Dynamic Optimization and Machine Learning Final Project

Design and Dispatch of Nuclear Renewable Hybrid Energy Systems

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Abstract

Electrical power grids around the world struggle to provide sufficient reliable electrical power in an economic and carbon-free manner. Nuclear-renewable hybrid energy systems (NHES) are proposed as a potential solution to this challenge, yet lack sufficiently accurate and tractable optimization strategies. For NHES, both the unit capacity and dispatch optimization problems are tightly interrelated and further complicated by the need to account for stochastic system elements. This work explores methods of combining the design and dispatch optimization problems in a computationally efficient manner while examining the scalability of the problem and the robustness of the solution.

Keywords— hybrid energy, optimization, combined design, stochastic optimization

Introduction

Modern society requires reliable access to abundant amounts of electrical power and there is an increasing interest in supplying this power in carbon-neutral or carbon-free ways (4). Current-fleet nuclear power plants were designed for steady or "baseload" operation and do not perform well economically in increasingly dynamic grid conditions (7). Coal and combined cycle natural gas power plants can perform quite economically, yet continue to be a source of carbon emissions unless combined with carbon sequestration technologies, which vastly reduce the overall efficiency of these plants. Variable energy resources (VER), like wind and solar, can produce carbon-free power, but the power output of these systems is subject to weather conditions and increases in VER penetration strains existing power grids (6; 3).

A potential solution to the clean, reliable energy problem is hybridization of next-generation nuclear and renewable energy resources. These nuclear-renewable hybrid energy systems (NHES) combine nuclear power generation and renewable energy resources with other energy system components to provide reliable, carbon-free and economically-viable solutions to our current energy challenges.

A leading challenge in the development of these systems is the optimization of the design and dispatch of the various system components. Both the unit capacity sizing and the system dispatch must be co-optimized as the optimal system design is highly interdependent on the system dispatch (1). This problem is further complicated by the need to account for stochastic time series (5) in the optimization problem. This results in a complex optimization problem where some variables are fixed over the lifetime of the system (unit capacities) and other variables must be adjusted at each point in the time horizon.

Some authors have used a nested-loop optimization methodology where the unit capacities are optimized in an outer loop and stochastic optimization techniques are used in an inner loop to optimize the system dispatch (12). This method successfully accounts for both the interrelated nature of the two optimization problems and the stochastic nature of the various time-series involved, but becomes excessively computationally demanding. In this work we propose methods to improve the computational tractability of the problem through reformulation and use of advanced optimization tools.

Model Description

The NHES model is comprised of 3 generating units, a thermal energy storage unit and a system electrical load. The generating units are: a solar PV farm, a wind farm, and a traditional steam turbine. The steam turbine can be fed from a SMR, the TES system or both. The three of these generating units need to be able to provide power for the given load profile. The solar, wind and load data is scaled data from the California Independent System Operator (CAISO) for the period from 29 Mar 2020 to 12 Apr 2020. The data is scaled by 0.01836 in order to make it a reasonable scale for a realistic hybrid energy system while maintaining realistic dynamics. An outline of the model design is shown in Figure 1.

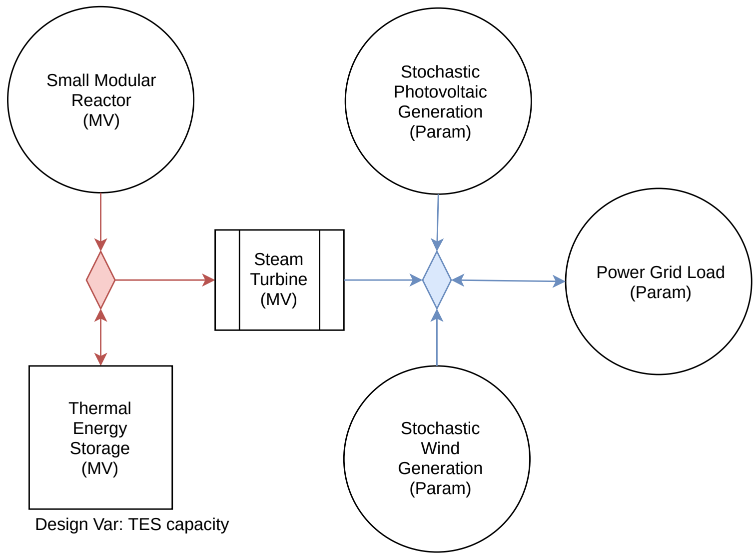

Figure 1: NHES Model Outline

The SMR generation (A_{SMR}) is modeled as a manipulated variable over the dispatch time horizon. It has upper ($A_{SMR,max}$) and lower ($A_{SMR,min}$) bounds to mimic the capabilities of a NuScale SMR power plant (11) consisting of 6 power modules. The thermal energy generated by the SMR can be directly converted to electricity in the steam turbine, or stored and retrieved from the TES. The TES is modeled similar to a charging and discharging battery. The change in energy stored in the TES (S_{TES}) is equal to power entering or leaving the TES (A_{TES}) multiplied by the efficiency of the TES (η_{TES}) as shown in Equation 1.

$$\frac{dS_{TES}}{dt} = A_{TES}\,\eta_{TES} \tag{1}$$

$$0 \leq S_{TES} \leq S_{TES,max} \tag{2}$$

The capacity of the TES ($S_{TES,max}$), shown in Equation 2, is a fixed variable in the optimization to allow the design capacity of the TES to be co-optimized with the unit dispatch.

The net thermal power produced from the SMR and TES is sent to the steam turbine ($A_{tur,th}$).

$$A_{tur,th} = A_{SMR} - A_{TES} \tag{3}$$

The steam turbine converts the thermal power to electrical power ($A_{tur,el}$) with a given efficiency (η_{tur}).

$$A_{tur,el} = \eta_{tur} A_{tur,th} \tag{4}$$

$$A_{tur,el} \geq 0 \tag{5}$$

Finally, the net electrical power generation must equal the electrical load on the system.

$$A_{tur,el} + A_{wind} + A_{solar} = A_{load} \tag{6}$$

The goal of the design and dispatch optimization problem is find the ideal TES capacity ($S_{TES,max}$) and system dispatch (A_i) that minimizes the system levelized cost of electricity (LCOE) while satisfying system constraints. For the purposes of this project, the authors took a system wide view on LCOE rather than an individual generating view. This system wide view on LCOE gives the following formulation:

$$LCOE = \frac{\sum_i^n \left(Cost_{Cap,i} + Cost_{FOC,i} + A_i Cost_{VOC,i} \right)}{\sum_0^t A_{load}} \tag{7}$$

In this formulation, $Cost_{Cap,i}$, $Cost_{FOC,i}$ and $Cost_{VOC,i}$ represent the capital cost, fixed operating cost and variable operating cost for component i of n components. The various system components have differing expected lifetimes and the system dispatch length is shorter than the expected lifetime of the plant. To account for this, the capital and fixed operating costs for each unit as well as the system load are scaled to an expected 30 year lifetime. A summary of the physical parameters is given in Table 1 and a summary of the economic parameters is given in Table 2.

