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A MIXED-INTEGER FORMULATION TO OPTIMIZE THE RESUPPLY OF COMPONENTS FOR THE INSTALLATION OF OFFSHORE WIND FARMS

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ABSTRACT

Over the last decade, offshore wind energy has become a viable source of sustainable energy. During the installation of offshore wind farms, the dimensioning of related base ports became increasingly important. Base ports act as central logistics hubs for the installation and, thus, need to provide sufficient space and equipment to store and handle required components. Thereby, current developments tend to larger and heavier components as well as to an increase in simultaneously occurring installation and decommissioning projects. This article proposes a Mixed-Integer formulation for the optimization of supply deliveries to the base port. Moreover, it presents an example of this formulation's integration with an optimization of the base port capacity and, furthermore, a simulation study on the effects of different resupply cycles on the efficiency of installation projects. Results show that the resupply cycle has a minor influence on the project's efficiency but highly affects the base port capacity.

1 INTRODUCTION

Wind energy has evolved into one of the most promising technologies to produce sustainable energy reliably. Consequently, the last decade witnessed a close to exponential increase in produced wind energy (REN21 2018). In particular, offshore wind farms provide large amounts of energy, due to higher wind speeds at sea. Within the first half of 2019, Germany increased its offshore energy production by more than 6.6 GW by installing over 1350 new offshore turbines (Deutsche WindGuard GmbH 2019). While offshore wind farms produce larger amounts of energy than their onshore counterparts, the highly dynamic weather conditions at sea complicate their installation. Literature attributes about 15–20% of an offshore wind farm's overall cost to logistics during the installation (Lange et al. 2012; Dewan et al. 2015; Muhabie et al. 2018). On the one hand, these costs result from quickly changing strong weather dynamics, which interfere with planned operations. On the other hand, the high specialization of required resources, like, heavy-lift vessels, jack-up vessels, or heavy-duty cranes and storage facilities, imposes a high base-line cost.

While most of the literature relating to the installation of offshore wind farms focuses on an efficient use of vessels under dynamic weather conditions, only a few works investigate the impact of related port-side resources, e.g., storage spaces or heavy-duty handling equipment. On the one hand, these resources need to be chartered before the actual installation project starts. On the other hand, an unsuitable dimensioning of the base ports can drastically interfere with efficient installations and, consequently, incur additional costs, as, e.g., described by Rippel et al. (2019a). Current literature suggests that the availability of port-side resources might pose a bottleneck for future installation projects due to the observed trends towards larger

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and heavier components, a higher number of concurrent installations, and the upcoming decommissioning of old wind farms (Oelker et al. 2020; Beinke et al. 2020).

This article proposes a Mixed-Integer Linear Programming model to support decision-makers in determining the most effective resupply cycle for a planned installation project. Thereby, the model focuses on optimizing a limited set of round-trips between the base port and the geographically distributed production ports for turbine components. Furthermore, this article presents an exemplary integration of this model with other approaches for the dimensioning of the base port and the simulation of the planned installation project. This simulation aims to assess the impact of resupply cycles on the overall project. Thereby, the resupply cycle constitutes one of two major streams for the optimization of a base port's storage capacity. On the one hand, the cycle needs to provide a steady stream of component sets, each consisting of at least one tower, one nacelle, and one set of blades. On the other hand, the cycle determines the overall storage capacity required at the base port, as deliveries (inputs) and installations (outputs) need to be balanced.

The next section first introduces the general process of installing an offshore wind farm and discusses current literature in this area. Afterward, Section 3 describes the proposed model. Section 4 first presents an evaluation of the model itself to highlight its characteristics and to verify its results against a reference scenario found in the literature. Afterward, it presents the simulation study mentioned above to assess the impact of different resupply cycles on the base port capacity and the overall installation project. Table 1 summarizes the most relevant parameters and variables used throughout this article. Additional constants and parameters may be introduced in the appropriate subsections.

Table 1: Nomenclature.

Variable	Value Set	Parameters
T	$\mathbb{N}^+$	Number of round-trips to be planned
C	$\mathbb{N}^+$	Number of component types, usually 3 (Tower, Blades, Nacelle)
$cost_c^{setup}$	$\mathbb{R}_0^+$	Setup time for components of type c
$cost_c^{load}$	$\mathbb{R}_0^+$	Loading time for components of type c
$cost_c^{unload}$	$\mathbb{R}_0^+$	Unload time for components of type c
$cost_r^{route}$	$\mathbb{R}_0^+$	Travel times for each possible round-trip
$weight_c$	$\mathbb{R}_0^+$	Weight of component c
$space_c$	$\mathbb{R}_0^+$	Space required by component c on the vessel
$weight^{max}$	$\mathbb{R}_0^+$	Maximum combined weight of payloads for the vessel
$space^{max}$	$\mathbb{R}_0^+$	Maximum space for payloads on the vessel
		Indices
k	$\mathbb{N}^+$; $k \leq T$	Index of the current round-trip
c	$\mathbb{N}^+$; $c \leq C$	Index of the current type of component
r	$\mathbb{N}^+$; $r \leq 2^C$	Index of the current route within the round-trip
		Decision Variables
$X_{k,c}^{loadout}$	$\mathbb{N}_0^+$	Number of components c to be loaded in round-trip k
		Dependent Variables
$X_{k,c}^{setup}$	$\mathbb{N}_0^+$	Number of loading slots for components of type c to be removed or added in round-trip k
$Y_{k,c}^{location}$	Binary	1 if the vessel transports components of type c in the current round-trip k; 0 otherwise
$Y_{k,r}^{route}$	Binary	1 if route r conforms to the current round-trip k; 0 otherwise

2 STATE OF THE ART

This section shortly introduces the conventional installation process for offshore wind farms, as it remains the most common installation concept found in practice and literature. Afterward, it summarizes approaches and models found in the current literature, which explicitly deal with the installation of wind farms.

