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Scheduling of Offshore Wind Farm Installation using Simulated Annealing *

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Abstract: This paper focuses on the scheduling problem in the offshore wind farm installation process, which is strongly influenced by the offshore weather condition. Due to the nature of the offshore weather condition, i.e., partially predictable and uncontrollable, it is urgent to find a way to schedule the offshore installation process effectively and economically. For this purpose, this work presents a model based on Timed Petri Nets (TPN) approach for the offshore installation process and applies simulated annealing algorithm to find the optimal schedule.

Keywords: Scheduling, Offshore Wind Farm, Timed Petri Nets, Simulated Annealing

1. INTRODUCTION

Driven by the needs of the renewable energy market, the offshore wind energy (OWE) industry has been developed rapidly, and wind power has become the fifth-largest source for electricity generation worldwide by the end of 2019 (IEA, 2019). Still, it is more expensive than other renewable energy resources, e.g., hydropower. Its high cost partially results from the installation phase of an offshore wind farm (OWF). The offshore weather conditions delay offshore installation projects frequently. A prominent solution to this problem is to schedule the OWF installation efficiently and agilely. However, Peng et al. (2020b) have shown that the scheduling of offshore installation exhibits the classical exponential growth in the search space. Thus, the planning horizon is restricted to a small scale to lower down computational cost. This work aims at extending, improving, and validating the approach proposed in Peng et al. (2020a,b). Firstly, the scheduling strategy is modified to reduce the search space. Secondly, the simulated annealing (SA) algorithm is integrated to find the optimal solution or at least a solution close to the optimum instead of using numerical search. Furthermore, the scheduling strategy is modified to decouple the installation cycles to eliminate the exponential growth in the waiting time combinations. Last but not least, the schedules obtained through the Timed Petri Nets (TPN) model and a Mixed Integer Linear Programming (MILP) model are compared. The strategy proposed in Rippel et al. (2019b) is applied to deal with weather disturbances, in which operation times are estimated by discrete-time Markov chain using historical weather data from Germany's North Sea.

This paper contributes to the literature in several senses. First, it presents a valid and agile scheduling strategy for the OWF installation problem. Secondly, a further runtime improvement is given by using stochastic metaheuristics, i.e., simulated annealing. Last but not least, it firstly, to the knowledge of the authors, compares results of DES models with MILP models for validation purposes.

2. LITERATURE REVIEW

Rippel et al. (2019a) have given a review of the current situation and challenges about the OWF installation. Essentially, mathematical approaches have been applied to model the offshore installation process to solve the planning and scheduling problems by the majority of the researchers. The Mixed Integer Linear Programming (MILP) model proposed by Scholz-Reiter et al. (2010) aims at scheduling offshore installation activities under the consideration of a single weather scenario, which has been extended by Ait-Alla et al. (2010) with an aggregate planning strategy for minimizing the installation cost. Rippel et al. (2019c) have embedded the MILP model into the model predictive control (MPC) scheme to cope with the weather conditions in a realistic environment. 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 resulted from the severe weather condition. It aims at mitigating the risks caused by offshore weather conditions.

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A few works have 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. A review of the studies regarding offshore logistics is given by Chartron (2019). It points out that offshore installation is strongly dependent on the season and geographical feature on the construction site, and suggests to combine different logistic strategy to achieve the best performance. Peng et al. (2020a) focus on the optimization of the system buffer, i.e., the base port, using a model based on Generalized Stochastic Petri Nets (GSPN) approach. Furthermore, the authors have proposed a TPN model to schedule the OWF installation process using numerical search (Peng et al. (2020b)).

