HEURISTIC OPTIMISATION AND SIMULATION AS DECISION SUPPORT FOR OPERATION AND MAINTENANCE OF OFFSHORE WIND FARMS

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ABSTRACT

The rise of offshore wind energy production poses a complex resource allocation problem with respect to operation and maintenance (O&M) of offshore wind farms: O&M tasks need be performed by teams of specialists, subject to limited availability of qualifications, means of transport and appropriate weather conditions. Among others, NP-complete problems like shortest return routing ("Travelling Salesman") and job scheduling are embedded into the challenge of determining O&M schedules, which in real-world wind farm operation is often still conducted by hand. In this work, we address this problem by proposing a heuristic approach based on a "compatibility rating", attempting to anticipatorily allocate tasks to teams such that the remaining tasks *not* yet allocated can still be conducted efficiently, e.g. by a different team. This means of decision support relies on simulation to evaluate the feasibility of the schedules generated.

Keywords: scheduling, simulation, offshore wind farms, decision support system

1. INTRODUCTION

One of the most important and risky undertakings of today's Germany is the energy transition. It is expected that by the year 2050 up to 80 percent of Germany's energy supply may be provided by renewable sources (BMWi 2015). Offshore wind energy, as one of the generously available sources of renewable energy in the North of Germany, has become a key part of energy transition, without which the targets of this venture cannot be met (WAB 2017). Since average wind speed off the coast is significantly higher than on land, offshore power plants can generate more electricity at a steadier rate and almost every hour of the year (BMWi 2015).

Furthermore, achieving an ecologically and economically successful transition requires a reliable and reasonably priced energy (BMWi 2015). Specifically for the case of offshore wind energy, reducing the costs of operation and maintenance (O&M) of the wind farms are particularly seen as a challenge in this area. Operating experiences of existing offshore wind farms show that the share of operating costs over the service life is relatively high. Likewise, the costs of produced electricity have not yet reached the level of the onshore wind (Greiner, Appel, Joschko, Renz and Albers 2015).

Constructing wind farms further away from the shore can on the one hand increase the turbine performance and hence the financial revenue (Prognos AG and The Fichtner Group 2013). But on the other hand the distance of the offshore wind farm from the port extends its influence over the specific operating and maintenance costs (BMWi 2015). Giant turbines and their foundations have to endure the harsh conditions of the high seas. Repair and maintenance of turbines located far away from the coast is a tough challenge for the operators. Highly trained personnel and modern transport infrastructure have to come together in order to successfully provide maintenance services.

In fact the level of expertise in operating and maintenance of offshore wind farms can reduce up to 19 percent of the specific annual operating costs (BMWi 2015). Such expertise is unfortunately not always documented or verified (Mostajeran, Joschko, Göbel, Page, Eckardt and Renz 2016). Having a relatively low level of experience can result in an unpredictable loss.

The use of Decision Support Systems (DDS) in this context can potentially reduce the pressure on authorities and save the ultimate costs. However, existing systems are still very limited for the area of offshore wind farms. The results of a questionnaire (Pahlke 2007) sent to 350 institutions related to development of offshore wind farms in the North sea region suggest that the demand to use DDS specially for planning is very high (73.9%).

The individuals who are in charge of making planning decisions have to not only deal with the complexity of the resource planning problem but also make their decisions efficiently in a limited time. A typical wind farm has up to 80 turbines (BMWi 2015). Aggregating the O&M of several wind farms would enable more resource-efficient work, but also increase the planning complexity. Therefore, a sustainable decision support algorithm should scale well with the size of given turbine and resource clusters.

This paper proposes a research prototype to support decision makers during the O&M phase of offshore wind farms, particularly for the purpose of resource planning using simulation technology. It has to be emphasised that simulation cannot autonomously find the optimal result, but rather compare given proposals for the solution. In this work, we show how to generate promising O&M plans to select the best solution by means of an adjusted simulation component. This objective is accomplished in three main steps (compare Figure *1*):

1. Identifying and collecting essential input data (Data Model)
2. Generating feasible resource and action plans (Scheduling)
3. Assessing and suggesting the best plans (Simulation)

The following sections describe each step and our approach in more detail.

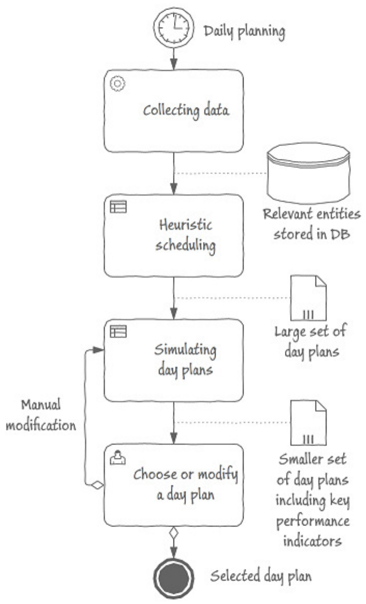

Figure 1: Main steps of the proposed Decision Support System

2. DATA MODEL

The first step in developing a DDS is to identify all relevant data entities and their relationships. In general, not every data entity required for optimisation purposes is very well-known in industry. There are often data gaps and identifying them has to be initially done in optimisation and simulation projects.