Table 1: System Physical Parameters

Parameter	Value	Units	Description
η_{TES}	0.95	N/A	TES roundtrip efficiency
η_{tur}	0.8	N/A	Turbine efficiency
$A_{SMR,max}$	550	MWth	SMR maximum capacity
$A_{SMR,min}$	200	MWth	SMR minimum capacity
$S_{TES,max}$	NA	MWh	TES maximum capacity

Table 2: System Economic Parameters

Parameter	Value	Units	Description	Source
$C_{Cap,SMR}$	1.906e9	\$	Scaled SMR and turbine capital cost	(2)
$C_{Cap,TES}$	15000	\$/MWh	TES capital cost	(8)
$C_{Cap,solar}$	4.720e8	\$	Scaled solar farm capital cost	(13)
$C_{Cap,wind}$	1.544e8	\$	Scaled wind farm capital cost	(13)
$C_{FOC,SMR}$	1.850e7	\$	Scaled SMR and turbine fixed operating costs	(9)
$C_{FOC,TES}$	1.000e7	\$/MWth	TES fixed operating costs	Approximated
$C_{FOC,solar}$	1.421e8	\$	Solar fixed operating costs	(13)
$C_{FOC,wind}$	9.794e7	\$	Scaled wind fixed operating costs	(13)
$C_{VOC,SMR}$	1.0	\$/MWh	SMR variable operating costs	Approximated (10)
$C_{VOC,tur}$	1.0	\$/MWh	Turbine variable operating costs	Approximated (10)
$C_{VOC,TES}$	0.0	\$/MWh	TES variable operating costs	Approximated
$C_{VOC,solar}$	0.0	\$/MWh	Solar variable operating costs	(13)
$C_{VOC,wind}$	0.0	\$/MWh	Wind variable operating costs	(13)

Baseline case

The model is originally optimized using a one week dispatch period to get baseline values for TES storage size and LCOE. The baseline case provided a system LCOE of $68.40/MW and a TES storage size of 150.9 MWh. Figure 2 shows the results of the week-long baseline case. A periodic boundary condition was imposed on the optimization case so that the thermal energy storage started empty and ended empty.

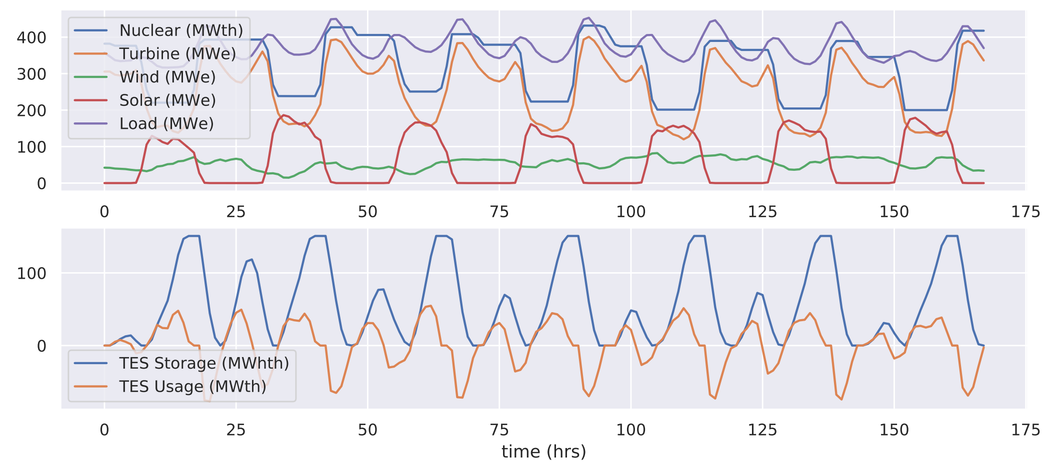

Figure 2: Baseline Solution

In the baseline case, the TES is charged when solar power production is high (during the middle of the day) and discharged as solar power diminishes and into the night when there is no solar power. The optimized TES dispatch follows a cycle proportional to the load. The baseline case is used as a comparison for the various expansions of the study.

Time-horizon Study

One of the various goals of this project is to determine the potential lengths of time horizons that can be feasibly solved using a combined design and dispatch approach. Longer time-horizons lead to more realistic and comprehensive studies for development of new power plants, yet become increasingly computationally demanding.

The length of the time-horizon is increased in increments of 200 hours starting from the 200 hours and continued until running out of prepared data at 3000 time points (over 4 months). All involved data are scaled from the same CAISO source for subsequent time points. The longest problem results in a total of 77976 variables, 74975 equations and 11996 slack variables. It was not anticipated that GEKKO would be able to handle nearly this large of a problem, so no more data was prepared, but it appears that GEKKO could continue to handle significantly larger problems. The final optimized solution covering 3000 hours is shown in Figure 3. Note that the height and intensity of the peaks in the system load become increasingly pronounced as the length of the time horizon increases.

Interestingly, GEKKO is unable to solve the problems using 400 hour and 2200 hour time horizons, despite the fact that longer problems are feasible. It is possible that better bounds on the TES design parameter would help improve the feasibility of the solution at these points.

