CEE 6880 Final Project: Exploring the Value of Wave Energy with a Capacity Expansion Model

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Contents

For my project, I added ocean wave energy as a resource in a capacity expansion model, ran this model systematically for a combination of input parameters, and found the sensitivity of total economic value to those parameters. My code is open-source and can be found in my fork of the GenX repository at `https://github.com/symbiotic-engineering/GenX`.

1 Introduction and Motivation

Energy system models, such as capacity expansion modeling (CEM), unit commitment, and economic dispatch (ED) are optimization models that determine the cost-optimal investment and allocation of generators in an electricity market. They are typically formulated as linear programs and can be useful for planning grid operations and understanding the potential role of different generation technologies in future energy systems. This is particularly true for less mature technologies such as ocean wave energy. Incorporating ocean wave energy in a capacity expansion model can give insights about which aspects of the technology provide the most value, which can in turn drive R&D and design efforts to make the technology as impactful as possible. In particular, it would be valuable to be able to incorporate the results of energy systems models into the engineering design optimization of the generation technology itself.

1.1 Literature Review - Energy System Models which Incorporate Wave Energy

Unfortunately, very few existing studies of energy system models incorporate wave energy. In a literature review, only four relevant papers were identified, three of which were published within the last year. The authors of [2] create a simplified CEM with monthly resolution to determine the optimal grid mix of a 100% renewable California 2045 grid, focusing on the sensitivity to wave energy $LCOE$ and CF. The EU-funded Evolve project considers an ED model with hourly resolution in 2030, 2040, and 2050 in the UK, Ireland, and Portugal [1]. The authors of [3] create a capacity expansion model with 3 hour resolution for North Carolina to find the pareto-efficient tradeoff between $LCOE$ and σ_{CF} for portfolios containing various capacities of wave and tidal energy. Finally, [8] runs a CEM for the entire US at various levels of wave energy $LCOE$. Despite its comprehensiveness, [8] is over a decade old and assumes low renewables penetration, so its results have limited utility here. Table 1 summarizes these studies.

In my PhD research, I have previously used the results of the studies mentioned above to estimate the sensitivity of system value to wave energy LCOE, CF, and CF [6]. However, the three papers have inconsistent assumptions and are not comprehensive in scope. The current project has the potential to solve this problem and conclusively assess sensitivities. Another finding of [6] is that the avoided operational costs are small compared to the avoided investment

Study	**Coe et al. [2]**	**EVOLVE [1]**	**de Faria et al. [3]**	**Previsic et al. [8]**
Year Published	2022	2023	2022	2012
Geographic Scope	California	UK, Ireland, Portugal	North Carolina	Contiguous US
Temporal Resolution	1 month	1 hour	3 hours	Seasonal and Diurnal
Model	Custom Capacity Expansion	PyPSA Economic Dispatch	Temoa Capacity Expansion	ReEDs Capacity Expansion
Parameters	LCOE, CF	Capacity	σ_{CF}	LCOE

Table 1: Results of a literature review to find studies which consider wave energy in an energy systems model.

costs. This motivates the decision to pursue a capacity expansion model rather than an economic dispatch model in the present project.

1.2 Literature Review - Energy System Models which Assess Technology Value

A separate literature review was conducted about the broader idea of using energy system models to assess the value of certain features of a particular technology. Literature on this is much more common, and a subset of the relevant papers are described here. One paper by NREL uses a capacity expansion, economic dispatch, and price taker model to investigate the value of seasonal energy storage [4]. Several papers from the Princeton ZERO lab explore the value and design space of various technologies including geothermal [9], fusion [10], and long-duration energy storage [11].

