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Optimizing offshore renewable portfolios under resource variability

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HIGHLIGHTS

- A novel portfolio model to analyze offshore wind, wave and ocean current is proposed.
- Mean-variance portfolio theory is used to combine LCOE and resource availability.
- We propose a model relaxation to allow the simulation of large-size instances.
- Our optimal energy portfolios are incorporated in a capacity expansion model.
- Synergies between renewable resources and targets for cost reduction are estimated.

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ABSTRACT

The deployment of offshore wind, wave, and ocean current technologies can be coordinated to provide maximum economic benefit. We develop a model formulation based on Mean-Variance portfolio theory to identify the optimal site locations for a given number of wind, wave, and ocean current turbines subject to constraints on their energy collection system and the maximum number of turbines per site location. A model relaxation is also developed to improve the computational efficiency of the optimization process, allowing the inclusion of more than 5000 candidate generation sites. The model is tested using renewable resource estimates from the coast of North Carolina, along the eastern US coast. Different combinations of technology-specific offshore technologies are compared in terms of their levelized cost of electricity and energy variability. The optimal portfolio results are then included in a capacity expansion model to derive economic targets that make the offshore portfolios cost-competitive with other generating technologies. Results of this work indicate that the integration of different offshore technologies can help to decrease the energy variability associated with marine energy resources. Furthermore, this research shows that substantial cost reductions are still necessary to realize the deployment of these technologies in the region investigated.

1. Introduction

With the world's rising concern about climate change and sustainability, renewable energy technologies have improved substantially over the last two decades as a result of technology innovation and policy support. According to the International Renewable Energy Agency (IREA) [1], in 2020, renewables represented 80 % of total capacity additions in the world, continuing to outpace fossil fuels. In this context, onshore wind and solar currently lead the deployment of renewables accounting for 91 % of its added capacity.

In addition to the large deployments of onshore wind and solar photovoltaics, marine-based generating technologies, including offshore wind, wave, and ocean current have the potential to further diversify electricity supply. The complementarity between different renewable energy resources can be utilized to reduce energy variability and increase system security [2,3].

In 2019 the IEA [2] reported 28 GW of offshore wind energy capacity in the world (1 % of total renewables), of which 77 % was located in Europe. However, it is expected that offshore wind will grow by at least 15-fold in the next 20 years, potentially accounting for more than \$1 trillion in investment [2]. Finally, despite being currently more expensive than onshore wind energy, offshore wind has lower hourly variability, can be deployed at higher capacity factors (average energy generated divided by maximum electrical energy output), and is seen (in some instances) as a solution to many of the siting concerns that arise

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Nomenclature

Indices and sets

$e \in E$ Set of energy technologies (wind, wave, and ocean current).
$i \in I_e$ Set of feasible site locations associated with the technology e.
$j \in J_e$ Set of relaxed site locations associated with the technology e.
$k \in D^R_{w(e,j)}$ Set of $x_{e,i}$ variables that have its correspondent site location (e,j) farther than R kilometers from the site location of $w_{e,j}$.
$k \in D^R_{v(e,i)}$ Set of $y_{e,i}$ variables that have its correspondent site location (e,i) farther than R kilometers from the site location of $v_{e,i}$.

Parameters:

$C_{e,i}$ Annualized cost of deploying one turbine of the technology e at the site location $i \in I_e$ [$/Year-Turbine].
$CT_{e,i}$ Annualized cost of a transmission system build for the technology e with substation located at the site $i \in I_e$ [$/Year].
$EG_{e,i}$ Expected annual energy generation of one turbine of the technology e at the site location $i \in I_e$ [MWh].
$\overline{LCOE}$ Upper bound in the Levelized Cost of Energy [$/MWh].
$\overline{Nt_{e,i}}$ Maximum number of turbines of the technology e that can be deployed at the site location $i \in I_e$.
R Maximum radius of the energy collection system [km].
TNt_e Total number of turbines deployed of the technology e.
$\sum$ Variance covariance matrix for the available energy generation at each site location for each technology considering a 3 h time scale.

Decision variables

$v_{e,i}$ Binary variable responsible for controlling the center of the energy collection system for each energy technology, $v_{e,i} \in \{0,1\}$.
$w_{e,j} \in W$ A relaxation for the binary variable responsible for controlling the center of the energy collection system for each energy technology, $w_{e,j} \in \{0,1\}$. Upscaled version of $v_{e,i}$.
$x_{e,i} \in X$ A relaxation for the number of turbines deployed of the technology $e \in E$ at the site $i \in I_e$, $x_{e,i} \in \mathbb{R}^+$.
$y_{e,i} \in Y$ Number of turbines deployed of the technology $e \in E$ at the site $i \in I_e$, $y_{e,i} \in Z^+$.

Functions:

$CT\_P_e(\bullet)$ Annualized cost of the transmission system for the technology e considering the deployments (Y) defined by the optimization model [$/Year].

with onshore wind turbines, which can negatively impact local tourism and land value [4].

Wave energy technology is still largely in the research and development phase, with only small deployments used to conduct pilot and demonstration studies [5]. For this technology, the project design can vary significantly with the characteristics of the wave energy resource, including wave height and wave period, making it difficult to establish a convergent design model that could help to accelerate its development. Nonetheless, wave energy has a higher power density than solar, wind, and even ocean current [6,7]. Also, since ocean waves propagate with little attenuation, they can be detected several miles offshore, allowing for skilled forecasts many hours in advance [8,9].

Finally, although the use of ocean currents as a hydrokinetic energy resource has been studied for many decades [10,11], this technology is still in the early stages of development with no commercial deployments. As in the case of wave energy, ocean current technology is attractive because of its high power density and availability. Also, the design of ocean current turbines has been adapted in part from existing commercial wind turbines [12]. However, ocean current resources can exhibit significant spatiotemporal variation, therefore limiting the regions where it can be utilized cost-effectively [13,14,15]. Other aspects such as ocean depth and distance from shore are also critical considerations, narrowing further the set of practical locations for energy extraction. As an example, the Gulf Stream, one of the most well-studied ocean currents in the world, starts from the Gulf of Mexico, follows a significant portion of the US east coast, and departs the continental shelf near Cape Hatteras (located in the state of North Carolina) [13]. Despite the Gulf Stream's long reach, the most viable regions for energy extraction are in the Florida Straits and off the North Carolina Coast, where the current makes its closest approach to shore [13].

As previously mentioned, resource variability is a common concern regarding renewable energy technologies [16]. The electric power system needs to balance electricity supply and demand in real time such that fluctuations in voltage and frequency can be minimized, thereby avoiding power outages and damage to various grid components. In this context, the variability of many renewable energy resources adds complexity to the operation and planning of the electrical system, leading to larger requirements for reserve power (e.g., storage, and natural gas turbines), capable of responding over short time intervals to ensure that the grid remains balanced.

Many studies have investigated alternatives to cost-effectively address the problem of renewable energy variability. Lund et al. [17] performed an extensive review of the topic, discussing alternatives such as demand-side response, energy storage, and regulatory practices, showing that a substantial amount of system flexibility can be obtained without massive economic investments. Several studies have explored the benefits of resource diversification and complementarity between different renewable energy technologies as a strategy for reducing energy variability.

Solomon et al. [18] investigated different levels of wind-solar penetration in California's electricity grid, showing a substantial reduction in energy storage for the hybrid wind-solar system when compared to the scenarios with only wind or solar. Kalogeri et al. [19] investigated the complementarity between offshore wind and wave in Europe, showing that the combination of these resources can lead to portfolios with lower energy variability and fewer hours of zero production. Halamay et al. [20] analyzed the energy reserve requirements of the US Pacific Northwest given different levels of penetration for solar, wind, and wave energy, showing that an equal combination of these resources provides the best solution for the system analyzed. Bhattacharya et al. [21] showed that the electric grid can benefit from higher penetrations of marine renewable energy reducing energy balance requirements and variability; his work considered tidal, wave, and ocean current technologies and focused on the U.S. and Great Britain. Finally, Zhang et al. [22] investigated the problem of optimal allocation of wind power in China using a clustering model to aggregate similar geographic regions showing the importance of portfolio optimization in reducing short-term energy variations and increasing the firm energy capacity of the system.

