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A SELF-ADAPTIVE SEARCH SPACE REDUCTION APPROACH FOR OFFSHORE WIND FARM INSTALLATION USING MULTI-INSTALLATION VESSELS

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ABSTRACT

As an important part of renewable energy resources, offshore wind energy has great potential compared to its onshore counterpart despite the vast developments in recent decades. However, due to the more complex environmental condition and physical restrictions the installation of an offshore wind farm is hard to plan and predict, which often results in delays. This paper focuses on the scheduling problem in the installation phase of an offshore wind farm. We propose an adaptive search strategy based on the *Apriori* property and information entropy. The purpose is to prune the search space effectively and intelligently to realize an agile and swift rescheduling according to the environmental changes. For the numerical experiments, we use the environmental data obtained from the German North Sea from the year 1958 to 2007 in hourly resolution.

1 INTRODUCTION

Renewable energy is, without doubt, the key to mitigating or even solving global warming, which is a severe environmental problem mainly resulting from the usage of dirty energy resources, such as fossil, coal, and fracking gas. As a crucial contributor to renewable energy resources, offshore wind energy (OWE) has drawn attention in the last 20 years. A recent report shows an exponential growth of OWE capacity worldwide from the year 1998 to the year 2020 (Lee and Zhao 2021). However, it also points out that the overall contribution of offshore wind energy to worldwide energy consumption is still at a low level. Furthermore, the offshore wind counts for only around 5% of the installed wind energy offshore and onshore combined.

Similar to other industrial projects, the OWT installation is encountering project delays. An effective way to overcome this issue is to improve the scheduling of the installation vessels under consideration of the dynamic weather conditions on the sea. In a recent study, Lerche et al. (2022) have analyzed the impact of different factors, such as financial, organizational, and environmental factors, on the project delay in OWF installation. Unsurprisingly, the weather is one the most significant factors that cause project delays regarding offshore operations. Besides, compared to the onshore wind farm installation, the offshore wind farm installation is more sensitive to the environment and has more physical restrictions. For example, the installation vessel cannot be jack-uped twice on the same construction site since the damaged sea bed cannot provide sufficient stability. This infers that once the installation process begins, it cannot be stopped even if the weather condition deteriorates during the installation. Such circumstance leads often directly to delays in the installation project. A closer look at the differences between onshore and offshore wind power is given by Bilgili et al. (2011) and a technical report regarding the *state of the art* of offshore wind turbine installation is given by Jiang (2021). Some other issues appearing in the offshore wind installation process are summarized in Rippel et al. (2019). It has been shown that computer-aided tools can help to schedule the installation projects efficiently and, thus, reduce project delays. Yet, studies have shown that the search space of such scheduling problems is positively correlated to factors such as desired time span, number of vessels, and desired workload. Improvements have been made regarding computational efficiency. For example, Peng et al. (2021a) have suggested using stochastic optimization methods such as simulated annealing. However, the nature of stochastic optimization methods leads to the fact that the global optima are not ensured. Another issue is that the overall optimal schedule is considered as a sequence of local optima. However, the strategy produces comparative predictions to the MILP approach (Rippel et al. 2020) despite the negligence of correlation. This work aims at improving the *decision-support system* proposed in Peng et al. (2021b) in the following manner: i) we first take advantage of the Apriori property to prune the search space and then we investigate the advantages and disadvantages of this approach; ii) we improve the pruning strategy by adding adaptivity.

The rest of the paper is organized as follows: section 2 gives a literature review of the *state of the art* regarding offshore installation and adaptivity. In section 3 the problem in the OWF installation is introduced and formulated as an optimization problem. Furthermore, we elaborate on the concept of search space pruning and propose an adaptive version using information entropy in section 4. The numerical results are presented in section 5 and the conclusion is drawn in section 6.

2 STATE-OF-THE-ART

In this section, we are going to review the related works in the literature. This will be separated into two parts. In the first part, we look at the state-of-art regarding OWF installation. In the second part, we focus on the application of *adaptivity*.

OWF Installation As stated in section 1 the best way to overcome the project delay caused by the weather is to consider it in the schedule of the OWF installation. In Chartron (2019), the authors have reviewed recent studies regarding offshore logistics. Essentially, mathematical approaches have been applied to model the offshore installation process to solve the planning and scheduling problems of the majority of the researchers. The Mixed Integer Linear Programming (MILP) model proposed by Scholz-Reiter et al. (2011) aims at scheduling offshore installation activities under the consideration of a single weather scenario, which has been extended by (Ait-Alla et al. 2013) with an aggregate planning strategy for minimizing the installation cost. To deal with the uncertainties in offshore weather, Herroelen and Leus (2005) have reviewed the fundamental approaches for scheduling that consider uncertainties, e.g., stochastic project scheduling, fuzzy project scheduling. Cardoso et al. (2013) have introduced uncertainty of products' demand into their MILP model for the designing and planning of the general supply chains with reserve flows. A decomposition strategy proposed by Ursavas (2017) aims at improving the planning and scheduling to reduce the cost resulting from severe weather conditions.

Nonetheless, another bunch of recent works has focused on discrete-event simulations (DES) to investigate problems in the offshore wind industry. Vis and Ursavas (2016) proposed a decision-support tool based on DES to investigate the coherency between the logistical concepts and project performance. Muhabie et al. (2018)have investigated different assembly strategies used in the offshore installation by DES, including weather uncertainties, distances, vessel properties, and different assembly scenarios. It points out that offshore installation is strongly dependent on the season and geographical features of the construction site, and suggests combining different logistic strategies to achieve the best performance. Peng et al. (2020a) have proposed a TPN-based model to schedule the OWF installation process using a numerical search. Later on, the authors have presented a more general form of the TPN-based model using the Generalized Stochastic Petri Nets (GSPN) approach Peng et al. (2020b), which focused on the optimization of the system buffer, i.e., the base port. To improve the numerical efficiency of the search problem, Peng et al. (2021a) have shown the possibility of embedding a meta-heuristic algorithm into the DES model. In Peng et al. (2021b), the authors have presented a comprehensive study regarding the scenario where multiple installation vessels are considered in the installation process and compared the quality of the schedules using DES simulation and mathematical programming method. Rippel et al. (2020) have shown the possibility of the complementary application of discrete-event simulation and mathematical optimization methods using a metamodel-based transformation framework. However, such methods are often associated with a large search space as the complexity of the problem increase. In order to increase the agility in the DES-based approaches, a strategy to reduce the search space is required.

