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An Open-Source Scheduling Optimization Module for Marine Operations

Preprint

Stein Housner, Ryan Davies, Matthew Hall, Yuksel R. Alkarem, Felipe Moreno, and Elena Baca

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AN OPEN-SOURCE SCHEDULING OPTIMIZATION MODULE FOR MARINE OPERATIONS

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ABSTRACT

The design of marine energy systems often overlooks the details and requirements of the operational procedures of the project—such as installation, operations, and maintenance—which can lead to delayed deployment schedules and unexpected costs. The planning and scheduling of tasks and assets to perform these activities can be challenging but can be automated using various approaches, most notably mixed-integer linear programming, which optimizes the scheduling decisions through a combination of binary, integer, and continuous variables. However, automated scheduling is not common practice, and most existing scheduling tools rely on proprietary solvers, limiting developers and researchers from using a standard and accessible framework for planning and decision-making. This paper presents a new, open-source schedule optimization module as part of a larger modeling toolset for planning marine energy system installation, operations, and maintenance activities. The module develops informative schedules by assigning assets to perform tasks that minimize process cost for any type of individual marine energy system or array of systems. We provide an overview of the mathematical framework behind the module's methodology and then present a detailed case study to demonstrate its capabilities. The module aims to provide marine energy developers and the broader community with a fast and reliable platform to generate and analyze operation schedules, enabling better planning of tasks and asset assignments, resulting in more efficient and cost-effective deployment strategies.

Keywords: scheduling, optimization, marine energy, logistics, mixed-integer linear programming

1. INTRODUCTION

Marine renewable energy systems—such as wave energy converters (WECs) and tidal energy converters—have the potential to provide reliable and low-cost power to meet global energy demands. A wide range of technologies have been proposed and demonstrated, with goals of reducing the levelized cost of energy, demonstrating efficient power production, and strengthening the system's commercial viability. While most research and design efforts justifiably emphasize the development of the energy-harvesting technology itself, other critical aspects of project execution—such as installation, operations, and maintenance (IO&M)—are often neglected or simplified during the design and cost estimation stages of the project. These operational processes, if not planned appropriately, can lead to significant schedule delays and unanticipated project costs.

Schedule optimization—or the process of generating a plan for tasks to be accomplished by different resources to minimize an objective—is a well-established field of research and has been documented as far back as the 1950s [1]. The field has grown extensively and has a wide range of applications, including project management, healthcare, packaging, transportation logistics, and computer science. A variety of solution methods have been developed for determining the most efficient order of tasks [2]. Exact methods—such as branch-and-bound, dynamic programming, integer linear programming, and constraint programming—can provide optimal results but can become computationally expensive for large problems. In contrast, heuristic and metaheuristic methods—such as priority rules, greedy algorithms, simulated annealing, and ant colony optimization—can find cheaper, near-optimal solutions. We aim to leverage the topic of schedule optimization and its solution methods to create a schedule optimization module for marine energy IO&M modeling and planning.

Many aspects of marine energy project scheduling have previously been studied. Operations and maintenance (O&M) scheduling of offshore wind farms has been found to largely depend on weather windows, vessel routing, and downtime mitigation (e.g., [3,4]). Lütgen and Karimi [5] developed a scheduling approach to determine an optimized configuration for

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the inventory of offshore wind turbine components at port and on vessels. Rippel et al. [6] used a mixed-integer linear programming (MILP) formulation for offshore wind supply chain deliveries to port to optimize the port's capacity and study different resupply cycles. Irawan et al. [7] proposed a model for scheduling the decommissioning of offshore wind farms, considering factors such as vessel availability and planning delays. Many other operational processes can be modeled and optimized in similar frameworks and with similar methods.

The scheduling of installation activities for offshore wind farms has been one of the most popular research topics for schedule optimization and is how the research topic gained footing for marine energy. Rippel et al. [8] reviewed common offshore wind installation tasks and constraints, arguing for a mathematical optimization formulation and selection of an effective evaluation algorithm to help with decision-making. Schotz-Reiter et al. [9] first introduced an installation schedule model for offshore wind farms using MILP that considers different weather conditions (e.g., good, medium, and bad), highlighting that the weather contributes the most to project delays. Schotz-Reiter et al. [10] used this model and a new heuristic algorithm to analyze longer time horizons, multiple vessels, and more weather scenarios. Ait-Alla et al. [11] proposed a scheduling model to minimize the cost of installation of offshore wind farms, but it considers aggregate installation planning over longer-term schedules. Irawan et al. [12] developed one of the most comprehensive installation scheduling models using MILP with competing objectives of cost and duration, which considers vessel availability and weather conditions while comparing exact methods with metaheuristic algorithms. Ursavas [13] proposed an installation scheduling model that considers the uncertainty of weather conditions, stating that a deterministic model is not suitable to capture the required uncertainties. Barlow et al. [14] developed a mixed-method decision-support tool for developers to (1) run simulations using user-defined assets to estimate cost and duration of an installation process and (2) run schedule optimizations that include weather uncertainties, both of which were verified by external experts. More recently, Amorosi et al. [15] formulated a deterministic version of the installation scheduling problem using MILP and then derived other MILP models to consider uncertainties in cost and weather, which has been validated against existing installation projects. These models and frameworks primarily focus on scheduling and vessel assignment problems for offshore operations as opposed to other operations research problems like vessel routing or inventory optimization.

