Demand-Driven Supply of Offshore Wind Turbine Components by Cascading Simulation and Optimization

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Abstract. The installation of offshore wind farms constitutes a highly weather-dependent process. Despite this dynamic, practice and research generally assume fixed resupply cycles to deliver components from their production sites to the installation's base port, resulting in high storage requirements. This article proposes a cascading discrete-event simulation framework combined with offline mathematical optimizations to decide demand-driven on suitable resupply cycle from a pool of routes. This approach combines the advantages of both methods by allowing high flexibility to cope with weather dynamics while reducing the search space to a few optimal alternatives. The evaluation uses two real-world use cases. It demonstrates that selecting cycles based on estimated weather developments reduces the required base port storage capacity. Moreover, in some cases it additionally maintains lower capacity levels after an initial ramp-up phase.

Introduction

Over the last years, wind energy has developed into a primary green, sustainable energy source. Since 2010 the installed capacity of offshore wind farms has increased exponentially, from 2.9 Gigawatts to 35 Gigawatts in 2020 [14]. Moreover, over the last years, most countries increased their targeted shares of renewable energy or moved forward their targeted dates [14].

Compared to their onshore counterparts, offshore wind farms allow for higher capacities due to larger accessible areas at the open sea and higher wind speeds. Nevertheless, the same advantages result in additional challenges for installing such wind farms, e.g., due to harder to reach installation sites, stronger winds and weather dynamics, and more expensive resources [16].

High wind speed poses a challenge for installation operations at the open sea. Due to the sheer size of turbines, installations require crane operations in approximately 100 meters of height. Thereby, high waves or wind speeds result in sways of several meters, rendering installations unsafe for the crew, components, or even the vessel and crane. Consequently, installation operations have defined limits considering these parameters. Rippel et al. (2019) [16] provide an overview over such limits assumed in the literature. Generally, weather conditions at the open sea tend to change quickly due to the large open area. In contrast, planners can only rely on forecasts or historical records and their experience when planning installations, which introduces high uncertainties, especially during the installation's operative phase. Literature attributes between 15% and 30% of a wind farm's overall costs to logistics costs during the installation resulting from this uncertainty and the costly resources involved in installations (e.g., [5, 11]).

Most of the literature that considers offshore installations focuses on efficient scheduling of vessels, fleet mixes, or viable project start dates. Only a few approaches emerged over the last years that focus on the operative phase and include forecasts in their planning. Very few contributions include port-side resources, like storage areas, loading bay availability, or heavy-duty handling equipment. Nevertheless, studies show ongoing trends to increasing numbers of installation, refurbishing or decommissioning projects with higher numbers of turbines [3], paired trends to larger and heavier turbines [22], which could quickly lead to bottle necks within the base port availability [12].

This article proposes a cascading simulation framework to support operations in determining suitable resupply cycles for components to adapt these cycles to the current, predicted needs at the base port. Therefore, the framework applies an online simulation as digital twin of the installation process. At each decision point, i.e., when the transport vessel starts a new resupply cycle, the digital twin evaluates some previously optimized alternatives given the current state of the installation and current forecasts as nested simulations. As the framework allows each of these child-simulation runs to apply the same decision process, it denotes each set of alternatives as a cascade. In general, the approach aims to reduce the required base port storage capacity and initial inventory level to reduce costs and save spaces for concurrent projects.

This article is an extended version of a contribution that was presented at the 2021 ASIM conference "Simulation in Produktion und Logistik" [15]. In extension, this article provides a detailed description of the framework, proposes a different method to select viable weather data for the nested child simulations, and extends the discussion of the approach's advantages and disadvantages by adding a second real-world use case, modeling the installation of the wind farm "Hohe See".

1 Methods for Offshore Wind Farm Installations

Compared to other areas in the offshore sector, only a few articles consider installing offshore wind farms [21]. Most articles deal with optimizing or evaluating the installation process [16], e.g., focusing on ways to simulate weather conditions [11], different installation concepts [21], or fleet mixes [1]. Other authors provide models to schedule the commissioning of vessels [8] or operations in various resolutions, e.g., [7, 20].