Adaptivity The application of *adaptivity* is multifaceted in the literature. For example, *adaptivity* is one of the core values of the modern software development scheme *SCRUM*. Adaptivity in this context is to make appropriate adjustments to the development process according to the feedback obtained from daily scrums (Schwaber, Ken and Sutherland, Jeff). However, within the scope of an algorithm adaptivity refers to the ability of the algorithm, that can adjust its behavior at runtime based on information available and/or a *priori* defined reward mechanism (Zaknich 2005). By adding adaptivity to the high-dimensional model representation (HDMR) technique, Ma and Zabaras (2010) have proposed an adaptive version of HDMR which detects the important dimensions automatically and constructs higher-order terms using only the important dimensions. Pang et al. (2016) focused on solving a non-smooth trajectory optimization problem, in which they proposed an adaptive method for mesh refinement, i.e., to detect the important location where a finer mesh is required. An *adaptive* approach was proposed by Li et al. (2019) to handle the uncertain log data in process mining. Ahmad et al. (2017) have given an overview on the application of *adaptivity* in human-robot interaction systems. Additionally, a bibliometric review on *adaptivity* was presented by Caya and Neto (2018). In numerical mathematics, there exist quite amount of work dealing with the numerical integration problem. Genz (1991) has proposed a globally adaptive algorithm for numerical multiple integration over an n-dimensional simplex. A dimension-adaptive quadrature method is proposed by Gerstner and Griebel (2003), which is based on sparse grid method. The fundamental idea is to select the integration points adaptively by evaluating the rewards obtained by considering the candidate integration points. Another field where *adaptivity* puts value is reconfigurable system. For example, Jung et al. (2006) have suggested an error threshold to the multiple model adaptive control scheme to guarantee its stability in closed-loop systems. Beck et al. (2014) addressed major drawbacks in reconfigurable systems, i.e., lack of transparency and lack of adaptivity in applications with different behaviors and characteristics. Thus, a binary translation mechanism, called Dynamic Instruction Merging, was proposed to handle these problems. Furthermore, *Adaptivity* has also been applied in solving flexible job shop problem. Cao et al. (2019) have proposed an A-HEFT scheduling algorithm, which extends the heterogeneous earliest finishing time (HEFT) algorithm by adding adaptivity, to handle the problem of scheduling stochastic jobs. Tang et al. (2015) suggested a platform-specific self-adaptive algorithm to reduce the make-span of tasks. In this work, a strategy is proposed for the offshore scheduling task, which aims at lowering the computational cost by adaptively reducing the search space with the help of predicted environmental information.

3 PROBLEM DESCRIPTION

A scheduling problem is a universal problem that exists in different domains. Different from the scheduling tasks in fields, such as CPU, and distributed computing, the scheduling of OWF installation is characterized by dynamic external weather conditions and physical restrictions. These obstacles result in immense project delays and are the main reason for the much lower construction efficiency compared to its onshore counterpart (Bilgili et al. 2011). In Section 3.1 we describe the fundamental knowledge of the offshore wind installation process, which is modeled with the TPN approach illustrated in Subsection 3.2. In Subsection 3.3 we formulate the scheduling task of OWF installation as an optimization problem. The notations used in this work are summarized in Table 1.

Table 1: Summary of notations used in this work.

Notations	Description
$\mathbf{J}$	the set of all possible jobs, which can be performed by the agents, $\mathbf{J} = \{J_1, \cdots, J_k, \cdots, J_K\}$
K	denotes the highest complexity level of the jobs. In other words, K is the magnitude of $\mathbf{J}$,i.e., $L = \lvert\mathbf{J}\rvert$
J_k	the k-th job of set $\mathbf{J}$, which is defined as a sequence of operations. $J_k = \left\{O_{k,1}, \cdots, O_{k,m}, \cdots, O_{k,M}\right\}$
$O_{k,m}$	denotes the m-th operation in k-th Job
t_w	specifies the integer *waiting time* in base port after loading operation with $t_w \in \mathbb{N}_0$
t_{max}	is a pre-defined maximal waiting time in base port with $t_{max} \in \mathbb{N}_0$
$\mathbf{S}$	the set of all possible schedules, $\mathbf{S} = \{\mathbf{s}_1, \cdots, \mathbf{s}_n, \cdots, \mathbf{s}_N\}$ with a magnitude $\lvert\mathbf{S}\rvert = N$
$\mathbf{s}_n$	represents a schedule, which is a tuple of job and associated waiting time $\mathbf{s}_n = (J_k, t_w)$
$\mathbf{s}_{opt}$	denotes the optimal schedule, which means the optimal job has started in optimal time: $\mathbf{s} = \left(J_{opt}, wt_{opt}\right)$
$d_{O_{k,m}}$	denotes the duration of operation $O_{k,m}$ in h
v	represents the wind speed, the upper limit for operations is denoted as v_{max}
h	represents the wave height, the upper limit for operations is denoted as h_{max}
τ	the fixed threshold for the *Apriori* algorithm.
$\tilde{\tau}$	denotes the adaptive threshold.
C	denotes the cost, for example $\mathsf{C}(\mathbf{s}_n)$ represents the cost of schedule $\mathbf{s}_n$
C_{opt}	denotes the optimal cost, which is $\mathsf{C}_{opt} = \mathsf{C}\left(\mathbf{s}_{opt}\right)$
f_t	denotes the firing time function in the TPN approach
$\mathscr{D}$	denotes a dataset with $\mathscr{D} = \{X_1, \cdots, X_i, \cdots, X_I\}$
$\mathscr{P}$	denotes a probability distribution function
p_i	denotes the probability of an instance