One important question is how the engineering design optimization (typically nonlinear, with order $10^1 - 10^2$ design variables) can combine with the energy system model (typically linear, with order $10^5 - 10^6$ design variables). While none of the papers cited above perform design optimization, [9] and [10] both take the approach of embedding linearized versions of the nonlinear design constraints into the capacity expansion model. In this project, however, the ultimate goal is to use the energy systems optimization to inform the design optimization, not the other way around. This means that linearizing the nonlinear design problem is not viable. Meanwhile, the computational cost associated with the large number of design variables in energy system models prohibits model execution within the design optimization loop, as in the top of Figure 1, and likewise prevents the problems from being combined in a single nonlinear optimization. Therefore, the chosen approach is to run the energy system model ahead of time for various inputs, and to curve fit the results for inclusion in the design optimization as a surrogate model. This is shown in the bottom half of Figure 1. The present project implements the capacity expansion model portion of this framework, running a capacity expansion model for a variety of input combinations and working towards the development of a surrogate model.

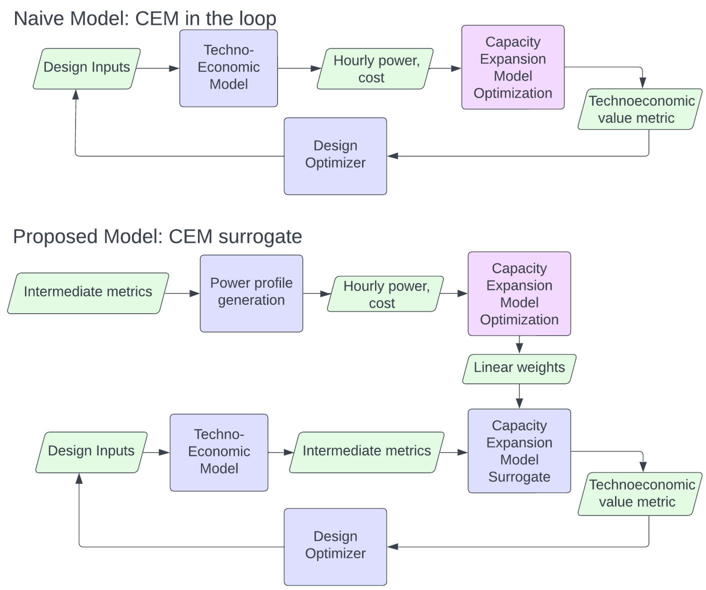

Figure 1: Depiction of two possible methods for including a capacity expansion model or other energy systems model in a design optimization. The bottom approach uses a surrogate model to reduce computational cost.

2 Methods

This section describes the methods used to determine the inputs, outputs, and model implementation of the project. First, we choose a way to parameterize the wave energy design space and select what inputs to sweep in the capacity expansion model. Next, we choose the relevant outputs from the capacity expansion model that will be used to represent value in the design optimization. Subsequently, we choose the GenX software to run the model in, after a comparison to several other alternatives. Finally, we discuss the GenX model settings to be used for the runs, and the implementation of the sweep in code.

2.1 Choosing Technology Parameters to Sweep

A variable renewable energy generator is represented in a capacity expansion model by two types of data: cost and availability. Therefore, at minimum it is desirable to have at least one technology design parameter for each of these. In this project, for simplicity we parameterize both the investment and the operations/maintenance cost of a wave energy generator with a single cost parameter, by keeping the ratio between the two fixed. The results shown here will use a ratio of investment cost ($/MW-yr) to fixed O&M cost ($/MW-yr) of 10, and a variable O&M cost ($/MWh) of zero. The investment cost is swept through a range of five equally-spaced values between 50 and 300 $k/MW-yr.

To reflect the design space of availability, the power limit fraction is chosen as the parameter. The power limit fraction is defined as the rated power capacity of the device divided by the maximum possible power in the resource out of any hour in the year. Essentially the raw resource power timeseries is capped at this power limit to get the generator power, and the resulting signal can be averaged to find the capacity factor. This simplification assumes that the wave energy converter harnesses all the power in the resource that is below the power limit equally, whereas a more realistic model would also take into account the wave frequencies and how the device's resonance affects its power conversion. A higher power limit allows for higher average power, but has the downside of a lower capacity factor due to more variability. The relationship between power limit, capacity factor, and average power can be visualized in Figure 2. The dots represent the five values of the power limit fraction that are swept here: the equally-spaced set from 0.02 to 0.10. The relationship intuitively makes sense from the power probability density function in Figure 3.