Even fewer articles explicitly include port-side resources like storage spaces or the resupply of components. For example, Beinke et al. (2017) [2] evaluated sharing heavy-lift vessels between several installation projects to reduce downtime due to bad weather conditions. Newer works demonstrate an increasing demand for jack-up vessels and, in consequence, port-side resources, as first wind farms reach the end of their life and require refurbishing or decommissioning [3]. Oelker et al. (2020) [12] evaluate available heavy-duty storage areas at the base port in Eemshaven using a simulation study. The study shows that the port's capacity will reach its limits soon if current trends continue. Rippel et al. (2020) [18] describe a mathematical model to determine optimal resupply cycles based on their efficiency that will be introduced later in this article.

In conclusion, the current state of the art mainly focuses on the actual installation and generally assumes that the base port offers sufficient components. Only a few of the presented models consider the resupply, but all assume a fixed and reliable resupply of components in defined intervals.

2 Process Description

Different installation concepts for offshore wind farms exist in the literature and practice, ranging from the so-called conventional concept, where all assemblies take place at the installation site, over preassembly concepts to floater concepts, where all assemblies take place in the base port. Practice and research mainly apply the conventional concept, depicted in figure 1. While this section shortly summarizes this concept, a more detailed description can, e.g., be found in [13, 21].

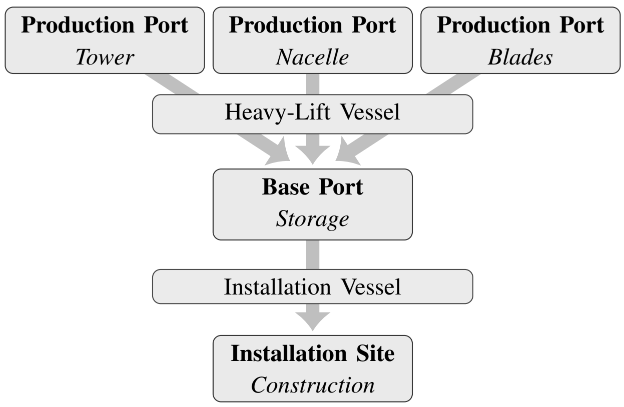

Figure 1: Conventional installation concept (c.f. [17]).

In this concept, a heavy-lift vessel travels between the components' production ports and the base port, which buffers the components for the installation. An installation / jack-up vessel loads sets of components and travels to the installation site to perform the assembly. Jack-up vessels possess retractable pillars to mount themselves at the installation site, effectively puncturing the sea bed to steady themselves against high waves. While this process allows mitigating the influence of higher waves, it results in the vessel's need to remain stationary until it finishes installing a turbine. Additional jack-up operations close to an already visited location can easily damage already installed foundations or even the vessel itself due to the already loosened sea bed. Consequently, installation vessels always need to load complete sets, i.e., all tower segments, the nacelle and hub, and all blades required for a turbine. Their capacity in terms of deck area and maximum payload restrict the number of sets. Most vessels currently available on the market can handle four sets.

Accordingly, installation operations require complete sets to be available at the base port to start, which, in turn, requires careful planning of the resupply of components. Therefore, practice and research assume that the heavy-lift vessel follows a predefined resupply cycle, visiting the production ports in a given sequence. At the end of each cycle, a defined number of complete sets become available at the base port. For example, such a cycle could consist of two trips: the first trip fetches two towers while the second trip visits the other two ports and fetches two nacelles and six blades. In this example, the first trip does not allow further installation operations as it is not possible to install only the towers. Nevertheless, after the second trip, two additional installation operations become available.

Generally, project planners decide on a single installation cycle during the planning stage of installation projects, which the heavy-lift vessel repeats until it finishes delivering all sets. On the one hand, this approach ensures the reliable delivery of components. On the other hand, this approach does not consider the current situation during the project execution. The actual demand varies depending on the current weather situation and forecasts. For example, fixed cycles can quickly deplete the storage when facing a good weather period. In contrast, bad weather periods heavily reduce the demand and can result in inventory overflows, requiring expensive additional storage areas or disrupting the supply chain. In practice, planners tend to include safety margins to the base port capacity and initial inventory levels to circumvent these problems.

Nevertheless, both examples can be faced by adjusting the resupply cycle according to the predicted demand. For example, longer cycles can bridge bad weather periods by slowing down the delivery. Accordingly, shorter cycles provide lower amounts faster to the base port to fully exploit good weather periods.

