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Demand-Driven Resupply of Offshore Components by Cascading Simulation and Linear Optimization

Bedarfsgerechte Bereitstellung von Offshore-Komponenten durch die Kombination kaskadierender Simulation mit Linearer Optimierung

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Abstract: The installation of offshore wind farms constitutes a highly weather-dependent process. Despite this dependency, practice and research generally apply a single, rigid resupply cycle to transport components from their production sites to the installation's base port, resulting in high storage costs. This article proposes combining mathematical optimizations with a cascading discrete-event simulation framework to select a viable resupply cycle online from a previously optimized pool of cycles during the project execution. This combination brings the best of both methods together by allowing high flexibility while reducing the possible search space drastically and guaranteeing that each route remains optimal by itself. The evaluation shows that dynamically selecting cycles using current weather measurements and forecasts reduces the required base port storage capacity by approximately 17% while still maintaining full installation efficiency.

1 Introduction

Over the last decade, wind energy has evolved into one of the primary sources of sustainable, green energy. It has witnessed an exponential increase in installed capacity, e.g., shown by REN21 (2020). Offshore wind farms provide advantages over their onshore counterparts. The open sea offers larger areas to install wind farms without interfering with local populations, allowing more capable wind farms. Additionally, higher wind speeds and availability result in higher energy yields. Nevertheless, the same advantages result in additional challenges for installing such wind farms, as, e.g., summarized by Rippel et al. (2019a).

Especially the high wind speeds at sea interfere with necessary installation operations. These installations require crane operations in approximately 100 meters height and highly depend on current weather conditions. When planning and executing installation projects, planners and operatives need to rely on historical data or forecasts introducing a high amount of uncertainty into the planning process. Consequently, literature attributes 15% to 30% of a wind farm's overall lifetime cost to logistics during the installation (Dewan et al., 2015; Muhabie et al., 2018). These costs result from vessels' charter rates, heavy-duty handling equipment, and port spaces to store and process turbine components. Consequently, such projects include large safety margins for charter times or spaces.

While most literature focuses on efficient vessel schedules or fleet-mixes, only very few articles consider port-side resources and storage spaces. Nevertheless, current studies show that trends towards larger and heavier components (Wiser; Bolinger, 2018) and an increasing number of concurrent installation, refurbishing, and decommissioning projects, e.g., indicated in Beinke et al. (2020), might result in bottlenecks considering port-side storage areas (Oelker et al., 2020).

The article at hand focuses on the resupply of components to the base port. It proposes a framework to combine (offline) mathematical optimization with a cascading, simulation-based online approach to reduce the required capacity at base ports during the installation phase. Instead of applying metaheuristics to determine an optimized resupply cycle, this approach uses linear optimization to generate a small set of resupply cycles consisting of optimal routes and pickup amounts. The simulation model tracks the installation progress as online simulation until the real-world system requests a new resupply cycle. It then creates and evaluates additional instances using historical weather recordings. Each of these sub-simulations might create further instances, resulting in a cascading hierarchy of nested simulations.

1.1 Installation Process for Offshore Wind Farms

While several concepts exist for the installation of offshore wind farms, research and practice mainly apply the so-called conventional installation concept, e.g., described in Oelker et al. (2017). This concept includes three supply-chain stages. First, the production and (re-)supply of components to the base port. Second, the base port itself as a decoupling point between the first and the last stage, and, third, the actual installation (Fig. 1). In practice, companies conduct the installation sequentially, i.e., they first install all foundations and then the top-structures as both phases require the same resources but with different equipped tools for the vessels.

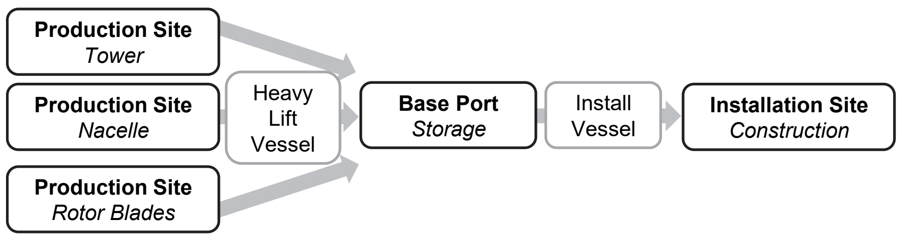

Figure 1: *Conventional Installation Concept (Rippel et al., 2019b)*

The base port stores delivered components and provides these for installation. On the one hand, its capacity needs to accommodate incoming components even when current weather conditions prohibit installations as planned. On the other hand, the base port needs to provide sufficient inventory to continue installations even if the weather turns out better than expected. During the installation, a jack-up vessel travels between the base port and the installation site. It has to be noted that the jack-up vessel needs to finish installing a turbine once started. This requirement results from jack-up operations puncturing the seabed, rendering additional jack-up operations a risk to the vessel and already installed foundations and components.