3.1 Offshore Wind Installation Process

Fundamentally, the offshore installation is a process that consists of five different operations: ① Loading (L), ② Sailing Forward and Backward (SF & SB), ③ Reposition (R), ④ Jack-Up and Jack-Down (JU & JD), and ⑤ Construction (C). The most important characteristic of offshore scheduling is that these base operations are restricted by external conditions, i.e., the wind speed, v, and wave height, h. The duration and weather limits of each operation are given in Table 2, which are typical values found in the literature for the conventional logistic concept (Peng et al. 2020b). For example, a *construction* will take 14 hours and during this operation the wind speed has to be less than $10\,\mathrm{m/s}$. Different from some industrial job shop problems, where the jobs are modeled as Directed Acyclic Graph (DAG) (Birgin et al. 2015), an OWF installation job is a cycle of operations illustrated in Figure 1. In this work, we only consider the conventional installation concept. Some other installation concepts exist in the literature, such as the innovative ones (Oelker et al. 2018), but the conventional one is the most commonly used in the industry due to the reliability given by the system buffer, i.e., the base port (Rippel et al. 2019). However, offshore installation jobs have different length depending on the number of components loaded onto the *agent*, i.e., installation vessel in the context of OWF installation, which is the core of the complete offshore operations. As shown in Figure 2, at time t_w an agent can be loaded with components up to the maximal capacity of the installation vessel. In this work, we consider that the maximal capacity of an installation vessel to be four OWTs. Based on the number of components loaded, there are different job variants. If the installation vessel is loaded with k OWTs at time t_w, then the agent can choose jobs from the set $\mathbf{J} = \{J_1, \cdots, J_K\}$, where the subscript simply indicates the number of wind turbines to be installed in the job. For example, the job J_2 means the agent will construct two wind turbines.

3.2 TPN Model

The Petri nets (PN) approach and its extensions, such as Timed Petri Nets (TPN) are widely used in modeling systems, which are characterized as being concurrent, asynchronous, distributed, parallel, non-deterministic, and/or stochastic (Murata 1989; Marsan et al. 2007). Originally, the PN approach was constructed without

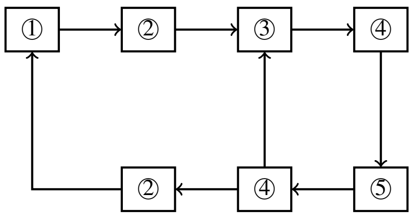


Figure 1: OWF installation process with conventional logistic concept.

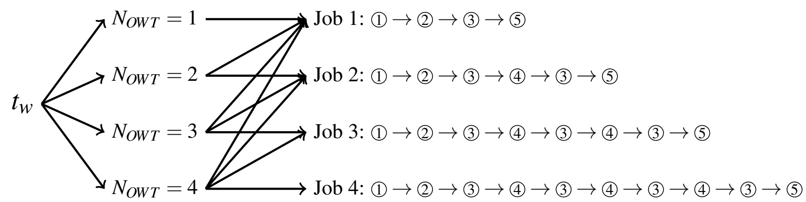


Figure 2: Possible job variants at with t_n.

the notion of time. The inclusion of the notion of time yields the PN extension, i.e., Timed Petri Nets (TPN). In difference from the conventional PN approach, transitions of a TPN model are assigned with time units, which define the time distances between the enabling and the firing of timed transitions. Same as to conventional PN model, a TPN model is still a bipartite graph with three different elements: places, timed transitions, and arcs, which are graphically illustrated as ○, □, → respectively.

In this work, we distinguish the graphical representation of the temporal transition from the conventional one, □, by adding diagonal lines to the graphical representation, ⊠. Because the firing time function, ft, assigned to each temporal transition is evaluated using Discrete-Time Markov Chain (DTMC) approach proposed by Rippel et al. (2019). Whenever the transition is enabled, it asks the DTMC sub-procedure to calculate the firing time based on the actual information and historical data. Thus, the prediction of the operation duration is given by the firing time function $f_t(d_{op}, v_{max}, h_{max}, t_c, v_{data}, h_{data})$, which is a function of *operation duration*, *operation limits*, *current time*, and *historical data*. Here, we use the historical data measured on the German North Sea from 1958 to 2007 with an hourly resolution. The TPN representation of the OWF installation process is shown in Figure 3 (Peng et al. 2020a).

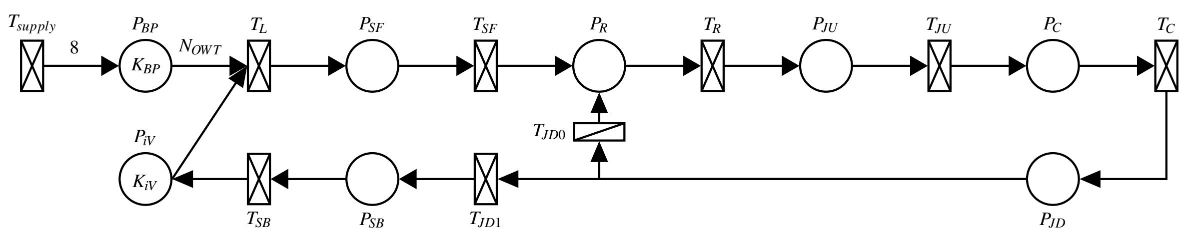


Figure 3: TPN model: offshore logistic with **BP**: base port; **iV**: idle vessel; **SF**: sail forward; **JU**: jack-up; **C**: construction; **JD**: jack-down; **OWF**: offshore wind farm; **R**: reposition; **SB**: sail back.

Table 2: Base operation duration and weather limitations.