Previous studies have also applied Mean-Variance Portfolio theory to develop optimal renewable energy portfolios. Li et al. [15] developed an optimization model to create portfolios consisting of diversified site locations for ocean current energy turbines. In their formulation, the optimization model minimizes the total variance in electricity production subject to a target capacity factor. Their results indicate that it is possible to significantly reduce the variability in electricity generation by optimally diversifying the selection of site locations where the turbine units are placed. In [23], a similar methodology was used to investigate the geographical optimization of solar and wind energy in China, showing the importance of portfolio diversification and the complementarity between different resources.

This paper represents a significant extension of the existent literature by modifying the portfolio optimization to constrain the levelized cost of electricity (LCOE: Cost per MWh generated) while minimizing variance, including offshore wind and wave energy in the resource mix, and embedding the optimal portfolios in an electric sector capacity expansion model that indicates the required cost reductions necessary to make the offshore portfolios economically competitive with other technologies. We design a novel and general optimization framework based on Mean-Variance portfolio theory to determine the site selection of renewable energy technologies – including offshore wind, wave, and ocean current – considering technical constraints in the length of the energy collection system [24] and the levelized cost of energy. A convex relaxation of our original formulation is also proposed to allow the representation of a larger number of site locations without prohibitive computational times. Once the optimal offshore portfolios are identified they are incorporated into a capacity expansion model, allowing us to estimate the capital cost reduction that would make offshore renewable technology cost-competitive within the interconnected power system. The proposed framework is then applied to analyze renewable offshore resources along the US East coast. To our knowledge, this work is the first to evaluate the optimal selection of wind, wave, and ocean current sites simultaneously, providing valuable information regarding the synergies between these resources and the economic targets for the future deployment of these technologies. Moreover, this research also contributes to the development of more detailed portfolio optimization models where the structural constraints related to the energy collection system can be incorporated directly into a large-scale mixed-integer nonlinear optimization.

The remainder of this paper is divided as follows: Section II describes the portfolio optimization and discuss the link with the capacity expansion model used; Section III describes the data used in this work; Section IV presents the results, and Section V concludes the paper.

2. Methods

2.1. Mean-Variance portfolio model

The Mean-Variance Portfolio Theory was developed by Harry Markowitz in the mid-20th century [25]. His work enforced the importance of risk in the selection of optimal portfolios, suggesting the use of an efficient frontier curve, where the expected return and risk (variance in return) are considered together in the analysis.

This method has been extensively used in many fields including the area of energy planning. Roques et al. [26], applied the technique to identify optimal baseload generation portfolios in a liberalized electricity market; the study considered gas, coal, and nuclear generation, as well as costs associated with CO_2 emissions. Kitzing [27], used a Mean-Variance approach to compare different support instruments for renewable energy, showing the importance of a proper risk representation when designing policy schemes. Li et al. [15] used a Mean-Variance model for the portfolio optimization of ocean current devices, considering the tradeoff between total energy generation and energy variability.

The Mean-Variance Portfolio formulation considered in this work is presented in Model I (1–6). The model's goal is set to optimize the number of turbines at each viable site location such that it minimizes the total energy variability of the portfolio ($Y^T\Sigma Y$) given an upper bound on the LCOE and a set of other structural constraints (4–7). The LCOE is the average cost of each MWh generated by the portfolio. The goal is to identify portfolios with low LCOE and low energy variability. However, there is typically an existent tradeoff between the two: sites that minimizes LCOE may have high variability, and vice versa.

To simplify the Mean-Variance portfolio formulation, we assume that each technology has its own transmission and energy collection system, which is not shared among different technology groups. Also, each site location defined by the indices (e,i) has assigned an annualized turbine cost value ($C_{e,i}$), and a turbine generation capacity ($EG_{e,i}$). The annualized turbine cost value ($C_{e,i}$), takes into consideration the CapEx, and OpEx of the energy conversion device, and an equivalent fractional value associated with the transmission and energy collection system infrastructure.

Given the total number of turbines for each technology e (TNt_e) it is possible to estimate the annualized transmission system costs at any site $i \in I_e$ where offshore substations can be built ($CT_{e,i}$). Considering a solution ($y_{e,i}$) of the portfolio optimization model, a reasonable estimate of the transmission system can be derived by doing a weighted average of the ratio $CT_{e,i}/TNt_e$ with the number of turbines at each site ($y_{e,i}$), as in equation (1).

By assigning a fractional transmission cost ($CT_{e,i}/TNt_e$) for each site location, it is possible to use the formulation presented in Model I to indirectly incorporate complex aspects of the transmission system such as distance from shore, depth, and electric configuration (AC/DC or AC/AC) in a computationally efficient way. Additional information regarding collection and transmission costs is provided in the Supplementary Notes.

$$CT\_P_e(Y) = \sum_{i\in I_e}\frac{CT_{e,i}}{TNt_e}y_{e,i}\,\forall e \in E \tag{1}$$

Regarding the turbine generation capacity ($EG_{e,i}$) parameter, its value takes into consideration the characteristics of the energy conversion devices, the renewable energy available at each site location $i \in I_e$, losses associated with the energy collection system (considered constant), and losses associated with the transmission system. The efficiency of the transmission system depends on its distance from shore and system configuration (AC/DC or AC/AC). In this context, since the location of the offshore substation is not defined by the optimization model, we attribute a transmission energy efficiency for each individual site (e,i). All considerations regarding cables, power capacity, voltage, and losses are detailed in the Supplementary Notes.

In Model I, constraint (3) limits the LCOE of the portfolio, (4) limits the number of turbines for each energy technology investigated (wind, wave, and ocean current), (5) limits the number of turbines for each site location, and (6–7) control the extent of the energy collection systems for each technology. These last two constraints ensure that the optimization model will not choose to deploy spatially distant turbines, which could lead to higher energy losses and high energy collection system costs.

Model I: Mean-Variance Portfolio Optimization.

$$\min Y^T\Sigma Y \tag{2}$$

s.t

$$\frac{\sum_{e\in E}\sum_{i\in I_e}C_{e,i}y_{e,i}}{\sum_{e\in E}\sum_{i\in I_e}EG_{e,i}y_{e,i}} \le \overline{LCOE} \tag{3}$$

$$\sum_{i\in I_e}y_{e,i} = TNt_e\forall e \in E \tag{4}$$

$$y_{e,i} \le \overline{Nt_{e,i}}\forall(e,i) \in (E,I_e) \tag{5}$$

$$\sum_{k\in D^R_{v(e,i)}} y_{e,k} \ge v_{e,i}TNt_e\forall(e,i) \in (E,I_e) \tag{6}$$

$$\sum_{i\in I_e}v_{e,i} = 1\forall e \in E \tag{7}$$

The complexity of the model described above increases severely with the number of integer variables, which represent the number of site locations. Simulating (2–7) for a large coastal area can lead to prohibitive computational times. Thereafter, a relaxation procedure, described in *Subsection B*, was developed to help decrease the computational complexity of the problem.

2.2. Model relaxation

A model relaxation is a mathematical strategy that consists of approximating a difficult problem by a simpler one, which is easier to solve. The relaxed model is strategically constructed such that all the solutions of the original model are still present after the relaxation. However, the relaxed model normally contains additional feasible solutions that do not exist in the original model formulation. In this context, for a minimization model such as Model I, a relaxed solution would lead to a lower bound for the original problem. A model relaxation offers a faster way of investigating the problem feasibility space and can provide valuable information for decreasing the problem size and finding near-optimal solutions.

After a series of attempts to create a relaxed model formulation, the best strategy to reduce simulation time was to modify Model I by making the variable $y_{e,i}$ a continuous variable, which we name $x_{e,i}$, and reduce the number of $v_{e,i}$ variables by creating an upscaled version of it, defined here as $w_{e,i}$. In our analysis, we notice that different from the $x_{e,i}$ variable, it is important to keep the $w_{e,i}$ variable integer in order to achieve tighter relaxed solutions (close to the global optima). In this work, the relaxed version of Model I is called Model II.

Fig. 1 exemplifies the process of upscale for the $v_{e,i}$ variable and its consequence in constraints (6–7). The example shown in this figure ignores the index e for simplicity.