3 Demand-driven Resupply by Cascading Simulation and Optimization

This section introduces the cascading simulation framework used to select viable resupply cycles based on the current state of the installation process. The framework relies on a set of optimal resupply cycles that differ in duration and number of delivered sets but provide an optimal cycle considering the number of allowed roundtrips between one or more production ports and the base port. At each decision point, i.e., before a new cycle starts, the framework initializes several nested simulations, each evaluating the influence of an alternative cycle on the overall installation project using aggregates of historical weather records as depicted in figure 2. Please refer to, e.g., Kindler (2004) [9] for more information on nested simulation in general.

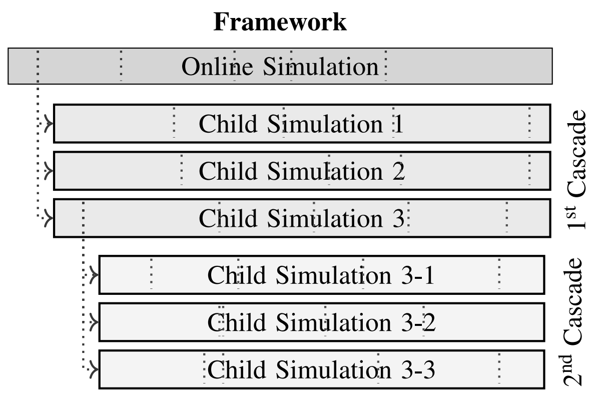

Figure 2: Schema of the cascading simulation concept using three alternatives and two cascades. Dotted lines represent decision points within each simulation.

This article uses the framework's digital twin (online simulation) to simulate installation projects using real-world scenarios and historical weather records to be as close to real-world applications as possible. Overall the framework consists of three major components: first, the optimization of resupply cycles, second the simulation model used for online and nested offline simulations; and third, a simulation manager to instantiate the nested child simulations and evaluate their results. While the optimization model supplies inputs to the framework, the later components, i.e., the simulation model(s) and the manager, interact directly during the simulation run as indicated in Figure 3.

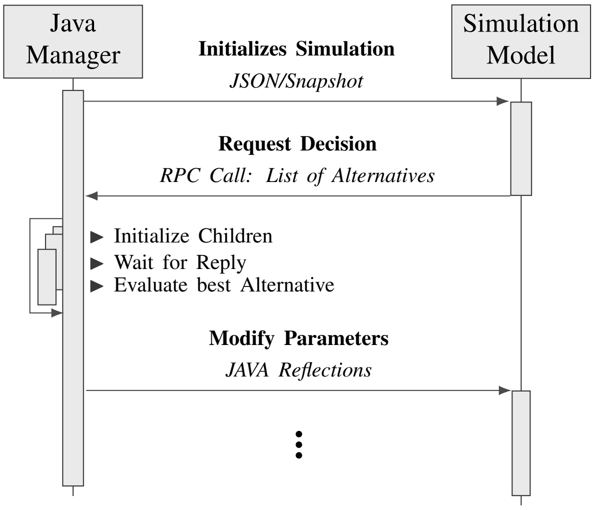

Figure 3: Interaction between the manager and the simulation components.

Once the manager starts, it initializes and runs its simulation model using a definition of the current state in a JSON file and, if it is a nested simulation, an additional copy of the parents state using AnyLogic's Snapshot feature. While both files contain partly redundant information, the JSON state contains additional information, e.g., which set of historical data a nested simulation should use or if the simulation could inquire the manager about decisions (given by the number of allowed cascades). Moreover, the manager registers itself within the simulation model as an external listener, allowing the simulation to call specified interfaces, e.g., when finishing or requesting a decision.

After initialization, the simulation model starts and proceeds until it reaches a decision point. It generates a list of alternative decisions, for example, by looking up already stored resupply cycles, pauses itself, and provides the alternatives to its manager by requesting a decision.

Upon receiving a request, the manager spawns additional instances of itself, providing one of the alternatives and a Snapshot of its simulation's state to each child manager. Each of these new managers then follows the same procedure. After concluding their simulation runs, the child managers report their results to their parent, which evaluates their results, and decides on the best alternative. Finally, it directly modifies its simulation using JAVA Reflections and instructs the model to resume simulation with the new settings. This process repeats for each decision point until the online simulation finishes.