3. SYSTEM DESCRIPTION

The OWF installation can be seen as a process that consists of numerous installation cycles (ICs), in which the installation vessel sails back and forth between the base port and the construction site and executes the sequential offshore operations. Fundamentally, an IC can be divided into 5 different operation categories: ① Loading, ② Sailing, ③ Reposition, ④ Jack-Up (JU), and Jack-Down (JD), ⑤ Construction. Operations, except ②, occur in an IC at least once, and at most $N_{C,max}$ times, where $N_{C,max}$ is the maximal capacity of the installation vessel. Besides, each operation owns a base operation duration and is limited by the offshore weather conditions in different magnitude. The base operation duration and weather limitations of each operation are summarized in table 1.

Table 1. Base Operation Duration & Weather Limitations

Operation	d (h)	v_{max} (m/s)	h_{max} (m)
Loading	12	-	-
Sailing	4	21	2.5
Jack-Up & Jack-Down	2	14	1.8
Construction	14	10	-
Reposition	2	14	2

Furthermore, the conventional logistic concept is considered in this work, which is described in detail in Rippel et al. (2019a). The OWF installation with the conventional logistic concept is depicted in Fig. 1.

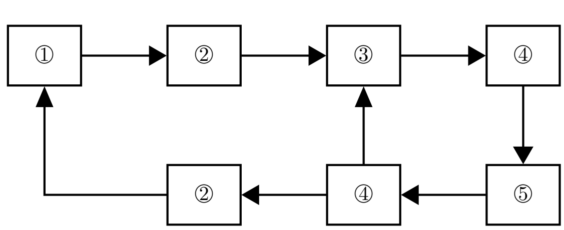

Fig. 1. OWF Installation Process with Conventional Logistic Concept

4. METHODOLOGY

The system introduced in section 3 is modeled with *Timed Petri Nets* (TPN) following Peng et al. (2020b), in which the authors have used numerical search to find the optimal schedule and addressed that the plan size is limited to a small number in order to prevent the exponential growth of the search space. Thus, we introduce the *Simulated Annealing* (SA) algorithm to overcome this problem, which allows the model to generate schedules for larger time horizons. Furthermore, the *scheduling strategy* is summarized, of which the advantages and disadvantages are discussed in short. Finally, we compare the results to an optimizes schedule resulting from a MILP-Formulation found from previous work.

4.1 Timed Petri Nets

Petri nets and their extensions are widely used in the literature to describe systems, which are characterized as being concurrent, asynchronous, distributed, parallel, nondeterministic and/or stochastic. Fundamentals and developments of PN theory are summarised in Murata (1989); Marsan et al. (2007). Graphically, a TPN model is a bipartite graph, which possesses three different elements: places, timed transitions, and arcs. It is mathematically defined as a 6-tuple:

$$\mathcal{TPN} = \{P, T, A, w, \boldsymbol{M}_0, f\}, \tag{1}$$

where P is the set of places; T is the set of transitions with $P \cap T = \emptyset$; $A \subseteq (P \times T) \cup (P \times T)$ is the set of arcs. Specifically, A can be divided into two sub-classes: i) input arcs, I, pointing from a place to a transition, and ii) output arcs, O, pointing from a transition to a place. An input arc formulates the firing rule for a transition, that there must be at least w tokens in the input place, where w is the multiplicity or weight of the arc defining how many tokens should be removed from the input place once the transition fires. Besides, the firing of the transition does not remove tokens from the input place. Generally, the arcs show in which direction the thresholds are transported. $\boldsymbol{M}_0$ is the initial marking of the TPN model. $f : T \to P^+$ is a firing time function that assigns a positive real number to each transition on the net. Wang (1998) and Popova-Zeugmann (2013) are refereed for more details and information on TPN.

