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Modelling of Spare Parts Storage Strategies for Offshore Wind

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Purpose: The production costs of offshore wind energy are currently very high compared to other means of energy production. During the operational phase of an offshore wind park 17% of the operational costs are logistics cost. To reduce the costs, innovative strategies have to be implemented, like improved spare part strategies.

Methodology: In this paper, an agent-based model for the Operation and Maintenance (O&M) supply chain of offshore wind farms is developed analyzing if the storage of spare parts of different offshore wind parts at a central shared warehouse is beneficial.

Findings: Shared storage units for two offshore wind farms serviced from different harbours only yield larger profits for large spare parts transported by a crane vessel. For all other components, rapid access and the resulting higher availability of the wind turbines outweigh the cost savings realized by a central warehouse.

Originality: The developed model is unique as it comprises two storage levels, two wind parks, and different means of transportation for small, medium, and large spare parts on water and land. Until now, no comparable research exists determining the optimal storage level for spare parts in shared storage infrastructure.

Keywords: Offshore Wind, Operation and Maintenance, Agent-Based Simulation, Spare Parts

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1 Introduction

The recent trend for decarbonisation is growing steadily, and the shift from conventional production of energy to renewable production of energy plays an essential role in this transition to cleaner energy production (Kost et al., 2018). Especially offshore wind, with its steady and little fluctuating supply of energy, can play a crucial role in this shift (Reimers and Kaltschmitt, 2014).

The costs of offshore wind energy, however, are currently very high compared to other means of energy generation. Using Levelized Cost of Energy (LCOE), it is possible to compare the costs of different means of energy production by calculating the quotient of average total cost of construction and operation of the power plant over its lifetime divided by the total energy output over the lifetime based on weighted average costs (Astariz, Vazquez and Iglesias, 2015).

For the LCOE of German offshore wind projects, Fraunhofer ISE gives a range from 74,9 to 137,9 EUR/MWh in 2018 (Kost et al., 2018). In comparison, the LCOE of lignite are 45,9 to 79,8 EUR/MWh, of hard coal 62,7 to 98,6 EUR/MWh, of onshore wind 39,9 to 82,3 EUR/MWh and for photovoltaics 37,1 to 115,4 EUR/MWh (Kost et al., 2018). This makes offshore wind the most expensive form of energy production compared to fossil as well as other renewable energy sources. In the long run, the success of offshore wind projects is based on their economic feasibility and thus, a significant reduction in LCOE (Reimers and Kaltschmitt, 2014).

The Operation & Maintenance (O&M) phase is with 20 years the longest and also the only phase during the lifetime of an offshore wind park (OWP) in which revenues are generated. Therefore efficient O&M processes are highly relevant since the availability, and thus the generated power of an offshore wind turbine (OWT) depend on them (Shafiee, 2015). During the O&M phase, logistics costs account for 17% of operational expenditure (Poulsen, Hasager and Jensen, 2017).

Even though the overall number of OWT is globally increasing, the number of manufacturers has declined. Consolidation on the market for OWT has taken place; several smaller companies have merged with Siemens Gamesa which had in 2017 a market share of 44% in Europe where Vestas MHI had 29% (Wind Europe, 2018). Therefore, many OWP share large amounts of spare parts, which allows for the consolidation of spare part inventories to reduce O&M costs.

In this paper, an agent-based model for the O&M supply chain of offshore wind farms is developed to analyse if the storage of spare parts of different offshore wind parts at a central shared warehouse is beneficial compared to the decentral storage at the service harbours of the OWP.

The structure of the paper will be outlined by a literature review of offshore O&M with a particular emphasis on papers for the use of simulation in the O&M phase of offshore wind farms. Then the structure of the agent-based simulation will be developed with an explanation of the input factors leading to the results, and in the last part, the paper will be closed with a discussion of the results.

2 Literature Review

This literature review gives a short overview over the most important literature in the field of O&M of Offshore Wind Turbines (OWT) related to spare parts and inventory management as well as resource sharing and the methods used in this context.

The literature regarding the O&M phase of offshore wind is extensive. Most of these publications are concerned with strategic maintenance decisions like wind farm design, location of service personnel, or outsourcing decisions (Shafiee, 2015). The literature on pooling of resources and spare part management during the O&M phase, however, is very scarce. Three master thesis are looking at inventory policies in combination with maintenance strategies: Dewan (2014) develops a logistics and service model to compare different policies and strategies; Nnadili (2009) focuses floating OWT and Jin et al. (2015) focus on third-party logistics providers. Lindqvist and Ludin (2010) did their Master Thesis about spare part logistics investigating methods for storage and supply of spare parts focusing on stock levels and reorder sizes. Lütjen and Karimi (2012) investigate inventory management during the installation phase. Gallo, Ponta and Cincotti (2012) develop a model which helps to find the right combination of maintenance strategy and warehouse location. Tracht, Westerholt and Schuh (2013) describe an approach for the spare parts management under consideration of the restrictive factors of limited availability of service vessels and changing weather conditions. Rauer, Jahn and Münsterberg (2013) develop a forecasting model to predict the number and type of spare parts required for an Offshore Wind Park (OWP) considering the O&M strategy used.

Rinne (2014) did his dissertation on the topic of spare parts strategies for offshore wind farms during after-sales services. Ferdinand, Monti and Labusch (2018) propose an algorithm to determine the optimized spare part inventory. Zhang et al. (2018) develop an optimization scheme to determine the right update cycle and the number of spare parts necessary. Of all these publications, only the student paper by Lindqvist and Lundin (2010) encompasses the aspect of collaboration by looking at joined warehouses. In the whole literature on the O&M phase of offshore wind, the aspect of resource sharing is only regarded scarcely (Shafiee, 2015). This can be attributed to the infancy of the industry and the competitive nature of the Original Equipment Manufacturers (OEM), there is not much sharing of resources/spare parts done like it is done in other industries.

