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SIMULATION AND OPTIMIZATION OF OPERATIONS FOR OFFSHORE INSTALLATIONS PLANNING USING A MODEL PREDICTIVE CONTROL SCHEME

Daniel Rippel
Nicolas Jathe
Michael Lütjen

BIBA - Bremer Institut für Produktion
und Logistik GmbH at the University of Bremen
Hochschulring 20
28359 Bremen, GER

Helena Szczerbicka

Institute for Systems Engineering
Leibnitz University of Hannover
Welfengarten 1
30167 Hannover, GER

Michael Freitag

Faculty of Production Engineering
University of Bremen
Bibliothekstraße 1
28359 Bremen, GER

ABSTRACT

Wind energy is a promising technology to cover the world's need for sustainable energy production. Nevertheless, the construction of offshore wind farms imposes particular challenges. While about 15% to 20% of the costs for offshore wind farms can be attributed to logistics during the construction, highly dynamic weather conditions render accurate planning difficult. This article presents an approach for the installation planning, which uses the model predictive control scheme to combine short-term control with model-based simulations. The latter is used to optimize over mid- to long-term plans. Besides, the article presents a new approach to incorporate the uncertainties of weather predictions into the operations planning by estimating the expected duration of offshore operations. Results show increased efficiency of generated plans with growing planning horizons, limited by the accuracy of weather forecasts.

1 INTRODUCTION

Wind energy constitutes one of the most promising technologies to cover the world's need for renewable and sustainable energy production. In 2017, wind farms with a capacity of around 52 Gigawatts were constructed worldwide, increasing the total amount of energy produced by wind turbines by approximately 11% to a total of 539 Gigawatts (REN21 2018). Due to higher wind speeds and wind availabilities at sea, offshore wind farms are capable of producing large amounts of energy (Breton and Moe 2009; Sun et al. 2012). As a result, the amount of energy generated by offshore wind farms shows an exponential increase over the last decade (REN21 2018). While offshore wind farms are more capable of providing high amounts of steady energy compared to their onshore counterparts, the construction and operation of offshore wind farms pose particular challenges due to their increased weight and dimensions. In addition, highly specialized and expensive vessels are required for the installation process (Junginger et al. 2004; Rippel et al. 2019). In general, about 15% to 20% of the costs for offshore wind farms can be attributed

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to logistics during the construction process, demonstrating high potentials for optimization (Lange et al. 2012; Dewan et al. 2015; Muhabie et al. 2018). While long-term plans can lead to high cost reductions, uncertainties in forecasting highly dynamic weather conditions at sea can render mid- and long-term plans inaccurate, thus, increasing the risk of additional costs. Consequently, a dynamic planning approach is required, which allows for quickly adapting plans on demand to counteract the financial risks implied by dynamic weather conditions.

In previous work, we identified several planning tasks, which together, make up the overall planning problem for the installation of offshore wind farms. These cover different time horizons and range from an overall long-term capacity planning for vessels and storage, over the production and transport planning of components to the short-term operations planning at sea (Rippel et al. 2019). As most of these problems rely on or provide constraints to the operative planning of installation activities, this article proposes a novel approach for operations planning. Therefore, this approach applies methods from control theory, namely the Model Predictive Control (MPC) scheme (Grüne and Pannek 2017). The aim is to achieve a trade-off between the optimality of mid- to long-term plans and the high reactivity of short-term control, minimizing the risk imposed by changing weather conditions. MPC combines closed-loop control, which retrieves feedback from the controlled system, and model-based, open-loop simulations to determine optimized plans for longer planning horizons. Moreover, the proposed approach include weather dynamics and uncertainties in forecasts during the planning. Thereby, the resulting restrictions are preprocessed to reduce the overall optimization efforts while achieving accurate representations of their influences on the process.

2 OPERATIVE INSTALLATION PLANNING AND PRACTICAL RESTRICTIONS

This section describes the operative installation process for offshore wind farms. It provides information derived from literature as well as information gained through interviews with process experts throughout several previously conducted research projects.

In general, the operative installation process can be divided into three stages (Vis and Ursavas 2016): First, the installation of founding structures and the connection to the energy grid. The second stage comprises the assembly of the top structure. These usually consist of three tower segments, the nacelle, three blades, and a hub. The final stage includes the commissioning of the assembled offshore wind turbines and their ramp-up. In practice, different companies install the top structures and the foundations. Moreover, these two stages are usually performed consecutively, i.e., the installation of top structures only commences after all foundations are installed. This article focusses on the assembly of top structures, although the proposed method can be applied to the installation of foundations without limitations.

