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A CASCADING ONLINE-SIMULATION FRAMEWORK TO OPTIMIZE INSTALLATION CYCLES FOR OFFSHORE WIND FARMS

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ABSTRACT

Offshore wind energy constitutes a promising technology to achieve the world's need for sustainable energy. However, offshore wind farm installations require sophisticated planning methods due to increasing resource demands and the processes' high dependence on viable weather conditions. Current literature provides several models that either provide strategic or tactical decision support using historical data or operative support using current measurements and forecasts. Unfortunately, models of the first type cannot support the operative level. In contrast, the second type provides decision support using local, short-term optimizations that do not consider these decisions' effect on the overall installation project. This article proposes a cascading online-simulation concept that optimizes local decisions using current data. However, it estimates the effects of each decision using nested simulation and aggregates of historical data. The results show that this approach achieves a good trade-off between the project's duration and cost-inducing delays at comparably low computational costs.

1 INTRODUCTION

On- and offshore wind energy constitute promising technologies to generate sustainable, green energy. Over the last decade, the amount of energy produced by these technologies has increased exponentially (REN21 2020), resulting from continuous trends towards more capable turbines (BVGassociates 2019) and an increasing number of installation projects (Beinke et al. 2020). In comparison to onshore farms, offshore wind farms provide a larger amount of energy due to their high wind exposure at the open sea (Breton and Moe 2009). Current trends indicate a strong increase in installed offshore wind farms over the next years. For example, in 2019, Germany had ten wind farms under construction with nine more projects in preparation, expected to finish until 2030 (Deutsche WindGuard GmbH 2019). Moreover, in 2020, Germany just increased their offshore targets to install an additional 20 Gigawatt by 2030 and another 40 Gigawatt by 2040 (WindSeeG 2020).

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While offshore wind farms provide more energy than onshore farms, their construction poses additional challenges: Their primary advantage of higher wind exposure renders the installation more complicated. Additionally, the increased size and weight of components lead to construction works at even greater heights. This combination results in an increasingly weather-dependent installation process at hard-to-reach offshore construction sites. Consequently, the construction requires highly specialized resources, e.g., installation, so-called jack-up vessels. These vessels provide the ability to mount themselves onto the sea bed to stabilize themselves for the required crane operations. Besides the high costs of such vessels of up to 120.000 € / day (Meyer 2014), operative planning can only rely on weather forecasts or historical weather records. Due to the high resource costs and involved weather uncertainties, current literature attributes between 15 % and 30 % of an offshore wind farm's costs, including operations and maintenance costs, to logistics during the installation (Dewan et al. 2015; Muhabie et al. 2018).

On the one hand, the initially described trends show an increasing demand for offshore wind farm installations. On the other hand, studies show that this demand might not be accomplishable without more efficient resource management concepts. For example, Beinke et al. (2020) describe a simulation study that shows an increasing demand for installation vessels. Moreover, Durakovic (2020) describes a study that predicts a drastic increase in installation vessel demand from an annual rate of 13 working years in 2020 to over 40 by 2025. The report additionally states that only a small subset of the currently available 32 installation vessels can handle current generations of turbines due to their large dimensions and weight. Consequently, existing vessels might not cover the increased need without new approaches that increase their utilization. Such methods need to provide efficient and reliable schedules to reduce vessel downtimes. Moreover, these methods need to carefully handle weather forecasts and predictions, as weather conditions heavily impact offshore operations and constitute one of the main causes for delays.

In the literature, various authors propose some simulation- or optimization-based models to find viable schedules. Nevertheless, most of these models solely rely on historical or abstracted data, which cannot handle current measurements or forecasts required for operative decision support. Recently, some authors also proposed models designed as digital twins or online optimizations, which only use forecasts and current data for short-term (operative) planning. However, these models limit their focus to local optimizations, which, e.g., do not allow tradeoffs between local delays and the global installation speed.

In extension to the current state of the art, this article proposes a cascading online-simulation framework that applies nested simulation runs, combining current forecasts and historical data to achieve a globalized optimization. Therefore, the framework uses a primary online simulation, which ties into the real-world process, collecting and processing current weather measurements and forecasts. Whenever this model requires a decision, it instantiates a series of nested child simulation runs that assess the impact of local decisions on the overall installation process by using aggregates of historical weather data. These aggregates consist of the hourly mean value and variance of a predefined number of past years, combined with current short-term weather forecasts. This article focuses on the so-called installation cycles as decisions. Every time an installation vessel enters the base port, it decides how many turbines it will load and install in its next cycle. It considers the effects of this decision on the overall project duration and, depending on the forecasts, possible weather-induced delays during the next cycle. Depending on the vessel's capacity, such cycles could span a few days to several weeks.

