expenditures	0.02377907	% operating revenue	
HUMS	POLICY	Lobbying Spend	NEE	2018	3470000	$ expenditures	0.020778443	% operating revenue	
HUMS	POLICY	Lobbying Spend	DUK	2014	5870000	$ expenditures	0.021400707	% operating revenue	Open Secrets [31]
HUMS	POLICY	Lobbying Spend	DUK	2015	5762000	$ expenditures	0.019567358	% operating revenue	
HUMS	POLICY	Lobbying Spend	DUK	2016	6770000	$ expenditures	0.02158801	% operating revenue	
HUMS	POLICY	Lobbying Spend	DUK	2017	6631595	$ expenditures	0.019761592	% operating revenue	
HUMS	POLICY	Lobbying Spend	DUK	2018	5345592	$ expenditures	0.014857947	% operating revenue	
HUMS	POLICY	Lobbying Spend	EXC	2014	5135000	$ expenditures	0.02327848	% operating revenue	Open Secrets [31]
HUMS	POLICY	Lobbying Spend	EXC	2015	6100000	$ expenditures	0.027267444	% operating revenue	
HUMS	POLICY	Lobbying Spend	EXC	2016	5230000	$ expenditures	0.022996087	% operating revenue	
HUMS	POLICY	Lobbying Spend	EXC	2017	4520000	$ expenditures	0.019180989	% operating revenue	
HUMS	POLICY	Lobbying Spend	EXC	2018	5625000	$ expenditures	0.022939521	% operating revenue	
HUMS	POLICY	Charitable Giving	NEE	2014	10981356	$	0.064596212	% operating revenue	NextEra Energy, By The Numbers [11]

HUMS	POLICY	Charitable Giving	NEE	2015	12774801	$	0.072998863	% operating revenue	
HUMS	POLICY	Charitable Giving	NEE	2016	12308826	$	0.076452335	% operating revenue	
HUMS	POLICY	Charitable Giving	NEE	2017	13830536	$	0.080410093	% operating revenue	
HUMS	POLICY	Charitable Giving	NEE	2018	13755679	$	0.082369335	% operating revenue	
HUMS	POLICY	Charitable Giving	DUK	2014	73400000	$	0.267599985	% operating revenue	Sus Report, 2014 [24]
HUMS	POLICY	Charitable Giving	DUK	2015	48600000	$	0.165042279	% operating revenue	Sus Report, 2015 [25]
HUMS	POLICY	Charitable Giving	DUK	2016	53600000	$	0.170918367	% operating revenue	Sus Report, 2016 [26]
HUMS	POLICY	Charitable Giving	DUK	2017	52400000	$	0.156147565	% operating revenue	Sus Report, 2017 [27]
HUMS	POLICY	Charitable Giving	DUK	2018	59800000	$	0.166212686	% operating revenue	Sus Report, 2018 [22]
HUMS	POLICY	Charitable Giving	EXC	2014	31400000	$	0.142345528	% operating revenue	Corporate Sustainability Report, 2018 [23]
HUMS	POLICY	Charitable Giving	EXC	2015	33000000	$	0.147512404	% operating revenue	
HUMS	POLICY	Charitable Giving	EXC	2016	46100000	$	0.202699732	% operating revenue	
HUMS	POLICY	Charitable Giving	EXC	2017	53100000	$	0.225334182	% operating revenue	
HUMS	POLICY	Charitable Giving	EXC	2018	51300000	$	0.209208434	% operating revenue	
HUMS	HEALTH	OSHA Rec Rate	NEE	2014	0.61	incidents/100 workers	0.61	incidents/100 workers	NextEra Energy, By The Numbers [11]
HUMS	HEALTH	OSHA Rec Rate	NEE	2015	0.73	incidents/100 workers	0.73	incidents/100 workers	
HUMS	HEALTH	OSHA Rec Rate	NEE	2016	0.7	incidents/100 workers	0.7	incidents/100 workers	
HUMS	HEALTH	OSHA Rec Rate	NEE	2017	0.53	incidents/100 workers	0.53	incidents/100 workers	
HUMS	HEALTH	OSHA Rec Rate	NEE	2018	0.56	incidents/100 workers	0.56	incidents/100 workers	
HUMS	HEALTH	OSHA Rec Rate	DUK	2014	0.58	incidents/100 workers	0.58	incidents/100 workers	Sus Report, 2014 [24]
HUMS	HEALTH	OSHA Rec Rate	DUK	2015	0.41	incidents/100 workers	0.41	incidents/100 workers	Sus Report, 2015 [25]
HUMS	HEALTH	OSHA Rec Rate	DUK	2016	0.4	incidents/100 workers	0.4	incidents/100 workers	Sus Report, 2016 [26]

HUMS	HEALTH	OSHA Rec Rate	DUK	2017	0.36	incidents/100 workers	0.36	incidents/100 workers	Sus Report, 2017 [27]
HUMS	HEALTH	OSHA Rec Rate	DUK	2018	0.43	incidents/100 workers	0.43	incidents/100 workers	Sus Report, 2018 [22]
HUMS	HEALTH	OSHA Rec Rate	EXC	2014	0.73	incidents/100 workers	0.73	incidents/100 workers	Corporate Sustainability Report, 2015-2018 Interactive [30]
HUMS	HEALTH	OSHA Rec Rate	EXC	2015	0.91	incidents/100 workers	0.91	incidents/100 workers	
HUMS	HEALTH	OSHA Rec Rate	EXC	2016	0.65	incidents/100 workers	0.65	incidents/100 workers	
HUMS	HEALTH	OSHA Rec Rate	EXC	2017	0.52	incidents/100 workers	0.52	incidents/100 workers	
HUMS	HEALTH	OSHA Rec Rate	EXC	2018	0.57	incidents/100 workers	0.57	incidents/100 workers	
HUMS	HEALTH	Fatalities	NEE	2014	0	fatalities	0	% of workforce * 100	OSHA, Establishment Search [32]
HUMS	HEALTH	Fatalities	NEE	2015	0	fatalities	0	% of workforce * 100	
HUMS	HEALTH	Fatalities	NEE	2016	2	fatalities	1.360544218	% of workforce * 100	
HUMS	HEALTH	Fatalities	NEE	2017	0	fatalities	0	% of workforce * 100	
HUMS	HEALTH	Fatalities	NEE	2018	0	fatalities	0	% of workforce * 100	
HUMS	HEALTH	Fatalities	DUK	2014	4	fatalities	1.411233418	% of workforce * 100	2018 Annual Report [20]
HUMS	HEALTH	Fatalities	DUK	2015	5	fatalities	1.729804532	% of workforce * 100	
HUMS	HEALTH	Fatalities	DUK	2016	0	fatalities	0	% of workforce * 100	
HUMS	HEALTH	Fatalities	DUK	2017	2	fatalities	0.686271146	% of workforce * 100	
HUMS	HEALTH	Fatalities	DUK	2018	3	fatalities	1.002573271	% of workforce * 100	
HUMS	HEALTH	Fatalities	EXC	2014	0	fatalities	0	% of workforce * 100	Corporate Sustainability Report, 2015-2018 Interactive [30]
HUMS	HEALTH	Fatalities	EXC	2015	0	fatalities	0	% of workforce * 100	
HUMS	HEALTH	Fatalities	EXC	2016	0	fatalities	0	% of workforce * 100	
HUMS	HEALTH	Fatalities	EXC	2017	2	fatalities	0.579223262	% of workforce * 100	
HUMS	HEALTH	Fatalities	EXC	2018	1	fatalities	0.299553665	% of workforce * 100	

WEALTH	PRESSURE	Debt to Equity	NEE	2014	2.762251	unitless	2.762251	%	Financial Modeling Prep [19]
WEALTH	PRESSURE	Debt to Equity	NEE	2015	2.653717	unitless	2.653717	%	
WEALTH	PRESSURE	Debt to Equity	NEE	2016	2.697178	unitless	2.697178	%	
WEALTH	PRESSURE	Debt to Equity	NEE	2017	2.468059	unitless	2.468059	%	
WEALTH	PRESSURE	Debt to Equity	NEE	2018	2.037195	unitless	2.037195	%	
WEALTH	PRESSURE	Debt to Equity	DUK	2014	1.953125	unitless	1.953125	%	Financial Modeling Prep [19]
WEALTH	PRESSURE	Debt to Equity	DUK	2015	2.049714	unitless	2.049714	%	
WEALTH	PRESSURE	Debt to Equity	DUK	2016	2.235469	unitless	2.235469	%	
WEALTH	PRESSURE	Debt to Equity	DUK	2017	2.304200	unitless	2.3042	%	
WEALTH	PRESSURE	Debt to Equity	DUK	2018	2.318164	unitless	2.318164	%	
WEALTH	PRESSURE	Debt to Equity	EXC	2014	2.839968	unitless	2.839968	%	Financial Modeling Prep [19]
WEALTH	PRESSURE	Debt to Equity	EXC	2015	2.698058	unitless	2.698058	%	
WEALTH	PRESSURE	Debt to Equity	EXC	2016	3.447266	unitless	3.447266	%	
WEALTH	PRESSURE	Debt to Equity	EXC	2017	2.908631	unitless	2.908631	%	
WEALTH	PRESSURE	Debt to Equity	EXC	2018	2.889806	unitless	2.889806	%	
WEALTH	PRESSURE	Eff Tax Rate	NEE	2014	0.322634	unitless	32.2634	%	Financial Modeling Prep [19]
WEALTH	PRESSURE	Eff Tax Rate	NEE	2015	0.307769	unitless	30.7769	%	
WEALTH	PRESSURE	Eff Tax Rate	NEE	2016	0.315178	unitless	31.5178	%	
WEALTH	PRESSURE	Eff Tax Rate	NEE	2017	-0.139919	unitless	-13.9919	%	
WEALTH	PRESSURE	Eff Tax Rate	NEE	2018	0.214363	unitless	21.4363	%	
WEALTH	PRESSURE	Eff Tax Rate	DUK	2014	0.403725	unitless	40.3725	%	Financial Modeling Prep [19]
WEALTH	PRESSURE	Eff Tax Rate	DUK	2015	0.320522	unitless	32.0522	%	
WEALTH	PRESSURE	Eff Tax Rate	DUK	2016	0.309588	unitless	30.9588	%	
WEALTH	PRESSURE	Eff Tax Rate	DUK	2017	0.280356	unitless	28.0356	%	
WEALTH	PRESSURE	Eff Tax Rate	DUK	2018	0.145786	unitless	14.5786	%	
WEALTH	PRESSURE	Eff Tax Rate	EXC	2014	0.267900	unitless	26.79	%	Financial Modeling Prep [19]
WEALTH	PRESSURE	Eff Tax Rate	EXC	2015	0.322222	unitless	32.2222	%	
WEALTH	PRESSURE	Eff Tax Rate	EXC	2016	0.382604	unitless	38.2604	%	
WEALTH	PRESSURE	Eff Tax Rate	EXC	2017	-0.03328	unitless	-3.328	%	
WEALTH	PRESSURE	Eff Tax Rate	EXC	2018	0.053763	unitless	5.3763	%	
WEALTH	PRESSURE	Operating Expen	NEE	2014	5602000000.00	$	30.07	$/MWh	Annual Report, 2016 [33]
WEALTH	PRESSURE	Operating Expen	NEE	2015	5327000000.00	$	26.81	$/MWh	
WEALTH	PRESSURE	Operating Expen	NEE	2016	3992000000.00	$	20.61	$/MWh	Annual Report, 2018 [34]
WEALTH	PRESSURE	Operating Expen	NEE	2017	4071000000.00	$	21.52	$/MWh	
WEALTH	PRESSURE	Operating Expen	NEE	2018	3732000000.00	$	19.33	$/MWh	
WEALTH	PRESSURE	Operating Expen	DUK	2014	7732000000.00	$	31.63	$/MWh	Annual Report, 2016 [35]
WEALTH	PRESSURE	Operating Expen	DUK	2015	7355000000.00	$	33.63	$/MWh	
WEALTH	PRESSURE	Operating Expen	DUK	2016	6625000000.00	$	30.21	$/MWh	Annual Report, 2018 [20]
WEALTH	PRESSURE	Operating Expen	DUK	2017	6350000000.00	$	27.94	$/MWh	
WEALTH	PRESSURE	Operating Expen	DUK	2018	6831000000.00	$	29.30	$/MWh	
WEALTH	PRESSURE	Operating Expen	EXC	2014	13003000000.00	$	73.06	$/MWh	Annual Report, 2015 [36]
WEALTH	PRESSURE	Operating Expen	EXC	2015	13084000000.00	$	72.68	$/MWh	
WEALTH	PRESSURE	Operating Expen	EXC	2016	12640000000.00	$	67.65	$/MWh	

WEALTH	PRESSURE	Operating Expen	EXC	2017	14035000000.00	$	72.07	$/MWh	Annual Report, 2018 [37]
WEALTH	PRESSURE	Operating Expen	EXC	2018	16670000000.00	$	85.83	$/MWh	
WEALTH	STATUS	Return on Equity	NEE	2014	0.12377	unitless	12.377	%	Financial Modeling Prep [19]
WEALTH	STATUS	Return on Equity	NEE	2015	0.12191	unitless	12.191	%	
WEALTH	STATUS	Return on Equity	NEE	2016	0.119634	unitless	11.9634	%	
WEALTH	STATUS	Return on Equity	NEE	2017	0.190655	unitless	19.0655	%	
WEALTH	STATUS	Return on Equity	NEE	2018	0.194412	unitless	19.4412	%	
WEALTH	STATUS	Return on Equity	DUK	2014	0.046067	unitless	4.6067	%	Financial Modeling Prep [19]
WEALTH	STATUS	Return on Equity	DUK	2015	0.070884	unitless	7.0884	%	
WEALTH	STATUS	Return on Equity	DUK	2016	0.052446	unitless	5.2446	%	
WEALTH	STATUS	Return on Equity	DUK	2017	0.073289	unitless	7.3289	%	
WEALTH	STATUS	Return on Equity	DUK	2018	0.060844	unitless	6.0844	%	
WEALTH	STATUS	Return on Equity	EXC	2014	0.071789	unitless	7.1789	%	Financial Modeling Prep [19]
WEALTH	STATUS	Return on Equity	EXC	2015	0.08797	unitless	8.797	%	
WEALTH	STATUS	Return on Equity	EXC	2016	0.043891	unitless	4.3891	%	
WEALTH	STATUS	Return on Equity	EXC	2017	0.09023	unitless	9.023	%	
WEALTH	STATUS	Return on Equity	EXC	2018	0.012937	unitless	1.2937	%	
WEALTH	STATUS	Return on Assets	NEE	2014	0.032898	unitless	3.2898	%	Financial Modeling Prep [19]
WEALTH	STATUS	Return on Assets	NEE	2015	0.033366	unitless	3.3366	%	
WEALTH	STATUS	Return on Assets	NEE	2016	0.032358	unitless	3.2358	%	
WEALTH	STATUS	Return on Assets	NEE	2017	0.054975	unitless	5.4975	%	
WEALTH	STATUS	Return on Assets	NEE	2018	0.06401	unitless	6.401	%	
WEALTH	STATUS	Return on Assets	DUK	2014	0.015599	unitless	1.5599	%	Financial Modeling Prep [19]
WEALTH	STATUS	Return on Assets	DUK	2015	0.023243	unitless	2.3243	%	
WEALTH	STATUS	Return on Assets	DUK	2016	0.01621	unitless	1.621	%	
WEALTH	STATUS	Return on Assets	DUK	2017	0.02218	unitless	2.218	%	
WEALTH	STATUS	Return on Assets	DUK	2018	0.018337	unitless	1.8337	%	
WEALTH	STATUS	Return on Assets	EXC	2014	0.021060915	unitless	2.106091465	%	Financial Modeling Prep [19]
WEALTH	STATUS	Return on Assets	EXC	2015	0.023588862	unitless	2.358886186	%	
WEALTH	STATUS	Return on Assets	EXC	2016	0.010404343	unitless	1.040434268	%	
WEALTH	STATUS	Return on Assets	EXC	2017	0.033193457	unitless	3.319345722	%	
WEALTH	STATUS	Return on Assets	EXC	2018	0.017415139	unitless	1.74151388	%	
WEALTH	RESPONSE	CF/CAPEX	NEE	2014	1.603966	unitless	1.603966	unitless	Financial Modeling Prep [19]
WEALTH	RESPONSE	CF/CAPEX	NEE	2015	1.572572	unitless	1.572572	unitless	
WEALTH	RESPONSE	CF/CAPEX	NEE	2016	1.502123	unitless	1.502123	unitless	
WEALTH	RESPONSE	CF/CAPEX	NEE	2017	1.186042	unitless	1.186042	unitless	
WEALTH	RESPONSE	CF/CAPEX	NEE	2018	1.097005	unitless	1.097005	unitless	
WEALTH	RESPONSE	CF/CAPEX	DUK	2014	1.223254	unitless	1.223254	unitless	
WEALTH	RESPONSE	CF/CAPEX	DUK	2015	0.986698	unitless	0.986698	unitless	
WEALTH	RESPONSE	CF/CAPEX	DUK	2016	0.860397	unitless	0.860397	unitless	
WEALTH	RESPONSE	CF/CAPEX	DUK	2017	0.823895	unitless	0.823895	unitless	
WEALTH	RESPONSE	CF/CAPEX	DUK	2018	0.765364	unitless	0.765364	unitless	
WEALTH	RESPONSE	CF/CAPEX	EXC	2014	0.733421	unitless	0.733421	unitless	

