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ANALYSIS OF NUCLEAR HYBRID ENERGY SYSTEMS WITH BATTERY STORAGE

USING LEVELIZED COST OF ELECTRICITY

By Ted Baker

A thesis

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To the Graduate Faculty:

The members of the committee appointed to examine the thesis of Ted Baker find it satisfactory and recommend that it be accepted.

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Thesis Abstract

ANALYSIS OF NUCLEAR HYBRID ENERGY SYSTEMS WITH BATTERY STORAGE USING LEVELIZED COST OF ELECTRICITY

Thesis Abstract – Idaho State University (2016)

As popular demand and regulation enable the rapid expansion of variable renewable generation, the electrical grid is seeing new challenges in providing reliable, stable electricity to customers. In order to meet these challenges, additional flexibility will need to be introduced to the electrical grid. Nuclear Hybrid Energy Systems are predicted to offer significant flexibility by combining some or all of renewable, fossil, and nuclear generation with energy storage and a secondary product production capability. This study aims to demonstrate the value of battery electric storage to such a nuclear hybrid system, as well as to examine the effectiveness of Levelized Cost of Electricity (LCOE) as a figure of merit for such a hybrid system. In this study, battery storage provided notable improvements in the utilization of variable wind generation. LCOE was found ineffective at capturing the benefits of storage and a revenue stream.

Introduction

Electricity is a requirement for modern living. Today's energy supply chain is the culmination of over one hundred years of development, and is a complex system of generation, transmission, and distribution that is regulated by federal and state electricity market rules. Since the early days of electricity, it has been closely tied to environmental regulations. This is because the primary sources of energy generation – coal, oil, and natural gas – all have negative environmental and health effects when used without emissions and waste mitigation efforts. The side effects include respiratory distress, water contamination, acid rain, cancer, and climate change. As concern for negative environmental and health effects of energy generation increase, and the means to transition to a better system grows, people are looking to cleaner forms of energy generation to replace or improve existing technologies.

Clean energy sources include renewable sources, such as hydroelectric, solar, and wind, and nuclear energy. Greenhouse gas (GHG) emissions can also be reduced by utilizing non-carbon heat sources for refining, scrubbing pollutants from emissions, and implementing carbon capture and storage technologies. The most popular approach to a greener energy system is to replace all "dirty" generation with clean wind and solar. This option theoretically solves the problem of emissions, but would impose severe technical consequences due to the variable nature of renewable energies (Denholm, O'Connel, et al. 2015), and can potentially increase emissions depending on the source of backup power for times of under generation from renewables.

Energy consumption habits are fairly predictable, and our entire electrical infrastructure was built to meet this demand pattern. Figure 1 shows a representative 24hr period of energy consumption in Texas. The 24-hour time period from January 1, 2016 shows energy consumption dipping at night when most people are resting, and peaking around 14:00 during peak daytime activity. The 1-year period shows minimal usage in this region during spring and winter, and peak use in the summer and fall. While these trends vary somewhat seasonally and annually, they are predictable within some margin of error. In contrast, the energy generated by variable sources such as wind and solar is highly stochastic. When these sources contribute a significant portion of the total generation, they cause disturbances in the net load curve as seen by traditional generators. The net load curve refers to the load after renewable resources are dispatched, and can be seen in Figure 3.

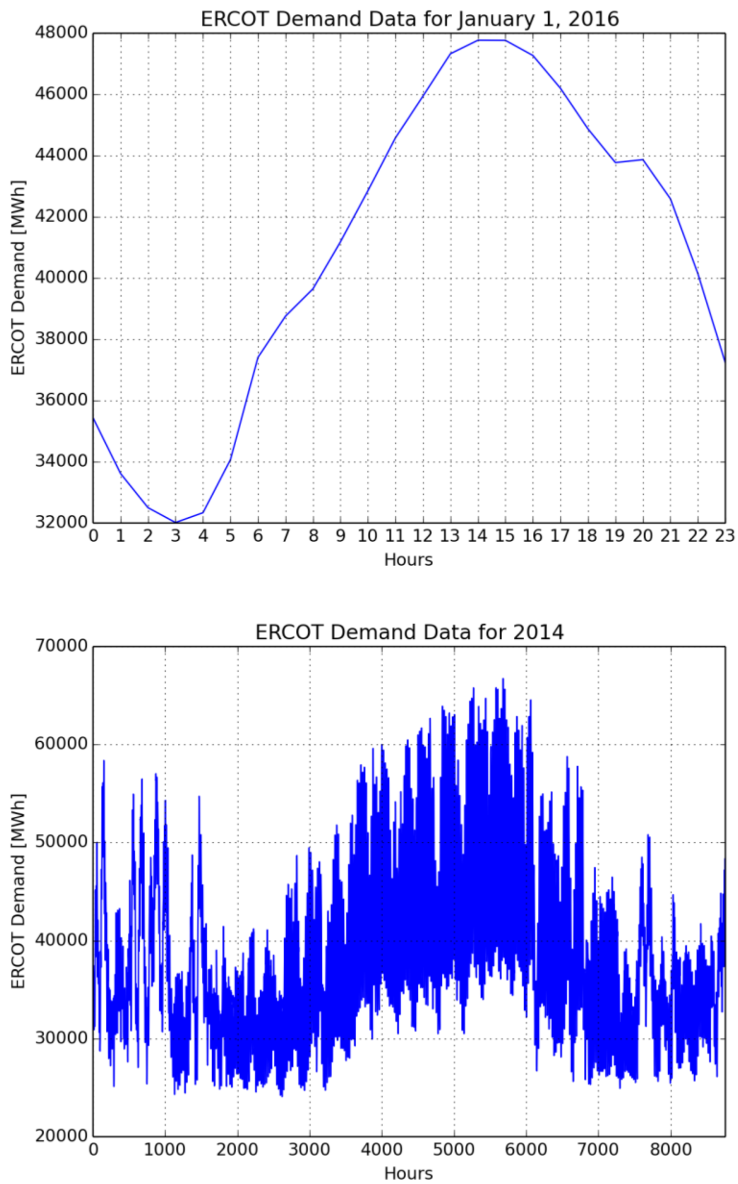

Figure 1: Demand data for the ERCOT grid for 24hrs (top), and 1 year (bottom) (Energy Reliability Council of Texas 2016)

To understand net demand, it is important to first explore how the order of dispatch for various energy sources is determined. Independent system operators (ISO) decide which energy sources to dispatch to meet demand from hour to hour. This decision is based on which source will provide the lowest cost electricity to the customer at that time. Figure 3 shows a "dispatch curve" which displays the cost of production, the capacity of each source, and the intersection at which it becomes economical to dispatch different technologies to meet demand. As Figure 3 shows, renewables such as wind, solar, and hydro have very low marginal cost and are therefore usually dispatched first. This means that the demand curve seen by other traditional technologies such as nuclear, coal, and natural gas can be represented as net demand, given by Equation 1.

Equation 1: Net Load

$$Net\ Load = Total\ Load - Variable\ Generation$$

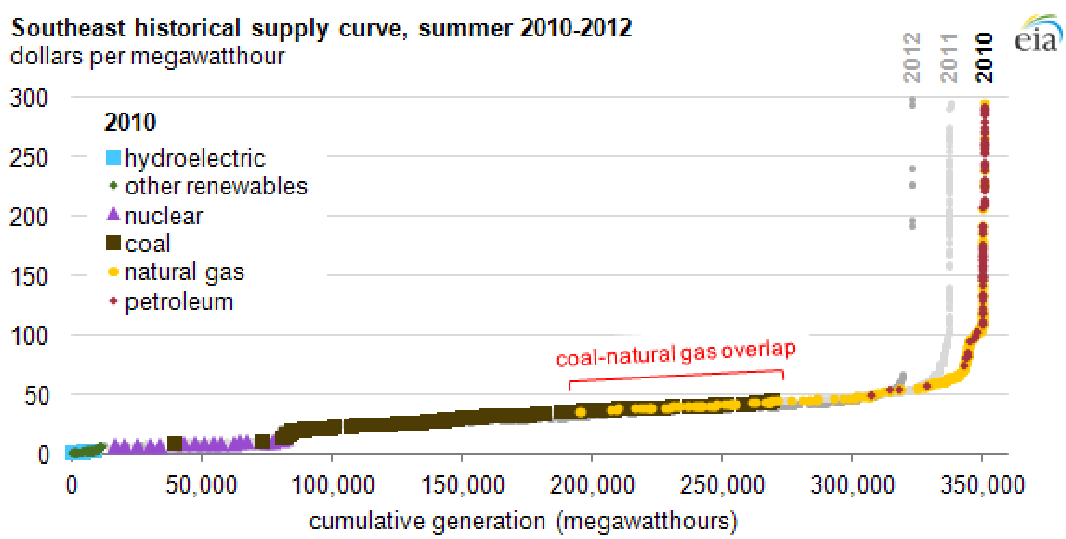

Figure 2: Demand stack curve for Southeastern US (Energy Information Administration 2010)