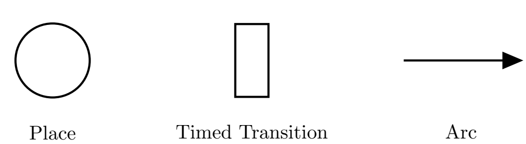

Fig. 2. OWF Installation Process with Conventional Logistic Concept

A state of a TPN is given by marking, which reveals the number of tokens in each place element. We denote the number of tokens in place p_i as $M(p_i)$, then the state of a PN can be written formally as a vector with $|P|$ components

$$\boldsymbol{M} = (M(p_1), ..., M(p_i), ..., M(p_{|P|})). \tag{2}$$

4.2 Simulated Annealing Algorithm

Generally, simulated annealing (algo. 1) is a stochastic metaheuristic to approximate the optimum in the feasible region of an optimization problem. The goal of this algorithm is to bring the system from an arbitrary valid initial state to a state with the minimum energy. This approach extends the idea of local search, which is widely used to find the local optimum by making *bad* trades (Henderson et al., 2003). The *bad* trades are accepted using the following criterion

$$\exp\left(-\frac{\Delta f}{t}\right) > rand[0,1] \tag{3}$$

and

$$\Delta f = f(s') - f(s), \tag{4}$$

where s is the current state, s' is the randomly picked state in the neighbourhood of s, t is the temperature at the current step, and f is the objective function of the optimization problem. At each iteration of the simulated annealing algorithm, a new point s' is randomly generated. The distance of the new point from the current point is based on a probability distribution with a scale proportional to the temperature t (equation (3) and (4)). The algorithm accepts all new points that lower the objective, but also, with a certain probability, points that raise the objective. If the value of t is large, then the *bad* trades will also have a larger possibility to be accepted. This allows the solver to explore more of the possible space of solutions. Theoretically, the neighbours of a state s are generated by applying small changes to state s. In this case, all the valid states are simply enumerated, and the enumerations are converted to its binary presentation. The systematic decline of the temperature affects the acceptance of the *bad* solutions directly. The chance of a *bad* solution is dropping while the temperature drops in every iteration. In the literature, there are several different strategies for cooling plans.

Algorithm 1. (Simulated Annealing).

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procedure SIMULATEDANNEALING(s:S)
  Initialization
  $t \leftarrow T(0)$; $n \leftarrow 0$; $s \leftarrow rand(S)$; $s_{best} \leftarrow s$;
  while $n > n_{max}$ **do**
    choose $s' \in \mathcal{N}(s)$
    if $g(s', s) > 0$ **then**
      $s = s'$;
    else if $\exp\left(\frac{g(s',s)}{t}\right) > rand[0,1)$ **then**
      $s = s'$;
    end if
    if $\mathrm{g}(s, s_{best})$ **then**
      $s_{best} = s$;
    end if
    $t = T(n)$;
    $n = n + 1$;
  end while
  return s_{best}
end procedure

4.3 Scheduling Strategy

Peng et al. (2020b) have proposed a scheduling strategy, which discretizes the complete workload into smaller parts. This discretization can be attributed to the decreasing accuracy of the weather forecast over time and physical limitations, i.e., the capacity of installation vessels. The main advantage of this idea is that it ensures the agility in scheduling and allows to reschedule the work if the weather forecast does not meet reality. However, this strategy encounters an exponential growth in the search space when the discretization is coarse, i.e., planning a lot of works at one time, and the waiting time of each installation cycle is considered. Thus, the authors have limited the application to a very fine discretization level without waiting times. This limitation mainly results from the coupling of installation cycles. To improve the functionality of this approach, we modify the discretization with a cycle-based strategy. In this way, the cycles are decoupled and, thus, the exponential growth resulted from waiting time is eliminated. The search space is reduced to $|\boldsymbol{S}| \times t_{w,max}$, where $|\boldsymbol{S}|$ represents the cardinality of the possible schedules in an installation cycle and $t_{w,max}$ is the maximal waiting time defined for each installation cycle.

4.4 Mixed Integer Linear Programming Model

The results generated by using the MILP model presented in Rippel et al. (2019c) are used here for comparison with the results of the TPN model. The model itself provides an optimal schedule for offshore operations while considering the uncertainty if weather forecasts. The model's objective function aims to minimize costs incurred by offshore times while maximizing the number of turbines installed in a given time interval. The authors embed the MILP-optimization within a model predictive control scheme to counteract the increasing uncertainty of weather forecasts by applying predictive online optimization.

