BASE-PORT CAPACITY OPTIMIZATION FOR THE INSTALLATION OF OFFSHORE WIND FARMS

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ABSTRACT

Offshore wind farms provide the means to generate significant streams of sustainable energy. The installation of such farms comes at high costs due to the large dimensions and weight of turbine components and the high specialization of involved resources. During the installation of wind farms, companies need to provide vast areas, capable of buffering high-weight components at the respective base-ports. This article proposes a method to optimize the capacity of these buffers to reduce the risk of renting too much or too less spaces. While formulations exist to solve the actual inventory stock problem, this article proposes and evaluates different approaches to estimate time- and weather-dependent in- and output flows, using historical weather information. The results show that, on average, both proposed approaches result in good estimates for the inventory's capacity and initial stock levels. Thereby, the computationally more expensive scheduling-based approach results in slightly better results.

Keywords: Storage Capacity Optimization, Mixed-Integer Linear Programming, Offshore Wind Farms, Installation Planning, Weather Dynamics

1 INTRODUCTION

Over the last years, wind energy has become one of the main contributors to green and sustainable energy. Thereby, offshore wind farms become increasingly important, due to the higher and steadier availability of wind and free areas at the open sea. For example, during the first half of 2019, Germany installed over 1350 new offshore turbines with a cumulative energy output of more than 6.6 GW (Deutsche WindGuard GmbH 2019). These numbers fall in line with the observed global trend of an exponential increase of produced wind energy over the last decade (REN21 2018). Nevertheless, while higher wind speeds and availabilities at sea render offshore wind farms very attractive, these conditions also introduce high uncertainties and costs during the installation of these farms. Literature attributes about 15-20% of the overall cost of a wind farm to logistics costs during the installation (Lange, Rinne, and Haasis 2012), (Dewan, Asgarpour, and Savenije 2015), (Muhabie et al. 2018). These high costs result from weather uncertainties at sea, which generally result in inefficient use of the involved resources. Due to the large dimensions and weight of a wind turbine's components (e.g., Figure 1a), an installation requires highly specialized resources, e.g., jack-up (installation) vessels, heavy-duty cranes and storage facilities (e.g., Figure 1b), and heavy-lift vessels. For a more detailed review of dedicated resources, see, for example (Rippel et al. 2019). Most of the literature in this area focuses on efficient use of the installation vessels, but only a few research deals explicitly with related resources, e.g., storage and handling at the installation project's base-port (c.f. Section 1.2). While installation vessels constitute the highest cost factor with charter rates of up to 145,000 € per day (Meyer 2014), the influence of heavy-duty resources in base-ports cannot be ignored and highly influences the efficiency of applied vessels (Rippel et al. 2019c). Moreover, if the current trends towards larger and heavier components, and towards an increase in constructed wind farms continue, port-side resources may quickly become bottlenecks if not planned and used efficiently (Oelker et al. 2020). For example, Deutsche WindGuard GmbH (2019) lists 19 wind farms of varying sizes currently planned to be constructed in Germany's Northern and Eastern Sea until 2030.

(a) (b)

Figure 1: (a) Loading rack for turbine blades. (b) Loading equipment at a container terminal.

Consequently, this article proposes and evaluates a method to estimate the required storage capacities at the base-port for a given project. While the actual inventory stock optimization (storage capacity and initial storage amount) more or less resembles a standard optimization problem, this article focuses on methods to estimate the buffer's in- and output streams. Especially the estimation of the output stream, given by the number of wind turbines constructed during a defined time interval, poses a particular challenge. On the one hand, the number of constructible turbines heavily depends on the current weather conditions, for example, shown in (Rippel et al. 2019b). On the other hand, it is impossible to precisely predict these conditions with a sufficient prediction horizon to render strategic decisions during the selection and the dimensioning of the base-port. Consequently, this article uses historical weather data and proposes two approaches to estimate the expected number of constructible turbines for each time step over the project duration.

The following subsections describe the installation process for offshore wind farms and shortly present the current state of the art. Section 2 describes the proposed method and the used approaches to estimate the in- and output streams. Afterward, section 3 provides an evaluation of these approaches before the article closes with a conclusion and a description of future work.

