# Optimizing Investments in Offshore Renewable Energy in the North Carolina Electric Sector

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**Final Project Report**


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## I. PROJECT DESCRIPTION, OBJECTIVES AND PROGRESS

### Project description and objectives

The FY2019-2020 goal was to perform cost-optimization analysis of electricity generation derived from offshore wind, ocean current, and wave energy off the North Carolina coast and evaluate the potential role of these technologies in the state's future generation portfolio. Building on our previous work, we performed a novel portfolio analysis using hourly data and identified the most promising offshore locations and generation technologies. Additionally, we integrated the optimal offshore energy portfolio into our open source capacity expansion model of the NC electric power sector to evaluate the cost-effectiveness of offshore renewable energy in North Carolina. The intent is to provide two deliverables: (1) an analysis that demonstrates how different renewable resources can be deployed in a cost-optimal configuration off the North Carolina coast considering hourly energy data, and (2) a modeling tool that will be made available to investors and researchers.

### Summary of progress

We acquired hourly data associated with offshore wind, wave, and ocean current, and converted this raw data into synthetic time series of electricity production at different site locations. Additionally, we formalized a cost structure for all these technologies in North Carolina, considering characteristics such as distance from shore and deployment depth. We also developed a portfolio optimization model using Python as a modeling platform to integrate the offshore energy resources and performed simulations with different combinations of wave, wind, and ocean current turbines. Finally, we evaluated these different portfolios in an open-source framework for conducting energy system analysis (Temoa). In these analyses, we were able to better understand how the North Carolina electricity system behaves when combined with these different offshore renewable energy technologies. Figure 1 is a flow diagram that briefly describes the main development steps, which are further discussed below.

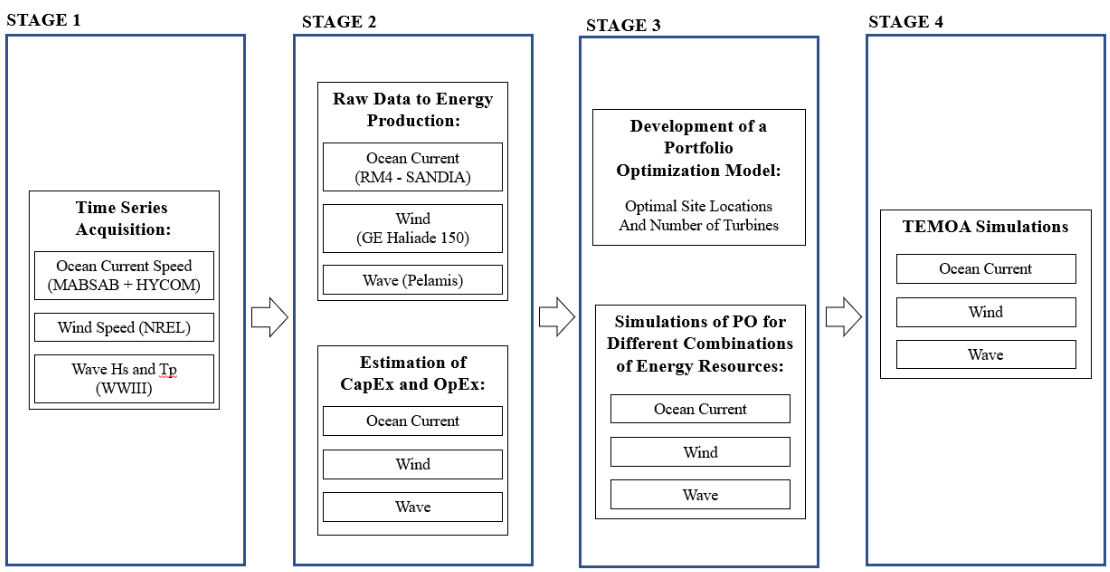


**Figure 1.** Flow diagram summarizing the project stages.

**Wind Data**

Hourly offshore wind speed data is drawn from the NREL Wind Integration National Dataset (WIND) Toolkit (NREL, 2019). The dataset is represented in 2 km × 2 km grid cells ranging from 2007-2013. Wind speed is converted to energy using the same assumptions adopted in NREL (2016) for offshore wind, which include the selection of feasible site locations and wind turbine characteristics. Each 2 km × 2 km grid cell can accommodate four 6 MW turbines with hub height of 100 m. As study domain, we adopted (78°00' W to 74°00' W, 34°00' N to 36°33' N), which includes 1692 potential wind turbine sites after eliminating those locations not considered in NREL (2016).