Figure 3 shows how net demand changes as variable renewable (VR) generation increases. Actual net demand curves for the years 2012 – 2013, and projected curves for 2014-2020 are shown with levels of VR generation projected to increase continually. Although the rate of increased VR generation is not specified, the figure shows that increased VR generation causes the ramp rates (both up and down ramping) to dramatically increase. During peak and minimum VR generation, too much or too little electricity can be supplied to the grid. This has a few negative effects, including the risk of damaging or destroying electrical infrastructure and blackouts. More commonly, this leads to times of price surging and suppression, causing volatility in the electricity market. When too much electricity is supplied, prices can fall to very low or even negative prices, meaning that producers have to shut down the plant, curtail their generation, or pay for consumers to use electricity. This has an especially negative effect on nuclear power plants, as discussed below.

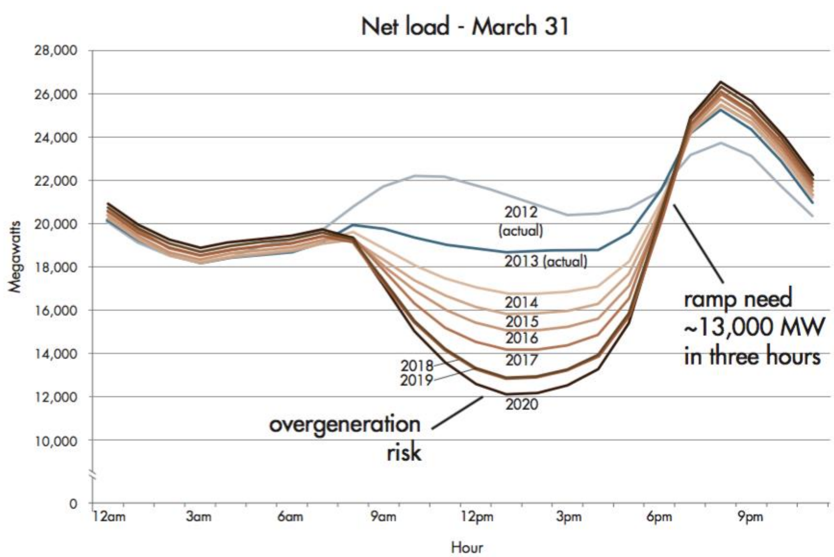

Figure 3: California Independent System Operator (ISO) "duck curve" (Denholm, O'Connel, et al. 2015)

First, nuclear power plants have physical and regulatory constraints on their flexibility. In times of rapid change, they often cannot adapt fast enough, or provide deep enough curtailment, to follow demand curves. In times of price suppression or negative pricing this can mean paying consumers to use electricity, or paying other generators to not produce, making room for the nuclear-generated electricity on the grid. Second, whereas fuel prices are a large portion of production for fossil power plants, nuclear power plant production costs are largely in capital and operations. This means that when they are not selling electricity, their costs remain high and the economic impact is greater than for other baseload (e.g. fossil-fueled) power plants.

These challenges mean that increased VR capacity on the grid requires increased flexibility from other grid entities. There are many approaches to increasing flexibility, including flexible generators, grid-scale energy storage, and demand-side management (Cochran, et al. 2014), (North American Electric Reliability Council 2010). Nuclear Hybrid Energy Systems (NHES) is a concept that addresses the challenges if increased variability in the grid while reducing GHG emissions, and maintaining viable economic performance. NHES consist of loosely or tightly coupled, co-controlled components that can include nuclear, renewable, and fossil generation sources, energy storage systems, and the production of electricity and a secondary commodity. Loosely and tightly coupled configurations refer to whether thermal energy (tightly coupled) or electrical energy (loosely coupled) is used in the production of a secondary product (Bragg-Sitton, Boardman, et al. 2016).

By co-controlling the traditional and variable generation systems, along with the inclusion of small-scale energy storage and flexible load (secondary product) components within the energy system, the system can provide multiple ancillary services such as load following, frequency and voltage regulation, and operating reserves. Another benefit is that the system essentially can act as its own ISO, dispatching its services and products to maximize revenue internally – at least within the constraints of its contractual obligations for grid services and production requirements.

Levelized cost of electricity (LCOE) is a common measure used to determine the lowest price of electricity at which a system can sell to break even. This is the figure of merit selected for the current study to evaluate NHES configurations for specific regional scenarios. LCOE takes into consideration capital, fuel, and operational costs, as well as capacity factor (CF), depreciation rates, and the lifetime of the equipment. However, LCOE has some limitations when it comes to considering variable generation. Due to fluctuations in market prices, systems with low CFs can accumulate large errors in LCOE if there is a mismatch between peak production and peak pricing (Joskow 2011). Generators with a high CF minimize this error due to an averaging effect. LCOE was chosen for this study because, by definition, minimizing LCOE maximizes the CF for a given NHES configuration.

The focus of this study was to develop a tool to model a nuclear hybrid energy system with four free parameters: renewable energy (RE) generation capacity, natural gas (NG) generation capacity, battery electric storage (BES) capacity, and mean grid demand. Additional sensitivity variables include fuel prices, emissions limits, and secondary product pricing. The model infrastructure developed for this study allows for a grid-based parametric analysis of the optimization space, and a limit surface search for demand coverage reliability. This design enables the user to find the best configuration within a discrete search space. In order to find the optimal configuration, an optimization algorithm will need to be implemented in the modeling framework. The selected modeling tool is currently unable to accept synthetic time histories for variable generation and demand data, and relies instead on historical databases. This limits the probabilistic reliability analysis that can be performed.

Background

The future energy grid will likely need to accommodate large amounts of variable generation from nondispatchable renewable sources, such as wind and solar. Presently, solar and wind generation technologies are being deployed rapidly at a global level as a measure to combat climate change, and to decrease reliance on foreign energy resources such as oil and natural gas. In 2014, renewables accounted for nearly 60% of global net power capacity additions, and make up nearly 30% of global total installed capacity, with a third of that consisting of variable generating capacity (Sawin, Sverrisson and Rickerson 2015). Though it was a big year for renewable installations - adding around 92GW of installed capacity - Sawin estimates that VR contributed only 4% of total global electricity production for 2014. VR generation shows tremendous promise for carbon emissions, but it is widely acknowledged that as more and more generation is added, the grid will face major technical challenges, and the marginal cost of adding renewables will rise. While the cost of VR generation itself is decreasing, the higher marginal cost can be attributed to the electricity supporting technologies that it will require such as energy storage, backup capacity (usually NG), and virtual inertia (voltage and frequency regulation)

The obvious challenge associated with renewable energy is the variability. Wind and solar are not available continuously and their availability does not always coincide with demand. With high penetration of renewables, in order to make up the energy needed when variable resources are not available, dispatchable energy sources that can follow the net load must be available to avoid brownouts and blackouts. The addition of variable renewables also means that net load has steeper ramps, and deeper troughs. The dispatchable resources must therefore be able to react quickly, and curtail deeply. There are a few ways to mitigate this problem including over-installation of renewables, increasing transmission capabilities (interconnections with neighboring balancing areas), and installation of grid-scale energy storage to increase total system flexibility. Over-installation means that there will be more periods of over-generation, creating low capacity factors for generators, additional curtailment of renewables, and tremendous volatility in the electricity market prices (price surging and suppression). Increased transmission capabilities mean that electricity can be "shipped" from where it is being produced to where it is needed, but the hardware is expensive, and sending electricity over long distances means increased line losses. Grid scale energy storage offers the capability of storing excess renewable energy during times of over generation, and producing electricity during times of under generation.