1.1 Installation Process

According to the literature, the installation process for offshore wind farms separates in three consecutive phases: The installation of foundations, the installation of the actual turbines (top structures), and finally, the commissioning (Vis and Ursavas 2016), (Quandt et al. 2017). As all three phases need different resources, these generally take place in consecutive seasons. Each season mostly ranges from April to October of a given year, as these months provide suitable weather conditions for offshore installation tasks. This article focuses on the installation of top structures, whereby the proposed methods apply to the installation of foundations without limitations.

In terms of the installation itself, literature proposes several types of processes, for example, feeder-based processes as described in (Oelker et al. 2018), or preassembly concepts in (Vis and Ursavas 2016). Nevertheless, in practice and research, the so-called conventional installation concept still takes up a predominant role and is described, e.g., in (Oelker et al. 2017) or (Quandt et al. 2017). The conventional installation concept assumes that a specific production site produces each type of component. Heavy-lift transport vessels perform transportation between these production sites and the base-port, which acts as the logistics hub for the installation. One or more installation vessels pick up the components in the base-port and proceed to the installation site, where they assemble the actual turbines. These installation vessels possess the ability to mount themselves onto the sea bed, stabilizing the vessels, which facilitates required crane operations even under harsh weather conditions. After this so-called jack-up operation, the vessels remain stationary until it finishes the top structure and proceeds to the next installation. As jacking up and down damages the sea bed, installation vessels should, in practice, only perform these operations once for each turbine construction site. Once the vessel has used all loaded components, it returns to the base-port to load the next sets and continues the installation. Thereby, strict weather restrictions in terms of maximum wind speeds and maximum wave heights limit offshore operations. An operation can only be conducted if the weather is good enough for the full duration of an operation. If current conditions exceed the limits, the vessel needs to abort the operation and restart it later on, resulting in additional waiting times. See, for example (Rippel et al. 2019) for a list of limitations given throughout the literature.

The process description above shows that the base-port constitutes the major logistics hub for the installation of offshore wind turbines. Thereby, the base-port needs to offer sufficient resources to buffer and handle turbine components. Particularly smaller areas like Germany's Northern Sea only provide a limited number of suitable base-ports. Consequently, existing resources at each base-port can quickly become bottlenecks during the installation, if the trends towards more parallel construction projects and larger and heavier components continue. To mitigate this problem and to reduce the financial investments in chartering port-side resources, planners require a good estimation of necessary storage capabilities per project.

1.2 Process Planning for the Installation of Offshore Wind Farms

In comparison to other topics like the maintenance of offshore turbines, only a few articles in the literature explicitly deal with the installation of offshore wind farms (Vis and Ursavas 2016). Thereby, most of these articles focus on the scheduling or simulation of installation vessels under the influence of weather dynamics as major cost factors. During the last years, researchers have conducted several simulation studies, e.g., to evaluate the influence of different assumptions about the weather (Muhabie et al. 2018), different preassembly (Vis and Ursavas 2016), or installation concepts (Ait Alla et al. 2017). Moreover, several articles propose scheduling approaches to optimize offshore operations, e.g., by scheduling the commissioning and decommissioning of vessels (Kerkhove and Vanhoucke 2017), generating plans under different weather assumptions (Scholz-Reiter et al. 2011), (Ursavas 2017), (Rippel et al. 2019a), or to evaluate different (multi-objective) cost functions (Irawan, Wall, and Jones 2017), (Irawan, Wall, and Jones 2019).

In current literature, only very few articles explicitly investigate the limitation of resources. Beinke, Ait Alla, and Freitag (2017) propose a model to investigate the influence of sharing heavy-lift transport vessels between different installation projects, demonstrating high potential for cost reductions. Beinke et al. (2020) conduct a simulation study, which shows that the demand for installation can be expected to increase drastically over the next years when the first offshore wind farms need to be decommissioned. In previous work, Rippel et al. (2019c) investigated the influence of limited loading bays if several installation vessels use the same base-port, recommending that additional bays should be charted if considering more than two vessels.

Oelker et al. (2020) describe a simulation study for the base-port at Eemshaven, showing that the capacity of this base-port might be exceeded if the mentioned trends continue. These articles highlight the need for new concepts and advanced approaches to optimize the capacity utilization at the base-port.

This state of the art shows that current literature mostly focuses on efficient use of installation vessels, but, in most cases, assumes unlimited resources at the base-port. Consequently, the remainder of this article proposes a method to estimate the required storage capacity for a project in the base port.

1.3 Nomenclature

Table 1 provides an overview of the most important parameters and variables used throughout this article. Additional notation is introduced at the appropriate places if required.