The resupply applies one (or rarely more) heavy-lift vessel, which fetches components from the production ports and transports those to the base port. In practice and science, these vessels usually follow a predefined resupply cycle determined by project planners before the project starts. These cycles include a defined number of round-trips between the base port and one or more production ports. Each round-trip fetches a given number of components. As described above, the installation vessel always requires full sets of components, consisting of a tower, one nacelle, one hub, and three blades to perform an installation. Therefore, this article omits partial deliveries.

1.2 Approaches to Support Offshore Wind Farm Installations

Compared to other areas, like the maintenance of offshore installations, only a few works focus on installing offshore wind farms (Vis and Ursavas, 2016). Thereby, most authors focus on optimizing or evaluating the installation part of the supply chain (Rippel et al., 2019a), e.g., in terms of different weather assumptions, e.g., (Muhabie et al., 2018), installation concepts, e.g., (Vis and Ursavas, 2016), or fleet mixes, e.g., (Ait Alla et al., 2013). Other articles provide models to schedule, e.g., the commissioning of vessels (Kerkhove and Vanhoucke, 2017) or operations in various resolutions, e.g., (Ursavas, 2017; Irawan et al., 2019)

Even fewer articles explicitly include evaluations of port-side resources or the resupply part of the supply chain. For example, Beinke et al. (2017) evaluated the impact of sharing heavy-lift vessels between several installation projects to reduce downtime. In their current work, the authors describe a simulation study that demonstrates an increasing demand for jack-up vessels, and in consequence port-side resources, when the first wind farms need refurbishing or decommissioning over the following years (Beinke et al., 2020). Oelker et al. (2020) describe a simulation study that evaluates available heavy-duty storage areas at the base port in Eemshaven. The study demonstrates that the port's capacity will be exceeded soon if current trends to larger turbines and the increasing number of concurrent projects continue. Rippel et al. (2020a) describe a mathematical model to determine optimal resupply cycles for varying round-trips numbers. Further, that article selects a fixed, optimal resupply cycle for a practical use-case using additional optimization models.

The models denoted above primarily provide support for the installation stage of the supply chain. They assume that the base port offers sufficient components. A few models assume that a fixed number of components become available periodically.

1.3 Optimization of Resupply Routes

This section summarizes the optimization model proposed in Rippel et al. (2020a), as this article applies it to generate alternative resupply cycles. The model uses a combination of traveling salesmen problems with a customized multi-periodic knapsack formulation to determine a sequence of N^{rt} round-trips, that maximize the number of delivered component sets while minimizing the overall cycle duration. The formulation exploits the small size of the transportation network to calculate optimal routes for each combination of visited ports. Assuming symmetrical traveling times, each round-trip uses one of eight possible routes (Fig. 2).

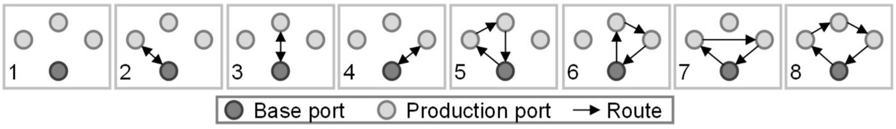

Figure 2: *Possible routes for one base-port and three production ports*

The model first determines the traveling times for each possible route by solving a traveling salesman problem. Afterward, it solves a multi-periodic knapsack problem to determine the optimal number of components of each type to fetch in each round-trip. The model uses a binary encoding to map each combination of visited ports to the precalculated traveling times of the respective route.

Consequently, the model obtains an optimized sequence of routes for a given number of round-trips N^{rt}, considering the supply network's geographical locations and the heavy-lift vessel's characteristics, e.g., its speed, deck area, and maximum payload. Finally, the article discusses the characteristics of different cycles. Finally, it shows that allowing four round-trips yields the most efficient cycle and results in the evaluated scenario's lowest capacity requirement.