Operation	d (h)	v_{max} (m/s)	h_{max} (m)	unit cost (€/h)
L	12	-	-	1200
SF & SB	4	21	2.5	2400
JU & JD	2	14	1.8	1800
C	14	10	-	1800
R	2	14	2	1800
W	-	-	-	400

3.3 Optimization Problem

In this subsection, we summarize the information above and formulate the scheduling problem as an optimization problem. First of all, for each installation cycle, there are $|\mathbf{S}|$ numbers of different options, where $\mathbf{S} = \{\mathbf{s}_1, ...\mathbf{s}_n, ...\mathbf{s}_N\}$ is the set of all possible schedules that can take place in an installation cycle. Second, each installation cycle can be postponed up to t_{max} hours. This yields a discrete search space with the size of $|\mathbf{S}| = |\mathbf{J}| \times t_{max}$. Thus, the optimal schedule for an installation cycle is defined as $\mathbf{s}_{opt} = (J_{opt}, wt_{opt})$. To find this optimum, an objective function is needed, which is used to measure the quality of an allowed set of inputs. The goal of this optimization problem is apparently to minimize the cost resulting from the installation. Thus, the following objective function is proposed:

$$\min f(\mathbf{s}) = \mathsf{C}(J_k) + \mathsf{C}(t_w)\,. \tag{1}$$

Function $\mathsf{C}()$ computes the cost of each operation based on the unit cost given in Table 2 and the cost of waiting time. The first term on the right-hand side in Equation (1) represents the regular cost of the Job J_k, which is obtained by summing up the cost of each operation, i.e., $J_k = \sum_{m=1}^{M} \mathsf{C}(O_{k,m})$. The second term can be seen as a penalty term. Otherwise, the system will try to push all the work into the future since doing nothing leads to zeros cost and, thus, it is always the cheapest solution for the current scheduling step.

4 ADAPTIVE SEARCH ALGORITHM FOR OWF SCHEDULING

In this section, we first introduce the idea of using the *Apriori* property to prune the search space in subsection 4.1 and elaborate on the problem in this strategy while using a fixed threshold with the help of a numerical example. As an improvement to the strategy, we propose an adaptive threshold based on the *maximum entropy principle* in Subsection 4.2 to mitigate the problem of overlooking the optimum.

4.1 Search Space Pruning Using Apriori algorithm

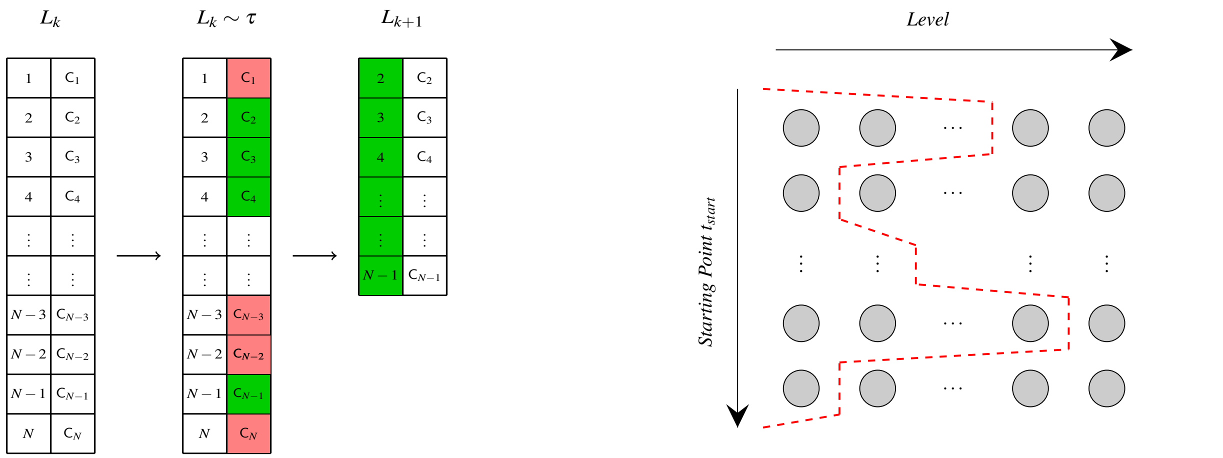
The *Apriori* property has been widely used in solving *frequent item set mining* (FIM) problems. For a more detailed understanding of the subject, literature such as (Tan et al. 2019) is recommended. The *Apriori* property reveals the fact that if an itemset, X, is frequent then all its subsets, Y, are frequent against a threshold τ, i.e., if X is frequent then $Y \subset X$ is frequent. Thus, it yields the inverse property, which infers if Y is not frequent, then all its supersets are not frequent. Indeed, the inverse property is the one that helps us to reduce the candidate itemsets set by pruning non-promising itemsets in the FIM task.

In this work, we use this concept in an analogical sense to prune the search space of a scheduling task. In Subsection 3.1 we have already introduced four different offshore installation jobs. Let k be the level of potential jobs, which also reveals their complexity, i.e., the higher the level the more complex the job and its duration will be; t_{start} be the starting time of a job. Besides, we assume that a job at level k, I_k, is included in a schedule at level $k+1$, i.e., $J_k \subset J_{k+1}$. In this case, the *Apriori* property implies that if it is good to start job J_{k+1} at time t_{start}, then it is also good to start job J_k at time t_{start}. Thus, the inverse property allows to prune the search space, since if a job J_k starting at t_{start} is bad, then all its supersets are potentially bad as well.

It is important to measure the quality of a job, J_k, i.e., to figure out whether it is meaningful to investigate a job at a higher level, J_{k+1}. For this purpose a predefined threshold, τ is required. In the FIM task, the threshold, τ, is defined as a frequency or probability of occurrence. In scheduling tasks, we assume first τ as a deviation in percentage to the optimal cost of a job. For example, the optimal cost of a job, J_k, is $C_{opt}(J_k)$. Then this job is considered to be good, if $\frac{\mathsf{C}_{opt}(J_k)}{\mathsf{C}_{real}(J_k)} = \tilde{C} \geq \tau$.

The optimal cost, $C_{opt}(J_k)$, is obtained by performing J_k under ideal conditions, i.e., every operation has been performed on time and no delay has occurred. The real cost, $C_{real}(J_k)$, is determined by performing J_k under the current situation at time step t_w, where delays caused by weather conditions and insufficient resources are taken into account. Apparently, the threshold τ takes a value from 0 to 1, where 0 represents the worst case, where the operation never finishes, and 1 represents the best case, i.e., the reality is ideal.