It is also interesting to note how the solution dynamics change as the time horizon length increases. The initial solution, shown in Figure 2, only uses the TES for peak-shifting the load within a day and never stores thermal energy between days. This pattern continues up until approximately 1400 hours after which some inter-day storage is observed. A sample of "inter-day" storage is shown in Figure 4. The pattern of minimal inter-day storage continues until approximately 2400 hours, after which all profiles include significant storage across days or even weeks. The full 3000 hour

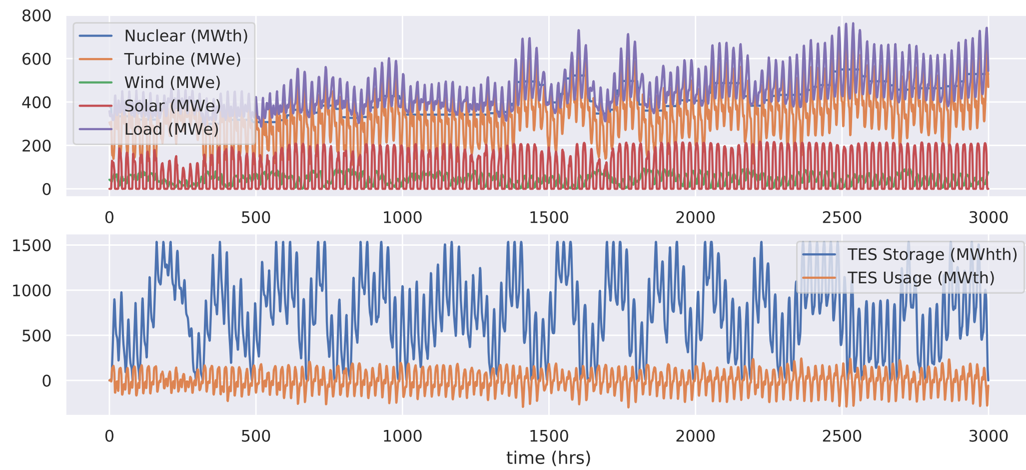

Figure 3: Final solution covering 3000 hours

solution in Figure 3 is a good example of the significant inter-day storage pattern.

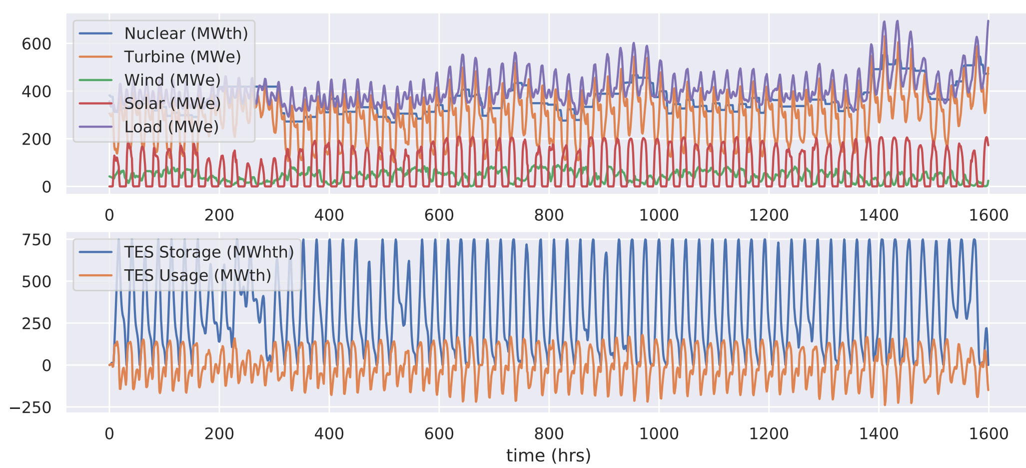

Figure 4: Solution covering 1600 hours

The LCOE, optimal TES capacity and required solution time were tracked throughout the scale-up process to determine how the problem scales with increasing complexity. The results are shown in Figure 5.

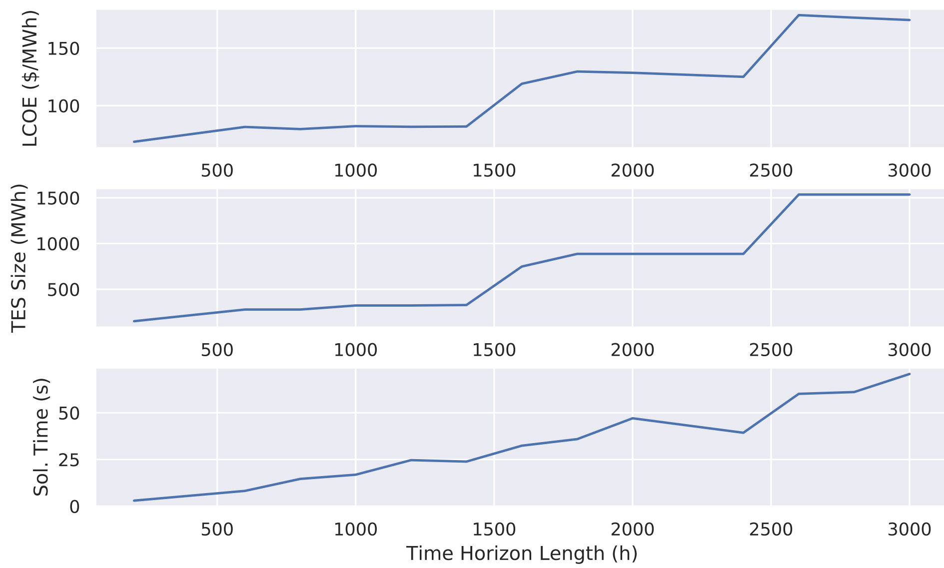

Figure 5: LCOE, TES capacity and solution time variation with increasing time horizon length

The LCOE, optimal TES size and solution time all increase as the time horizon gets longer. The LCOE and optimal TES size show striking correlation as they seem to be the same profile, but on different scales. This makes some sense as the overall cost of the system will be closely related to the TES capacity.

The sharp increases or "jumps" in LCOE and optimal TES capacity correlate closely to the changes in TES usage pattern discussed above. The first jump in LCOE/TES capacity occurs when the TES starts to be used for inter-day storage in addition to simple peak shifting. The second jump occurs when the TES begins to be used for much more significant inter-day storage. This also makes sense as the TES would need to be sized quite differently for each of these usage patterns.

When the effect of increasing the TES capacity is removed it appears that the LCOE slowly decreases with increasing time horizon. This indicates that for a consistent TES capacity and usage pattern, the LCOE tends to decrease slightly over longer times, likely due to the increasingly effective ways the optimizer can find to use the storage over increasing time horizons.

Together with the insight on distinctly different usage patterns for the TES, the slow consistent decrease in LCOE with time horizon length indicates that there are likely distinct classes of battery usage that have drastically different optimal configurations. In short, it appears that optimal storage capacity has a non-linear relationship to the expected optimal LCOE. Small increases in storage may yield significant improvements at some points in the design space and no improvement at other points.