Model II: Relaxed Mean-Variance Portfolio Model.

$$\min X^T \Sigma X \tag{8}$$

s.t

$$\frac{\sum_{e\in E}\sum_{i\in I_e} C_{e,i}x_{e,i}}{\sum_{e\in E}\sum_{i\in I_e} EG_{e,i}x_{e,i}} \le \overline{LCOE} \tag{9}$$

$$\sum_{i\in I_e} x_{e,i} = TNt_e \forall e \in E \tag{10}$$

$$x_{e,i} \le \overline{Nt_{e,i}} \forall (e,i) \in (E, I_e) \tag{11}$$

$$\sum_{k\in D^R_{w(e,j)}} x_{e,k} \ge w_{e,j} TNt_e \forall (e,j) \in (E, j_e) \tag{12}$$

$$\sum_{j\in J_e} w_{e,j} = 1 \forall e \in E \tag{13}$$

In Model I, for each $y_{e,i}$ variable there is a correspondent $v_{e,i}$ variable responsible to limit the spatial extent (i.e., radius) of the energy collection system (R) for each technology (Fig. 1a). In the example shown in the left panel of Fig. 5, $v_{45} = 1$ and $R = 5km$, which means that all cells in the light red area are candidates for the deployment of turbines ($D^R_{v(e,i)}$). The problem with this approach is that it is still necessary to represent as many integer variables ($y_{e,i}$, and $v_{e,i}$) as two times the number of site locations. Even with the relaxation of $y_{e,i}$ as a continus variable ($x_{e,i}$), the model would still have a prohibitively large number of integer variables.

In order to reduce the number of integer variables associated with the energy collection system ($v_{e,i}$), it is possible to aggregate the $v_{e,i}$ variables that are "close" to each other. The right panel of Fig. 1 shows an example where four $v_{e,i}$ variables are aggregated (dark red) and represent a single integer variable (w_{22}). The w_{22} variable corresponds the energy collection system of the variables v_{44}, v_{45}, v_{54}, and v_{55}, and therefore in Model II, $D^{5km}_{w(22)}$ must be the union of $D^{5km}_{v(44)}$, $D^{5km}_{v(45)}$, $D^{5km}_{v(54)}$, and

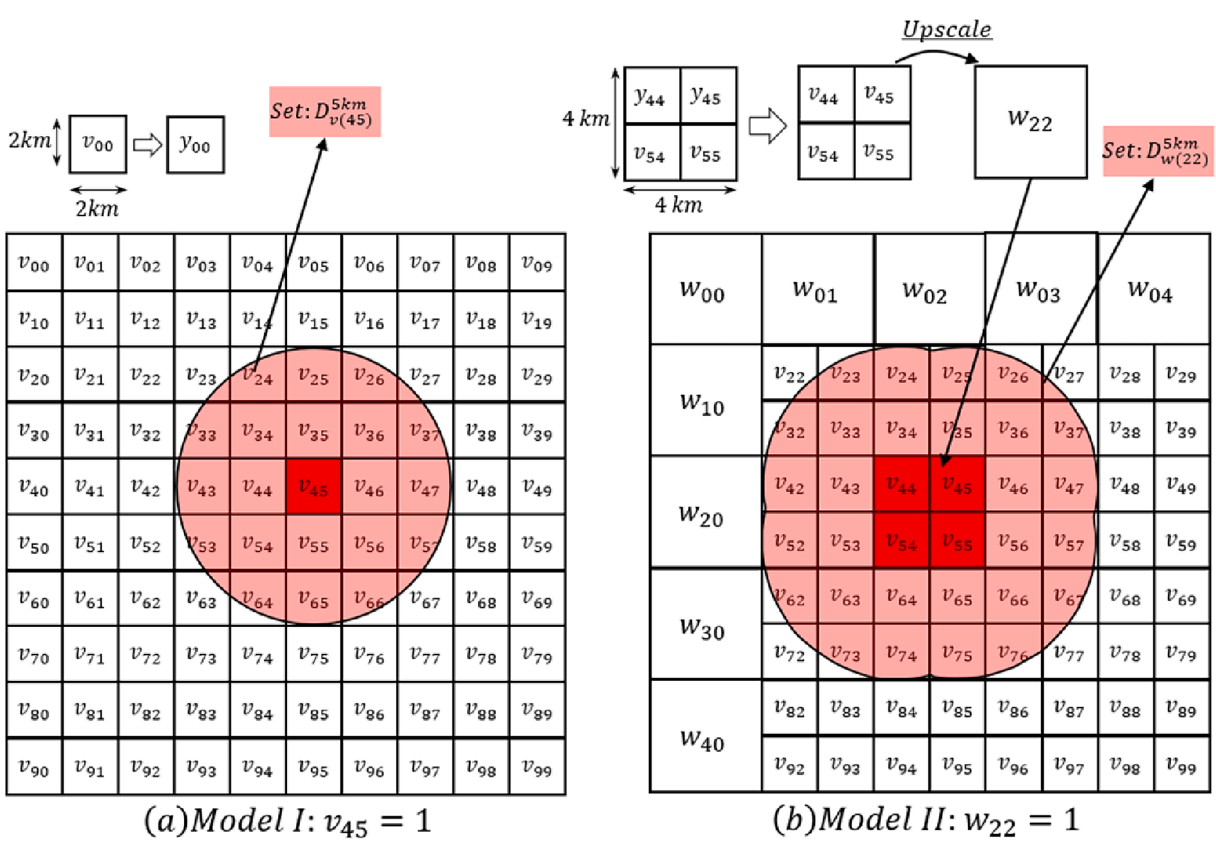

Fig. 1. Model I relaxation of the site locations. Nearby sites are aggregated to reduce the number of integer variables.

$D^{5km}_{v(55)}$.

It is important to notice that if $v_{45} = 1$ is optimal for Model I, this solution is still a feasible solution for Model II when $w_{22} = 1$. However, from the perspective of Model I, solutions obtained with Model II will be a lower bound.

2.3. Two-stage optimization and efficient frontier

The solution of Model II provides a lower bound for the original model formulation and an approximate location for the energy collection system ($w_{e,i} = 1$). At this stage, Model II results can be used to limit the site locations analyzed, and Model I can be solved considering the region limited by $w_{e,i} = 1$ (light red area in Fig. 5b). This constrained solve of Model I will only provide an upper bound for the original problem. If the difference between this upper bound and the lower bound from Model II is small enough, our constrained Model I simulation can be considered close to the global optimal solution of the original problem.

Finally, given a specific portfolio with a predefined number of wind, wave, and ocean current turbines, we can run the two-stage relaxed model for different $\overline{LCOE}$ levels and build an efficient frontier representing the optimal tradeoff between LCOE and variability in energy output. Fig. 2 is a flow diagram summarizing the process described in this section.

2.4. Capacity expansion model

After finding the efficient frontiers associated with different offshore energy portfolios, we incorporate our optimal portfolios into a capacity expansion model that represents the North Carolina energy system to estimate the level of reduction in LCOE in order to see the deployment of these portfolios by 2030 and 2050.

The capacity expansion model used in this work is called Tools for Energy Model Optimization and Analysis (Temoa) [28]. Temoa minimizes the present cost of energy supply by deploying and utilizing energy technologies and commodities overtime to meet a set of constraints that ensure proper system performance. The model has been extensively used in the literature [29,30,31]. We use Temoa-compatible input database representing the North Carolina electric sector (Base case file), which is publicly available for download and is documented in [32]. This dataset has been used in several other studies for the North Carolina Region [30,31], and thereafter was also considered in this work. It is also important to mention that many of the system projections considered in the dataset used in this work [32] are based on the Annual Technology Baseline reports [33] from NREL, which do not consider resource availability changes due to climate changes that is likely to affect resources and technology efficiency/costs during the years 2030–2050 [34].