2.1 Installation Process

The installation of offshore wind farms can be separated into three distinct phases, which, in practice, follow sequentially one after the other (Vis and Ursavas 2016; Quandt et al. 2017): The first phase comprises the installation of the turbines' foundations and the required infrastructure to connect the wind farm to the energy grid. The second phase focuses on the installation of the so-called top structures, consisting of the turbines' tower, nacelle, and blades. The final phase finally commissions the turbines and includes their final testing and ramp-up. This article focuses on the second phase, while the proposed model and the general approach is easily applicable to the first phase without limitation.

Within the conventional installation concept (Figure 1), the process relies on a geographically distributed logistics and production network. This network consists of the production ports for the components, the base port as a logistics hub, and the actual offshore installation site (Oelker et al. 2017; Quandt et al. 2017). Thereby, heavy-lift vessels perform the transport between the production ports and the base port to guarantee a steady supply of components for the installation. So-called jack-up vessels obtain sets of components at the base port, transport these to the installation site, and construct a number of turbines before returning to the base port.

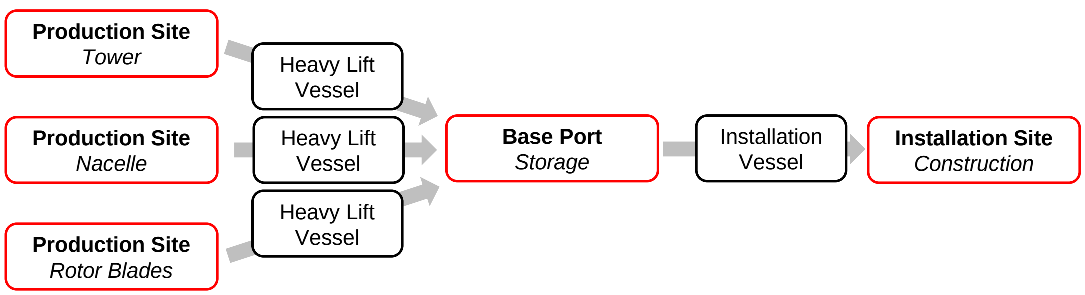

Figure 1: Conventional installation concept for top structures (Rippel et al. 2019a).

Thereby, installation operations performed by the jack-up vessel are highly susceptible to unstable weather conditions at sea. In the case of high wind speeds or wave heights, the installation cannot start or has to be aborted (Rippel et al. 2019b). Consequently, weather dynamics and forecasts impose high uncertainties on the planning of the overall installation project. Nevertheless, planners need to charter storage and equipment at the base port long before the actual installation begins. On the one hand, they need to ensure that sufficient resources will be available to avoid supply shortages. On the other hand, these specialized resources, like cranes or heavy-duty storage facilities, only have a limited supply and come at high costs for the project planners.

2.2 Models and Approaches for the Installation of Offshore Wind Farms

Over the last decade, several authors proposed models and approaches to increase the efficiency of offshore wind farm installations. Nevertheless, compared to other topics in the offshore area, literature on the topic of offshore wind farm installations is still sparse (Vis and Ursavas 2016).

Most literature, thereby, proposes models to schedule or simulate the installation process with a focus on an efficient application of jack-up vessels under weather dynamics. For example, Ait Alla et al. (2017) propose a simulation study to compare the conventional installation concept with feeder concepts. Vis and Ursavas (2016) present a simulation study to assess the efficiency of different pre-assembly concepts, where they assumed that parts of the top-structure are already assembled within the base port. Muhabie et al. (2018) propose a simulation model to evaluate different assumptions about weather conditions. While these studies focus on the process itself, other authors present optimization models, e.g., for the scheduling of jack-up vessels (Scholz-Reiter et al. 2011; Ursavas 2017; Rippel et al. 2019b; Irawan et al. 2017; Irawan et al. 2019) or for an cost-efficient commissioning and decommissioning of additional jack-up vessels (Kerkhove and Vanhoucke 2017).

While all these models mainly investigate the application of vessels, more recent literature shows increasing interest in the role of the base port and its related resources on a broader scope. For example, Beinke et al. (2017) propose a model to investigate potential cost reductions by sharing heavy-lift vessels between different installation projects. In Beinke et al. (2020), the authors present a simulation study showing that resource availability may become a bottleneck if the current trends of concurrent installation projects continue, showing increasing both number and size. Thereby, they highlight that, over the next years, the first wind farms need to be decommissioned again, which requires the same resources and spaces. In a similar context, Oelker et al. (2020) present a simulation study of the base port in Eehmshaven. This study shows that the requirement for heavy-duty storage areas might exceed the available spaces if the size of wind farms and components continues to increase. The authors highlight the need for new concepts and advanced approaches to optimize the use of these port-side resources in the future.

In previous work, Rippel et al. (2020) proposed a model to optimize the capacity of base ports for installation projects. Thereby, the article focuses on the estimation of the base port's output stream (number of installed turbines per time step) using aggregated, historical weather records. Nevertheless, as described in the introduction, an efficient installation process requires a steady stream of components as input. Therefore, the following section proposes an algorithm to optimize resupply cycles that continuously deliver a number of component sets to the base port with a defined frequency.