2 PROCESS DESCRIPTION AND STATE OF THE ART

First, this section shortly describes the installation process for offshore wind turbines regarded in this article. Afterward, it summarizes the current state of the art and characterizes available scheduling and simulation models in terms of their advantages and disadvantages.

2.1 Process Description

Within the literature, several concepts exist for installing offshore wind farms, e.g., pre-assembly concepts (Vis and Ursavas 2016) or feeder concepts (Ait Alla et al. 2017). Nevertheless, the so-called conventional installation concept constitutes the most common concept found in literature and practice. Figure 1 depicts the supply chain involved with most of the installation concepts for the installation of a turbine. Most of these concepts only differ in the use of jack-up vessels in the last part of the supply chain. Generally, the installation can be separated into three phases (Vis and Ursavas 2016): first, the installation of the foundations, second, the installation of the actual turbines and, third, the commissioning. The first two phases have very similar supply chains, and both employ jack-up vessels for the installation. Nevertheless, the vessels require a different set of tools for the installation process. As changing tools on these vessels is associated with high setup times and costs, companies usually conduct these phases sequentially, i.e., they first install all foundations and then all turbines. The commissioning could theoretically commence as soon as the first turbines have been installed, as this phase mainly relies on crew transport vessels and a team of technicians. Nevertheless, the commissioning usually relies on high wind speeds to test the turbines, while the installation requires calm weather conditions. Consequently, these phases are usually decoupled, too. This article focuses on the second phase, the installation of turbines. Nevertheless, the results and methods apply to the installation of foundations with no limitations.

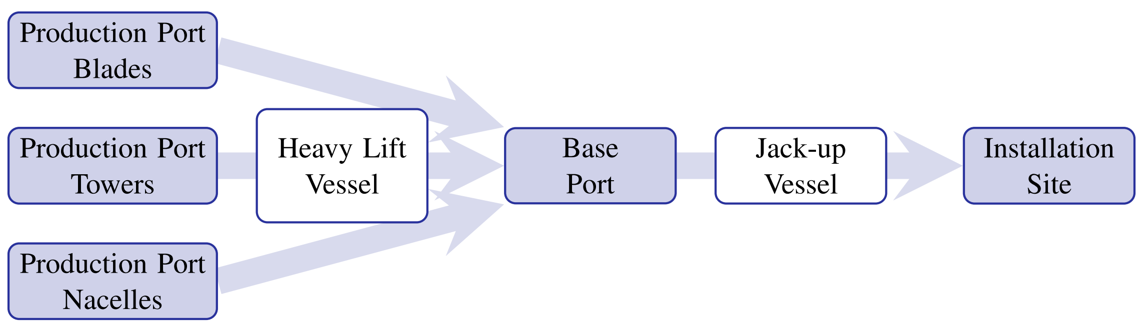

Figure 1: Conventional installation concept for offshore wind turbines (adapted from Rippel et al. 2019).

Figure 1 shows the regarded supply chain for this article. Generally, the production of turbine components, i.e., the blades, the tower (segments), and the nacelles, takes place at geographically distinct locations. In most cases, each facility connects to a so-called production port that stores the produced components for later pick-up. An installation project usually employs one (or sometimes more) heavy-lift vessel to transport the components from these production ports to the so-called base port. The base port acts as a decoupling point and buffer between the component provision and the actual installation to guarantee a sufficient supply of components but also sufficient storage areas if weather conditions interfere with the installation process. The conventional installation concept then assumes that one or (rarely) more jack-up vessels move between the base port to acquire components and the installation site to install them.

Consequently, the planning of such an installation project requires precise planning and estimation of offshore operations early on but also during operations. For example, planned installation operations determine the required capacity of the base and production port or the heavy-lift vessels' transport cycles on the strategic and tactical levels. On the operative level, delays on the installation site lead to high additional costs, e.g., considering the vessels' charter rates, fuel, or personnel costs. Additionally, such delays may affect the storage at the base port or even the resupply of components. Consequently, the tools and models for decision support for offshore installations require the capability to provide support on all levels, from strategic and tactical support using historical or expected weather information to the operative level using current forecasts and measurements.