The manager evaluates several characteristics of its child simulations' results to select the best alternative. First, it selects those alternatives that resulted in the shortest project duration as a prolonged time indicates missing inventory. Second, it selects those instances that would result in the lowest added storage capacity. If several instances remain, the manager selects the alternative cycle that delivers the most components as tie-breaker.

3.1 Optimization of Resupply Routes

The framework's primary objective in this article is selecting viable resupply cycles based on the current state of the installation process. This article defines a resupply cycle by the round-trips that the heavy-lift vessel takes, the number of delivered sets by the end of the cycle, and its duration. Thereby, the efficiency of a cycle depends on the number of allowed round-trips N, the geographical location of the ports, i.e., traveling times, and the vessel's capacity in terms of deck area and payload, i.e., the number of components that it can transport in one round-trip. Figure 4 shows the possible round-trips for the offshore domain when assuming symmetric traveling times.

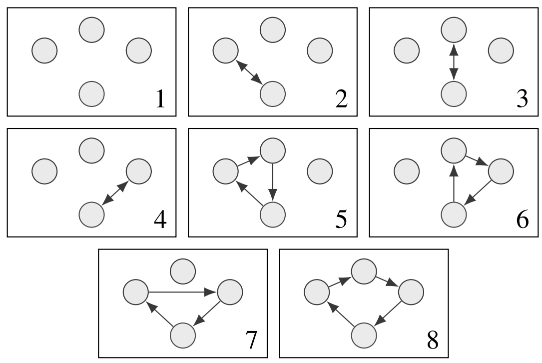

Figure 4: Possible round-trips for three production ports (top) and one base port (bottom).

It shows a total of eight possible round-trips when considering one base port and three production ports for the towers, blades, and nacelles. Consequently, the search space for creating a set of alternative resupply cycles that allow different numbers of round-trips is given as $\sum_{n=1}^{N} 8^n$. For example, assuming the framework wanted to evaluate the best alternative for allowing one to ten round-trips, the search space would already comprise 1.2 billion possible combinations. Assuming that evaluating a single alternative would take about one second, the sheer number of combinations would result in computational times of approximately 13.888 days. It has to be noted that this example only includes combinations of visited ports and completely neglects different loading scenarios at each port. In conclusion, the framework requires additional methods to reduce this search space.

Instead of applying meta-heuristics or other search-based techniques that still need to search large parts of the search space, the framework relies on mathematical optimization to generate optimal alternatives as soon as the supply network, i.e. the locations of the ports and the heavy-lift vessel are defined. The framework uses the model proposed in Rippel et al. (2020) [18] to derive a set of optimized alternatives for each allowed number of round-trips.

In general, the creation of a resupply cycle constitutes a combined routing (traveling-salesmen) and knapsack problem to determine (a) which ports to visit in each round-trip and (b) which components to load at each visited port. The problem aims to maximize the yield while minimizing the traveling-, loading-, and possibly setup times. The model exploits the small size of the transport network by enumerating possible routes for each round-trip (one to eight as shown in Figure 4)). It then calculates the traveling times for each of these routes using the well-established haversine formulae, solving a number of traveling salesman problems. The actual optimization model is then given as a customized multi-periodic knapsack formulation to maximize the number of delivered sets over N round-trips (periods). The model tracks visited ports in each round-trip as a binary vector, using a standard binary encoding to map these visits to the index of the precalculated traveling times. In addition, the model includes loading and unloading and setup times, e.g., for installing or removing transport frames on the heavy-lift vessel.

The framework applies this model to generate alternative cycles for one to N round-trips before the simulation run starts. While this offline optimization assumes that transport processes are mainly unaffected by weather conditions, planners could choose a safety margin to the expected cycle duration or even earlier, to the corresponding loading and unloading times. Nevertheless, most operations involved in the resupply show comparably high weather limits, which renders the assumption quite realistic. As a result of applying this offline optimization, the framework only evaluates N alternatives at each decision point instead of possibly millions of combinations.

