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Generalized portfolio optimization for efficiently coordinating offshore energy deployments

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Abstract

Offshore energy, including wave, ocean current, and offshore wind energies, is underutilized. Many devices designed to harvest these energies exist. Coordinating the use of these offshore energy-harvesting devices has the potential to increase the maximum power able to be delivered to shore for a given levelized cost of energy constraint. Efficiently coordinating the deployment of these devices necessitates the use of a previously developed portfolio optimization framework. This framework determines the optimal suite of devices, and their optimal mapping such that the chosen suite of designs maximizes power for a given LCOE constraint. This portfolio optimization requires accurate input device models which have different sets of decision variables, resource inputs, constraints, and model fidelities, and designs may be developed using different software packages and programming languages. To address these issues, a generalized portfolio optimization framework has been developed. Within this updated framework is a uniform framework for cost and performance modeling implemented at the interface between device characterization and portfolio optimization; this accounts for differences in type and number of decision variables, specialized cost models, and power characterization structures. Moreover, a user interface was designed such that portfolio optimization can be available as an open-source tool for offshore energy analysis. Using this generalized framework, a test case focused on the optimization of a portfolio of devices for a domain off the North Carolina coast was performed using a variety of offshore energy-harvesting devices. Results utilizing this generalized framework validated its functionality.

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1 Introduction

Offshore energy, including wave, ocean current, and offshore wind energies is underutilized [1]. Many methods and devices designed to harvest these energies exist, which include wave energy converters (WECs), marine hydrokinetic (MHK) kites, current-driven turbines, and wind turbines. For stakeholders to invest in offshore energy, offshore energy harvesting must cost-effective and reliable enough that it is able to displace fossil fuels and other land-based sustainable energy sources. With offshore energy being an emerging industry [2], many energy-harvesting device designs are nascent, and as such, it is difficult to analyze their grid-scale costs and energy production; this complicates measures of competitiveness as compared to more mature offshore energy-harvesting devices (such as wind turbines). Portfolio optimizations provide a method for performing energy and cost related analysis on energy-harvesting devices.

Portfolio optimizations were pioneered in [3] as a risk management through diversification strategy, and demonstrated that riskier investments may be made, provided they are balanced by investments with lower expected risk [4]. In the energy sector, portfolio optimizations have been shown to be an effective tool for coordinating deployments and analyzing their risks and rewards as in [5], [6], [7], [8], and [9]. In [5], the portfolio optimization framework determines the optimal suite of devices and their mapping such that the chosen suite of designs maximizes power for a given levelized cost of energy (LCOE) constraint. However, this framework requires accurate input device models. These models may differ in sets of decision variables, resource inputs, constraints, as well as model fidelities. Furthermore, designs may be developed using different software packages and programming languages, making the expansion of the portfolio of devices difficult. To address these issues, a generalized portfolio optimization framework has been developed. Within this updated framework is a uniform framework for cost and performance modeling that is implemented at the interface between device characterization and portfolio optimization; this accounts for differences in type and number of decision variables, and specialized cost models, and power characterization structures. Moreover, a user interface was designed such that portfolio optimization can be available as an open-source tool for offshore energy analysis. This benefits device designers analyzing their device's competitiveness as well as stakeholders looking to invest grid-scale offshore energy. Section 2 discusses the methods with which the generalized portfolio optimization was developed. Section 3 demonstrates the efficacy of the novel framework via a test case. Section 4 provides a conclusion to this work.

2 Methodology

The base for the portfolio optimization in this work is based on the work in [5] and [10]. To summarize the formulation, the portfolio optimization takes in various energy-harvesting devices, a domain of interest, and environmental data for the domain. Then, it outputs the maximum energy to shore that can be attained for a given levelized cost of energy (LCOE) constraint as well as the optimal configuration of energy-harvesting devices. Figure 1 shows the inputs and outputs of the portfolio optimization. Constraints include those on LCOE, aggregate costs, energy curtailment, types of devices, number of device designs, device packing densities, and transmission system radius. The rest of this section discusses how the device inputs to the portfolio optimization were standardized, the interfacing between devices inputs and portfolio optimizations, and the computational modeling and software used to develop the user interface (UI).