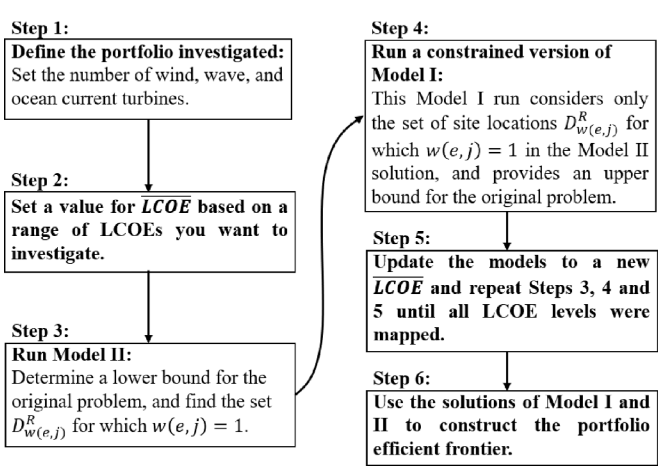

Fig. 2. Process for Estimating the Portfolio Efficient Frontier.

3. Data

This work considers as study domain a portion of the US east coast representing the state of North Carolina (NC). This state has among the largest offshore wind and wave energy potential along the US east coast [35,36]. In addition, the North Carolina represents one of the few locations where energy extraction from ocean currents is considered viable [13,37].

When integrating different energy resources in a portfolio optimization analysis it is important to maintain the same time scale and time interval across all resources, for the US east coast, the largest common time interval available for wind, wave, and ocean current data was from January 2009 to December 2013 at a 3-hour time discretization. Therefore, this is the period of analysis chosen in this work.

3.1. Wind

Offshore wind speed data is drawn from the NREL Wind Integration National Dataset (WIND) Toolkit [38], which contains data at 2 km × 2 km grid resolution and was sampled at 3-hour time intervals to be consistent with the other data sources used in this work. This dataset contains more than 11,000 site locations for North Carolina, which would be a computational challenge for the portfolio optimization model. However, the WIND-Toolkit [38] provides documentation specifying the set of viable site locations for offshore wind deployments in the United States based on depth, distance from shore, and wind speed, also considering environmental and land-use criteria. This documentation is used to limit the number of wind sites evaluated in this work, leading to the analysis of 1692 wind energy sites in North Carolina.

Wind speed is converted into energy assuming a 6 MW wind turbine with rotor diameter of 155 m and hub height of 100 m [33,39], with an associated power curve drawn from [40]. Additionally, it is assumed that each 2 km × 2 km grid cell can accommodate a maximum of four 6 MW turbines [33,39]. This turbine model was chosen following the common practices of NREL [39]. Fig. 3 depicts the site locations analyzed for wind energy, along with the corresponding capacity factors (CFs).

The capital expenditures (CapEx) and operational expenditures (OpEx) for wind energy were obtained from [33], which defines 15 different cost groups based on depth and distance from shore. More information regarding the resource characterization, turbine parameters, as well as cost estimates can be found in the Supplementary Notes.

3.2. Wave

For the wave energy resource, data of significant wave height and wave period were obtained from the WAVEWATCH III model [41] from January 2009 to December 2013 at a spatial resolution of 1/15° (∼6.7 × 6.7 km) and time resolution of three hours. WAVEWATCH III is a third-generation wave model developed at NOAA/NCEP, and is widely used for the assessment of wave energy resources [42,36,43].

As for the energy conversion device, after investigating a set of four alternative energy converters, see Supplementary Note 2, we considered a scaled version of the Pelamis model [44] developed by the University of Edinburgh [45]. This is an attenuator-type model of 1.5 MW scaled to operate at regions with lower wave heights when compared to the original Pelamis model [44], which would perform well off the North Carolina coast.

For the scaled Pelamis energy converter, its project design [45] limits the deployment depth to 50–150 m, leading to 82 feasible sites in North Carolina, each corresponding to cells of approximately 6.7 × 6.7 km, where a maximum packing density of 12.5 devices per km^2 is allowed.

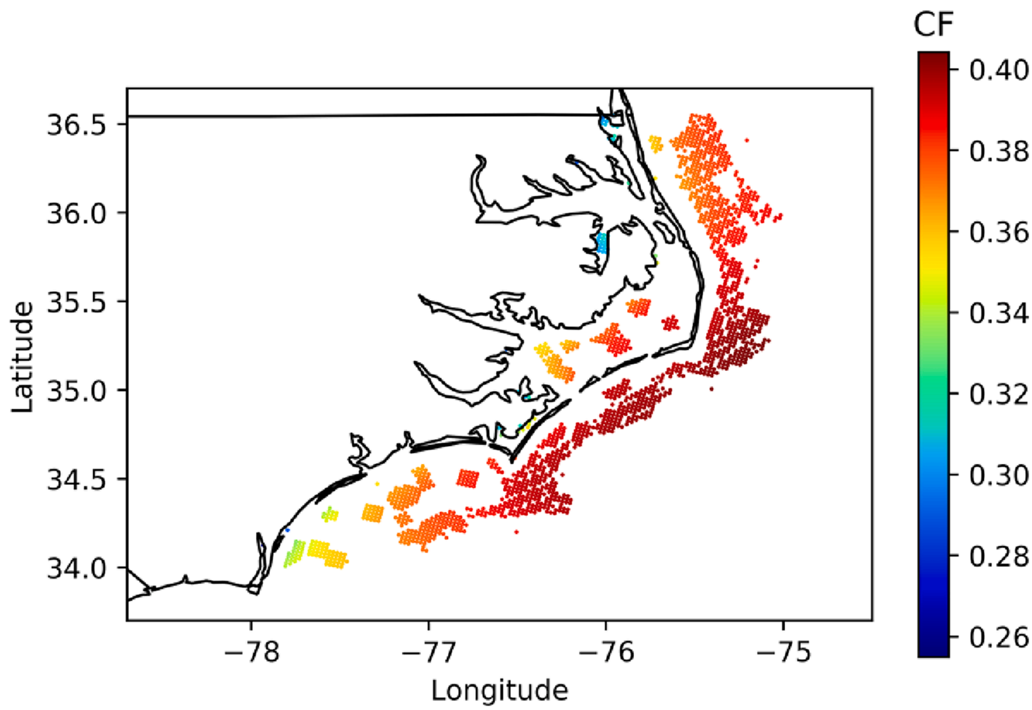

Fig. 3. Average site-specific capacity factor estimates for wind energy off the North Carolina coast from 2009 to 2013.

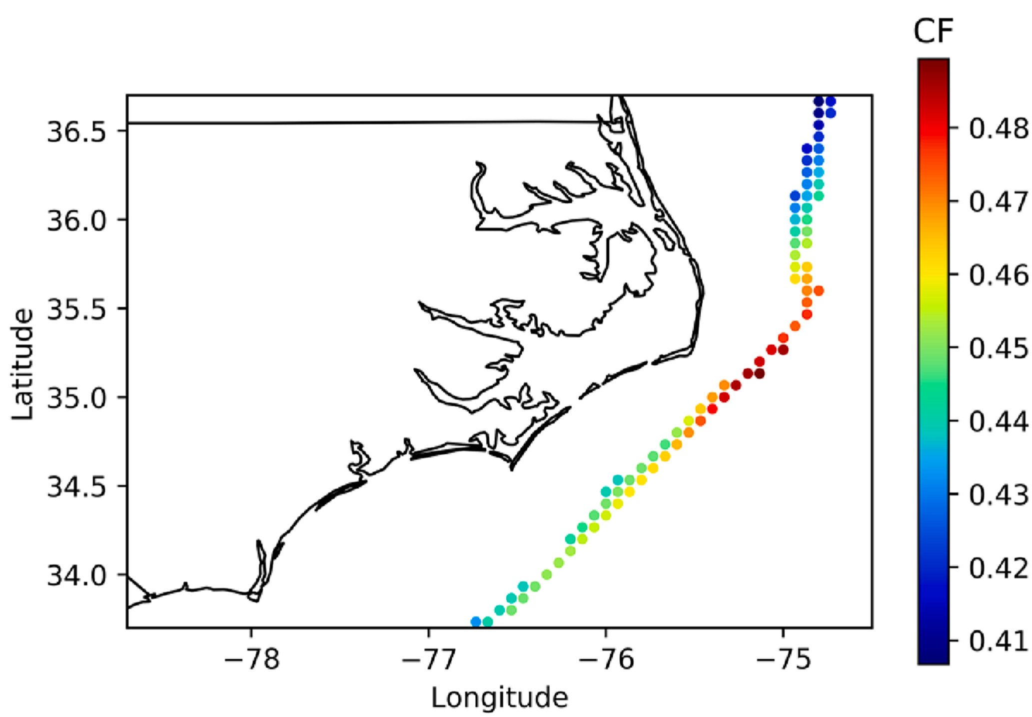

Fig. 4. Average site-specific capacity factor estimates for wave energy off the North Carolina coast from 2009 to 2013.