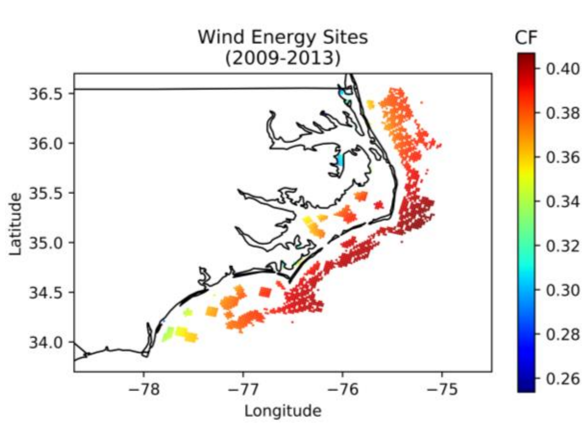


**Figure 2.** Capacity facto (CF) of the available wind energy production sites across the study domain.

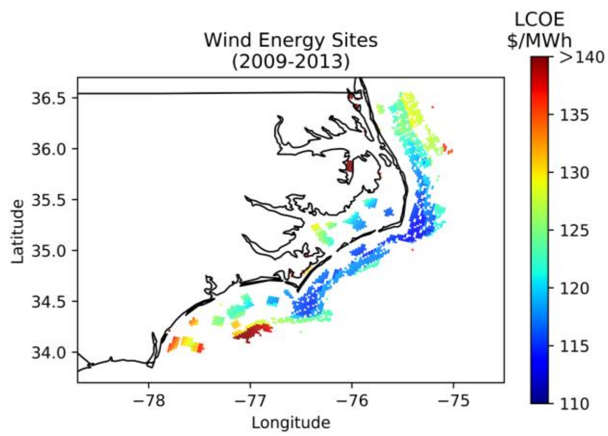


**Figure 3.** Expected levelized cost of electricity (LCOE) at individual site locations with a deployment of 50 turbines.

**Wave Data**

For wave energy, our data comes from the WAVEWATCH III model (NOAA, 2019) at the resolution of 1/15° and time-frequency of 3 hours, ranging from the years 2005-2019. In order to convert the historical values of significant wave height $H_s$ and wave period $T_p$ to energy, we used the scaled version of the Pelamis energy conversion model developed by the University of Edinburgh in 2006. This is an attenuator type model, with a rated power of 1.5 MW, which performed significantly better for the North Carolina region when compared with other models such as PB150 from OPT (2014), RM3 from SANDIA (2014), and Wavebob (2012).

In this case, the selection of feasible site locations is solely dependent on the chosen turbine model. For the Pelamis energy converter, its project documentation (University of Edinburgh, 2006) limits the deployment depth to 50-150m, which was the only constraint used in our model representation of wave energy converters.