In addition to developing optimized schedules, these models and tools can also provide valuable insights into new operational strategies. Frijlink et al. [16] developed a MILP-based optimization framework incorporating weather forecasts to compare two installation strategies of shuttling (repeatedly transiting to and from port) and feedering (using smaller vessels to supply a larger on-site vessel), finding that shuttling is more efficient when manufacturing ports are far from site or if the feeder vessels are too small. Backe and Haugland [17] developed a MILP model to analyze different installation strategies, finding that focusing on smaller sections of a large project in the scheduling tool can improve logistics and installation time. Vis and Ursavas [18] recommended a pre-assembly strategy of minimizing the number of components installed on-site but maximizing the number of turbines on a vessel. The module we are developing aims to produce similar findings.

There are only a few accessible tools for general marine energy IO&M modeling. Morandeau et al. [19] discussed a software package called Mermaid for marine energy installations, which can perform holistic analyses of installation processes using weather data and vessel characteristics. Topper et al. [20] presented the DTOcean tool, which models ocean energy converter array design and deployment, including duration calculations and scheduling of installation and maintenance activities. The SELKIE Logistics and O&M tool is an open-source decision-support tool for the logistics of marine energy devices that uses hourly metocean data and Monte Carlo simulations to model the lifetime of a project [21]. A Wave Energy Scotland O&M Simulation model also uses Monte Carlo simulations and failure rates of devices in wave energy arrays over a project lifetime [21]. While these tools provide valuable capabilities for modeling of IO&M activities, they vary in the breadth of analyses they support, such as schedule optimization, and are not all free, open-source, or user-friendly.

This paper presents the foundational development of an open-source scheduling optimization module for marine energy systems as part of a larger toolset for marine IO&M modeling. The larger toolset is intended to be interoperable with other toolsets for use by both researchers and industry developers across a wide range of project types. The scheduling module is designed to generate optimized schedules for IO&M activities rapidly, regardless of project scale. A primary objective of this work is to ensure accessibility and usability by providing a free and open-source framework with an easy-to-use interface to support widespread adoption. By providing a standardized framework for operational planning, the module aims to enhance consistency across projects and offer insights to developers for various IO&M strategies. The module is also designed to be extensible and eventually incorporate additional features such as weather uncertainty and vessel routing. The remainder of the paper presents the methodology behind the scheduling framework and a case study demonstrating its capabilities.

2. METHODOLOGY

In marine operations scheduling, multiple tasks must be completed by capable assets over a discrete planning horizon, subject to weather windows and other scheduling dependencies. The proposed automated scheduling module aims to coordinate (1) the assignment of assets to required tasks and (2) the timeline organization of when each task should be performed, all while minimizing an objective. The scheduling module discussed in this paper makes these assignments and timelines through three types of scheduling decisions:

- Whether an asset group (a) is assigned to a task (t)

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- Whether a task (t) occurs in a certain period (p)
- Whether a task (t) starts in period (s)

A **task** is defined as a logical group of actions to be performed in one consecutive time frame. In marine operations, this typically means all actions performed between a starting port and an ending port. An **action** is defined as an indivisible operation to be performed within a task with a list of requirements, which are specific attributes that are needed to perform the action. In marine operations, this could mean the transport of a WEC from port to site (with a requirement of propulsion) or the loading of a power cable (with a requirement of storage space for the cable). An **asset** is defined as a resource with capabilities to perform specific requirements of different actions. In marine operations, this is typically represented as a vessel that can have varying capabilities, such as lifting or stationkeeping. Assigning an asset to perform an action results in a calculated time duration and cost based on the action's requirements and the asset's capabilities. An **asset group** is defined as a combination of one or more assets to be used in conjunction to perform a set of actions within a task. In marine operations, this could be a tugboat and a barge, for example, to perform a mooring system installation. A **period** is defined as one unit of time specified by the user. The combined durations of actions across all defined tasks must fit in the planning horizon, discretized by periods. These features have been parameterized this way to efficiently make decisions on the scheduling of marine operations.

The scheduling optimization module assumes that the number of tasks, assets and asset groups, and periods are all known. Given these inputs, the objective of the scheduler is to determine which asset groups should be assigned to each task and when each task should start and occur within the planning horizon. Any effort to optimize the definition of tasks or assets within asset groups is a topic for future work but is also significant when optimizing marine operational procedures.

To make feasible and optimal scheduling decisions, the scheduling module is built around the basis of MILP, in which binary decision variables are used to make asset group assignment and task timing decisions to minimize an objective, subject to operational constraints. The remainder of this section provides a mathematical overview of the MILP formulation.