As described, the top structures consist of several parts, which have to be assembled sequentially, beginning with the tower, over the nacelle and blades and finishing with the hub. Although different approaches for preassemblies exist in literature, these only have a small impact on the general planning problem, resulting in different restrictions and durations. Studies of the economic effects of preassemblies can be found in Vis and Ursavas (2016) and Sarker and Faiz (2017). During the assembly of each component, the process requires an uninterrupted time window of specific weather conditions, i.e., a maximum wave height and a maximum wind speed for the assembly operation to be conducted. For example, if the assembly takes three hours, wind speeds and wave heights have to remain under specific thresholds for the three hours. Otherwise, the assembly cannot be started or has to be aborted. In literature, there exist different categories of installation concepts. The classical installation concept used in this article assumes that the components, are stored at a base port. Installation vessels, so-called jack-up vessels, pick up sets of components in port and sail for the installation site. After all components are used up, the installation vessel returns to port and proceeds to load the next set of components (Oelker et al. 2017). In contrast, feeder concepts assume that the installation vessel remains stationary at the construction site and specialized heavy-lift vessels take over the transport between the base port or the manufacturing sites and the construction site. For examples of these concepts, see Ait Alla et al. (2017) and Oelker et al. (2018).

Jack-up barges and platforms are suitable to perform all of the mentioned top structure assembly tasks, as they are equipped with cranes. Moreover, they are equipped with retractable pillars, which allow them to shore up on the seafloor, rising themselves several meters above the sea level. After jacking-up, these vessels are generally unaffected by waves, whereas high wind speeds still interfere with crane operations. During the jack-up process, the retractable pillars dig themselves into the sea floor, loosening it during jack-down. As a result, each position can only be used once for a jack-up in practice without risking damage to the foundation or even to the jack-up vessel itself. This implies that the installation vessel has to finish the construction of an offshore wind turbine in a single session. This holds true in practice: Once the installation of a turbine has started, it is usually finished before the installation vessels jacks-down again. If weather conditions prohibit finalizing the turbine, the installation vessel remains in place and waits until the process can continue. As a result, uncertain weather conditions lead to high financial risks associated with the construction of offshore wind farms. According to Meyer (2014), jack-up barges come at charter rates between €70,000 and €145,000 per day, whereby contracts often set different charter rates for the vessel being in port and for being out on the sea. According to the statement of experts in this field, it can be assumed that these costs differ by approximately 30% of the base cost.

3 LITERATURE REVIEW

In the literature, only a few works deal with the installation planning for offshore wind farms. In Rippel et al. (2019) we provided a comprehensive overview of articles in this area over the last years. Even fewer articles explicitly deal with the generation of operative plans for offshore installation activities. This section shortly summarizes the general state of the art and further investigates those articles, explicitly dealing with operations planning. Therefore, approaches in the planning of offshore wind farms can be classified according to their underlying type of model (mathematical simulation/optimization and discrete-event simulation) as well as according to their purpose (evaluation or plan generation/optimization).

For discrete-event-based approaches, there exists no related work, which aims to generate plans for the offshore installation in current literature. All the approaches focus on the simulation part, where the behavior of actors (usually vessels) or a predefined plan is evaluated. Muhabie et al. (2018) present such an approach to compare the effect of deterministic and stochastic assumptions concerning weather conditions throughout their model. Vis and Ursavas (2016) propose a simulation model to evaluate different preassembly strategies and to assess their impact on the overall installation process. Ait Alla et al. (2017) propose a multi-agent-based model to compare the conventional installation concept with feeder concepts, later extending the simulation model in Oelker et al. (2018). Whereas all of these approaches simulate the behavior of vessels and thus, can be used to derive a plan after the simulation finished, they do not include an optimization component to evaluate different plans or configurations. Thus, it can be stated that current discrete-event-based approaches only focus on the evaluation, not on the generation of feasible plans.

On the mathematical side, both types of approaches can be found. The majority of literature in this topic focuses on the generation of plans on different levels of abstraction. Only two models could be identified, which only focus on the evaluation. Thereby, Quandt et al. (2017) propose a mathematical model to evaluate the impact of information sharing of the overall supply chain performance. Beinke et al. (2017) use a mathematical formulation to evaluate cost reductions for resource sharing of involved heavy-lift transport vessels. For the generation of plans, several models using mixed integer linear programming can be identified. Kerkhove and Vanhoucke (2017) apply a heuristic approach to plan the deployment and decommissioning of vessels. Scholz-Reiter et al. (2010) combine a precedence-based job-shop scheduling formulation with a multi-periodic production formulation to derive optimal plans for small scenarios with a daily resolution. The approach was extended in Scholz-Reiter et al. (2011) by heuristics for solving larger instances of the problem. Weather dynamics are considered in form of a randomly generated sequence of weather classes (good, medium and bad weather), restricting the execution of operations. For these classes, the authors propose to estimate likelihood values for each class using stochastic programming. This approach was later extended by Ursavas (2017) to deal with probabilistic weather assumptions. Ait Alla et al. (2013) propose another model, which closely resembles a time-indexed job-shop formulation. For each indexed period of twelve hours, the optimizer determines the number of foundations, cables, and top structures to be build using a predefined vessel configuration. Similar to the approach described before, an ordered set of weather classes is provided to indicate if the corresponding operations can occur within this window. Irawan et al. (2017) propose a bi-objective optimization model, aiming to find a trade-off between minimal construction times and minimal costs. The integer linear programming model thereby relies on identifying timeslots with a daily resolution where the overall offshore operation can start and will finish. Therefore, the optimizer uses predefined, daily weather classes to determine if an operation can commence or not. In cases where the weather gets too bad to conduct an operation, the timeslot is extended by this duration to represent waiting times on a daily basis. This model was later extended and adapted for the decommissioning of offshore wind farms in Irawan et al. (2019).