Table 1: Nomenclature

		Parameters	
n^{owt}	$\mathbb{N}^+$	Integer	Number of turbines to build
n^{steps}	$\mathbb{N}^+$	Integer	Number of time steps in the capacity optimization
n^{years}	$\mathbb{N}^+$	Integer	Number of past years considered in the duration estimation
in^{frq}	$\mathbb{N}^+$	Integer	Amount of hours between component deliveries
in_k	$[0; n^{owt}]$	Integer Array	Number of component sets delivered per time step
out_k	$[0; n^{owt}]$	Integer Array	Number of component sets used per time step
min^{inv}	$[0; n^{owt}]$	Integer	Minimum inventory to be kept during optimization
min^{cap}	$max(in_k) + min^{inv}$	Integer	Minimum capacity to be maintained
		Indices	
k	$[1; n^{steps}]$	Integer	Index of the current time step
		Decision Variables	
$Y^{capacity}$	$[min^{cap}; n^{owt}]$	Integer	Storage capacity at the base-port
$Y^{initial}$	$[0; n^{owt}]$	Integer	Initial storage amount at the base-port
$Y_k^{current}$	$[min^{inv}; Y^{capacity}]$	Integer Array	Current storage at base-port for each time step

2 BASE-PORT CAPACITY OPTIMIZATION

The proposed algorithm consists of three major parts. First, the estimation of the buffer's input (restock) rate and amount. Second the estimation of the output amount per time step, and third, the actual optimization. Thereby, the algorithm does not distinguish between the individual components but considers sets, each consisting of one tower (or of tower segments), one nacelle, three blades, and a connection hub, including the required wiring. As given in the process description in section 1.1, the installation of a turbine cannot commence until the installation vessel has loaded at least one full set of components.

2.1 Estimation of the Input Rate and Amount

Generally, planners can derive the restock rate in^{frq} and number of components delivered per cycle in_k directly from the planned supply network. These values mainly depend on the locations of the base-port and production ports, and the deck-layouts of the employed heavy-lift vessel. While the former determine the traveling times for each required trip, the deck-layout determines how many components of which type the vessel can transport simultaneously. In practice, layouts for heavy-lift vessels generally focus on a single type of component to use available spaces as efficiently as possible (Beinke, Ait Alla, and Freitag 2017). Planners can determine how many trips to each production port a vessel requires to obtain a number of full sets (in_k) from these deck-layouts. Adding together the expected traveling time, loading time, and finally, the unloading time for each trip results in an estimation of the restock frequency in^{frq}.

2.2 Estimation of the Output Amount and Problem Size

While the proposed algorithm can derive the restock frequency and amount directly from the scenario description, the number of turbines an installation vessel can build directly depends on current weather conditions. These conditions cannot be known or sufficiently predicted beforehand. Consequently, the algorithm uses historical information to estimate the number of turbines constructed within the required time frame. The algorithm uses the approach proposed in (Rippel et al. 2019c) to estimate the duration of weather-dependent operations. This article uses a database containing 50 years of historical measurements of wind speeds and wave heights with an hourly resolution. In the first step, the algorithm preprocesses this database by estimating the duration of an installation operation for every hour in the database. The resulting dataset describes how long an installation would have taken if it started at that particular hour. The algorithm saves this new dataset so that the durations can simply be looked-up to speed up later calculations. In the second step, the algorithm uses these durations to estimate the output amount. In this context, this article proposes and evaluates two methods, which come at different complexities and, therefore, calculation times. Based on the estimated output amounts, the algorithm finally defines the dimension of the capacity optimization as the number of timesteps n^{steps} of length in^{frq}, required to install the amount of turbines to build n^{owt}.

2.2.1 Estimation by Aggregation

The first method estimates the output amount for each time step k by calculating the mean duration of an installation d_k^{owt} over a time window conforming to the size of the restock frequency in^{freq} and the number of past years given by n^{years}. The output amount for each time step is calculated according to Equation (1). Therefore, the estimated installation duration is summed up with the duration of loading the required components d^{load} and with a fraction of the required transition time between the base-port and the installation site d^{move} relative to the loading capacity of the vessel denoted as cap_v. The algorithm repeats this calculation until the sum of entries in out_k is larger or equal to the number of turbines to build n^{owt} to determine the number of time steps n^{steps} for the capacity optimization.

$$out_k = \frac{in^{frq}}{d^{owt} + d^{load} + \left(d^{move} \cdot \frac{2}{cap_v}\right)} \tag{1}$$

The quality of the estimated output amount, strongly depends on the selected number of past years n^{years} and the regarded restock frequency (window size) in^{frq}. As an advantage, this method computes very quickly, thanks to the preprocessing of the durations. As a drawback, this approach results in a comparably coarse estimation as it aggregates all values within the requested window size without further distinction. Section 3.1 provides an evaluation of these parameters' influence on the estimation of the process duration.