The above values rely on hourly resource data. In this case, the Water Power Technologies Office hourly hindcast data for 2010 is used. This dataset includes a convenient API that allows the user to query the power profile at any latitude and longitude off the coast of the US, which will be helpful for extending this project to other locations in the future. The location here is chosen as 43.5^o N latitude, 70^o W longitude, which is off the gulf of Maine.

2.2 Choosing Value Metrics to Output

Next we must decide what outputs are meaningful to use from the model. Although not an output that makes sense to use in the design optimization, the first metric that is retrieved from the capacity expansion model is the capacity of wave energy that is built at the end of the model. This is expressed as a fraction of the total generation capacity at that time. Nonzero capacity built means that wave energy is economically viable, since the model will not build any wave generators if it is not economical to do so.

In determining the actual design-relevant value metrics, both economic and environmental considerations are important, so one metric from each is chosen. For economic, the total system-wide cost is chosen, since this is the optimization objective and is broadly representative of the full value in an avoided costs sense.

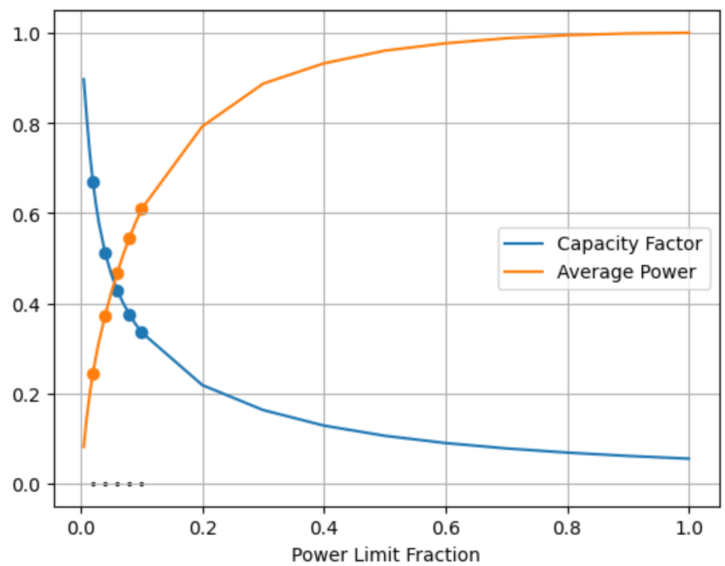

Figure 2: Relationship between the power limit fraction, capacity factor, and normalized average power. Dots correspond to the values of the power limit fraction that are used in the model sweep.

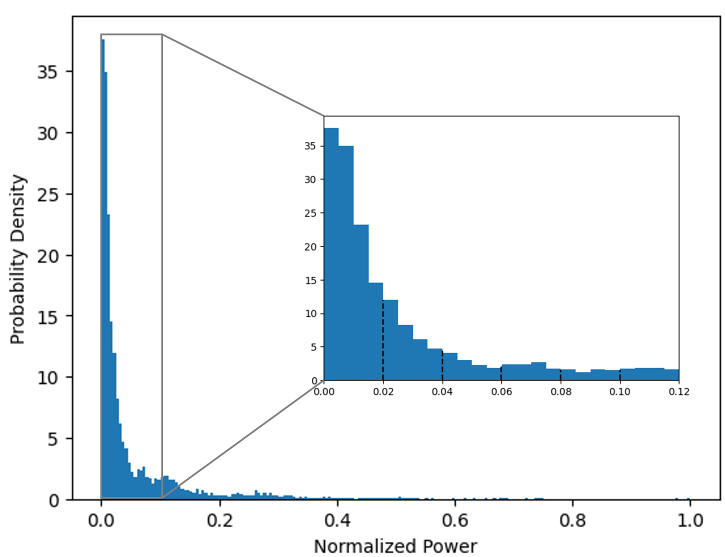

Figure 3: Probability density function for the WPTO hourly wave resource hindcast data from 2010. The dashed lines in the inset show the selected set of normalized power limits that are swept in this work.