In the offshore wind farm context, many entities play important roles and engage in complicated relationships. We identified the most important data entities relevant for resource planning and their relationships. Furthermore, data gaps and their potential sources of information were identified. While the original version of the identified data model was too comprehensive for the purpose of this paper, a simplified version is given in Figure *2*.

The O&M of offshore wind farms are normally controlled from service stations on land. For example, the service station of the Riffgat wind farm in North Sea is 15 kilometres away on the island of Borkum. Despite Riffgat, which is relatively close to the shore, other offshore wind farms are located further away (e.g. BARD Offshore I for around 100 km) from the coast. Additionally, each service station can potentially manage more than one wind farm.

Activities representing the O&M tasks that have to be conducted on the site are the most influential entities in this context. Their type, duration, priority, location and qualifications form the basis of planning and resource allocation. Taking into consideration that activities are rarely unique and often repeat themselves in the case of more or less homogeneous wind turbines (WTs) in an offshore wind farm, identifying reusable types of activities makes sense. Consequently, common characteristics of each type of activity, most importantly the duration, can be gathered from empirical data. Naturally, due to the sea conditions, the precise duration of an activity cannot be predicted reliably. However, expected fluctuations can be estimated from empirical data, and consequently reproduced in stochastic simulation experiments (see section 5).

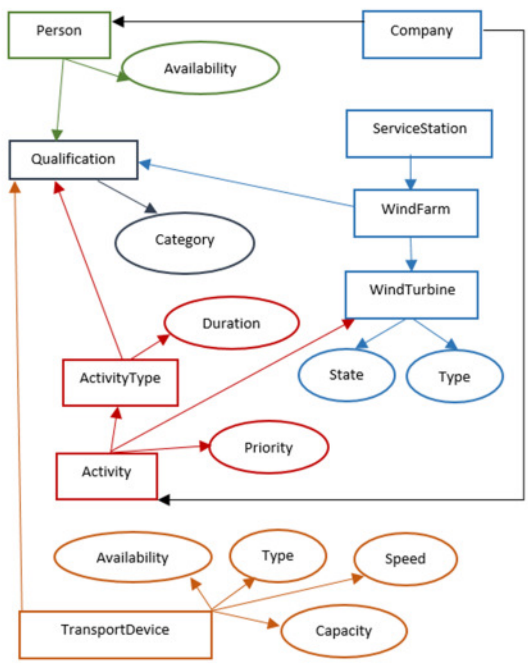

Figure 2: Simplified Input Data Model

The most important resources required for O&M activities are the personnel in charge of service and the means of transportation. Also the availability, i.e. the dates on which they are available for service, plays a crucial role for planning. The same applies to speed, capacity, and type of each means of transport.

Moreover, there are typically different companies involved in operating and maintenance of each wind farm, each of which brings its own resources and activities. Therefore, a dedicated entity for each company seems reasonable. This entity is also connected with personnel and activities.

Finally, qualifications and certificates are of significant importance for the entire decision making process since they bear a direct relationship to almost every other entity in the data model. For example, a safety briefing may be mandatory for just entering a wind farm. Activities may demand a certain level of expertise (e.g. industrial climber, electrician qualification). Apart from the activities, using a means of transportation (e.g. helicopter) may also require specific skills from passengers (e.g. hoist training). Only personnel who possess all related qualifications may be assigned to a task and enter the means of transport.

During the course of several sessions with O&M practitioners, we presented our data model and received their assurance that our designed model is valid.

3. OPTIMISATION CHALLENGES

The next step after identification and collection of the necessary data is to generate feasible O&M plans. This is a challenging task, as the number of determining factors is relatively large. It consists of several complex partial problems, which can also impact on one another.

3.1. General

For resource planning, the first step is to check whether the marine weather is safe to conduct any mission on the site. After that, the requirements (e.g. qualifications) and characteristics (e.g. priority, typical duration, etc.) of the pending tasks can be considered. The pending tasks are the ones which are already known but not yet executed.

Figure 3 illustrates the distribution of a sample of pending tasks within a wind farm, which we use as an example in this paper. Having the triangles as WTs, our sample wind farm represents 30 homogeneous WTs, which are arranged in 3 lanes. Each WT is identified with a number, starting from the most upper left tringle as WT1 and ending to the lowest right triangle as WT30. In Figure 3, the distribution of the tasks are shown with the help of a heat map. In addition to their location, the intensity of the heat represents the number and duration of the tasks.