WEALTH	RESPONSE	CF/CAPEX	EXC	2015	0.998951	unitless	0.998951	unitless	
WEALTH	RESPONSE	CF/CAPEX	EXC	2016	0.987373	unitless	0.987373	unitless	
WEALTH	RESPONSE	CF/CAPEX	EXC	2017	0.986287	unitless	0.986287	unitless	
WEALTH	RESPONSE	CF/CAPEX	EXC	2018	1.138267	unitless	1.138267	unitless	
WEALTH	RESPONSE	Dividend Payout	NEE	2014	0.511562	unitless	51.1562	%	Financial Modeling Prep [19]
WEALTH	RESPONSE	Dividend Payout	NEE	2015	0.50327	unitless	50.327	%	
WEALTH	RESPONSE	Dividend Payout	NEE	2016	0.553571	unitless	55.3571	%	
WEALTH	RESPONSE	Dividend Payout	NEE	2017	0.343064	unitless	34.3064	%	
WEALTH	RESPONSE	Dividend Payout	NEE	2018	0.316511	unitless	31.6511	%	
WEALTH	RESPONSE	Dividend Payout	DUK	2014	1.186405	unitless	118.6405	%	
WEALTH	RESPONSE	Dividend Payout	DUK	2015	0.800426	unitless	80.0426	%	
WEALTH	RESPONSE	Dividend Payout	DUK	2016	1.083643	unitless	108.3643	%	
WEALTH	RESPONSE	Dividend Payout	DUK	2017	0.800915	unitless	80.0915	%	
WEALTH	RESPONSE	Dividend Payout	DUK	2018	0.926857	unitless	92.6857	%	
WEALTH	RESPONSE	Dividend Payout	EXC	2014	0.656192	unitless	65.6192	%	
WEALTH	RESPONSE	Dividend Payout	EXC	2015	0.486999	unitless	48.6999	%	
WEALTH	RESPONSE	Dividend Payout	EXC	2016	1.028219	unitless	102.8219	%	
WEALTH	RESPONSE	Dividend Payout	EXC	2017	0.458797	unitless	45.8797	%	
WEALTH	RESPONSE	Dividend Payout	EXC	2018	3.346734	unitless	334.6734	%	

Raw Data: Annual Net Generation (MWh)

Year	NextEra Energy	Duke Energy	Exelon
2014	186,321,699	244,467,000.00	177,970,939
2015	198,721,613	218,719,000.00	180,032,937
2016	193,676,081	219,285,000.00	186,855,579
2017	189,160,001	227,277,000.00	194,728,907
2018	193,086,226	233,128,000.00	194,224,000
	NextEra By The Numbers [11]	Duke Energy, Sustainability Reports [22], [25]–[27]	MJ Bradley Emissions Reports [1]

Raw Data: Total Employees

Year	NextEra Energy	Duke Energy	Exelon
2014	13,800	28,344	28,993
2015	14,300	28,905	29,762
2016	14,700	28,790	34,396
2017	13,900	29,143	34,529
2018	14,300	29,923	33,383
	NextEra By The Numbers [11]	Duke Energy, Sustainability Reports [22], [25]–[27]	Exelon, Annual Reports [36], [37]

Raw Data: Annual Operating Revenue ($)

Year	NextEra Energy	Duke Energy	Exelon
2014	17,000,000,000.00	27,429,000,000.00	22,059,000,000.00
2015	17,500,000,000.00	29,447,000,000.00	22,371,000,000.00
2016	16,100,000,000.00	31,360,000,000.00	22,743,000,000.00
2017	17,200,000,000.00	33,558,000,000.00	23,565,000,000.00
2018	16,700,000,000.00	35,978,000,000.00	24,521,000,000.00
	NextEra By The Numbers [11]	Duke Energy, Financials & Performance [38], [39]	Statista [40]

Appendix II: Normalization Curves

Basic Indicator	Type
1. Clean Generation	Lower is Better
2. CO_2 emissions	Lower is Better
3. Spills	Lower is Better
4. Solid Waste	Lower is Better
5. Hazardous Waste	Lower is Better
6. Total Water Withdrawal	Lower is Better
7. Percent of Water Consumed	Lower is Better
8. Lobbying Spending	Lower is Better
9. Charitable Giving	Higher is Better
10. OSHA Recordable Rate	Lower is Better
11. Fatalities	Lower is Better
12. Debt to Equity Ratio	Middle is Better
13. Effective Tax Rate	Lower is Better
14. Operating Expenses	Lower is Better
15. Return on Equity	Middle is Better
16. Return on Assets	Higher is Better
17. CF/CAPEX	Higher is Better
18. Dividend Payout Ratio	Middle is Better

Rational is explained in Basic Indicators & Data Collection.

