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SIMULATION-BASED ANALYSIS OF ONSHORE WIND FARM INSTALLATION STRATEGIES

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ABSTRACT

Wind energy constitutes a main contributor to clean and renewable energy. While the offshore sector has received much attention from research and industry, onshore wind farms still make up the largest share of installation projects. Thereby, onshore installations retain similar wind speed restrictions as their offshore counterparts but additionally introduce limits and wait time restrictions between installation operations. This article proposes extending a planning method initially designed for offshore wind farms to cover these additional requirements and proposes a simulation model capable of evaluating the resulting plans. The results show that the extended approach prevents violations of these requirements, mitigates the influence of weather forecast uncertainties, and provides efficient plans for installation operations.

1 INTRODUCTION

Over the last decade, the worldwide installed wind capacity nearly quadrupled from 238 gigawatts (GW) in 2011 to 845 GW in 2021 (REN21 2022). While offshore wind energy gains increasing importance due to its higher potential, the largest share, approximately 81 GW of the added 102 GW capacity in 2021, accounts for onshore installations (IRENA 2022). By the end of 2021, 135 countries aim to increase the share of renewable energy production or even target a 100% coverage with renewables (REN21 2022). For example, in 2022, Germany revised its renewable energy laws, increasing the targeted share to 80% of its yearly consumption by 2030. Recent laws increased the targeted installed capacity to 115 GW by 2030 (160 GW by 2040) and aim to achieve a coverage of 2% of Germany's land area by 2030 (currently 0.9%).

By 2021 Germany had an installed wind power capacity of about 63.8 GW (BMWK 2022). Accordingly, the current capacity needs to be nearly doubled by 2030, resulting in a required annual increase of approximately 6 GW. The average yearly increase amounted to 3.3 GW between 2011 and 2021. This historical development, paired with the new targets, indicates an increasing demand for installation and repowering projects over the following years. Current turbines have average hub heights of about 140 meters, with some reaching 200 or more meters and easily weighing several hundred tons. Accordingly, the onshore sector will require new, efficient methods for installation logistics to achieve the targeted goals.

1.1 Research Contribution

This article provides a scheduling approach for onshore installations capable of providing operative support by including weather forecast uncertainties and interdependencies between installation operations. The approach was originally developed for offshore wind farm installations, which impose different constraints on the installation process. Therefore, this article modifies the original approach to include specific requirements and constraints only applicable to onshore wind farm installations. In general, the state of the art provides limited literature on the onshore installation process. During the literature review, only a single method could be identified that includes weather forecasts in the planning/scheduling. In contrast, other methods for weather-dependent construction planning usually rely on historical or generated weather data. Similar to the original offshore approach, the identified method uses forecast data to estimate the duration of operations, e.g., due to work stoppage, but does not consider weather-related constraints between operations, which are imposed during onshore installations.

1.2 Process Description

The process of installing onshore and offshore wind turbines is fairly similar. In both cases, the installation process usually separates the preinstallation of the first segments (foundations for offshore turbines or the first tower segment for onshore turbines) from the main installation. This separation results from requiring different machinery and personnel, e.g., tools to prepare the floor/sea bed, cable laying, etc. During the main installation, engineering teams assemble the turbines bottom-up, i.e., first, the tower (segments), the nacelle and hub, and finally, the blades. The main installation requires large cranes to conduct operations at over hundred-meter heights. As high wind speeds interfere with crane operations at such heights, companies impose wind speed limits. For example, the crane may only install a nacelle if the wind speed remains under 7 m/s for the whole operation. The operation needs to be aborted or cannot be started if installation crews expect the wind speed to exceed this limit or if it actually exceeds the limit during the operation.

In contrast to the offshore area, onshore installations impose additional "wait-time" requirements that regulate the maximum waiting time and maximum wind speed limit between operations. The first requirement demands that only a specified period can pass between the end of two operations. For example, the nacelle and the drive train need to finish installation within 30 days of finishing the last tower segment. The second requirement introduces wind speed limits that the process needs to retain between finishing two consecutive operations. For example, after finishing the last tower segment, the wind speed should not exceed 5 m/s until the nacelle has been completed. Depending on the current component, these requirements may be bypassed by additional safety devices to stabilize the installed components, which, however, impose additional costs. As the models used in this article do not include cost parameters, the article interprets these additional requirements as hard constraints, i.e., a component will not be installed if the models expect the wind speed to exceed the specified limit.

The weather limits and operating times listed in Table 1 result from inquiries to installation companies. The values in Table 1 are close to real-world limits but have been averaged and slightly adapted to obfuscate company-specific information.

Table 1: Operating times, wind speed limits and max. waiting times for onshore installation operations.