2.2.2 Estimation by Scheduling

The second method applies the scheduling model proposed in (Rippel et al. 2019c) to obtain an estimation of the number of turbines that can be built in each time step k. It, therefore, solves the scheduling problem for each time step with a planning horizon of in^{frq}. Instead of calculating the duration of installation operations from forecasts, this algorithm uses the mean durations for that particular date and hour from a selected set of past years given as n^{years}. For example, the duration for performing that operation on the 22nd May 1982 at 11 o'clock would be calculated as the mean duration for that time and date in the years 1971 - 1981 if $n^{years} = 10$. Moreover, to reduce the risk of underestimating the output amount, the optimizer assumes that each vessel is already fully loaded and out at sea. After scheduling a time step k, the algorithm extracts the number of installed turbines from the schedules and denotes it in the vector out_k. As in the previous method, the algorithm repeats this scheduling until the sum of entries in out_k is larger or equal to the number of turbines to build n^{owt}, determining the number of time steps n^{steps} for the capacity optimization.

As with the previous method, the quality of estimations depends on the number of years considered n^{years}. As an advantage, this approach does not depend on the window size in^{frq}. As a drawback, this method requires solving several computationally expensive scheduling problems, with a problem size conforming to the window size in^{frq}.

2.3 Optimization Model

The proposed algorithm uses a Mixed-Integer-Linear Program to perform the actual optimization. Therefore, the optimizer minimizes the cost function J in Equation (2) given the constraints (3) - (6). The program relies on three integer decision variables: $Y^{capacity} \in [min^{cap}; n^{owt}]$ defines the maximum storage capacity in the base-port. $Y^{initial} \in [min^{inv}; Y^{capacity}]$ describes the initial inventory level required before the installation starts, and $Y_k^{current} \in [min^{inv}; Y^{capacity}]$ describes the current inventory level at each time step k. The parameter $n^{owt} \in \mathbb{N}^+$ refers to the number of turbines to be built during the project. $min^{inv} \in \mathbb{N}_0^+$ describes a minimum inventory level the optimizer needs to maintain during the optimization. Finally, $min^{cap} = min^{inv} + max(in_k)$ describes the minimal capacity to ensure new deliveries can be stored at the base-port. Furthermore, the constraints rely on the parameters in_k and out_k, which describe how many sets of components will be delivered to and used from the port in each time step k.

$$J = Y^{capacity} + Y^{initial} \tag{2}$$

The constraints (3) and (4) limit the initial inventory and the current inventory never to exceed the selected capacity. Constraints (5) defines the current capacity at time step k to be equal to the last time step, plus the current inputs, minus the current output amount. Finally, Constraint (6) ensures that the optimizer chooses the base port capacity large enough to fit delivered components at each time step.

$$Y^{initial} \leq Y^{capacity} \tag{3}$$

$$Y_k^{current} \leq Y^{capacity} - max(in_k) \qquad \forall k \in n^{steps} \tag{4}$$

$$Y_k^{current} = Y_{k-1}^{current} + in_k - out_k \qquad \forall k \in n^{steps} \tag{5}$$

$$Y^{capacity} \geq Y_k^{current} + in_{k+1} \qquad \forall k \in n^{steps} \tag{6}$$

The optimizer needs to choose $Y^{capacity}$ and $Y^{initial}$ in a way, that the values in $Y^{current}$ never decrease below $min^{inv} \in \mathbb{N}_0^+$. This formulation ensures that the current inventory level never becomes negative and, if $min^{inv} > 0$, it enforces a minimum inventory level. The later allows the introduction of a security stock. This formulation tries to keep the initial stock, as well as the capacity as low as possible. Nevertheless, the capacity cannot fall below maximum number of components delivered during a time step. In cases, where the inflow cannot sustain the outflow, this formulation increases the initial storage to satisfy the demand.