3 ALGORITHM AND OPTIMIZATION MODEL

The algorithm aims to determine a sequence of round-trips between the base port and the production ports, which maximizes the number of delivered component sets while minimizing the overall time needed. Thereby, a round-trip always starts and ends at the base port and visits at least one production port. The general type of problem resembles a transshipment problem (Agadaga and Akpan 2017), which aims to find optimal routes to deliver cargo from several storages (sources) to several depots (sinks). This particular instance provides three sources (production ports) and a single sink (base port). Thereby, this instance limits the capacity of the transport vehicle in a way that the combination of transported components cannot exceed its capacity in terms of space and weight. Consequently, the overall problem consists of a combination of a routing problem to determine the shortest paths with an assignment problem, determining which components to fetch. In contrast to classic transshipment problems, the problem at hand does not aim to satisfy the global demand, i.e., to deliver all components, but to find a set of round-trips that deliver a certain number of sets in a minimized time.

3.1 Simplification of the Routing Problem

The proposed model exploits the small size of the transportation network to reduce the problem formulation from a transshipment problem to a multi-periodic knapsack problem. Knapsack models aim to maximize the amount and composition of items to carry, while constraining the available capacity. As each round-trip can only consist of a maximum of three visited nodes (production ports), there only exist $2^3 = 8$ possible routes, assuming that the trips are symmetric, i.e., trips between port A and port B take the same time as the trip between port B and port A. Consequently, each route is defined by the combination of visited ports, which the proposed model represents as a binary array $Y_{k,c}^{location}$, where k denotes the current round-trip and c the type of component, i.e., its respective production port. Thereby, this article enumerates components and ports as *1 = Tower, 2 = Blades, 3 = Nacelles*. Thus, $Y_{k,c}^{location} = [1,0,0]^T$ denotes that the vessel only visits the production port for towers during this single round-trip, while the vector $Y_{k,c}^{location} = [1,0,1]^T$ denotes that the vessel visits the production ports for towers and nacelles. Moreover, this representation enables a unique mapping of each route to a specific index $r \in [0..7]$ by applying a simple binary encoding as given in Equation (1).

$$r = Y_{k,1}^{location} \cdot 2^0 + Y_{k,2}^{location} \cdot 2^1 + Y_{k,3}^{location} \cdot 2^2 \qquad \forall k, \quad k \leq T \tag{1}$$

This mapping allows the optimization for using the costs for a selected route, instead of considering the actual routing itself. Therefore, the proposed model precalculates the optimal route for each combination of visited ports offline in advance by solving a standard traveling salesman problem and storing the duration (cost) of each route as vector $cost_r^{route}$. Consequently, the model itself constitutes a modified version of a multi-period knapsack problem, which uses a set of dependent variables to determine the actual costs for each assignment. Another example of a multi-periodic knapsack problem can be found, for example, in (Samavati et al. 2017) for the planning of sequence-dependent mining operations.

3.2 Formulation of the Optimization Problem

This section presents a Mixed-Integer formulation for the optimization problem. In contrast to a standard knapsack problem, this formulation minimizes the cost function J given in Equation (2) subject to the constraints (3) to (11) described below. This formulation relies on four optimization variables, whereas three of them fully depend on the variable $X_{k,c}^{loadout}$, as shown in Figure 2. Using this variable, the optimizer determines the number of components a vessel should fetch in each round-trip k. By using the constraints (6) and (7), the optimizer denotes the differences between the loadout for each round-trip to determine the required setup times. Additionally, constraints (8) and (9) represent a larger-or-equal-to-zero operator to denote the visited production ports for each round-trip in $Y_{k,c}^{location}$. Finally, the formulation uses a binary encoding of this variable to map the visited production ports in each round-trip into a vector denoting the selected route as part of the variable $Y_{k,r}^{route}$.

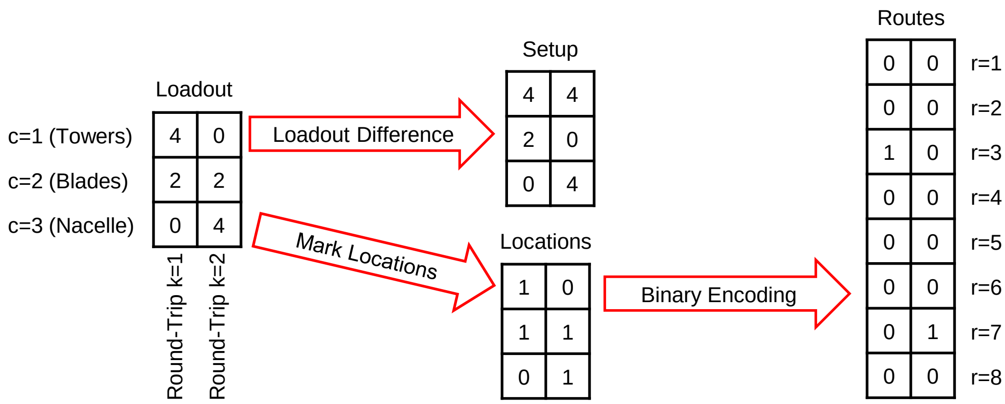

Figure 2: Schematic structure of the optimization formulation.