3.2 Simulation Model

Both the online and nested child simulation runs use the same underlying model extended from Rippel et al. (2019) [19] but use different weather data. The online simulation uses actual, hourly weather records from the simulated period. Child simulations only have access to historical data, usually records of years prior to the simulation period.

The simulation model has been implemented in AnyLogic 8.7.9 professional. Figure 5 shows a screenshot of the simulation model. It contains agents for all vessels (installation and heavy-lift transport), the installation site, and the respective base and production ports. Therefore, ports and the installation site mainly manage their data, e.g., current storage levels or the number of installed turbines. In contrast, vessel agents can decide their following actions, e.g., creating and selecting installation cycles using weather forecasts. In the context of this article, the model has been modified for heavy-lift vessels. Heavy-lift vessels can access all predefined alternatives instead of only applying a single predefined resupply cycle. They can inquire the external framework which of these to choose for the next iteration. In general, the model contains various functions to estimate the duration of operations given a weather forecast and the operations' weather limits as proposed in the literature [17].

As noted, child simulations only access historical records as the framework cannot know how the weather will be in practical applications, even if this article only simulates historical projects. While the previous article proposed to use 20 years of historical weather data, i.e., mean values from 1979 to 1999 when simulating the year 2000 for the child simulations, this article proposes to search for similar years within the available data set to find better matches. The approach was modeled as a simplified version of known K-Nearest Neighbor Searches known in time series prediction (e.g., [10]). Therefore, the framework selects three months prior to the simulated project and calculates the duration of installation operations within this period. Afterward, it

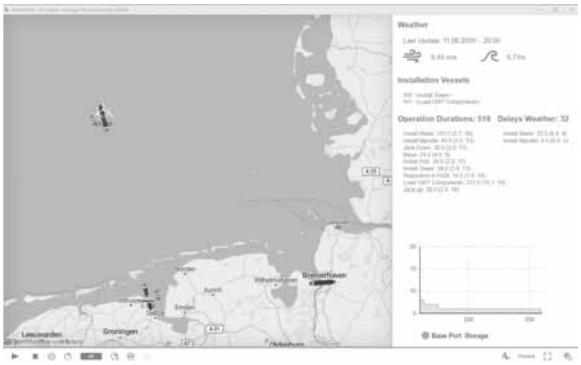

Figure 5: Simulation model implemented in AnyLogic 8.7.

iterates through the database, selecting each year Y^s in the database and a viable number of historical years $Y^N \in \{0,1,2,5,10,20\}$ and calculates the mean value and hourly standard deviation. The framework again estimates the duration of installation operations using the Markov-Chain-based approach described in [17] using these values as input. Finally, it calculates the Pearson-Correlation Coefficient between these sets and the last three months to decide for a constellation that matches the current data as good as possible. Earlier tests show that this approach represents the expected weather data better in most cases than just picking the last 20 years as originally proposed in [15]. In the following, the first use case still chooses to pick the last 20 years as these still show the highest correlation. In contrast, the second use case chooses a data set comprising five historical years from 1982 as the best match.

In addition to the aggregated historical data, parent simulations can provide actual weather forecasts to their nested child simulations, usually spanning a short period of 2-3 weeks. If provided, the simulation model interpolates between the forecast and its weather data using the expected uncertainty of the forecasts. This model uses data taken from the homepage of the German Weather Foundation [4], stating that the uncertainty of forecasts starts at 0.0 for the first hour (measurement), increases to approximately 0.25 at one week, 0.65 at two weeks, and rises to 0.95 at three weeks. Interpolating these values as $u(t)$ the model calculates the current weather conditions as function f over the time in hours t and the two vectors of weather conditions for historical data d_h and forecast data d_c: $f(t,\, d_c,\, d_h) = (1-u(t)) \cdot d_c + u(t) \cdot d_h$.

4 Experimental Setup

This article applies the cascading simulation framework to two different use cases. Both use cases model real-world installation projects in Germany's Northern Sea with different characteristics considering the projects' dimensions, supply network, and applied vessels.