3 EVALUATION

The following subsections provide numeric experiments to evaluate the approach described above. The first experiment aims to evaluate the influence of the number of past years and the window size on the precision of the estimation. The second experiment aims to compare the results of both proposed approaches to estimate the output amounts. These evaluations use the mentioned data set of weather recordings from Germany's Northern Sea. Thus, these results relate to this geographic region. Nevertheless, this dependency results from the used dataset, while the proposed algorithms should apply to all regions without limitations.

3.1 Evaluation of the Window Size and Number of Past Years on the Duration Estimation

This section presents an evaluation of the influence of the parameters n^{years} and the window size on the precision of the duration estimation. The window size thereby depends on the restock frequency in^{frq} and thus, cannot be freely chosen during the optimization. This numeric experiment uses a fully factorial design over the parameters given in Table 2. As the dataset contains recordings, approximately, from 1957 to 2005, the parameters were selected not to exceed the dataset. E.g., the combination using the oldest data is given by $1980 - 20 = 1960$, which ensures that the required information is available. The same accounts for the window size: As the window always centers around the requested date, the experimental design has to ensure that the database contains sufficient data. E.g., requesting a window size of one month for January 1st, 1960, requires data for the latter half of December 1959. This experiment uses window sizes of 3 hours, one day, one week, two weeks, and one month (31 days).

Table 2: Experimental setup: Duration Estimation

Parameter	Notation	Values
Year to evaluate		{1980, 1985, 1990, 1995, 2000}
Past Years to regard	n^{years}	{2, 5, 10, 15, 20}
Window Sizes (hours)	$\sim in^{frq}$	{3, 24, 168, 336, 744}

Figure 2 presents the results of the evaluation. The figure presents the mean absolute error (MAE) between the estimation and the measured data, including its standard deviation within the dataset, aggregated over all included years. Additionally, the figure shows the mean deviation (non-absolute) for the same data. Figure 2 (a) thereby shows these errors for differently selected numbers of past years while aggregating all years and all window sizes. Figure 2 (b) shows the errors for different window sizes while aggregating the selected number of past years and years to evaluate.

The results show that the number of past years strongly influences the estimation result. The mean absolute error decreases with the inclusion of more historical data. In contrast, the standard deviation of this error does not change much after including ten or more years. Moreover, the result shows that including more years comes at diminishing returns so that the data only shows a slight difference in error between 10 and 20 past years. In contrast, the mean deviation (sum over non-absolute errors) tends towards zero at a higher amount of used historical data. This trend shows that, on average, more data results in a more equalized amount of over and underestimated durations across the year.

In terms of the window size, the results show no noticeable difference between small and large window sizes - neither the mean absolute error nor its standard deviation change remarkably. In contrast, an increasing window size results in a slight increase in the mean deviation, showing an increased tendency to overestimate the duration with larger window sizes.

In conclusion, the results show that including more historical data proves beneficial. However, the results also imply that including more than 20 years will not noticeably increase the results. Depending on the

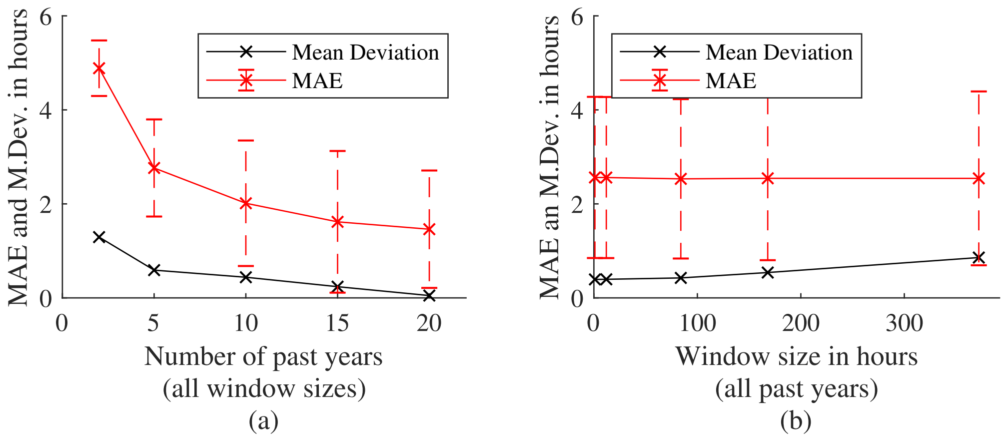

Figure 2: Mean deviation and mean absolute error of the duration estimation for different values of n^{years} (a) and in^{frq} (b)

available data, 10 - 20 years seem to deliver comparably good results. Moreover, the selected window size only slightly influences the quality of estimations. It has to be noted that the estimation tends to overestimate the duration with increasing window sizes.