This represents the absolute net value that wave energy provides, as opposed to the marginal net value which will be driven to zero by the optimization model's enforcement of equilibrium at the optimum. As a sanity check, we also save the marginal net value, equal to the net profit (revenue minus cost) for the wave generator, to confirm whether it is near zero. On the environmental side, the total equivalent carbon dioxide emissions are used. This reflects avoided emissions that could occur when wave energy displaces fossil fuel generation.

2.3 Choosing a Model

A variety of open-source capacity expansion models exist. The decision must be based on the following requirements:

1. Language: Python (or easily callable from Python)
2. Availability: free, open source
3. Temporal scope: In the long term, the model would span several decades, in 5-year increments from 2025 to 2050, to see the trends over time.
4. Temporal resolution: The model must contain within-day (hourly or 3-hourly) resolution in order to assess the effect of short-term power variation, as well as seasonal variation because wave energy's winter peak is expected to provide substantial value.
5. Spatial scope: Simulating just one region/ISO of the coast at a time seems acceptable, assuming that the effect on transmission to other areas of the country is small
6. Spatial resolution: wave resource characteristics differ from state to state, but for the most part they do not very much between different parts of the same state. Therefore, state resolution is acceptable.

The lists of power systems modeling software at `https://g-pst.github.io/tools/` and `https://wiki.openmod-initiative.org/wiki/Overview_of_models` were useful for comparisons. Alternatives are presented in Table 2 with their temporal and spatial resolutions and scopes.

Although ReEDs is highly developed and vetted by NREL, it has higher spatial resolution and scope than is necessary for this problem, especially because wave energy can be built only at coastal states. While it is possible to reduce the spatial resolution by aggregating regions, it would require more development effort, and it is unclear if the spatial scope can easily be reduced, since the model is intended to be national. Also, while ReEDS itself is open source, the algebraic modeling software it is built on GAMS requires a paid license. This reduces the ability for other researchers to replicate and extend the project in the future.

Other options include GenX, Switch, Temoa, and PyPSA. Ultimately, GenX [7] is chosen, because it is the software used in several other studies of technology

Model	Language	Author	Spatial Scope and Resolution	Temporal Scope and Resolution	Wave Energy	Notes
GenX	Julia, with python wrapper	MIT Energy Initiative	User specified, ISO NE with 3 regions provided as example	Hourly timesteps with optional time-domain reduction	Could be represented as "Generic VRE"	Used in [10, 9, 11]
ReEDS	GAMS, with python API	NREL	National. 134 balancing areas, 356 wind regions. Contiguous states only. Option for aggregated regions.	Models one day for each season, but VRE uses hourly data with internal DP	Historic capability from [8] that would require re-integration	Used in many national studies; GAMS needs paid license
Switch	Python (pyomo)	University of Hawaii	State resolution, typically regional scope, can be whole country.	Hourly resolution	Not included	Documentation appears limited
Temoa	Python (pyomo)	NC State University	Example has 2 regions	Specify seasonal/day/night capacity factor by default. Hourly timesteps available	Used in [3], which includes wave	Parametric sensitivities and uncertainty analysis, PySP interface for stochastic programs
PyPSA	Python (linopy)	KIT	National, typically Europe	Hourly	Used in [1], which includes wave	Targeted for optimal power flow

Table 2: Comparison of open source CEM softwares.

value, and because it is very similar to the Julia models in the CEE 6880 homework problems so the required development time is lower. Note that although the model is in Julia, a python wrapper is available.