Operation	**Duration**	**Crane Wind Limit**	**Op. Height**	**Max. Wind Speed since last Op.**	**Ref. Operation and Max. Waiting Time**
1. Tower (Mid. 2)	2 h	9.5 m/s	70 m	-	- / -
2. Tower (Mid. 3)	2 h	9.5 m/s	100 m	20 m/s	- / -
3. Tower (Top)	2 h	9.5 m/s	133 m	10 m/s	- / -
4. Nacelle	2 h	7.0 m/s	135 m	5 m/s	3 / 30 days
5. Drive Train	4 h	7.0 m/s	135 m	3 m/s	3 / 30 days
6. Hub	4 h	7.0 m/s	135 m	-	5 / 21 days
7. Blades	7 h	7.0 m/s	135 m	-	5 / 21 days
8. Move to next site	60 h	-	10 m	-	- / -

2 LITERATURE REVIEW

While the demand for onshore wind farms has consistently increased over the last decade, research has not yet adapted well to this field. A structured literature analysis by searching within the engineering sciences on science direct with the terms `(onshore ∧ wind farm ∧ installation ∧ ¬ offshore)` over the last ten years (2013–2023) resulted in a total of 114 publications. Categorizing these articles according to their title and abstract places them roughly in the categories shown in Figure 1.

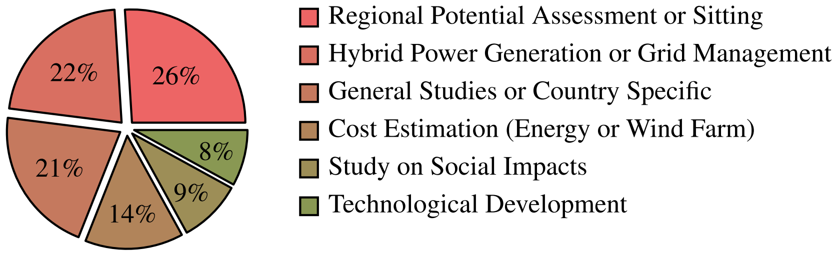


Figure 1: Distribution of published articles.

Broadening the search using google scholar revealed one article explicitly describing a method for the planning of onshore installations using weather forecasts. Mohamed et al. (2021) describe a hybrid simulation framework (discrete and continuous) that uses a set of rules, e.g., wind speed > 14 m/s results in work stoppage, and 14 day weather forecasts to estimate the duration of operations. This method relies on a daily replanning to compensate for weather uncertainties and does not include the previously described requirements between installation operations. Similar approaches to estimate weather induced production losses purely using historical datasets or weather generators can be found in different construction areas, e.g., for onshore wind farm installations (Guo et al. 2017; Atef et al. 2010) or highway construction (Pan 2005; Apipattanavis et al. 2010).

While most of these construction related methods focus on the estimation of production loss in terms of project delays, planning methods from the offshore installation area cover a broader spectrum of applications relating to schedule generation. Similar to the installation process of onshore wind farms, only a few articles consider installing offshore wind farms, compared to other areas like the maintenance planning (Vis and Ursavas 2016). The majority focus on the optimization or evaluation of historical processes, e.g., by proposing ways to simulate weather conditions (Muhabie et al. 2018), evaluating different installation concepts (Vis and Ursavas 2016), or by providing optimized fleet mixes (Ait Alla et al. 2013). Some articles consider support processes or resources like storage spaces or the resupply of components. Beinke et al. (2017) describe a simulation study on resource sharing between different installation projects. Rippel et al. (2020) describe a mathematical model to determine optimal resupply cycles. Nevertheless, several articles provide scheduling models for the commissioning of vessels (Kerkhove and Vanhoucke 2017) or the operations planning (Irawan et al. 2019; Ursavas 2017). Except for a single approach, all of these simulation or optimization models assume that the weather is already known during the planning stages. Consequently, these approaches offer support for strategic decisions, e.g., when to start an installation project using historical data. In contrast, Rippel et al. (2019) propose an approach to provide decision support during the installation by using weather forecasts instead of historical data. The article at hand extends this approach for the scheduling of operations in the onshore context.

3 SCHEDULING APPROACH AND BENCHMARK

As shown in the literature review, only a single approach tackles the challenge of weather forecast uncertainties for the scheduling of installation operations. As noted, the approach was developed for the installation of offshore and not onshore wind farms. The main differences lie in the use of aggregated operations and the lack of a way to include the onshore-specific requirements of maximum waiting times and weather limits between operations. Consequently, this section first briefly describes the original approach and its steps. A detailed description can be found in Rippel et al. (2019). Afterward, it describes the modifications necessary to apply the approach to onshore projects. Table 2 provides an overview of the parameters, indices, and variables used in this section.

Table 2: Nomenclature.