5. OPTIMIZATION PROBLEM

The search for an optimal schedule for the OWF installation can be formulated as an optimization problem as follows. First of all, for each installation cycle, there are $|\boldsymbol{S}|$ numbers of different options, where $\boldsymbol{S} = \{\boldsymbol{s}_1, ...\boldsymbol{s}_i, ...\boldsymbol{s}_n\}$ is the set of all possible schedules that can take place in an installation cycle. Second, each installation cycle can be postponed up to $t_{w,max}$ hours. This yields to a discrete search space with the size of $|\boldsymbol{S}| \times t_{w,max}$. Thus, the optimal schedule for an installation cycle is the pair $(\boldsymbol{s}_{opt}, t_{w,opt})$. To find this optimum, an objective function is needed, which is used to measure the quality of an allowed set of inputs. The objective function used in this work is given as follows

$$\min f(\boldsymbol{s}, t_w) = \mathsf{Cost}(\boldsymbol{s}) + \mathsf{Cost}(t_{wait})\,. \tag{5}$$

The $\mathsf{Cost}()$ is a function that calculates the cost of each operation based on their unit cost given in table 4 and the cost of waiting time. The first term on the right-hand side in equation (5) represents the regular operational cost. The second term can be seen as a penalty term. Otherwise, the system will try to push all the work into the future since do nothing leads to zeros cost and, thus, it is always the cheapest solution for the current scheduling step.

6. NUMERICAL STUDY

With the scenario described in subsection 6.1, this numerical study intends to compare the optimal schedules generated by different models, i.e., TPN and MILP model, and show the improvement in computational time by using SA instead of a numerical search.

6.1 Scenario

The installation of an OWF should be completed on the German North Sea. The scheduling of this installation process is made with increasing planning horizons, i.e., up to 40 OWTs. Furthermore, we consider that the construction of all the fundaments and electricity girds are completed. The installation process should be started on the 1st. April 2001, at 8 a.m. The historical measurements from the year 1958 to 2000 in this area are used to estimate the weather influences on each offshore operation. The historical data contain measurements of wind speed and wave height in hourly resolution. The parameter setting of TPN model for this scenario is summarized in table 2.

Table 2. Parameter

Parameter	Value	Unit	Description
N_V	1	Vessel	Number of vessel used
C_{max}	4	OWT	Maximal vessel capacity
S_{ini}	12	OWT	Initial storage in base port
S_{max}	32	OWT	Maximal base port capacity
S_{min}	4	OWT	Minimal base port storage
S_{OWF}	40	OWT	Size of OWF

6.2 TPN with SA Algorithm

The TPN model used for the simulation is depicted in Fig. 4. A detailed explanation of this model can be found in Peng et al. (2020b). The motivation of applying SA to find the optimum schedule for OWF installation via the TPN model is elaborated in subsection 4.2. The efficiency and quality of SA are strongly related to the control parameter, i.e., the initial temperature and the cooling schedule. With a low initial temperature or a fast cooling speed, the algorithm can be trapped in a sub-optimal state. The temperature function used in this work is given as follows

$$T = T_0 \cdot k \cdot c, \tag{6}$$

where T_0 is the initial temperature, k is the annealing parameter, which holds the same as the iteration number until reannealing. c is the cooling parameter, which controls the cooling speed. The initial temperature and the cooling parameter used in this numerical study are given in table 3. The annealing parameter k is set to the upper bound of each variable, and the value of cooling parameter c is adopted from the literature (Fidanova (2006)). Indeed, the determination of the global optimum is not guaranteed by the SA algorithm, since there are always possibilities of accepting *bad trades* (see. section 4.2). Thus, a maximal number of iterations is applied in this work to ensure a 99.5% probability of reaching the global optimum and maintain the computational cost at a relatively low level.