Traditional steam turbine generators have built in voltage and frequency regulation characteristics due to the electromechanical coupling in the spinning machinery. Unless equipped with hardware and controls to provide this service, renewables do not offer the same grid stabilization services. Adding this hardware also increases the cost of renewable installations.

NHES offer the opportunity to increase renewable generation while maintaining baseload generation, load following capabilities, and voltage and frequency regulation services. The NHES concept has been developed through the collaboration between several U.S. Department of Energy (DOE) national laboratories, including Idaho National Laboratory (INL), Oak Ridge National Laboratory (ORNL), Argonne National Lab (ANL), and the National Renewable Energy Laboratory (NREL). Although the proposed application for hybrid systems spans many regions and industries, the anticipated benefits are similar. Key benefits are expected to include (Bragg-Sitton, Boardman, et al. 2016):

- Provide dispatchable, flexible, and carbon-free electricity generation for the grid
- Provide synchronous electromechanical inertia to the grid
- Reduce the carbon footprint of the industrial sector
- Levelize and reduce energy costs (i.e., support stabilization of energy costs).

Hybrid grids have been analyzed in detail with consideration for multiple generation sources, energy storage devices, and traditional back-up generators. One such study considers an optimization of a hybrid system for rural use. This system provides a small amount of electricity (~13kW average) to a small transmission grid. It was allowed to include micro-hydroelectric, wind, and solar photovoltaic (PV) generators, as well as battery electric storage (Ashok 2001). Ashok utilizes simplified models of each generator technology to identify viable configurations to cover a given demand profile. The assumed cost of each technology is used to identify the optimal configuration for a given case. Ashok demonstrates an effective method for optimization of such a system.

The tool developed for the current study provides the additional capability of a nuclear-hybrid system that can generate electricity and/or a secondary product as required by electricity demand and grid reliability constraints. It also enables sensitivity analysis to varying renewable profiles based on historical wind and solar data, varying demand histories, potential carbon tax, fuel prices, and emissions limits.

INL and its partners in NHES research have conducted initial case studies for NHES configurations that could be sited in West Texas and Northeast Arizona. This study determined that, in both cases, NHES demonstrated favorable economic and technical performance, while providing reliable grid services and robust operations (Garcia, et al. 2015). While researchers continue to develop physical models of NHES components, it is valuable to analyze the behavior of NHES from a high level to determine fundamental behavioral characteristics. The analysis tool created for this study offers the ability to quickly identify regions within the configuration search space of NHES for various demands, markets, and products.

A similar study was conducted previously by INL, and is documented in the NHES Modeling and Simulation Status Report (Bragg-Sitton, Rabiti, et al. 2015). The previous economic assessment tool was a simplified model of a NHES consisting of wind generation, a small modular reactor (SMR), a secondary commodity production system, a natural gas generator, and electricity production. Its free variables were wind capacity factor, fraction of total generation by clean resources (SMR plus renewables) and the ratio of renewable generation to SMR. The natural gas subsystem was sized to make up the remainder of the total generation such that the fraction of all three added to one.

The previous study conducted by INL did not consider the revenue generated by the secondary production system in the calculation of LCOE. In order to account for this in the LCOE, the current study includes capital costs, operational costs, and a revenue stream from the secondary commodity. Additionally, the current study builds on the previous work and includes battery electric storage capability within the NHES.

Normalizing the system to fractional generations demonstrates the concept of a simplified cost analysis tool, and provides key information on how the relative sizes of different technologies affect performance and cost. The INL study showed that the LCOE was highly sensitive to the capacity factor estimation. This was also confirmed in a report from NREL that analyzed the LCOE sensitivity of wind projects under various financing strategies to changing cost variables. (Cory and Schwabe 2009).

Methodology

This study consisted of three major components: the LCOE cost parameters, the external Python model, and the RAVEN wrapping architecture. These are discussed below in detail.

Overview

The tool developed for this project consists of a simplified cost model developed in Python (van Rossum and Drake 2016), which is perturbed by a search strategy implemented in RAVEN (Rabiti, et al. 2016)(Risk Analysis and Virtual control Environment). Python was chosen because of its extensive libraries that allow for simple mathematical implementations and data management. RAVEN is an INL developed tool designed for probability risk assessment. It interacts easily with external codes, and has built in capabilities for limit surface search, probabilistic analysis, visualization, and reduced order model generation. It has the additional capabilities for optimization under development. Although the tool developed for this study can be used with these functions, this work only used the grid search and limit surface search capabilities to generate the model output data.

As shown in Figure 4, RAVEN provides input parameters to the external Python code. The external model accepts four parameters at a time from RAVEN: RE generating capacity, NG generating capacity, BES capacity, and mean total demand. The three capacity parameters define the NHES configuration, and the mean demand parameter establishes the size of the grid in which the system participates.

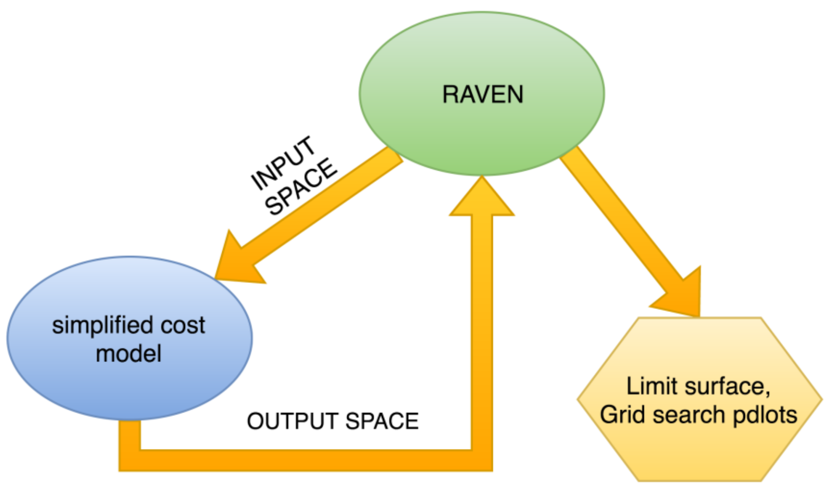

Figure 4: Top level diagram of model

Wind and Demand Data

The Python model uses historical Electric Reliability Council of Texas (ERCOT) data (ERCOT 2016) for the demand time series. This consists of hourly data points over the course of a year, or 8760 discrete points. The demand data is scaled by the ratio of the mean demand parameter provided by RAVEN to the original mean of the ERCOT as shown in Equation 2.

Equation 2: Scaling the Demand

$$Demand = Demand * \frac{RAVEN\ Mean}{ERCOT\ Mean}$$

The wind data history is generated by randomly sampling a beta probability distribution whose shape can be seen in Figure 5. This distribution was inherited from the prior study conducted by INL (Bragg-Sitton, Rabiti, et al. 2015). It was used there due to the relevant shape of the distribution compared to actual wind data, and its associated capacity factor (expected value) of ~0.28.

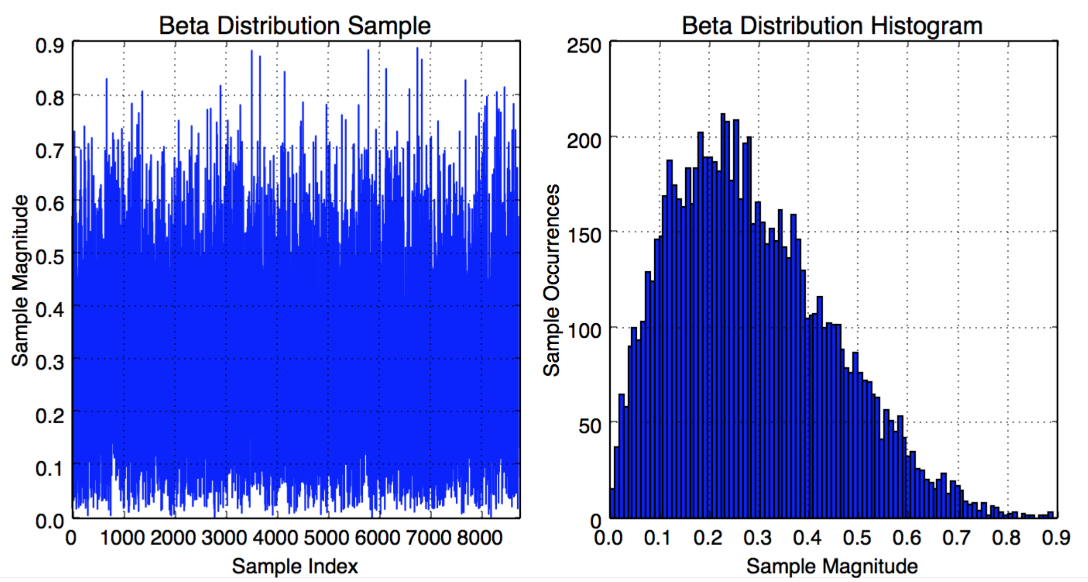

Figure 5: Beta Distribution Sampling and Histogram

The wind data sampled from the beta distribution ranging from zero to one was multiplied by the installed capacity, resulting in a distribution range from 0 to the full installed capacity. This results in the maximum use of the wind installation.