Indices:		
$t \in J$	$\mathbb{N}^+$	Max. number of turbines (jobs) that should be scheduled in an iteration.
$o \in O$	$\mathbb{N}^+$	Number of operations.
$k \in N$	$\mathbb{N}^+$	Planning horizon in hours ($N = P \cdot T$).
$w_o \in W_o$	$\mathbb{N}^+$	Index of time window w_o for operation o. These windows cannot exist between the end of operation o and the end of its predecessor $o-1$.
Parameters:		
$OP_o^{duration}$	$\mathbb{N}^+$	Duration of operation o.
$OP_{o,k}^{start}$	Binary	If operation o can start at instance k.
OP_o^{ref}	$[1\ldots(o-1)]$	Reference to a previous operation that determines the maximum wait time.
OP_o^{wait}	$\mathbb{N}^+$	Maximum time to finish installing after the reference operation has finished.
$OP_{o,w_o}^{wndStart}$	$\mathbb{N}^+$	Start of time windows that cannot take place between operations o and $o-1$.
OP_{o,w_o}^{wndEnd}	$\mathbb{N}^+$	End of time windows that cannot take place between operations o and $o-1$.
M_i	$\mathbb{N}^+$	Big-M. Uses $M_1 = 10$, $M_2 = N + 50$, and $M_3 = N + max(OP^{wait})$
Decision Variables:		
$X_{t,o,k}^{start}$	Binary	Determines if an operation o for turbine t starts at instance k
Dependent / Support Variables:		
$Y^{makespan}$	$\mathbb{R}^+$	Makespan, i.e., end time of the last operation within the plan.
$Y_{t,o,k}^{end}$	$\mathbb{R}^+$	End time of operation o for turbine t that started at instance k.
$X_{t,o,w}^{wndAfter}$	Binary	Denotes if operations o and $o-1$ finish after a window w for turbine t.
$X_{t,o,w}^{wndBefore}$	Binary	Denotes if operations o and $o-1$ finish before a window w for turbine t.
$X_{t,o,w}^{wndPlan}$	Binary	Denotes if operation o or $o-1$ has not been scheduled for turbine t.

3.1 General Approach

The general approach uses rolling horizon planning to mitigate the influence of weather forecast uncertainties. It follows a model predictive control scheme and, thus, consists of two control loops. The "outer" closed-loop ties into the real-world system or a simulation model of that system. This loop obtains updated information, like weather forecasts or progress information on the installation project. This loop derives a plan that covers T hours (step-width) and forwards it to the real-world system for execution. Internally, the approach uses a so-called open-loop optimization to determine optimal plans for $N = P \cdot T$ hours, with N being the planning horizon and P denoting the number of planning periods. The open-loop uses a model of the real-world system that covers the effects of selected actions, their interconnections (e.g., operation two is always followed by operation three), and information on the progression of time (e.g., weather forecasts). Overall, the approach consists of three steps:

In the first step, the approach measures the current state of the installation process and preprocesses weather information by converting them into discrete operation times. Hence, it assumes that forecasts consist of a minimum and maximum expected wind speed for each hour within the planning horizon N. The approach generates a Markov Chain for each sequence of operations. It performs a stochastic simulation for each possible starting hour and each sequence by updating the transition matrix between states (hours of an operation) depending on the probability that the wind speed will remain below or above the operation's, i.e., crane's threshold. These updates continue until the probability of reaching the final state exceeds 99.7%. The approach returns the number of updates (hours progressed in the planning horizon) as the sequence's

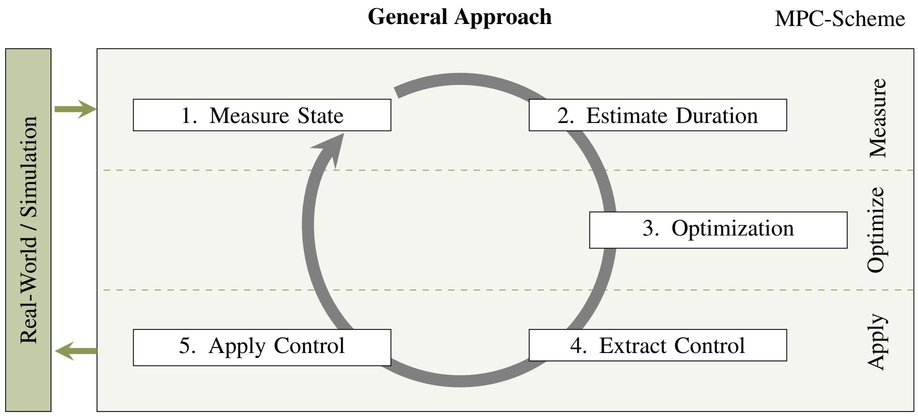


Figure 2: Steps of the general approach (Rippel et al. 2019).

duration. The original approach constructs a single Markov Chain for the complete installation process as the stochastic simulations include waiting times between operations.

During the second step, the approach uses this discretized information to obtain an optimal plan. The original model uses a time-indexed formulation to handle the time-dependent operation times. For example, an installation started at hour 10 might take 19 hours, while an installation started one hour later might take 26 hours due to adverse-weather windows. The last step extracts a plan of approximately T hours from the open loop's result and forwards it to the real-world system for execution. After the execution, the cycle starts again by obtaining updated information and devising a new plan.