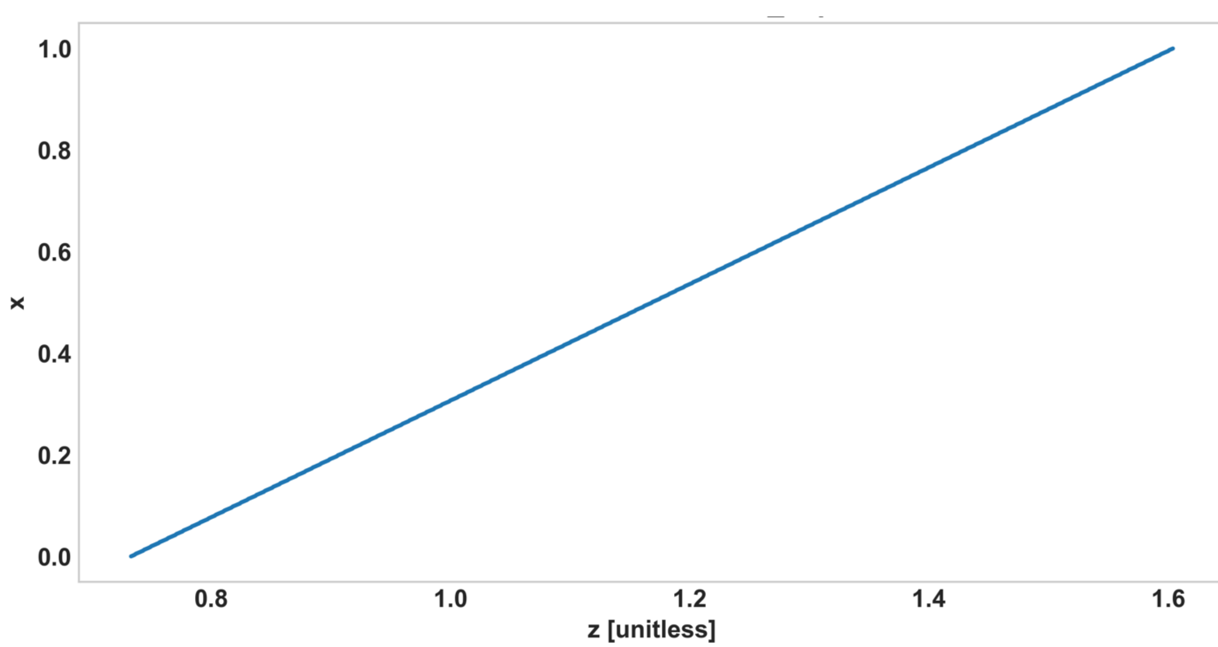

Figure II-1: CF/CAPEX Basic Indicator Normalization Curve

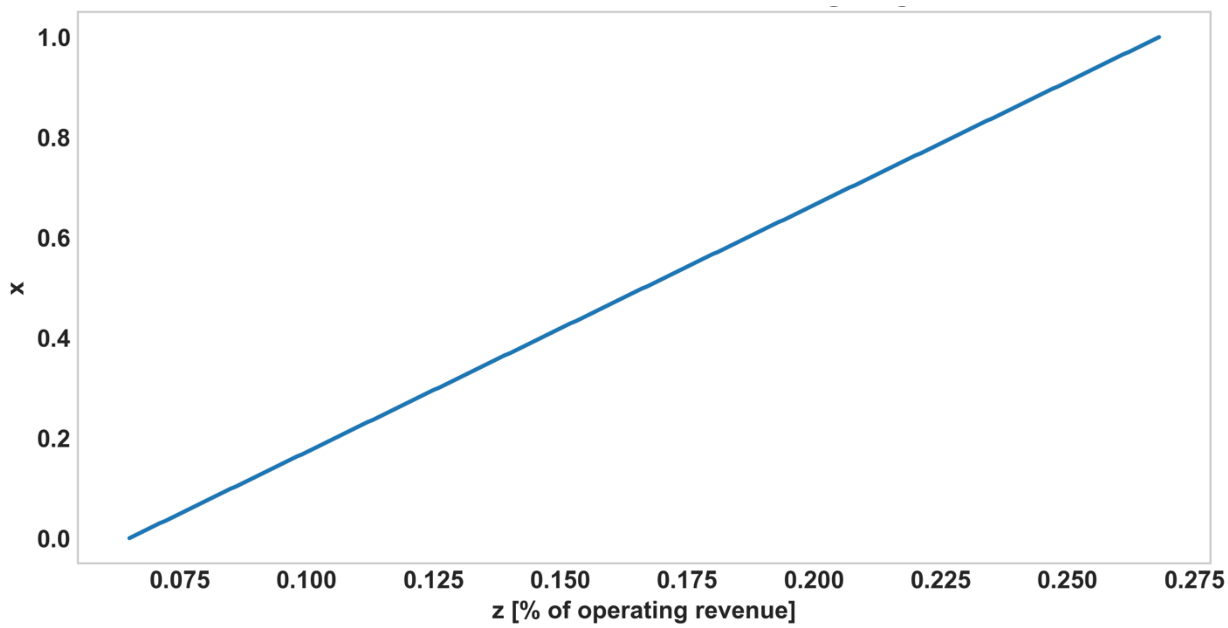

Figure II-2: Charitable Giving Basic Indicator Normalization Curve

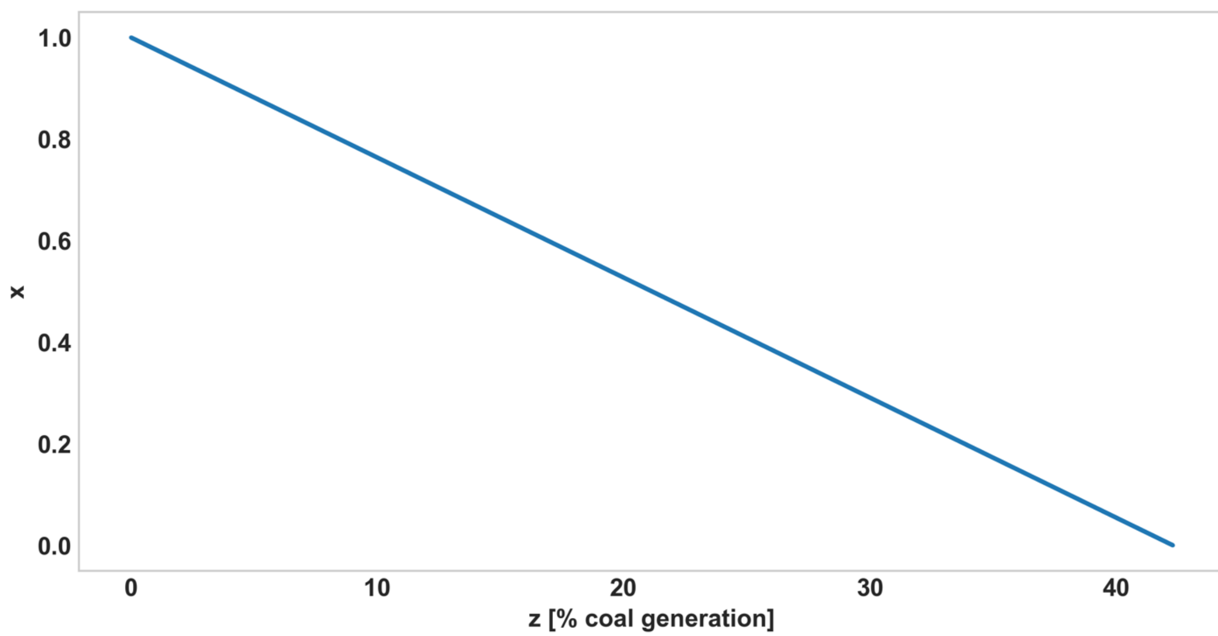

Figure II-3: Clean Generation Basic Indicator Normalization Curve

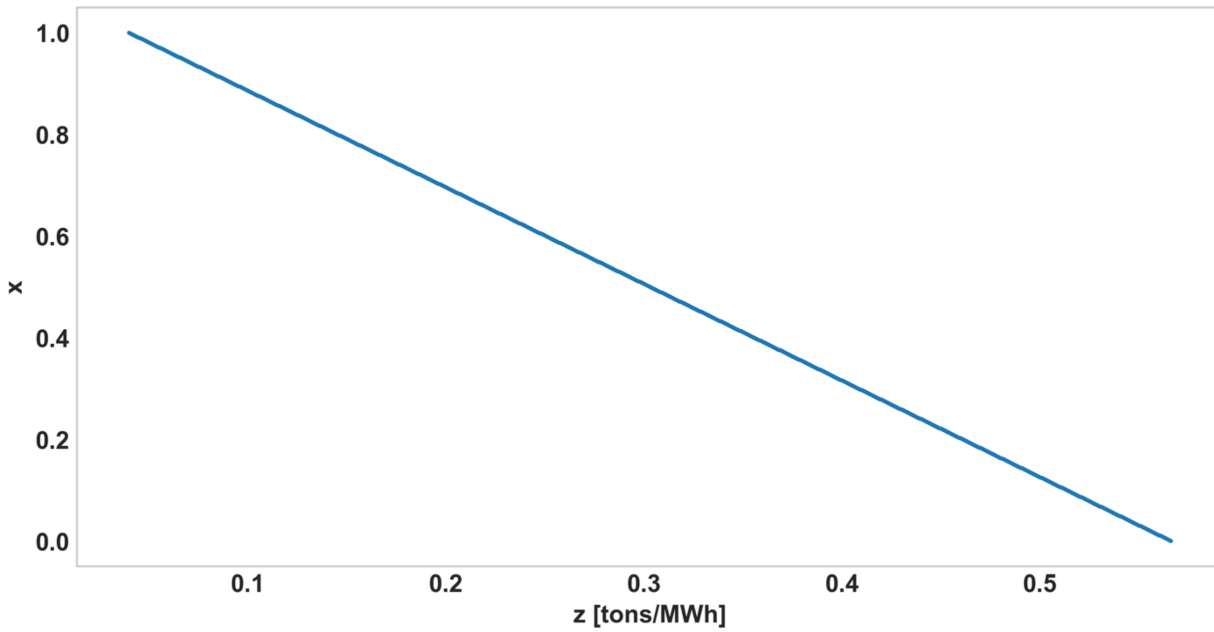

Figure II-4: CO_2 Emissions Basic Indicator Normalization Curve

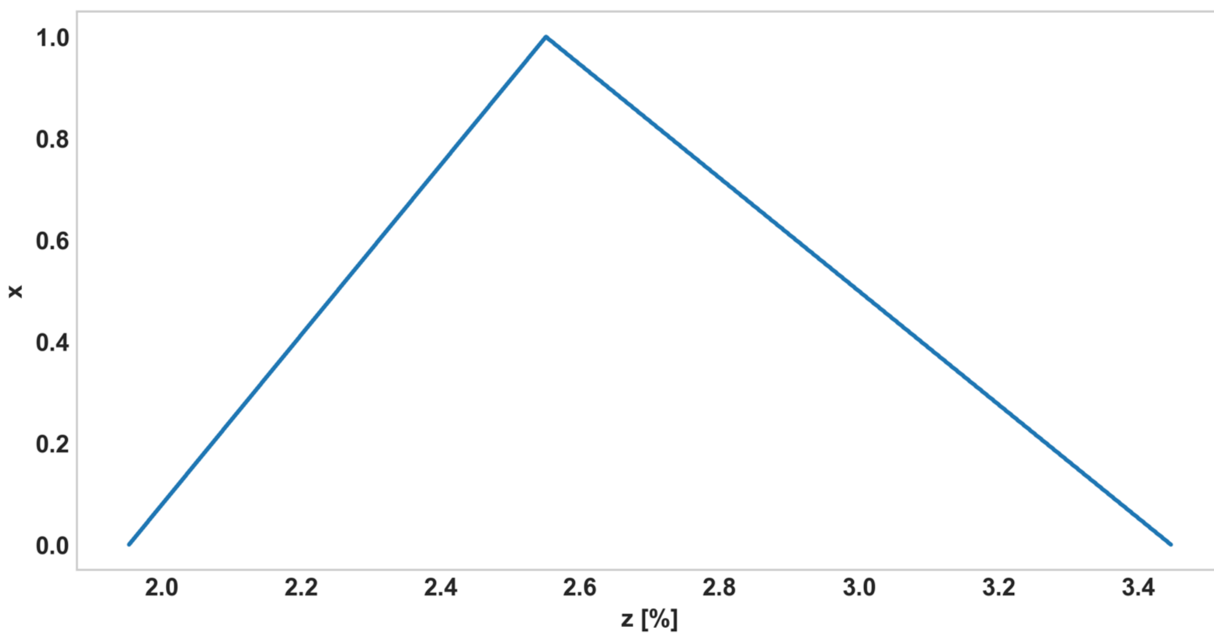

Figure II-5: Debt to Equity Ratio Basic Indicator Normalization Curve

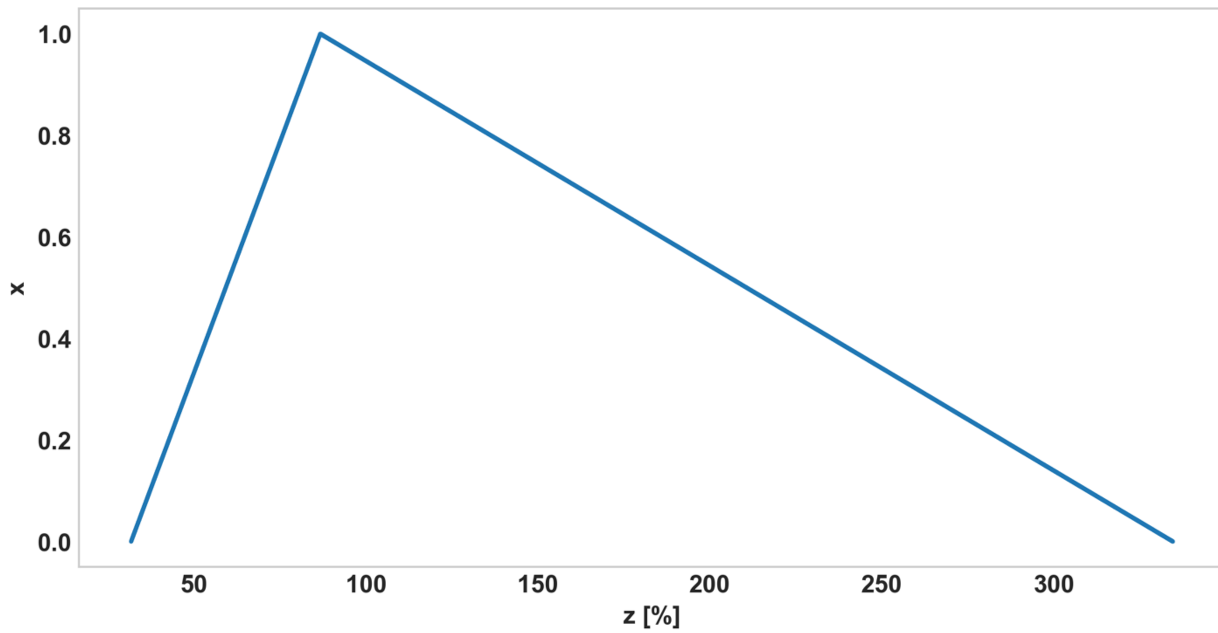

Figure II-6: Dividend Payout Ratio Basic Indicator Normalization Curve

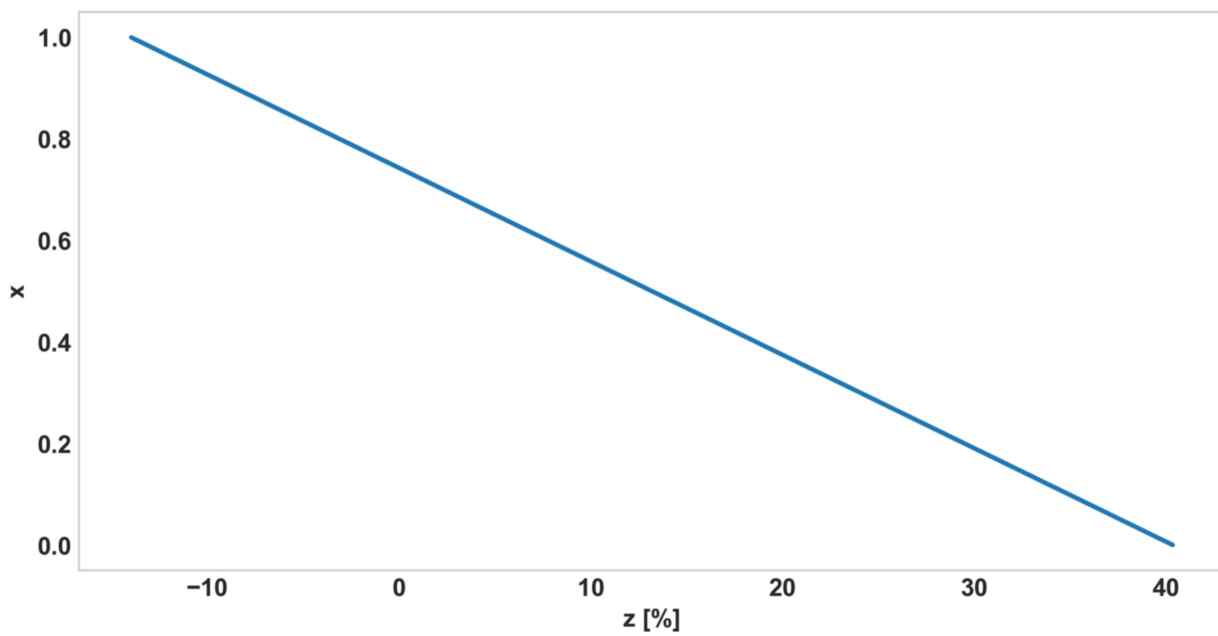

Figure II-7: Effective Tax Rate Basic Indicator Normalization Curve

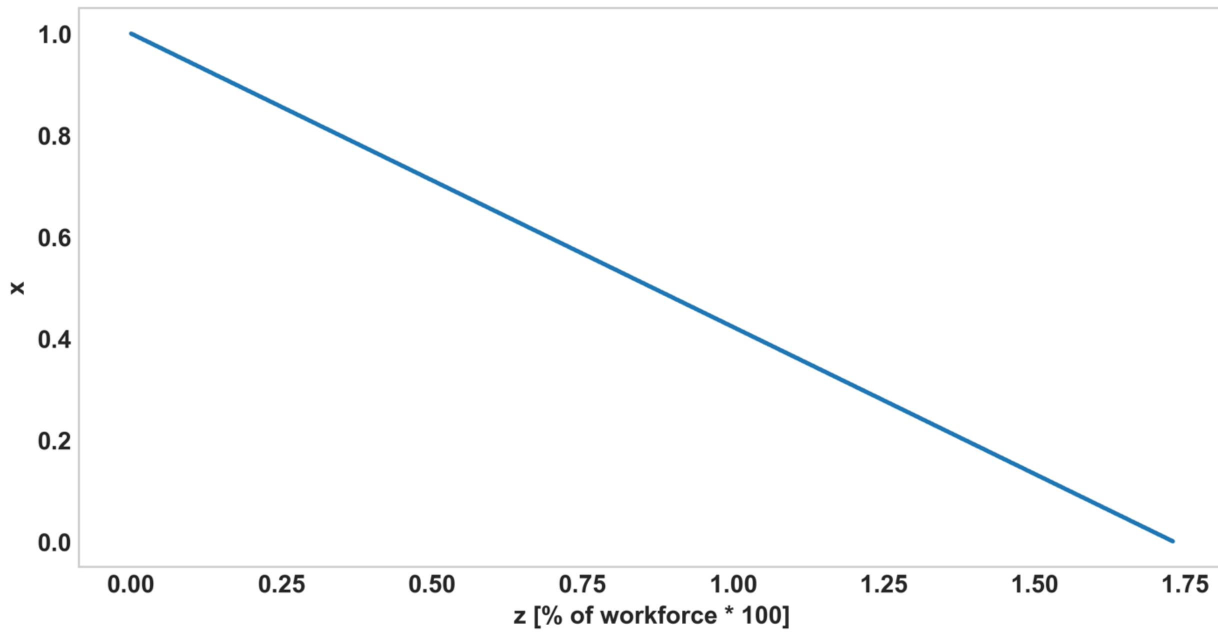

Figure II-8: Fatalities Basic Indicator Normalization Curve

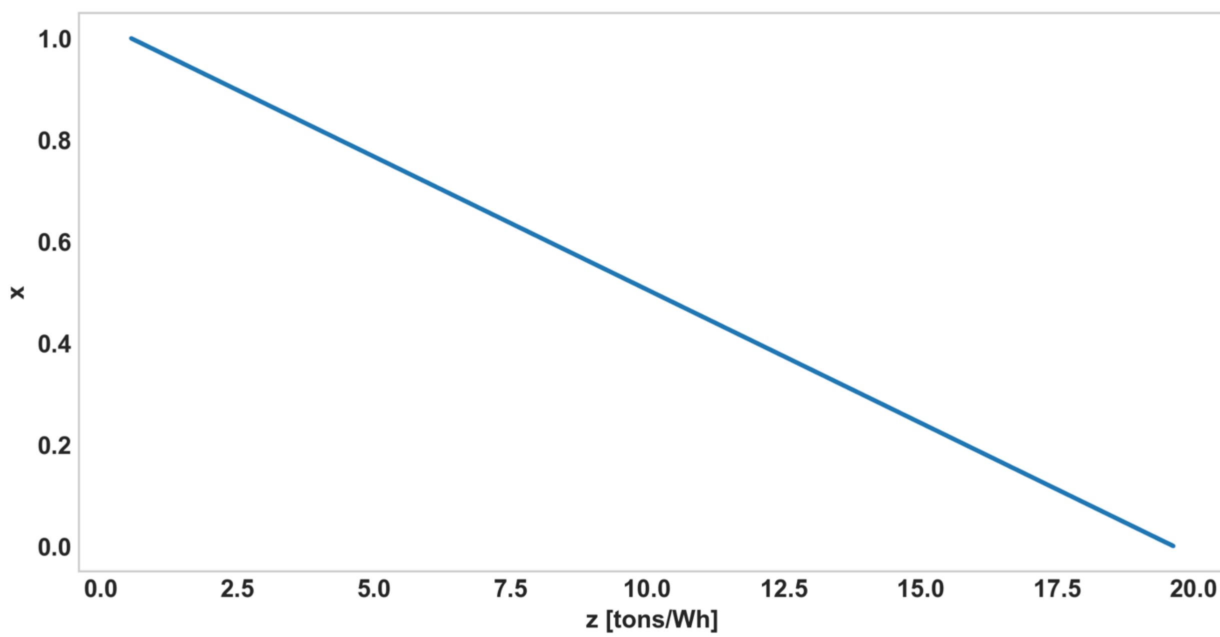

Figure II-9: Hazardous Waste Basic Indicator Normalization Curve

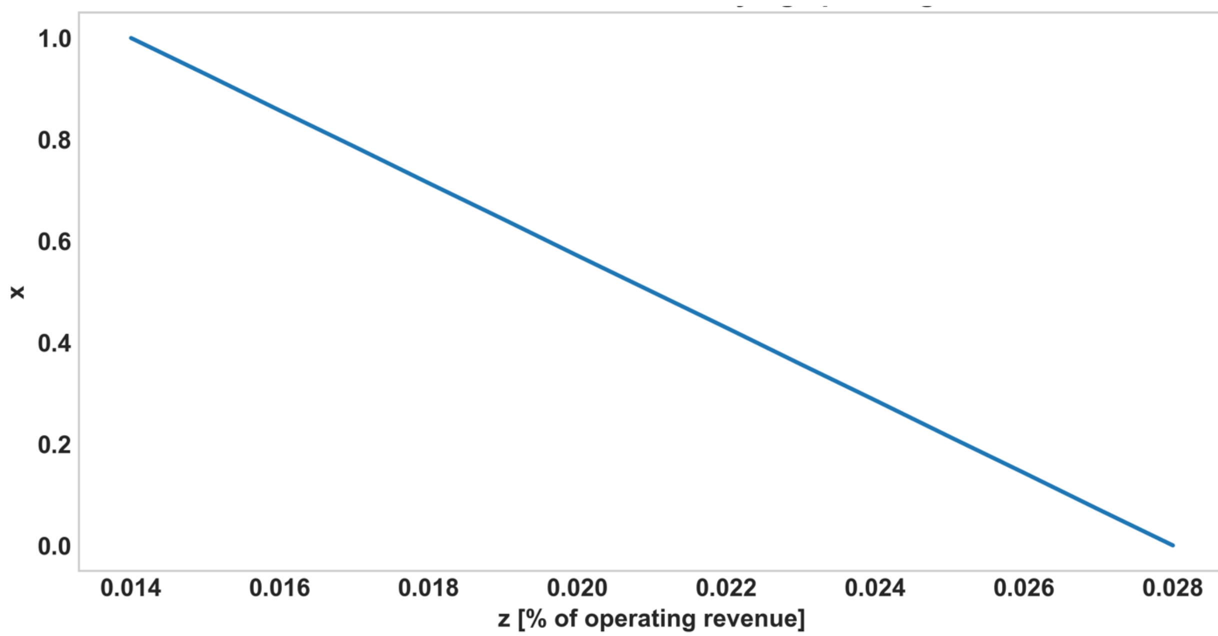

Figure II-10: Lobbying Spending Basic Indicator Normalization Curve

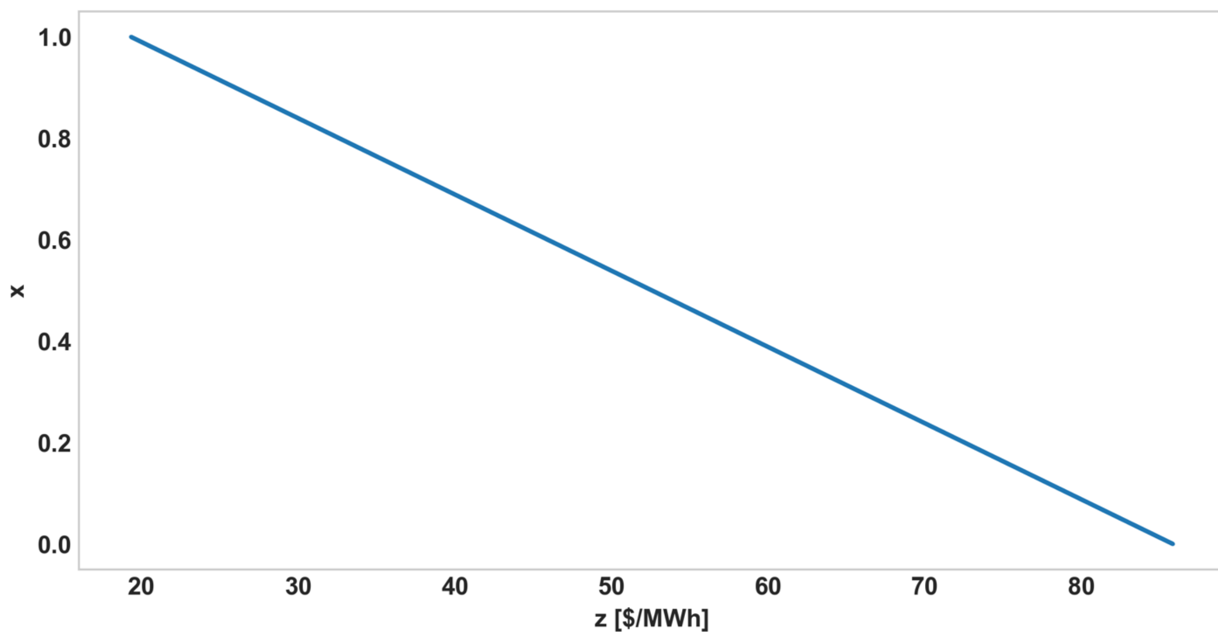

Figure II-11: Operating Expenses Basic Indicator Normalization Curve

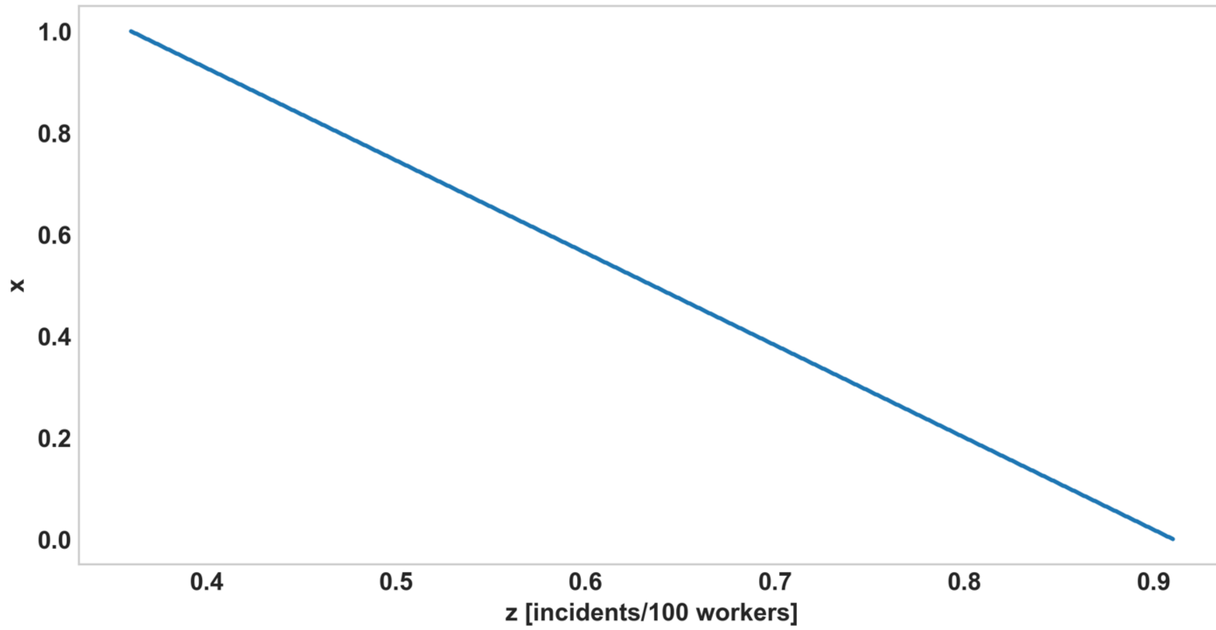

Figure II-12: OSHA Recordable Rate (TCIR) Basic Indicator Normalization Curve

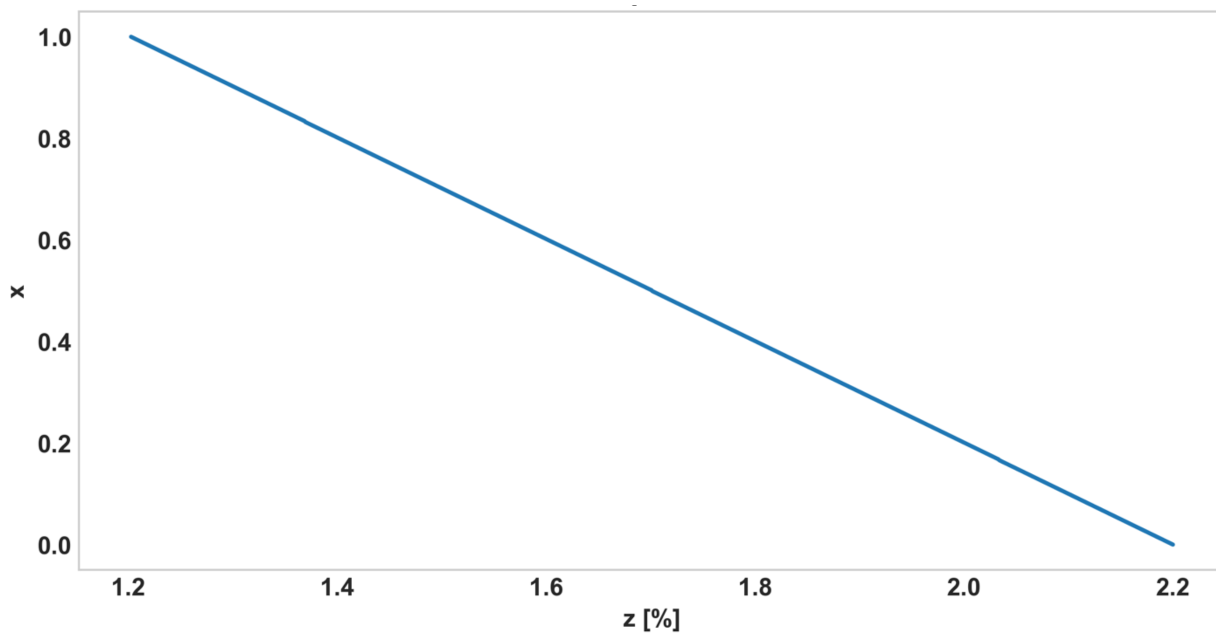

Figure II-13: Percent Water Consumed Basic Indicator Normalization Curve

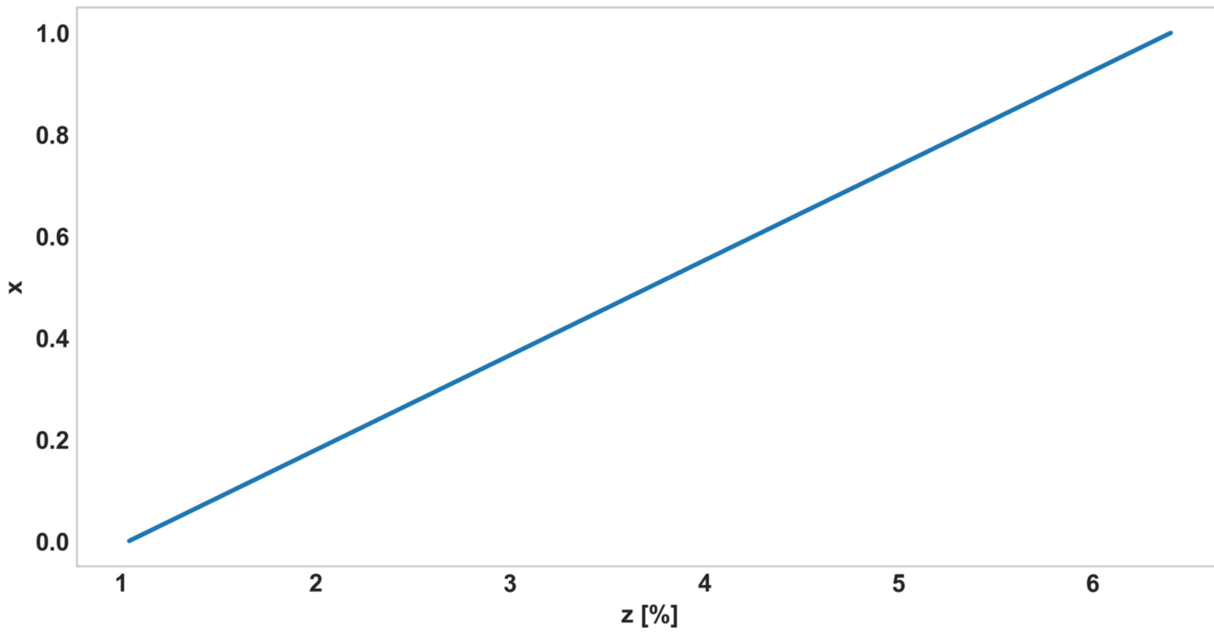

Figure II-14: Return on Assets Basic Indicator Normalization Curve

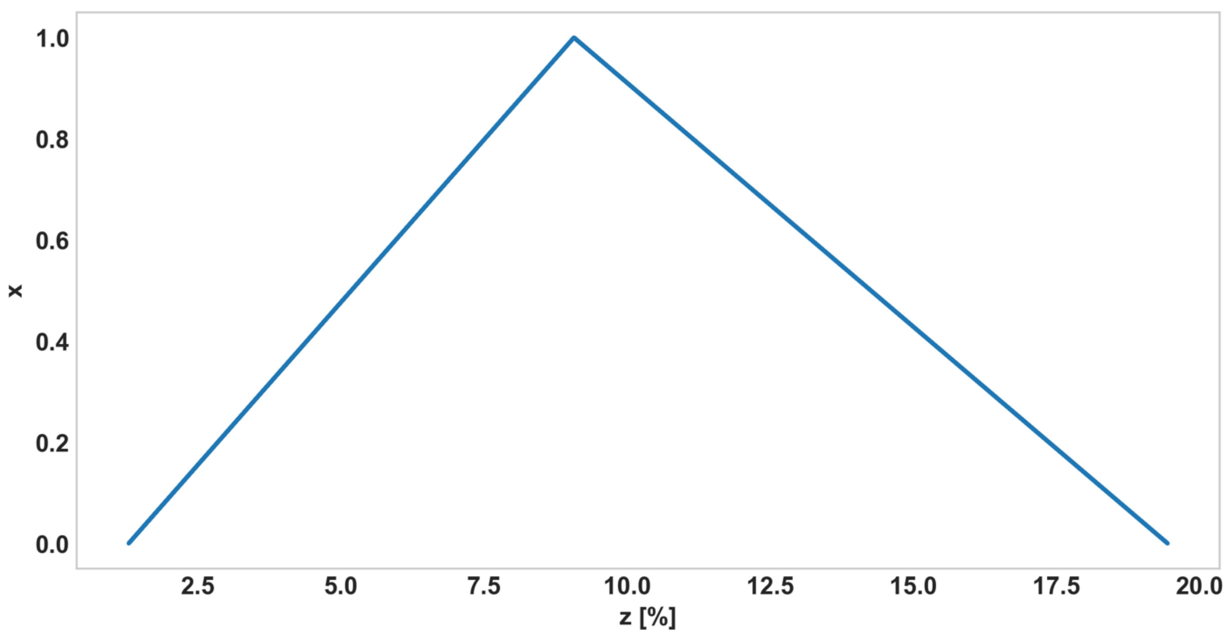

Figure II-15: Return on Equity Basic Indicator Normalization Curve

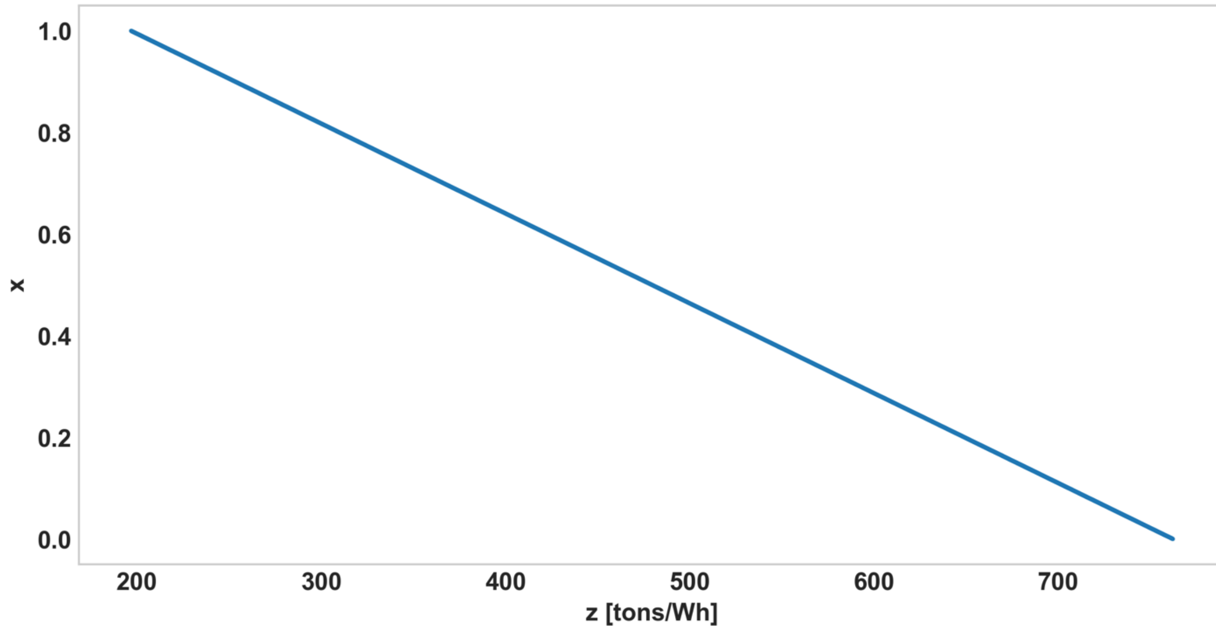

Figure II-16: Solid Waste (Non-Hazardous) Basic Indicator Normalization Curve

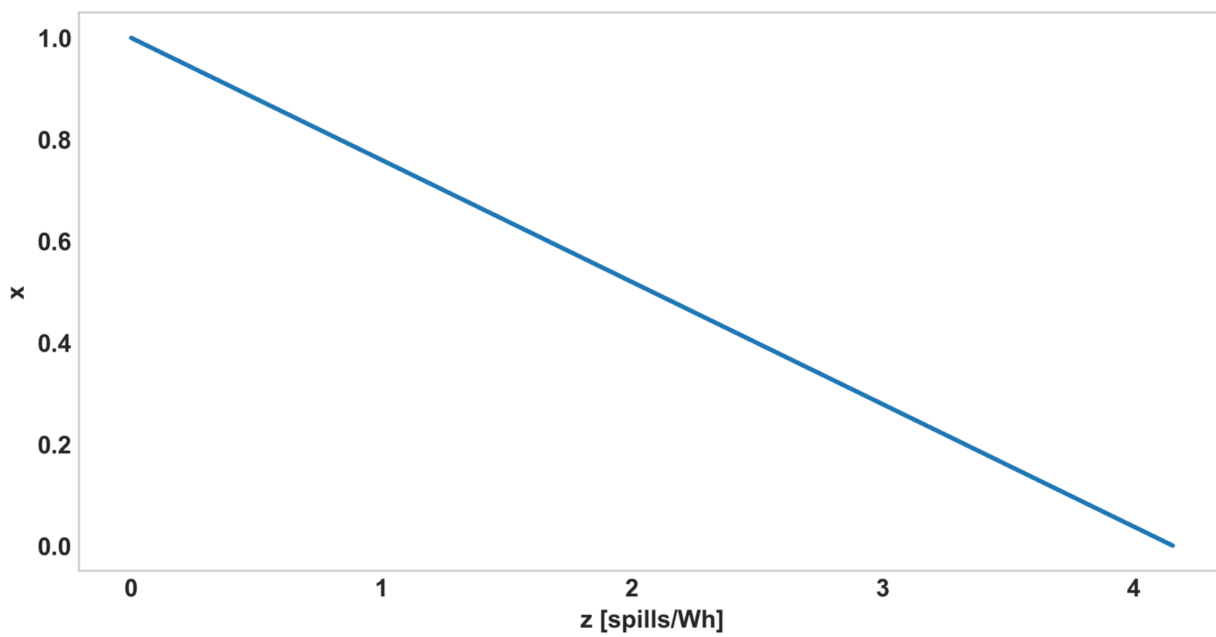

Figure II-17: Spills Basic Indicator Normalization Curve

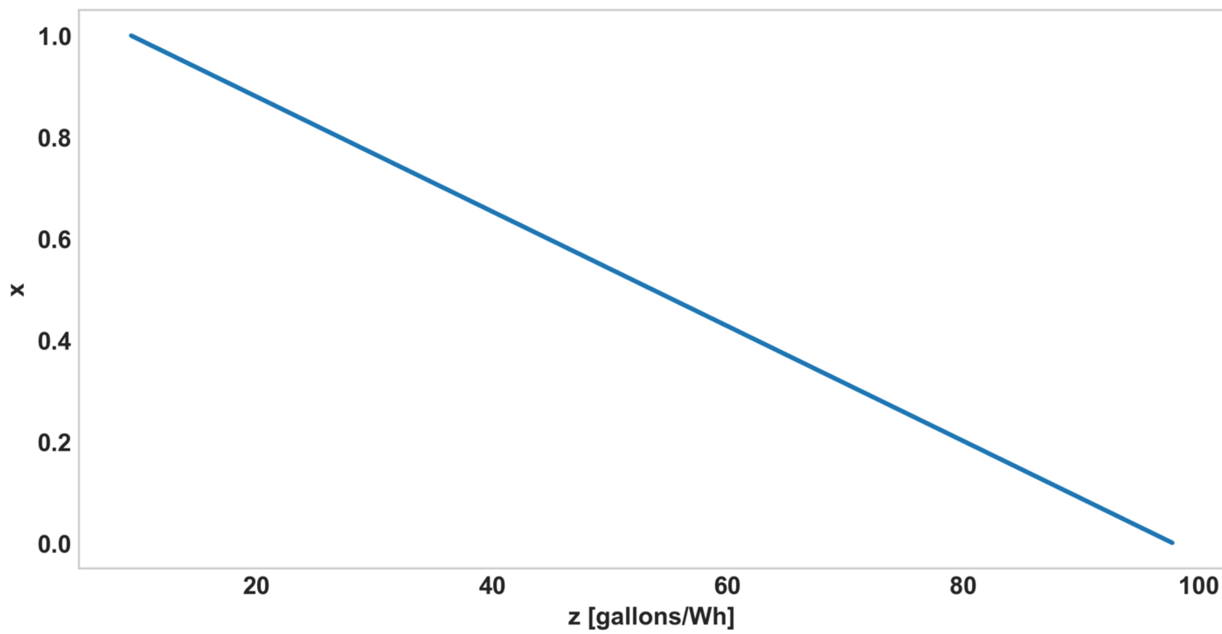

Figure II-18: Total Water Withdrawal Basic Indicator Normalization Curve

Appendix III: Basic Indicator Rule Bases

The rule base constructed for the analysis of AIR is copied below. The relative weights given to each basic indicator is as follows:

Clean Generation	CO_2 Emissions
1.5	2

The relative weighting for the AIR rule base was initially assigned as CO_2 emissions having twice the weight as the clean generation basic indicator. The CO_2 emissions indicator was initially weighted because the clean generation indicator specifically targets coal generation, whereas the emissions indicator is technology agnostic. After the sensitivity analysis revealed clean generation to be too low on the list of most impactful basic indicators (Figure 4-2), the relative weight of the clean generation indicator was increased to 1.5.

Rule	Clean Generation	CO_2 Emissions	AIR
1	W	W	VB
2	W	M	B
3	W	S	A
4	M	W	B
5	M	M	A
6	M	S	G
7	S	W	A
8	S	M	G
9	S	S	VG

The rule base constructed for the analysis of LAND is copied below. The relative weights given to each basic indicator is as follows:

Spills	Solid Waste	Hazardous Waste
1	2	3

Spills are harmful to land and can occur for several reasons, but many of them are not a company's explicit 'fault'—for example, a transformer can leak oil after it is damaged in a storm. Therefore, it was weighed the least and solid waste was weighed twice as much. Hazardous is especially harmful to the environment so it was weighed the most.

Rule	Spills	Solid Waste	Hazardous Waste	LAND
1	W	W	W	VB
2	W	W	M	B
3	W	W	S	A

4	W	M	W	B
5	W	M	M	A
6	W	M	S	G
7	W	S	W	B
8	W	S	M	A
9	W	S	S	G
10	M	W	W	VB
11	M	W	M	B
12	M	W	S	A
13	M	M	W	B
14	M	M	M	A
15	M	M	S	G
16	M	S	W	A
17	M	S	M	G
18	M	S	S	VG
19	S	W	W	B
20	S	W	M	A
21	S	W	S	G
22	S	M	W	B
23	S	M	M	A
24	S	M	S	G
25	S	S	W	A
26	S	S	M	G
27	S	S	S	VG

The rule base constructed for the analysis of WATER is copied below. The relative weights given to each basic indicator is as follows:

Tot. Water Withdrawal	% Water Consumed
1	1