Finally, the time required to solve the optimization problem also increases roughly linearly with increasing time horizon length. This is likely due to the highly efficient algorithms used in GEKKO for calculating exact derivatives.

At some point during the project, it was discovered that GEKKO uses a default penalty on the derivative of manipulated variables in an optimization, commonly referred to as a "DCOST". This DCOST is implicitly added to the objective function. As the SMR generation is defined as a manipulated variable, GEKKO implicitly added a DCOST for this variable to the objective function that is not reflected in the LCOE. This DCOST is not considered at this point in the analysis and is discussed further in the section covering the effects of SMR ramping costs. It should be noted however, that the DCOST is not scaled for the system lifetime like the other economic values. This results in an increasing incentive to flatten the SMR generation as the time horizon length increases. Ultimately this invalidates any real conclusions from the time horizon length study, but suggests that the study may have been effectively a parametric study on the effect of a slowly increasing DCOST. More study would be needed to fully determine the effects.

Overall, GEKKO is capable of solving increasingly large time horizon lengths until no more data was available. The implementation appears to scale very linearly in terms of solution time, allowing very long time horizons to be analyzed.

Losing Generation Study

Another goal of the project is to analyze the effects of losing renewable generation capacity and nuclear generation capacity for brief periods of time. The goal is to see how the TES can respond to meet the dispatch as well as to see how the LCOE changes. The first scenario tested is where both renewable energy generation sources are lost for 48 hours. Interesting, the LCOE for this case is slightly lower than the baseline case at $68.26 /MW and the TES storage remains at the same capacity of 150.9 MWh. This may suggest having renewables for this system increases the LCOE.

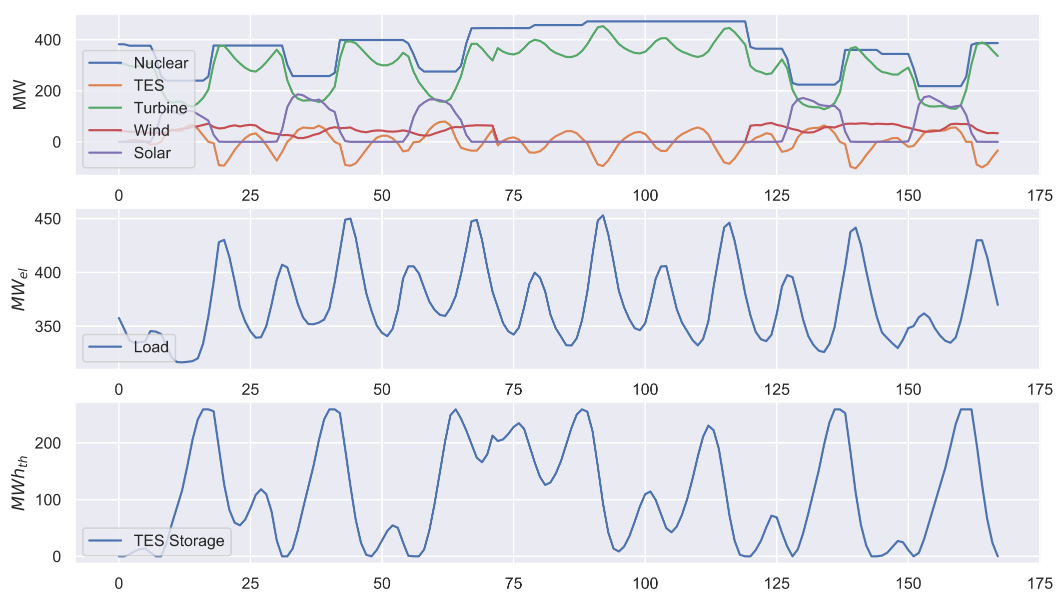

Figure 6: Power Generation Profile with 48 Hours of No Renewable Generation

The next case is when only solar is lost for 48 hours. Again, the LCOE increases compared to losing both wind and solar to $68.46/MW suggesting solar causes a higher LCOE. The storage of TES again remained the same at 150.9 MWh.

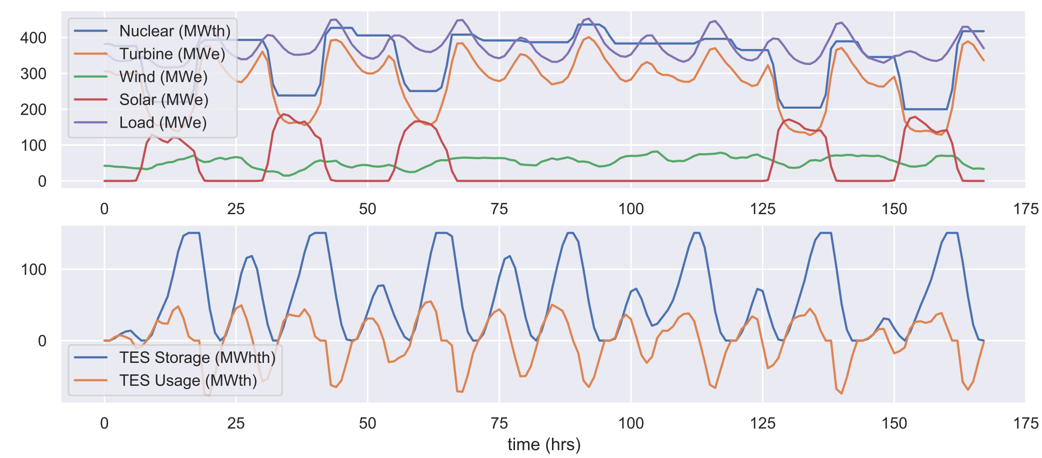

Figure 7: Power Generation Profile with 48 Hours of No Solar Generation

The next case is when wind is lost for 48 hours. For this case the LCOE decreases compared to just losing solar to $68.20/MW and the same storage capacity of 150.9 MWh.