This pruning strategy is done in two steps at each level. In the first step, the candidates at level L_k are investigated. The results of each candidate are examined with the predefined threshold, and those bad



(a) The 2-step pruning strategy.

(b) Visualization: pruning via apriori algorithm.

Figure 4: Illustration: search space pruning using apriori algorithm.

solutions are filtered out. The remained candidates are delivered to level L_{k+1} for further investigation. Figure 4a gives an example of this two-step pruning strategy at level L_k. Figure 4b shows an example of a pruned search space. The search space can be effectively reduced by using this strategy. However, there is a problem with the fixed threshold, i.e., the overlooking of the real optimum. In another word, we cannot always find the best schedule and there is no guarantee of the quality of the solution found. A numerical example is made to clarify this issue in Section 5. To overcome this problem we introduce an adaptive threshold.

4.2 Adaptive Threshold

It is hard to find a fixed threshold that is suitable to prune the search space as the complexity of the jobs and the external conditions are changing. To mitigate this problem, we introduce an adaptive threshold based on the concept of information entropy. As presented in Section 2 the concept of *adaptivity* has been used across many fields of study. Here, the notion of *adaptivity* refers to the ability of an algorithm, that it can adjust its behavior during the simulation based on information available and/or the *Apriori*-defined reward mechanism.

Information Entropy The entropy of a probability distribution can be interpreted as a measure of uncertainty, or lack of predictability, associated with a random variable drawn from a given distribution. For example, suppose we observe a sequence of symbols $X_n \sim \mathscr{P}$ generated from distribution $\mathscr{P}$. If $\mathscr{P}$ has high entropy, it will be hard to predict the value of each observation X_i. Hence we say that the dataset $\mathscr{D} = \{X_1, \cdots, X_i, \cdots, X_I\}$ has high information content. by contrast, if p is a degenerate distribution with 0 entropy (the minimal value), then every X_i will be the same, so $\mathscr{D}$ does not contain much information (Murphy 2022).

Let $\mathsf{C}_{k,w} = \mathsf{C}(J_k, t_w)$ be the cost of the schedule on time t_w and at level L_k with $w \in [0, t_{max}]$ and $k \in [1, K]$. The probability of the cost of i-th schedule is given as $p_i = \frac{N_i}{N}$, where N_i is the number of occurrences of $\mathsf{C}_{k,w}$ in the population, and N is the number of data points in total. The adaptive threshold here means that the q-th cost value is set as the threshold for the level L_k. This means that the $1 \sim q-1$-th schedules will be eliminated and will not be considered in the level L_{k+1}. In this way, we obtain the two following probability distributions:

$$A : \frac{p_1}{P_A}, \frac{p_2}{P_A}, \cdots, \frac{p_{q-1}}{P_A} \quad \text{and} \quad B : \frac{p_q}{P_B}, \frac{p_{q+1}}{P_B}, \cdots, \frac{p_N}{P_B},$$

where $P_A = \sum_{i=1}^{q-1} p_i$ and $P_B = 1 - P_A = \sum_{i=q}^{N} p_i$. The information entropy is given as follows (Mohri et al. 2018):

$$\mathscr{H}_n = -\sum_{i=1}^{N} p_i \cdot \ln(p_i).$$

Thus, the information entropy of the two groups A and B can be calculated as follows respectively:

$$\mathscr{H}(A) = -\sum_{i=1}^{q-1} \frac{p_i}{P_A} \cdot \ln\left(\frac{p_i}{P_A}\right) = \ln(P_A) + \frac{\mathscr{H}_{q-1}}{P_A}$$
$$\mathscr{H}(B) = -\sum_{i=q}^{N} \frac{p_i}{P_B} \cdot \ln\left(\frac{p_i}{P_B}\right) = \ln(1-P_A) + \frac{\mathscr{H}_N - \mathscr{H}_{q-1}}{1-P_A}.$$

The total information entropy is simply the combination of the two parts:

$$\begin{aligned} h(s) &= \mathscr{H}(A) + \mathscr{H}(B) \\ &= \ln(P_A) + \ln(1-P_A) + \frac{\mathscr{H}_{s-1}}{P_A} + \frac{\mathscr{H}_N - \mathscr{H}_{q-1}}{1-P_A}. \end{aligned}$$

Our interest would be looking for the index q which maximizes the entropy according to the *maximum entropy principle*: $q = \mathsf{argmax}(h(q))$. Thus, the cost value C_q is selected as the threshold for the current level L_k, i.e., the C_q is different for each level based on the information obtained from the current level. In this way, the threshold for pruning is selected adaptively according to the knowledge obtained in the actual situation.

5 NUMERICAL EXPERIMENTS

Here, we consider the desired OWF with a size of 40 Offshore Wind Turbines (OWTs) located in the German North Sea. In this numerical study, we consider the application of two installation vessels. Theoretically, much more vessels can be dispatched to one OWF installation project, however, it has been shown that the application of more than two installation vessels in one installation project is not financially advisable (Peng et al. 2021b). Besides, we consider that an agent (i.e., an installation vessel) can be loaded with components for at most four OWTs. Furthermore, the *base port* has storage of components for 12 OWTs at the beginning of the simulation. As the system buffer, the base port can be stored with components for maximal of 32 OWTs. The bottom line of the base port storage is set as 8 OWTs, which means as long as the storage reaches this limit it will request for supply. The parameter setting of the TPN model for this scenario is summarized in Table 2.

5.1 Search Space Pruning

via Apriori algorithm In conclusion, the computational results show that it requires at least 6 installation cycles for each agent to finish the installation of 40 OWTs. For the convenience of graphical illustration, we take the results of the first installation cycle as an example. Figure 5 shows the search space of the first installation cycle with different pruning thresholds. Each dot in the figures represent a schedule run under the corresponding combination of *job level* and the *postpone*. It is clear that with the increasing value of the fixed threshold, τ, the search space is effectively pruned. For example, with $\tau = 0.95$ around 65% of the search space of agent 1 has been pruned in the first installation cycle. However, we also notice that with a higher value of τ it is possible that the optimal solution, marked with a red triangle, is overlooked.

via adaptive threshold The last subfigures in Figure 5a and 5b show the pruned search space of agent 1 and agent 2 in the first installation cycle using adaptive threshold, $\tilde{\tau}$, respectively. As we can see that the search space is effectively pruned, meanwhile it mitigates the problem of overlooking the optimal solutions. As we can observe that the optimal solution for agent 1 is found, however, the algorithm finds a slightly more expensive solution for agent 2.