In terms of a practical application, the generation of a static, holistic plan can be a drawback. Weather predictions become more and more inaccurate with an increasing time horizon, thus rendering the overall plan inaccurate and increasing the risk of miscalculations in terms of operational times and costs. For larger projects, a realistic estimation of weather windows can be unachievable. Furthermore, most approaches combine the installation of top structures, foundations, and cables into a single optimization problem. In practice, these are considered two separate problems, as different companies conduct these tasks sequentially. Another drawback of current approaches is the aggregation of weather conditions to discrete classes. Each assembly operation, e.g., for tower segments or blades, imposes its own restrictions and delays. While most approaches only plan aggregate activities, i.e., installation of top structure or foundation, when sufficient time of good weather is available, Irawan et al. (2017) at least allow operations to commence and wait for good weather by extending the aggregate operations' duration. Nevertheless, this representation still does not regard specific restrictions of delays of the underlying assembly tasks.

In order to retain the advantages of these long-term plans but to reduce the risks of these plans becoming infeasible at later stages of the plan execution, the next section introduces a novel approach for deriving plans using the Model Predictive Control (MPC) scheme. According to Grüne and Pannek (2017) MPC was first introduced in 1963 and has since seen several adaptations, e.g. for robust or stochastic MPCs (Kouvaritakis and Cannon 2016) or for non-linear models (Grüne and Pannek 2017). Thereby, the general scheme underlying all of these adaptations combines short-term feedbacks from the real-world operational system, with model predictive simulations using varying types of system models for longer planning horizons. This article applies the MPC scheme to retrieve optimal short-term plans from simulated, longer planning horizons. Furthermore, it presents a more detailed approach to include weather dynamics and forecast uncertainties.

4 MPC-BASED APPROACH FOR THE INSTALLATION PLANNING

As mentioned earlier, the Model Predictive Control scheme consists of two distinct control loops, which act on different time scales as sketched in Figure 1. The closed-loop thereby receives feedback from the real-world system and provides a control for the system at distinct time instances, denoted as t_i. These controls, in case of this article describing plans for offshore operations, generally cover sampling steps of length T. To obtain these short-term plans, MPC applies a simulation-based open-loop optimization. In contrast to the closed-loop, the open-loop does not receive feedback from the real-world system apart from its initial state but simulates the system's behavior and possible feedback using predictive system models. As the open-loop acts disconnected from the real-world system, longer planning horizons can be simulated to achieve better optimizations over mid- to long-term horizons, resulting in an optimal control sequence. In this article, these planning or prediction horizons are selected as a multiple of the original sampling step and are denoted as $N = P * T$ whereby P describes the length of the planning horizon. After the optimal solution for the mid- to long-term plans is obtained, the first control value, in this case, the plan for the next sampling step t_i is extracted. After execution, the time is shifted, and the real system state is measured, repeating the described procedure until a defined termination condition is matched.