Unfortunately, a Mixed-Integer model cannot express fractions between variables as part of the cost function or the constraints and, thus, cannot minimize the time per delivered set of components directly. In consequence, this formulation uses an alternative cost function. As commonly applied in knapsack formulations, the cost function maximizes the number of delivered component sets, and in extension, minimizes the associated costs (travel time):

$$\begin{aligned} J = -100 \cdot \sum_{k=1}^{T} X_{k,1}^{loadout} + \sum_{r=1}^{2^C} \Big((\sum_{k=1}^{T} Y_{k,r}^{route}) \cdot cost_r^{route} \Big) \\ + \sum_{c=1}^{C} \Big((\sum_{k=1}^{T} X_{k,c}^{setup}) \cdot cost_c^{setup} + (\sum_{k=1}^{T} X_{k,c}^{loadout}) \cdot (cost_c^{load} + cost_c^{unload}) \Big) \end{aligned} \tag{2}$$

The cost function consists of two parts. The first term assigns a bonus (negative cost/penalty term) for each delivered set of components. Therefore, it multiplies the sum over all delivered sets, represented by any single component as the optimizer needs to deliver full sets, with an arbitrarily chosen negative value. The remaining terms denote the actual cost part of the function: These consist of a summation of the loading and unloading times, the setup times, and the traveling times. The formulation uses the following constraints to ensure that all of these variables contain the correct values and to constrain the problem itself.

$$\sum_{k=1}^{T} X_{k,c}^{loadout} = \sum_{k=1}^{T} X_{k,(c-1)}^{loadout} \qquad \forall c, \quad 2 \leq c \leq C \tag{3}$$

Constraint (3) requires the optimizer to ensure that across all round-trips, only full sets of components, each consisting of one tower, one nacelle, and one (set of) blades, are delivered to the base port.

$$\sum_{c=1}^{C} \left(X_{k,c}^{loadout} \cdot weight_c \right) \leq weight^{max} \qquad \forall k, \quad k \leq T \tag{4}$$

$$\sum_{c=1}^{C} \left(X_{k,c}^{loadout} \cdot space_c \right) \leq space^{max} \qquad \forall k, \quad k \leq T \tag{5}$$

Constraints (4) and (5) ensure that the payload in all round-trips k does not exceed the vessel's maximum capacity, neither in terms of weight nor in terms of space.

$$X_{k,c}^{setup} \geq X_{k,c}^{loadout} - X_{(k-1),c}^{loadout} \qquad \forall k,c \quad 2 \leq k \leq T, c \leq C \tag{6}$$

$$X_{k,c}^{setup} \geq X_{(k-1),c}^{loadout} - X_{k,c}^{loadout} \qquad \forall k,c \quad 2 \leq k \leq T, c \leq C \tag{7}$$

Constraints (6) and (7) force the optimizer to note the absolute difference of loaded components between two round-trips as part of the dependent variable $X_{k,c}^{setup}$. This formulation enforces the entry always to be larger or equal to the positive and negative difference between those round-trips for each component. The cost function uses $X_{k,c}^{setup}$, to determine slot-specific setup times. Given the example in Figure 2 for $k = 2$, these constraints ensure that $X_{2,c}^{setup} \geq (4-0, 2-2, 0-4)^T \wedge X_{2,c}^{setup} \geq (0-4, 2-2, 4-0)^T$. The minimization of $X_{k,c}^{setup}$ results in $X_{2,c}^{setup} = (max(-4,4), max(0,0), max(-4,4))^T = (4,0,4)^T$, as given in the figure.

$$X_{k,c}^{loadout} \leq Y_{k,c}^{location} \cdot C_c^{max} \qquad \forall k,c \quad k \leq T, c \leq C \tag{8}$$

$$X_{k,c}^{loadout} \geq Y_{k,c}^{location} \qquad \forall k,c \quad k \leq T, c \leq C \tag{9}$$

Constraints (8) and (9) ensure that the optimizer marks the type of transported components in the current round-trip k within the dependent, binary variable $Y_{k,c}^{location}$. While constraint (8) also limits the maximum number of components to a precalculated value, this limitation is redundant to the one imposed by the constraints (4) and (5) and only serves as relaxation support. Thereby, the algorithm calculates the maximum number of loadable components as $C_c^{max} = min(\frac{weight^{max}}{weight_c}, \frac{space^{max}}{space_c})$ for all component types c. The algorithm uses this binary combination of used slots to determine the actual route for each round-trip k.

$$\sum_{c=1}^{C} (Y_{k,c}^{location} \cdot 2^{c-1}) \leq (r-2) \cdot z_{k,r}^{-} + (r-1) \cdot Y_{k,r}^{route} + UB \cdot z_{k,r}^{+} \qquad \forall k,r \quad k \leq T, r \leq 2^C \tag{10}$$

$$\sum_{c=1}^{C} (Y_{k,c}^{location} \cdot 2^{c-1}) \geq LB \cdot z_{k,r}^{-} + (r-1) \cdot Y_{k,r}^{route} + r \cdot z_{k,r}^{+} \qquad \forall k,r \quad k \leq T, r \leq 2^C \tag{11}$$

Finally, the constraints (10) and (11) translate the combination of visited production ports, i.e., of transported components, into a unique route. Therefore, these constraints use a binary encoding of the transported components in $Y_{k,c}^{location}$ to assign a unique route index $1 \leq r \leq 2^C$, as given on the left-hand-side of the constraints. The constraints exploit a variant of a so-called Big-M formulation, which uses two support variables $z_{k,r}^{+}$, and $z_{k,r}^{-}$ to denote if the index r is larger or smaller than the round-trips' encoded route-index. Finally, these constraints ensure that $Y_{k,r}^{route}$ only takes on the value 1, if this index and r are equal. The lower and upper bound for this formulation are given as $LB = 0$ and $UB = (2^C) - 1$.