Fig. 4 depicts the site locations analyzed for wave energy and the corresponding CFs.

Finally, estimates for the CapEx and OpEx of the wave devices were based on the information presented in [46] and [47]. Similar to wind energy, a detailed description of the cost assumptions and generator model associated with wave energy technology is available in the Supplementary File.

3.3. Ocean current

For hindcasts of ocean current speed in the North Carolina region, two different models were considered, namely HYCOM/NCODA [48] and MABSAB [49].

The Hybrid Coordinate Ocean Model (HYCOM) is a primitive equation ocean general circulation model that evolved from the Miami Isopycnic-Coordinate Ocean Model (MICOM) [50]. It is a multi-institutional effort sponsored by the National Ocean Partnership

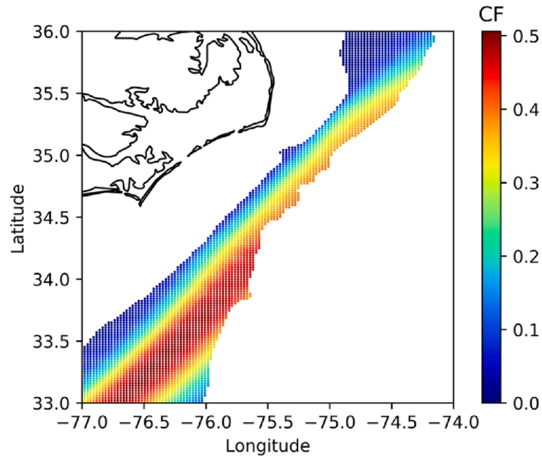

Fig. 5. Average site-specific capacity factor estimates for Ocean Current off the North Carolina coast from 2009 to 2013.

Program and has been used in many studies for the assessment of hydrokinetic energy resources [51,52,53]. In this work, the abbreviation HYCOM/NCODA is used to represent data coming from the HYCOM model in which the Navy Coupled Ocean Data Assimilation System (NCODA) was used for data assimilation.

The MABSAB model [49] was developed 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) [54], a high-resolution, free-surface, terrain-following coordinate oceanic model extensively explored in the literature [55,56]. For open boundary conditions, the MABSAB model is nested inside the 1/12° global data assimilative HYCOM/NCODA output [49], assuring consistency between the hindcast generated by the two models used in this work.

Because the process of simulating ocean circulation 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, however, data on ocean current speed from January 2009 to December 2013 is available from HYCOM/NCODA [48] at a 3-hour discretization and 1/12° grid resolution (~8 × 8 km), and for MABSAB [49] at daily discretization and 2 × 2 km grid resolution. Therefore, in this work, we constructed a synthetic dataset with the objective of capturing the hourly variability presented in HYCOM, while keeping the better spatial resolution of MABSAB.

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

This synthetic dataset for ocean current speed has 3-hour time resolution and 2 × 2 km 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 North Carolina.

For the ocean current energy conversion device, we consider the RM4 model developed by Sandia National Laboratory [47], since this design is well-documented and used in other analyses made for the U.S. east coast [47,15]. However, a few modifications were made to the turbine design in order to adjust its characteristics to the North Carolina ocean current resource. The original RM4 model was developed to operate along the coast of Florida in faster ocean currents compared to North Carolina. To compensate for this reduction in current speed, we increase the rotor diameter of this turbine from 33 m (original model) to 45 m, which results in a larger energy capture area. This change leads to additional modifications in the model design, CapEx and OpEx values, all of them detailed in the Supplementary Notes.

Finally, in this project, we assume that ocean current turbines will operate with its buoyancy tank and rotor at 50 m depth and that a maximum packing density of four devices per 2 × 2 km grid cell is allowed, as done in [47] and [15] to assure the safety and efficiency of the system. Additionally, a minimum ocean depth of 100 m and a maximum of 2500 m is considered in the definition of feasible site locations in order to satisfy constraints related to the turbine model [47] and its anchoring system [57].

Fig. 5 depicts the site locations analyzed in this work for the ocean current technology (4108 sites) and their corresponding CFs.

4. Results

We utilize the models described in Section II to develop optimal portfolios consisting of different resource mixes. We specify the capacity mix of the three resources exogenously in order to explore the decision space, in each case allowing the model to optimally select the locations. We choose technology-specific capacity combinations that are large but plausible for the North Carolina power system. Thus we analyze the deployments of 300 and 600 MW of wind energy, 150 MW of wave energy, and 200 MW of offshore ocean current, as well as different combinations of these technologies. These deployment sizes were also chosen to ensure that most benefits from economies of scale would already be incorporated into the CapEx and OpEx of the portfolio, following references [33] and [47].

A total of eleven different portfolio sizes were simulated, and the Mean-Variance portfolio model proposed in this work was used to construct the efficient frontier of these portfolios. Temoa was then used to estimate the levels of cost reduction necessary for these offshore technologies to reach cost parity with other generating technologies in North Carolina.

4.1. Mean-variance portfolio optimization

Fig. 6 presents the efficient frontier for the various capacity combinations. The y-axis represents the LCOE of a specific portfolio, and the x-axis represents the square root of the variance in the CF. The size of the portfolio is described by three capacity numbers in the following sequence: wind, wave, and ocean current. For each portfolio size, there is a blue and red curve representing the results of Stage 1 and 2 from the models described in Section II. Finally, it is important to understand that each point in a given curve represents one solution of the Mean-Variance Portfolio model, and therefore is associated with a unique deployment pattern across the respective technologies in the portfolio.

As discussed in Section II, the relaxed model formulation proposed in this work is good when the distance between the Stage 1 and Stage 2 solution is small, since the global optimal solution is between these two curves. Based on the results shown in Fig. 6, it is possible to see that the relaxation proposed in Section II is tight for most of the portfolios, showing that the model is reaching results close to the global optima.

The model relaxation performed worse for the portfolio with only ocean current. In this case, there is a maximum gap of 0.012 between the bounds of $\sigma(CF)$ for an LCOE of 344[$/MWh]. However, given the uncertainty associated with cost estimates and energy generation estimates, the gap seen in this case will not substantially affect the analysis associated with this portfolio.

Additionally, Fig. 6 shows that the North Carolina region has a very diversified offshore energy potential and that although the costs of wave and ocean current technology far outweigh the costs of wind, the combination of these different resources can promote significant reductions in energy variability. As an example, the portfolio with 300/150/200 MW of wind/wave/ocean current had the best performance in terms of the variance in its capacity factor, and although the portfolios with only