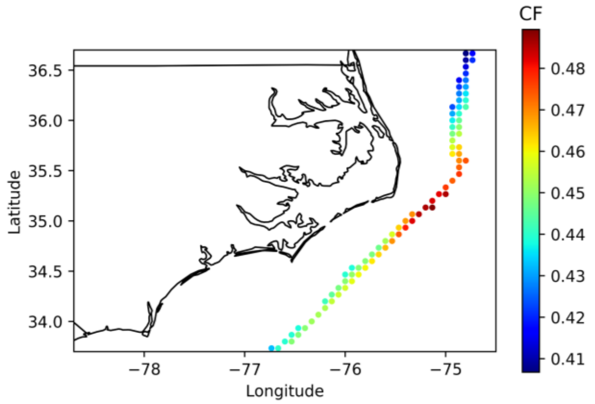


**Figure 4.** Capacity factor **(**CF) of the available wave energy production sites across the study domain.

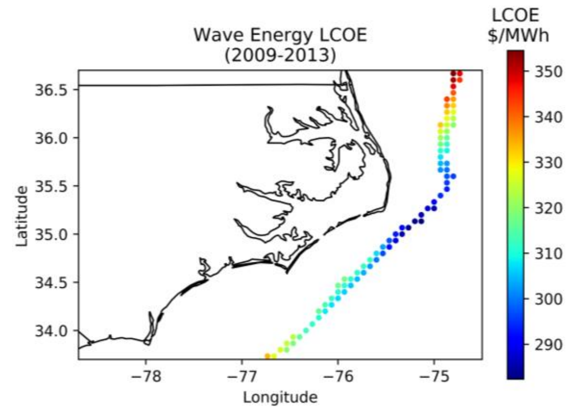


**Figure 5.** Expected levelized cost of electricity (LCOE) value at individual site locations associated with a deployment of 100 wave turbines.

## Ocean Data

For hindcasts of ocean current speed in the North Carolina region, two different models were considered, namely HYCOM/NCODA (HYCOM, 2020) and MABSAB (Gong et al., 2015).

The Hybrid Coordinate Ocean Model (HYCOM) is a primitive equation ocean general circulation model that evolved from the Miami Isopycnic-Coordinate Ocean Model (MICOM). It is a multi-institutional effort sponsored by the National Ocean Partnership Program and has been used in many studies for the assessment of hydrokinetic energy resources. The MABSAB model (Gong et al., 2015) to hindcast and diagnose ocean circulation variability in the Middle Atlantic Bight (MAB) and the South Atlantic Bright (SAB). It is based on the Regional Ocean Modeling System (ROMS), a high-resolution, free-surface, terrain-following coordinate oceanic model extensively explored in the literature. For open boundary conditions, the MABSAB model is nested inside the 1/12° global data assimilative HYCOM/NCODA output, assuring consistency between the hindcast generated by the two models used in this work.

Because the process of simulating ocean circulation models is extremely complex, often requiring a substantial amount of computational resources, there are very few datasets available with high spatial resolution and high time-frequency. In the case of the North Carolina region, however, ocean current velocity data from January 2009 to December 2013 is available for HYCOM/NCODA at 3-hour discretization and 1/12° grid resolution (~8×8km), and for MABSAB at daily discretization and 2×2km grid resolution.

In this work, we constructed a synthetic dataset with the objective of capturing the hourly variability present in HYCOM, while keeping the higher MABSAB spatial resolution. This synthetic dataset is created as follows:

1) First, normalize the HYCOM data. In each day of ocean current speed from the HYCOM/NCODA dataset, the eight current estimates (3-hour discretization) for each grid cell are divided by their correspondent average.
2) Next, for each MABSAB cell, find the closest HYCOM cell and transfer the data of HYCOM into the MABSAB resolution (2×2km) multiplying the normalized HYCOM data (eight estimates each day) by the daily ocean current speed of MABSAB.

This synthetic dataset for ocean current speed has 3-hour time resolution and 2×2km grid resolution ranging from January 2009 to December 2013, and is used thereafter in this work for the analysis of the ocean current resources in the North Carolina.

To convert ocean current energy to electrical energy, we used as reference the ocean current turbine model RM4 detailed in Neary (2017), which has a rated capacity of 4MW. However, a few modifications were made to the model in order to adjust the turbine performance to the characteristics of the North Carolina region. A detailed description of all changes, as well as the cost breakdown structure of the new turbine model, is detailed in Faria (2020).

In this project, the maximum deployment depths of 100-2500m assumed in the RM4 model (Neary, 2017) were used to define the set of feasible site locations studied. Also, in order to reduce the size of the dataset analyzed, sites with less than 0.01 of capacity factor were excluded from our investigation.