3.2 Evaluation of the Optimization

This section aims to evaluate the results of the optimization against a simulation that uses real, measured weather conditions. The evaluation uses different values for the project's start date, and the minimum requested inventory level, as given in Table 3. This experiment follows the first scenario described in (Beinke, Ait Alla, and Freitag 2017): The scenario uses a base-port located in Eemshaven, Netherlands, whereby it uses production ports in Bremerhaven, Germany (nacelle and rotor blades) and Cuxhaven, Germany (towers). A full restock cycle provides eight sets of components and comprises one trip to fetch the blades (24), one trip to fetch the towers (8), and two trips to obtain the nacelles and hubs (2×4), resulting from different deck layouts for each component type. Summing up the loading, unloading, and traveling times, a restock cycle takes approximately 310 hours (close to two weeks) for eight full sets of components.

Table 3: Experimental setup and results: Optimization

Parameter	Notation	Values
Year to evaluate		{1980, 1985, 1990, 1995, 2000}
Month to evaluate		{April, June, August}
Turbines to install	n^{owt}	50
Minimum Inv. Level	min^{inv}	{1, 2, 5}
Past Years to regard	n^{years}	20
Window Size (hours)	in^{frq}	310
Restock amount	in_k	$in_k = 8, \forall k \in n^{steps}$

The experiment first applies both estimations to obtain the required capacity and initial inventory level for each start date. Afterward, the experiment evaluates both scenarios using an extended version of the simulation presented in (Rippel et al. 2019c). This simulation uses a Model Predictive Control scheme to incrementally generate optimal schedules for the involved vessels using a Mixed-Integer Linear Program under weather forecast uncertainties. It then evaluates these plans against measured weather data during the simulation part. For this article, we extended the Mixed-Integer model to regard port-side storage, i.e., the optimizer only schedules loading operations if component sets are available. Moreover, the model allows the optimizer to schedule *restock operations*. These operations always restock $in_k = 8, \forall k \in n^{steps}$ component sets, and require a minimum waiting time of $in^{frq} = 310$ hours between each other. This formulation allows the optimizer to delay restock operations if the port-side storage could not fit an incoming delivery. Nevertheless, if it delays one such operation, it still needs to wait 310 hours until it can schedule the next delivery as the experiment only assumes a single heavy-lift vessel to perform restocking.