While the general approach could be applied to installing onshore wind farms, it requires several modifications to include the onshore-specific requirements. The offshore area does not impose requirements between operations, allowing several steps to be aggregated into a single, aggregated installation operation. In the onshore context, this aggregation is impossible as interdependencies between operations play a vital role. Consequently, the adapted approach does not rely on process chains but treats each operation separately. As a result, it extends the conversion of weather forecasts into operation durations by an additional step: This new step provides a binary matrix $OP^{start}_{o,k}$ that denotes if an operation can start at this hour (1) or if it would incur additional delays (0) for each operation o and each hour $k \leq N$. Consequently, the optimization model can work with discrete "can start / can not start" information instead of variable operation times. Additionally, the adapted approach preprocesses the weather forecasts to determine weather windows that cannot exist between every two consecutive operations. Therefore, the preprocessing uses the minimum and maximum wind speed in the forecast, calculates the probability that the wind speed will be under the limit and compares this probablility to a predefined threshold ω. It adds the time instance to such an operation-dependent window w_o if the probability falls below the threshold.

As a result of treating each operation separately and introducing additional requirements regarding waiting times and weather limits between operations, the open-loop optimization model used in the original approach becomes obsolete. The following section describes a new optimization model that, first, treats each operation separately and only allows operations to start when there is no delay. Second, the new model introduces constraints for the maximum waiting time between specific operations and variable wind speed limits between consecutive operations.

3.2 Adapted Optimization Model

Like the original model, the proposed model uses a time-indexed formulation, which allows the integration of weather windows and limitations on if an operation can start or not. Therefore, the model uses a single decision variable $X^{start}_{t,o,k}$ that denotes for each turbine t if an operation o starts at time instance k. Moreover, $Y^{makespan}$ records the current makespan, i.e., when the latest operation ends. This value depends on the variable $Y^{end}_{t,o,k}$ that records the end time of each operation. The model uses three additional binary support variables to handle weather limits between operations: $X^{wndBefore}_{t,o,w_o}$ denotes if the operation o and $o-1$ for turbine t finished before the start of the time window w_o. Similarly, $X^{wndAfter}_{t,o,w_o}$ denotes if both operations finish after the end of the window. In addition, $X^{wndPlanned}_{t,o,w_o}$ records if both operations will be started in the current plan. The adapted model tries to minimize the overall makespan but obtains a negative incentive for each final operation o_{last} in the plan.

$$min\Big(Y^{makespan} - \sum_{t=1}^{T}\sum_{k=1}^{N} X^{start}_{t,o_{last},k} \cdot N\Big)$$

Constraint (1) assures that the makespan is always larger or equal to the last operation's end time, and Constraint (2) records the finish time of each operation. Constraint (3) ensures that each operation is only scheduled once, while Constraint (4) only allows operations to start if the discretized weather data in $OP^{start}_{o,k}$ allow it. Constraint (5) ensures that only a single activity occurs at instance k.

$$Y^{makespan} \geq \sum_{k=1}^{N} Y^{end}_{t,o,k} \qquad \forall t \in J, o \in O \tag{1}$$

$$Y^{end}_{t,o,k} = X^{start}_{t,o,k} \cdot \Big(k + OP^{duration}_{o} - 1\Big) \qquad \forall t \in J, o \in O, k \in N \tag{2}$$

$$\sum_{k=1}^{N} X^{start}_{t,o,k} \leq 1 \qquad \forall t \in J, o \in O \tag{3}$$

$$X^{start}_{t,o,k} \leq OP^{start}_{o,k} \qquad \forall t \in J, o \in O, k \in N \tag{4}$$

$$\sum_{t=1}^{T}\sum_{o=1}^{O} X^{start}_{t,o,k} \leq 1 \qquad \forall k \in N \tag{5}$$

Besides the start of operations, the model denotes if an operation is still progressing using Constraint (6). Therefore, it adds an extra "busy" operation to the binary decision Variable X^{start} and ensures that the cells between $k+1$ and $k+OP^{duration}_{o}$ are set to one if o starts at instance k.

$$Y^{start}_{t,o,k} \cdot (OP^{duration}_{o} - 1) \leq \sum Y^{start}_{t,|O|+1,[k+1;k+OP^{duration}_{o}]} \qquad \forall t \in J, o \in O, k \in N \tag{6}$$

Constraints (7) and (8) ensure that the installation of a turbine t can only start after the previous turbine $t-1$ has finished. Therefore, the first constraint ensures that the first operation of t needs to end after the last operation o_{last} of $t-1$ ends. The second constraint implies that if the first operation of t starts (right-hand side), the first operation in t and the last operation in $t-1$ have to be started, not just one of them. The model uses this type of Big-M formulation to introduce the "if the operation has started" part, which allows to optimizer not to schedule all turbines if it cannot fit them into the planning horizon.