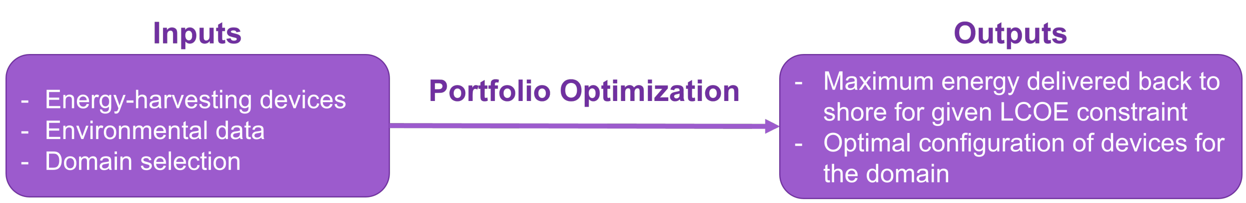

Figure 1: Inputs and outputs of the portfolio optimization model

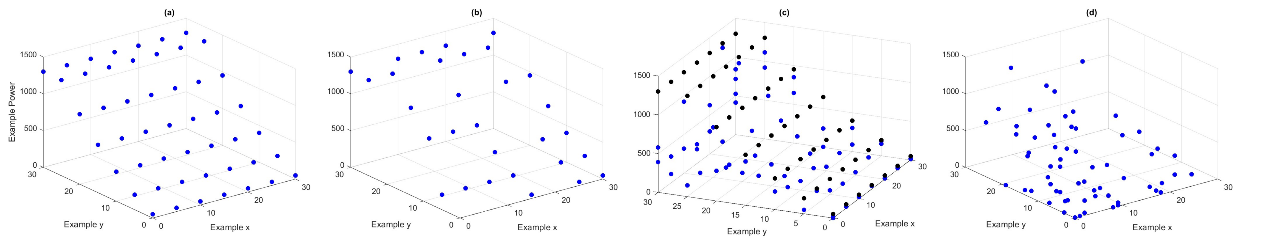

Figure 2: Summary of the options for inputting power data into the generalized portfolio optimization framework

2.1 Input standardization

To facilitate the generalization of the portfolio optimization such that it is able to support the addition of new energy-harvesting devices with ease, decisions were made regarding input standardization for devices and envrionemntal data. It was decided that four device-specific inputs are necessary:

1. A library of pre-optimized designs that span a variety of operating conditions
   (a) This may be just one device if a library of multiple devices is not available
2. Accompanying power surfaces and/or power curves for each design in the library for the best power output and/or best performance
3. Capital expenditures (CapEx) and operational expenditures (OpEx) for each device in the library
4. Technology specific constraints, limitations and other details regarding its placement as an individual energy converter or as a group

The allowable formats of this input data will now be discussed. Each power surface or curve showcases the amount of power a device will produce under a range of environmental parameters. The portfolio optimization framework developed in this work requires the creation of a gridded power surface or curve, however, data received from device designers may vary in format. Code has been created such that the generalized framework is capable of taking in four types of input data and creating a gridded power surface or curve from that input data. These four types of input data are shown in Figure 3. Clearly, option (a) is the easiest to handle as it is already in gridded format with the optimal power output available at each combination of environmental parameters. Option (b) is similar to option (a) – it is optimal power data – but this data may be scattered such that certain data points are missing for a given combination of environmental parameters. To handle this format, one can use a scattered interpolation method in Python to generate a grid like in option (a). Option (c) is not as simple, it is gridded like in (a), so there are no “missing” data points, but this grid is not indicative of the optimal power at each combination of environmental parameters. To account for this, the maximum power is found at each given combination of environmental parameters, and then use a gridded interpolation to create a surface or curve as in option (a). Option (d) is the most complex; the data is essentially a random point cloud. To get the gridded optimal power surface for option (d), one must begin with a list of the points. Then, the entire space is gridded along the non-power axes. Next, a threshold around the initial grid points is defined in which to search. For each grid point, the points located within each threshold are found, and select the maximum power value. Grid locations with no points located within their threshold are discarded. Going forward, these may be set to zero instead of being discarding. Finally, using a gridded interpolant, the scattered points are interpolated to yield a gridded surface or curve. It is important to note that all inputs will be required to be represented in .csv file type and require headers for their respective environmental parameters.
Input data for each device is used to calculate time series power, annualized costs, capacity factors (CFs) and LCOEs for each site within the domain. The portfolio optimization uses these for device comparison. To facilitate the addition of new devices in a modular manner, a new framework within the code was introduced to calculate these values. This framework is shown in Figure 3 and is implemented at the interface between device characterization and the portfolio optimization itself. Previously, there was not a uniform method for these calculations, which led to difficulties when adding new devices to the portfolio and changing the domain. The new framework takes in user-selections of devices, and uses the standardized device input data to uniformly calculate time series power generation on a site-by-site basis for each device. Using this information, the CFs, LCOEs, and annualized costs are calculated.