The available and qualified personnel for performing these tasks can in the next step be arranged into small teams. According to the location and duration of the tasks, the order of sending and picking up the teams by available and suitable transport devices could form the last step that finalizes the schedule.

An automated resource planner should at the same time consider all these factors. But the complexity of this problem is so enormous (NP-equivalent) that simply evaluating all combinations and finding the best solution (Brute-force algorithm) is not an option for real-world instances. Therefore, only a heuristic optimization algorithm can account for all partial problems at the same time and generate time and cost efficient yet not necessarily optimal resource plans. Moreover, the complexity of such algorithm, the quality of the outcomes and the difficulty of implementation have to be examined.

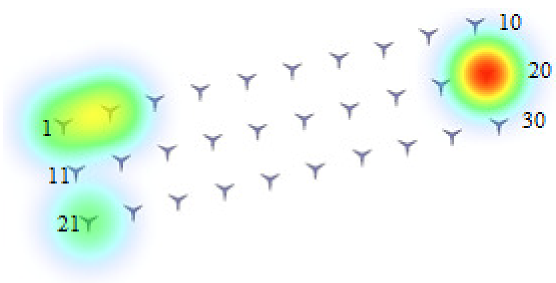

Figure 3: Heat-map of sample pending tasks. The intensity of the heat represents the number and duration of the tasks.

3.2. Weather

The weather conditions off the coast on the one hand give economic viability to offshore wind farms, but on the other hand challenge the personnel to maintain the turbines. Due to safety regulations, dropping off personnel at the turbines is only allowed when the weather and sea conditions are compliant to safety measures.

Therefore, an automated resource planner should also account for the weather forecast in order to provide feasible suggestions. Given perfect weather conditions, the time windows may also depend on legal regulations or availability of sunlight.

For evaluation purposes, historical data instead of a weather forecast can be used. Another approach is described in (Joschko, Widok and Page 2013). They proposed a software tool for simulation of the processes of O&M, which includes stochastic marine weather generator. It supplies a simulation tool with realistic weather data, which are generated by analysing the historic weather data and containing their distributions.

3.3. Team Building

The planned activities in offshore wind farms are assigned not to single individuals, but rather to small teams of personnel. Although the size of such teams can be different for different types of activities, their minimum size has been determined as three by the security policies of many wind farms.

An important criterion for building these teams is the qualifications of their members. Since performing each task demands certain qualifications, the potential performers of the tasks can be arranged in the associated teams, only if they hold the required qualifications. Building teams of available personnel is a challenging task since each person may possess quite different qualifications, which gives rise to combinatorial explosion of possible team combinations. Assuming a team size of *t* and availability of *n* persons, equation (1) shows the number of possible team combinations. For instance, building teams of the size of 3 from 24 personnel, when each of them has a unique qualification and hence cannot be replaced by others, results in nine trillion combinations (2).

$$\text{team combinations} = \frac{\binom{n}{t}\binom{n-t}{t}\binom{n-2t}{t}\dots\binom{t}{t}}{\frac{n}{t}!} \tag{1}$$

$$\text{e.g.}\ \frac{\binom{24}{3}\binom{21}{3}\binom{18}{3}\dots\binom{3}{3}}{8!} = 9.161.680.528.000 \tag{2}$$

In practice, the problem is often less drastic, since a lot of personnel have the same set of qualifications. In addition, some offshore wind farm operators may delegate a pre-selection of tasks to sub-contractors. Thus, the planner has a pre-selected set of teams in terms of the sub-contractors' staff.

Assigning the planned tasks to qualified personnel is similar to the knapsack problem in combinatorial optimization, having the duration and priority of tasks as respectively weight and value criteria. Preliminarily, we implemented a greedy algorithm for solving this problem. For this purpose, the tasks were ordered by their priority. Starting from the highly prioritized tasks and considering their required qualifications, the qualified personnel were arranged in teams and assigned to the tasks. This process was repeated until the duration of all tasks assigned to each team does not exceed their working time limit, e.g. an offshore wind farm working day.

3.4. Transport Routing

After having the teams assigned to the activities, the best route for traveling to and returning from the wind farm should be calculated. Similar to the classic Traveling Salesman Problem (TSP), this partial problem deals with the shortest path with maximum gain. Since the movements of the transport device within the wind farm has direct relationship with the costs of transportation, i.e. consuming time and fuel, finding the best route for the transport device can save this part of the O&M costs.

Considering a wind farm as a Euclidean graph with WTs (only those which require service activities) as its nodes and the port as the start node, the distance between each WT can be seen as the weighted edges of the graph. However, the influence of the weather, like wind speed and direction, can potentially cause different weights for different directions of the edges, resulting in an asymmetric TSP, in which the distance from node A to B can be unequal to the distance from B to A. Besides, there are many other sea conditions and dependencies to different types of ships, which were not considered in detail for this work. A project which goes more into detail is described in (Quandt, Beinke, Ait-Alla and Freitag 2017).