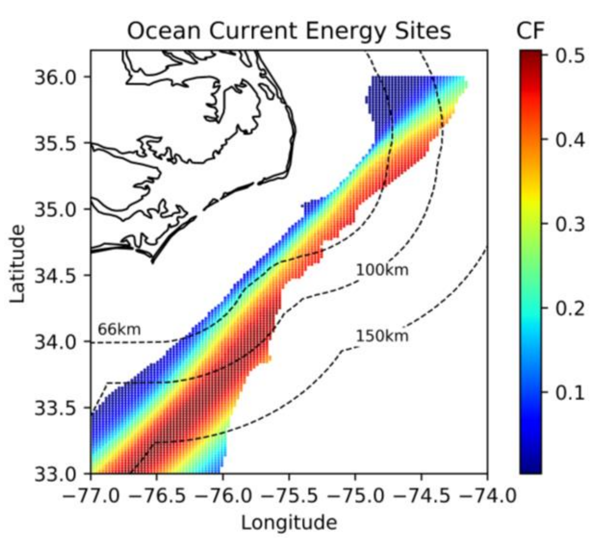


**Figure 6.** Capacity factor (CF) of the available ocean energy production sites across the study domain.

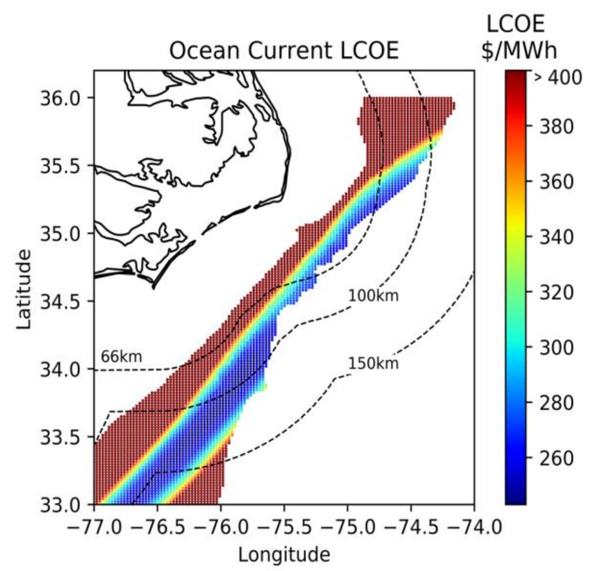


**Figure 7.** Expected levelized cost of electricity (LCOE) value at individual site locations associated with a deployment of 50 turbines.

**Portfolio Optimization Model**

In order to optimize the selection of site locations for each energy technology, we apply the mean-variance portfolio theory (Markowitz et al., 2000). In our work, the optimization model minimizes the variance of the total generated energy of the portfolio subject to a limit on the LCOE value. This model is described in Equations (1-6).

In addition to (2), which bounds the LCOE value, the model also has constraints related to the total number of turbines deployed (3), maximum number of turbines per site location (4), and maximum distance of deployment between sites of the same technology (5). This last constraint is used to ensure the feasibility of the energy collection system. In (5), the integer variable $v$ is responsible for determining the center site location from which all deployments of a particular technology will maintain a distance less than a predefined value (30km for Model I). Figure 8.a shows in light red a region of deployment based on $v_{45} = 1$.

The complexity of the model described above increases significantly with the number of integer variables, which are used to designate the number of site locations. As a result, the model based on Equations (1-6) for the entire North Carolina coast can be very challenging, in some cases making the model computationally intractable. Thus, a relaxation procedure was developed to help decrease the computational complexity of the problem.

The relaxed version of Model I is represented in Equations (7-12). In this version, the integer variable ($y$) is substituted by a real variable $x$, and the integer variables responsible for ensuring the maximum deployment distance between site locations ($v$) are also substituted by an upscaled version $w$ (Figure 8), such that the total number of integer variables in Model II can be decreased even further.