SMR and Commodity Hybrid

Small modular reactors are defined as having a capacity of less than three hundred megawatts of electric generation. For this study, the size of the SMR was chosen to be 300MW.

The commodity analyzed in this study was potable water, produced via brackish water reverse osmosis (RO) desalination. RO offers the advantage of requiring only electrical coupling in the hybrid system, eliminating the hurdles associated with co-location of a production facility with a nuclear generating station. Additionally, this system offers the benefit of stable electricity pricing, and the opportunity to reduce the water impacts of the SMR cooling loops. Data for the RO infrastructure is detailed below in Secondary Product Costs and Revenue.

Detailed Model Description

Model Flow

For each hour of the demand history, the configuration specified by the RAVEN input parameters is used to supply electricity. Each included generation technology is dispatched based on its marginal cost of generation from least expensive to most expensive. The exception is the SMR, which produces secondary product rather than putting electricity on the grid unless the other energy sources fail to cover demand in a given hour. As shown in Figure 6, renewable generation is dispatched first because of its assumed zero marginal cost of generation. If excess wind energy is available it is then used to charge the integrated battery. If the demand is not covered by wind, electricity stored in the battery is dispatched second, then electricity from natural gas and the SMR. This dispatch order was based on the assumption that energy from the SMR is more economically used to produce potable water than to produce electricity. The SMR energy used for electricity generation to meet grid demand, and the energy used for secondary commodity production are stored in separate variables. In this manner the revenue from the secondary product can be calculated later. Once the demand is covered or all resources have been dispatched, the utilization of each technology is calculated using Equation 3, and a flag variable is set to indicate whether the hour was successfully covered by the given configuration. The utilization factor for each technology is then passed to the LCOE calculator, along with the specific cost variables shown in Appendix A.

Equation 3: Energy Source Utilization

$$Utilization = Energy\ Used/(Total\ Possible\ Generation)$$

Table 1 shows the system inputs and outputs with the variable names used within the Python code. Appendix B contains the Python cost model code.

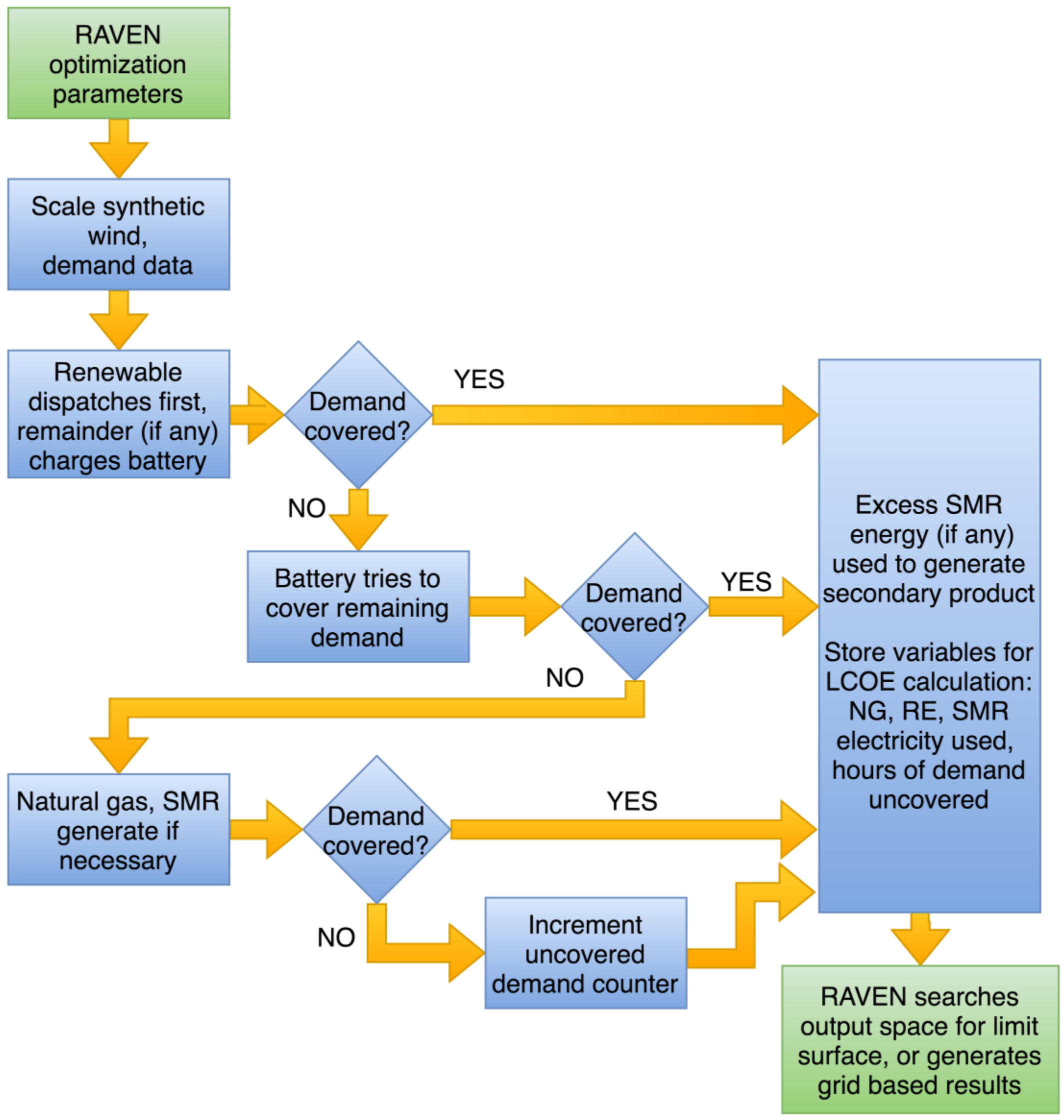

Figure 6: Flow Diagram of Python Cost Model

Table 1: Python Model Input and Output Variable Names

Inputs:	**Description**
recapacity	Installed capacity of renewable generation
ngcapacity	Installed capacity of NG generation
bescapacity	Installed battery electric storage capacity
meandemand	Scaling value for demand data
Outputs:	
hourlost	Failure flag for demand coverage (used in limit surface search)
utilre	Utilization factor for renewable generation
utilng	Utilization factor for NG generation
utilbes	Utilization factor for battery electric storage
utilsmr	Utilization factor for SMR
lcoe_total	Configuration total cost of electricity production
co2_total	Configuration total CO_2 emissions
product_revenue	Revenue generated by selling secondary product
lostdemand	Failure flag for demand coverage (used in parameter grid search)
emis_pass	Failure flag for CO_2 emissions limits

Levelized Cost Calculation

Equation 4, from Open Energy Information (Open EI), shows how the LCOE is computed. The result is multiplied by 10 to convert from cents/kWh to $/MWh. Capital Costs and operation and maintenance (O&M) costs for the energy generation and storage technologies were taken from Open EI's Transparent Cost Database (Open EI 2016). The capital recovery factor (CRF) and the tax rate (T) were computed using the discount rate (D) from Open EI's Levelized Cost Calculation web page (OpenEI 2016), and Equation 6. The lifetime of the investment (N) was chosen to be thirty years, although this may vary between technologies.

In order to normalize the LCOE for each source, the specific LCOE is multiplied by the total energy used for each source. The sum of all specific LCOEs is then divided by the sum of the demand data. This weights each source by its contribution to coverage. This calculation is shown in Equation 5.