2.4 Choosing Model Assumptions

Within GenX, the ISO New England Singlezone example system is used for the initial exploration of this project. There are 58 generators in the system including renewables, fossil fuels, storage, and demand sinks, with a total of 59 once wave energy is added. The resulting model has 694,920 rows, 317,927 columns and 2,828,328 nonzeros. The Gurobi solver is used with parallel capabilities. Each run takes around one minute with the 14 core, 20 thread Intel i9 laptop used for the computation. This is a significant improvement over the first trial run of the optimization using the HiGHS solver without parallel processing, where the same run took around 1.5 hours.

One important note about the setup here is that no capacity limit is placed on the wave generator, which means that if the price is sufficiently low, the optimization could output a solution where the amount of wave energy built exceeds the resource potential of the waves for this region. This is an acceptable assumption for this exploratory modeling. In future work, capacity constraints could be added to enforce a more realistic upper bound.

The previous sections described the set of five costs and five power limits to be run, for a combinatoric total of 25 model runs. To accomplish this efficiently, the SimpleGenXCaseRunner utility is used, which automatically generates and runs GenX Run.jl files based on a csv of desired run parameters. I created two python Jupyter notebooks, one to generate the run parameters csv from hourly wave data and the other to plot and analyze the results after the models ran. The results are described in the next section.

3 Results and Discussion

First, we show the amount of wave capacity built, in Figure 4. Notice that for sufficiently high prices and high power limits (low capacity factors), no wave energy is built, as expected. This area is marked with a red box, which will be repeated on the figures to follow for easy comparison. As expected, as the cost gets lower and the power profile gets more consistent, more wave energy is built. A maximum of nearly 30% of the total capacity is wave energy for the cheapest, flattest wave power profile tested. This is quite large, approaching the 34% estimate for the nationwide technical resource potential [5].

Two sets of results on this graph show unexpected results. The first is $(50, 0.08), (50, 0.10)$, where there is a slight reversal of the trend, and the higher power limit (less consistent power, expected to be less desirable) actually produces a higher wave capacity: 25.9% vs 25.2%. The second is $(162.5, 0.06), (162.5, 0.08)$, where again the higher power limit performs better.

It is unclear whether this is due to numerical imprecision or some other artifact, or whether this is truly a local minimum in the capacity. This requires further investigation by testing parameter combinations with resolutions higher than a 5x5 grid and seeing if the trend continues.

The next result to examine is Figure 5, the profit. This gives a sanity check that the model has resulted in an equilibrium, so the profit should be zero. Indeed, the value is on the order of 10^{-6}, which is sufficiently small. We also see that the profit is exactly zero for the cases where no wave is built. This makes sense because the revenue and cost are both exactly zero.

The most interesting result is the system cost, in Figure 6. At first glance, the results generally make sense, with higher wave energy costs and power limits corresponding to higher system costs. However, one confusing result is that we would expect the system cost to be constant for the cases where no wave energy is built (inside the red box). However, the cost varies nontrivially in this region,