Initially, total water withdrawal was weighed twice as much as water consumed, since we wanted to incentivize reduced water consumption over unnecessary consumption. Furthermore, filtering and returning water to its source consumes energy. However, initial sensitivity studies showed that the relative weighting between the two indicators was causing '% water consumed' to show up high on the list and above total water withdrawal. This result was considered to be misleading. Instead, we chose to weight them the same so that the model produced a sensitivity list more consistent with what we thought was generally important for the sustainability of a utility company.

Rule	Tot. Water Withdrawal	% Water Consumed	WATER
1	W	W	VB
2	W	M	B
3	W	S	A

4	M	W	B
5	M	M	A
6	M	S	G
7	S	W	A
8	S	M	G
9	S	S	VG

The rule base constructed for the analysis of POLICY is copied below. The relative weights given to each basic indicator is as follows:

Lobbying Spending	Charitable Giving
1	2

The POLICY rule base included the assigned relative weights of 1 for obbying spending and 2 for charitable giving. A slightly higher weighting was assigned to charitable giving because we felt it was a better indicator of how good company management was at crafting good company policies. We believed it was more likely that a company with high charitable giving would have good policies in other parts of the business than one with high lobbying spending.

Rule	Lobbying Spending	Charitable Giving	POLICY
1	W	W	VB
2	W	M	B
3	W	S	G
4	M	W	B
5	M	M	A
6	M	S	G
7	S	W	B
8	S	M	G
9	S	S	VG

The rule base constructed for the analysis of HEALTH is copied below. The relative weights given to each basic indicator is as follows:

OSHA TCIR	Fatalities
1.3	1

The HEALTH rule base included the assigned relative weights of 1.3 for OSHA Total Case Incident Rate (TICR) and 1 for fatalities recorded. The relative weights were assigned with the knowledge that OSHA TICR was likely a more reliable metric for overall company sustainability than fatalities. Ultimately the weight for TCIR was tuned to 1.3 to achieve a better ordering for basic indicators in the sensitivity analysis.

Rule	OSHA TCIR	Fatalities	HEALTH
1	W	W	VB
2	W	M	B
3	W	S	A
4	M	W	B
5	M	M	A
6	M	S	G
7	S	W	A
8	S	M	G
9	S	S	VG

The rule base constructed for the analysis of PRESSURE is copied below. The relative weights given to each basic indicator is as follows:

Debt to Equity Ratio	Operating Expenses	Effective Tax Rate
2	2	1

The effective tax rate indicator was weighed the least because it is largely determined by state and federal policy; in fact, you can see a significant reduction in 2016 when the new administration started in Raw Data. Operating expenses and debt to equity ratio were both important indicators for financial pressure so they were both weighed equally more than the effective tax rate. We felt like pressure from increased fuel and electricity costs (operating expenses) were about equal in importance to pressure to pay back debts.

Rule	Debt to Equity Ratio	Operating Expenses	Effective Tax Rate	PRESSURE
1	W	W	W	VB
2	W	W	M	VB
3	W	W	S	B
4	W	M	W	B
5	W	M	M	B
6	W	M	S	A
7	W	S	W	A
8	W	S	M	A
9	W	S	S	A
10	M	W	W	B
11	M	W	M	B
12	M	W	S	A
13	M	M	W	A
14	M	M	M	A
15	M	M	S	A
16	M	S	W	A
17	M	S	M	G
18	M	S	S	G

19	S	W	W	A
20	S	W	M	A
21	S	W	S	A
22	S	M	W	A
23	S	M	M	G
24	S	M	S	G
25	S	S	W	G
26	S	S	M	VG
27	S	S	S	VG

The rule base constructed for the analysis of STATUS is copied below. The relative weights given to each basic indicator is as follows:

Return on Equity	Return on Assets
1.3	1

Although both returns on equity and return on assets are indicators of how successful the management is with running a company, ultimately we weighted return on equity more because it provides a more direct measure of how well a company is compensating its shareholders. This was accurately reflected in the sensitivity analysis rankings, with return on equity as being the most impactful and return on assets being the third most impactful.