Mathematically, the results of Model II are a lower bound (since it is a relaxation) on the original model, but nonetheless, it is possible to extract important information about the location of the most promising site locations using the integer variables $w$. In this way, we developed a modeling strategy whereby the results of Model II are used to constrain the feasible space of Model I by reducing the number of integer variables and obtaining a feasible bound for the original problem. The quality of our algorithm can be assessed by the gap between both simulations, which proved to be small for all scenarios investigated, meaning that your procedure can achieve results very close to the global optimal solution.

Figure 8 illustrates the difference between the $w$ and $v$ variables. For each feasible site location, there exists a correspondent $v$ variable in the formulation for Model I; if the value of this variable is equal to one it means that all deployments of a certain technology ($y$ variables) will be placed in a radius $R$ (5km in the example of this figure) of this site location. The $w$ variables used in the formulation for Model II are an upscaled version of the $v$ variables, such that one $w$ variable may represent more than one nearby $v$ variable. As such, if a specific $w$ variable is equal to one, it means that all deployments of a certain technology will be placed in a radius $R$ of at least one of the site locations aggregated under the $w$ variable.

**NOMENCLATURE**

| **Decision Variables** | | **Sets** | |
|---|---|---|---|
| $v$: | True or False for Active Site Perimeter ($\{0,1\}$), $v_i$ for $i \in I$ | $EC$: | Set of Energy Conversion Technologies |
| $w$: | True or False for Active Site Perimeter ($\{0,1\}$), $w_k$ for $k \in W$ | $DW_k^{<30km}$ | Set of Site Locations That are Less Than 30km Away from Site $k \in W$. |
| $x$: | Number of Turbines in Each Site Location ($\mathbb{R}_+$) | $I$: | Set of All Site Location (original scale) |
| $y$: | Number of Turbines in Each Site Location ($\mathbb{N}_+$) | $I_{EC} \subset I$: | Set of All Site Location for the technology $EC$ |
| $D_i^{<30km}$: | Set of Sites Locations That are Less Than 30km Away from Site $i$ | $W$ | Upscaled Set of Site Locations |
| | | $W_{EC} \subset W$ | Upscaled Set of Site Locations for the technology $EC$ |
| **Deterministic Parameters** | | | |
| $\Sigma$: | Variance-covariance Matrix | $\overline{LCOE}$: | LCOE Target [$/MWh] |
| $COST_i$: | Annualized Cost per Turbine of the $i$th Site Location [$] | $N_{T_{EC}}$: | Total Number of Turbines For Each Technology (EC) |
| $ENERGY_i$: | Expected Generated Energy Per Year Per Turbine for the $i$th Site Location [MWh] | $N_{U_{EC}}$: | Maximum Number of Turbines per Site Location per Energy Technology (EC) |
| **Functions** | | | |
| $size(\cdot)$ | Number of Elements in a Given Set | | |

**Model (I):** $$\min\ Y^T \Sigma\, Y \tag{1}$$

$$\text{s.t.}\ \sum_{i \in I} (COST_i) \cdot y_i \leq \overline{LCOE} \sum_{i \in I} (ENERGY_i) \cdot y_i \tag{2}$$

$$\sum_{i \in I_{EC}} y_i = N_{T_{EC}} \qquad \forall\ EC \in \{Wind; O\_Current; Wave\} \tag{3}$$

$$y_i \leq N_{U_{EC}} \qquad \forall\ i \in I_{EC},\ and\ EC \in \{Wind; O\_Current; Wave\} \tag{4}$$

$$\sum_{k \in D_i^{<30km}} y_i \leq (1 - v_i) \cdot size(I_{EC}) \qquad \forall\ i \in I_{EC},\ and\ EC \in \{Wind; O\_Current; Wave\} \tag{5}$$

$$\sum_{i \in I_{EC}} v_i = 1 \qquad \forall\ EC \in \{Wind; O\_Current; Wave\} \tag{6}$$