4 EVALUATION AND RESULTS

This article uses a scenario proposed by Beinke et al. (2017) to evaluate the described model. According to the authors, this scenario relies on empirically collected real-world data obtained from research projects related to the installation of a wind farm in Germany's Northern Sea. It uses a base port in Eemshaven, Netherlands. This scenario locates the production port for rotor blades and nacelles in Bremerhaven, Germany, and the production port for towers in Cuxhaven, Germany. The authors provide the required data to obtain a manually optimized route for the resupply cycle, the required round-trips and processing times: The heavy-lift vessel performs a total of four trips to obtain eight sets of components. Therefore, it performs one trip to obtain eight sets of blades, one trip for eight towers, and two trips for four nacelles each. The overall cycle time is calculated as 310 hours (Beinke et al. 2017; Rippel et al. 2020). While most of the required values in Table 2 can be calculated based on this scenario, the article does not provide values for the weight and size of components or the vessel's capacities.

Table 2: Base scenario parameterization.

Parameter	Tower	Blade	Nacelle
Base port		Eehmshaven	
Vessel Capacity - Space		2646 m^2	
Vessel Capacity - Weight		8900 t	
Production Port	Cuxhaven	Bremerhaven	Bremerhaven
Loading Time per Component	2 h	8 h	10 h
Unloading Time per Component	1.2 h	4.8 h	6 h
Setup Time per Component	0	0	0
Weight per Set of Component	600 t	240 t	500 t
Space required per Set of Component	650 m^2	300 m^2	263 m^2

Therefore, this article relies on the average characteristics for 10 MW turbines given in BVGassociates (2019). Table 3 shows the relevant characteristics and the resulting limitations. Due to the use of transport racks, this article assumes that it is possible to stack two sets of blades (6 single blades) on top of each other, effectively assuming only half the required size for the optimizer's input.

Table 3: Characteristics of turbine components.

Component	Stackable Sets	Length	Width	Required Area	Weight of Stacked Sets
Tower	1	100 m	6.5 m	650 m^2	500 t
Blade	2	100 m	6	300 m^2	240 t
Nacelle	1	25 m	10.5	262.5 m^2	500 t

This article employs the average values for the fleet of a randomly chosen shipping company to obtain realistic limitations for the vessel's capacity. This fleet comprises 22 heavy-lift vessels with an average weight capacity of 438 TEU $\approx$ 8,900 tons and a usable deck area of approximately 2,464 m^2.

4.1 Evaluation of the Number of Round-Trips and Verification

This subsection presents an evaluation of the impact of different configurations for the number of allowed round-trips per resupply cycle. Figure 3 shows the results of the proposed algorithm for $T = 2$ to 40 round-trips. The figure omits the scenario for $T = 1$ to improve readability, as it shows a very high average cycle time of 46 hours. In Figure 3, the solid line depicts the average resupply time per set of components, while the dotted line shows the total time of the resupply cycle. The numbers at the points show the total number of sets obtained within that resupply cycle. For example, the vessel obtains a total of four sets with two round-trips, or a total of 86 sets, if it performs 40 round-trips.

Considering the reference scenario for verification of the proposed optimization model, the manually optimized route comprises four round-trips in 310 hours and obtains eight sets. In the case of configuring the optimizer to use four round-trips, it obtains a cycle time of 312 hours and a total of 8 sets. This result only differs by two hours from the manually optimized cycle described in the reference scenario. Nevertheless, this difference can be traced back to different assumptions between this article's scenario and the one described in Beinke et al. (2017). While the reference scenario assumes that the vessel needs two trips to obtain all nacelles but only a single trip to obtain all towers, the restrictions described in the previous subsection impose the exact opposite. While the vessel can load all eight nacelles on a single trip, it requires two trips to fetch all eight towers. Thus, while the structure of the solution remains the same, the vessel visits a different location twice, resulting in varying travel times for both solutions. Adjusting the obtained 312 hours be the difference in travel time between the respective production ports, i.e., assuming the locations for towers and nacelles would be switched, the optimizer obtains the same 310 hours of cycle time for eight full sets of components. Thus, the proposed method achieves the same optimal resupply cycle as the manual optimization conducted in the reference scenario.

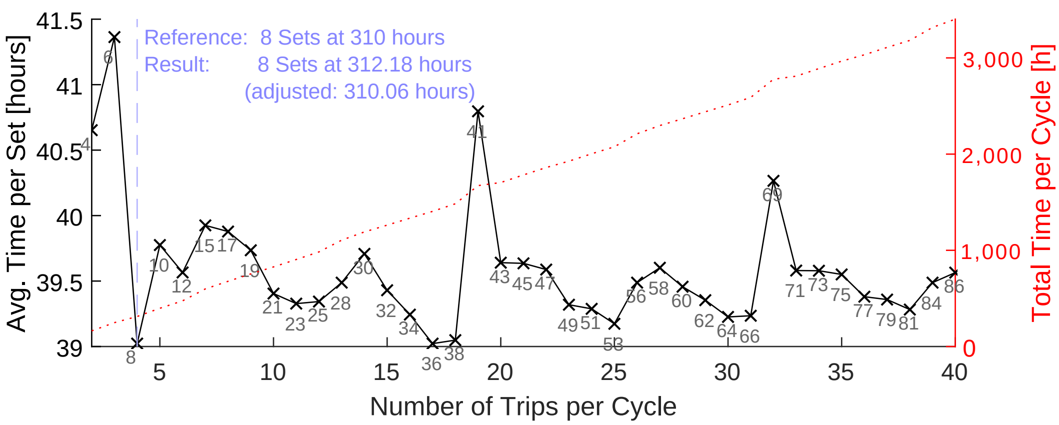

Figure 3: Results of the transport optimization for $T \in [2..40]$ round-trips.