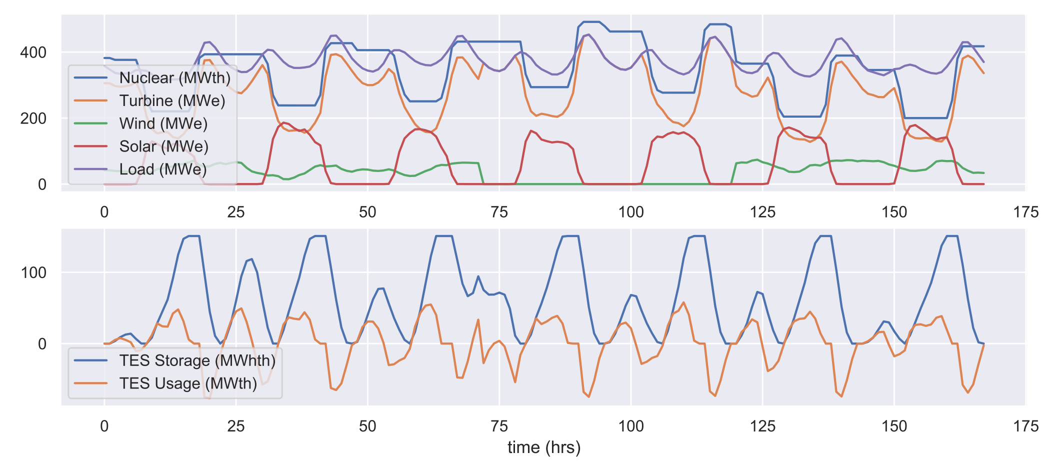

Figure 8: Power Generation Profile with 48 Hours of No Wind Generation

Lastly, a case is presented where there are no renewables for the entire time horizon. The nuclear hybrid system was sized to be able to meet the load so it is able to meet this dispatch requirement. The LCOE is significantly lower for this case at $46.22/MW which confirms that having renewables for this system increases the overall system LCOE.

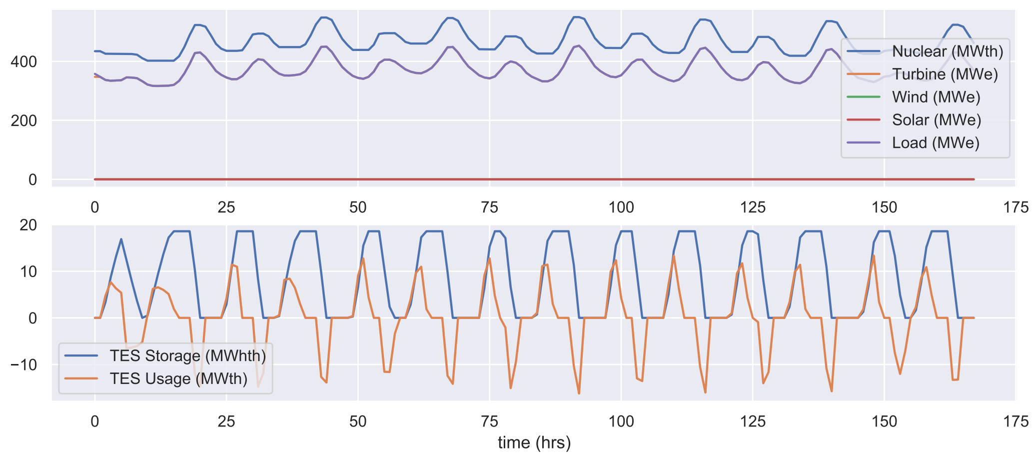

Figure 9: Power Generation Profile with No Renewables

A summary of all the cases is shown in Table 3.

Table 3: Summary of Lost Generation

Case	LCOE ($/MW)	TES (MWh)
Baseline	68.40	150.9
No Renewables (48 hours)	68.26	150.9
No Solar (48 hours)	68.46	150.9
No Wind (48 hours)	68.20	150.9
No Renewables	46.22	18.6

The system responds well to losing generation showing that it could be a reliable system for varying conditions. It should be emphasized, though, that this system is sized so that the nuclear can handle the entire load so losing renewables when the future load is known during optimization isn't a problem and only the economics change. As evidenced by the results in Table 3 having no renewables on the system at all provides the lowest LCOE. This is likely due to a couple of reasons.

One of the reasons is the capital costs of each system are scaled by the lowest system lifetime of 30 years for a wind farm. The nuclear lifetime is 60 years so its relative LCOE is proportionally less for the NHES system lifetime. The next reason having renewables make for a more expensive LCOE is likely just representative that renewables are sometimes cost inefficient. Another interesting finding is that when looking at losing solar for 48 hours vs. wind it can be seen that losing solar increases the LCOE suggesting solar is more cost prohibitive. This is perhaps due to its less frequent power generation. Lastly, for a system where the load goes above the nuclear generation's capacity, the TES would likely be utilized significantly more. This uncertainty would add a large benefit to having a TES system to help create a more reliable system when various generation problems arise especially if the load is uncertain. When solving this problem, the load is exactly known so the TES is sized perfectly for that load. If the load is uncertain a larger TES solution would be expected and in turn a higher LCOE, but the benefit would be a more robust generation system.

Effects of SMR Ramping Costs

Another insight from this project is the effect of adding and removing a cost on changes to the SMR generation. As the SMR generation is formulated as a manipulated variable in GEKKO, it has a default derivative cost or “DCOST" of 0.00001. This was not understood initially, but this small DCOST actually proves to be quite significant. Setting “DCOST" equal to zero results in minimal use of the TES as shown in Figure 10. In this case, the TES capacity is reduced significantly and the SMR generation matches the required net load much more closely. The only apparent need for the TES comes from the lower bound on the SMR generation being set at 200 MWth. The resulting value of the objective function is 68.40, which is the same as the calculated LCOE. The optimal TES capacity is determined to be 150 MWh.