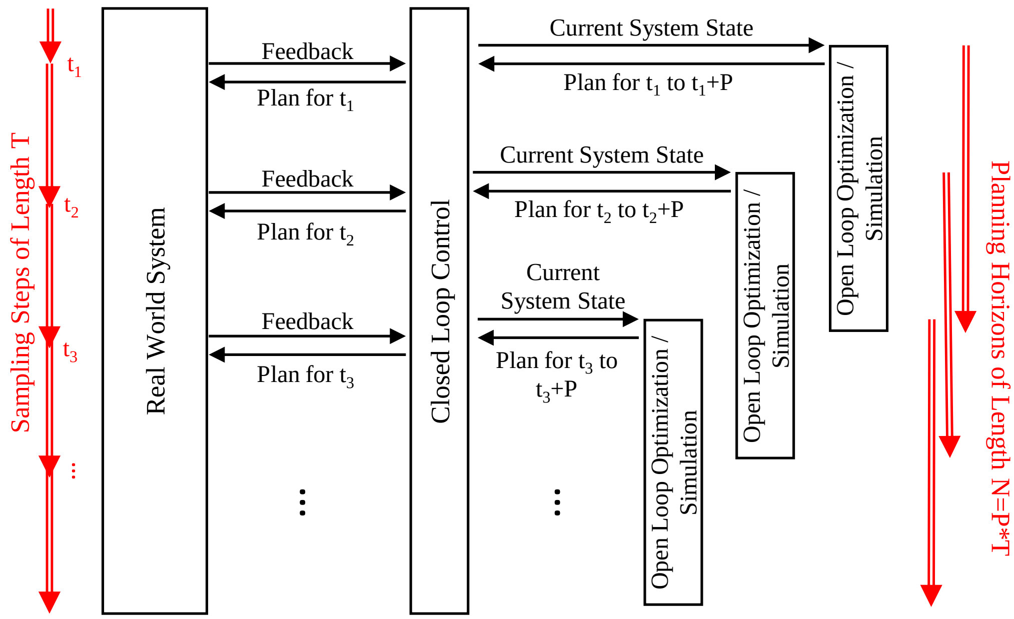

Figure 1: Model predictive control scheme.

Although MPC is usually applied to solve continuous optimal-control problems, the underlying optimization model can be adapted for the optimization of operative plans for the installation of offshore wind farms. As a result, the proposed approach combines both high reactivity to changing conditions while maintaining the advantages of mid- to long-term plans. For example, if T is chosen as one week and $P = 3$ is selected, the open loop would generate an optimal plan that covers $P * T = 3$ weeks at time instance t_1. From this plan, a short-term plan of length $T = 1$ week would be extracted and applied to the real world system by the closed-loop. As a result, the system would progress by one week to the second time instance t_2, and the actual state of the system would be measured and used to initiate the next open-loop simulation. The selection of suitable values for T and P thereby highly depends on the dynamics and control needs of the real-world system, as well as on the quality of the open-loop system model. For a detailed description of the MPC scheme and applications for optimal control problems see, e.g., Grüne and Pannek (2017).

The proposed approach is split up into six consecutive steps, which are repeated for every time instance t_i and cover the closed and open-loop parts of the MPC scheme as given in Figure 2. In the first step, the current state of the system is updated by measuring the state of its real-world counterpart. This information is passed to the open-loop simulation. In a second step, the open-loop simulation preprocesses the obtained weather forecast, to calculate probabilities for every time step (hour) to determine, if an assembly task can be conducted. This is performed for every task, e.g., assembly of the blades, jack-up, or sailing. Using this information, the expected duration of aggregate operations, i.e., port operations, moving between the construction site and the port, and the construction of a top structure, is calculated as a third step. Afterward, an optimized mid- to long-term plan is calculated, simulating a planning horizon of $N = P * T$ time steps (hours) as the fourth step. This plan is passed back to the closed-loop, where a short-term plan is extracted (fifth step) and applied to the real-world system (sixth step). After application, the cycle starts again by retrieving measurements about the state of the plan execution and updated weather predictions.

5 IMPLEMENTATION AND MODEL DESCRIPTION

The following subsections describe proposed methods and models for each of the steps described in the last section, which are suitable for optimizing an operative installation plan, consisting of aggregate operations. This article uses hourly, historic weather information about wind speeds and wave heights in the northern

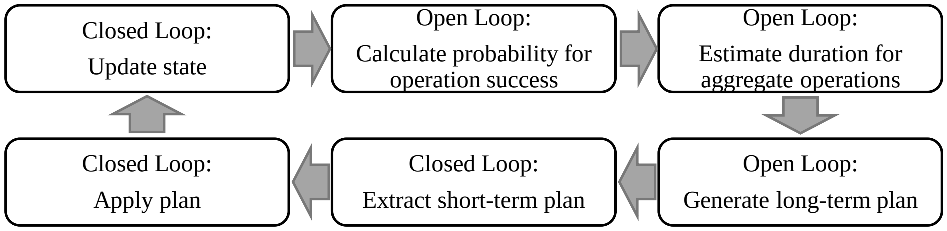

Figure 2: Steps of the MPC-based planning of offshore operations.

sea to emulate the real-world system. Therefore, the recorded information is used in the application part of the planning, while forecasts are generated based on these records for the open-loop simulation. In terms of weather restrictions, this article closely follows the restrictions given in Oelker et al. (2018) and extends those by restrictions gained from process experts.

5.1 Scenario and State

The state comprises all static settings concerning processing times, restrictions, vessel configurations, weather data, and information on the current state of the installation process. Therefore, the current state is summarized by the number of turbines already built, the current time instance, the current location of each vessel (in port or offshore) and its current loading state, i.e. components for how many turbines are currently loaded on each vessel. For the static parameters, Table 1 summarizes the non-aggregate operations considered in this scenario together with their respective duration and weather restriction.

For the plan generation, aggregate tasks are defined as given below. Therefore, an aggregate operation is defined by the cumulative duration of all its non-aggregate operations at the given time step. The procedure to calculate the duration of aggregate operations is further specified later in this section.