2.1 Decision Variables

In MILP, optimization variables may be binary, integer, or continuous variables. In this marine operations scheduling formulation, all optimization variables are assumed to be binary decision variables, as shown in Equation 1. These decision variables indicate whether specific scheduling decisions are selected (i.e., turned on or off), such as asset group assignment and task occurrence. Future model development may consider integer or continuous variables for additional operational details.

$$X_i \in \{0, 1\} \tag{1}$$

The number of decision variables is set by the number of tasks (T), the number of asset groups (A), and the number of periods (P) within the problem. The number of start periods (S) is identical to the number of periods (P), where start periods are used to identify the periods when tasks start. Using these values, three types of binary decision variables (X) are generated to represent asset group assignment, task occurrence over time, and task start time, shown in the following equations:

$$X_{t,a} \in \{0, 1\} \tag{2}$$

$$X_{t,p} \in \{0, 1\} \tag{3}$$

$$X_{t,s} \in \{0, 1\} \tag{4}$$

where $X_{t,a}$ determines whether asset group a is assigned to task t, $X_{t,p}$ determines whether task t occurs in period p, and $X_{t,s}$ determines whether task t starts in period s. The total decision variable vector (x) then takes the form of:

$$\vec{x} = \left[X_{t,a}, X_{t,p}, X_{t,s}\right] \quad \forall \mathrm{t}, \mathrm{a}, \mathrm{p}, \mathrm{s} \tag{5}$$

for every ($\forall$) task in T, asset group in A, period in P, and start period in S.

2.2 Objective

The default objective of the scheduling module is to minimize total cost. Other objectives can also be considered and implemented, but cost provides a reasonable basis to make decisions. The total cost (C) can be represented as

$$C = \sum c_{t,a}\, \vec{x} \tag{6}$$

where $c_{t,a}$ represents a vector of the same dimension as the decision variable vector (x), with entries corresponding to the $X_{t,a}$ decision variables equal to the costs of assigning asset group a to task t. When $c_{t,a}$ is multiplied by x, only task-asset group assignments for which the corresponding decision variables are equal to 1 contribute to the total cost. All entries of $c_{t,a}$ associated with $X_{t,p}$ decision variables are all set to zero.

The entries of $c_{t,a}$ that correspond to the $X_{t,s}$ decision variables, however, can include nonzero values, or penalties, to penalize the decisions of starting tasks in certain time periods. Typically, tasks are scheduled as early as possible. These penalty values are arbitrary and negligible compared to actual task-asset group costs but need to have higher values for start periods that are to be penalized more.

There is also a duration vector ($d_{t,a}$) of the same length as $c_{t,a}$ that defines the time durations necessary for each asset group to perform each task in units of periods. All other entries in $d_{t,a}$ not corresponding to the $X_{t,a}$ variables are set to zero.

2.3 Constraints

Many constraints are necessary to formulate the MILP optimization problem, both fundamental constraints in how the decision variables need to be logically organized, and practical

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constraints specific to the scheduling problem. In linear programming, all constraints can be categorized into three types of linear constraints: upper bound, lower bound, and equality constraints:

$$A_{ub}x \leq b_{ub} \tag{7}$$

$$A_{ub}x \geq b_{ub} \tag{8}$$

$$A_{ub}x = b_{ub} \tag{9}$$

Each of the following constraint descriptions formulate multiple sets of these equations to fully represent each constraint. All constraint equations are then combined in the setup of the optimization problem.

The first constraint (Equation 10) ensures **task-asset validity**. This fundamental constraint ensures an asset group can only be assigned to a task if that asset group can perform the task. Mathematically, this constraint says:

$$X_{t,a} = 0 \quad \forall t, a, c_{t,a} < 0 \tag{10}$$

which prevents $X_{t,a}$ variables that correspond to invalid asset group assignments from being set to 1. For example, a barge assigned to a propulsion task would be invalid. We know before the optimization the cost and duration of assigning each asset group to each task and if the assignment is not feasible, then the cost is represented as an arbitrary negative value, and the corresponding $X_{t,a}$ variable cannot be turned on.

The second constraint (Equation 11) ensures only **one asset group per task**. This fundamental constraint ensures that each task can only be performed by one asset group. Parameterizing into asset groups inherently allows multiple assets to perform a task but only those that are defined in the group. Allowing other assets to be assigned to tasks defeats the purpose of predefining asset groups, which groups the collective asset capabilities to perform the cumulative task requirements. This constraint ensures only one asset group is assigned to one task. Mathematically, this constraint is represented as:

$$\sum_{a=0}^{A-1} X_{t,a} = 1 \quad \forall t \tag{11}$$

where the sum of all $X_{t,a}$ decision variables for each task (t) need to sum to exactly 1, meaning only one $X_{t,a}$ decision variable for a given task can be set to 1.

The third constraint (Equation 12) ensures **each task has one start time**. This fundamental constraint prevents a task from starting in multiple periods. Mathematically, this constraint is represented as:

$$\sum_{s=0}^{S-1} X_{t,s} = 1 \quad \forall t \tag{12}$$

where the sum of all $X_{t,s}$ decision variables over one task—similar to the second constraint—need to sum to exactly 1. Tasks starting in multiple periods do not make logical sense.