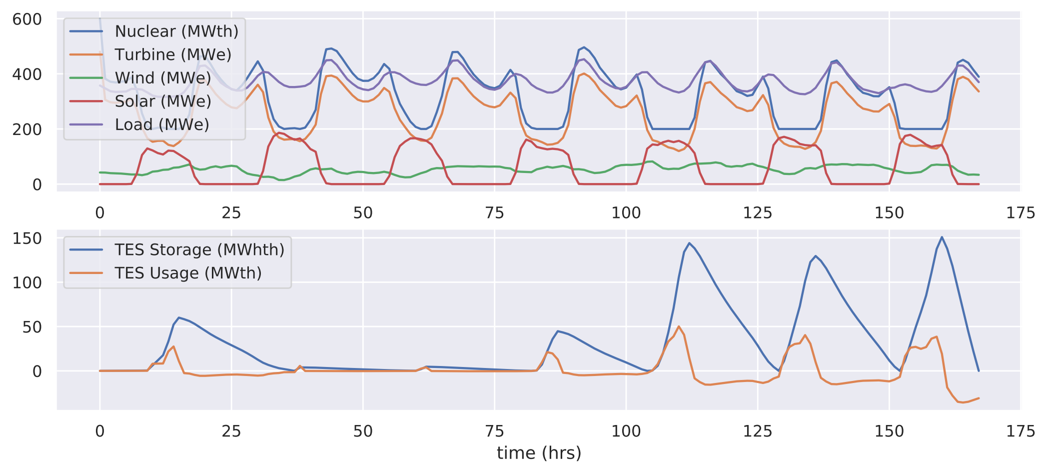

Figure 10: Optimal System Dispatch with DCOST = 0.0

Increasing the DCOST beyond the default to DCOST=0.1, has the opposite effect and results in the SMR being operated at a nearly fixed level with the TES being used to absorb nearly all net load variations as shown in Figure 11. The resulting objective function value is 222.791, which is far higher than the calculated LCOE value of 142.24 \$/MWh. The optimal TES capacity is determined to be 866 MWh.

The addition of the DCOST parameter to the SMR generation modifies the objective function of the optimization problem. The objective function previously could be described by Equation 8 where the objective is to minimize the system LCOE by varying the TES capacity and dispatch of the individual components.

$$\min_{A, S_{TES,max}} \quad LCOE \tag{8}$$

With the addition of the DCOST, the objective function is now represented by Equation 9

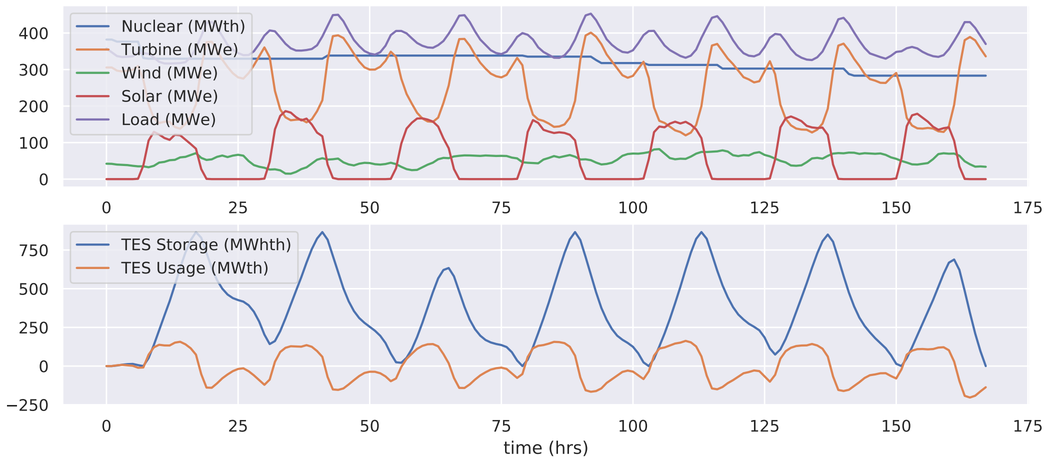

Figure 11: Optimal System Dispatch with DCOST = 0.1

were $DCOST$ represents the "DCOST" set on the manipulated variable in GEKKO.

$$\min_{A, S_{TES,max}} LCOE + DCOST \left| \frac{dA_{SMR}}{dt} \right| \tag{9}$$

Overall, the addition of a DCOST has very large implications on this work that came too late in the project to be fully analyzed or accounted for, but have a large impact on the results of the study. Further study would need to be carried out to fully understand how the DCOST affects the various aspects of the system discussed in this work.

Effects of Lowering SMR Lower Bound

As discussed above, there is an inherent cost to nuclear ramping that causes the SMR generation to remain somewhat constant. In addition to a cost of ramping, a lower bound on the SMR generation is also imposed in the base case of 200 MW. This lower bound ends up causing the TES to be utilized. During the day, when both solar and wind are generating power, the SMR has to ramp down to meet the load dispatch requirement. When the lower bound of the SMR generation is at 200 MW, the only way to meet the dispatch requirement is to add power to the thermal energy storage. When the SMR generation lower bound is below 150 MW then the TES won't be utilized at all.

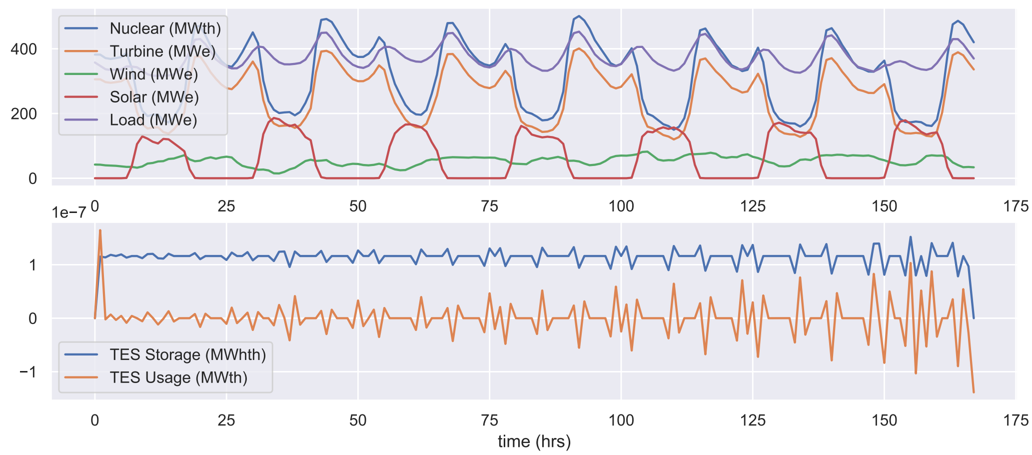

Figure 12: Optimal System Dispatch with No Lower Bound

For the case when there is no lower bound on the SMR generation, the LCOE is lower compared to the baseline case at $52.83/MW. This is a very interesting finding. It highlights that although TES may not make sense financially in terms of the LCOE method presented in this report, the TES is essential to the system because it helps deal with renewable energy generation profiles, specifically solar, during the middle of the day as well as just helping handle a variable load better. This is an important finding because modern nuclear generation, such as the NuScale system modeled, has much better ramping capabilities then traditional nuclear, but it cannot realistically ramp down to levels below 200 MW. This means that the TES can play a vital part in helping more renewables be on the grid in a stable way as well as help the system hit a dynamic load. This finding is slightly counter-intuitive because one would expect the TES would be used to hit high load requirements (and for a different scaled load it likely would), but for this system it is used as a buffer to help meet the dispatch requirement making it a invaluable asset in a reliable generating system.