5.2 Summary and Discussion

In this subsection, we mainly discuss 1) the findings of using different values of fixed threshold τ and the difference between the fixed one and the adaptive one $\tilde{\tau}$; 2) the problem of overlooking the optimum in the search space. For the discussion about the financial benefits of using the scheduling approach and the comparison between different approaches, we refer to Peng et al. (2021a) and Peng et al. (2021b).

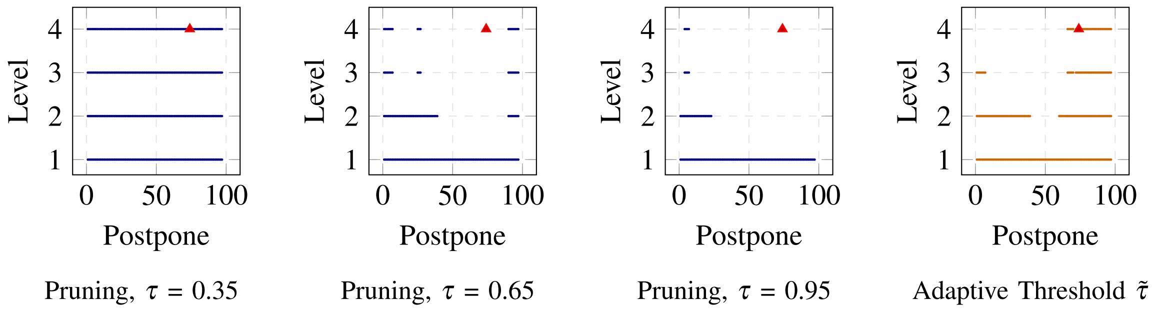
Comparison between fixed τ and adaptive threshold $\tilde{\tau}$ As we can see in Figure 5, the higher-level jobs are significantly pruned as the value of the fixed threshold τ increases, i.e., the scheduler prefers lower-level jobs, where the dark blue dots and the orange dots represent one schedule in the search space. In another word, this results in schedules with more installation cycles. For example, the installation of the desired OWF can be finished within 6 installation cycles for each agent as we set $\tau = 0.35$, which does not prune the search space at all in this case; however it will take 10 installation cycles for each agent if we increase the fixed threshold τ to 0.95. This simply reveals that the higher the value of the fixed threshold τ the swifter the schedules, thus, more installation cycles will be needed.

Compared to fixed thresholds, the computational results show that the usage of an adaptive threshold, $\tilde{\tau}$, based on information entropy is meaningful. It adjusts itself according to the situation at the current step and effectively prunes the search space. The problem of overlooking the optimal solution still exists, for example, in Figure 5b agent 2 has missed the optimal solution marked as a red triangle while using an adaptive threshold. However, the algorithm is still able to find a solution that is close to the optimal solution. Figure 6 illustrates the computational costs and the sizes of search space using different thresholds relative to the case $\tau = 0.35$. As reference the computational cost of case $\tau = 0.35$ is about 7 min and the size of the search space is 4656 schedules. For example, the case where $\tau = 0.5$ has a computational cost and a search space about 80% of the reference value, i.e. 5.6min and 3725 schedules. It is easy to notice that the computational cost and search space size are positively correlated. In conclusion, we believe that the usage of the adaptive threshold is a reasonable tradeoff between computational time and the quality of results.

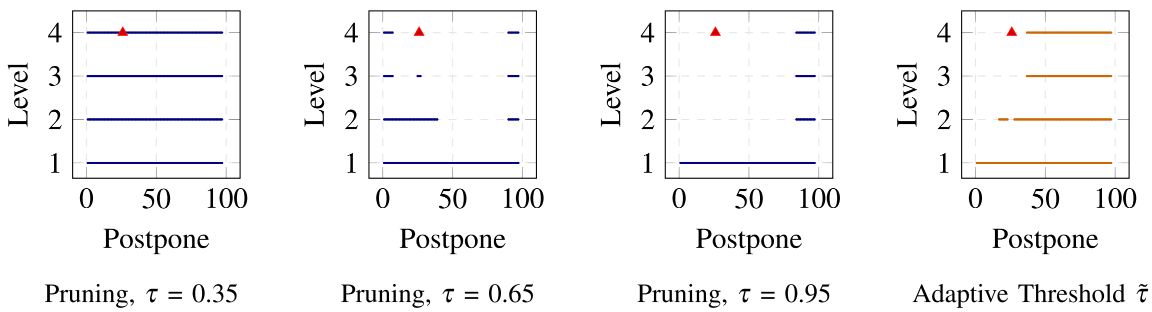
Overlooking of the optimum In previous work, the problem of overlooking the optimum has been addressed while using the Simulated Annealing (SA) approach (Peng et al. 2021a). However, the reasons for the occurrence of this phenomenon are different. In the SA approach, the search space is investigated in a stochastic way, since there is always a probability of rejection for the neighborhood of a data point. Thus, it is possible, that the solution found via SA is not the optimum but somewhere near the optimum. This phenomenon also cannot be improved by changing the parameters, such as temperature, and the number of loops as long as the probability of rejection exists. To investigate the overlooking rate, we have simulated about 200 installation cycles starting from random dates for different threshold values. Figure 7 shows that the adaptive threshold, $\tilde{\tau}$, has captured 86% of the optima. There is a about 40% loss of optima with $\tau = 0.65$. The overlooking of the optimum observed in the proposed strategy is given by the dependency between the complexity levels. When the candidates are already eliminated in the lower levels, they will not be delivered as candidates to the higher levels. In the authors' opinion of view, this could be solved by decoupling the complexity levels and by using back-propagation. Even though the proposed strategy provides satisfying results.