2.2 Existing Models and Tools for the Scheduling of Offshore Operations

As noted in the introduction, several authors propose models that either provide schedules for offshore operations, e.g., (Scholz-Reiter et al. 2011; Ait Alla et al. 2013; Kerkhove and Vanhoucke 2017; Ursavas 2017; Barlow et al. 2018; Irawan et al. 2019) or could be used to determine viable schedules via simulation, e.g., (Lange et al. 2012; Vis and Ursavas 2016; Ait Alla et al. 2017; Beinke et al. 2017; Quandt et al. 2017; Cheng et al. 2019). These models incorporate weather conditions either directly in the form of measurements (mostly simulation-based approaches) or using a more abstract representation of good, moderate, and bad weather windows. Authors either determine the sequence of these windows directly from historical data or learn distributions from historical data to provide probable but randomized sequences. Consequently, none of these articles describe the planning of operations that involves forecasts or uncertainty. Most models assume that the upcoming weather data are fully known and not changing over the installation process. Therefore, these models can provide support on the strategic and tactical level by simulating years with weather conditions that might be comparable to expected weather conditions. Unfortunately, these models' inability to work with uncertain (short-term) forecasts or continuous weather measurements renders them unsuitable for decision support on an operative level.

In contrast, recent literature presents a few models that focus on the operative level (Rippel et al. 2019; Peng et al. 2020; Rippel et al. 2020). While all these models use different underlying modeling techniques, i.e., mathematical optimization, Petri-nets, or multi-agent systems, the models all tie into a real-world system that delivers current measurements and forecasts. Consequently, these models can be interpreted as digital twins that mirror the real-world process and provide decision support based on current forecasts using a rolling or receding horizon. For some of these models, the authors also show their models' ability to work with aggregate historical data to provide decision support on the strategic and tactical level. In such cases, the models also emulate or use forecasts from historical data. Nonetheless, as the decision-making purely relies on forecasts, these models only perform local optimizations and cannot regard their local decision's global effects.

In summary, current literature contains several models that provide decision support either on the strategic and tactical level by relying on historical data or the operative level by using current measurements and forecasts. The first type of model thereby provides globally optimized plans but uses historical data as a base-line. In contrast, the second type of model provides locally optimized plans based on short-term forecasts. This article proposes a cascading, simulation-based framework to combine the advantages of both types. On the one hand, the framework ties into the real-world system to acquire current data for its online simulation. On the other hand, it uses a cascading hierarchy of nested or child simulation runs to estimate the effects of decisions on the overall installation project using historical data aggregates. Consequently, the framework allows for rendering local decisions based on their expected influence on the global efficiency.

3 CASCADING SIMULATION FRAMEWORK

This section describes the proposed cascading simulation framework and the underlying simulation model. Moreover, it shortly summarizes a mathematical model used as a benchmark approach. In the literature, authors have proposed other approaches with comparable structures to the proposed cascading online simulation framework, e.g., in the area of risk-management using the term *nested simulation* (Xie et al. 2019) or in other areas using the terms *Dynamic Data Driven Application Systems* (Fujimoto et al. 2018) or *Symbiotic Online Simulation* (Becker and Szczerbicka 2015). The original concept of nested simulation runs dates back to the 1960's simulation language SIMULA by Eugene Kindler (Kindler 2004) and has since been applied to various applications. For example, Xie et al. (2019) describe a production system where the machine regularly decides which priority rule to select for the next time interval. The noted approaches instantiate child- or nested simulation runs that evaluate each decision alternative for each decision point. The framework proposed in this article shows two distinctions compared to the majority of approaches presented in the literature. First, it does not limit the nesting of simulation models to a single level, i.e., depending on its settings, nested simulation runs can instantiate additional cascades or levels of nested simulation runs. Second, the presented framework explicitly differentiates between an online simulation using current data and forecasts and the nested (offline) simulation runs, which rely on (aggregated) historical data for their estimations.

Apart from the mentioned terms, the cascading concept shows similarities to the approximate dynamic programming paradigm. Following the definition of Powell (2009), this paradigm incrementally optimizes larger problems be solving the involved sub-problems (decisions of installation cycles) over a finite horizon using a state transition function $S_{t+1} = S(S_t, x_t, W_{t+1})$. In this function, S_t denotes the current state (state of the installation, locations and loading state of vessels, etc.), x_t the taken action (installation cycle), and W_{t+1} denotes additional information gained between these steps (weather data and forecasts). This paradigm then uses a so-called cost-to-go function to evaluate the expected costs of each combination of decisions to select the optimal decision policy $X^{\pi} = \{x_1, x_2, \dots, x_{\pi}\}$. In case of the proposed framework, the nested child simulation runs replace the cost-to-go function by determining critical parameters, e.g., delays, installation times, or costs, directly as part of their simulation.