The fourth constraint (Equation 13) ensures a **task duration does not exceed the planning horizon**. This fundamental constraint ensures a task cannot start in a period where the duration of that task would extend beyond the available periods defined. Mathematically, this constraint is represented as:

$$\begin{gathered} X_{t,a}[t,a] + X_{t,s}[t,s] \leq 1 \quad \forall t, a, s \\ \text{where } d_{t,a} > 0 \text{ and } s + d_{t,a} < \max(P) \end{gathered} \tag{13}$$

where if a task-asset group assignment is made and the given start time plus that task-asset group's duration (discretized in units of periods) is greater than the total number of periods available, then that $X_{t,s}$ variable cannot be set to 1. This constraint creates multiple upper-bound constraints as a function of the duration of each task-asset group assignment for every task-asset group assignment and start time.

The fifth constraint (Equation 14) and sixth constraint (Equation 15) together ensure a **task is active for its start time and duration**. The fifth constraint itself simply ensures a task must occur in the time period that it starts in. Mathematically, it is represented as:

$$\begin{gathered} X_{t,s}[t,s] \leq X_{t,p}[t,p] \quad \forall t, s \\ \text{where } s = p \text{ and } s < \max(P) \end{gathered} \tag{14}$$

which ensures that if an $X_{t,s}$ decision variable is set to 1, then at least the $X_{t,p}$ decision variable corresponding to the same period is also set to 1. The sixth constraint ensures that the task is active in periods of the start period plus the task's duration. Mathematically, the sixth constraint is represented as:

$$\begin{gathered} X_{t,a}[t,a] + X_{t,s}[t,s] - X_{t,p}[t,p] \\ \leq 1 \quad \forall t, a, s, p \\ \text{where } d_{t,a} > 0 \text{ and } s \leq p < s + d_{t,a} \end{gathered} \tag{15}$$

which ensures that when an asset group is assigned to a task and starts in a certain period, then all $X_{t,p}$ decision variables that are between the current start time s and the task-asset group's duration $d_{t,a}$ are set to 1. For example, if a certain task-asset group assignment required a duration of two periods and started in period 3, then $X_{t,p=3}$ and $X_{t,p=4}$ must both equal 1. Additionally, whenever an $X_{t,s}$ decision variable is set to 1, the sixth constraint inherently sets the corresponding $X_{t,p}$ decision variable to 1, rendering the fifth constraint redundant. However, the fifth constraint is still included since it can easily and quickly discard schedules with improper $X_{t,s}$ and $X_{t,p}$ assignments without having to use the sixth constraint.

The seventh constraint (Equation 16) ensures **each task is active for exactly its duration**. This constraint works in conjunction with the fifth and sixth constraints to help ensure the

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necessary $X_{t,p}$ variables are set to 1 for a given start time and task duration. The fifth and sixth constraints ensure that tasks are active in the periods that they are assigned to based on start time and duration, but it does not necessarily prevent periods from being active outside of the ones assigned. The seventh constraint implements an equality constraint on the sum of the $X_{t,p}$ decision variables and the duration of the given task. Mathematically, it can be represented as:

$$\sum_{p=0}^{P-1} X_{t,p} = \sum_{a=0}^{A-1} X_{t,a}\, d_{t,a} \quad \forall t \tag{16}$$

which uses the duration of the task that has been assigned to set the total number of $X_{t,p}$ decision variables to 1. Using constraints 5, 6, and 7, the total number and order of active periods for a task can be correctly set.

The eighth constraint (Equation 17) is one of the most crucial constraints in that it ensures **asset conflict prevention**. This fundamental constraint prevents the same asset defined in different asset groups from being used simultaneously by multiple tasks. Mathematically, the constraint is represented as:

$$X_{t,a}[t_1, a_1] + X_{t,a}[t_2, a_2] + X_{t,p}[t_1, p] + X_{t,p}[t_2, p] \leq 3 \quad \forall t_1, t_2, a_1, a_2, p \quad \text{where assets overlap in asset groups} \tag{17}$$

The constraint requires looping through each asset, finding the asset groups that contain each asset, and then looping over pairs of possible tasks and determining whether the same asset could be used in each task. If so, then the constraint prevents the tasks from occurring in the same period. For a simple scheduling problem, this can create on the order of 30 individual constraint equations to constrain each possible pair of task-asset group assignments that share the same asset from being active in the same period.

The ninth constraint (Equation 18) considers **weather**. Weather windows are an important factor for a schedule optimization, as it determines which assets can be used in which time periods. In the definition of the assets, each asset is assigned a maximum weather threshold to define the most extreme metocean conditions it can operate in, such as a maximum wind speed or significant wave height. If the weather in a period exceeds that threshold, then that asset cannot operate in that period. Mathematically, this is represented as:

$$X_{t,a}[t, a] + X_{t,p}[t, p] \leq 1 \quad \forall t, a, p \quad \text{where} \quad w_p > W_a \tag{18}$$

where w_p is the weather severity in period p and W_a is the maximum weather threshold of any asset in asset group a. This means that even if there are assets in an asset group that are able to operate in a given weather period but one of the assets in the asset group cannot, then the entire asset group cannot be scheduled for that period. This constraint is also dependent on the input external weather forecast, which can include uncertainty based on the tools used to generate it.