Equation 4: Levelized Cost of Electricity

$$LCOE = \left(\frac{Capital\ Cost * CRF * (1 - T * Dpv)}{8760 * CF * (1 - T)} + \frac{fixed\ O\&M}{8760 * CF} + \frac{variable\ O\&M}{1000\ \frac{kWh}{MWh}} + \frac{Fuel\ Price * Heat\ Rate}{1{,}000{,}000 \frac{BTU}{mmBTU}} \right) * 10$$

Equation 5: LCOE Weighting

$$LCOE_{Total} = \frac{\begin{pmatrix} LCOE_{RE} * sum(RE_{used}) + LCOE_{NG} * sum(NG_{used}) + \\ LCOE_{SMR} * sum(SMR_{used}) + \ LCOE_{BES} * sum(BES_{used}) \end{pmatrix}}{sum(DemandData)}$$

Equation 6: Capital Recovery Factor

$$CRF = \frac{D * (1 + D)^N}{(1 + D)^N - 1}$$

Secondary Product Costs and Revenue

The revenue generated from selling the secondary product (e.g. potable water via RO purification of brackish water) was calculated using information from several sources. The capital cost of the plant was calculated using data from the Texas Water Development Board (TWDB). Their report (Arroyo and Shirazi 2012) provides cost values for several brackish water reverse osmosis plants. The values for this study are the averaged capital and O&M costs of six brackish groundwater plants in Texas. The efficiency of the plant was taken from a study conducted by TWDB on a flexible RO desalination system, including 3.8 kWh/kgal for RO and 6 kWh/kgal for filtration prior to desalination (Chapman and Leitz 2010). Equation 7, 9 and 10 in Appendix A detail the calculation of sizing the RO plant, and the capital and O&M Costs for the desalination process.

In order to value the revenue generated by selling secondary product, the selling price for water in [$/kgal] was converted to [$/kWh]. This conversion is shown in Equation 10 in Appendix A. The electricity from the SMR used for the secondary product is multiplied by this conversion factor to calculate the revenue from selling the water. The [$/MWh] revenue rate is subtracted from the total LCOE to show the net LCOE. The price of fresh water was calculated using values from Fisher (2006) by averaging the price of water for five Texas cities: Houston, San Antonio, El Paso, Dallas, and Fort Worth (Fisher, Whitehead and Melody 2006).

RAVEN Grid and Limit Surface Search

RAVEN perturbs the model with various configuration parameters to produce data sets. This study used two different methods to generate data and perform analysis. The first is a simple grid search, in which RAVEN generates a four-dimensional search space with the range specified by the user. This produced a set of results including failure flags for meeting demand and producing emissions. These data sets are filtered by the user in Microsoft Excel and used by RAVEN to visualize the results. This method allows for quick visual interpretations of the data to identify trends within the input search space, and to verify expected performance.

The limit surface search method uses algorithms built into RAVEN. In this method, RAVEN uses results from the Python external model to train a reduced order model (ROM) to speed up calculations. RAVEN samples this ROM to find the surface dividing the search space by failure and success as determined by the user specified constraints. In this study, two constraints are used – reliability and emissions. The reliability ensures that the model covers demand with less than 30 hours of uncovered demand over a full year. The emissions constraint ensures that the configuration reduces emissions by half compared to a business-as-usual case of purely natural gas generation. This method produces a dataset that closely follows the limit between “success” and “failure” according to the applied constraints. This study compares the limit surface with increasing NHES battery storage with and without emissions constraints. This study analyzes the effects of battery storage on the reliability limit surface, and examines the effectiveness of LCOE for NHES analysis.

Input Search Space

The range of values for each input parameter was chosen to demonstrate the full spectrum of system performance from under-generation to grid saturation. Parameter values were adjusted and limited in order to highlight key behaviors and to aid in visualizing the results.

Results

Limit Surface Search

In this data set the limit surface plots show the ngcapacity, recapacity, and meandemand variables along the x, y, and z dimensions. The white dots correspond to “successful” data points, and black dots denote “failure” points. In this set, only the failure criterion of meeting demand was considered. As shown in Figure 7, the limit surface shows a thickness caused by the hidden dimension, bescapacity. However, it is easily seen that the demand met by a configuration has a 1:1 linear relationship to ngcapacity. This makes sense because with the assumed 100% capacity factor for NG production, 1 added MW of generation means 1MW of demand covered.

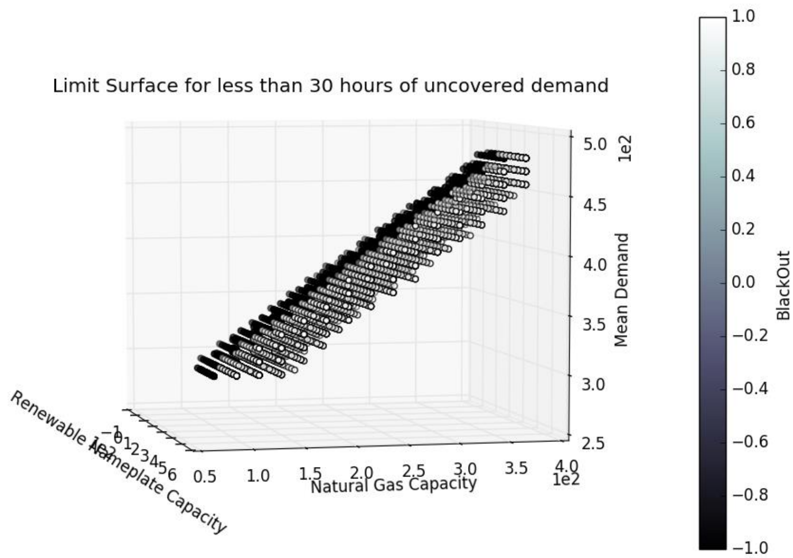

Figure 7: Side view of limit surface

Figure 8 shows an alternate view of the limit surface, parallel to the surface and perpendicular to the recapacity axis. From this perspective, it is easy to see the correlation between mean demand and recapacity. While it shows a positive correlation, it demonstrates a slope of approximately 0.29, corresponding to the capacity factor for the synthetic wind data.

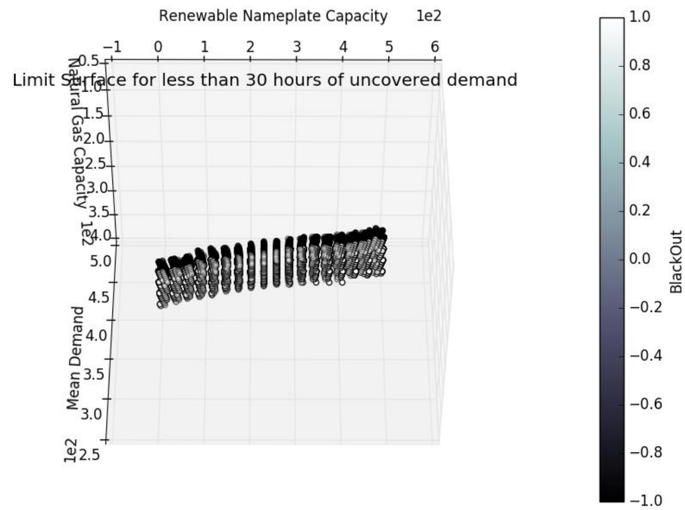

Figure 8: Alternate limit surface view

Grid Search

Alternatively, the model was perturbed using a grid input space, and post-processed in Microsoft Excel to remove "failure points" according to the demand constraint.

In order to visualize the effects of BES, NG capacity was removed from the model. The only search parameters used were recapacity and meandemand. For each plot, a single value of bescapacity was used to see the effects of increasing storage capacity. Figure 9 shows the demand coverage with no battery storage capacity, Figure 10 shows it with 50MWh of installed storage capacity, and Figure 11 shows it with 100MW of installed storage capacity. These plots demonstrate that increasing the battery storage increases the demand coverage, as seen by the increased are of the coverage region in the plots. It is also possible to detect an increased correlation between recapacity and meandemand. The first plot shows a slope of approximately 0.018, the second shows a slope of ~0.25, and the third a slope of ~0.035. This indicates that a higher level of battery storage increases the utilization of RE generation and results in a greater correlation to demand coverage.