3.1 Cascading Online Simulation Framework using Nested Simulation Runs

The proposed framework consists of two simulation models and an external manager, which manages the spawning of child simulation runs and evaluates their results. The first (online) simulation model represents the real-world system. It collects and uses real-world weather measurements to ensure a realistic process simulation. Whenever the simulated vessel agents need to decide on a new installation cycle, this model forwards the decision request to its manager. The manager then spawns a number of (nested) child simulation runs. Therefore, the manager instantiates each child simulation with the current state of its simulation and passes one alternative decision for the next cycle to the child. It repeats this process for each possible decision candidate. Then, the manager collects the child simulation runs' results and returns the best candidate to the requesting model. The framework repeats this process for each decision point, i.e., whenever the online simulation needs to decide on the next installation cycle, forming the first cascade of child simulation runs. Finally, the framework's design allows child simulation runs to request decisions on their own, forming additional cascades up to a predefined depth. Once the framework reaches this depth, the simulation model's default decision strategy applies as a fallback rule to avoid an uncontrolled exponential growth. Figure 2 schematically depicts the proposed concept.

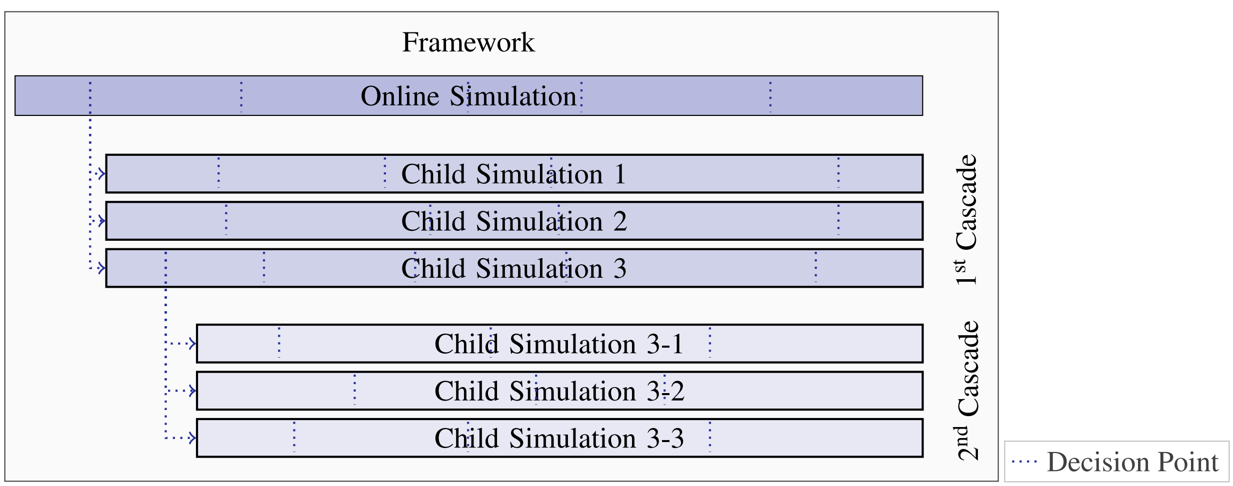

Figure 2: Schema of the cascading simulation concept using three alternatives and two cascades.

The framework implemented for this article uses the same AnyLogic simulation model for the online and the child simulation runs but provides different weather data for both. Generally, the simulation uses hourly historical weather recordings from Germany's Northern Sea between 1956 and 2006. The online simulation accesses these records directly, i.e., if simulating a project that starts on July 1st, 2000, the model uses the recordings from this period to represent a realistic process. In contrast, the child simulation models cannot access these records directly, but receive aggregates of historical weather and forecasts from their parent simulation. For example, the implementation used in this article uses aggregates of the last 20 years in terms of an hourly mean value and variance to estimate expected weather conditions. Thus, following the example above, if the online simulation runs a scenario for the year 2000, the child simulation models use the mean values and variances from 1979 to 1999. Additionally, the child simulation models receive the current short-term forecasts from their parent simulation. Depending on the parent, these forecasts constitute either a current real-world forecast, if the parent is the online simulation, or result from historical data, if the parent is one of the nested simulation runs. As described in Rippel et al. (2019), each forecast has an increasing uncertainty the further it reaches into the future. The authors refer to the verification of the Deutscher Wetterdienst, which evaluates the correlation between their forecasts and measured weather conditions for time intervals between 24 and 168 hours. Consequently, the child simulation runs blend the forecast and their aggregate historical data according to this uncertainty. For example, suppose the uncertainty remains at 0.0 (first hour of the forecast). In that case, the child simulation only uses the forecast. At an uncertainty of 0.5, the simulation would use the mean value of the forecasts and its aggregate historical conditions, slowly traversing towards full use of aggregated historical data, the closer the forecast uncertainty draws to 1.0.