6 CONCLUSION

In this work, we have addressed one of the major problems in the offshore wind problem installation process, which is the delay resulting from the changeable offshore weather conditions. We have proposed an adaptive search space pruning strategy based on the *Apriori* algorithm and information entropy to improve the computational efficiency of the OWF scheduling task. The numerical results show that the proposed strategy makes a reasonable tradeoff between computational time and the quality of the solution. However, they also show that the phenomenon of overlooking the optimal solution is in this case unavoidable since there are still dependent effects on the pruning strategy. The reason for the occurrence of this phenomenon is discussed shortly compared to the SA approach. The opinion of the authors is that the problem in the



(a) Search space of agent 1.



(b) Search space of agent 2.

Figure 5: Search space of the first installation cycle constructing an OWF = 40 OWTs using two agents with fixed and adaptive pruning thresholds. Legends: a) Schedules calculated using τ: (●); b) Schedules calculated using $\tilde{\tau}$: (●); c) Optimal Schedule: (▲).

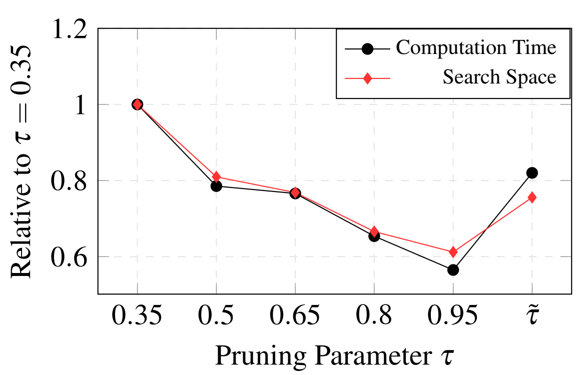


Figure 6: Computational time and search space using different thresholds relational to $\tau = 0.35$.

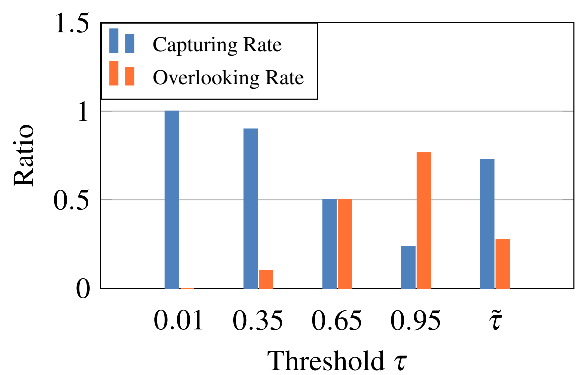


Figure 7: The rate on overlooking the optimal solution of different threshold values.

proposed strategy is solvable by decoupling the complexity and back-propagation, which can be considered topics for future works. Another aspect that is worth further investigation is other adaptive strategies for pruning the search space.

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REFERENCES

Ahmad, M., O. Mubin, and J. Orlando. 2017, July. "A Systematic Review of Adaptivity in Human-Robot Interaction". *Multimodal Technologies and Interaction* 1(3):1–25.

Ait-Alla, A., M. Quandt, and M. Lütjen. 2013. "Simulation-Based Aggregate Installation Planning of Offshore Wind Farms". *International Journal of Energy* 7:1–8.

Beck, A. C. S., M. B. Rutzig, and L. Carro. 2014, July. "A Transparent and Adaptive Reconfigurable System". *Microprocessors and Microsystems* 38(5):509–524.

Bilgili, M., A. Yasar, and E. Simsek. 2011, February. "Offshore Wind Power Development in Europe and Its Comparison with Onshore Counterpart". *Renewable and Sustainable Energy Reviews* 15(2):905–915.

Birgin, E., P. Feofiloff, C. Fernandes, E. De Melo, and M. Oshiro. 2015. "List Scheduling and Beam Search Methods for the Flexible Job Shop Scheduling Problem With Sequencing Flexibility". *European Journal of Operational Research* 165:1417–1431.

Cao, Z., L. Zhou, B. Hu, and C. Lin. 2019. "An Adaptive Scheduling Algorithm for Dynamic Jobs for Dealing with the Flexible Job Shop Scheduling Problem". *Bus Inf Syst Eng* 61:299–309.

Cardoso, S., A. Barbosa-Póvoa, and S. Relvas. 2013. "Design and Planning of Supply Chains with Integration of Reverse Logistics Activities under Demand Uncertainty". *European Journal of Operational Research* 226:436–451.

Caya, R., and J. J. Neto. 2018. "A Bibliometric Review about Adaptivity". *Procedia Computer Science* 130:1114–1119.

Chartron, S. 2019. "Improving Logistics Scheduling and Operations to Support Offshore Wind Construction Phase". *Logistics Research* 8:1–14.

Genz, A. 1991. "An Adaptive Numerical Integration Algorithm for Simplices". In *Computing in the 90's*, edited by G. Goos, J. Hartmanis, N. A. Sherwani, E. de Doncker, and J. A. Kapenga, Volume 507, 279–285. New York, NY: Springer New York. Series Title: Lecture Notes in Computer Science.

Gerstner, T., and M. Griebel. 2003, August. "Dimension Adaptive Tensor Product Quadrature". *Computing* 71(1):65–87.

Herroelen, W., and R. Leus. 2005. "Project Scheduling under Uncertainty: Survey and Research Potentials". *European Journal of Operational Research* 165:289–306.

Jiang, Z. 2021. "Installation of Offshore Wind Turbines: A Technical Review". *Renewable and Sustainable Energy Reviews* 139:1–21.

Jung, B., Y. Kim, and C. Ha. 2006, October. "Multiple Model Adaptive Control Scheme for Nonlinear Reconfigurable System". In *International Joint Conference SICE-ICASE, 2006*, 4926–4930. Bexco, Busan, Korea: SICE-ICASE.

Lee, J., and F. Zhao. 2021. "GWEC Global Wind Report 2021". Technical report, Global Wind Energy Council, Brussels, Belgium. Accessed: 2022-03-02.