The marine weather can be also a reason for choosing between different types of transport devices (e.g. helicopter or ship), impacting on traveling costs. For instance, travelling with a helicopter is on the one hand much faster, but on the other hand much more expensive than any ship. They have also a smaller capacity than ships. Observe that also multiple travels for a mission are possible, for example if apart from the team, bulky materials need be transferred.

The main difference between the classic TSP and our offshore wind farm scenario under investigation is that we require each node being visited usually twice, namely for drop-off and pick-up of the team, subject to conducting planned activities in-between.

Therefore, a TSP solver for offshore wind farm scenario suggested by (Korff 2015) was used for this part of the problem. In the first place and before running the algorithm, some preparations have to be done. First, due to the weather influence, the Euclidean graph of the wind farm has to be mapped into an asymmetric graph. After that, the nodes which have to be visited, i.e. the location of the maintenance tasks, have to be identified. Finally, calculation of the best route is done only on a partial graph of the entire wind farm graph, from which irrelevant nodes were omitted. After dropping off all the teams on their working sites, the algorithm listens on the pick-up calls from the teams. As soon as a team is ready to be picked up, the TSP includes their locations into its graph and re-calculates the best path. This continues until all teams are picked up. Only then will the journey back to the harbour begin (Korff 2015).

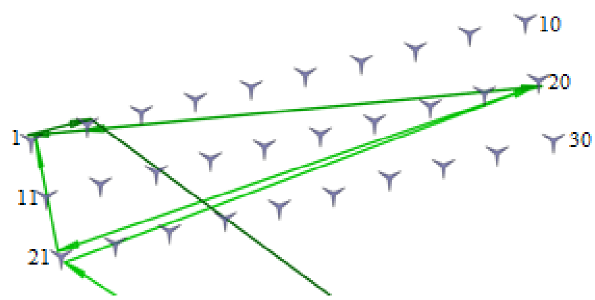

Figure 4: A sample transport route

Figure 4 shows a sample route for a ship within our wind farm example. In addition, Table 1 lists and explains every step of this route in detail.

Table 1: The steps of a sample transport route

Step	Location	Action
1	Harbour	Pick up Team1 and Team2
2	WT21	Drop Team1
3	WT20	Drop Team2
4	WT21	Pick up Team1
5	WT1	Drop Team1
6	WT20	Pick up Team2
7	WT2	Drop Team2
8	WT1	Pick up Team1
9	WT2	Pick up Team2
10	Harbour	Drop Team1 and Team2

4. HEURISTIC APPROACH

The problems described in the previous sections are already very complex themselves. However, the more fundamental problem is that all these sub-problems have an impact on each other, which makes it nearly impossible to find an optimal solution at all.

The planner has to regard different priorities, qualifications, time durations, means of transport and tasks needed on different sites. In order to solve this matter, we developed a compatibility rating for O&M activities, which considers all the relevant characteristics at the same time. Through this, it is possible to compare how similar activities are to be grouped into clusters (see section 4.2).

4.1. Compatibility rating

We propose a compatibility rating defined as weighted average of a tuple of aspects. Each aspect describes how far apart activities are in one respective dimension.

For example, in the case of locations, being "apart" uses a natural definition: If two activities are planned for the same turbine, the return value is 1, representing the ideal case. If they are located diametrically opposite in the wind farm, the return value is 0, indicating the worst case. Everything in-between is linearly interpolated. When we compare two clusters of activities, we consult the geometrical centre of the geo-coordinates of each turbine. We call this the Location Aspect.

All other aspects are non-spatial. The Qualification Aspect describes how similar the demands for qualifications are. If there are two sets of qualifications (Q_{c1}, Q_{c2}) required for two sets of activities (C_1, C_2), the "distance" d between these demands can be evaluated as ratio of qualifications shared per union of all qualifications required as shown in equation (3):

$$d = |Q_{c1} \cap Q_{c2}| \,/\, |Q_{c1} \cup Q_{c2}| \qquad (3)$$

The Priority Aspect suggests that important tasks have to be preferred. This does not mean that one task is strictly to be performed before another, but rather that for economic, safety or environmental reasons this order is recommended. The priority has to be manually set by the human planner, e.g. on a discrete scale like [very low, low, medium, high, very high]. We normalize this scale to a continuous value between [0,1]. Then, we evaluate the average of the tasks to be compared as the return value for the Priority Aspect. As a result, higher priority tasks will receive a higher compatibility rating than lower priority tasks, which is completely independent from the similarity of the tasks.

We can add any further aspects, which return continuous values between [0,1] when two activity clusters are given as input parameters. For each aspect a factor has to be provided for evaluating a weighted average.