2 Cascading Simulation using Optimized Routes

While the model presented above produces optimal cycles for a given supply network, it still assumes that the project repeats a single cycle. Nevertheless, the demand for components depends on current weather conditions, which cannot be known during planning. Consequently, this article extends that work by using nested simulations, as, e.g., introduced by Kindler (2004), at different cascades to choose the best cycle for the current state and expected weather conditions.

In contrast to widespread meta-heuristics or search-based approaches, the proposed method applies the optimization model to reduce the search space drastically. For example, allowing the heavy-lift vessel to decide between cycles with one to ten round-trips only requires evaluating a maximum of ten optimized routes. In contrast, evaluating the same space, e.g., using a simulation-based exhaustive search or a meta-heuristic, would require checking the complete or at least large parts of the search space. Therefore, a cycle with a single round-trip offers eight alternatives, as shown in Figure 2. Adding a second round-trip increases the search space multiplicatively, as each of the previous routes can combine with each one in the new trip. Thus, the total search space is given as $\sum_{n=1}^{N^{rt}} 8^n$, resulting in over 1.2 billion combinations if evaluating all options for $N^{rt} = 10$. Even assuming a single second to generate and either discard or simulate each alternative requires over 13.888 days for all alternatives. Additionally, these alternatives do not include the decision on how many components to pick up at each port.

In terms of a mathematical approach, the model would need to incorporate the interdependence between resupply cycles, time progression, weather-dependent installation times, and the influence of historical weather data. Such a high level of detail probably requires full-time-indexing of the project or a vast number of constraints. Consequently, this model would require excessive time to solve.

2.1 General Concept

The general concept consists of four major components. First, the real-world system, i.e., a current installation process that delivers current measurements and information to the framework and requests decisions on how to proceed. Second, the cascading simulation framework. This framework contains and manages a series of simulations on different levels. The underlying simulation model constitutes the third component. Thereby, this model takes on two tasks. On the one hand, it acts as an online simulation or digital twin, tracking the current real-world system's progress. The framework updates this model each time it receives updates from the real world, e.g., if an operation starts or ends or if new weather measurements or forecasts become available. On the other hand, the framework uses the simulation model to decide between alternatives. While the online simulation follows the real-world in terms of time progression and weather measurement, these nested simulations rely on forecasts and historical data. After all simulation on a cascade finish, the framework evaluates their results and updates the requesting simulation. Finally, the offline optimization model constitutes the fourth component to provide a set of optimized resupply cycles that act as inputs for the cascades.

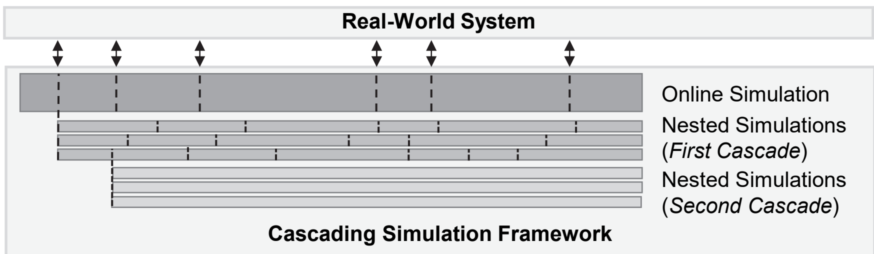

Figure 3: *General Concept of the framework. The real-world system updates and request decisions from the framework (arrows). Internally, each such decision point (dotted line) spawns new nested simulations to evaluate three alternatives.*

Figure 3 schematically shows this process for the first decision on each level. In this figure, dotted lines depict decision points, where, e.g., the heavy-lift vessel needs to decide on the next resupply cycle. The framework then instantiates a series of nested simulations (only three in the figure) based on the number of alternatives delivered from the offline simulation. If the framework allows for more cascades, each of these simulations may request the same decision, resulting in a new cascade for the decision points on this level too. In addition to what the figure shows, each decision point (dotted line) generates a set of simulations, e.g., resulting in six complete simulation sets in the first cascade.