Effects of Solar and Wind Curtailment and Scaling

Our objective is to produce a carbon-free generation system at the lowest cost possible. In the past, when solar and wind has been mixed with carbon-based generation sources, it was preferable to prioritize the renewable generation. However, since this generation system breaks from the norm, it makes sense to investigate the effects of allowing curtailment of the renewable sources. In the event where excess renewable generation would cause costly fluctuations in the required nuclear output, it may be preferable to use only a portion of the renewable energy in an optimal mix. We do just this by allowing the optimizer to throttle down the accepted wind and solar power independently at each time step. Table 4 gives a summary of the results, which will be discussed in detail.

Table 4: Summary of Allowed Renewable Curtailment

Case	LCOE ($/MW)	TES (MWh)	% LCOE Reduction	% TES Reduction
Base	68.40	150.8		
Curtail	53.00	0.0	22.5%	100.0%
Scale Renewables and Curtail	44.9	0.0	34.4%	100.0%
Scale All and Curtail	40.64	9.3	40.6%	93.8%

Wind and Solar Curtailment

First, we examine the 7 day horizon matching the baseline introduced at the beginning of this paper. From the summary above, there is a 22.5% decrease in LCOE. The optimizer chooses to heavily curtail the existing wind and solar during their peaks to help compensate for the fluctuating load. This enables the complete removal of the thermal storage. Comparing Figure 13 to Figure 2, there are three key differences. First, as the total renewable generation increases (due to a steady and increased wind) after 50 hours, the system chooses flatten out the nuclear production. Second, since the thermal storage is not required to store excess renewable energy, it becomes unneeded entirely since the nuclear is able to ramp quickly enough. Third, it curtails mainly the solar, while using the majority of the wind except during peak solar time where the sum of the two sources are generally mixed to make a relatively steady renewable generation level.

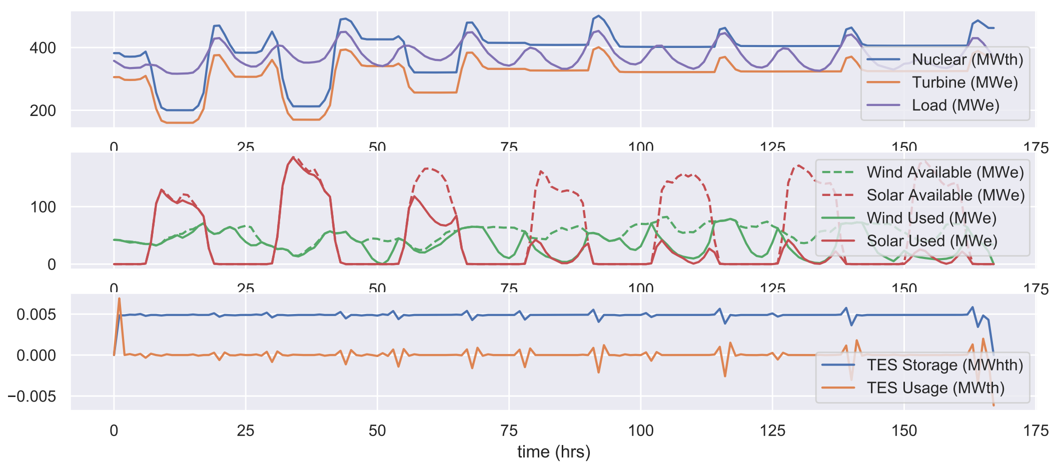

Figure 13: Renewable curtailment allowed.

Renewable Curtailment and Scaling

When we add renewable generation scaling in addition to curtailment, this further decreases the LCOE to 34% below the baseline. This scaling was done directly to the available generation as a single value for the entire time horizon that affects both the available power and cost. Solar and wind were independently scaled. The optimizer removes nearly all renewable generation except for a quarter of the original wind capacity as is shown in Figure 14. It also removes all thermal energy storage.

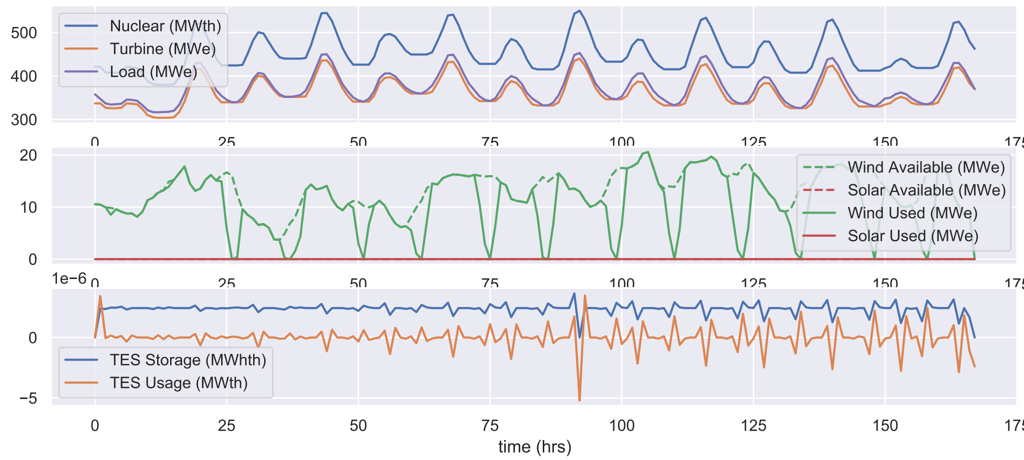

Figure 14: Curtailment and renewable scaling allowed.

Renewable Curtailment and Scaling with SMR Scaling

Though our generation plant is required to maintain a given level of capacity, it is insightful to also consider if the SMR capacity was also scaled. Considering only the 7 day horizon shown, the optimal mix including SRM scaling results in a mix of twice the wind generation as baseline, no solar, and a small 9.3 MWh thermal energy storage as shown in Figure 15. The optimal solution uses curtailed wind to soak up the majority of the load fluctuation, with the thermal energy storage being used in anticipation of lost wind capacity to reduce reactor fluctuation.