1. **Port operations**: Refers to the non-aggregate task *Loading in port*. During the execution of port operations, the installation vessel loads all required components to build one offshore wind turbine.
2. **Move to port**: Directly refers to the non-aggregate task *Move to port/site*.
3. **Move to site**: Directly refers to the non-aggregate task *Move to port/site*.
4. **Install top structure**: The installation of top structures is represented as a sequence of non-aggregate tasks given as *Reposition in Field*, *Jack-up*, *Assemble Tower*, *Assemble Nacelle*, *Assemble Blade*, *Assemble Blade*, *Assemble Blade*, *Assemble Hub*, *Jack-down*.

In addition, to these definitions, the state describes how many installation vessels are used – for this article only a single one – and how much capacity for components these vessels provide, i.e. how many turbines can be assembled in a single offshore trip. Moreover, the state describes the sampling step and planning horizon length, used for closed-loop and open-loop planning.

Table 1: Basic operations with base duration and weather restrictions.

Task name	Base duration in h	Max. wind speed in m/s	Max. wave height in m
Assemble Tower	3	12	*
Assemble Nacelle	3	12	*
Assemble Blade	2	10	*
Assemble Hub	2	12	*
Move to port/site	4	21	2.5
Reposition in Field	1	14	2
Jack-up / Jack-down	2	14	1.8
Loading at Port	2	-	-

* Operation unaffected by wave height as the vessel is jacked-up

5.2 Generation of Weather Forecasts

As only historic measurements of actual wave heights and wind speeds were available, an intermediate step was introduced to emulate weather forecasts as part of the state update. Using this data, increasingly wide intervals of probable weather conditions are generated as illustrated in Figure 3 (left). These forecasts follow the assumption of increasing uncertainties between provided fix points, as shown in Figure 3 (right): At 5 days into the future, the forecast has an uncertainty of 10%. At day 7, it increases to 20%. Until the 14^{th} day, the uncertainty increases to about 50% and grows strongly from this point. These values resemble common weather forecasts as given on weather websites. For the generation of the forecast intervals, this uncertainty is used as a factor, multiplied with the average wave height or respectively the average wind speed for the planning period and is added/subtracted from the measurement as interval bounds.

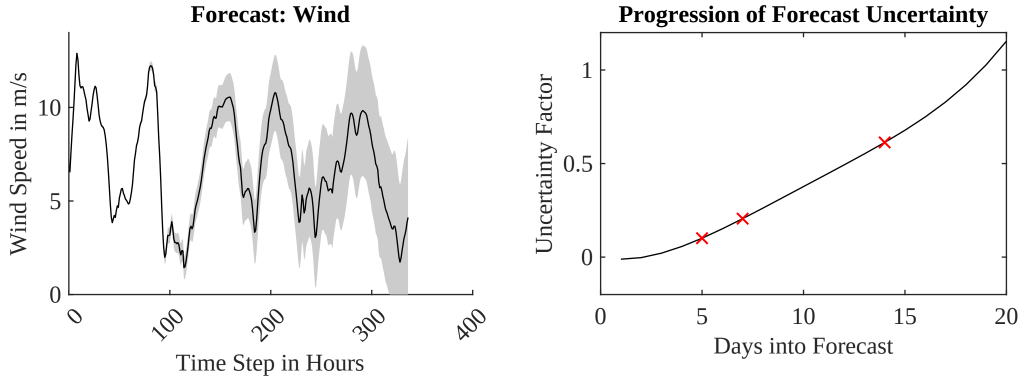

Figure 3: Left: Forecast for the next 336 hours of wind speed with the black line as measurement, and the gray area as the forecast interval. Right: Development of the uncertainty factor for 20 days.

5.3 Calculation of Probabilities for Successful Operations

In preparation of the open-loop simulation, the forecast intervals are converted into a probability matrix. For each non-aggregate operation and each time step (hour), the probability of meeting the weather requirements is calculated. For wind and wave values, the minimum of these probabilities is selected for that particular hour. To calculate the probabilities, the algorithm assumes a uniform distribution within the provided forecast-interval. Consequently, the probability can be expressed as the fraction of the forecast-interval, which is below its respective threshold, given in Table 1. For example, a forecast interval for wind speeds of $[10,14]$ would result in a probability of 1.0 for *Reposition in Field* (max 14), 0.5 for *Assemble Tower* (max 12) and close to 0 for *Assemble Blade* (max 10).