Lerche, J., S. Lindhard, P. Enevoldsen, H. H. Neve, D. E. Møller, E. L. Jacobsen, J. Teizer, and S. Wandahl. 2022. "Causes of Delay in Offshore Wind Turbine Construction Projects". *Production Planning & Control* 1:1–14.

Li, W., Y. Fan, W. Liu, M. Xin, H. Wang, and Q. Jin. 2019. "A Self-Adaptive Process Mining Algorithm Based on Information Entropy to Deal with Uncertain Data". *IEEE Access* 7:131681–131691.

Ma, X., and N. Zabaras. 2010, May. "An Adaptive High-Dimensional Stochastic Model Representation Technique for the Solution of Stochastic Partial Differential Equations". *Journal of Computational Physics* 229(10):3884–3915.

Marsan, M. A., G. Balbo, G. Conte, S. Donatelli, and G. Franceschinis. 2007. *Modelling with Generalised Stochasitc Petri Nets*. Michigan: Wiley.

Mohri, M., A. Rostamizadeh, and A. Talwalkar. 2018. *Foundations of Machine Learning*. Second edition ed. Cambridge, Massachusetts: The MIT Press.

Muhabie, T., Rigo, Cepeda, de Almeida D'Agosto, and Caprace. 2018. "A discrete-event simulation approach to evaluate the effect of stochastic parameters on offshore wind farms assembly strategy". *Ocean Engineering* 149:279–290.

Murata, T. 1989. "Petri Nets: Properties, Analysis and Applications". *Institute of Electrical and Electronics Engineers, Inc.* 77:541–580.

Murphy, K. P. 2022. *Probabilistic Machine Learning: An Introduction*. Cambridge, Massachusetts: The MIT Press.

Oelker, S., A. Ait-Alla, M. Lewandowski, M. Lütjen, M. Freitag, and K.-D. Thoben. 2018. "A Simulation Study of Feeder-Based Installation Concepts for Offshore Wind Farms". In *Proceedings of the 28th International Ocean and Polar Engineering Conference*, edited by J. S. Chuang, B.-S. Hyun, D. Matskevitch, and A. M. Wang, 578–583. Sapporo, Japan: International Society of Offshore and Polar Engineers.

Pang, W., X. Xie, P. Fan, and J. Liu. 2016, August. “An Adaptive Collocation Method and Mesh Refinement for Solving Non-Smooth Trajectory Optimization Problems”. In *Proceedings of 8th International Conference on Intelligent Human-Machine Systems and Cybernetics*, edited by J. E. Guerrero, 405–409. Hangzhou, China: IHMSC: Institute of Electrical and Electronics Engineers, Inc.

Peng, S., D. Rippel, M. Becker, and H. Szczerbicka. 2021a. “Scheduling of Offshore Wind Farm Installation Using Simulated Annealing”. *IFAC* 54(1):325–330.

Peng, S., D. Rippel, M. Lütjen, M. Becker, and H. Szczerbicka. 2020a. “Simulation-Based Scheduling for Offshore Wind Farm Installation Using Timed Petri Nets Approach”. In *Proceedings of the 2020 Summer Simulation Conference*, edited by J. Denil, A. Del Barrio, and M. Traore, 1–12. San Diego, CA, United States: Society for Computer Simulation International.

Peng, S., D. Rippel, M. Lütjen, M. Becker, and H. Szczerbicka. 2021b. “Decision-Support System for Offshore Wind Farm Installation”. In *Proceedings of the 31th International Ocean and Polar Engineering Conference*, edited by J. S. Chung, I. Buzin, H. Kawai, H. Liu, I. Kubat, B.-F. Peng, A. Reza, V. Sriram, S. H. Van, D. Wan, S. Yamaguchi, and S. Yan, 1–8. Rhodes, Greece: International Society of Offshore and Polar Engineers.

Peng, S., H. Szczerbicka, and M. Becker. 2020b. “Modeling and Simulation of Offshore Wind Farm Installation with Multi-Leveled CGSPN Approach”. In *Proceedings of the 30th International Ocean and Polar Engineering Conference*, edited by J. S. Chung, O. M. Akselsen, I. Buzin, H. Jin, H. Kawai, H. Liu, D. Matskevitch, B.-F. Peng, V. Sriram, S. H. Van, D. Wan, and S. Yamaguchi, 1–8. Shanghai, China: International Society of Offshore and Polar Engineers.

Rippel, D., N. Jathe, M. Becker, M. Lütjen, H. Szczerbicka, and M. Freitag. 2019. “A Review on the Planning Problem for the Installation of Offshore Wind Farms”. *IFAC* 52:1337–1342.

Rippel, D., N. Jathe, M. Lütjen, and M. Freitag. 2019, November. “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., S. Peng, M. Lütjen, H. Sczcerbicka, and M. Freitag. 2020. “Model Transformation Framework for Scheduling Offshore Logistics”. In *Proceedings of the 30th Hamburg International Conference of Logistics (HICL)*, edited by C. Jahn, W. Kersten, and C. M. Ringle, 520–552. Hamburg, Germany: epubli.

Scholz-Reiter, B., J. Heger, M. Lütjen, and A. Schweizer. 2011. “A MILP for installation scheduling of offshore”. *International Journal of Mathematical Models and Methods in Applied Sciences* 5:371–378.

Schwaber, Ken and Sutherland, Jeff. “The Scrum Guide - The Definitive Guide to Scrum: The Rules of the Game”. https://scrumguides.org/docs/scrumguide/v2020/2020-Scrum-Guide-US.pdf, accessed Janurary 15th, 2022.

Tan, P.-N., M. Steinbach, V. Kumar, and A. Karpatne. 2019. *Introduction to Data Mining*. Second edition ed. New York, United States: Pearson. OCLC: 1089593316.

Tang, Z., L. Jiang, J. Zhou, K. Li, and K. Li. 2015, February. “A Self-Adaptive Scheduling Algorithm for Reduce Start Time”. *Future Generation Computer Systems* 43-44:51–60.

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 Assessment* 14:80–91.

Zaknich, A. 2005. *Principles of Adaptive Filters and Self-Learning Systems*. Advanced Textbooks in Control and Signal Processing. London, UK: Springer.

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