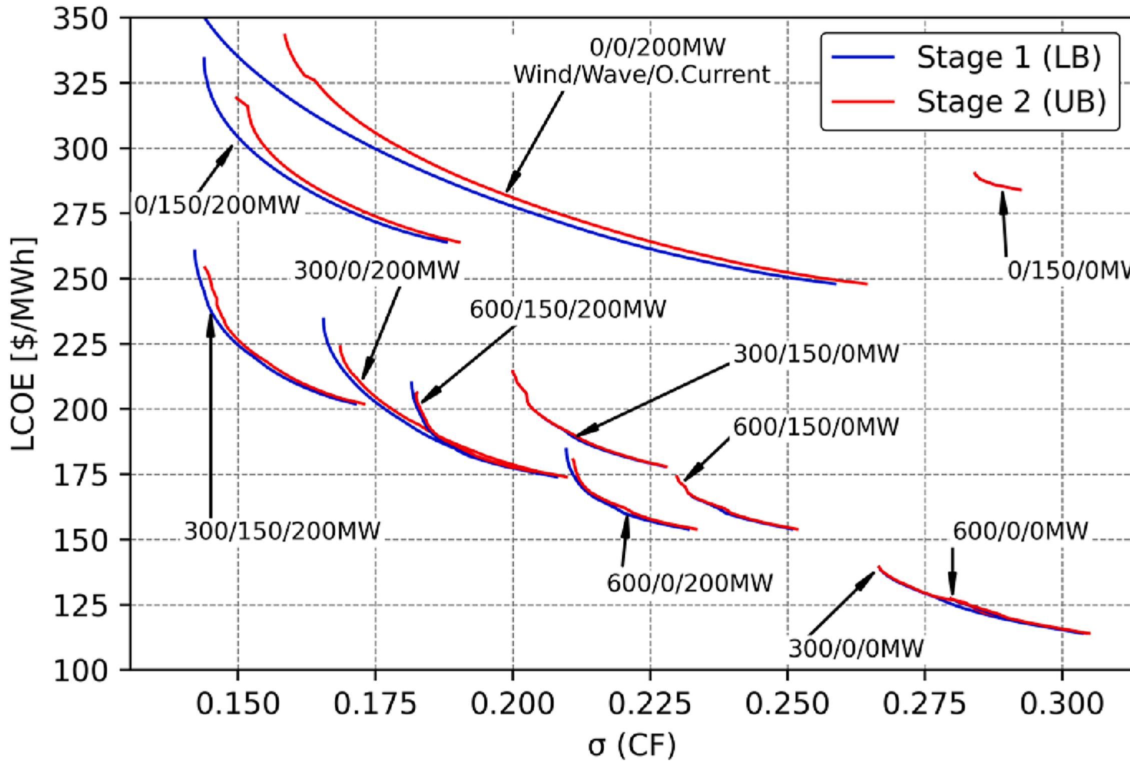

Fig. 6. Efficient Frontier For Different Deployments of Wind, Wave, and Ocean Current.

wind energy performed better in terms of LCOE, these portfolios are among the worse in terms of energy variability.

Still analyzing Fig. 7, it is possible to see that the ocean current portfolio (0/0/200 MW) has a very elongated efficient frontier, with a wide range in energy variance, which illustrates the diversity of this energy resource in the North Carolina region. Another interesting aspect shown in Fig. 6 is the strong synergy that wind and ocean current have with wave energy. This characteristic can be seen in all instances where wave is added to a portfolio (e.g. 300/0/200 MW to 300/150/200 MW, and 600/0/0MW to 600/150/0MW). In these cases, after wave energy is added, there is a substantial reduction in the energy variability of the equivalent portfolio.

Finally, Fig. 7 depicts the site location selection for a few of the portfolios shown in Fig. 6. The locations chosen for the wind, wave, and ocean current are represented by open squares, open triangles, and crosses, respectively. Additionally, the CF of all feasible site locations with an average value larger than 0.25 are shown to provide information regarding the spatial distribution of the offshore energy resource in the region. Fig. 7a-b shows the portfolios of three different system configurations 300/0/0MW, 0/150/0MW, and 0/0/200 MW, for the lower LCOE region (a), and lower CF region (b); Fig. 7c and Fig. 7d shows, respectively, the configuration 0/150/200 MW, and 300/150/200 MW for the lower CF region.

Regarding the interpretation of Fig. 7 and its connection with Fig. 6 it is important to notice that a low LCOE region in the efficient frontier implies in a high variance in the CF, and that a high LCOE implies in a low variance in the CF.

4.2. Capacity expansion model

Table 1 shows the capacity expansion model results from Temoa for all of the different portfolio options shown in Fig. 6. For each of these configurations, the portfolio with the lowest LCOE, the portfolio with medium LCOE, and the portfolio with the highest LCOE were investigated. In each LCOE configuration (low, medium, high), the first column represents the current LCOE estimate, and the second and third columns represent the LCOE values required to fully deploy this specific portfolio in the NC Energy system by 2030 and 2050, respectively. The values in the "2030" and "2050" columns can also be interpreted as the maximum price that the system operators in North Carolina would be willing to pay per MWh generated by each of our portfolios.

Based on Table 1, it is possible to see that offshore wind energy (Portfolios 1 and 2) is the technology closest to being deployed by the capacity expansion model, needing a reduction of 56 % in its cost to be integrated into the system by 2030, and a 34 % cost reduction to be incorporated by 2050. Still, it is interesting to notice that the capacity expansion model values the energy of Portfolios 1 and 2 at a much lower price than it values the energy of more diversified portfolios. As an example, a value of up to 101 [$/MWh] was attributed to Portfolio 7 (wind/wave) in 2050, but a maximum of 92 [$/MWh] was attributed to the wind portfolios in the same period.

Through Table 1, it is also possible to see that as the variance in the portfolios' capacity factor decreases, its LCOE [$/MWh] value increases and that offshore renewable energy technologies will gradually benefit from the North Carolina energy system evolution, improving the LCOE level required for their deployment from 2030 to 2050.

5. Conclusion

This work investigates the problem of defining optimal portfolios for wind, wave, and ocean current technologies. A Mean-Variance portfolio formulation is proposed to determine the optimal site location for each turbine, considering constraints on the energy collection system and maximum number of turbines per site location. Due to the complexity associated with running a large-scale nonlinear mixed-integer optimization model, a relaxation was proposed for the original Mean-Variance portfolio formulation in order to allow the simulation of instances with more than 5000 site locations in suitable computational times.

This relaxed portfolio formulation was then used to investigate the deployment of offshore wind, wave and ocean current out of the North