As a result of this input standardization, it became easier to add new devices to the portfolio. Interviews were performed with device developers to expand the portfolio of devices. The authors interviewed Vinson Williams from NCSU and Dr. Wesley Williams from UNC Charlotte. As a result of these interviews, coaxial turbines, repositionable dual-rotor turbines for harvesting ocean currents, were added to the portfolio. Furthermore, models from available data were used to add two different WECs to the portfolio: the Pelamis [11] and the RM3 [12].

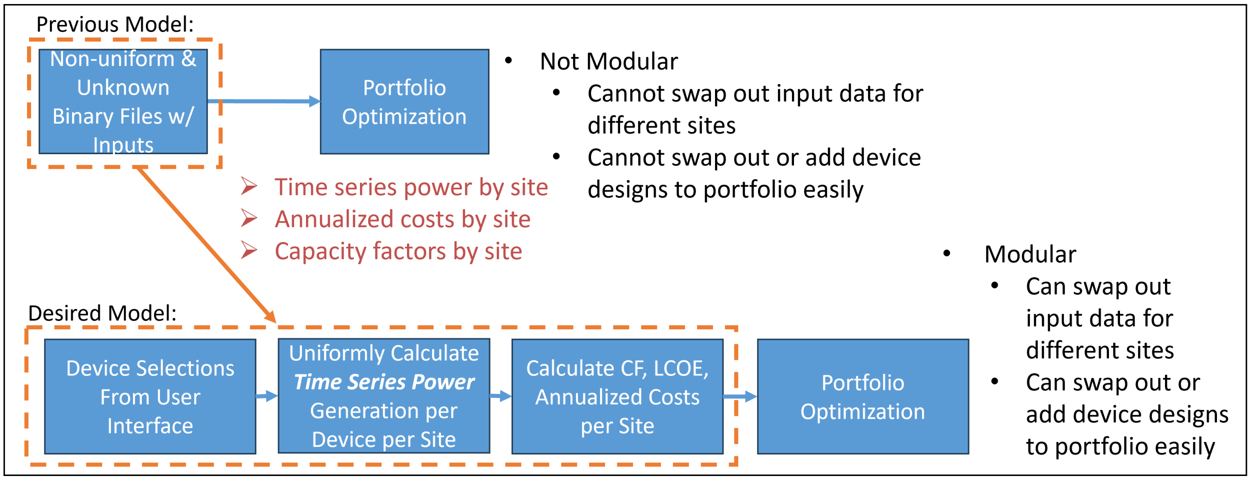

Figure 3: Generalization of input data structures from the previous model to the centralized model. The new methodology is more modular, and more intuitive. This leads to ease of inputting new devices

2.2 Computational model framework software and design

The entire system can be broken down into four primary modules: (i) Download: used to gather the energy-specific data from different sources and make it ready to be used as input for the computational framework, (ii) Preprocessing: apply certain pre-processing methods to make the data readable and remove potential inconsistencies, (iii) Scaling: used for scaling data to process data efficiently, and (iv) Analysis & Optimization: responsible for providing an optimized portfolio analysis. This also provides the output visualizations from the portfolio optimization outputs. To facilitate this computational framework, a full-stack website was developed using the model-view-controller (MVC) design pattern. This pattern separates the business logic, data, and UI while writing modular code. To set up the MVC architecture, a variety of programming tools and languages were used. Flask [13] was selected for use in the backend. Flask is a python-based web framework that is lightweight, easy to use, and extensible. For the frontend, Next.js [14] was selected. Next.js is web development framework which provides react-based web applications with server-side rendering and static website generation. Furthermore, it can generate static websites, automatically optimizes images and fonts, has dynamic HTML streaming, provides caching, and builds application programming interface (API) endpoints to securely connect with third-party services. To communicate between frontend and backend, Postman [15] was selected as an API platform. It simplifies the API lifecycle, enabling developers to design, build, test, document, and collaborate on APIs. Tailwind CSS [16] was selected for styling. It is an open-source cascading style sheet (CSS) framework which creates a list of "utility" CSS classes that can be used to style each element by mixing and matching. Additionally, Docker [17] containers were set up for the frontend and backend. A compose.yaml file was designed to manage the communication between the two containers. A shell script was used to build and run the docker containers on the local machine. The user can simply double-click to run this file or type a command (bash run.sh) in the command line interface. By leveraging a modular approach we use an ES6 component-based approach to develop the UI. Dynamic state management is handled using web hooks. APIs are seamlessly integrated using Axios [18]. TypeScript is used to program the Next.js application to provide enhanced code quality compared to JavaScript.