In general, the results show a steady, close-to-linear increase in the total time of resupply cycles as well as in the total number of sets delivered. Nevertheless, concerning the average time per set of components, Figure 3 shows slight variations between 39 and approximately 41.5 hours. Moreover, it shows a slight trend towards increasing average times with an increased number of round-trips. Increasing the number of round-trips allows the heavy-lift vessel to deliver two additional sets in most cases. Thereby, the initial experiments using two and three round-trips show very high average delivery times as no efficient cycle can be constructed. Some cases, e.g., for 19 and 32 round-trips, add three more sets instead. These cases usually result in a high increase in the average time, which slowly declines again into another local minimum before increasing again. This shows that some configurations enable slightly more efficient routes than others. Moreover, Figure 3 indicates a repeating pattern, starting with the experiments using 3, 19, and 32 round-trips.

In conclusion, the results show that the proposed model achieves quite consistent results in optimizing resupply cycles with a provided number of round-trips. The verification against the manually optimized resupply cycle from Beinke et al. (2017) results in the same cycle if the scenario is adapted accordingly. While this model provides optimized resupply cycles, the next subsection shows an evaluation of different cycles in the context of a simulated offshore installation project. This experiment aims to provide further insights into a suitable selection of the number of round-trips T considering a broader context.

4.2 Simulation of Installation Projects using Optimized Resupply Cycles and Base Port Capacities

This experiment integrates the results of the proposed model with previously published models and approaches, to evaluate the influence of the number of round-trips T on the overall installation project, as given in Figure 4. Therefore, this experiment uses the generated resupply cycles to optimize the capacity of the base port as proposed in Rippel et al. (2020). Afterward, the experiment uses these optimized settings to schedule the offshore installation as proposed in Rippel et al. (2019a) and Rippel et al. (2019b). It finally evaluates these schedules against a simulation of the real world's weather conditions, relying on real historical recordings. These recordings consist of hourly recordings of the wind speed and wave height in Germany's Northern Sea between 1958 and 2007. The capacity optimization thereby relies on the base ports' in- and output streams. While the optimized resupply cycle determines the base port's input stream (frequency and amount of delivered components), the output stream relies on the current weather conditions. Thus, the capacity optimization includes the simulation of an installation project using aggregated historical weather recordings.

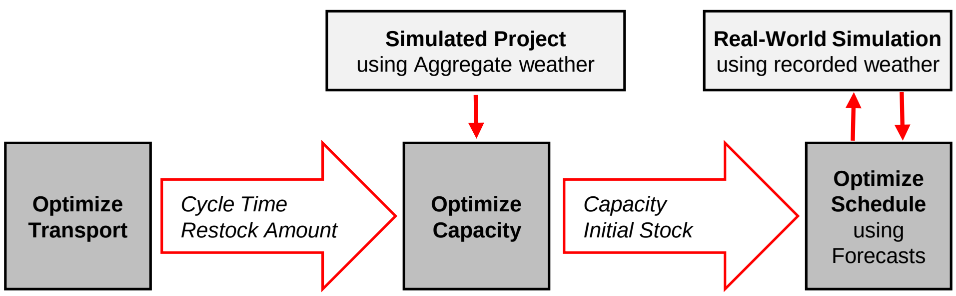

Figure 4: Schematic of the experimental setup.

The simulation uses the geographical layout and the characteristics of the heavy-lift vessel described at the beginning of this section. Moreover, the simulation assumes a single jack-up vessel for the installation of 50 turbines. The simulation starts on the first of June 2000 as the weather records show a moderate mix of conditions, i.e., no perfect weather but also no long periods of really bad weather. Consequently, the capacity optimization applies historical weather records from 1979 to 1999. The simulation uses actual records for the year 2000, while the scheduling relies on generated forecasts for the year 2000. It shall be noted that the average installation project takes about 2.5 months. Thus, the simulation and the optimizations at least require records for June, July, and August.

Table 4 summarizes the results of the simulation and the optimization models for $T = 1$ to $T = 16$ applied round-trips. Thereby, $T = 16$ constitutes the last scenario where the capacity optimization found a feasible solution. Investigating the latter cases, the results show that only a single delivery could be made at the beginning of the project. At the same time, a second resupply cycle would exceed the project's duration. Thus, in all follow-up scenarios, we can assume that the project requires a capacity of 50 sets and an initial stock as high as the difference between the capacity and the resupply amount.

The table indicates the same results for the transport optimization, as described in the previous subsection. The results clearly show that reliable resupply cycles require at least four round-trips to be efficient (avg. time per set). The results depict an increase in the required maximum capacity with an increase in round-

Table 4: Simulation results, including transport, capacity, and schedule optimization for $T \in [1..16]$.