$$\sum_{k=1}^{N} Y^{end}_{t-1,o_{last},k} - \sum_{k=1}^{N} Y^{end}_{t,1,k} \leq M_2 \cdot \Big(1 - \sum_{k=1}^{N} X^{start}_{t,1,k}\Big) \qquad \forall t \in J \tag{7}$$

$$\sum_{k=1}^{N} Y^{start}_{t,1,k} - \sum_{k=1}^{N} Y^{start}_{t-1,o_{last},k} \leq M_2 \cdot \Big(1 - \sum_{k=1}^{N} X^{start}_{t,1,k}\Big) \qquad \forall t \in J \tag{8}$$

Similarly, Constraints (9) and (10) enforce that each operation o needs to finish after its previous operation $o-1$ and that both operations have been scheduled, if o is scheduled. Constraint (11) enforces that o takes place within the time frame given by OP^{wait}_{o}, starting at the end of reference operation OP^{ref}_{o}.

$$\sum_{k=1}^{N}\Big(Y^{end}_{t,o-1,k} - OP^{duration}_{o-1} - 1\Big) - \sum_{k=1}^{N}\Big(Y^{end}_{t,o,k} - OP^{duration}_{o} - 1\Big) \leq M_2 \cdot \Big(1 - \sum_{k=1}^{N} X^{start}_{t,o,k}\Big) \quad \forall t \in J, o \in O \tag{9}$$

$$\sum_{K=1}^{N} Y_{t,o,k}^{start} - \sum_{K=1}^{N} Y_{t,o-1,k}^{start} \leq M_2 \cdot \left(1 - \sum_{k=1}^{N} X_{t,o,k}^{start}\right) \quad \forall t \in J, o \in O \quad (10)$$

$$\sum Y_{t,o,k}^{end} - \left(\sum_{k=1}^{N} Y_{t,OP_o^{ref},k}^{end} + OP_o^{wait}\right) \leq M_3 \cdot \left(1 - \sum_{k=1}^{N} X_{t,o,k}^{start}\right) \quad \forall t \in J, o \in O \quad (11)$$

Constraints (12) – (16) ensure that the optimizer does not place wind-sensitive operations around the discretized time windows that violate the maximum wind requirement for waiting times. Therefore, the parameters $OP_{o,w_o}^{wndStart}$ and OP_{o,w_o}^{wndEnd} determine the time instances where each window for each operation w_o starts and ends. Constraint (12) ensures that the binary support variable $X^{wndAfter}$ can only turn to one if operation o starts after the time window w_o and $o-1$ ends at or after the end of this time window. In contrast, Constraint (13) ensures that the binary support variable $X^{wndBefore}$ only turns one if both operations finish before the start of the time window w_o. Moreover, Constraints (14) and (15) ensure that the binary support variable $X^{wndPlan}$ assumes a value of one if, and only if, one or both operations o and $o-1$ have not been scheduled, i.e., their start and end time are zero. Finally, the last Constraint (16) ensures that only one of the three support variables assumes a value of one. Thus, either the operations are not planned, finish before each time window or finish after it.

$$\sum_{k=K_1}^{N} X_{t,o-1,k}^{start} + \sum_{k=K_2}^{N} X_{t,o,k}^{start} - 2 \geq -M \cdot \left(1 - X_{t,o,w_o}^{wndAfter}\right) \qquad \forall t \in J, o \in O, w_o \in W_o \qquad (12)$$

$$\text{with } K_1 = OP_{o,w_o}^{wndEnd} - OP_{o-1}^{duration} - 1$$

$$\text{and } K_2 = OP_{o,w_o}^{endEnd} + 1$$

$$\sum_{k=1}^{K_1} X_{t,o-1,k}^{start} + \sum_{k=1}^{K_2} X_{t,o,k}^{start} - 2 \geq -M \cdot \left(1 - X_{t,o,w_o}^{wndBefore}\right) \qquad \forall t \in J, o \in O, w_o \in W_o \qquad (13)$$

$$\text{with } K_1 = OP_{o,w_o}^{wndStart} - OP_{o-1}^{duration} - 2$$

$$\text{and } K_2 = OP_{o,w_o}^{wndStart} - OP_{o}^{duration} - 2$$

$$\sum_{k=1}^{N} X_{t,o-1,k}^{start} + \sum_{k=1}^{N} X_{t,o,k}^{start} + X_{t,o,w_o}^{wndPlan} \leq 2 \qquad \forall t \in J, o \in O, w_o \in W_o \qquad (14)$$

$$\left(1 - \sum_{k=1}^{N} X_{t,o-1,k}^{start}\right) + \left(1 - \sum_{k=1}^{N} (X_{t,o,k}^{start}\right) \leq M_1 \cdot X_{t,o,w_o}^{wndPlan} \qquad \forall t \in J, o \in O, w_o \in W_o \qquad (15)$$

$$X_{t,o,w_o}^{wndAfter} + X_{t,o,w_o}^{wndBefore} + X_{t,o,w_o}^{wndPlan} = 1 \qquad \forall t \in J, o \in O, w_o \in W_o \qquad (16)$$