3 Results: User interface and test case

The user interface is shown in Figure 4a. It is a comprehensive solution that provides the user with multiple customizable inputs to fit to distinct use cases. These include controlling the domain, transmission system capacities and

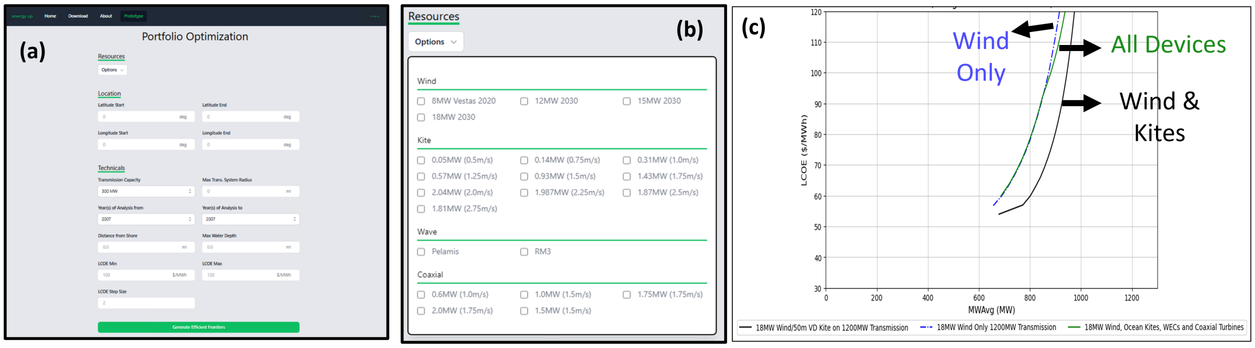

Figure 4: Left: Prototype of frontend UI, Middle: Resource options tab of the UI, Right: Efficient frontiers (LCOE vs Energy Delivered to Shore) from offshore wind portfolios along the NC coast considering distinct turbine types

LCOE minimums and maximums. Figure 4b shows the expanded resources tab. This is where the user will select which devices to include in the portfolio optimization. It should be noted that when the user selects a device, further user selections governing packing density and minimums of the specific device to be deployed become available.
Furthermore, test runs using the UI and generalized portfolio optimization were performed using available wind speed, ocean current data, ocean wave data. and models for wind turbines [19], marine hydrokinetic energy-harvesting (MHK) kites, coaxial turbines [20], [21], and the RM3 [12] and Pelamis wave energy converters [11], [22].
These test runs were performed for locations off the coast of North Carolina. The test runs validated the new structure. Figure 14 shows different efficiency frontiers from these test runs and Figure 15 shows an example deployment map from the point on the efficiency frontier corresponding to an LCOE of 112 $/MWh. Note that for this example, a constraint was set such that the portfolio optimization must elect to deploy at least one of each device. Because not all devices are competitive in terms of LCOE in this particular location, the configuration of all devices is outperformed by the configuration of only wind turbines and MHK kites.

4 Conclusion

This work focused on the generalization of a portfolio optimization model and the development of an open-source UI which allows the user to analyze their choice of devices in their selected domain. By generalizing the portfolio optimization, it became more modular, leading to ease of expansion. This expansion was shown through the test case performed for a domain off the coast of NC, which analyzed three new devices as well as two legacy devices. This test case validated the generalized structure as well as the UI. Future work should include expanding the portfolio of devices further and expanding the domain users can select from. Furthermore, it was seen in the test case that not all devices are competitive in terms of LCOE depending on the domain. Considering the nascency of many offshore energy-harvesting devices, certain cost disparities may be a result of cost-model uncertainties at grid scale. Therefore, another avenue for future work is incorporating device readiness rating and device design and cost model uncertainty into the analysis, which may lead to more informed comparisons.

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