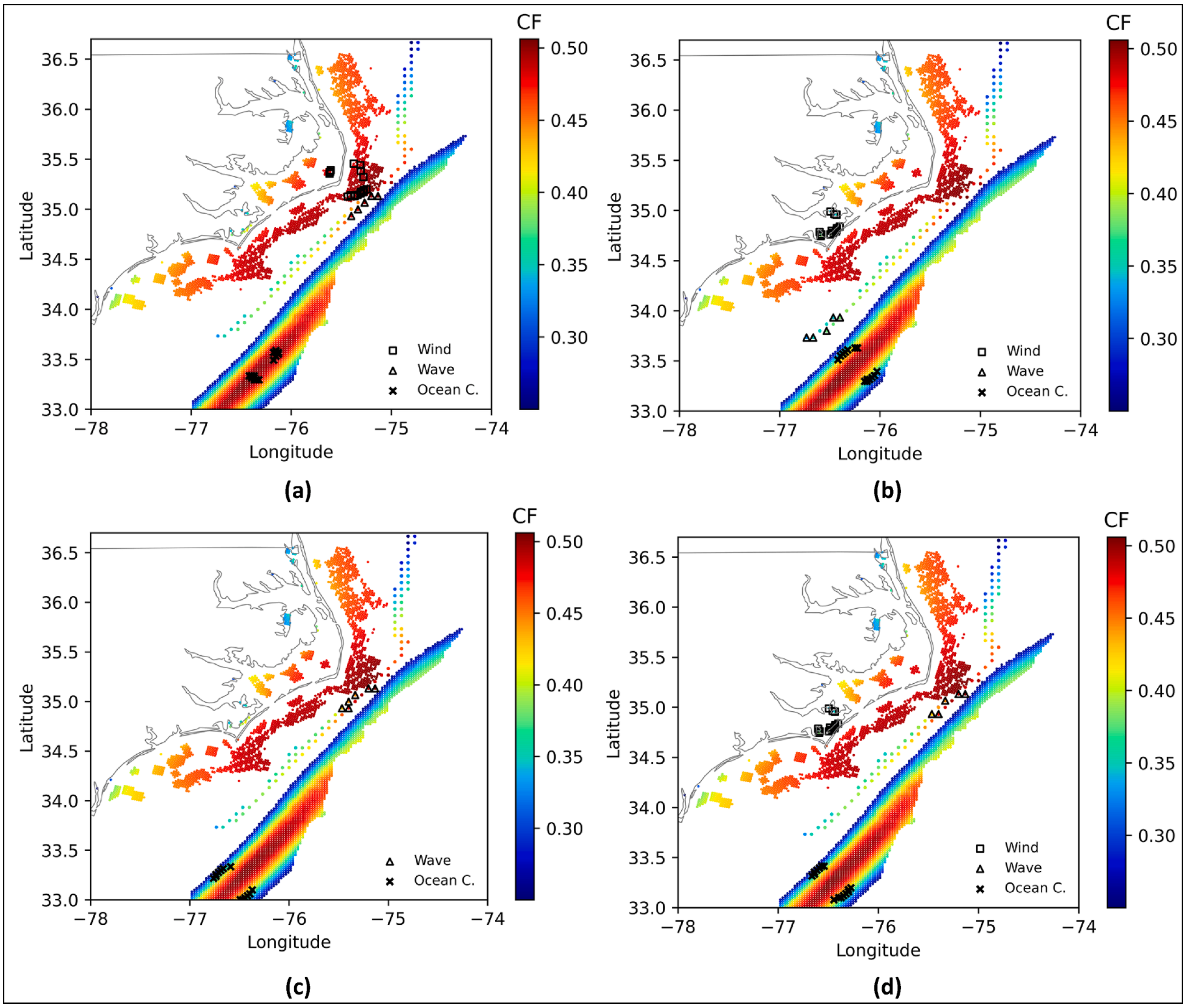

Fig. 7. **(a)** Optimal Site Locations For The Lowest LCOE in the 300/0/0, 0/150/0, and 0/0/200 MW Portfolios; **(b)** Optimal Site Locations For The Lowest $\sigma(CF)$ in the 300/0/0, 0/150/0, and 0/0/200 MW Portfolios; **(c)** Optimal Site Locations For The Lowest $\sigma(CF)$ in the 0/150/200 MW Portfolio; **(d)** Optimal Site Locations For The Lowest $\sigma(CF)$ in the 300/150/200 MW Portfolio.

Carolina Coast. After building the efficient frontier for portfolios with different, exogenously specified installed capacities, these results were then incorporated into a capacity expansion model of the North Carolina electric sector to estimate the required reduction in the costs of each portfolio such that it can be fully deployed by 2030 or 2050.

Our results show that North Carolina has a very diverse offshore energy potential and that different offshore energy technologies can be combined to reduce energy variability.

More specifically, we show that the efficient frontier of the ocean current technology is very elongated in the region investigated, providing conditions for low and high energy variability. We also showed that despite the high energy variability of wave energy, this resource can be easily integrated with wind or ocean current, improving substantially the energy variability of the equivalent portfolio.

Additionally, the simulations made using the capacity expansion model show that substantial cost reductions are still necessary for the deployment of the offshore portfolios examined in this work. For 2030, the required cost reduction is between 56 % and 84 %, but for 2050 this level is between 34 % and 74 %, showing that these portfolios will get progressively more attractive as time passes. The capacity expansion simulations presented in this work also highlight the benefit of portfolios with low variability in output. The model results indicate that portfolios with low CF variance have higher break-even costs compared with higher variance portfolios.

Finally, despite the considerable effort made to provide accurate estimates for the CapEx, OpEx, and LCOEs of the offshore energy technologies investigated, a reasonable amount of uncertainty may still exist in our analysis, given the limited amount of data pertaining offshore deployments. In this context, future works should explore the use of robust and/or stochastic optimization as an alternative to incorporate the uncertainties related to technology cost and resource availability (wind speed, ocean current speed, significant wave height, and period). Future work also could explore the application of the presented methodology to investigate deployments of offshore renewable portfolios in other regions considering synergy with other technologies such as battery and hydrogen storage.

CRediT authorship contribution statement

Victor A.D. de Faria: Data curation, Methodology, Writing – original draft, Software. **Anderson R. de Queiroz:** Methodology, Writing – review & editing, Software. **Joseph F. DeCarolis:** Methodology, Writing – review & editing, Software.

Table 1
Required LCOE values for portfolio deployment in the North Carolina Energy System by 2030 and 2050.

Portfolio Installed Capacity Wind/ Wave/Ocean Current [MW]		Low LCOE Portfolios (High CF Variance)			Medium LCOE Portfolios (Medium CF Variance)			High LCOE Portfolios (Low CF Variance)		
		Current LCOE Estimate [$/MWh] (2021)	NC Energy System (TEMOA) Required LCOE (% Reduction from the Current Values)		Current LCOE Estimate [$/MWh] (2021)	NC Energy System (TEMOA) Required LCOE (% Reduction from the Current Values)		Current LCOE Estimate [$/MWh] (2021)	NC Energy System (TEMOA) Required LCOE (% Reduction from the Current Values)	
			2030	2050		2030	2050		2030	2050
(1)	600/0/0	114	50 (56 %)	75 (34 %)	121	53 (56 %)	80 (34 %)	128	56 (56 %)	84 (34 %)
(2)	300/0/0	114	50 (56 %)	75 (34 %)	126	55 (56 %)	83 (34 %)	139	61 (56 %)	92 (34 %)
(3)	0/150/0	284	58 (80 %)	93 (67 %)	288	58 (80 %)	94 (67 %)	290	54 (81 %)	95 (67 %)
(4)	0/0/200	247	56 (77 %)	87 (65 %)	296	55 (82 %)	90 (70 %)	343	56 (84 %)	89 (74 %)
(5)	600/ 150/0	153	52 (66 %)	85 (45 %)	164	56 (66 %)	90 (45 %)	174	57 (67 %)	94 (46 %)
(6)	600/0/ 200	153	52 (66 %)	83 (46 %)	168	55 (67 %)	91 (46 %)	180	57 (68 %)	93 (48 %)
(7)	300/ 150/0	178	54 (70 %)	90 (50 %)	195	59 (70 %)	99 (49 %)	214	60 (72 %)	101(53 %)
(8)	300/0/ 200	174	53 (70 %)	88 (50 %)	198	56 (72 %)	93 (53 %)	224	60 (73 %)	100(55 %)
(9)	0/150/ 200	291	55 (81 %)	92 (68 %)	315	55 (83 %)	92 (71 %)	319	56 (82 %)	90 (72 %)
(10)	300/ 150/200	202	54 (73 %)	90 (55 %)	227	59 (74 %)	85 (63 %)	254	59 (77 %)	94 (63 %)
(11)	600/ 150/200	176	54 (70 %)	89 (50 %)	192	58 (70 %)	90 (53 %)	206	57 (72 %)	96 (54 %)

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2022.120012.