Transport				Capacity		Simulation				
Num. Trips	Cycle Time [h]	Num. Sets	Avg. Time Per Set [h]	Initial Storage	Capacity	Project Duration [h]	Storage Min	Storage Max	Empty storage [h]	Delayed Cycles [h]
1	92.1	2	46.0	27	27	1,792	11	26	0	0
2	162.6	4	40.7	18	18	1,792	6	17	0	0
3	248.2	6	41.4	17	17	1,792	2	16	0	0
4	312.2	8	39.0	17	17	1,792	1	16	0	0
5	397.7	10	39.8	15	15	1,828	0	14	150	0
6	474.8	12	39.6	18	18	1,792	0	17	8	0
7	598.9	15	39.9	29	29	1,792	7	28	0	0
8	677.9	17	39.9	21	21	1,823	0	20	135	0
9	755.0	19	39.7	27	27	1,792	2	26	0	0
10	827.5	21	39.4	33	34	1,792	6	32	0	0
11	904.5	23	39.3	40	40	1,792	11	39	0	0
12	983.6	25	39.3	46	48	1,792	17	45	0	0
13	1,105.7	28	39.5	34	35	1,792	2	33	0	0
14	1,191.2	30	39.7	38	40	1,792	3	37	0	0
15	1,261.8	32	39.4	43	45	1,792	5	42	0	0
16	1,334.3	34	39.2	48	49	1,792	8	47	0	0

trips. Applying these settings to the simulation shows that the majority of resupply cycles allow for an optimal installation project with an overall duration of 1,792 hours $\approx$ 75 days. Only two instances show an extended project duration, resulting from empty storages at the base port. Both show comparably low values for the initial storage and capacity. Comparing the simulation's maximum storage with the optimized capacity, the results show that the capacity usually exceeds the requirements by a single set of components for resupply cycles up to 9 round-trips. Afterward, the discrepancy increases, showing an overestimation of the required capacities for long resupply cycles. No instance underestimated the required capacity as given by the non-existence of delayed resupplies. Overall, the scenario using four round-trips per resupply cycle provides the best overall result. This result falls in line with the manually optimized resupply cycle given in the reference scenario of Beinke et al. (2017). While another scenario (5 round-trips) results in a lower base port capacity, which constitutes one of the main cost drivers for the installation project, it also results in an extended project duration, imposing additional costs for jack-up vessels. In contrast, the scenario using only three round-trips does not require additional capacity or impose a higher project duration. The similarity between these scenarios shows that a higher average cycle time does not necessarily impact the overall project negatively. Nevertheless, the scenario using three round-trips slightly overestimates the required capacity and provides a slightly less efficient resupply cycle.

5 CONCLUSION AND FUTURE WORK

This article presents a Mixed-Integer Linear Programming Model for the strategic optimization of resupply cycles for the installation of offshore wind farms. The formulation exploits the small transportation network to reduce the problem to a variant of a knapsack problem by moving the actual routing into an offline computation. Furthermore, the article presents an evaluation of this model in the broader context of an installation project. Therefore, the experiments use the model's results to optimize the related base port capacity and simulate the installation of an offshore wind farm.

The verification against a scenario from the literature shows that the proposed model achieves the same result as a manually optimized resupply cycle. Even when simulating the corresponding installation project, the optimized resupply cycle achieves the most efficient results. These results show that the number of round-trips per resupply cycle has no significant impact on the overall installation project. Nevertheless, the dimensioning of the base port strongly correlates to the planned cycle. Consequently, cycles with a lower number of round-trips provide a higher cost efficiency as they reduce the required port storage.

Future work will focus on a more in-depth evaluation of this model in terms of different weather conditions and extended geographical layouts. Moreover, future work will evaluate if this particular optimization already needs to regard the influence of weather dynamics. The current article assumes that transportation remains unaffected by weather conditions and, thus, relies on determined traveling times. While the literature shows that sailing operations have quite high limits of wind speeds up to 21m/s and wave heights of up to 2.5m (Oelker et al. 2018), they might still introduce certain stochasticity to the optimization. Moreover, future work will try to integrate the production ports' characteristics in terms of manufacturing rates and storage capacities. These values might limit the availability of components at each production port and, therefore, influence the viability of resupply cycles.

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REFERENCES

Agadaga, G. O., and N. P. Akpan. 2017. "Transshipment Problem and Its Variants: A Review". *Mathematical Theory and Modeling* 7(5):19–32.

Ait Alla, A., S. Oelker, M. Lewandowski, M. Freitag, and K.-D. Thoben. 2017. "A Study of New Installation Concepts of Offshore Wind Farms by Means of Simulation Model". In *Proceedings of the Twenty-seventh (2017) International Ocean and Polar Engineering Conference (ISOPE)*, edited by J. S. Chung, M. S. Triantafyllou, and I. Langen, 607–612. Cupertino: ISOPE.

Beinke, T., A. Ait Alla, and M. Freitag. 2017. "Resource Sharing in the Logistics of the Offshore Wind Farm Installation Process based on a Simulation Study". *International Journal of e-Navigation and Maritime Economy* 7(6):42–54.

Beinke, T., A. Ait Alla, S. Oelker, and M. Freitag. 2020. "Demand for Special Vessels for the Decommissioning of Offshore Wind Turbines in the German North Sea – A Simulation Study". In *Proceedings of the 30th International Ocean and Polar Engineering Conference (ISOPE)*, October 12$^{\text{th}}$-16$^{\text{th}}$, Shanghai, China.