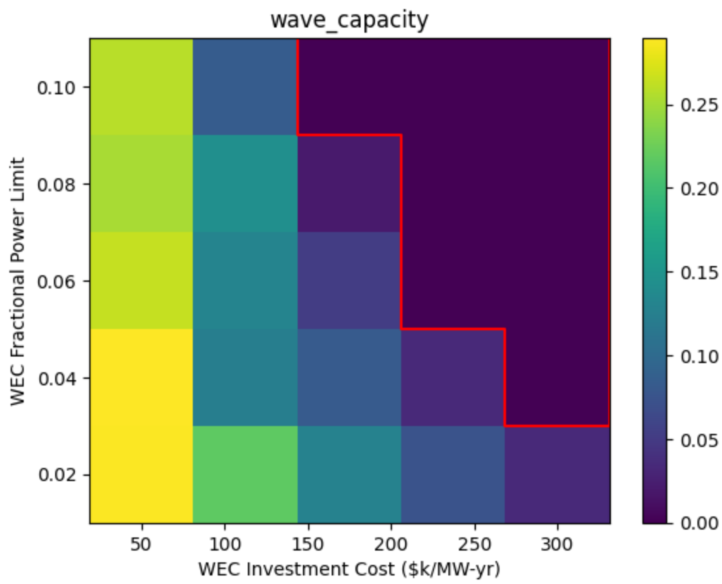

Figure 4: Wave capacity as a fraction of total capacity

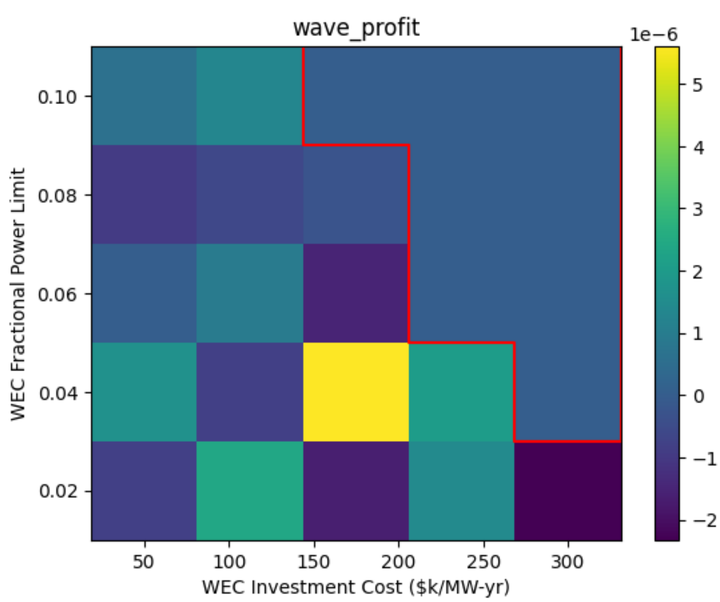

Figure 5: Wave energy profit = revenue - cost

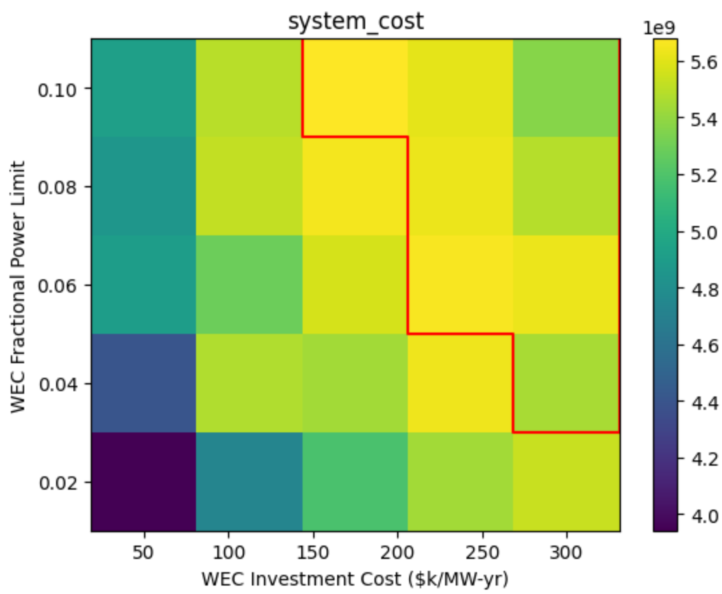

Figure 6: System cost

in fact starting to display a trend in the opposite direction. This seems indicative of some larger problem with the formulation, where the WEC parameters are unintentionally influencing other generator parameters, or perhaps where the solver does not return the true global optimum for some of these runs. This requires further investigation.

A second confusing result in the region where wave energy is being built is that there are a couple local reversals in the global trend, as in the previous result.

Finally, we examine the equivalent carbon emissions in Figure 7. Unlike the system cost, the carbon dioxide does saturate at a maximum value. However, the saturation extends beyond the region where no wave energy is built, far into the rest of the design space. This is unexpected but could be due to a maximum carbon constraint getting activated. The model settings need to be examined more closely to understand if any carbon constraints are unintentionally turned on and could be the cause of these results. For the three runs in the bottom left where the carbon is not constant, the trend is as expected, with cheaper and more consistent wave power resulting in lower carbon emissions.