5.4 Estimation of the Duration for Non-Aggregate and Aggregate Operations

In a final preparation step, the duration of aggregate and non-aggregate operations is estimated for each time step (hour) of the planning horizon. Therefore, the algorithm first calculates the expected duration of each non-aggregate operation for each possible starting hour. For aggregate operations, the expected duration is represented as the sum over the sequence of its non-aggregate operations, considering their respective durations and starting dates as given in the gray cells in Figure 4 on the right side. The left side of Figure 4 depicts the process of estimation for the duration of non-aggregate operations. Therefore, the algorithm first retrieves the operations base duration (in this example 3 hours). Starting from the currently selected starting hour (here 0), the algorithm calculates the probability of this time slot for success as product of individual probabilities (given inside the gray time slots). If the probability is higher than a user-specified value ω, the time slot is accepted, and the duration is returned as the index of the last cell. If the time slot is rejected, the window is shifted forward by one hour and reevaluated. In the figure's example, these shifts are shown as rows. ω thereby denotes the minimal probability for a successful operation that a user is willing to accept and thus, allows to generate more robust (higher ω) or higher-risk plans (lower ω).

Hour	0	1	2	3	4	5
Probability	.5	.6	.75	.9	1	1
Duration 3		0.225				
Duration 4			0.405			
Duration 5				0.675		
Duration 6					0.9	

Base Duration = 3 hours ω = 0.75

Hour	0	1	2	3	4	5	6	7	...
Reposition	2	1	1	1	1	3	2	1	...
Jackup	4	3	2	2	2	4	3	2	...
Tower	4	3	3	3	3	4	3	3	...
...	...	...	...	...	...	...	...	...	...

Figure 4: Left: Estimation of the duration for non-aggregate operations. Grey cells provide the joint probability. Rows depict shifted time frames if the probability is too low. Right: Duration of aggregate operations at a given starting time 0. Gray cells mark the selected durations to be summed up.

5.5 Generation of Long-Term Plans

Finally, the open-loop plan is generated using the expected duration for aggregate operations. Therefore, the optimizer simulates different sequences of activities for evaluation. As described earlier, the optimization problem for this step can be implemented as a mixed integer linear program. Therefore, a time-indexed formulation of the problem was chosen as given below. The used variables are summarized in Table 2. In addition to the actual schedule $Y^{job}_{o,k}$, the optimizer uses two utility variables, describing the number of loaded components X^{cap}_k at each hour, and the location Y^{loc}_k of the vessel at each time step.

Table 2: Variables used in the mixed integer linear program.

N	Integer	Length of the planning horizon $N = P*T$
$\mathcal{O}$	$\{1\dots5\}$	Set of all operations as {1: Start Installation, 2: Start Move to Port, 3: Start Move to Site, 4: Start Port Operations, 5: Vessel is Busy}
$D_{o,k}$	Integer	Estimated duration of operation o at hour k.
c_o	Integer	Cost for being offshore per hour
c_m	Integer	Cost for moving between port and construction site per hour
c_p	Integer	Cost for port operations per hour
b	Integer	Benefit for installing a turbine
o,k	Indices	Indices for operations ($o \in \mathbb{N}^+, o \leq \lvert\mathcal{O}\rvert$) and time instances ($k \in \mathbb{N}^+, k \leq N$)
Decision variables:		
X^{cap}_k	Integer	Amount of currently loaded components.
Y^{loc}_k	Binary	Denotes if the vessel is in port (0) or offshore (1)
$Y^{job}_{o,k}$	Binary	Matrix of size $\lvert O \rvert xN$. Denotes for every time step (hour) if a vessel is currently starting an operation or is still busy.

The cost function J aims to minimize the time at sea for each vessel. Thereby, it is defined as the sum of costs for being offshore, fuel costs for moving between the construction site and the base port, and the cost for port operations. For each installed turbine a predefined benefit is subtracted from the cost.

$$J = \sum_{k=1}^{N} Y^{loc}_k * c_o + \sum_{o=2}^{3}\sum_{k=1}^{N} Y^{job}_{o,k} * D_{o,k} * c_m + \sum_{k=1}^{N} Y^{job}_{4,k} * D_{4,k} * c_p - \sum_{k=1}^{N} Y^{job}_{1,k} * b$$

The optimization is subject to the following constraints:

$$\sum_{o=1}^{|O|} Y_{o,k}^{job} = 1 \qquad \forall k \in \{1 \dots N\} \tag{1}$$

$$X_k^{cap} = X_{k-1}^{cap} - Y_{1,k}^{job} + Y_{4,k}^{job} \qquad \forall k \in \{2 \dots N\} \tag{2}$$

$$Y_k^{loc} = Y_{k-1}^{loc} - Y_{2,k}^{job} + Y_{3,k}^{job} \qquad \forall k \in \{2 \dots N\} \tag{3}$$

$$Y_{o,k}^{job} \leq max(0, (N-k) - D_{o,k}) \qquad \forall k \in \{1 \dots N\}; \forall o \in \mathscr{O} \tag{4}$$

$$\sum_{t=k+1}^{k+D_{o,k}-1} Y_{5,t}^{job} \geq Y_{o,k}^{job} * D_{o,k} \qquad \forall k \in \{1 \dots N\}; \forall o \in \{1 \dots 4\} \tag{5}$$

Constraint (1) ensures that the vessel is not involved in more than one activity concurrently. Constraint (2) defines the amount of loaded component as equal to the preceding time step minus one for the installation of a turbine and plus one for port operations. Constraint (3) defines the location of the vessel similarly, referring the movement operations. Constraint (4) ensures that only operations are scheduled, which can be finished within the current planning horizon. Constraint (5) defines that the vessel is busy for the respective duration if an operation is commenced.