Table 3. Parameter: Simulated Annealing Algorithm

Parameter	Value
T_0	[4, 97]
c	0.95
$iter_{max}$	100

6.3 Numerical Results

The optimal schedules found by TPN and MILP model regarding different planning sizes are given in Fig. 6-9. It is shown that both models have determined *identical* optimal schedules for each case. These optimal schedules are identical in two ways. First, they consist of the same number of installation cycles with identical workloads, i.e., the number of loadings and constructions. Second, the start and endpoint of each operation are the same as well. The schedules are optimal, since an earlier execution of any offshore operations, i.e., all the operations except loading, is not possible without violating the weather limitation. Furthermore, both models have efficiently evaded the major bad weather windows marked with red blocks in Fig. 5. It is shown that the optimal schedule of a lower planning size (e.g., 8 OWTs) is contained in the higher level (e.g., 10 OWTs), i.e., the local optimum is a part of the global optimum. This makes the discretized planning plausible, i.e., one can plan the work in small steps without missing the global optimum.

A comparison of the computational costs of three different approaches is shown in Fig. 3.

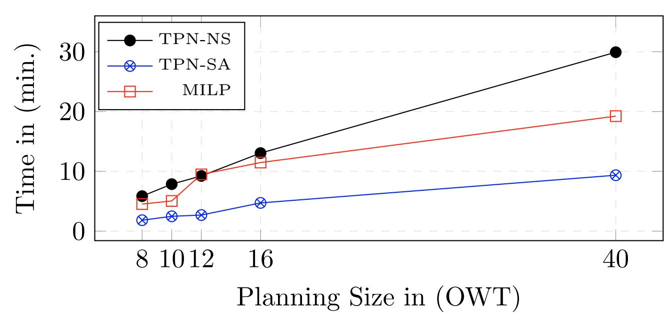

Fig. 3. Comparison: Computational Cost

The computational cost of the TPN model with numerical search (TPN-NS) is comparable to that of MILP model. The MILP has used almost the same cost as TPN-NS for planning size up to 16 OWTs. Due to the upcoming bad weather conditions, there is a significant rise when it schedules 12 OWTs. The computational cost of TPN-NS is slightly higher than MILP for 40 OWTs. The advantage of using simulated annealing (TPN-SA) is rather obvious. In general, TNP-SA is up to three times faster than the TPN-NS and MILP approaches. For example, the computational cost for scheduling 16 OWTs has dropped from about 14 min to about 5 min. The speedup obtained by using SA algorithm is summarized in table 5. Besides, the increase of the computational cost using SA is strictly related to the total number of installation cycles. For example, the computational cost has stayed in plateau for 10 OWTs and 12 OWTs, since both schedules possess the same number of installation cycles.

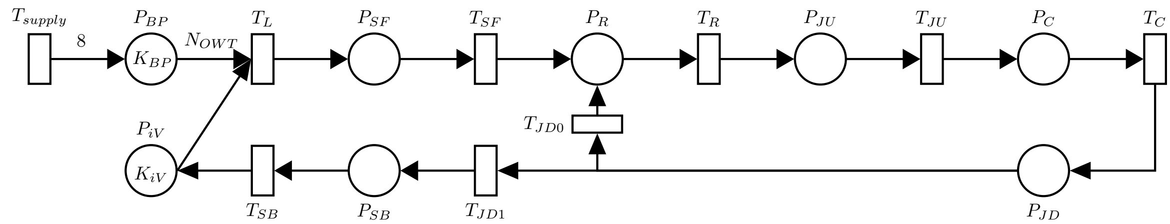

Fig. 4. TPN Model: Offshore Logistic with **BP**: base port; **iV**: idle vessel; **SF**: sail forward; **JU**: jack-up; **C**: construction; **JD**: jack-down; **OWF**: offshore wind farm; **R**: reposition; **SB**: sail back