In addition to continuous aspects, further Boolean "knock-out" criteria may describe whether two activities are compatible. There may, for example, be activities which have to be processed by a specific company, but this company must not process other types of tasks. The return value indicates whether two given sets of activities may be processed by the same company (Company Aspect). Some tasks require specific type of ships, e.g. a jack-up barge, some do not (Transportation Aspect). Our Goal is to develop clusters for given time slots, which must not be exceeded. The Duration Aspect returns true, if two given activity clusters could be processed together in time, and false if not.

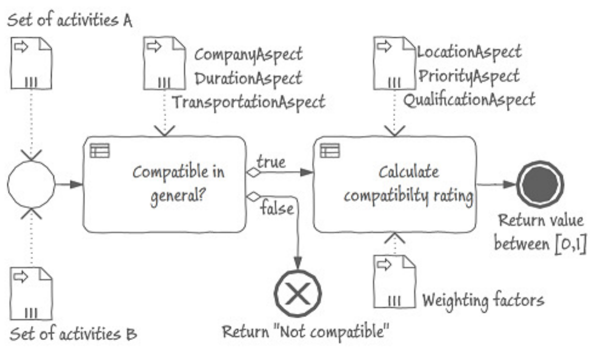

Figure 5: Conceptual process of the calculation of the compatibility rating as BPMN diagram

When a set of knock-out criteria and a set of tuples (Aspect, Weight) are defined, the overall result value for the compatibility rating is calculated as follows (compare Figure 5):

1. if any knock-out-aspect is true, return 0.0
2. evaluate each continuous aspect
3. return weighted average of continuous aspects

Adding aspects or changing the weighting factors for the continuous aspects will lead to a different return value.

4.2. Clustering

As mentioned before, a permanent waiting queue holds the O&M activities that need be performed. We therefore can create a matrix (see Figure 6), which shows the compatibility ratings as described in the last section for all tuples of activities. Figure 6 shows activities on four different WTs. Every cell shows the rating for the activities listed in the respective column and row titles. On this basis, we can form clusters of tasks. One cluster applies to being executed by one team and within one day. Thus, the maximum size of a cluster corresponds to the given time window (section 3.2).

A very simple clustering algorithm puts the two items which have the highest ranking together in one cluster (flagged with a 'C' in Figure 6). After that, the matrix has to be partially re-evaluated, since two items have been removed and a new item was added, representing the items aggregated into a cluster of tasks. Then, again the two best fitting items (single tasks or clusters of tasks) will be merged. The algorithm stops, when there are no ratings left which are higher than zero, indicating no further aggregation being possible. In a typical case, such a limit will be due to the Duration Aspect.

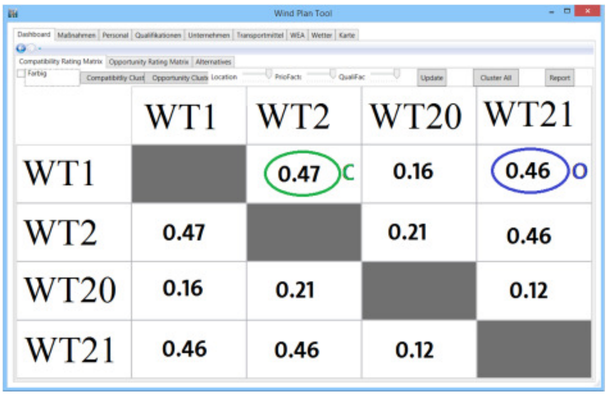

Figure 6: Screenshot of GUI showing compatibility matrix

However, such an approach is only optimal in the very short term. In Figure 6, the best compatibility rating 0.47 is given for the tuple (WT1, WT2). But using the pre-assumption that the time slot given by weather conditions allows only clusters with up to two activities, and the activities WT1 and WT2 would be merged, there will remain no adequate partner for activities at WT20 and WT21, because their compatibility rating is very low at 0.12.

Our clustering algorithms focuses on overall gain, which has an efficient utilization of calculation time but finds a more 'long-term' satisfying solution. We applied the concept of "opportunity cost" from economics when we implemented a heuristic algorithm, which calculates the resulting loss when an item does not get its favourable partner task.

First, the compatibility ratings for each activity are stored in a sorted list, so that the best partner is the first item and the worst is the last. Then, we calculate the difference (Δ) between compatibility ratings of the first and the second item, between the first and the third item and so on and store results into a new sorted list. Every entry quantifies a lower bound to the loss incurred in case not being allocated to its best partner, to none of its best two partners, to none of its best three partners and so on.