5.6 Short-Term Plan Extraction, Application, and State Update

After the long-term plan is generated, the algorithm extracts all aggregate operations that have been started between the current time instance t_i and the closed-loop sampling step $t_i + T$. As the short-term plan relies on started operations, the actual length of these plans can differ. For example, if the last operation finishes some time before $t_i + T$, the plan will end up shorter.

To emulate the application of this plan in the real-world system, each operation is checked against the recorded, non-forecast weather conditions. Therefore, the steps proposed for the duration-estimation are repeated for the actual weather data. This changes the probability matrix to only containing 1 or 0 to indicate if the weather is good enough or not. After calculating the duration matrix, each planned operation is applied sequentially by comparing the planned duration d_e and the real duration d_r as follows: If both durations are *equal*, the algorithm proceeds to check the next planned operation. If the real operation took *longer* than expected, the algorithm evaluates if the next operation can still commence as planned. If not, the plan execution is aborted, and a new closed-loop iteration is initiated. If the real operation was *faster* than expected, the current implementation aborts the plan execution. As described, the primary objective is to minimize offshore times and costs. Therefore, the algorithm derives a new, optimized plan. Nevertheless, other scenarios could be implemented and evaluated to determine the best behavior.

After the plan application, the state is updated. Therefore, the current date, location, amount of loaded components, and the number of built turbines are updated to the last time index of the last applied aggregate operation. Afterward, new forecasts are generated, repeating the cycle given in Figure 2.

6 SIMULATION RESULTS

This section shows the results of the proposed approach as proof of concept. Therefore, the initial state is set to June, 1^{st} 2000, with a single vessel in port, no loaded components, and a capacity of 4. The closed-loop sampling step is set to a week while the open-loop simulation's horizon is varied. An overall time frame of 5 weeks is considered. The approach was implemented in MATLAB r2018 on an office computer (i7-3770K, 8GB RAM). The maximum optimization time was limited to one day. As MATLAB does not support parallelization for mixed integer problems, the results can be improved drastically by choosing a different optimizer. A single optimization never exceeded a CPU load of approximately 13% on a single core.

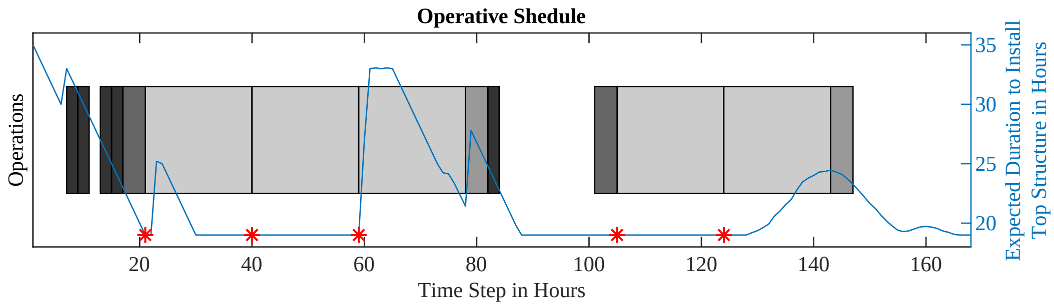

Figure 5: Planning results for the first week of $P = 1$.

The optimizer generates optimal sequences of aggregate operations, as shown in Figure 5. Gray scales depict operations from dark to light as port operations, movement, installation. The blue line shows the expected duration of the installation operation if started at a given time. Red markers indicate the starting hour of planned installation activities. Figure 6 shows the results for different open-loop planning horizons of 1 to 5 weeks ($P = 1$ to $P = 5$). For plans marked with $*$, the optimizer was not able to find the optimal solution in time. As can be seen, this holds particularly true for $P = 4$, where the plans for the last two weeks were strongly sub-optimal. For $P = 5$, the plans were not optimal but close to it. In general, it can be seen that even small planning horizons result in comparably dense and efficient plans. The right side of Figure 6 shows the incurred cost for each scenario (dashed) and the number of finished turbines (solid). It can be seen that the cost, as well as the increase in built turbines, start to flat-out with a planning horizon of approximately three weeks. This can be explained by the currently implemented way to generate weather forecasts. At around two to three weeks, the uncertainty of these forecasts becomes so high, that no more time slots for offshore operations can be determined. Thus, longer planning horizons do not lead to better results, but instead, only increase the computational requirements.