It should be noted that while higher levels of installed battery storage capacity increase demand coverage, it does not necessarily correspond to greater certainty in reliability. In these plots, the successful region (implying reliable coverage) is populated by blue dots, and the failure region is represented by an absence of dots. The uncertainty in reliability was observed in the gaps between successful configurations along the limit surface between the success and failure regions.

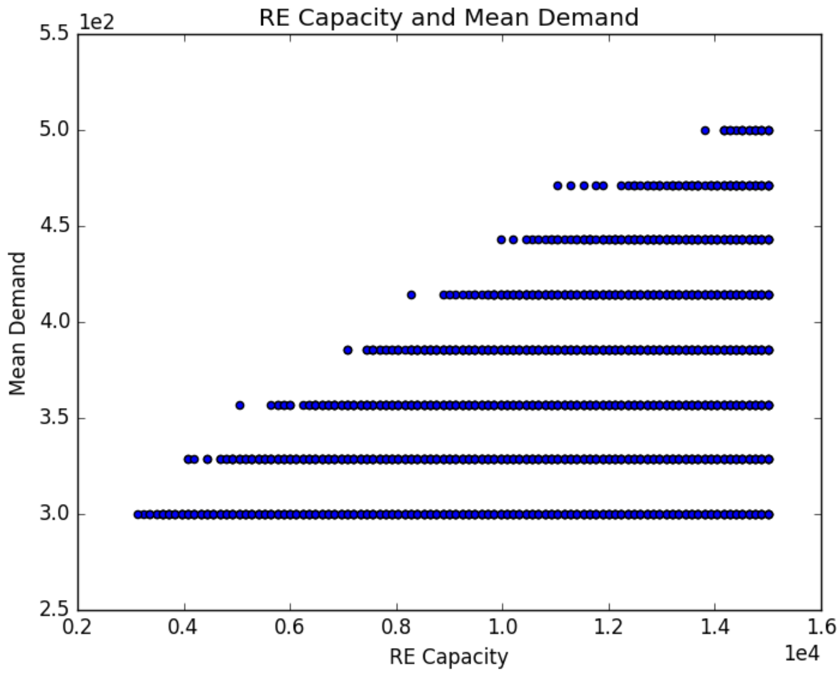

Figure 9: Mean Demand and RE Capacity with 0MWh of battery electric storage installed

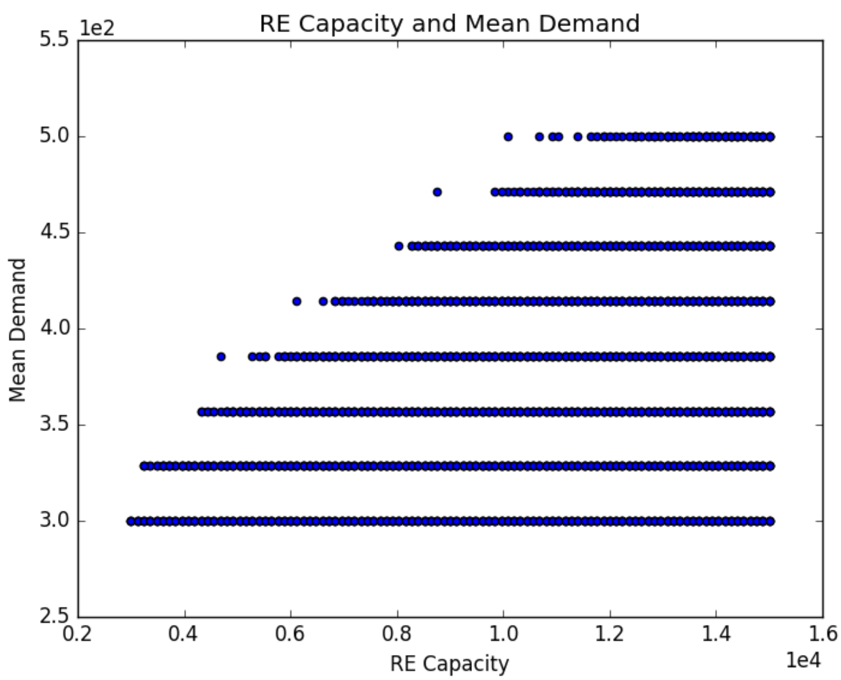

Figure 10: Mean Demand and RE Capacity with 50MWh of battery electric storage installed

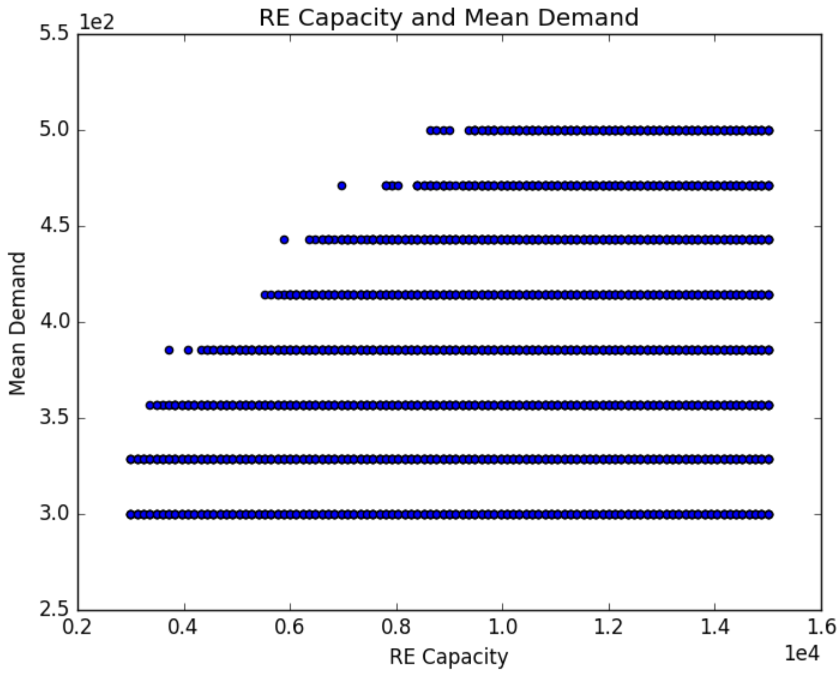

Figure 11: Mean Demand and RE Capacity with 100MWh of battery electric storage installed

As shown in Figure 12, the model reacts predictably in the face of increasing demand. It was observed that NG has a direct linear correlation to increased demand coverage, while RE is weakly correlated to increased demand coverage. LCOE increases with both RE and NG, but with a stronger correlation to RE. As mean demand increases, the utilization of natural gas increases and cost decreases. This also results in increased emissions as shown in Figure 14. Upper surface of this plot represents the reliability limit surface. The optimal configuration would lie somewhere along this limit surface, since this is the area with the least over-installed capacity. The points below the limit surface represent over-installed capacity, but increased certainty in reliability.

Figure 13 shows the LCOE with additional emissions constraint imposed. For demonstration purposed, the emissions limit was chosen to be one one-hundredth of the emissions that would be generated if the entire demand was met with NG. It shows that the model eliminates configurations with high NG, and low RE generation. This limit removes configurations with the lowest LCOE.