Within this framework, several simulation manager components exist, which each tie to one of the running simulation models (online or nested). These managers start their corresponding simulation runs, parameterize them, and register themselves as event-listener within the simulation. Currently, the managers listen for *decision request* and *simulation finished/aborted* events. On finish, the manager reports back to its parent manager and forwards the simulation results for evaluation before closing the simulation and itself. On a decision request, the manager instantiates and executes a number of child managers, and, thus, child simulation runs, depending on the number of provided decision alternatives. Once the child managers report their results, the requesting manager evaluates the results according to the following priorities: First, it selects those alternatives that result in the lowest installation project duration. If several alternatives with the same duration exist, the manager selects those that imply the lowest offshore waiting times. These delays induce high additional costs, e.g., for personnel or fuel. Finally, as a tie-breaker, it selects the alternative that installs the largest number of turbines from the remaining alternatives. Afterward, the parent manager forwards the best alternative back to its simulation model.

Currently, the framework has been implemented in JAVA to connect to the AnyLogic simulation models directly. It registers itself as a listener and interacts with the simulation using remote procedure calls. As the manager and the simulation run in separate threads, the manager pauses the simulation when called, exports its state, and, upon finish, modifies the targeted decision variables and resumes the simulation. The current implementation uses JAVA-Reflections to modify the simulation. Thus, each request consists of several maps containing the parameter names and their settings for each alternative. Moreover, the request includes the class name of a viable comparator for the request, which implements the priorities stated above. The use of JAVA-Reflections achieves a high versatility, allowing the manager to handle various parameters and even different simulation models with only minor changes to the code.

3.2 Baseline Simulation Model and Benchmark

The proposed framework uses a simulation model implemented in AnyLogic 8.7.2. The model closely follows the ones proposed in the literature, e.g., Ait Alla et al. (2017) and Oelker et al. (2018). An early version of the model has been used and described in previous work (Rippel et al. 2020). This publication also describes a model transformation framework that this article uses to generate similar inputs for the framework and the mathematical simulation used as a benchmark. Moreover, the same files generated by this framework serve to exchange the model state (e.g., position of vessels, installed turbines, ...) between parent and child simulation runs. Figure 3 shows screenshots of the simulation and model generation tools.

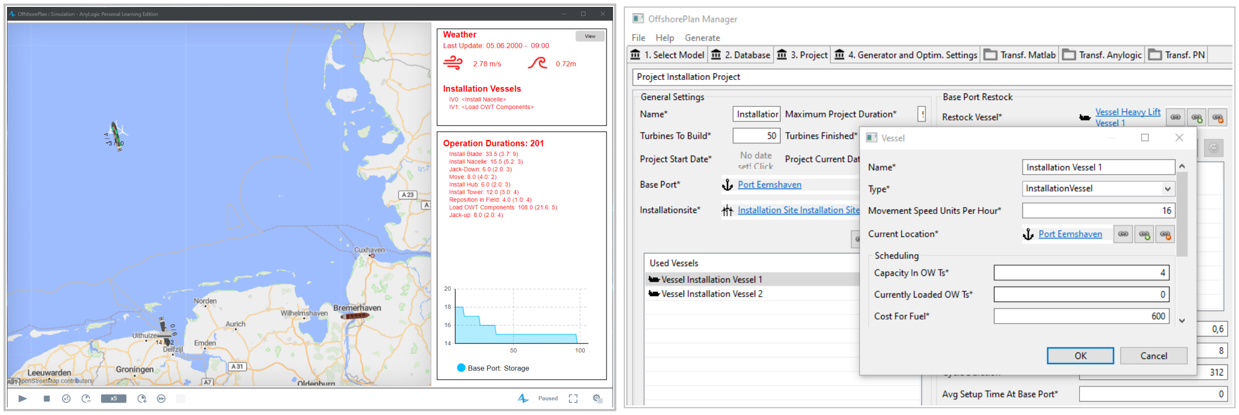

Figure 3: Screenshots of the AnyLogic simulation (left) and the model generation tool (right).