Now, we establish the weighted average of these Δ-values, while the weighting factor for every Δ can be calculated with a selection of formulas. Let n be the number of list items to be regarded (begin counting at the second best partner which is compared to the best partner), and p is the position in the sorted list of Δ, we use equation (4) for a simple linear approach of determining weighing factors w_p for every Δ_p.

$$w_p = n + 1 - p \,/\, \sum_{k=1}^{n} \mathrm{k} \tag{4}$$

Table 2 shows the linear weighting factors for the case of 4 potential partners, compared to 5 potential partners in Table 3.

Another approach is a recursive algorithm, see Equation (5). The procedure requires to set a descent factor f. In table 1 and 2, $f = 0.6$ was chosen. The weighting factor for the first Δ is f, the rest r_1 is $1–f$. The weighting factor for the second Δ is $r_1 f$. There still remains a rest r_2 of $(1–f)\,(1–f)$. At the end, a rest of $(1–f)^n$ resides, which has to be distributed proportional to the already calculated factors.

$$w_p = f(1-f)^{p-1}(1+(1-f)^n) \tag{5}$$

As it is shown in the tables, the recursive algorithm places more weight on the first Δ, while the linear algorithm places more weight on the last Δ. Thus, the linear approach will tend to avoid worst case scenarios earlier than the recursive approach. Additionally, the recursive approach offers an additional degree of freedom in terms of the possibility of adjusting the impact of the first Δ by changing the value for f.

Table 2: Weighting factors for opportunity rating regarding the best five partners (n=4)

	p	linear	recursive
$\Delta_1(1^{st}, 2^{nd})$	1	40 %	61.5 %
$\Delta_2(1^{st}, 3^{rd})$	2	30 %	24.6 %
$\Delta_3(1^{st}, 4^{th})$	3	20 %	9.8 %
$\Delta_4(1^{st}, 5^{th})$	4	10 %	3.9 %

Table 3: Weighting factors for opportunity rating regarding the best six partners (n=5)

	p	linear	recursive
$\Delta_1(1^{st}, 2^{nd})$	1	33.3 %	60.6 %
$\Delta_2(1^{st}, 3^{rd})$	2	26.7 %	24.2 %
$\Delta_3(1^{st}, 4^{th})$	3	20.0 %	9.6 %
$\Delta_4(1^{st}, 5^{th})$	4	13.3 %	3.8 %
$\Delta_5(1^{st}, 6^{th})$	5	6.7 %	2.5 %

Now having a matrix containing compatibility ratings for activity tuples (respectively tuples of activity clusters) and one opportunity rating for each activity (respectively activity cluster), the algorithm proceeds as follows:

1. The activity with the highest opportunity rating (highest potential loss) is selected.
2. This activity is merged with its best partner due to the compatibility rating.
3. The matrix has to be re-evaluated, and afterwards the algorithm starts at step one again, until there are no ratings left, which are bigger than zero.
4. The result is a set of clusters, within which all activities are potentially appropriate of being processed by one team and in one day.

In Figure 6, the worst opportunity rating applies to WT21. Therefore WT21 gets its best partner WT1 first (flagged with an O), although the best partner for WT1 would be WT2. This approach finds a more 'long-term' efficient solution than the solution described at the beginning of this section, because the remaining activities at WT2 and WT20 have a compatibility rating of 0.21, which is significantly better than the rating of 0.12 for WT20 and WT21.

Once we have clustered all the O&M activities in the waiting queue, we can run the team building algorithm from section 3.3 on these clusters rather than running it on the whole waiting queue. Thus, the possible search space becomes very much smaller, because activities with similar needs for qualifications tend to lie in the same cluster. At the same time, we have a better basis for transport routing described in section 3.4, because activities located spatially close to each other, tend to lie in the same cluster, too. Figure 7 shows four tasks, scheduled in 2 clusters. The first cluster contains the tasks, located at WT1 and WT21 and assigned to Team1. Cluster 2 contains the assigned tasks of Team2 located at WT2 and WT20.

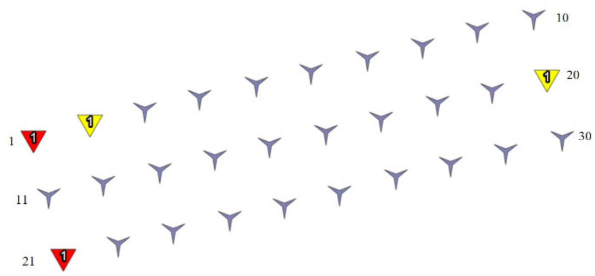

Figure 7: Scheduled tasks in two clusters: C1 (WT1 & WT21) for Team1 and C2 (WT2 & WT20) for Team2

Changing the parameters for the compatibility rating will result in different clusters, which is an appropriate method to get alternative proposals for solutions for daily plans. On that basis, we are able to compute a large set of promising solutions in a short time without having to iterate the whole solution space.

5. SIMULATION

Once we have generated a set of promising day plans in reasonable time, each plan will be analysed in detail. The goal is to identify the best performing plans and to sort out the worse plans, so that a reasonable amount of plans remain for the human decision maker.