2.2 Simulation Model and Weather Data

This article's simulation model has been implemented in AnyLogic 8.7.2, while the self-developed BIBA Cascading Simulation Framework (BCSF) has been implemented in Java. The framework consists of manager-classes that each reference one AnyLogic-Simulation and register themselves as listeners on this simulation. This structure allows for two-way access. On the one hand, the manager can update the simulation and control its execution. On the other hand, the simulation can request decisions or actively notify if it finishes. For each decision request, the manager creates more instances of itself. It then monitors these child-instances for completion and selects the best result for its own simulation. This article uses the following decision rules: First, select the child-instances with the lowest project duration. Second, select the instances which added the lowest value to the required base port capacity. Third, select the instances with the highest minimum inventory. Last, select the instance with the longest resupply cycle as a tie-breaker. While this article only considers resupply cycles as decision alternatives, the manager can influence basically all parameters and variables present within the simulation model. Its implementation uses Java-Reflections to modify variables "by name" which allows a high degree of freedom when formulating the request. Basically, when requesting a decision from the manager, the simulation provides a list of parameter names and values for each alternative, in this case resulting from the optimization model described earlier.

The installation uses a decision strategy that obtains current measurements and forecasts and applies the algorithms described in Rippel et al. (2019b) to estimate operations' durations. It then constructs different installation cycles, consisting of the number of loading and installation operations, to install between one and four (vessel capacity) turbines. It finally selects the alternative that incurs the lowest offshore waiting time, as these times inflict comparably high project costs. For more information on the simulation model, please refer to Rippel et al. (2020b).

Finally, this article uses a database of hourly historical weather recordings from Germany's Northern Sea between 1959 and 2006. The online simulation uses this database directly to provide "current" measurements and generates forecast data. The nested simulations cannot use this data directly but use aggregates of "historical" data as they would have been available at that time. For example, if the online simulation uses data from the year 2000, the nested simulations use hourly mean values from 1979 to 1999. The simulations slowly transition from current forecasts (2000) to the historical data (1979-1999) to accommodate for the forecasts' limited scope. According to the homepage of Deutscher Wetterdienst (2020), the forecasting uncertainty $u(t)$ of current models starts at 0.0 for the first hour (measurement), increases to approximately 0.25 at one week and 0.65 at two weeks. Afterward, it increases quickly to 0.95 at three weeks. The nested simulations use these values to mix the forecasts and current measurements with the mean aggregates as $f(t, d_c, d_h) = \big(1 - u(t)\big) \cdot d_c + u(t) \cdot d_h$ with t being the difference between the nested simulation time and the one of its parent, d_c being the vector of current measurements (2000), and d_h containing the historical aggregates (1979-1999). This procedure allows simulating an installation project with realistic data. The online simulation uses current measurements (of that time) while the child-simulations can only use historical data that would have been available at that time.

3 Experimental Setup

The evaluation applies the same parametrization and use-case as the original experiment in Rippel et al. (2020a), as it uses the same algorithm to generate optimized resupply cycles. This experiment follows a practical use-case originally described by Beinke et al. (2017). Moreover, it applies averaged data from different studies and websites to estimate the characteristics of turbine components (size and weight) and heavy-lift vessels (deck area, payload, speed). Table 1 summarizes the most relevant parameters for this evaluation. In contrast to the original experiment, the article at hand applies different decision strategies for the installation vessel. Moreover, this article selects the project start date as the first of August 2000 to have more volatile weather conditions, i.e., more time windows where no installation can occur. Both slightly change the results considering project durations and capacity requirements between the original results and those presented later.

Table 1: *Summary of relevant parameters*

Parameter	Tower	Blade	Nacelle
Base Port		Eemshaven	
Installation Site		Northern Sea	
HLV – Deck Area / Payload		2646 m² / 8900 t	
HLV – Agv. Speed		9.5 knots	
Production Prot	Cuxhaven	Bremerhaven	Bremerhaven
Loading/ Unloading / Setup Time [h]	2 / 1.2 / 0	8 / 4.8 / 0	10 / 6 / 0
Weight	600 t	240 t	500 t
Required Space	650 m²	300 m²	263 m²

4 Results and Discussion

The presented experiment aims to verify if the cascading framework can reduce base port capacity requirements by selecting viable resupply cycles online. Therefore, the simulations assume an infinite capacity and measure the maximum inventory level observed during the simulation. The original experiment concluded that cycles with three or four round-trips constitute the optimal choice. Therefore, these settings serve as the baseline for the evaluation by simulating the installation with fixed, repeated cycles. This article only depicts the results for four round-trips, as both simulation runs show equal results. Furthermore, the evaluation provides two sets of experiments allowing a single cascade (only the online simulation may create child-instances) and two cascades (instances on the first cascade can instantiate a second cascade). Each experiment includes ten simulation runs, each assuming an increasing initial inventory level, assessing this level's influence on the project duration and capacity requirement. Figure 4 depicts the results for fixed and cascading experiments. The graphs show the project duration, capacity requirement, and mean inventory levels observed during the simulation run for initial inventory levels between zero and twenty.