The tenth constraint (Equation 19) involves the implementation of **task dependencies**. Tasks are likely to depend on each other. For example, one task involving the installation of mooring lines will typically start depending on the progress of another task involving the installation of anchors, since the mooring lines require hookup to the anchor. Mathematically, the general constraint for start times of dependent tasks is represented as:

$$X_{t,s}[t, s] \leq \sum_{s_d=0}^{s-d_d} X_{t,s}[d, s_d] \quad \forall t, s \quad \text{where task } t \text{ depends on task } d \tag{19}$$

The constraint compares two tasks, t and d, where task t depends on task d. For each start period s, the start period of task t is set based on whether the start period of task d (s_d) has been set in a period between s_d and $s - d_d$, where d_d is the duration of task d. To use the same mooring and anchor installation example (where the anchor installation task requires 1 period [d_d]), for the mooring installation task t to start in period $s = 2$, the sum of $X_{t,s}$ decision variables for the anchor installation task d between start periods 0 and $s - d_d$ (where $s - d_d = 2 - 1 = 1$) must be 1. Meaning, the anchor installation task must start in either periods 0 or 1 to allow the mooring installation task to start in period 2. The constraint can be expanded to consider "dependency offsets," which are specific time period offsets between the start and finish times of tasks, as well as changes in task durations due to different asset group assignments. These extensions introduce additional terms into the constraint equation but still preserve the fundamental constraint logic provided in Equation 19.

2.4 MILP Setup

Based on the number of tasks to be evaluated (T), the number of asset groups (A), and the number of period intervals (P), a large list of constraints in the form of Equations 7, 8, or 9 are compiled and used as input to a MILP solver. The total cost of task assignment is set as the objective of the solver, which attempts to find the series of 1s and 0s to assign to the decision variables in x that, when multiplied by $c_{t,a}$, minimizes the resultant without violating the constraints.

Many commercial and noncommercial solvers exist to solve MILP problems [22], which use variations of branch-and-bound, branch-and-cut, or heuristics to iterate between different sets of binary decision variables. The scheduling module presented here employs the MILP solver as part of the open-source SciPy Python package, which wraps the HiGHS linear optimization software [23]. This software package efficiently sets the decision variables to find the lowest-cost solution of asset group assignments to tasks in a given timeframe.

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3. CASE STUDY

To demonstrate the capabilities of the scheduling optimization module, we present a case study for the installation of the RM3 wave energy point absorber [24]. While the RM3 already has a high-level deployment strategy [24], this case study is intended only to illustrate the functionality of the scheduling module using many simplifications and assumptions.

3.1 Problem Setup

The RM3 wave energy point absorber is a two-body floating system where a surface float oscillates up and down with wave motion relative to a vertical column and bottom reaction plate, which is designed to be submerged 35 m below the waterline. Its mooring system consists of three mooring lines spread at 120° angles around the WEC and three anchors. Each mooring line consists of a 146 mm nominal diameter nylon rope of 267 m length, a small section of 89 mm chain attached to the anchor with a 10 t clump weight, subsea buoys with a net buoyancy of 55 kN, and short sections of wire rope attached to the device. The anchors are 9 t drag-embedment Bruce anchors [24] (Figure 1).

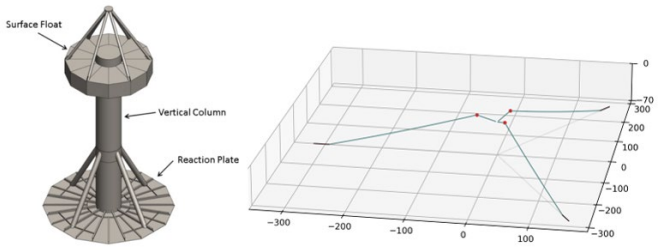

FIGURE 1: RM3 WEC AND MOORING SYSTEM [24,25]

Based on the system description, we can list the discrete actions that need to be performed to install each component:

- Load Anchor (3x)
- Install Anchor (3x)
- Load Mooring (3x)
- Install Mooring (3x)
- Tow WEC
- Hookup WEC to Mooring (3x)

We can then combine these actions into discrete tasks (explained in the next section) where each action needs to be performed within a task. The dynamic power cable and other, non-component-related activities—like vessel mobilization or transits to and from port—are excluded in this initial case study for simplicity but can contribute to a large portion of the total operational costs [24]. The anchor and mooring line actions are differentiated because they have the option to be performed separately or simultaneously within a task. The process of defining actions within tasks is assumed to be a manual, user-defined process for the purposes of this paper but could be automated to search through different strategies of organizing different actions in different tasks.

Each action is further defined by its requirements. Requirements are built into the tool for each action but can also be customized by the user. They are listed in Table 1.