For calculating key performance indicators of interest, we use stochastic, event-discrete simulation. The main indicators to be provided as a basis for decision are:

- Success probability of each task in a plan
- Resource utilization and costs
- Generated wind energy (or opportunity costs for stagnant turbines)
- Identification of the critical path

Durations of tasks depend on external influences, which are abstracted with help of stochastic distributions. The critical path is the chain of transport and O&M activities, which has no time buffers. If a delay occurs, the whole day plan is deferred. The available time window depends on the weather conditions (see 3.2). Because all teams must leave the turbines within that time windows, it may happen that some tasks have to be aborted. The 'success probability' quantifies the probability that a task can be completed in time. This does not indicate whether the task was completed successfully in technical manner. Another point of interest for the planner is the utilization of resources, i.e. personnel and means of transport should use offshore time efficiently to process tasks. The last indicator relates to the actual objective of wind farm operation: generating energy. Energy productions depends on the wind speed and the turbine properties cut-in speed, cut-off speed and rated power (Byon, Perez, Ding and Ntaimo 2011). For our objectives, generated power is less interesting than the power which was not generated, because a turbine was not ready for operation. Minimising these opportunity costs is the main goal of O&M optimisation.

Some works have already been successful in the simulation of offshore wind farms' O&M processes. (Lange, Rinne and Haasis 2012) describes how different logistic strategies can be compared already in the planning process. (Joschko, Widok and Page 2013) describes how operative O&M processes can be described abstractly as BPMN-Models and simulated in order to identify critical system parts. These works inspired us to focus on in short-term planning – independently from the long-term strategy of choice.

As always, we have to determine our requirements first and identify the relevant area of the O&M system afterwards to find a suitable approach for implementing the simulation model. The system to be mapped into a model was introduced in the previous sections. Relevant entities are the same for the simulation component: means of transports, teams, activities and wind turbines. Some, but not all entities' attributes are furthermore needed for simulation experiments. E.g. we can abstract from people's qualifications, because we already have a plan fixed in time, describing which team is responsible for which O&M activity without need to double-check this. In contrast, the duration of an activity and the speed of a ship or helicopter are relevant for simulation, because we now take a deeper look at the time-dependent behaviour of entities and their concurrent execution of tasks.

There are no dynamic entities which enter or leave the system. Only static entities exist, which are announced before starting the simulation experiment. They may interact with each other, which could be interpreted as 'dynamic behaviour'. However, this only implies waiting in queues for transports and all other activities based on shared resources. But also these tasks are already announced before the simulation run.

Thus, it was not necessary to use a scheduler or an event-list, which is typically for dynamic, event-discrete simulation. A more basic and much faster approach fits our needs: A task is built up of a start-event and an end-event. Durations of tasks (time-spans between start- and end-events) are samples from different stochastic distributions, as well as in event-discrete simulation. First, we announce all tasks with their stochastic parameters. Afterwards, instead of scheduling such tasks on concrete time instants on an event-list, it suffices to determine their execution order, so that each task has a defined set of references to its predecessors and successors.

Hereby, we need only one method call, which contains recursive (pending a potentially even more efficient iterative implementation) method calls for every task to calculate the start- and the end-points of all tasks in a day plan, depending on stochastic samples. The critical path, which has no time buffer, is identified.

Because we don't need any list operations or dynamic objects' instantiations, a lot of computing power is saved compared to dynamic simulation. In our first approach, which still used a scheduler and an event list, we computed 100,000 experiments in about 13 minutes on a single standard PC. The elaborated generation of reports also played a role here. But since any component not strictly required was removed, the transition to the model logic described above, we are now able to compute 1,000,000 experiments in 1.5 seconds. Since the simulation is stochastic, we have to repeat experiments for every scenario to get reliable results. But even if we require 100 to 1000 experiments for every scenario, we are still able to compare more than 1000 day plans in less than two seconds for a wind park of medium size.

As simulation engine we have used DESMO-J, which is an open-source, discrete event simulation framework developed at the University of Hamburg. It offers several ready-to-use components for developing simulation applications in the object-oriented languages Java or C#. DESMO-J provides an experimentation framework, abstract model components, waiting queues, stochastic distributions, as well as several statistic data collectors for quantifying the dynamic system behaviour. (Göbel, Joschko, Koors and Page 2013).

Every time a model is implemented with DESMO-J by deriving entities and events from DESMO-J classes, a 'domain-specific application' is written. In this case, however, we have made adjustments to the library itself. DESMO-J offers a lot of technical simulation components, like a scheduler or an event-list which are commonly needed for dynamic simulation, or optional add-ons like a 2D animation module. As described above, we deactivated most of these components, which was quite straightforward due to the clear structure of the freely available DESMO-J source code. We just used selected components like queues, stochastic and statistic classes.