Rule	Return on Equity	Return on Assets	STATUS
1	W	W	VB
2	W	M	B
3	W	S	A
4	M	W	B
5	M	M	A
6	M	S	G
7	S	W	A
8	S	M	G
9	S	S	VG

The rule base constructed for the analysis of RESPONSE is copied below. The relative weights given to each basic indicator is as follows:

CF/CAPEX	Dividend Payout Ratio
1	5

Dividend payout was weighed significantly more than dividend payout because CF/CAPEX can be a change significantly year to year as a company goes through investment cycles. Dividend payout, on the other hand, is consistently important for utility companies shareholders, and having a high dividend payout ratio is important for attracting and keeping investors.

Rule	CF/CAPEX	Dividend Payout Ratio	RESPONSE
1	W	W	VB
2	W	M	A
3	W	S	G
4	M	W	VB
5	M	M	A
6	M	S	VG
7	S	W	B
8	S	M	A
9	S	S	VG

Appendix IV: Fuzzy Secondary Indicator Values

Duke Energy Corporation						
	Year	VB	B	A	G	VG
AIR	2014	1	0	0	0	0
	2015	0.61	0.34	0.05	0	0
	2016	0.55	0.38	0.06	0	0
	2017	0.49	0.42	0.09	0	0
	2018	0.41	0.47	0.13	0	0
HEALTH	2014	0.1	0.67	0.22	0	0
	2015	0	0.3	0.7	0	0
	2016	0	0	0	0.24	0.76
	2017	0	0	0.14	0.86	0
	2018	0	0.17	0.48	0.35	0
LAND	2014	0	0	0.29	0.71	0
	2015	0	0	0.16	0.84	0
	2016	0	0.02	0.84	0.14	0
	2017	0	0	0.02	0.98	0
	2018	0	0	0.13	0.87	0
POLIC	2014	0	0	0	1	0
	2015	0.05	0.37	0.57	0	0
	2016	0.1	0.44	0.46	0	0
	2017	0.07	0.41	0.52	0	0
	2018	0	0.29	0.17	0.54	0
PRESSURE	2014	0	0.62	0.38	0	0
	2015	0	0.55	0.43	0.01	0
	2016	0	0.18	0.75	0.08	0
	2017	0	0.07	0.78	0.16	0
	2018	0	0.06	0.64	0.3	0
RESPONSE	2014	0	0	0.43	0.11	0.46
	2015	0	0	0.4	0.35	0.25
	2016	0	0	0.29	0.56	0.15
	2017	0	0	0.4	0.51	0.09
	2018	0	0	0.08	0.87	0.05
STATUS	2014	0.34	0.58	0.08	0	0
	2015	0	0.56	0.39	0.05	0
	2016	0.23	0.66	0.11	0	0
	2017	0	0.51	0.41	0.08	0
	2018	0.1	0.72	0.19	0	0
WATER	2014	0	0.08	0.53	0.39	0
	2015	0	0	0.15	0.63	0.22
	2016	0	0	0.35	0.48	0.17
	2017	0	0	0.24	0.5	0.26
	2018	0	0.12	0.48	0.4	0

Table IV-1: Summary of secondary indicator values calculated for Duke Energy Corporation

Exelon Corporation						
	Year	VB	B	A	G	VG
AIR	2014	0	0	0	0.01	0.99
	2015	0	0	0	0.01	0.99
	2016	0	0	0	0.09	0.91
	2017	0	0	0	0.08	0.92
	2018	0	0	0	0.06	0.94
HEALTH	2014	0	0	0.53	0.47	0
	2015	0	0	1	0	0
	2016	0	0	0.32	0.68	0
	2017	0	0.05	0.92	0.03	0
	2018	0	0.07	0.56	0.37	0
LAND	2014	0.13	0.47	0.4	0	0
	2015	0.13	0.47	0.4	0	0
	2016	0.48	0.52	0	0	0
	2017	0	0.16	0.59	0.25	0
	2018	0.05	0.52	0.43	0	0
POLIC	2014	0.22	0.5	0.28	0	0
	2015	0.37	0.57	0.06	0	0
	2016	0.01	0.49	0.5	0	0
	2017	0	0.06	0.65	0.29	0
	2018	0	0.48	0.5	0.03	0
PRESSURE	2014	0.02	0.71	0.26	0	0
	2015	0	0.39	0.58	0.03	0
	2016	0.61	0.39	0	0	0
	2017	0.07	0.46	0.48	0	0
	2018	0.11	0.89	0	0	0
RESPONSE	2014	0.12	0	0.88	0	0
	2015	0.56	0	0.44	0	0
	2016	0	0	0.22	0.46	0.33
	2017	0.63	0	0.37	0	0
	2018	1	0	0	0	0
STATUS	2014	0	0.58	0.37	0.05	0
	2015	0	0.08	0.61	0.31	0
	2016	0.43	0.57	0	0	0
	2017	0	0.01	0.4	0.6	0
	2018	0.81	0.19	0	0	0
WATER	2014	0.18	0.59	0.24	0	0
	2015	0.32	0.5	0.18	0	0
	2016	0.2	0.53	0.27	0	0
	2017	0	0.48	0.43	0.09	0
	2018	0	0	1	0	0

Table IV-2: Summary of secondary indicator values calculated for Exelon Corporation

For NextEra Energy see Table 3-11: Summary of fuzzy primary values calculated for NextEra Energy.

Appendix V: Primary Indicator Rule Base

The rule base constructed for the analysis of ECOS is copied below. The relative weights given to each primary secondary is as follows:

AIR	LAND	WATER
9	1	1

AIR impacts are by far the most important environmental impact for utilities because electricity emissions constitute a significant portion of an economy's GHG production. The exact parameter for 9 was tuned based on initial results from the sensitivity analysis; clean generation was located somewhere in the middle of the list so the parameter was slowly increased until a satisfactory ranking was achieved. LAND and WATER impacts were considered to be about the same in relative terms.