TABLE 1: LIST OF REQUIREMENTS FOR EACH ACTION IN THE CASE STUDY

Action	Requirements
Load Anchor	Anchor Storage, Anchor Onboarding
Install Anchor	Anchor Overboarding, Anchor Lowering, Anchor Orienting, Anchor Embedding
Load Mooring Line	Line Storage, Line Handling
Install Mooring Line	Line Handling, Subsea Connection
Tow WEC	Towing
Hookup Mooring Line	Line Handling

Each requirement can be met by various asset capabilities. Capabilities are certain features or equipment of assets that can perform a requirement of an action. For example, the anchor overboarding requirement can be met by one of two capabilities: a crane or a stern roller. The scheduling module will search the list of assets within asset groups and find vessels that have a crane or a stern roller to perform the anchor overboarding requirement within the install anchor action.

Additionally, the module will ensure the limits of assets' capabilities are included when matching capabilities to requirements. For example, the maximum weight limit of a vessel's crane is compared to the weight of an anchor. So, even though a vessel may have a crane, the crane may not be large enough to support the size of anchors to be installed. Also, the anchor type is included in the matching process between requirements and capabilities, as drag-embedment anchors will have different specifications for anchor overboarding than suction piles. This feature is especially beneficial in early stages of design if vessel availability is known, which can influence technical design decisions like anchor type selection.

Like actions, the scheduling module uses a predetermined list of assets to possibly perform each action. In this case study, we assume two different vessel types are available to perform each of the actions:

1. Anchor handling tug supply vessel (AHTS)
2. Multipurpose support vessel (MPSV).

Public vessel data, in general, are typically difficult to access. These vessels are likely too large for the action requirements of small WEC deployments but can provide examples of the large breadth of capabilities supported in the tool. Additional details in vessel parameterizations are also easily supported.

In their parameterizations, each vessel has a list of capabilities and capability specifications. Specifications are defined as the metrics to quantify each capability, like maximum crane load or hook height. Table 2 lists capabilities for each vessel but excludes the exact numerical specifications of each for brevity. Capabilities like stationkeeping or monitoring are also not shown for brevity.

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TABLE 2: VESSEL CAPABILITIES

Capability	AHTS	MPSV
Deck Space	X	X
Bollard Pull	X	
Winch	X	X
Crane	X	X
Chain Locker	X	
Line Reel	X	
Stern Roller		X
Shark Jaws		X
Remotely Operated Vehicle		X

Each of these vessels is assumed to have some deck space to transport components, and a crane and winch to lift and handle components. The AHTS has the capability for bollard pull (to perform requirements such as towing or embedding a drag-embedment anchor) and storage for mooring lines. The MPSV has a stern roller and shark jaws, which can be used to hook up mooring lines to a floating system, and a remotely operated vehicle (ROV) to assist in anchor orienting.

Combining Table 1 and Table 2, we can show which vessels can perform each requirement of each action based on vessel capabilities, shown in Table 3. Additional details on weather thresholds and vessel costs are also listed.

TABLE 3: SUPPORT FOR EACH REQUIREMENT AND OTHER INPUTS FOR EACH VESSEL

Requirement	AHTS	MPSV
Anchor Storage	X	X
Anchor Onboarding	X	X
Anchor Overboarding	X	X
Anchor Lowering	X	X
Anchor Orienting		X
Anchor Embedding	X	
Line Storage	X	X
Line Handling	X	X
Subsea Connection		X
Towing	X	
Maximum Weather Threshold	2	1
Vessel Cost ($k)	107	122

From Table 3, we can determine that the tow WEC and install anchor actions must be done by an asset group that contains the AHTS since the towing and anchor embedding requirements need bollard pull. Similarly, the anchor orienting and subsea connection requirements need to be done by the MPSV since the MPSV is the only vessel with a ROV. The remaining requirements can be accomplished by either of the vessels using various vessel capabilities.

The maximum weather threshold is a basic integer value used to represent the maximum environmental severity that a vessel can operate in based on the vessel's operational limits. This case study suggests that the AHTS is a larger vessel than the MPSV and can operate in more severe conditions, such as higher wind speeds, wave heights, or tidal ranges.

The vessel cost values provide a simplified representation of all associated vessel expenses, such as vessel day rates, personnel costs, and fuel costs. The values are roughly based on existing estimations from an internal vessel dataset.

3.2 Schedule Results

Using the list of actions and assets from the problem setup, we can define a list of tasks and asset groups we want to schedule. The actions are organized into the following tasks:

1. Install All Anchors (T_1)
2. Install All Mooring Lines (T_2)
3. Tow and Hookup WEC (T_3)

The anchor installation task involves the loading and installing of all three anchors in one trip. The mooring line installation task involves the loading and installing of all three mooring lines in one trip. We assume that the anchors are installed by themselves, with only the small mooring chain and clump weight components attached. Then, the nylon ropes (and wire ropes and buoys) are connected as part of the mooring installation task. The tow and hookup task involves the towing of the WEC to site and the hookup of the mooring lines to the WEC. Each action is assumed to be performed sequentially in each task.