References

[1] IRENA, "RENEWABLE CAPACITY STATISTICS 2021," International Renewable Energy Agency (IRENA), 2021.
[2] IEA, "Offshore Wind Outlook 2019," International Energy Agency (IEA), 2019.
[3] European Ocean Energy Association, "Oceans of energy - European ocean energy roadmap 2010–2050," Imprimerie Bietlot, Belgium, 2010.
[4] Sunak Y, Madlener R. The impact of wind farm visibility on property values: A spatial difference-in-differences analysis. Energy Econ 2016;55:79–91.
[5] IRENA, "Wave Energy Technology Brief," International Renewable Energy Agency (IRENA), 2014.
[6] Czech B, Bauer P. "Wave Energy Converter Concepts," *IEEE INDUSTRIAL ELECTRONICS MAGAZINE,* 2012.
[7] Duerr AES, Dhanak MR. An Assessment of the Hydrokinetic Energy Resource of the Florida Current. IEEE J Oceanic Eng 2012;37(2):281–93.
[8] McArthur S, Brekken TKA. Ocean wave power data generation for grid integration studies. In: IEEE PES General Meeting, Providence, 2010.
[9] Mérigaud A, Ramos V, Paparella F, Ringwood JV. Ocean forecasting for wave energy production. J Mar Res 2017;75(3):459–505.
[10] U.S. Department of Commerce, Environmental Science, Atlantic Oceanographic and Meteorological Laboratories Miami, Florida, Boulder, 1978.
[11] Hanson HP, Skemp SH, Alsenas GM, Coley CE. Power from the Florida Current A New Perspective on an Old Vision. Am Meteorol Soc 2010;91(7):861–6.
[12] VanZwieten J, Driscoll FR, Leonessa A, Deane G. Design of a prototype ocean current turbine—Part I: mathematical modeling and dynamics simulation. Ocean Eng 2006;33:1485–521.
[13] Haas K, Yang X, Neary V, Gunawan B. Ocean Current Energy Resource Assessment for the Gulf Stream System: The Florida Current. Springer; 2017.
[14] Liu T, Wang B, Hirose N, Yamashiro T, Yamada H. High-resolution modeling of the Kuroshio current power south of Japan. J Ocean Eng Mar Energy 2018;4(1):37–55.
[15] Li B, Queiroz AR, DeCarolis JF, Bane J, He R, Keeler AG, et al. The economics of electricity generation from Gulf Stream currents. Energy 2017;134:649–58.
[16] Bird L, Milligan M, Lew D. Integrating Variable Renewable Energy: Challenges and Solutions,“ NREL, 2013.
[17] Lund PD, Lindgren J, Mikkola J, Salpakari J. Review of energy system flexibility measures to enable high levels of variable renewable electricity. Renew Sustain Energy Rev 2015;45:785–807.
[18] Solomon A, Kammen DM, Callaway D. Investigating the impact of wind–solar complementarities on energy storage requirement and the corresponding supply reliability criteria. Appl Energy 2016;168:130–45.
[19] Kalogeri C, Galanis G, Spyrou C, Diamantis D, Baladima F, Koukoula M, et al. Assessing the European offshore wind and wave energy resource for combined exploitation. Renewable Energy 2017;101:244–64.
[20] Halamay DA, Brekken TKA, Simmons A, McArthur S. Reserve Requirement Impacts of Large-Scale Integration of Wind, Solar, and Ocean Wave Power Generation. IEEE Trans Sustain Energy 2011;2(3):321–8.
[21] Bhattacharya S, Pennock S, Robertson B, Hanif S, Alam MJE, Bhatnagar D, et al. Timing value of marine renewable energy resources for potential. Appl Energy 2021;299.
[22] Zhang C, Lu Xi, Ren G, Chen S, Hu C, Kong Z, et al. Optimal allocation of onshore wind power in China based on cluster analysis. Appl Energy 2021;285:116482.
[23] Hu J, Harmsen R, Crijns-Graus W, Worrell E. Geographical optimization of variable renewable energy capacity in China using modern portfolio theory. Appl Energy 2019;253:113614.
[24] Pérez-Rúa J-A, Stolpe M, Das K, Cutululis NA. Global Optimization of Offshore Wind Farm Collection Systems. IEEE Trans Power Syst 2020;35(3):2256–67.
[25] Markowitz H. Portfolio Selection. J Finan 1952;7(1):77–91.
[26] Roques FA, Newbery DM, Nuttall WJ. Fuel mix diversification incentives in liberalized electricity markets: A Mean–VariancePortfolio theory approach. Energy Econ 2008;30:1831–49.
[27] Kitzing L. Risk implications of renewable support instruments: Comparative analysis of feed-in tariffs and premiums using a mean-variance approach. Energy 2014;64:495–505.
[28] DeCarolis J, Hunter K, Sreepathi S. The TEMOA Project: Tools for Energy Model Optimization and Analysis. In: International Energy Workshop 2010, 2010.

[29] de Queiroz AR, Mulcahy D, Sankarasubramanian A, Deane JP, Mahinthakumar G, Lu N, et al. Repurposing an energy system optimization model for seasonal power generation planning. Energy 2019;181:1321–30.
[30] Li B, Thomas J, de Queiroz AR, DeCarolis JF. Open Source Energy System Modeling Using Break-Even Costs to Inform State-Level Policy: A North Carolina Case Study. Environ Sci Technol 2020;54(2):665–76.
[31] Sodano D, DeCarolis JF, Rodrigo de Queiroz A, Johnson JX. The symbiotic relationship of solar power and energy storage in providing capacity value. Renewable Energy 2021;177:823–32.
[32] Temoa Project, "Tools for Energy Model Optimization and Analysis," [Online]. Available: https://github.com/TemoaProject/temoa. [Accessed 1 July 2021].
[33] NREL, "Annual Technology Baseline: Electricity: Offshore Wind," 2019. [Online]. Available: https://atb.nrel.gov/electricity/2019/index.html?t=ow. [Accessed 22 June 2020].
[34] Costoya X, deCastro M, Carvalho D, Gómez-Gesteira M. On the suitability of offshore wind energy resource in the United States of America for the 21st century. Appl Energy 2020;262:114537.
[35] NREL, "2016 Offshore Wind Energy Resource Assessment for the United States," National Renewable Energy Laboratory (NREL), Golden, CO, 2016.
[36] EPRI, "Mapping and Assessment of the United States Ocean Wave Energy Resource," Electric Power Research Institute (EPRI), 2011.
[37] Haas KA, Fritz HM, French SP, Neary VS. Assessment of Energy Production Potential from Ocean Currents along the United States Coastline. Georgia Tech Research Corporation , 2013.
[38] NREL, "Wind Integration National Dataset Toolkit," [Online]. Available: https://www.nrel.gov/grid/wind-toolkit.html. [Accessed 22 June 2020].
[39] Beiter P, Musial W, Smith A, Kilcher L, Damiani R, Maness M, et al. A Spatial-Economic CostReduction Pathway Analysis for U.S. Offshore Wind Energy Development from 2015–2030. National Renewable Energy Laboratory (NREL), Alexandria, VA, 2016.
[40] King , Clifton A, Hodge BM. Validation of Power Output for the WIND Toolkit," National Renewable Energy Laboratory (NREL), 2014.
[41] NOAA, "NWW3 Product Viewer," [Online]. Available: https://polar.ncep.noaa.gov/waves/viewer.shtml?-(none)-. [Accessed 22 June 2020].
[42] Gonçalves M, Martinho P, Soares CG. A 33-year hindcast on wave energy assessment in the western French coast. Energy 2018;165:790–801.
[43] Haces-Fernandez F, Li H, Ramirez D. Wave energy characterization and assessment in the U.S. Gulf of Mexico, East and West Coasts with Energy Event concept. Renewable Energy 2018;123:312–22.
[44] Yemm R, Pizer D, Retzler C, Henderson R. Pelamis: experience from concept to connection. Phil Trans R Soc A 2012;370(1959):365–80.
[45] University of Edinburgh, "Matching Renewable Electricity Generation with Demand," Scottish Executive, 2006.
[46] Bosserelle C, Reddy S, Krüger J. Wave and Coasts in the Pacific: Cost analysis of wave energy in the Pacific. Pacific Community, 2015.
[47] Neary VS, Previsic M, Jepsen RA, Lawson MJ, Yu YH, Copping AE, et al. "Methodology for Design and Economic Analysis of Marine Energy Conversion (MEC) Technologies," Sandia National Laboratories, 2014.
[48] HYCOM, "GOFS 3.1: 41-layer HYCOM + NCODA Global 1/12° Reanalysis," [Online]. Available: https://www.hycom.org/dataserver/gofs-3pt1/reanalysis. [Accessed 22 June 2020].
[49] Gong Y, He R, Gawarkiewicz GG, Savidge DK. Numerical investigation of coastal circulation dynamics near Cape Hatteras, North Carolina, in January 2005. Ocean Dyn 2015;65(1):1–15.
[50] Halliwell GR. Evaluation of vertical coordinate and vertical mixing algorithms in the HYbrid-Coordinate Ocean Model (HYCOM). Ocean Model 2004;7(3-4):285–322.
[51] Kabir A, Lemongo-Tchamba I, Fernandez A. An assessment of available ocean current hydrokinetic energy near the North Carolina shore. Renew Energy 2015;80:301–7.
[52] Haas KA, Yang X, Fritz HM. Modeling impacts of energy extraction from the gulf stream system. In: Proceedings of the 2nd Marine Energy Technology Symposium, Seattle, WA, 2014.
[53] Z. Yang and A. Copping (Eds), *Marine Renewable Energy—Resource Characterization and Physical Effects,* Cham, Switzerland: Springer International Publishing, 2017.
[54] Shchepetkin AF, McWilliams JC. The regional oceanic modeling system (ROMS): a split-explicit, free-surface, topography-following-coordinate oceanic model. Ocean Model 2005;9:347–404.
[55] Madec G. "NEMO ocean engine," Nucleus for European Modelling of the Ocean (NEMO), 2016.
[56] Gula J, Molemaker MJ. Submesoscale Cold Filaments in the Gulf Stream. J Phys Oceanogr 2014;44:2617–43.
[57] Chandrasekaran S, Jain AK. Ocean Structures Construction, Materials, and Operations. CRC Press; 2016.