Rule	AIR	LAND	WATER	ECOS
1	VB	VB	VB	VB
2	VB	VB	B	VB
3	VB	VB	A	VB
4	VB	VB	G	VB
5	VB	VB	VG	VB
6	VB	B	VB	VB
7	VB	B	B	VB
8	VB	B	A	VB
9	VB	B	G	VB
10	VB	B	VG	VB
11	VB	A	VB	VB
12	VB	A	B	VB
13	VB	A	A	VB
14	VB	A	G	VB
15	VB	A	VG	VB
16	VB	G	VB	VB
17	VB	G	B	VB
18	VB	G	A	VB
19	VB	G	G	B
20	VB	G	VG	B
21	VB	VG	VB	VB
22	VB	VG	B	VB
23	VB	VG	A	B
24	VB	VG	G	B
25	VB	VG	VG	B
26	B	VB	VB	B
27	B	VB	B	B
28	B	VB	A	B
29	B	VB	G	B
30	B	VB	VG	B
31	B	B	VB	B
32	B	B	B	B

33	B	B	A	B
34	B	B	G	B
35	B	B	VG	B
36	B	A	VB	B
37	B	A	B	B
38	B	A	A	B
39	B	A	G	B
40	B	A	VG	B
41	B	G	VB	B
42	B	G	B	B
43	B	G	A	B
44	B	G	G	B
45	B	G	VG	B
46	B	VG	VB	B
47	B	VG	B	B
48	B	VG	A	B
49	B	VG	G	B
50	B	VG	VG	A
51	A	VB	VB	A
52	A	VB	B	A
53	A	VB	A	A
54	A	VB	G	A
55	A	VB	VG	A
56	A	B	VB	A
57	A	B	B	A
58	A	B	A	A
59	A	B	G	A
60	A	B	VG	A
61	A	A	VB	A
62	A	A	B	A
63	A	A	A	A
64	A	A	G	A
65	A	A	VG	A
66	A	G	VB	A
67	A	G	B	A
68	A	G	A	A
69	A	G	G	A
70	A	G	VG	A
71	A	VG	VB	A
72	A	VG	B	A
73	A	VG	A	A
74	A	VG	G	A
75	A	VG	VG	A
76	G	VB	VB	A
77	G	VB	B	G
78	G	VB	A	G
79	G	VB	G	G
80	G	VB	VG	G
81	G	B	VB	G

82	G	B	B	G
83	G	B	A	G
84	G	B	G	G
85	G	B	VG	G
86	G	A	VB	G
87	G	A	B	G
88	G	A	A	G
89	G	A	G	G
90	G	A	VG	G
91	G	G	VB	G
92	G	G	B	G
93	G	G	A	G
94	G	G	G	G
95	G	G	VG	G
96	G	VG	VB	G
97	G	VG	B	G
98	G	VG	A	G
99	G	VG	G	G
100	G	VG	VG	G
101	VG	VB	VB	G
102	VG	VB	B	G
103	VG	VB	A	G
104	VG	VB	G	VG
105	VG	VB	VG	VG
106	VG	B	VB	G
107	VG	B	B	G
108	VG	B	A	VG
109	VG	B	G	VG
110	VG	B	VG	VG
111	VG	A	VB	G
112	VG	A	B	VG
113	VG	A	A	VG
114	VG	A	G	VG
115	VG	A	VG	VG
116	VG	G	VB	VG
117	VG	G	B	VG
118	VG	G	A	VG
119	VG	G	G	VG
120	VG	G	VG	VG
121	VG	VG	VB	VG
122	VG	VG	B	VG
123	VG	VG	A	VG
124	VG	VG	G	VG
125	VG	VG	VG	VG

Table V-1: ECOS Rule Base

The rule base constructed for the analysis of HUMS is copied below. The relative weights given to each primary secondary is as follows:

POLICY	HEALTH
0.75	2.5

Utility companies provide an essential service, so HEALTH was weighed higher than POLICY. It was determined that companies faced a bigger threat from employee injuries than from policies for charitable giving. The exact weights were tuned to get an appropriate ranking for the basic indicators within these two secondary indicators.

Rule	POLICY	HEALTH	HUMS
1	VB	VB	VB
2	VB	B	B
3	VB	A	A
4	VB	G	A
5	VB	VG	G
6	B	VB	VB
7	B	B	B
8	B	A	A
9	B	G	G
10	B	VG	G
11	A	VB	VB
12	A	B	B
13	A	A	A
14	A	G	G
15	A	VG	VG
16	G	VB	B
17	G	B	B
18	G	A	A
19	G	G	G
20	G	VG	VG
21	VG	VB	B
22	VG	B	A
23	VG	A	A
24	VG	G	G
25	VG	VG	VG

Table V-2: HUMS Rule Base

The rule base constructed for the analysis of WEALTH is copied below. The relative weights given to each secondary indicator is as follows:

STATUS	RESPONSE	PRESSURE
2.5	1.5	1

Status was weighed the highest because the basic indicators like return on equity and return on assets were deemed to be the most important predictors of long term financial sustainability. Pressure was deemed the lowest because of the cyclical nature of one of its basic indicators.

Rule	STATUS	RESPONSE	PRESSURE	WEALTH
1	VB	VB	VB	VB
2	VB	VB	B	VB
3	VB	VB	A	VB
4	VB	VB	G	B
5	VB	VB	VG	B
6	VB	B	VB	VB
7	VB	B	B	B
8	VB	B	A	B
9	VB	B	G	B
10	VB	B	VG	B
11	VB	A	VB	B
12	VB	A	B	B
13	VB	A	A	B
14	VB	A	G	B
15	VB	A	VG	B
16	VB	G	VB	B
17	VB	G	B	B
18	VB	G	A	B
19	VB	G	G	A
20	VB	G	VG	A
21	VB	VG	VB	B
22	VB	VG	B	B
23	VB	VG	A	A
24	VB	VG	G	A
25	VB	VG	VG	A
26	B	VB	VB	B
27	B	VB	B	B
28	B	VB	A	B
29	B	VB	G	B
30	B	VB	VG	B
31	B	B	VB	B
32	B	B	B	B
33	B	B	A	B
34	B	B	G	B
35	B	B	VG	A
36	B	A	VB	B
37	B	A	B	B
38	B	A	A	A
39	B	A	G	A
40	B	A	VG	A
41	B	G	VB	B
42	B	G	B	A
43	B	G	A	A
44	B	G	G	A

45	B	G	VG	A
46	B	VG	VB	A
47	B	VG	B	A
48	B	VG	A	A
49	B	VG	G	A
50	B	VG	VG	G
51	A	VB	VB	B
52	A	VB	B	B
53	A	VB	A	B
54	A	VB	G	A
55	A	VB	VG	A
56	A	B	VB	B
57	A	B	B	A
58	A	B	A	A
59	A	B	G	A
60	A	B	VG	A
61	A	A	VB	A
62	A	A	B	A
63	A	A	A	A
64	A	A	G	A
65	A	A	VG	A
66	A	G	VB	A
67	A	G	B	A
68	A	G	A	A
69	A	G	G	G
70	A	G	VG	G
71	A	VG	VB	A
72	A	VG	B	A
73	A	VG	A	G
74	A	VG	G	G
75	A	VG	VG	G
76	G	VB	VB	A
77	G	VB	B	A
78	G	VB	A	A
79	G	VB	G	A
80	G	VB	VG	A
81	G	B	VB	A
82	G	B	B	A
83	G	B	A	A
84	G	B	G	A
85	G	B	VG	G
86	G	A	VB	A
87	G	A	B	A
88	G	A	A	G
89	G	A	G	G
90	G	A	VG	G
91	G	G	VB	A
92	G	G	B	G
93	G	G	A	G

94	G	G	G	G
95	G	G	VG	G
96	G	VG	VB	G
97	G	VG	B	G
98	G	VG	A	G
99	G	VG	G	G
100	G	VG	VG	VG
101	VG	VB	VB	A
102	VG	VB	B	A
103	VG	VB	A	A
104	VG	VB	G	G
105	VG	VB	VG	G
106	VG	B	VB	A
107	VG	B	B	G
108	VG	B	A	G
109	VG	B	G	G
110	VG	B	VG	G
111	VG	A	VB	G
112	VG	A	B	G
113	VG	A	A	G
114	VG	A	G	G
115	VG	A	VG	G
116	VG	G	VB	G
117	VG	G	B	G
118	VG	G	A	G
119	VG	G	G	VG
120	VG	G	VG	VG
121	VG	VG	VB	G
122	VG	VG	B	G
123	VG	VG	A	VG
124	VG	VG	G	VG
125	VG	VG	VG	VG

Table V-3: WEALTH Rule Base

Appendix VI: Fuzzy Primary Indicator Values

Duke Energy Corporation						
	Year	VB	B	A	G	VG
ECOS	2014	0.72	0.28	0	0	0
	2015	0.15	0.8	0.05	0	0
	2016	0.42	0.51	0.06	0	0
	2017	0.12	0.79	0.09	0	0
	2018	0.26	0.61	0.13	0	0
HUMS	2014	0	0.78	0.22	0	0
	2015	0	0.3	0.7	0	0
	2016	0	0	0.02	0.63	0.35
	2017	0	0	0.2	0.8	0
	2018	0	0.17	0.48	0.35	0
WEALTH	2014	0	0.43	0.55	0.02	0
	2015	0	0.12	0.79	0.09	0
	2016	0	0.23	0.75	0.02	0
	2017	0	0.01	0.84	0.14	0
	2018	0	0.07	0.87	0.06	0

Table VI-1: Summary of fuzzy primary values calculated for Duke Energy Corporation

Exelon Corporation						
	Year	VB	B	A	G	VG
ECOS	2014	0	0	0	0.57	0.43
	2015	0	0	0	0.65	0.35
	2016	0	0	0.01	0.86	0.13
	2017	0	0	0	0.15	0.84
	2018	0	0	0	0.11	0.89
HUMS	2014	0	0	0.64	0.36	0
	2015	0	0	1	0	0
	2016	0	0	0.33	0.67	0
	2017	0	0.05	0.92	0.03	0
	2018	0	0.07	0.56	0.37	0
WEALTH	2014	0	0.49	0.5	0.01	0
	2015	0	0.39	0.53	0.08	0
	2016	0	0.71	0.29	0	0
	2017	0	0.26	0.64	0.1	0
	2018	0.81	0.19	0	0	0

Table VI-2: Summary of fuzzy primary values calculated for Exelon Corporation

For NextEra see Table 3-11: Summary of fuzzy primary values calculated for NextEra Energy.

Appendix VII: Rule Base for Overall Sustainability (OSUS)

The rule base constructed for the analysis of OSUS below. See commentary in Primary Indicator Sample Calculation for relative weight justification. The relative weights given to each primary indicator is as follows:

WEALTH	ECOS	HUMS
2	3	1

Rule	WEALTH	ECOS	HUMS	OSUS
1	VB	VB	VB	EL
2	VB	VB	B	EL
3	VB	VB	A	VL
4	VB	VB	G	VL
5	VB	VB	VG	VL
6	VB	B	VB	VL
7	VB	B	B	VL
8	VB	B	A	L
9	VB	B	G	L
10	VB	B	VG	L
11	VB	A	VB	L
12	VB	A	B	L
13	VB	A	A	FL
14	VB	A	G	FL
15	VB	A	VG	FL
16	VB	G	VB	FL
17	VB	G	B	FL
18	VB	G	A	I
19	VB	G	G	I
20	VB	G	VG	I
21	VB	VG	VB	I
22	VB	VG	B	I
23	VB	VG	A	FH
24	VB	VG	G	FH
25	VB	VG	VG	FH
26	B	VB	VB	VL
27	B	VB	B	VL
28	B	VB	A	VL
29	B	VB	G	L
30	B	VB	VG	L
31	B	B	VB	L
32	B	B	B	L
33	B	B	A	L
34	B	B	G	FL
35	B	B	VG	FL
36	B	A	VB	FL
37	B	A	B	FL
38	B	A	A	FL

39	B	A	G	I
40	B	A	VG	I
41	B	G	VB	I
42	B	G	B	I
43	B	G	A	I
44	B	G	G	FH
45	B	G	VG	FH
46	B	VG	VB	FH
47	B	VG	B	FH
48	B	VG	A	FH
49	B	VG	G	H
50	B	VG	VG	H
51	A	VB	VB	VL
52	A	VB	B	L
53	A	VB	A	L
54	A	VB	G	L
55	A	VB	VG	FL
56	A	B	VB	L
57	A	B	B	FL
58	A	B	A	FL
59	A	B	G	FL
60	A	B	VG	I
61	A	A	VB	FL
62	A	A	B	I
63	A	A	A	I
64	A	A	G	I
65	A	A	VG	FH
66	A	G	VB	I
67	A	G	B	FH
68	A	G	A	FH
69	A	G	G	FH
70	A	G	VG	H
71	A	VG	VB	FH
72	A	VG	B	H
73	A	VG	A	H
74	A	VG	G	H
75	A	VG	VG	VH
76	G	VB	VB	L
77	G	VB	B	L
78	G	VB	A	FL
79	G	VB	G	FL
80	G	VB	VG	FL
81	G	B	VB	FL
82	G	B	B	FL
83	G	B	A	I
84	G	B	G	I
85	G	B	VG	I
86	G	A	VB	I
87	G	A	B	I

88	G	A	A	FH
89	G	A	G	FH
90	G	A	VG	FH
91	G	G	VB	FH
92	G	G	B	FH
93	G	G	A	H
94	G	G	G	H
95	G	G	VG	H
96	G	VG	VB	H
97	G	VG	B	H
98	G	VG	A	VH
99	G	VG	G	VH
100	G	VG	VG	VH
101	VG	VB	VB	FL
102	VG	VB	B	FL
103	VG	VB	A	FL
104	VG	VB	G	I
105	VG	VB	VG	I
106	VG	B	VB	I
107	VG	B	B	I
108	VG	B	A	I
109	VG	B	G	FH
110	VG	B	VG	FH
111	VG	A	VB	FH
112	VG	A	B	FH
113	VG	A	A	FH
114	VG	A	G	H
115	VG	A	VG	H
116	VG	G	VB	H
117	VG	G	B	H
118	VG	G	A	H
119	VG	G	G	VH
120	VG	G	VG	VH
121	VG	VG	VB	VH
122	VG	VG	B	VH
123	VG	VG	A	VH
124	VG	VG	G	EH
125	VG	VG	VG	EH

Appendix VIII: OSUS Results Tables

The tables below summarize the crisp and fuzzy values of overall sustainability (OSUS) for NextEra Energy, Duke Energy, and Exelon over five years (2014-2018).