We also define three asset groups to accomplish the three tasks using the two individual assets:

1. AHTS (A_1)
2. MPSV (A_2)
3. The AHTS and the MPSV (A_3)

The scheduling module checks whether the cumulative capabilities of asset groups can perform the cumulative requirements of actions within tasks. Additional supporting vessels like barges or feeder vessels can be included in asset groups but are excluded here for simplicity.

With the tasks and asset groups defined, and matching action requirements to asset capabilities, we can calculate the costs and durations to perform each task by each asset group and store the information in "task-asset group matrices." Not all asset groups will be able to perform each task, but some could perform multiple tasks. The task-asset group matrices are as follows:

Cost ($k)

	A_1	A_2	A_3
T_1	[−	−	61]
T_2	[−	42	79]
T_3	[56	−	120]

Duration (hours)

	A_1	A_2	A_3
T_1	[−	−	6.25]
T_2	[−	8.25	8.25]
T_3	[12.5	−	12.5]

These matrices tell us that the third asset group A_3 is the only asset group capable of performing the first task, which installs all anchors in the same trip. This is because the AHTS is the only vessel that can embed the anchors, but the MPSV is the only vessel that can orient the anchors. For the second and third tasks, the time durations are the same across asset groups since the involvement of an additional vessel does not reduce operation time. For example, mooring line installation time does not reduce when using a second winch from another vessel; the install time is calculated as the highest winch speed between the two vessels.

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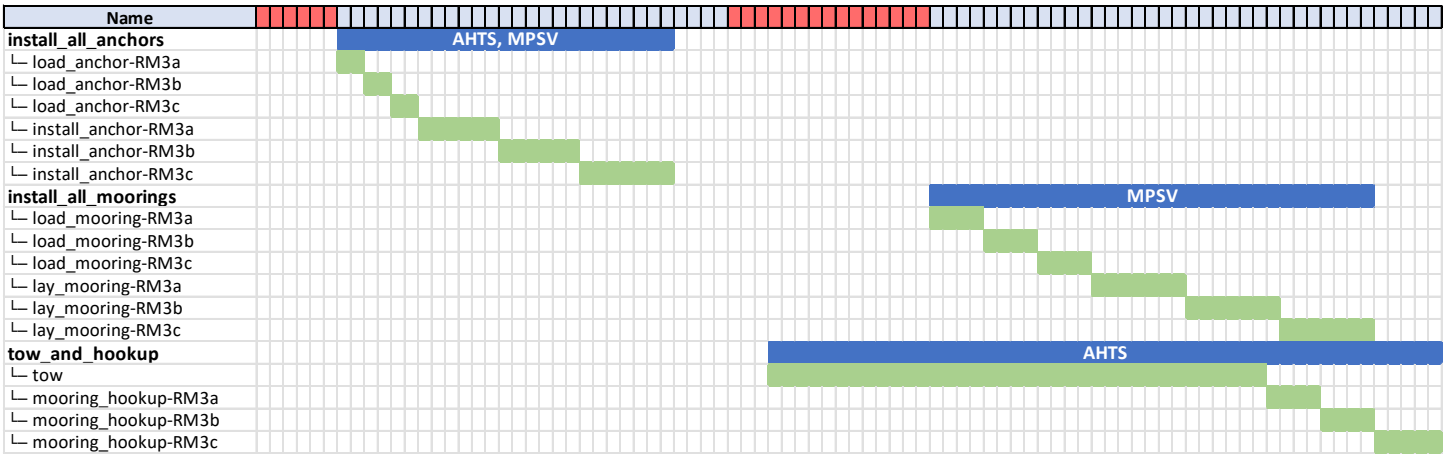

FIGURE 2: OPTIMIZED SCHEDULE FOR THE RM3 INSTALLATION WITH WEATHER (ROUGH WEATHER SHOWN IN RED) AND 15-MINUTE PERIODS (EACH COLUMN IS ONE PERIOD)

Different action types not included in this case study, however, may benefit from cooperative vessel operations. The total costs for the assets in each asset group to perform the tasks are then shown in the task-asset group cost matrix. All task durations assume actions are completed sequentially without interruptions and neglect vessel transit between actions.

We can then define the dependencies that tasks have between each other. The start of the mooring line installation task (T_2) depends on the start of the anchor installation task (T_1) and the start of the tow and hookup task (T_3) depends on the start of the mooring line installation task (T_2). Tasks can occur at the same time (using different asset groups), but the dependencies between actions of different tasks and the durations of those actions determine when dependent tasks have to start after prerequisite tasks. For instance, the mooring line installation task has to start in a period so that the start of the first mooring line installation action occurs after the end of the first anchor installation within the anchor installation task.