The model mainly covers four types of agents: installation vessels, transport vessels, the base port, and the installation site. Production sites, e.g., Bremerhaven or Cuxhaven, which are depicted in the screenshot, are currently only managed as locations without any internal logic or abilities. The base port agent manages the current component storage and loading bay availability. For example, if the base port only reserves a single bay, only a single vessel can perform loading or unloading operations at a time. The installation site agent only keeps track of finished turbines. The transport vessel follows a predefined resupply cycle, visiting production ports to pick up components and delivering them to the base port for further use. The installation vessels currently follow the conventional installation concept, i.e., they travel between the base port to pick up sets of components and the installation site to perform construction. Therefore, each operation has its specific limits considering the maximum allowed wind speed and wave height. If the current weather conditions exceed either of these maximum values for an operation that the vessel currently conducts, the agent aborts the operation and restarts it as soon as the conditions are met again. Such disruptions result in offshore delays, which induce high costs compared to waiting times at the port (Rippel et al. 2019). This article applies the same restrictions used in previous work, e.g., Rippel et al. (2019), to ensure comparable results.

The vessel agents process weather forecasts provided by the online simulation to avoid such delays. Therefore, the agents use discrete-time Markov Chains to estimate the duration of offshore operations, considering the expected weather conditions and the forecast's uncertainty (refer to Rippel et al. 2019 for a more detailed description of this approach). After estimating each possible duration, the vessels calculate alternative installation cycles, each consisting of a number of loading and installation operations. Therefore, they generate the most efficient cycle for loading and installing one turbine, two turbines, etc., up to their capacity. For example, if the vessel provides the capacity for four turbines, it generates four alternative cycles. These cycles already include the availability of loading bays and currently loaded component sets. For example, if a vessel already has two sets loaded when deciding on the next cycle, the first two alternatives would not include any loading operations. In contrast, the third and fourth would include one or two loading operations, respectively.

While the proposed framework uses these alternative cycles directly as input to spawn child simulation runs, the model provides a local decision strategy to decide for one of these cycles on its own. This strategy applies for all non-cascading runs and as a fallback strategy when the simulation may not spawn new children, i.e., when the maximum depth has been reached. The local decision strategy first calculates all alternatives and selects those with the lowest incurring offshore delays. If several candidates exist, the strategy selects the alternative with the higher number of installed turbines as a tie-breaker. The model implements this decision strategy as a JAVA-Comparator to simplify modifying this strategy if needed.

3.3 Benchmark: Optimization Model

The experiments described in the next section additionally apply the mathematical scheduling model proposed in previous work to benchmark the proposed cascading simulation framework (Rippel et al. 2019). Due to the use of the model transformation framework noted in the last subsection, the experiments can simply generate an additional instance of the scenario for this mathematical model to obtain another reference value for comparison. The model transformations ensure that both instances (AnyLogic and Matlab) receive the same scenario despite their different notations. It has to be noted that the optimization does not (yet) tie into the cascading framework and, consequently, only provides a benchmark for comparison as it uses the same scenario and weather data.

The mathematical model applies a model predictive control scheme to locally optimize all vessels' schedules over a given time interval, usually one or two weeks. Therefore, it applies the same Markov Chain approach to estimate durations under forecasting uncertainty and uses a customized Mixed-Integer formulation to generate optimal plans. It has to be noted that these plans only cover a specific time frame and, thus, the approach can also be considered a local optimization. After generating these plans, the model applies the first hours of the plan and simulates the installation process by verifying each operation against measured, non-forecasted weather conditions. If an operation cannot proceed as planned or all operations have finished, the model starts a new planning iteration by obtaining new forecasts.

The model's objective function instructs the optimizer to install as many turbines as possible within the interval while simultaneously minimizing the incurring costs. The costs consist of fuel costs for movement operations, rental costs for port-side equipment during loading operations, and hourly operational costs for vessels if these are currently offshore. Thus, the optimizer strongly focuses on reducing operating costs.