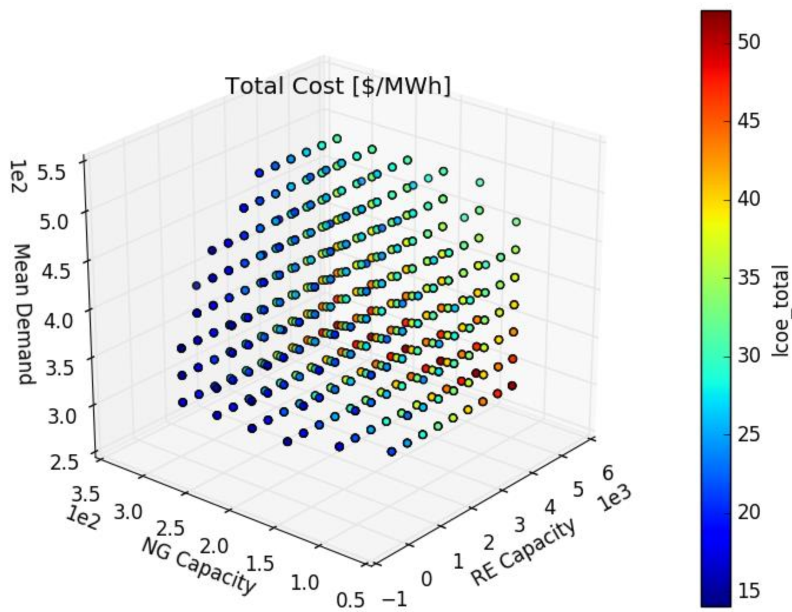

Figure 12: LCOE with reliability constraint imposed

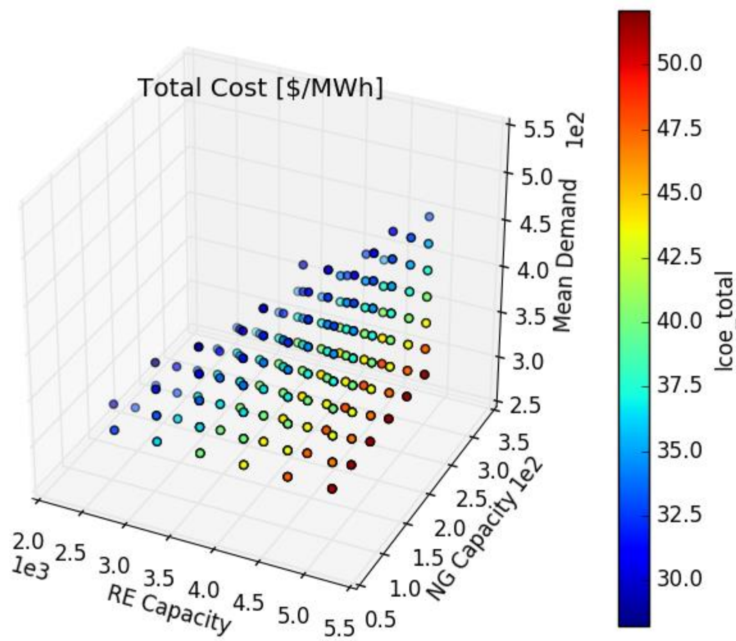

Figure 13: LCOE with reliability and emissions constraint imposed

Figure 14 shows the CO_2 emissions of each configuration. The model shows a strong correlation between NG and emissions, with the highest emissions corresponding to configurations with high NG and low RE. Figure 15 shows the CO_2 emissions with the additional emissions constraint of one one-hundredth of an NG only configuration imposed. It removes those options with high NG and low RE. It should be noted that it also removes some configurations with low NG and low RE, demonstrating the need for backup power for RE installations.

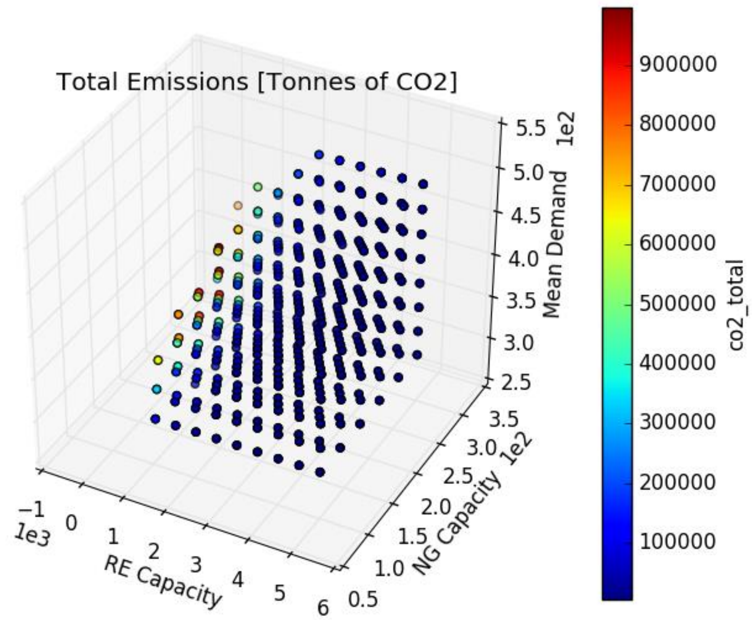

Figure 14:CO_2 emissions with reliability constraint imposed

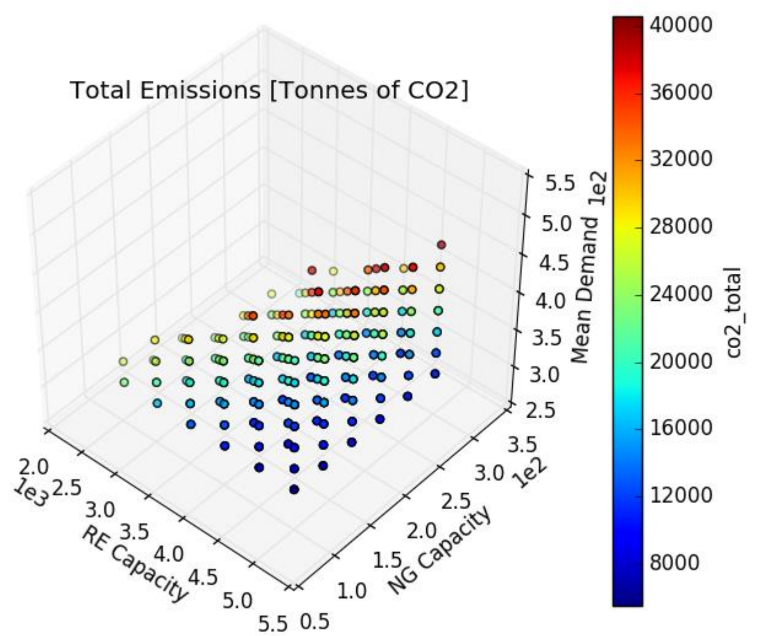

Figure 15: CO_2 emissions with reliability and emissions constraints imposed

Conclusions

Findings

The LCOE model performs as expected, capturing the basic NHES behaviors. The additional emissions constraint further limits the configurations that meet both success criteria. The limit surface tied only to a reliability constraint is strongly correlated to the NG capacity, and weakly correlated to the renewable generation.

Battery storage capacity has notable impacts on system performance. Increased levels of storage disproportionately increase the level of demand that can be covered reliability, showing that it also improves the utilization of wind energy. This results in a stronger correlation between RE installed capacity and the mean demand that can be covered.

Limitations

Conducting analysis using a simplified cost model is an effective way to see major performance trends in this system. It does, however, have limits, especially in regard to computing actual costs, revenues, and emissions. Each of these calculations is conducted under many simplifying assumptions, making them limited in effective scope. In cost calculations, it becomes very important to identify the ownership structure of the hybrid system. In order to properly value the electrical and secondary commodities, one must also consider the increased system flexibility, reduced emissions, and overall reliability. While LCOE provides a valuable figure of merit for comparing various energy generation technologies, it can create errors for variable generation and battery storage. In this study, an LCOE analysis proved to be quite ineffective especially for the revenue stream of the secondary product. A more detailed economic model is required to effectively capture the cost implications of a hybrid model.

While this tool provides a quick look at basic behaviors, a more thorough technical analysis is needed to verify that system components provide the necessary performance characteristics such as ramp rates, lifetime, reliability, and controllability. Creating a flexible, dynamic, high-resolution model of the systems and components will be required to identify viable configurations, controls strategies, and technologies.

Future Work

Additional work is required to capture the economic performance of a hybrid electricity and secondary commodity production system. The simplified LCOE approach employed here works well for analysis of electricity generation, but does not allow for effective analysis of the hybrid system.

The benefits of battery electric storage were observed to be notable in the results of this work. This result could derive from the stochastic wind data. True wind data tends to exhibit some sort of pattern. In this case, it is much more likely that it will either coincide more directly with the demand curve, or have some offset that could be smoothed by energy storage devices. In the case of truly stochastic wind data, harmonic feedback is just as probable as smoothing effects. In future work, it would be beneficial to utilize statistical methods to better represent the fundamental frequencies observed in true wind data, rather than using a purely stochastic signal. The same methods could be utilized to represent the stochasticity in demand histories.