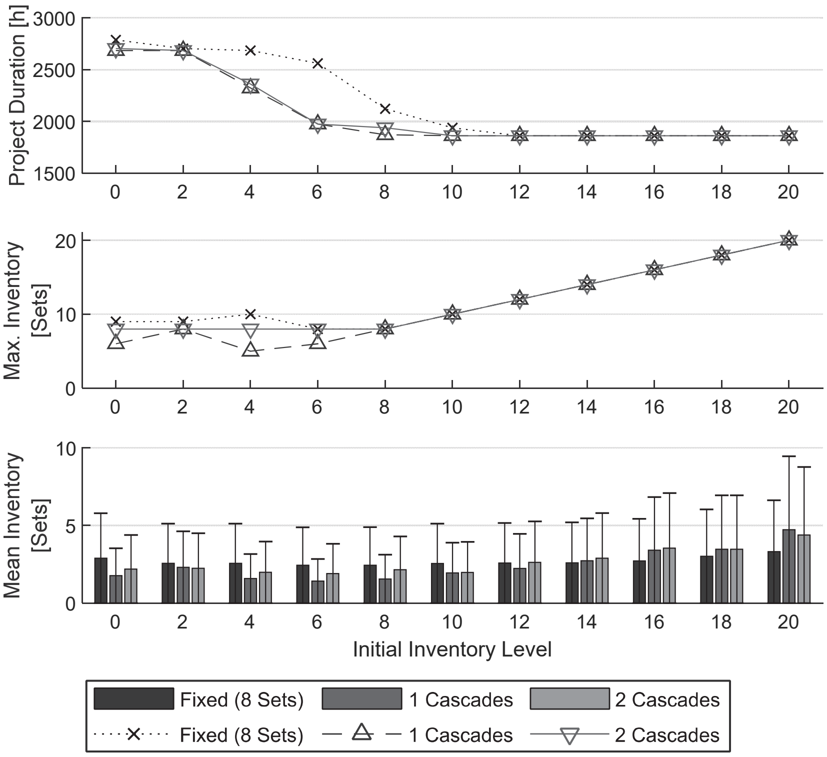

Figure 4: *Results for all three experiments, showing the project duration, capacity requirement, and mean inventory level for different initial inventory levels.*

The results show that the cascading approach outperforms the fixed cycle scenario by achieving an uninterrupted installation process at an initial inventory level of ten compared to twelve in the fixed case. Delays in the installation process result from missing components, also shown by the higher project durations at lower inventory levels. While expected for the fixed cycle experiment, the cascading approach also keeps the required capacity equal to the initial inventory. This stability and the low standard deviation of the mean inventory level show that the cascading approach reduces the impact of varying weather conditions quite well. Finally, the results show no notable differences between allowing one or two cascades for this example. Consequently, the reduced variance in inventory levels results from the framework's ability to adapt the resupply to the currently estimated demand. As the classical approach obtains the same number of component sets, good and bad weather periods have a stronger influence on the inventory level, even resulting in an undersupply. In contrast, the framework anticipates changing conditions and supplies components as needed, i.e., faster for good weather periods or slower for bad weather periods.

5 Conclusions and Future Work

This article presents a framework that combines mathematically optimized routing alternatives with a cascading simulation strategy to decide between them in an online simulation context. Compared to a purely simulation-based optimization, mathematical optimization guarantees optimal route alternatives and drastically reduces the search space. The approach further uses current weather data and forecasts for the online simulation but relies on historical data aggregates to estimate the project's progression in its nested simulations. The experiment shows that applying the framework to dynamically choose the most promising resupply cycle reduces the required capacity by approximately 17% compared to repeating the same cycle periodically as it is the current state of practice. Moreover, the results show that this application only requires a single cascade. Future work will focus on applying the proposed approach to other decisions, e.g., to decide between different installation cycles. It will also investigate if the current listener-based connection between the simulation and the framework can be replaced using web services. This change might increase flexibility and facilitate integrating additional decision points.

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