For each possible asset group assignment to each task, we can calculate the time durations to perform each action within each task and based on the dependencies between the actions of different tasks, we can determine the minimum time necessary for each task to start after another task starts. These times are stored as "offsets" within a set of dependency-offset matrices, where the rows of each matrix represent the dependent task, the columns represent the prerequisite task, and each row and column represent an asset group assignment to its corresponding task. The matrix for the dependency offsets between the tow and hookup task and the mooring installation task is shown below.

$$\begin{array}{c} \\ T_3A_1 \\ T_3A_2 \\ T_3A_3 \end{array} \begin{array}{c} \begin{array}{ccc} T_2A_1 & T_2A_2 & T_2A_3 \end{array} \\ \begin{bmatrix} - & -3 & -3 \\ - & - & - \\ - & -3 & -3 \end{bmatrix} \end{array} \text{(hours)}$$

This matrix was intentionally presented to highlight a unique aspect of the dependency offsets. The offsets in the matrices are the times necessary for the dependent task to start after the prerequisite task. Given that the tow action will require a long duration to complete regardless of asset assignment and that the mooring hookup actions depend only on the mooring line installation actions, the total tow and hookup task (T_3) can start at a minimum of three hours before the mooring installation action (T_2). The other entries of the matrix are null because A_2 is incapable of performing T_3 and A_1 is incapable of performing T_2. These dependency-offset matrices are created for every pair of tasks using action dependencies.

The remaining scheduling inputs are the number of periods defining the time horizon and the weather severity. Using period intervals of 0.25 h (15 min) and the sum of the maximum task durations and dependency offsets, we define a time horizon of 108 periods. In addition, we include a time-varying weather profile to classify periods of calm and rough weather, with rough weather periods shown in red in Figure 2. Rough weather could represent wave heights over a certain threshold, for example, but the exact definition is arbitrary for this simplified case study.

After all these inputs are set up and all the linear constraints are created, the MILP solver is run to decide which decision variables to set to 1 and which to set to 0 to minimize the objective. The resulting schedule, including task and action progression and asset group assignment, is shown in Figure 2.

The schedule agreed with the task-asset group matrix that the anchor installation task could only be done by the combination of the AHTS and MPSV (A_3). Because the only two vessels available are used for this task, no other tasks could occur at the same time. Also, this task could only start once a calm weather window occurred, since the MPSV can only operate in calm weather conditions. After the anchor installation task, the scheduler then decided that the mooring installation and the tow and hookup tasks would be done by separate vessels (using the MPSV and the AHTS, respectively) and occur during overlapping periods. This decision makes sense as their time durations are the same between different asset groups but their costs are much greater in asset groups with multiple assets. The mooring installation task occurs during calm weather since it

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uses the MPSV, and the tow and hookup task occurs in both weather conditions since it uses the AHTS. The scheduler also decided to start the tow and hookup task before the start of the mooring installation task to prioritize earlier start times while still satisfying the dependency offsets. These offsets ensured that each mooring line hookup action would start after each mooring line installation action was completed. The total minimized cost of performing this simplified schedule resulted in $159,000, which excludes many other realistic actions, but otherwise satisfies all constraints.

4. CONCLUSIONS

This paper presents the foundation of a scheduling optimization module as part of a larger toolset to better support the modeling and decision-making of marine IO&M planning. We present the mathematical framework behind the constraints and objective of the schedule optimization solver using MILP. We also present a simple case study of the installation of the RM3 WEC considering the installation of its anchors, mooring lines, and the towing and hookup of the WEC. The MILP solver quickly and efficiently made decisions to assign proper asset groups to each task across the entire time horizon, while considering varying weather conditions and task dependencies.

The goal of the scheduling module is to provide both researchers and developers with a reliable and accessible framework to generate optimized marine operations schedules in fast computation times. The module's features include:

- An open-source framework for accessible use
- Scheduling of asset group assignment to tasks and task planning across a time horizon
- The ability to discretely iterate between different sets of tasks and asset groups to analyze different deployment strategies
- The ability to parameterize different vessel capabilities to match different task and action requirements
- Weather severity for each time period to determine the operational timeframes of different vessels
- Dependencies between different actions
- Run times on the order of seconds for a typical personal machine
- Analysis of short- or long-term schedules for individual or arrays of marine energy systems

These capabilities lay the foundation for the automated planning of marine energy IO&M activities, which can lower project costs and provide more certainty to deployment activities.

The scheduling module can benefit from further improvements. The current setup assumes that actions can only be done in series and does not consider the ability for different assets within the same asset group to perform different actions within the same task at the same time (in parallel). The parameterization of vessels can further be verified with validated vessel data, which can be used to better model the actual capacities of installation trips. The weather modeling can be improved to support additional environmental severity levels while considering more detailed vessel limits. The cost models can also be improved to consider different cost components, such as standby rates and fuel costs, and how they factor into different actions. Further automation of varying the groupings of actions within tasks or assets within asset groups can help identify new operational strategies. Additionally, the action and task lists can be extended to larger arrays of marine systems, which can allow for future routing optimization capabilities. Through these modeling improvements, the non-technological aspects of project execution can be better quantified and included in the design process to enable more cost-effective and reliable marine energy designs and IO&M strategies.

The IO&M model is planned for public release later in 2026 by the National Laboratory of the Rockies via the U.S. Department of Energy's Hydropower and Hydrokinetic Office communications.

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