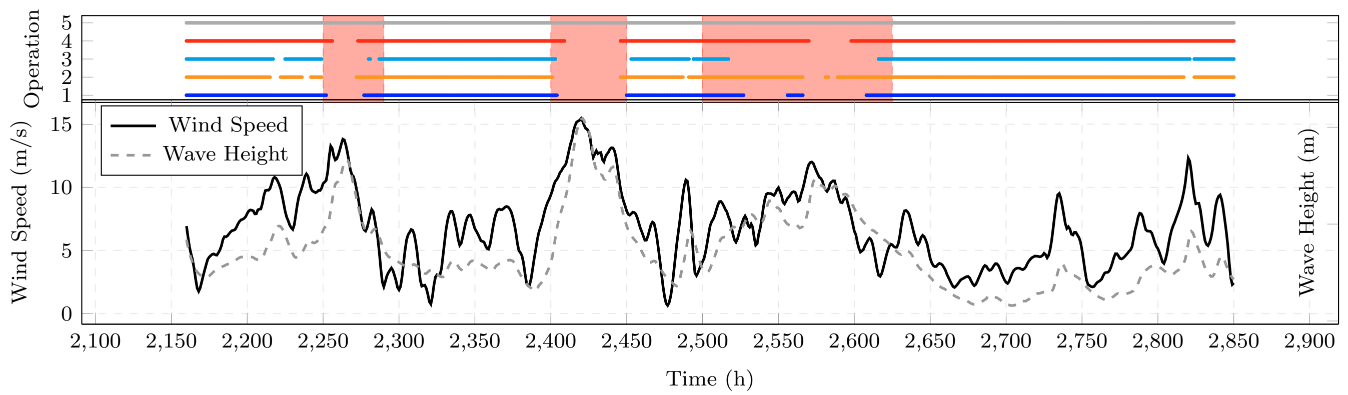

Fig. 5. Historical weather data in year 2001 on German North Sea and evaluation of weather restrictions for different operations with 5: Loading; 4: Sailing; 3: Jack-up and Jack-down; 2: Construction; 1: Reposition