Overall, the new model ensures that the optimizer adheres to the requirements regarding waiting times and weather limits between operations that are unique to onshore installations. While the time-indexed formulation decreases the model's efficiency, it allows a strict definition of time windows and a simple way of modifying the optimizer's behavior. For example, the current implementation allows the previous operation to finish at the last hour of a blocked weather window. It only tracks the weather conditions after finishing $o-1$ to the finishing hour of o. This behavior could be modified quickly, e.g., to require both operations to start after a time window, which provides great flexibility to adapt this formulation to practical needs.

3.3 Benchmark Algorithm – Local Search

As the state of the art offers no other methods to handle weather forecast uncertainties, this article uses a benchmark that assumes the weather data to be known. This benchmark approach has the advantage that the simulation experiments can assess the impact of (a) using a rolling horizon for this particular planning problem and (b) weather forecast uncertainties on the planning results.

The benchmark approach consists of a local search algorithm repeatedly determining a sequence of operations to finish each turbine as quickly as possible. As no constraints exist between turbines, and the modeled problem assumes all requirements to result in either "build" or "don't-build" decisions, the approach should result in an optimal schedule. This assumption holds as long as no trade-offs exist, e.g., by introducting costs or penalties for constraint violations.

Similar to the rolling horizon approach, the benchmark first converts weather data into a binary array that denotes if an operation can start at a given hour based on the crane wind limits. Compared to the rolling horizon approach, the benchmark uses historical measurements without forecast uncertainties. Then, it places each operation o at the first possible time slot. After placing an operation, the benchmark checks if this operation o adheres to the maximum waiting time and maximum wind requirements. If it does, the algorithm accepts the operation and moves on to the next. If an operation violates one or both of these constraints, the algorithm rejects operation o, backtracks to the last operation $o-1$ and shifts it to the next possible time slot. Afterward, it reevaluates the requirements for the new placement of $o-1$. Again, this reevaluation can result in a rejection, which results in backtracking to operation $o-2$. Figure 3 shows an example of this process.

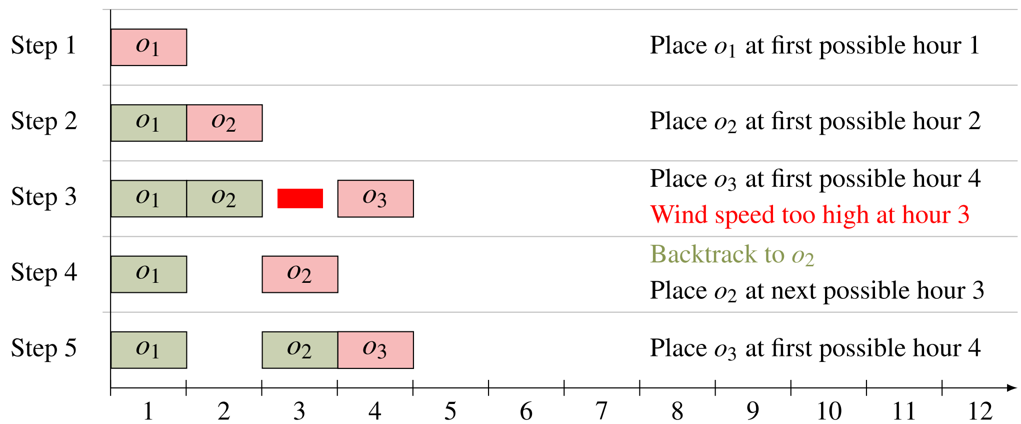


Figure 3: Example of the benchmark approach's search strategy.

The benchmark algorithm always backtracks to the last operation if one or both inter-operation requirements have been violated. This results from the nature of these requirements. The first requirement demands both operations to finish within a specific time from each other. As the algorithm already picks the first possible time slot for the second operation, it needs to shift the first one forward to prevent a violation. Similarly, the second requirement demands that the wind speed does not exceed a specific limit between the end of both operations. As its impossible to move the second operation forward, the only option is to postpone the first operation until after the adverse-weather window.

4 SIMULATION MODEL

The above planning methods use historical weather data and/or forecasts to devise a plan to install a wind farm. While the benchmark algorithm uses real-world weather measurements, the described rolling horizon method uses forecasts and, thus, might provide plans that do not strictly adhere to the imposed requirements. This article uses a simulation model to execute and verify if these plans comply to all the requirements. Accordingly, the current model does not disrupt the plan execution if any of the requirements are violated but instead records such violations to assess if the provided plan contains errors. Thus, the current model does not implement any recourse actions.