6. RESULTS

Finally, the proposed solutions of all partial problems were integrated in one working research prototype, which is a .Net based application, implemented in the C# programming language. Moreover, the input as well as output data models were used to create a database on a Microsoft SQL Server, whose tables were employed to automatically generate one-to-one Classes in C# using Entity Framework technology.

Besides, our heuristic algorithm is able to generate many alternative resource plans, which are compared using discrete event simulation. Thus, the best plans can be automatically preselected. These suggested plans are displayed in the form of a Gantt chart. Figure 8 shows a generated sample plan. For any selected date, several alternative plans can be accessed, each of which consists of multiple lanes for each team and transport device.

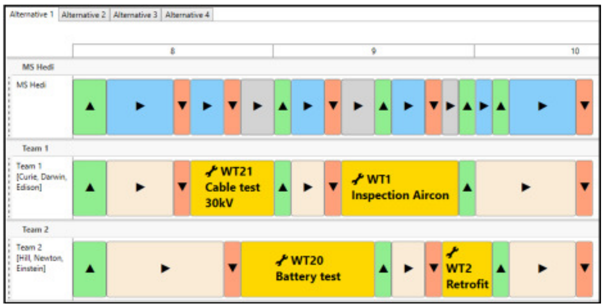

Figure 8: Suggested day plan

The lane of each transport device shows the suggested route for traveling to and returning from WTs. The bars with an upward or downward arrow show respectively the boarding and de-boarding of the teams and the ones with an arrow to the right show the movements of the transport device within the wind farm. These movements are also reflected in the lanes of teams. The team lanes show also the tasks, which are assigned to them.

Each plan is rated by the costs and execution probability. These information can be seen below each Gantt chart. Tabs allow users to display the automatically preselected plan proposals. The number of proposals should be small enough to be quickly overlooked by a human being. At the end, each plan is only a suggestion and can be modified by the human planner. The modified plan will be evaluated using simulation and stored as a new alternative plan for the day.

7. DISCUSSION

Resource planning during O&M of offshore wind farms is a very complex problem. However, our research prototype, as an automated resource planner, supports the decision makers by dividing the problem into partial problems and conquering its complexity.

Our novel heuristic algorithm considers various aspects of developing a valid resource plan. These aspects include the availability of the personnel and means of transportation, the priority, duration, location of the performance, and required qualifications of the activities. The proposed algorithm considers all these aspects and groups the activities into clusters. The clusters do not necessarily contain the most similar activities, but rather those which give an overall best result (regarding the cost and execution time). The qualified personnel are then arranged into teams and the best route for the transport device is calculated.

The results are presented in the form of several Gantt charts which represent the generated plans for the day. Each plan is additionally rated by means of discrete event simulation technique.

8. FUTURE WORK

In future we still need to conduct scheduling and simulation runs based on real historical data from our project partners for the purpose of validation. In scheduling, an extremely large spanning tree of resource plans shall intentionally be generated, which are then simulated in a multi-day experiment. This will enable us to find suitable factors for the weighting in the compatibility rating. As a result, the scheduling algorithm will be able to work more efficiently by requiring a much smaller spanning tree in real-life situations.

Besides, we would like to evaluate different algorithms for the partial algorithms of our heuristics algorithms, i.e. team building, task allocation, and transport routing.

Finally, it is of our interest to evaluate our research prototype in the service station of an offshore wind farm. Therefore, parallel to the human resource planner, our prototype will receive the input data, such as the planned tasks for the day, available personnel, etc. The quality of the suggested plans can then be evaluated in practice and with real data. This requires a live connection for weather forecasting to determine the available time windows.

As by the conditions of the research project grant, our implementation is intended as prototype and cannot be developed further into a commercial product by our research group. Of course, commercial software developers are free to contact us if they are interested in more details about our research results to provide a valuable supportive tool for O&M of offshore wind farms.

9. CONCLUSION

This paper described various aspects of resource planning during the O&M of offshore wind farms. Considering the immense complexity of the problem, a heuristic approach is necessary for generating time and cost efficient resource plans. We introduced a compatibility rating as core element of our heuristic algorithm. Lastly, with the help of discrete event simulation, our approach can be examined using artificial as well as real-world data.

Data management and saving useful pieces of information can make a huge difference in the quality of optimisation algorithms. More specifically, collecting important information about activities and their types can make their common characteristics, such as typical duration, clear for the planner. Having mobile solutions (e.g. documentation apps on tablets) can probably make the documentation and collection of data easier for the users on-site. It is important to mention that the sooner the authorities start collecting such data, the better the quality of the data provided for an optimisation algorithm can get.

Ultimately, due to the stochastic nature of on-site plan execution under stochastic conditions (e.g. weather), the heuristic algorithm to identify alternative plans in a live operation had to augmented with simulation technology for evaluation.

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