Year	NextEra Energy	Duke Energy	Exelon
2014	0.5530	0.2311	0.6421
2015	0.5616	0.3536	0.6302
2016	0.5423	0.3640	0.6103
2017	0.5585	0.3883	0.7120
2018	0.5676	0.3588	0.6134

Table VIII-1: Summary of crisp values calculated from the SAFE model

	Years	EL	VL	L	FL	I	FH	H	VH	EH
NextEra Energy Inc.	2014	0	0	0.528	0.09	0	0.375	0.007	0	0
	2015	0	0	0.571	0.071	0	0.353	0.004	0	0
	2016	0	0	0.441	0.099	0.003	0.451	0.005	0	0
	2017	0	0	0.547	0.073	0.002	0.378	0.004	0	0
	2018	0	0	0.595	0.05	0	0.353	0.002	0	0
Duke Energy Corp.	2014	0	0	0	0.158	0	0.001	0.528	0	0.311
	2015	0	0	0.003	0.666	0	0.085	0.224	0	0.019
	2016	0	0	0.018	0.483	0	0.187	0.307	0	0.002
	2017	0	0	0.012	0.689	0	0.188	0.106	0	0
	2018	0	0	0.007	0.571	0	0.145	0.265	0	0.012
Exelon Corp.	2014	0	0	0.517	0	0.301	0.176	0	0.006	0
	2015	0	0	0.48	0	0.239	0.255	0	0.029	0
	2016	0	0	0.686	0.002	0.098	0.211	0	0	0
	2017	0	0	0.311	0	0.565	0.038	0	0.084	0
	2018	0	0	0.787	0.006	0.062	0.143	0	0	0

Table VIII-2: Summary of fuzzy values calculated from SAFE model

Appendix IX: Sensitivity Analysis

Basic Indicator	Company	Crisp	-0.1	0.1	y	D_h	D_i	D	D_{rank}
cf_capex	duk	0.36	0.36	0.36	0.04	0.00	0.00	0.00	6.0
cf_capex	exc	0.61	0.61	0.61	0.47	0.00	0.00	0.00	15.5
cf_capex	nee	0.57	0.57	0.57	0.42	0.00	0.00	0.00	15.0
charitable giving	duk	0.36	0.36	0.36	0.50	0.00	0.00	0.00	17.0
charitable giving	exc	0.61	0.61	0.61	0.71	0.00	0.00	0.00	10.0
charitable giving	nee	0.57	0.56	0.57	0.08	0.00	0.00	0.00	6.0
clean generation	duk	0.36	0.34	0.37	0.28	0.01	0.01	0.01	2.0
clean generation	exc	0.61	0.57	0.61	1.00	0.00	0.00	0.00	15.5
clean generation	nee	0.57	0.53	0.58	0.97	0.00	0.00	0.00	8.0
co2 emissions	duk	0.36	0.34	0.37	0.22	0.01	0.01	0.01	1.0
co2 emissions	exc	0.61	0.57	0.62	0.98	0.00	0.00	0.00	8.0
co2 emissions	nee	0.57	0.55	0.60	0.66	0.01	0.01	0.01	1.0
debt to equity ratio	duk	0.36	0.36	0.36	0.61	0.00	0.00	0.00	8.0
debt to equity ratio	exc	0.61	0.61	0.61	0.62	0.00	0.00	0.00	15.5
debt to equity ratio	nee	0.57	0.56	0.57	0.14	0.00	0.00	0.00	7.0
dividend payout ratio	duk	0.36	0.35	0.36	0.98	0.00	0.00	0.00	15.0
dividend payout ratio	exc	0.61	0.61	0.62	0.00	0.01	0.00	0.01	3.0
dividend payout ratio	nee	0.57	0.57	0.57	0.00	0.01	0.00	0.01	3.5
effective tax rate	duk	0.36	0.36	0.36	0.47	0.00	0.00	0.00	9.0
effective tax rate	exc	0.61	0.61	0.61	0.64	0.00	0.00	0.00	15.5
effective tax rate	nee	0.57	0.57	0.57	0.35	0.00	0.00	0.00	9.0
fatalities	duk	0.36	0.36	0.36	0.42	0.00	0.00	0.00	11.0
fatalities	exc	0.61	0.60	0.62	0.83	0.00	0.00	0.00	6.0
fatalities	nee	0.57	0.54	0.57	1.00	0.00	0.00	0.00	15.0
hazardous waste	duk	0.36	0.35	0.36	0.97	0.00	0.00	0.00	14.0
hazardous waste	exc	0.61	0.60	0.62	0.64	0.00	0.00	0.00	5.0
hazardous waste	nee	0.57	0.57	0.57	0.97	0.00	0.00	0.00	15.0
lobbying spending	duk	0.36	0.36	0.36	0.93	0.00	0.00	0.00	18.0
lobbying spending	exc	0.61	0.61	0.61	0.36	0.00	0.00	0.00	12.0
lobbying spending	nee	0.57	0.56	0.58	0.50	0.01	0.01	0.01	2.0
operating expenses	duk	0.36	0.35	0.36	0.85	0.00	0.00	0.00	10.0
operating expenses	exc	0.61	0.61	0.61	0.00	0.00	0.00	0.00	11.0
operating expenses	nee	0.57	0.57	0.57	1.00	0.00	0.00	0.00	15.0
osha recordable rate (ticr)	duk	0.36	0.36	0.36	0.87	0.00	0.00	0.00	12.0
osha recordable rate (ticr)	exc	0.61	0.60	0.62	0.62	0.00	0.00	0.00	4.0
osha recordable rate (ticr)	nee	0.57	0.56	0.58	0.64	0.00	0.00	0.00	5.0

percent water consumed	duk	0.36	0.36	0.36	0.52	0.00	0.00	0.00	5.0
percent water consumed	exc	0.61	0.59	0.61	1.00	0.00	0.00	0.00	15.5
percent water consumed	nee	0.57	0.57	0.57	0.70	0.00	0.00	0.00	10.0
roa	duk	0.36	0.35	0.36	0.15	0.00	0.00	0.00	3.0
roa	exc	0.61	0.61	0.62	0.13	0.01	0.01	0.01	1.0
roa	nee	0.57	0.57	0.57	1.00	0.00	0.00	0.00	15.0
roe	duk	0.36	0.35	0.37	0.62	0.00	0.00	0.00	4.0
roe	exc	0.61	0.61	0.62	0.00	0.01	0.00	0.01	2.0
roe	nee	0.57	0.57	0.57	0.00	0.01	0.00	0.01	3.5
solid waste	duk	0.36	0.36	0.36	0.56	0.00	0.00	0.00	13.0
solid waste	exc	0.61	0.61	0.61	0.33	0.00	0.00	0.00	7.0
solid waste	nee	0.57	0.57	0.57	0.00	0.00	0.00	0.00	15.0
spills	duk	0.36	0.36	0.36	0.97	0.00	0.00	0.00	16.0
spills	exc	0.61	0.61	0.61	0.00	0.00	0.00	0.00	15.5
spills	nee	0.57	0.57	0.57	1.00	0.00	0.00	0.00	15.0
total water withdrawal	duk	0.36	0.35	0.37	0.86	0.00	0.00	0.00	7.0
total water withdrawal	exc	0.61	0.61	0.61	0.00	0.00	0.00	0.00	9.0
total water withdrawal	nee	0.57	0.57	0.57	0.99	0.00	0.00	0.00	11.0

Table IX-1: Sensitivity Study Results (2018 Data)

Appendix X: Python Code

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
plt.style.use('seaborn-whitegrid')

dx = 0.001 # dx for linguistic variable function
nd = 3

pkg_dir = 'C:\\Users\\tzave\\OneDrive - The Cooper Union for the
Advancement of Science and Art\\102-cooper\\150-
masters\\sustainability\\sustainability_project1\\IOU-Sustainability-
Model'


class Fuzzification:

    @classmethod
    def main(cls,primary_indicator,secondary_indicator,
basic_indicators,indicator_type,year, sensitivity_ind, delta):

        wms = cls.wms()
        pi_db = pd.read_excel('./databases/indicator_db.xlsx',
sheet_name=primary_indicator).round(nd)

        #FUZZIFICATION
        frames = []
        for basic_indicator in basic_indicators:
            df =
pd.read_csv('./outputs/normalization_curves/{}.csv'.format(basic_indicator
)).round(nd)
            s =
pd.Series(data=df.iloc[:,1].values,index=df.iloc[:,0].values)
            df_base =
pi_db[pi_db[indicator_type]==basic_indicator].drop(['raw_value_units','int
ensive_units','source'],axis='columns').reset_index(drop=True) #reset
index so that it concats properly
            z = df_base['intensive_value'].values

            x = s.loc[z] # pass through normalization curve

            if sensitivity_ind != None: #if its a sensitivity analysis,
perturb the normalized value
                assert delta != 0, 'Something may be wrong, you indicated
sensitivity analysis but enterd no perturbation'
                if basic_indicator == sensitivity_ind:
                    x = (x + delta).round(nd)
                    x[x>1]=1 #fix any values that were made greater than 1
or less than 0
                    x[x<0]=0
                    print('Perturbed {} by {}'.format(basic_indicator,
delta))
```

```
            wms_v = wms.loc[x.values].reset_index(); #fuzzify normalzed
values and reset index to make concat work
            df_out = pd.concat([df_base,wms_v],axis='columns')
            assert df_base.shape[0] == df_out.shape[0], 'different amount
of rows, error'
            frames.append(df_out)
        fuzz = pd.concat(frames).reset_index(drop=True)
        if year == 2018: #only have to do this once

fuzz.to_csv('./outputs/annuals/{}_{}_{}_intensive_normalized_basic_indicat
ors.csv'.format(delta, primary_indicator, secondary_indicator))

        #before inference, fix missing values based on flag in raw data
column
        fuzz = cls.missing_values(fuzz)

        #INFERENCE
        frames=[]
        for company in fuzz['company'].unique():
            company_year = fuzz[(fuzz['company'] == company) &
                                (fuzz['year'] == year)]
            b_indicators =
[company_year[company_year[indicator_type]==indicator].iloc[0] for
indicator in basic_indicators]
            frames.append(InferenceEngine.b_s(b_indicators)) #apply
inference engine
        secondary = pd.DataFrame(frames)
        return secondary

    @staticmethod
    def missing_values(in_fuzz):

        out_fuzz = in_fuzz

        return out_fuzz

    @classmethod
    def create_normalization_curves(cls,struct):
        """
        Creates normalization curves for ALL data statistically.
        """
        print('CREATING NORMALIZATION CURVES')
        for primary_indicator in struct.keys():
            pi_db = pd.read_excel('./databases/indicator_db.xlsx',
sheet_name=primary_indicator).round(nd)
            for secondary_indicator in struct[primary_indicator].keys():
                # CONSTRUCT NORMALIZATION CURVES
                for basic_indicator in
struct[primary_indicator][secondary_indicator].keys():
                    #print(secondary_indicator,basic_indicator)
                    assert pi_db[pi_db['basic']==basic_indicator].shape[1]
== 9 , 'Warning, not expected shape' #sensitve to number of companies
                    basic_df = pi_db[pi_db['basic']==basic_indicator]
```

```
                    iv = basic_df['intensive_value']
                    discourse = np.arange(iv.min(),
                                          iv.max()+dx,
                                          dx).round(nd)
                    x = cls.norm_type(iv=iv,

typeofnorm=struct[primary_indicator][secondary_indicator][basic_indicator]
,
                                      discourse=discourse)
                    ncurve = pd.Series(data=x.round(nd),
                                        index=discourse.round(nd),
                                        name=basic_indicator)

ncurve.to_csv('./outputs/normalization_curves/{}.csv'.format(basic_indicat
or))

                    # PLOT/SAVE NORMALIZATION CURVES
                    fig =
plt.figure(figsize=(10,5));plt.title('Normalization Curve:
{}'.format(basic_indicator));
                    ncurve.plot();
                    plt.grid();plt.xlabel('z
[{}]'.format(pi_db[pi_db['basic']==basic_indicator].iloc[0]['intensive_uni
ts']));plt.ylabel('x');

fig.savefig('./outputs/normalization_curves/{}.png'.format(basic_indicator
), dpi=300, bbox_inches='tight')
                    plt.close(fig)

    @classmethod
    def norm_type(cls,iv,typeofnorm,discourse):

        if typeofnorm == 'lower_is_better':
            x = cls.trapezoid(z= discourse,
                              c_l=iv.min(),
                              tc=iv.min(),
                              Tc=iv.min(),
                              c_u=iv.max());

        elif typeofnorm == 'middle_is_better':
            x = cls.trapezoid(z= discourse,
                              c_l=iv.min(),
                              tc=iv.mean(),
                              Tc=iv.mean(),
                              c_u=iv.max());

        elif typeofnorm == 'higher_is_better':
            x = cls.trapezoid(z=discourse,
                              c_l=iv.min(),
                              tc=iv.max(),
                              Tc=iv.max(),
                              c_u=iv.max())
        else:
            raise NameError('Not a recognized norm_type')
```

```
        return x

    @classmethod
    def create_linguistic_variables(cls):
        ling_dir = os.path.join(pkg_dir, 'outputs/linguistic_variables')
        if not os.path.exists(ling_dir): os.makedirs(ling_dir)

        cls.wms().to_csv(os.path.join(ling_dir,'wms.csv'))
        cls.vbbagvg().to_csv(os.path.join(ling_dir,'vbbagvg.csv'))

cls.elvllflifhhvheh().to_csv(os.path.join(ling_dir,'elvllflifhhvheh.csv'))

    @classmethod
    def trapezoid(cls,z,c_l,tc,Tc,c_u):
        """
        Trapezoid function that can be used to create linguistic values or
normalization curves.

        Rule #1 of Fuzzy System: Completeness of Inputs - Make sure z
covers the full universe of discourse.
        """

        if (c_l==tc) and (c_l==Tc): # DECREASING LINE
            out = np.piecewise(z,
                               [z<c_l, z>c_u, (z>=Tc)&(z<=c_u)],
                               [0    , 0    , lambda z: -z/(c_u-c_l) +
c_u/(c_u-c_l)])

        elif (c_u==tc) and (c_u==Tc): # INCREASING LINE
            out = np.piecewise(z,
                               [z<c_l, z>c_u, (z>=c_l)&(z<=tc)],
                               [0    , 0    , lambda z: z/(c_u-c_l) -
c_l/(c_u-c_l)])

        else: # TRAPEZOID AND TRIANGLE
            out = np.piecewise(z,
                               [z<=c_l, z>=c_u, (z>c_l)&(z<tc)
, (z>=tc)&(z<=Tc), (z>Tc)&(z<c_u)],
                               [0     , 0     , lambda z: (z-c_l)/(tc-
c_l), 1              , lambda z: (c_u-z)/(c_u-Tc)])
        out = out.round(nd) # critical - get rid of annoying decimals
        return out

    @classmethod
    def wms(cls):
        """
        Linguistic Variable WMS
        """
        x= np.arange(0,1+dx,dx).round(nd)

        medium_val = 0.7
        df = pd.DataFrame(data =
{'w':Fuzzification.trapezoid(x,0,0,0,medium_val),
```

```
'm':Fuzzification.trapezoid(x,0,medium_val,medium_val,1),

's':Fuzzification.trapezoid(x,medium_val,1,1,1)},
                         index = x)
        Fuzzification.check_ruspini_partition(df)
        Fuzzification.check_consistency(df)
        return df.round(nd)

    @classmethod
    def vbbagvg(cls):
        """
        Linguistic Variable VBBAGVG
        """
        x=np.arange(0,1+dx,dx).round(nd)
        d = 0.25
        data = {}
        for i,l in enumerate(['vb','b','a','g','vg']):
            data[l] =Fuzzification.trapezoid(x,d*(i-
1),d*(i),d*(i),d*(i+1))
        df = pd.DataFrame(data = data,index = x)
        cls.check_ruspini_partition(df)
        cls.check_consistency(df)
        return df.round(nd)

    @classmethod
    def elvllflifhhvheh(cls):
        """
        Linguistic Variable elvllflifhhvheh
        """
        x=np.arange(0,1+dx,dx).round(nd)
        d = 0.125
        data = {}
        for i,l in enumerate(['el','vl','l','fl','i','fh','h','vh','eh']):
            data[l] = Fuzzification.trapezoid(x,d*(i-
1),d*(i),d*(i),d*(i+1))
        df = pd.DataFrame(data = data,index = x)
        cls.check_ruspini_partition(df)
        cls.check_consistency(df)
        return df.round(nd)

    @staticmethod
    def check_ruspini_partition(df):
        """
        Special case of Rule #2 of Fuzzy System: Consistency of Unions for
WMS and VBBAGVG
        """
        assert any(df.sum(axis='columns').apply(lambda x: round(x,2)==1))
== True , 'Ruspini Partition Not Satisfied'

    @staticmethod
    def check_consistency(df):
        """
```

```
        Rule #2 of Fuzzy System: Consistency of Unions - for any input,
the membership functions of all the fuzzy sets it belongs too should be
less than or equal to 1.
        """
        assert any(df.sum(axis='columns').apply(lambda x: round(x,2)<=1))
== True , 'Not Consistent'


class InferenceEngine:

    @classmethod
    def s_p(cls,secondary_indicators,primary_ind_name,indictor_type):
        """
        SECONDARY TO PRIMARY INFERENCE ENGINE & PRIMARY TO OSUS
        *** ONLY WORKS FOR 2 AND 3 SECONDARY INDICATOR INPUTS
        """
        #checks
        assert all(i['company']==secondary_indicators[0]['company'] for i
in secondary_indicators), 'secondary indicators included dont have the
same company'
        secondary_ind_company = secondary_indicators[0]['company']


        assert all(i['year']==secondary_indicators[0]['year'] for i in
secondary_indicators), 'secondary indicators included dont have the same
year'
        secondary_ind_year = secondary_indicators[0]['year']

        #search the rule base for the secondary indicator
        rb = pd.read_excel('./databases/rulebase.xlsx',
sheet_name=primary_ind_name,skiprows=13)
        lval = []
        indices = []

        if len(secondary_indicators)==2: #if there are two secondary
indicators
            for in1_lv in ['vb','b','a','g','vg']:
                for in2_lv in ['vb','b','a','g','vg']:
                    lval.append(secondary_indicators[0][in1_lv] *
secondary_indicators[1][in2_lv]) #LARSEN IMPLICATION-sensitive to the
number of indicators
                    rule = rb[(rb[secondary_indicators[0][indictor_type]]
== in1_lv) &
                              (rb[secondary_indicators[1][indictor_type]]
== in2_lv)] #selecting the right row from the rulebase, sensitive to the
number of indicators
                    indices.append(rule[primary_ind_name].iloc[0]) #

        elif len(secondary_indicators)==3: #if there are three secondary
indicators
            for in1_lv in ['vb','b','a','g','vg']:
                for in2_lv in ['vb','b','a','g','vg']:
                    for in3_lv in ['vb','b','a','g','vg']:
```