3.4 Summary and Comparison of Applied Optimization Approaches

This article applies and compares three different decision strategies for the next section's experiment. The main difference between these strategies lies in the optimization scope (local or global) and the primary objective. While all approaches try to minimize the installation time and costs in terms of offshore delays, the mathematical formulation and the simulation's fallback strategy focus on its cost, specifically in terms of offshore delays. These delays occur whenever an installation vessel needs to wait for viable weather conditions offshore. Compared to waiting times in the port, these offshore waiting times or delays incur strongly increased operational costs, e.g., for contractual costs, fuel, personnel, etc., of up to 30% of a vessel's charter rate (Rippel et al. 2019). The focus of these methods on these delays results from the local nature of their decision-making. Both strategies can only decide on the best course of action for the next cycle or time step at each decision point. In contrast, the cascading framework applies historical data and forecasts to simulate each decision's effect on the complete installation project. Consequently, the cascading framework applies a rolling-horizon global optimization instead of rolling-horizon local optimizations. This approach focuses on reducing the entire (global) installation time instead of choosing only faster or cheaper cycles locally.

4 EXPERIMENTAL RESULTS

This section presents the results for applying the presented optimization methods to a realistic scenario presented by Beinke et al. (2017). This scenario aims to install 50 turbines, using the conventional installation concept and a base port in Eemshaven. The experiment applies the same process durations and restrictions summarized in previous work to ensure comparability with other results (Rippel et al. 2019). Table 1 summarizes relevant parameter settings used for this evaluation.

Table 1: Experimental settings.

Parameter	Unit	Values
Start Date (2000)	Month	April, May, June, July, August
Historical Years	Years	20
Turbines to Build	Number	50
Storage Initial/Capacity	Number	20/32
Installation Vessels	Number	1
Vessel Capacity	Comp. Sets	4
Planning Algorithm	Method	Local Simulation, Local Optimization, One Cascade, Two Cascades

The experiment first applies the local mathematical optimization and the simulation's local decision strategies to provide benchmark values. The experiment applies the proposed cascading concept with two settings: first, allowing only a single cascade and, second, using an additional second cascade before falling back to the default decision strategy. The experiment records the overall installation duration and the duration of offshore delays as primary quality criteria. These delays constitute one of the largest cost factors due to continuing operational costs for offshore vessels, e.g., including personnel and fuel costs for energy generation. The experiment includes five different project starting months in 2000 to cover different constellations of good and bad weather. Within these five months, April shows the lowest number of bad weather windows, allowing for a more or less steady installation process. In contrast, August provides comparably unsteady weather conditions, especially as the project extends into September. The remaining months show different mixtures of good and bad periods to assess the efficiency of different methods under various weather conditions. All experiments were conducted using a standard desktop computer with an Intel Core i7-10700 (8 physical cores) and 32GB of RAM. The framework and benchmark simulation use AnyLogic 8.7.2, while the mathematical optimization applies a combination of CPLEX 12.10 and Matlab R2018, using 15 logical threads for the optimization.

Figure 4 shows the installation duration for projects planned with each of the four algorithms and each starting date. The results show that the cascading approach achieves lower project durations compared to both benchmark approaches. On average, across all months, the local decision strategy requires about 3.1 % (54 h), and the optimization requires 2.7 % (47 h) longer. The results also show that this difference decreases for months with a high number of bad weather windows (July, August) for the local optimization. In contrast, the difference remains more or less unchanged for the local decision strategy and the cascading approach. Finally, the results show that the cascading algorithm results in very similar – nearly identical – results, no matter if applying only a single cascade or adding a second one.

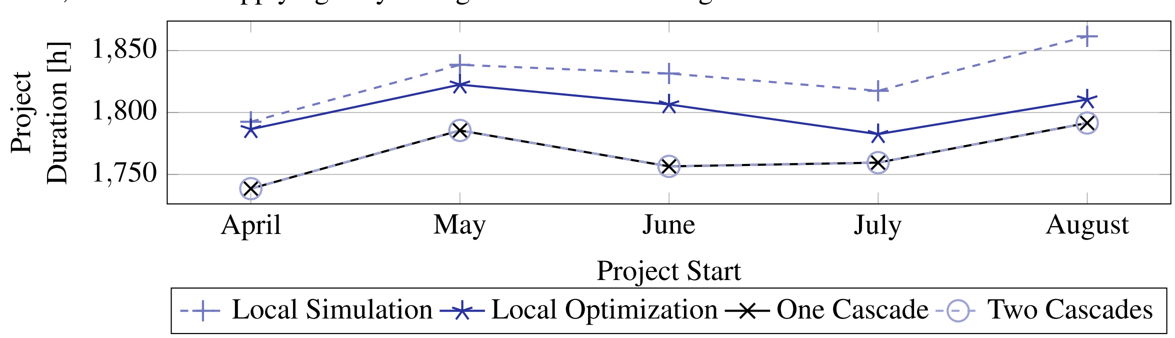

Figure 4: Installation duration for 50 OWTs by method and starting month.