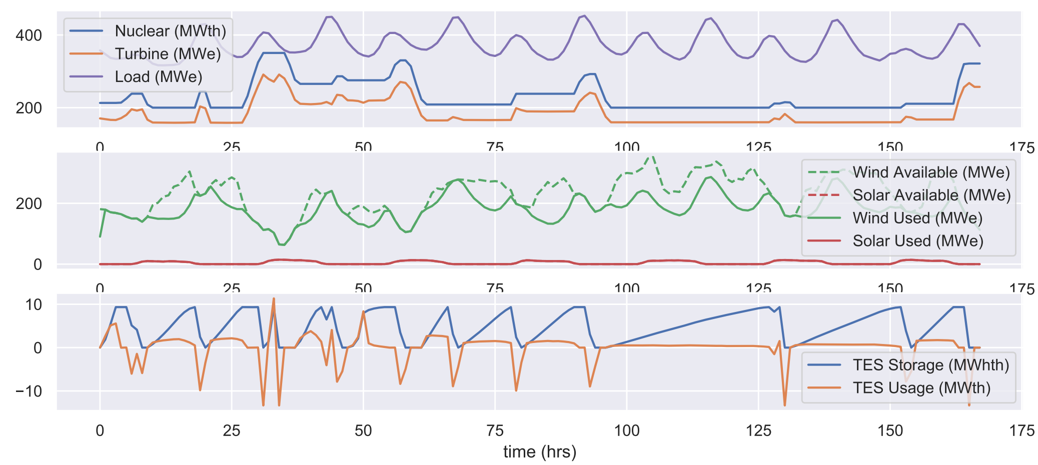

Figure 15: SMR scaling with renewable scaling and curtailment.

Conclusions and Future Work

After an exploratory analysis of the proposed NHES system, several considerable and notable conclusions can be drawn. First off, it is surprising and interesting that GEKKO was able to solve the design and dispatch problem for long time periods of time (4 months). This shows the robustness of the solver as well as the potential to gain more valuable insight into the design of the proposed system. The implicit DCOST became a confounding variable in the study and more research is needed to isolate those affects. The initial results indicate that there are several distinct patterns or categories of storage use depending on the system constraints and economic parameter. Each of these patterns appears to result in significantly different optimal design, but more investigation is needed to confirm this.

The next conclusion to be drawn from the study, which has been found in previous works, is that adding renewables to the system generally hurts the economics in terms of LCOE except for solar under the following scenarios. First, if renewables are required to be used, optimally curtailing the accepted generation can remove the need for thermal storage and reduce the LCOE by as much as 25%. Second, if the renewable generation/plant design can be scaled, then a small amount of consistent wind and no solar is optimal and further reduces LCOE to 34% below baseline. Third, if the SMR is allowed to be designed for a lower fraction of the required load, then a mix of a large amount of wind and small amount of thermal storage can lead to a further LCOE reduction to 40% lower than baseline. We expect these findings to be highly dependent on the relative cost between the energy generation sources and their intermittancy. For example, if we extended the horizon to a point where there was no wind for a significant period, the designed wind might decrease, or thermal storage increase. Future work should include relative cost and intermittancy sensitivity analyses to help guide the proper development of wind and solar installations.

Another notable finding is the importance of the TES to help with having renewables on the grid. To meet the dispatch requirements of the system and match the load, it is often required that the SMR charges the TES system when it meets its lower power production limit. This finding shows that having the TES can help with large cyclical fluctuations in load and production from renewables to help with a more reliable power production system. However, if the renewables can simply be curtailed, the need for thermal storage is removed entirely for a reactor with a relatively high capacity to load fraction.

One factor that was not investigated in this study was how uncertainty in future predictions affects the optimal design and dispatch of the system. When these profiles are uncertain and based on forecasts, the TES and curtail-able renewable generation could help immensely to meet the dispatch requirements. Future work should look into the design and dispatch of a system with uncertainty to help quantify the importance TES and curtail-able renewable generation could have on the proposed system.

References

[1] T.E. Baker, A.S. Epiney, C. Rabiti, and E. Shittu. Optimal sizing of flexible nuclear hybrid energy system components considering wind volatility. *Applied Energy*, 212:498–508, feb 2018.

[2] Geoffrey A Black, Fatih Aydogan, and Cassandra L Koerner. Economic viability of light water small modular nuclear reactors: General methodology and vendor data. *Renewable and Sustainable Energy Reviews*, 103:248–258, 2019.

[3] Paul Denholm, Matthew O'connell, Gregory Brinkman, and Jennie Jorgenson. Overgeneration from Solar Energy in California: A Field Guide to the Duck Chart. Technical report, National Renewable Energy Laboratories, 2013.

[4] EIA. Electric Power Annual 2019. Technical report, United States Energy Information Administration, 2019.

[5] A. Epiney, C. Rabiti, P. Talbot, and A. Alfonsi. Economic analysis of a nuclear hybrid energy system in a stochastic environment including wind turbines in an electricity grid. *Applied Energy*, 260(December 2018):114227, 2021.

[6] Aaron Epiney, Cristian Rabiti, Andrea Alfonsi, Paul Talbot, and Francesco Ganda. Report on the economic optimization of a demonstration case for a static n-r hes configuration using raven. Technical report, Idaho National Laboratories, 4 2017.

[7] EPRI. Program on Technology Innovation: Approach to Transition Nuclear Power Plants to Flexible Power Operations 2014. Technical report, Electric Power Research Institute, 2014.

[8] Greg Glatzmaier. Developing a Cost Model and Methodology to Estimate Capital Costs for Thermal Energy Storage. Technical Report December, National Renewable Energy Laboratory, 2011.

[9] D T Ingersoll, Z J Houghton, R Bromm, and C Desportes. NuScale small modular reactor for Co-generation of electricity and water. *Desalination*, 340:84–93, 2014.

[10] Rolf Kehlhofer, Bert Rukes, Frank Hannemann, and Franz Stirnimann. *Combined-Cycle Gas & Steam Turbine Power Plants*. PennWell Books, 2009.

[11] LLC NuScale Power. NuScale Plant Design Overview. Technical report, NuScale Power, LLC, 2012.

[12] Paul W. Talbot, Abhinav Gairola, Prerna Prateek, Andrea Alfonsi, Cristian Rabiti, and Richard D. Boardman. Light Water Reactor Sustainability Program HERON as a Tool for LWR Market Interaction in a Deregulated Market. Technical Report December, Idaho National Laboratories, 2019.

[13] United States Energy Information Administration. Capital Cost Estimates for Utility Scale Electricity Generating Plants. Technical Report November, United States Department of Energy, 2016.