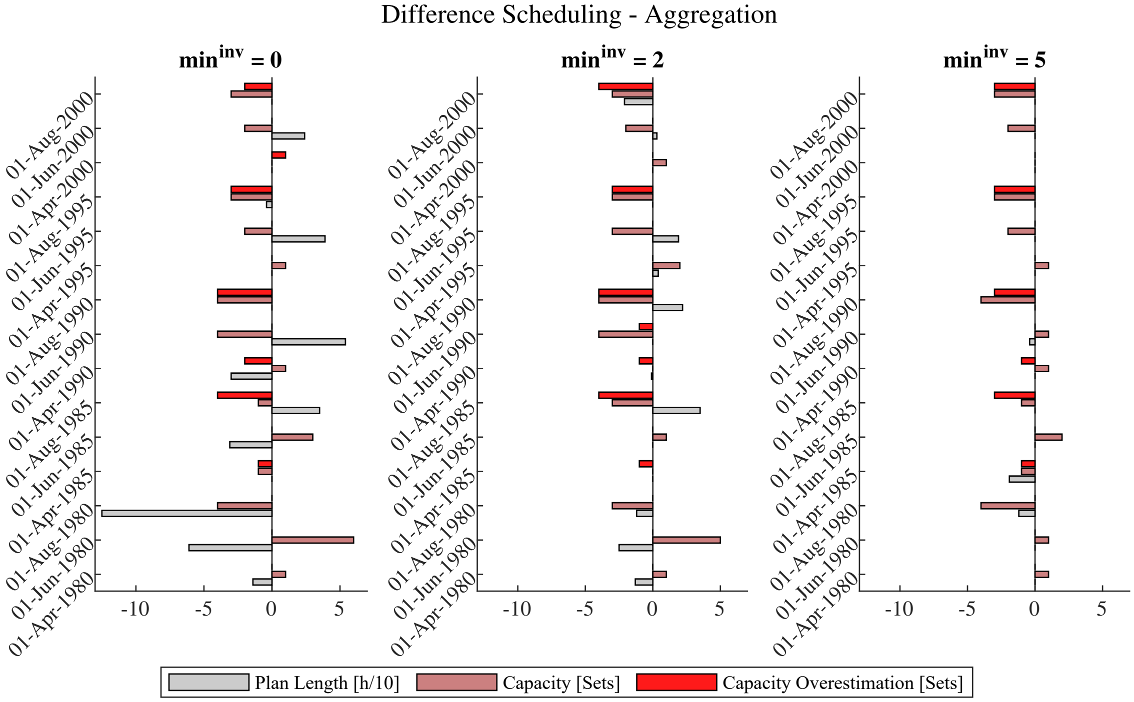

Figure 3: Comparison of relative simulation results for different minimal inventory levels.

Figure 3 shows the results of the simulation runs. Thereby, this figure shows relative values for the project (plan) length, the maximum capacity, and the difference between the capacity and the maximum inventory level during the simulation (capacity overestimation). As these values are hardly comparable between experiments, the figure depicts the difference of the scheduling-based results minus the aggregation-based results for each scenario. Thus, negative values show a better performance of the scheduling-based approach, while positive values favor the aggregation-based approach. These results show that the scheduling-based approach generally performs better in most instances but tends to underestimate the capacity if no safety margin in terms of $min^{inv} > 0$ is provided. This behavior can be observed in those instances where the scheduling-based approach proposes a smaller capacity but, in turn, requires longer for the project due to waiting times. Nevertheless, the plan length mostly differs by a small margin of some hours, showing that none of the approaches spend much time waiting for components.

Table 4 provides the results of the experiment as mean values across all start dates for each setting of the minimum inventory. The first three rows show the mean over the simulated project duration, the estimated capacity, and the initial stock level as the difference between the scheduling- (s) and the aggregation-based (a) approaches to maintain comparability. The following rows each show the mean result for each approach separately as these values can be compared directly. The table shows good average results for both approaches. Moreover the scheduling-based approach generally performs slightly better with lower project durations, fewer delayed restocking operations, and a lower overestimation of the capacity compared to the simulation's maximum inventory level. The averaged results show that both approaches adhere to the requested minimum stock level quite well.

Table 4: Results of the simulation runs as mean across all years and the given minimum inventory level.

Parameter	**Units**	**Approach**	$min^{inv} = 0$	$min^{inv} = 2$	$min^{inv} = 5$
Diff. Plan Length	[Hours]	(s-a)	-7.53	0.73	-2.33
Diff $Y^{capacity}$	[Sets]	(s-a)	-0.80	-1.00	-0.87
Diff $Y^{initial}$	[Sets]	(s-a)	0.27	0.27	0.27
Sum Delayed Restocks	[Hours]	(a)	20.33	4.20	40.73
Sum Delayed Restocks	[Hours]	(s)	0.00	31.73	0.00
$Y^{capacity}$ - Sim. Max Inventory	[Sets]	(a)	3.33	3.40	3.47
$Y^{capacity}$ - Sim. Max Inventory	[Sets]	(s)	2.33	2.20	2.53
Sim. Minimum Inventory	[Sets]	(a)	0.80	1.73	4.47
Sim. Minimum Inventory	[Sets]	(s)	0.80	2.20	4.53

4 CONCLUSIONS AND FUTURE WORK

This article presents a method to estimate the required storage capacity and initial inventory levels at the base-port for an offshore installation project. While the actual optimization resembles a standard inventory stock problem, this article focuses on estimating the required in- and outflows using historical data. The results show that both proposed methods show good results, whereby the approach based on scheduling results, on average, in slightly shorter project durations, fewer restock delays due to full storage, and a slightly lower overestimation of the required capacity. Nevertheless, this approach requires several schedules to be estimated, which comes with high computational efforts. These can easily amount to several hours of calculation time. As a result, planners have to decide if they want to invest more time in the estimation to obtain slightly better results or select the fast approach at the expense of estimation quality.

Future work will focus on extending the proposed optimization model by integrating the buffers at each production facility. This extension allows regarding production times and, more importantly, supply disruptions at these sites. Such disruptions can strongly influence the availability of components due to their long production times. Consequently, an estimation of the production sites' buffer capacity and, even more important, the initial inventory levels might reduce the risk of disruptions along the supply chain.

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