Data for the first use case has been empirically collected during several research projects, resulting in in-depth knowledge, e.g., about processing times, weather restrictions, loading scenarios, resupply cycles, or installation vessels (IV). Beinke et al. (2017) [2] first published this use case. Accordingly, this experiment applies the same weather limits. Apart from these data, the use case relies on averaged characteristics for the heavy-lift transport vessels (HLV) in terms of their speed, deck area, and payload, as presented in the literature [18]. Comparing the results of the optimization model introduced earlier with the resupply cycles used in the real-world scenario shows a close to perfect match between the results. This match indicates that the vessel used had similar characteristics [18]. Table 1 summarizes the relevant parameters for this first use case.

Parameter	**Tower**	**Blade**	**Nacelle**
Project Start	April 1st 2000		
Base Port	Eemshaven		
Installation Site	Northern Sea		
Number of Turbines	50		
Number of IVs	1		
HLV: Deck Area / Payload	2646m^2 / 8900 t		
HLV: Avg. Speed	9.5 knots		
Production Port	Cuxhaven	Bremerhaven	Bremerhaven
Loading / Unloading / Setup Time	2 h / 1.2 h / 0 h	8 h /4.8 h / 0 h	10 h / 6 h / 0 h
Weight	600 t	240 t	500 t
Req. Space	650 m^2	300 m^2	263 m^2

Table 1: Parameters of the first use case.

The second use case represents the installation for the wind farm "Hohe See" in Germany's Northern Sea. The use case relies on publicly available data about used vessels, the supply network, or the wind farm location, e.g., [6]. While keeping the same weather limits, process durations, and heavy-lift vessel characteristics, this use case features a much larger supply network, more turbines to install, and a second installation vessel as shown in Table 2.

Parameter	Tower	Blade	Nacelle
Project Start	April 1st 2019		
Base Port	Esbjerg		
Installation Site	Wind Farm "Hohe See"		
Number of Turbines	71		
Number of IVs	Blue Tern, Brave Tern		
Production Port	Rotter-damm	Aalborg	Cux-haven

Table 2: Modified parameters of the second use case.

Both use cases use the same data set for weather data, containing hourly measurements from 1956 to 2019 within a few kilometers of both installation sites. As noted before, the nested child simulations use aggregated weather data for 1979-1999 (first use case) and 1977-1982 (second use case).

The simulation tracks the inventory levels of the online simulation to evaluate the efficiency of the cascading framework compared to an optimized fixed cycle. Accordingly, the first use case applies a cycle consisting of four round-trips that deliver eight sets in 312 hours. This cycle has also been applied in the real-world project and has been proven to be the most efficient cycle possible [18]. As the applied cycle is unknown for the second use case, the experiment first applied the described optimization to determine the most efficient cycle. In this use case, again, a resupply cycle using four round-trips, delivering eight sets over 408 hours, provides the lowest time per set.

The experiment assumes an infinite storage capacity but tracks how much inventory was used during the simulation to determine the required capacity. The experiment varies the initial inventory level between 0 and 20 in steps of two for the first use case and between 0 and 50 in steps of 5 for the second use case to determine the lowest possible initial inventory for the fixed cycle and cascading framework. Finally, it tracks the actual inventory levels throughout the simulation to enable comparisons in the behavior of both approaches.

5 Results and Discussion

Figure 6 shows the results for the first use case. The top graph shows the project duration for different initial inventory levels. The results show that the cascading concept achieves an uninterrupted installation process starting at an initial inventory level of ten sets. In contrast, the fixed cycle requires at least twelve sets to avoid delays due to missing inventory. The graph in the middle shows the observed maximum inventory. Both approaches require a capacity equal to this level, starting from an initial inventory of eight sets. Finally, the lowest graph shows the current inventory level over time. The graph shows no relevant differences, resulting in similar average inventory levels.