**Model (II):** $$\min\ X^T \Sigma\, \mathrm{X} \tag{7}$$

$$\text{s.t.}\ \sum_{i \in I} (COST_i) \cdot x_i \leq \overline{LCOE} \sum_{i \in I} (ENERGY_i) \cdot x_i \tag{8}$$

$$\sum_{i \in I_{EC}} x_i = N_{T_{EC}} \qquad \forall\ EC \in \{Wind; O\_Current; Wave\} \tag{9}$$

$$x_i \leq N_{U_{EC}} \qquad \forall\ i \in I_{EC},\ and \tag{10}$$

$$EC \in \{Wind; O\_Current; Wave\}$$

$$\sum_{i \in DW_k^{>30km}} x_i \geq w_k \, N_{T_{EC}} \qquad \forall\, k \in W_{EC},\ and \quad EC \in \{Wind; O\_Current; Wave\} \tag{11}$$

$$\sum_{i \in I_{EC}} w_i = 1 \qquad \forall\, EC \in \{Wind; O\_Current; Wave\} \tag{12}$$

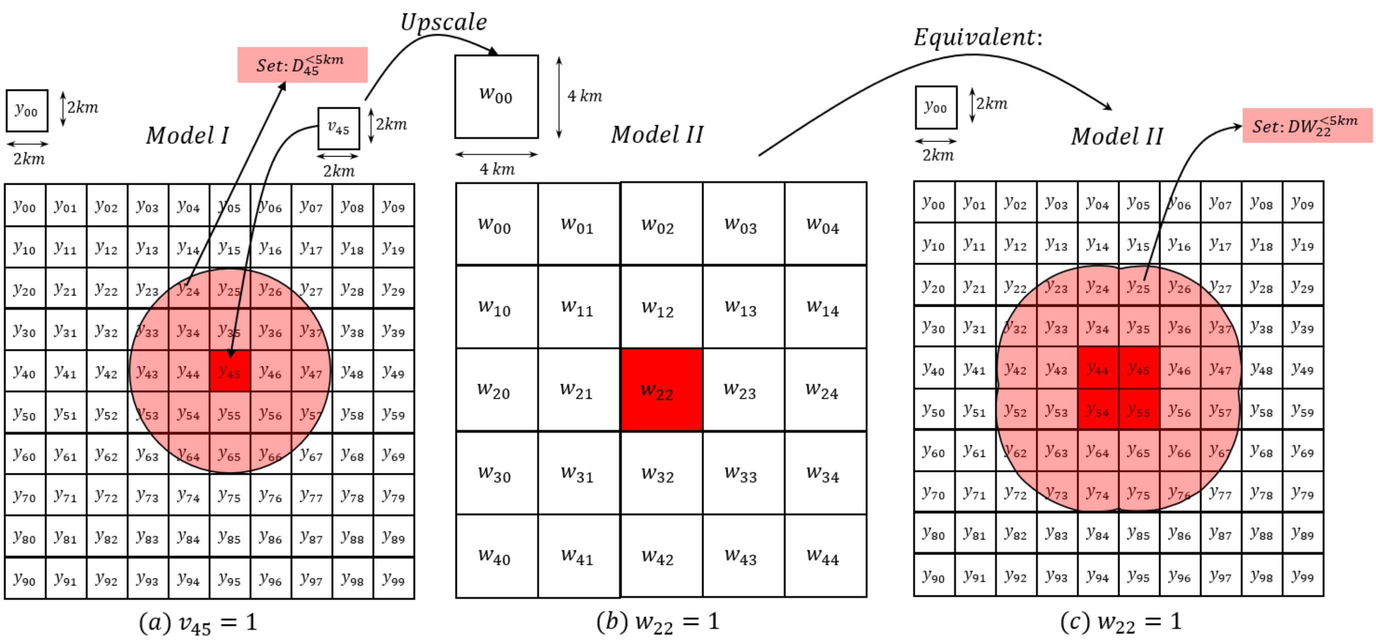


**Figure 8:** Example of How Model II Relaxes the Constraint that Limits the Length of the energy Collection System (Constraint 5 -Model I). The Relaxation Reduces the Number of Integer Variables by Grouping Nearby Grid Cells ($v$) in the Variables ($w$). This Grouping Procedure is Such that the Any Solution from Model I is Still Achievable from Model II.