The simulation model shown in Figure 4 (a) has been implemented in AnyLogic 8.7.11 as an agent-based simulation. Apart from the main agent that represents the models environment, the model consists of two types of agents: the crane agent and a specified number of turbine agents. Moreover, the simulation relies on a standard JAVA class to describe the initial scenario, e.g., the simulation's starting date, the number of turbines to be built, and the plan to execute. On startup, the main agent reads this scenario description from a JSON file, instantiates the appropriate number of turbine agents and synchronizes the historical weather data with the specified simulation start date.

The main agent tracks the current wind speeds based on a provided database of historical weather measurements. The current implementation uses a publicly available dataset from the German Weather Foundation (DWD) that contains hourly wind speed measurements between 1949 and 2022 at one of their weather stations near Nürnberg, Germany. This article uses Nürnberg as an example as its location is relatively central, not too high, and not close to the sea. Consequently, the dataset should provide a wide range of average weather data. At each hour, the main agent obtains the current measurement and interpolates the wind speed for different heights using the wind profile power law: $v = v_{10} \cdot \left(\frac{h}{10}\right)^{\alpha}$, with v_{10} being the known wind speed at 10 meters height, v being the interpolated wind speed at height h and $\alpha = \frac{1}{7}$ being the empirically derived coefficient for the neutral atmospheric stability. Moreover, the main agent tracks the imported plan and forwards operations to the crane agent.

The crane agent then commences the received operation at the given instance and finishes it as specified in the plan. During operations, the crane compares the operation's wind limit to the current wind speed at its operating height. It records any instance where the wind speed exceeds its operating limit. After concluding an operation, the crane agent informs the respective turbine agent. Like the crane agent, turbine agents monitor their current state, i.e., which component was installed last, and compare the required waiting time and wind speed limits with the current weather data provided by the main agent.

As noted above, the current model does not implement recourse actions to react to plan "failures" but only records and reports violations of the constraints. It aims at verifying if the generated plans contain any violations. The model is entirely viable for this task, as the current planning methods do not provide trade-offs, e.g., installing dampening devices that incur additional costs but mitigate the maximum wind wait-time constraint to a degree. Nevertheless, the model can quickly adapt to such changes and, e.g., decide if the plan actually fails or if the situation only incurs additional cost. Consequently, the simulation model provides excellent flexibility for future developments while covering the necessary basics.

5 EXPERIMENTAL RESULTS AND DISCUSSION

The experiments presented in this section aim to verify two hypotheses: First, the rolling horizon planning does not lower the plan efficiency. Second, the proposed method can mitigate the influence of forecast uncertainties with only small losses to the plans' efficiency. The experiments assume that longer planning horizons result in less efficient (longer) plans but only introduce few, if none, invalid operations.

5.1 Experimental Setup and Scenarios

This article uses two sets of experiments to verify the hypotheses. Both sets use the same base scenario and modify the values for the step-width T (how long should the plans be) and the acceptance threshold for possibly adverse-weather windows ω. The first set of experiments uses the benchmark approach to produce an optimal plan and, afterward, creates plans for different step-widths using the same weather measurements provided to the benchmark. Consequently, these plans use an acceptance threshold of $\omega = 0.99$ as no uncertainty exists. The second set aims to evaluate the plan efficiency for different combinations of T (one, two, and four weeks) and ω (0.99, 0.8, 0.6, and 0.4) to obtain an impression of delays and errors introduced by the growing forecast uncertainty. Table 3 summarizes the relevant scenario parameters. Both experiment sets validate the generated plans using the simulation model described above. The project start date for this scenario has been selected randomly from the dataset, while it was checked that it includes several adverse-weather windows. Like the original approach, the adapted approach assumes an increasing forecast uncertainty, turning forecasted values into a broadening interval of minimal and maximum forecast wind speed. Thereby, interval generation multiplies the uncertainty with the average wind speed over the prediction horizon and adds/subtracts this value from the current forecast. This article uses the same parameterization as Rippel et al. (2019), which relies on forecast accuracy assessments from the German Weather Foundation. The rolling horizon and benchmark approaches were implemented using Matlab 2022b using Gurobi 10.0.1 for the optimization.