BVG associates 2019. "Guide to an Offshore Wind Farm". Technical report. https://bvgassociates.com/publications/, accessed 25$^{\text{th}}$ May.

Deutsche WindGuard GmbH 2019. "Status des Offshore-Windenergieausbaus in Deutschland – Erstes Halbjahr 2019". Technical report. https://www.wind-energie.de/fileadmin/redaktion/dokumente/pressemitteilungen/2019/Status_des_Offshore-Windenergieausbaus_Halbjahr_2019.pdf, accessed 29$^{\text{th}}$ May.

Dewan, A., M. Asgarpour, and R. Savenije. 2015. *Commercial Proof of Innovative Offshore Wind Installation Concepts Using ECN Install Tool*. Petten: ECN.

Irawan, C. A., G. Wall, and D. Jones. 2017. "Bi-Objective Optimisation Model for Installation Scheduling in Offshore Wind Farms". *Computers & Operations Research* 78:393–407.

Irawan, C. A., G. Wall, and D. Jones. 2019. "An Optimisation Model for Scheduling the Decommissioning of an Offshore Wind Farm". *OR Spectrum* 41(3):513–548.

Kerkhove, L.-P., and M. Vanhoucke. 2017. "Optimised Scheduling for Weather Sensitive Offshore Construction Projects". *Omega* 66:58–78.

Lange, K., A. Rinne, and H.-D. Haasis. 2012. "Planning Maritime Logistics Concepts for Offshore Wind Farms: A Newly Developed Decision Support System". *Lecture Notes in Computer Science: Computational Logistics* 7555:142–158.

Muhabie, Y. T., P. Rigo, M. Cepeda, and M. A. D'Agosto. 2018. "A Discrete-Event Simulation Approach to Evaluate the Effect of Stochastic Parameters on Offshore Wind Farms Assembly Strategies". *Ocean Engineering* 149:279–290.

Oelker, S., M. Lewandowski, A. Ait Alla, J.-H. Ohlendorf, and A. F. Haselsteiner. 2017. "Logistikszenarien für die Errichtung von Offshore-Windparks – Herausforderungen der Wirtschaftlichkeitsbetrachtung neuer Logistikkonzepte". *Industrie 4.0 Management* 33(1):24–28.

Oelker, S., A. Ait Alla, S. Büsing, M. Lütjen, and M. Freitag. 2020. "Simulative Approach for the Optimization of Logistic Processes in Offshore Ports". In *Proceedings of the 30th International Ocean and Polar Engineering Conference (ISOPE)*, October 12$^{\text{th}}$-16$^{\text{th}}$, Shanghai, China.

Oelker, S., A. Ait Alla, M. Lütjen, M. Lewandowski, M. Freitag, and K.-D. Thoben. 2018. "A Simulation Study of Feeder-based Installation Concepts for Offshore Wind Farms". In *Proceedings of the Twenty-eighth (2018) International Ocean and Polar Engineering Conference (ISOPE)*, edited by J. S. Chung, B.-S. Hyun, D. Matskevitch, and A. M. Wang, 578–583. Cupertino: ISOPE.

Quandt, M., T. Beinke, A. Ait Alla, and M. Freitag. 2017. "Simulation Based Investigation of the Impact of Information Sharing on the Offshore Wind Farm Installation Process". *Journal of Renewable Energy* 2017:1–11.

Renewable Energy Policy Network for the 21st Century 2018. "Renewables 2018 Global Status Report". Technical report, Paris: REN21.

Rippel, D., N. Jathe, M. Lütjen, and M. Freitag. 2019a. "Evaluation of Loading Bay Restrictions for the Installation of Offshore Wind Farms Using a Combination of Mixed-Integer Linear Programming and Model Predictive Control". *Applied Sciences* 9(23):1–30.

Rippel, D., N. Jathe, M. Lütjen, and M. Freitag. 2020. "Base-Port Capacity Optimization for the Installation of Offshore Wind Farms". In *Proceedings of the 2020 Summer Simulation Conference (SummerSim'20)*, July 20th-22nd, Madrid, Spain.

Rippel, D., N. Jathe, M. Lütjen, H. Szczerbicka, and M. Freitag. 2019b. "Simulation and Optimization of Operations for Offshore Installations Planning using a Model Predictive Control Scheme". In *Proceedings of the 2019 Winter Simulation Conference*, edited by N. Mustafee, K.-H. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, 1719–1730. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Samavati, M., D. Essam, M. Nehring, and R. Sarker. 2017. "A Methodology for the Large-Scale Multi-Period Precedence-Constrained Knapsack Problem: An Application in the Mining Industry". *International Journal of Production Economics* 193:12–20.

Scholz-Reiter, B., H. R. Karimi, M. Lütjen, J. Heger, and A. Schweizer. 2011. "Towards a Heuristic for Scheduling Offshore Installation Processes". In *Proceedings of the 24th International Congress on Condition Monitoring and and Diagnostics Engineering Management. Advances in Industrial Integrated Asset Management*, edited by S. Maneesh, R. Rao, and J. P. Liyanage, 999–1008. Birmingham: COMADEM.

Ursavas, E. 2017. "A Benders Decomposition Approach for Solving the Offshore Wind Farm Installation Planning at the North Sea". *European Journal of Operational Research* 258:703–714.

Vis, I. F., and E. Ursavas. 2016. "Assessment Approaches to Logistics for Offshore Wind Energy Installation". *Sustainable Energy Technologies and Assessments* 14:80–91.

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