## Portfolio Optimization Results

Figure 9 shows the efficient frontier for different combinations of ocean energy portfolios. For each curve, there is a corresponding series of three numbers that indicate the installed capacity of wind, wave, and ocean current. The y-axis represents the LCOE and the x-axis represents the standard deviation in the hourly capacity factor (CF). Additionally, the rated power for the turbine models is 6 MW for wind, 1.5 MW for wave, and 4 MW for ocean current.

In Figure 9, a high level of energy variability implies a risk of low electricity production in a given year and more difficulty integrating these technologies into the electrical system, given that the variation in output that must be absorbed by the system.

The results indicate that the portfolios with only wind or wave have very high energy variability compared to the portfolios with only ocean current. Figure 9 also indicates a very strong complementarity between wind and wave energy, since both have very high variability when deployed alone, which decreases significantly when both technologies are deployed together. Finally, our results also show the relevance of ocean current technology: despite its high LCOE, the portfolios with wind/ocean current and wave/ocean current achieved significantly lower variances.

Although most of these technologies are still in their early stages of development with non-attractive LCOEs, the results presented in Figure 9 show the importance of an integrated planning strategy to accelerate the deployment of these energy systems in the North Carolina Coast.

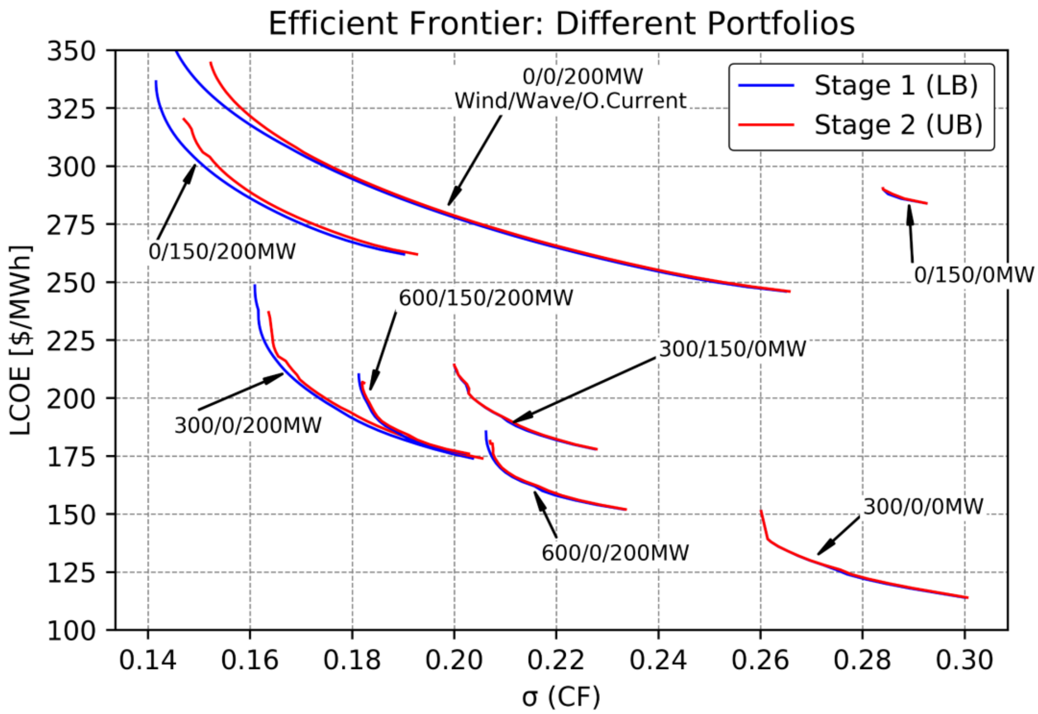


**Figure 9:** Efficient frontier for different ocean energy portfolios. The three numbers associated with each curve (from left to right) represent the allowable MW capacity of wind, wave, and ocean current technology.