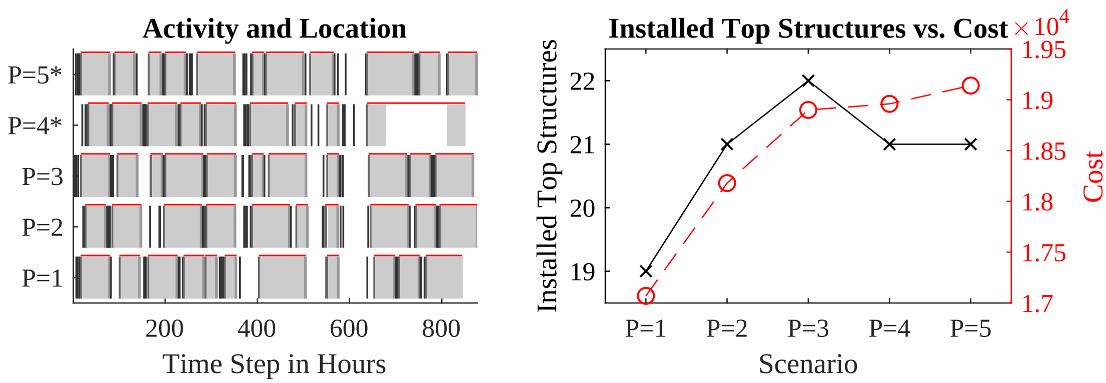

Figure 6: Planning results. Left: Applied operations for different open-loop planning horizons. Red lines additionally indicate offshore times. Right: Comparison of costs (dashed) to finished turbines (solid).

7 CONCLUSION AND FUTURE WORK

This article presents a novel approach for the planning of offshore activities for the installation of offshore wind farms. This approach uses the Model Predictive Control scheme to achieve high reactivity to changing weather conditions during the closed-loop control cycle while allowing for mid- to long-term plan optimization using weather forecasts during the open-loop simulation. Results show that even short planning horizons result in good plans, while long-term plans are restricted by the inaccuracy of forecasts.

Future work will focus on the extension of the optimization model to cover additional planning tasks as sketched in Rippel et al. (2019). Moreover, different strategies to compute weather forecasts and to estimate the duration of operations will be evaluated to quantify the impact of involved uncertainties on the overall operations planning. For example, Guo et al. (2017) propose a fuzzy-based approach to estimate the duration of offshore projects using a so-called *empirical productivity loss*, or Leontaris et al. (2016) propose a probabilistic method to provide more accurate forecasts. Besides mathematical optimization, discrete-event simulation-based approaches for the stated planning tasks will be implemented and evaluated to determine a combination of approaches to achieve the best results for specific tasks. In terms of the integration of these planning approaches with a real-world system, methods from the area of *Dynamic Data Driven Application Systems (DDDAS)* (Blasch et al. 2018) will be evaluated to enable integration with existing planning systems, as the underlying scheme is similar to the MPC scheme.

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AUTHOR BIOGRAPHIES

DANIEL RIPPEL is a research scientist at BIBA – Bremer Institut für Produktion und Logistik GmbH at the University of Bremen. He holds a Diploma degree in Computer Sciences from the University of Bremen. His research interests include modeling and simulation of logistic systems, the development of domain–specific modeling methods, as well as the application of prediction techniques from statistics and machine learning. His e–mail address is rip@biba.uni–bremen.de.

NICOLAS JATHE is a research scientist at BIBA – Bremer Institut für Produktion und Logistik GmbH at the University of Bremen. He received the B.SC. and M.Sc. degrees in industrial mathematics from the University of Bremen, Germany, in 2014 and 2018, respectively. His research interests are in digital signal processing and in developing deep learning solutions both in various application fields. He furthermore develops algorithms for different types of indoor localization techniques. His e–mail address is jat@biba.uni–bremen.de

MICHAEL LÜTJEN heads the department of Data Analytics and Process Optimization at BIBA – Bremer Institut für Produktion und Logistik GmbH at the University of Bremen. He holds a Ph.D. and a master's degree in Production Engineering from the University of Bremen. His research interests include modeling and simulation of complex production and logistics scenarios. His e–mail address is ltj@biba.uni–bremen.de.

HELENA SZCZERBICKA is a full professor at the Leibniz University of Hannover, faculty of electrical engineering and Computer science. Her research interests focus on modeling, simulation, and optimization. She is active on the Board of Directors of the Society of Modelling and Computer Simulation International SCS. Her e–mail address is hsz@sim.uni-hannover.de.

MICHAEL FREITAG is a full professor at the University of Bremen and Director of BIBA – Bremer Institut für Produktion und Logistik GmbH. He holds a Diploma degree in Electrical Engineering and a Doctoral degree in Production Engineering. His research interests include modeling, simulation, and optimization of complex production and logistics systems, the development of planning and control methods for logistic processes, and the automation of physical material flows through robots and flexible transport systems. His e–mail address is fre@biba.uni–bremen.de.