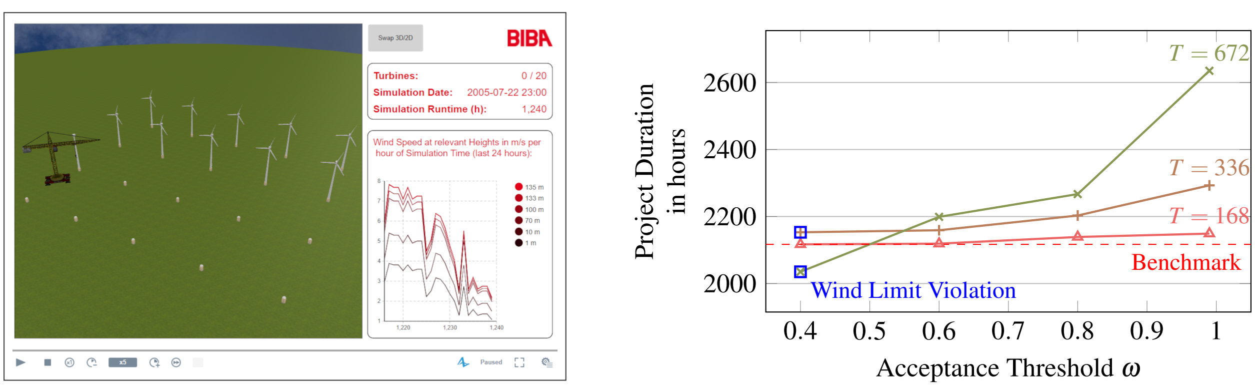
Table 3: Scenario parameters used in the simulation experiments.

Parameter	**Value(s)**	**Parameter**	**Value(s)**
Num. turbines to install	20	Start Date	June 1$^{\text{st}}$, 2005 8:00
Threshold ω	0.99, 0.8, 0.6, 0.4	Step-Width T	168, 366, 672 h
Forecast Uncertainty	0.0 at 0 h , 0.25 at 168 h, 0.65 at 336 h, 0.95 at 504 h, increasing afterward		

5.2 Results

The simulation runs for the first experiment set resulted in the same plans for the benchmark approach and the rolling horizon approach using actual weather measurements with different step-widths for one, two, and four weeks. These results confirm that the planning problem is particularly suited for rolling horizon planning, as it has no interdependencies between the installation of turbines. Trying to finish each turbine as fast as possible results in an overall optimal plan. As noted above, this hypothesis will likely not hold if additional devices and factors, like dampening devices, are included in future research.

The second experiment set aims to assess the influence of weather uncertainties by simulating plans that cover different planning horizons (step-widths). Therefore, longer step-widths should result in less efficient plans or even violations of the inter-operation requirements as the uncertainty increases. Figure 4 (b) summarizes the project durations for the different combinations of T and ω.



(a) (b)

Figure 4: (a) Screenshot of the simulation model. (b) Results for the different simulation scenarios.

Supporting the hypothesis, longer prediction horizons result in longer project durations. Similarly, higher acceptance thresholds prolong the project as the model broadens the no-build time windows. The figure shows, that combinations of long step-widths and high acceptance thresholds strongly increase the project duration, while even high thresholds only incur slight delays to shorter step-widths. This effect results form the increase in uncertainty for longer step-widths, which lets the approach assume even wider adverse-weather windows. Nevertheless, the results show that the model does prevent all violations to the inter-operation requirements even at $\omega = 0.6$. At lower values for ω the algorithm starts to introduce several instances of wind limit violations between operations. The four-weeks scenario with $\omega = 0.4$ achieves a lower makespan than the benchmark, but introduces several violations which render the plan invalid. The one-week scenario with $\omega = 0.4$ achieves the same plan as the benchmark as the uncertainty remains very low for such small horizons. Overall, the results indicate that such low acceptance thresholds favor constraint violations. Consequently, the result support using a step-width of one week (168h) and an acceptance threshold of $\omega = 0.6$, which only takes two hours longer than the benchmark approach (2,119 hours vs. 2,117 hours).

6 CONCLUSION AND OUTLOOK

This article proposes adopting a planning approach for installing offshore wind farms in an onshore context. Thereby, onshore installations impose additional wind speed and wait time requirements between operations not present in the offshore context. The approach relies on rolling horizon planning and provides tools to discretize weather forecast uncertainties to produce viable plans to support such projects on an operative level. Afterward, the article proposes a simulation model to evaluate these plans using real weather measurements. The results show that the rolling horizon approach prevents violations of the wind limit and wait time requirements at the expense of less efficient (longer) plans. The efficiency decreases with an increasing planning horizon as the uncertainty of weather forecasts increases similarly. Nevertheless, planning ahead for four weeks with a quite safe acceptance threshold ($\omega = 0.8$) only resulted in a delay of 150 h (2,267 h) compared to an optimal plan (2,117 h) created without weather uncertainty. Future work in this area will extend the planning approach and simulation models using advanced techniques used during such installation projects. Such techniques, e.g., include installing dampening devices to mitigate the influence of high wind speeds. This extension will address one of the major practical limitations of the currently proposed model. Currently, the model tries to avoid all violations of the wind and wait time constraints, while in practice, such violations may be acceptable, leading to higher costs but reducing the overall project duration. Unfortunately, such tradeoffs require cost information, e.g., for operations, personnel, resources, or dampening devices, requiring an adaptation of the overall optimization model and, in particular, its cost function. Theoretically, the proposed framework is mainly limited by prediction horizon N and the number of turbines per iteration J. While the plans used in this article could be calculated in a few hours, longer horizons or more planned turbines will require different approaches, e.g., heuristics to solve the described scheduling problem.

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