Figure 5 shows the offshore delays, again, for each of the four algorithms and each starting date. The results show that the local optimization achieves the lowest delays with the only exception of April. In this scenario, the cascading approach achieves the lowest delay with only 11.5 hours, compared to 38 hours for the optimization. Nevertheless, the optimizer achieves a sum of delays amounting to 78 hours compared to 225 (one cascade) and 236 (two cascades) hours for the cascading approach, and 158 hours for the local decision strategy. Similar to the first results, the experiment shows that increasing the number of cascades does not result in lower delays or faster installation projects. In contrast, adding a second cascade increases the computational needs exponentially, as each instance creates additional instances for each decision point.

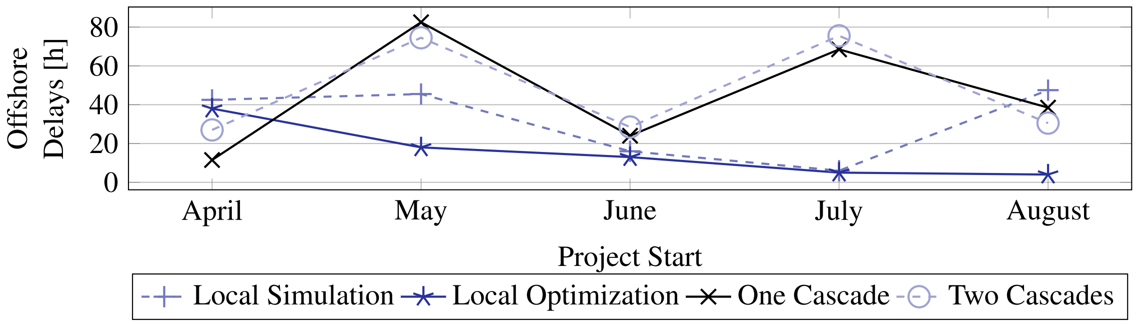

Figure 5: Installation duration for 50 OWTs by method and starting month.

5 DISCUSSION AND FUTURE WORK

In conclusion, the results fall in line with the expected priorities and limitations of each approach. The local optimization and the local decision strategy both reduce offshore waiting times as their primary performance indicator. This difference results from the fact that both algorithms only allow local decisions, either for the current installation cycle or the next few weeks. Both strategies do not estimate the overall project duration beforehand. In contrast, the cascading approach strongly reduces the project duration at higher delays. These delays result from the use of aggregated historical data in the child simulation models. While the other two methods only suffer the uncertainty induced by short-term forecasts, the cascading approach also needs to cope with the historical data's uncertainty.

This article conducted an additional experiment to investigate the influence of the selected cost function on the results. It repeated the same experiment with a modified cost function for the cascading framework. In contrast to the presented experiment, the second experiment favored alternatives with lower offshore delays over shorter installation times. The results were nearly identical. This additional experiment shows that focusing on either aspect achieves a similar tradeoff between delays and the overall duration when using the same historical weather data for the nested simulation runs. It further suggests that the increased delays result from the nested simulation runs' dependence on historical data as the estimated delays and project duration contain the uncertainty associated with the historical data. It can be assumed that the same uncertainty also prevents an additional cascade from achieving better results, as it still uses the same historical data as a base-line for its decision making.

As noted above, the cascading simulation approach achieves high-quality solutions with comparably low computational costs. The results demonstrate that a single cascade already achieves very good results. A complete run with a single cascade took an average of 6 minutes 41 seconds without additional parallelization, while simulation runs with two cascades took an average of one hour and 41 minutes. In comparison, a simulation run without cascades, i.e., only relying on the local decision strategy, took approximately one minute and 14 seconds. The mathematical optimization of the complete installation project took an average of 35 minutes.

In summary, these results show the approach's main advantages and drawbacks: Its ability to simulate the complete project before choosing an alternative allows a globalized optimization, but, in this use case, includes additional uncertainty. Additionally, these experiments demonstrate that the objective function could be exchanged easily, e.g., to provide more sophisticated cost functions that trade off expected costs with the expected installation duration. In this context, future work will investigate ways to include the mathematical optimizer's local plans into the cascading decision-making process. Additionally, future work will investigate ways to reduce the impact of uncertainty related to historical data, e.g., by evaluating different numbers for the included past years or other methods to aggregate this information.

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