Because of the unexpected shape of the system cost and carbon emissions graphs, the surrogate model was not constructed, as it would not be meaningful. Once the underlying errors are resolved and the two outputs show the expected trends, linearizations can be created for each of them in a similar way to those in [6].

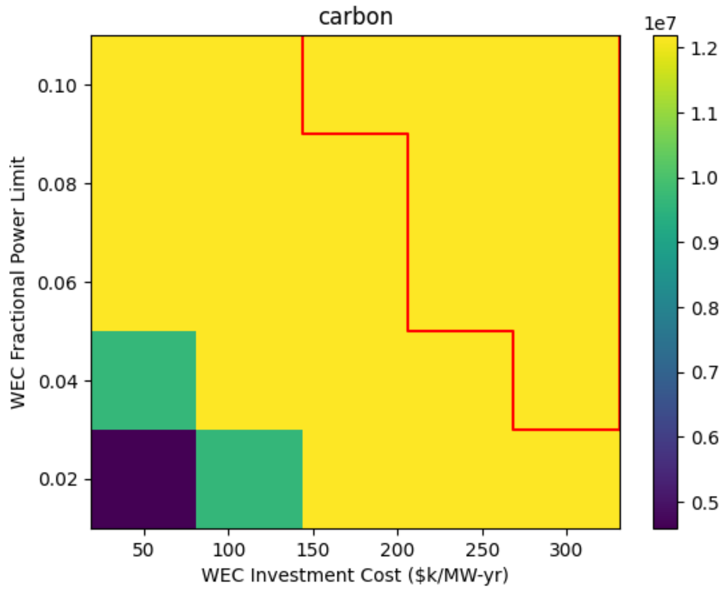

Figure 7: Equivalent carbon dioxide emissions

3.1 Future Work

In future work, a number of improvements and enhancements can be made to this project. Besides cost and power limit, a third technology parameter I would like to sweep is the frequency response of the WEC. This requires figuring out how to parameterize the resonant frequency and bandwidth in a way that is hydrodynamically realistic.

Additionally, in the future the model should be extended to other locations. Within the current ISONE model, this would entail adding zones for each state and enforcing the different wave resource profiles in each area. Plus, separate models should be created for the rest of the coastal US, including Alaska and Hawaii.

It would also be good to run several separate scenarios to capture uncertainty about the future energy system (for example, the level of decarbonization and extent of electrification) because this is expected to change the results.

A final area for improvement is related to computational speed. In this project, sweeping cost and power limit meant that we solved the same optimization problem many times but with slightly different parameters resulting in different optimal decisions x^* and objectives J^*. It would be preferable to take advantage of the similar solutions in each case to solve the sweep more efficiently than a brute-force sweep. One simple way to do this would be to use the warm-start capability of the solver, which is available in Gurobi. An even better method would leverage the fact that this sweep can be considered a parametric optimization problem. This means that the entire parameter sweep can be solved at once with a parallel geometric algorithm using a package such as ppopt. It remains to be seen how difficult it would be to take the LP matrices from Julia and input them to ppopt, and how the ppopt algorithms compare to Gurobi, but if this is doable it can potentially save significant model runtime.

4 Conclusion

This paper described the addition of wave energy to the GenX capacity expansion model and the results of a two dimensional parameter sweep to explore the design space. First, a literature review was conducted, analyzing four previous works which incorporated wave energy in a capacity expansion or economic dispatch model. Then, twenty five scenarios were run using real wave availability data, analyzing the effects of investment cost and a fractional power limit that affects the capacity factor.

In the results, the expected trends emerged overall, although system cost did not saturate as expected, and carbon emissions saturated at lower costs and power limits than expected. These discrepancies prevented the creation of a meaningful surrogate model, and instead detailed plans for future work were presented. Ultimately, this work enables the goal of informing wave energy design optimization with the sources of value in an energy systems context. This could have large impact going forward to advance the green energy transition for coastal communities.

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