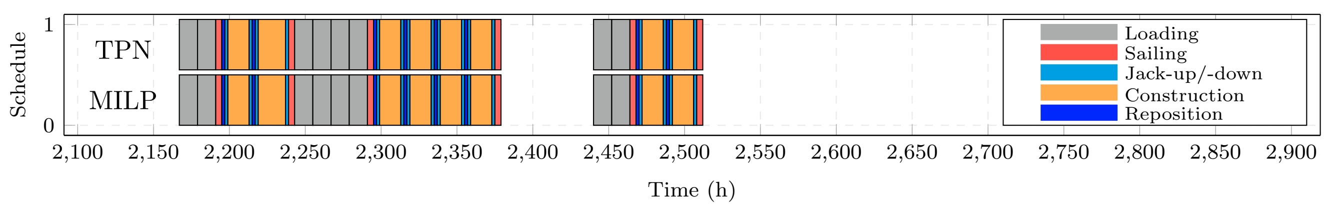

Fig. 6. Schedules with plan size = 8 OWT

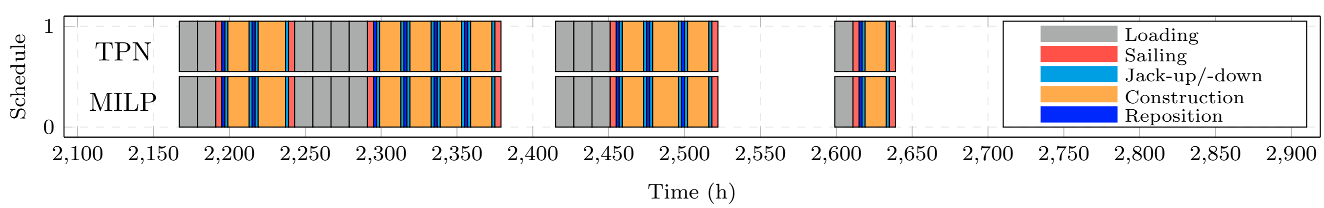

Fig. 7. Schedules with plan size = 10 OWT

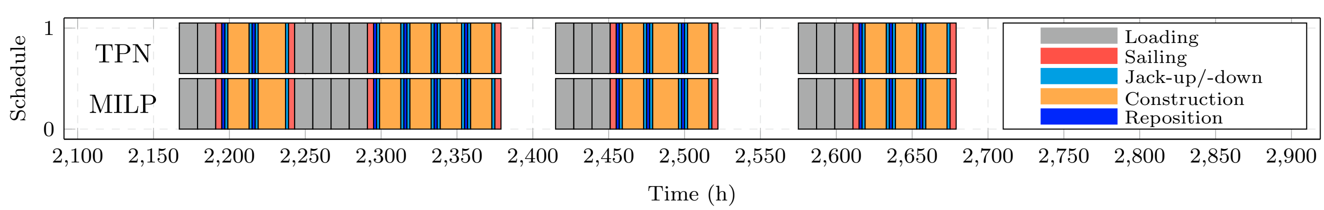

Fig. 8. Schedules with plan size = 12 OWT

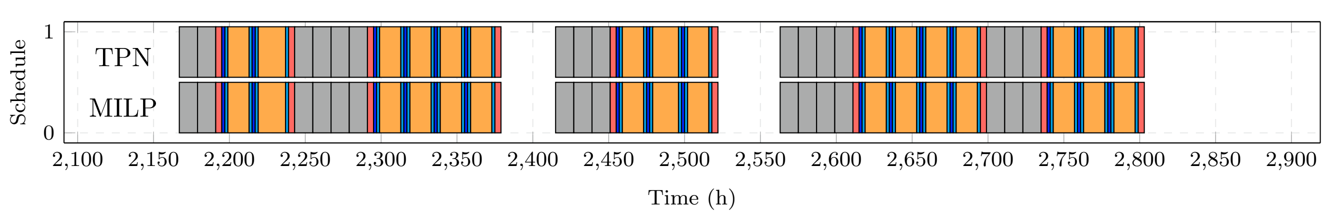

Fig. 9. Schedule with plan size = 16 OWT

Table 4. Operation Unit Cost

Operation	Cost (Euro/h)
Loading	1200
Sailing	2400
Rest	1800
Waiting	400

Table 5. Speedup: Simulated Annealing to Numerical Search

Plan Size	$Speedup_1 = \frac{t_{NS}}{t_{SA}}$	$Speedup_2 = \frac{t_{MILP}}{t_{SA}}$
8	3.20	2.47
10	3.16	2.04
12	3.43	3.53
16	2.76	2.43
40	3.2	2.06

7. CONCLUSION

This research has investigated the usage of simulated annealing algorithm on the TPN model presented by Peng et al. (2020b). Moreover, the scheduling strategy is modified to an installation-cycle-based search strategy, which has decoupled the installation cycles inside one schedule. It is shown in section 6, both TPN and MILP models have found identical optimal schedules for the defined scenario, which avoid the major inoperable weather windows effectively. It is shown in section 6.3 that the TPN model with numerical search possesses a comparable computational cost to the MILP approach. A significant improvement in computational efficiency is made by using simulated annealing, which is around three times faster than the other two approaches. Moreover, the TPN model possesses not only the computational efficiency. Different as MILP approach, the computational efficiency of TPN model is consistent and not influenced by the measurements. It has shown its flexibility in integration with different search algorithms. Nonetheless, the construction of the model, as well as the scheduling strategy, can be easily modified by the user. The future works will be concentrated on further improvements in the approach and comparisons of models in different scenarios.

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