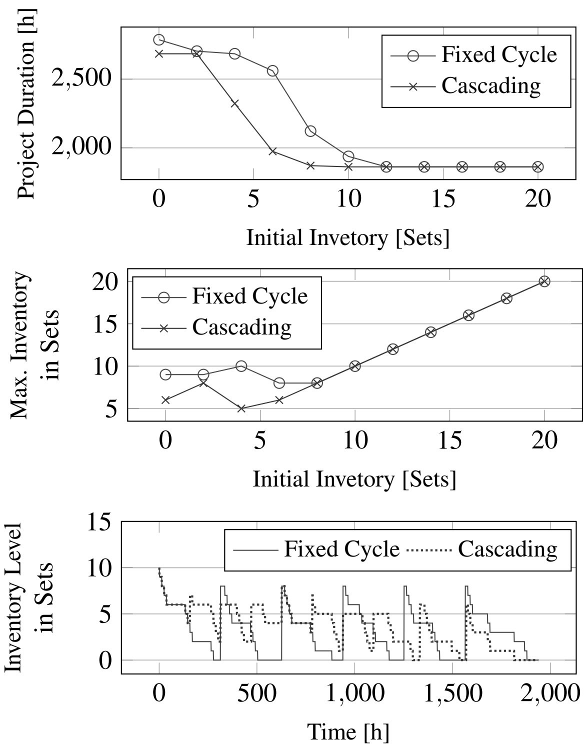

Figure 6: Results of the first use case.

Figure 7 shows the same graphs for the second use case. Considering the project duration, the second use case shows the same characteristic as the first use case: the cascading approach achieves an uninterrupted installation at an initial inventory level of 30 sets instead of 35 sets for the fixed cycle. Similarly, both approaches' required capacity is equal (second graph). In contrast to the first use case, the last graph shows interesting behavior. The cascading approach quickly reduces the initial inventory level, maintaining a lower average inventory level until the end of the project.

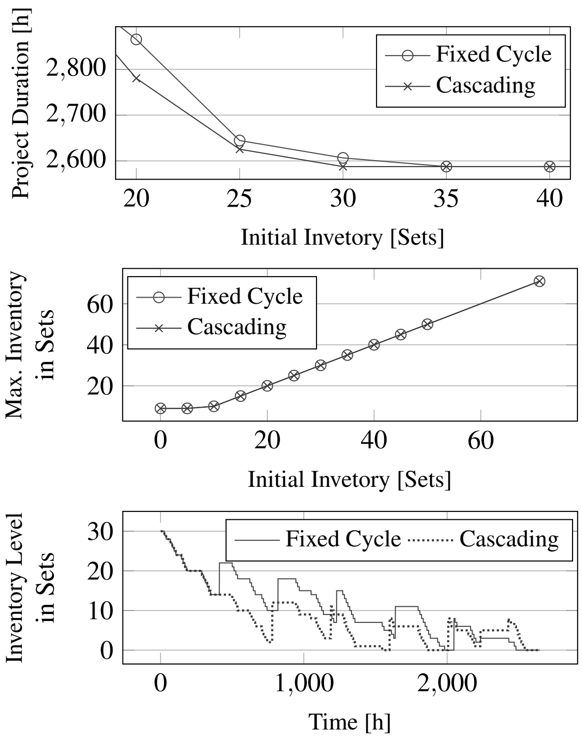

Figure 7: Results of the second use case.

6 Conclusion and Future Work

This article presents a framework to combine cascading simulation with offline mathematical optimization to choose viable resupply cycles for offshore installation projects based on the current state of the process, weather forecasts, and expected weather conditions. Compared to purely heuristic or search-based approaches, this combination limits the search space drastically, rendering it a viable alternative in practical applications. The same accounts for purely mathematical approaches. Combining the scheduling of vessels with the routing and knapsack problems involved with the resupply would probably result in a problem with vast amounts of constraints, probably unsolvable in a realistic context.

The results show that the approach reduces the required initial inventory level compared to optimized fixed resupply cycles. As the required capacity increases linearly with the initial level, the framework can provide a tool to reduce the strain on port-side resources. Moreover, the second use case shows that the framework can, in some cases, result in a heavy reduction of the average inventory level at the beginning of a project. This behavior can be exploited to free up reserved capacity. The advantage of the cascading concept also shows in its transparency. At each decision point, the framework offers its current decision. In the second use case, the framework decides for a long resupply cycle initially, resulting in the drop of the average inventory level. Moreover, planners could also evaluate the respective nested child simulation to predict the remaining project's behavior.

Future work will further investigate this effect and determine which constellations result in such behavior. Moreover, future work will investigate other applications for the cascading framework in the offshore area and other simulation-based optimizations. The current implementation allows easy integration of the cascading framework to various models implemented in AnyLogic by providing suitable interfaces to register the manager class and the means to provide it with decision alternatives.

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