In order to evaluate the cost-effectiveness of the portfolios presented in Figure 9, we used the open source energy system optimization model called 'Temoa' to estimate the reduction in portfolio-specific LCOE that would enable the deployment of these offshore portfolios in North Carolina. The Temoa-compatible input dataset represents the North Carolina grid mix, and utilizes linear optimization to perform capacity expansion and system dispatch through 2050. In these model runs, the offshore energy portfolios shown in Figure 9 must complete with other sources of electricity generation, including onshore wind, solar PV, natural combined-cycle turbines, nuclear, coal steam plants.

Table 1 shows the LCOE values that each portfolio should reach in order to be deployed in North Carolina in 2050 and 2030. Offshore wind is the technology closest to being deployed in North

Carolina, needing a reduction of at least 34% to reach deployment by 2050, and 60% to reach deployment by 2030.

Portfolio 3, which includes only ocean current technology, is also interesting. This portfolio ended up being deployed by the model in 2030 with an LCOE of 76 [$/MWh], much higher than any other case analyzed in the same year, showing the potential relevance of this technology in North Carolina.

It is also important to mention that wind energy technology is at a more advanced stage of development compared to wave or ocean current technology. As a result, the opportunities for significant cost reduction may be much more limited for wind energy compared to the other analyzed options.

Table 1: Percentage Reductions in the LCOE Values to Achieve Deployment in NC

| **Portfolio** | | **Current LCOE Estimate [$/MWh] (2020)** | **NC Energy System (TEMOA)** Required LCOE (% Reduction from the Current Values) | |
|---|---|---|---|---|
| | | | 2050 | 2030 |
| (1) | 600MW Offshore Wind & 200MW Ocean Current | 152 | 77 (49%) | 48 (68%) |
| (2) | 300MW Offshore Wind | 114 | 75 (34%) | 46 (60%) |
| (3) | 200MW Ocean Current | 246 | 81 (67%) | 76 (69%) |
| (4) | 150MW Wave | 284 | 82 (71%) | 50 (83%) |
| (5) | 300MW Wind & 150MW Wave | 178 | 84 (53%) | 52 (71%) |
| (6) | 200MW Ocean Current & 150MW Wave | 262 | 80 (70%) | 50 (81%) |
| (7) | 600MW Offshore Wind & 200MW Ocean Current & 150MW Wave | 176 | 83 (53%) | 50 (71%) |

## II. CONCLUSIONS AND MAJOR CONTRIBUTIONS

In this project, we proposed the application of mean-variance portfolio theory in the site selection of renewable energy technologies while also considering constraints pertaining to the length of the energy collection system and the deployment of offshore wind, wave, and ocean current capacity. A convex relaxation of our original formulation was implemented to allow the representation of a larger number of site locations without leading to prohibitive computational times. Our model is used to perform a techno-economic assessment of offshore renewable energy in North Carolina, and the optimal portfolios (with different shares of wind, wave, and ocean current) are further incorporated in a capacity expansion model, leading to valuable insights regarding how much the portfolio-specific LCOEs should decrease in order to get deployed in North Carolina.

This year's work represents a significant extension of existing work, allowing for more detailed portfolio optimization where structural constraints related to the energy collection system are incorporated directly into a large-scale mixed-integer nonlinear optimization. This work is also the first to evaluate the optimal site selection of wind, wave, and ocean current simultaneously, which provides valuable information regarding the optimal mix of these resources in North Carolina. In addition, this work establishes cost targets to enable deployment in the future.

## III. PUBLICATIONS AND PRESENTATIONS

V. A. D. Faria, A. R. Queiroz and J. DeCarlois (2020). Optimizing Investments in NC Offshore Renewable Energy. 2020 NC Renewable Ocean Energy Symposium.

## IV. STUDENTS

Victor Augusto Duraes de Faria. Degree: Ph.D. in Operations Research. Expected completion: 2023.

## V. EXPENSE REPORT

| | Allocation | Expense to date | Encumbered to Date | Balance |
|---|---|---|---|---|
| Total expenses | $32,420 | $32,420 | $0 | $0 |

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