It would be useful to explore other more sophisticated LCOE and LCOS (Levelized Cost of Storage) calculations for the analysis of hybrid systems, such as the approach used in Lazard's Levelized Cost of Storage Analysis (Lazard 2015) and in the study conducted by Pawel (Pawel 2014). These approaches may more effectively capture the contributions of variable generation and storage technologies to the total system cost of generation.

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Appendix A: LCOE Variables and Assumptions

Table 2: LCOE Cost Parameters

Technology Specific	Wind	Natural Gas	Battery Storage	SMR
Capital Cost [$/kW]	1922.99	947.5	1964	3317.8
Fixed O&M [$/kW]	30.3	11.7	51000	90.2
Variable O&M [$/MWh	0	2	0.49	5
DPV	0.83155	0.54407	1	0.59406
Fuel Price [US$/MMBtu]	0	4.67	0	0.5
Heat Rate [US$/MMBtu]	0	6752	0	10434
CO2 [Metric Tons/MWh]	0	0.4036	0	0
Global Parameters				
Tax Rate	0.392			
Discount Rate	0.07			
Lifetime of Investment	30			
Capital Recovery Factor	0.08059			

Equation 7: Computation of RO Capacity Required for Full Utilization of SMR [Million Gallons per Day]

$$300MW_{electric} * \frac{1000kW}{1MW} * \frac{24hr}{1day} * \frac{1kgal}{9.8kWh} * \frac{1MGD}{1000kGD} = 734.1MGD$$

Equation 8: Computation of Capital Costs [$/kWh installed]

$$\frac{1kgal}{9.8kWh} * \frac{24hr}{1day} * \frac{1000gal}{1kgal} = \frac{2449GPD}{kW\ (installed}$$

$$\frac{3.175\ \$}{GPD} * \frac{2449\ GPD}{kW\ installed} = \frac{7775.58\$}{kW\ installed}$$

Equation 9: Computation of O&M Costs [$/kWh]

$$\frac{0.837\$}{kgal} * \frac{1\ kgal}{9.8kWh} * \frac{1000\ kWh}{1\ MWh} = \frac{85.4\$}{kWh}$$

Equation 10: Conversion of [$/kgal] to [$/kWh] for Desalinated Water

$$\frac{2.86\$}{kgal} * \frac{1\ kgal}{9.8kWh} * \frac{1000kWh}{1\ MWh} = 291.84\frac{\$}{MWh}$$

Appendix B: External Python Model Code

```
# -*- coding: utf-8 -*-
"""
created on Mon feb 29 08:23:59 2016

@author: bakete - Ted Baker, ted.baker@inl.gov/tedb314@gmail.com
"""

# This file contains an external cost model of a nuclear-renewble hybrid
energy system.

import numpy as np


def initialize(self, runInfoDict, inputFiles):

   # load demand data from file
   self.demanddata = np.genfromtxt('2014_ERcoT_Hourly_Load_data.csv',
delimiter=',')


def run(self, Inputs):

   import costVariables

   # ---------------------------------------------------------------------------
   # sample random re generation and scale it such that the max value is the
installed capacity
   winddata = np.ones(len(self.demanddata))
   for hour in xrange(len(self.demanddata)):
      winddata[hour] = np.random.beta(2, 5)
   self.ranwind = winddata
   ranwind = self.ranwind * self.recapacity
   demanddata = self.demanddata * (self.meandemand /
np.mean(self.demanddata))


   # ---------------------------------------------------------------------------
   # initialize arrays to store the output variables.
   usedre = np.zeros(len(demanddata))  # initialize array to store RE
(renewable energy) electricity sold
   usedng = np.zeros(len(demanddata))  # initialize array to store NG
```

```
(natural gas) electricity sold
   usedbes = np.zeros(len(demanddata))  # initialize array to store BES
(battery electric storage) electricity sold
   usedsmrelec = np.zeros(len(demanddata))  # initialize array to store smr
(small modular reactor) electricity sold
   usedsmrtherm = np.zeros(len(demanddata))  # initialize array to store
smr energy used to generate secondary product
   besavail = np.zeros(len(demanddata))
   besavail[0] = self.bescapacity        # initialize first step with fully charged
battery
   self.smrcapacity = 300         # set smr capacity in MWth
   self.hourlost = 0

   # ----------------------------------------------------------------------------
   # for each hour in the demand profile, utilize generators for coverage

   for hour in xrange(len(demanddata)):
      remdemand = demanddata[hour]
      # for all hours after the first, set the available battery charge
      # to the level remaining from the previous hour
      if hour > 0:
         besavail[hour] = besavail[hour-1]

      # begin generating to cover demand, starting with RE
      remdemand -= ranwind[hour]
      if remdemand <= 0:  # if RE exceeds demand, set used RE to demand, all
SMR used for secondary product
         usedre[hour] = demanddata[hour]
         usedsmrtherm[hour] = self.smrcapacity
         besavail[hour] += ranwind[hour] - usedre[hour]  # use remaining RE
to charge battery
         if besavail[hour] > self.bescapacity:   # set BES to max, if its level
exceeds capacity
            besavail[hour] = self.bescapacity
         continue
      else:
         usedre[hour] = ranwind[hour]    # if demand not covered, used RE
equals the total generated

      # BES tries to cover remaining demand next
      remdemand -= besavail[hour]
      if remdemand < 0:
         usedbes[hour] = besavail[hour] + remdemand
         usedsmrtherm[hour] = self.smrcapacity
         continue
      else:
```

```
        usedbes[hour] = besavail[hour]

      # ng generates next
      remdemand -= self.ngcapacity
      if remdemand < 0:
        usedng[hour] = self.ngcapacity + remdemand
        usedsmrtherm[hour] = self.smrcapacity
        continue
      else:
        usedng[hour] = self.ngcapacity

      # smr generates last
      remdemand -= self.smrcapacity
      if 0 > remdemand:
        usedsmrelec[hour] = self.smrcapacity + remdemand
        usedsmrtherm[hour] = self.smrcapacity - usedsmrelec[hour]
        continue
      else:
        usedsmrelec[hour] = self.smrcapacity
        self.hourlost += 1

    # compute the utilization of each energy source
    self.utilre = sum(usedre)/float(self.recapacity * len(usedre))
    self.utilng = sum(usedng)/float(self.ngcapacity * len(usedng))
    self.utilsmr =
(sum(usedsmrelec)+sum(usedsmrtherm))/float(self.smrcapacity *
len(usedsmrelec))
    self.utilbes = sum(usedbes)/float(self.bescapacity * len(usedbes))

    def lcoe(gen, spc, cf):
      if cf == 0:
        # prevent divide by zero, inconsequential for later use of lcoe
        lcoe_val = 0
      else:
        # taken from [1], conversion factor added to convert to $/Mwh
        lcoe_val = gen[2] * (spc[0] * gen[0] * (1 - gen[1] * spc[3]) / float(8760
* cf * (1 - gen[1])) +
                    spc[1] / float(8760 * cf) + spc[2] / float(1000) + spc[4] *
spc[5] / float(1E6))
      return lcoe_val

    # find specific lcoe values using parameters and capacity factor
    lcoe_re = lcoe(costVariables.gen_lcoe_params,
costVariables.re_lcoe_params, self.utilre)
    lcoe_ng = lcoe(costVariables.gen_lcoe_params,
costVariables.ng_lcoe_params, self.utilng)
```

```
    lcoe_smr = lcoe(costVariables.gen_lcoe_params,
costVariables.smr_lcoe_params, self.utilsmr)
    lcoe_bes = lcoe(costVariables.gen_lcoe_params,
costVariables.bes_lcoe_params, self.utilbes)

    # sum up the used electricity, multiply by specific lcoe to find average
$/Mwh
    self.lcoe_total = (lcoe_re + lcoe_ng +
                    lcoe_smr + lcoe_bes)
    self.product_revenue = sum(usedsmrtherm) *
costVariables.thermalconversion

    # calculate co2 emitted
    # sum up emissions, multiply by specific co2 emissions to find average
co2/Mwh
    self.co2_total = (costVariables.co2_re*sum(usedre) +
costVariables.co2_ng*sum(usedng) +

costVariables.co2_smr*(sum(usedsmrelec)+sum(usedsmrtherm)))
    if self.hourlost < 30:
        self.lostdemand = 1
    else:
        self.lostdemand = -1

    if self.co2_total < 5E5:
        self.emis_pass = 1
    else:
        self.emis_pass = -1
```