```
                        lval.append(secondary_indicators[0][in1_lv] *
secondary_indicators[1][in2_lv] * secondary_indicators[2][in3_lv]) #LARSEN
IMPLICATION-sensitive to the number of indicators
                        rule =
rb[(rb[secondary_indicators[0][indictor_type]] == in1_lv) &

(rb[secondary_indicators[1][indictor_type]] == in2_lv) &

(rb[secondary_indicators[2][indictor_type]] == in3_lv)] #selecting the
right row from the rulebase, sensitive to the number of indicators
                        indices.append(rule[primary_ind_name].iloc[0]) #
        else:
            print('WARNING, THER ARE SOME OTHER NUMBER OF secondary
INDICATORS')

        s = pd.Series(data=lval,
                      index=indices).round(nd)
        s = s.groupby(s.index).sum() #add up all vals with same linguistic
var

        s['primary'] = primary_ind_name
        s['year'] = secondary_ind_year
        s['company'] = secondary_ind_company
        return s

    @classmethod
    def b_s(cls,basic_indicators):
        """
        BASIC TO SECONDARY INFERENCE ENGINE

        *** ONLY FOR 2 BASIC INDICATOR INPUTS
        """
        #checks
        assert all(i['company']==basic_indicators[0]['company'] for i in
basic_indicators), 'basic indicators included dont have the same company'
        secondary_ind_company = basic_indicators[0]['company']

        assert all(i['secondary']==basic_indicators[0]['secondary'] for i
in basic_indicators), 'basic indicators included dont have the same
secondary indicator'
        secondary_ind_name = basic_indicators[0]['secondary'] #status

        assert all(i['year']==basic_indicators[0]['year'] for i in
basic_indicators), 'basic indicators included dont have the same year'
        secondary_ind_year = basic_indicators[0]['year']

        #search the rule base for the secondary indicator
        rb = pd.read_excel('./databases/rulebase.xlsx',
sheet_name=secondary_ind_name,skiprows=13)
        lval = []
        indices = []

        if len(basic_indicators)==2: #if there are two basic indicators
            for in1_lv in ['w','m','s']:
```

```
                for in2_lv in ['w','m','s']:
                    lval.append(basic_indicators[0][in1_lv] *
basic_indicators[1][in2_lv]) #LARSEN IMPLICATIONsensitive to the number of
indicators
                    rule = rb[(rb[basic_indicators[0]['basic']] == in1_lv)
&
                              (rb[basic_indicators[1]['basic']] ==
in2_lv)] #selecting the right row from the rulebase, sensitive to the
number of indicators
                    indices.append(rule[secondary_ind_name].iloc[0]) #

        elif len(basic_indicators)==3: #if there are three basic
indicators
            for in1_lv in ['w','m','s']:
                for in2_lv in ['w','m','s']:
                    for in3_lv in ['w','m','s']:
                        lval.append(basic_indicators[0][in1_lv] *
basic_indicators[1][in2_lv] * basic_indicators[2][in3_lv]) #LARSEN
IMPLICATIONsensitive to the number of indicators
                        rule = rb[(rb[basic_indicators[0]['basic']] ==
in1_lv) &
                                  (rb[basic_indicators[1]['basic']] ==
in2_lv) &
                                  (rb[basic_indicators[2]['basic']] ==
in3_lv)] #selecting the right row from the rulebase, sensitive to the
number of indicators
                        indices.append(rule[secondary_ind_name].iloc[0]) #
        else:
            print('WARNING, THERE ARE SOME OTHER NUMBER OF BASIC
INDICATORS')

        s = pd.Series(data=lval,index=indices).round(nd)
        s = s.groupby(s.index).sum() #add up all similar vals

        s['secondary'] = secondary_ind_name
        s['year'] = secondary_ind_year
        s['company'] = secondary_ind_company
        return s[['secondary','company','year','vb','b','a','g','vg']]

------main.py------

from model import Fuzzification, InferenceEngine
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import time

plt.style.use('seaborn-whitegrid')
plt.rcParams['font.weight'] = 'bold'
plt.rcParams['font.size'] = 12
plt.rcParams['axes.labelweight'] = 'bold'
plt.rcParams['lines.linewidth'] = 2
plt.rcParams['axes.titleweight'] = 'bold'
```

```
struct = {'wealth':{
                    'status':{'roe':'middle_is_better',
                              'roa':'higher_is_better'},
                    'pressure':{'cf_capex':'higher_is_better',
                                'dividend payout
ratio':'middle_is_better'},
                    'response':{'debt to equity ratio':'middle_is_better',
                                'operating expenses':'lower_is_better',
                                'effective tax rate':'lower_is_better'}
                   },
          'ecos':{
                    'air':{'clean generation':'lower_is_better', #bc we
want to see a low percentage of coal
                           'co2 emissions':'lower_is_better'},
                    'land':{'spills':'lower_is_better',
                            'solid waste':'lower_is_better',
                            'hazardous waste':'lower_is_better'},
                    'water':{'total water withdrawal':'lower_is_better',
                             'percent water consumed':'lower_is_better'}
                   },
          'hums':{
                    'health':{'fatalities':'lower_is_better', #bc we want
to see a low percentage of coal
                              'osha recordable rate
(ticr)':'lower_is_better'},
                    'polic':{'lobbying spending':'lower_is_better',
                            'charitable giving':'higher_is_better'}
                   }
         }

def basic_to_secondary(year, delta, sensitivity_ind=None):
    print('Starting Basic -> Secondary')
    for primary_indicator in struct.keys():
        frames = []
        for secondary_indicator in struct[primary_indicator]:
            #print('{}-{}'.format(primary_indicator, secondary_indicator))

frames.append(Fuzzification.main(primary_indicator=primary_indicator,

secondary_indicator=secondary_indicator,

basic_indicators=struct[primary_indicator][secondary_indicator],
                                             indicator_type='basic',
                                             year=year,

sensitivity_ind=sensitivity_ind,
                                             delta=delta))
        secondary_agg = pd.concat(frames).reset_index(drop=True)
        out_file =
os.path.join(annuals_dir,'{}_{}_{}_{}_secondary_agg.csv'.format(delta,sens
itivity_ind, year,primary_indicator))
        secondary_agg.to_csv(out_file,index=False)
```

```
def secondary_to_primary(year, delta, sensitivity_ind=None):
    print('Starting Secondary -> Primary')
    frames2=[]
    for primary_ind_name in struct.keys():
        #print(primary_ind_name)
        in_file =
os.path.join(annuals_dir,'{}_{}_{}_{}_secondary_agg.csv'.format(delta,sens
itivity_ind, year,primary_ind_name))
        secondary_agg = pd.read_csv(in_file)
        indicator_type = 'secondary'
        #INFERENCE
        frames=[]
        for company in secondary_agg['company'].unique():
            company_year = secondary_agg[(secondary_agg['company'] ==
company) &
                                         (secondary_agg['year'] == year)]
            s_indicators =
[company_year[company_year[indicator_type]==indicator].iloc[0] for
indicator in secondary_agg[indicator_type].unique()]

frames.append(InferenceEngine.s_p(s_indicators,primary_ind_name,indicator_
type)) #apply inference engine
        primary = pd.DataFrame(frames)
        frames2.append(primary)
    primary_agg = pd.concat(frames2)

    out_file =
os.path.join(annuals_dir,'{}_{}_{}_primary_agg.csv'.format(delta,sensitivi
ty_ind,year))
    primary_agg.to_csv(out_file,index=False)

def primary_to_osus(year, delta, sensitivity_ind=None):
    print('Starting Primary  -> OSUS')
    in_file =
os.path.join(annuals_dir,'{}_{}_{}_primary_agg.csv'.format(delta,sensitivi
ty_ind, year))
    primary_agg = pd.read_csv(in_file)

    osus_ind_name = 'osus'
    indicator_type = 'primary'
    #INFERENCE
    frames=[]
    for company in primary_agg['company'].unique():
        company_year = primary_agg[(primary_agg['company'] == company) &
                                   (primary_agg['year'] == year)]
        s_indicators =
[company_year[company_year[indicator_type]==indicator].iloc[0] for
indicator in primary_agg[indicator_type].unique()]

frames.append(InferenceEngine.s_p(s_indicators,osus_ind_name,indicator_typ
e)) #apply inference engine
    osus = pd.DataFrame(frames)
```

```
    out_file =
os.path.join(annuals_dir,'{}_{}_{}_osus_fuzz.csv'.format(delta,sensitivity
_ind,year))
    osus.to_csv(out_file, index=False)

def defuzzification(year, delta, sensitivity_ind=None):
    print('Defuzzifing')
    in_file =
os.path.join(annuals_dir,'{}_{}_{}_osus_fuzz.csv'.format(delta,sensitivity
_ind,year))
    osus = pd.read_csv(in_file)
    elvllflifhhvheh = Fuzzification.elvllflifhhvheh()
    osus['crisp']= (elvllflifhhvheh['el'].idxmax()*osus['el'] +
                    elvllflifhhvheh['vl'].idxmax()*osus['vl'] +
                    elvllflifhhvheh['l' ].idxmax()*osus['l' ] +
                    elvllflifhhvheh['fl'].idxmax()*osus['fl'] +
                    elvllflifhhvheh['i' ].idxmax()*osus['i' ] +
                    elvllflifhhvheh['fh'].idxmax()*osus['fh'] +
                    elvllflifhhvheh['h' ].idxmax()*osus['h' ] +
                    elvllflifhhvheh['vh'].idxmax()*osus['vh'] +

elvllflifhhvheh['eh'].idxmax()*osus['eh'])/osus[['el','vl','l','fl','i','f
h','h','vh','eh']].sum(axis='columns')
    crisp = osus[['company','year','crisp']]

    out_file =
os.path.join(annuals_dir,'{}_{}_{}_osus_crisp.csv'.format(delta,sensitivit
y_ind,year))
    crisp.to_csv(out_file, index=False)

def generate_time_series_plot(years = range(2014,2019), delta=0):
    print('GENERATING TIME SERIES CHART')
    frames =
[pd.read_csv(os.path.join(annuals_dir,'{}_{}_{}_osus_crisp.csv'.format(del
ta,None,year))) for year in years]
    osus = pd.concat(frames).set_index('year',drop=True)
    osus.index= pd.to_datetime(osus.index.astype(str), format='%Y')
    fig, ax = plt.subplots(figsize=(10,5))
    for idx, gp in osus.groupby('company'):
        gp.plot(ax=ax,label=idx)
    plt.grid(True); plt.xlabel('Year');
plt.ylabel('OSUS');plt.legend(osus.groupby('company').indices)

    out_file = os.path.join(pkg_dir,'outputs/final_chart_output.png')
    fig.savefig(out_file, dpi=300, bbox_inches='tight')

def run_model(years = range(2014,2019), sensitivity_ind=None, delta=0):
    print('\n'); print('RUNNING MODEL')
    for year in years:
        print(year)
        basic_to_secondary(year=year, sensitivity_ind=sensitivity_ind,
delta=delta)
        secondary_to_primary(year=year, sensitivity_ind=sensitivity_ind,
delta=delta)
```

```
        primary_to_osus(year=year, sensitivity_ind=sensitivity_ind,
delta=delta)
        defuzzification(year=year, sensitivity_ind=sensitivity_ind,
delta=delta)
    print('MODEL RUN COMPLETE')

def run_sensitivity_analysis(sensitivity_year = [2018]):
    """
    Sensitivity analysis is only run on one year
    """
    print('BEGINNING SENSITIVITY ANALYSIS')

    basic_indicator_list = [] #get a list of the basic indicators
    for key in struct.keys():
        for key2 in struct[key].keys():
             basic_indicator_list =  basic_indicator_list +
list(struct[key][key2].keys())

    for delta in [-0.1, 0.1]: # normalized number purturbation
        for sensitivity_ind in basic_indicator_list:
            run_model(years = sensitivity_year, sensitivity_ind =
sensitivity_ind, delta = delta)

def compile_sensitivity_results(sensitivity_year = [2018]):
    basic_indicator_list = [] #get a list of the basic indicators
    frames = []
    for key in struct.keys():
        for key2 in struct[key].keys():
             basic_indicator_list =  basic_indicator_list +
list(struct[key][key2].keys())

             normalized =
pd.read_csv(os.path.join(annuals_dir,'{}_{}_{}_intensive_normalized_basic_
indicators.csv'.format(0,
                                                   key,
                                                   key2)))
             frames.append(normalized)
    df = pd.concat(frames)
    df = df[df['year']==sensitivity_year[0]]
    df.rename(columns={"basic": "sensitivity_ind"}, inplace=True)

    frames =[]
    for sensitivity_ind in basic_indicator_list:

        #crisp values
        base =
pd.read_csv(os.path.join(annuals_dir,'{}_{}_{}_osus_crisp.csv'.format(0,

'None',

sensitivity_year[0])))
        for delta in [-0.1,0.1]:
```

```
            pert =
pd.read_csv(os.path.join(annuals_dir,'{}_{}_{}_osus_crisp.csv'.format(delt
a,

sensitivity_ind,

sensitivity_year[0])))
            base[delta] = pert['crisp']

        base['sensitivity_ind'] = sensitivity_ind
        frames.append(base)
    df2 = pd.concat(frames)

    df3 =
pd.merge(left=df2,right=df,on=['sensitivity_ind','company','year'])
    df3['D_h'] = abs( (1-df3['index']) * (df3[0.1]-df3['crisp']) )
    df3['D_l'] = abs( (1-df3['index']) * (df3[-0.1]-df3['crisp']))
    df3['D'] = df3[['D_h', 'D_l']].max(axis=1)

    #full rank information
    frames = []
    for idx, gp in df3.groupby('company'):
        gp['D_rank'] = gp['D'].rank(ascending=False)
        frames.append(gp)
    df = pd.concat(frames)

df.to_csv(os.path.join(annuals_dir,'sensitivity_analysis.csv'),index=False
)

    # average rank data

avg_rank=df.loc[:,['sensitivity_ind','D_rank']].groupby('sensitivity_ind')
.mean().sort_values(by='D_rank',ascending=True)

avg_rank.to_csv(os.path.join(annuals_dir,'sensitivity_analysis_rank_stats.
csv'),index=False)

    # average rank plot
    fig, ax = plt.subplots(figsize=(5,10))
    y_pos = np.arange(len(avg_rank.index))
    ax.barh(y_pos, avg_rank['D_rank'], align='center')
    ax.set_yticks(y_pos)
    ax.set_yticklabels(avg_rank.index)
    ax.invert_yaxis()  # labels read top-to-bottom
    ax.set_xlabel('Average Rank')
    ax.set_title('Sensitivity Analysis: Average Basic Indicator Rank')

fig.savefig(os.path.join(pkg_dir,'outputs/sensitivity_average_rank_bar_cha
rt.png'), dpi=300, bbox_inches='tight')
    plt.close(fig)

pkg_dir = 'C:\\Users\\tzave\\OneDrive - The Cooper Union for the
Advancement of Science and Art\\102-cooper\\150-
```

```
masters\\sustainability\\sustainability_project1\\IOU-Sustainability-
Model'

annuals_dir = os.path.join(pkg_dir, 'outputs/annuals')
if not os.path.exists(annuals_dir): os.makedirs(annuals_dir)

norm_dir = os.path.join(pkg_dir, 'outputs/normalization_curves')
if not os.path.exists(norm_dir): os.makedirs(norm_dir)

if __name__ == '__main__':
    tic = time.perf_counter()

    #Fuzzification.create_normalization_curves(struct)

    run_model(); generate_time_series_plot() # BASELINE MODEL

    run_sensitivity_analysis(); compile_sensitivity_results() # you must
rerun baseline to get accurate sensitivity analysis

    toc = time.perf_counter()
    print('COMPLETED! Duration: {} mins'.format((toc-tic)/60))
```

Appendix XI: References

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