Most papers which are about sharing or optimizing resource use in the O&M phase are dealing with installation vessels and/or Crew Transfer Vessels (CTVs). Halvorsen-Weare et al. (2017) develop a metaheuristic solution method to do an optimisation for vessel fleets during the O&M phase or Stålhane et al. (2017) who propose a two-stage mathematical model for the optimal use of jack-up vessels for the O&M of offshore wind farms or Stålhane et al. (2016) who use a two-stage stochastic programming model to determine the optimal fleet size for maintenance activities. Schrotenboer et al. (2018) propose the sharing of personnel for the O&M of different offshore wind farms.

The methods applied in the O&M literature are very diverse; most of it based on quantitative modelling using analytical as well as simulation approaches. The most common simulation approach is Monte-Carlo-Simulation (Shafiee, 2015). There are therefore few approaches by authors to use simulation to optimize the O&M logistics, and when done, these authors do not use agent-based models.

Beinke, Ait Alla and Freitag (2017) did a simulation study on sharing of resources during the installation phase. Münsterberg, Jahn and Kersten (2017) as well as, Münsterberg and Jahn (2015) did event-based simulation for the O&M phase of offshore wind farms. Karyotakis (2011) did a model based on Monte-Carlo simulation based on the parameters affecting the O&M phase. Besnard (2013) used a Markov chain model for the O&M processes. Nielsen and Sørensen (2010) wrote a paper about risk-based O&M using Bayesian networks. Dalgic (2015) developed an expenditure model using a Monte-Carlo simulation approach for an optimized fleet of vessels for O&M. Dinwoodie (2014) did a multivariate auto-regressive model in combination with a Markov Chain Monte-Carlo simulation model for O&M. Sahnoun et al. (2015) propose a simulation model using a multi-agent system.

In summary, it can be concluded that no research on spare part strategies considering shared inventory has been done yet. Furthermore, even though the use of simulation is not new to the field, agent-based modelling has to the knowledge of the authors not been applied in the context of O&M of offshore wind logistics.

3 Methodology

In this paper, we develop a model of an Offshore Wind spare parts supply chain for two offshore wind parks using agent-based modelling. Agent-based modelling is a bottom-up methodology which allows a close representation of the of real-world phenomenon like a supply chain with a detailed representation of different actors in the form of agents (Datta and Christopher, 2011; Macal and North, 2014). The behaviour of the overall system is mapped by the interaction of individual agents. An agent is an active unit of the simulation, which is placed in an environment and can make autonomous decisions, underlying a specific set of rules, in order to achieve the goals assigned to it. For this purpose, an agent can perceive the environment and communicate with other agents in it (Wooldridge, 2009).

Borshchev and Filippov (2004) compare agent-based modelling (ABM) with the two other most common modelling approaches system dynamics and discrete event modelling. They find that the main difference is the bottom-up approach of ABM. Therefore the resulting system is decentral, and the global system behaviour is the result of the interaction of the different agents. This has some significant advantages. First, it allows the model to be built without knowledge about the interdependencies of the global system. Especially large and complex systems like supply chains can be easier modelled using ABM. Second, ABM is more general and powerful because it enables the representation of more complex structures and behaviours. Third, ABM allows the modelling of very heterogeneous entities like warehouses, trucks, or OWT. Due to these reasons, ABM is well suited to model an offshore wind spare parts supply chain, which is very complex and involves many different actors.

4 Model

The model aims to enable a comparison of two different spare part storage strategies. The first using a shared central warehouse for supplying two OWP, the other one using decentral warehouses at the service harbour of each OWP. Resulting in two storage levels: central and decentral. For this purpose, a model is developed, which includes the most important actors and interactions of a supply chain for offshore wind spare parts for two OWP. The model is developed using the guideline developed by Law (2007) using the software AnyLogic.

4.1 Model derivation

Following standard supply chain frameworks, the model includes material as well as information flow. The material flow is made up of different spare parts. The information flow is opposite to the material flow and includes spare part demands and mission planning. In total, the model (see Figure 1) includes eight different types of agents which will be shortly introduced hereafter.

The structure of the modelled supply chain is based on the best practice for shore based maintenance of OWP (GL Garrad Hassan, 2013). This enables a transfer of the results into practice. The two modelled OWP and the corresponding service ports match two OWP situated in the German North Sea. Furthermore, the central warehouse is situated at a feasible location between the two harbors. The OWT is composed of 17 different parts. The occurrence of a failure is modelled using a Poisson-distribution. If one of the parts fails, a failure notice is sent to the control centre, and the OWT is out of order until the required spare part is delivered. It is assumed that with the help of condition monitoring, the required spare part needed is always identified correctly and that only one spare part is needed per failure.

The model includes 17 different types of spare parts matching the components of the OWT. The spare parts are divided into three categories. Category A encompasses small and light spare parts which can be transported with the helicopter as well as the CTV. Category B includes all components that can be lifted with the board crane of the OWT; they are transported with the CTV. All the components which can only be transported with a crane vessel makeup category C. The different spare parts are implemented as variables which can be exchanged between the different agents and transported by them.

The material flow starts at the warehouse agent. Here all the spare parts are stored. The model allows for all the spare parts to be either stored in one central warehouse which is supplying both OWF or in two decentral warehouses situated directly at the service harbours. The warehouse operates using a reorder point (r, q)-policy.
The next agent in the model is the control centre. It is central for the information flow because all information comes together here. The control centre is receiving the failure notice from the OWT and then forwarding the order to the warehouse where the required spare part is stored. Additionally, it receives the weather forecast and determines which means of transport can leave the harbour to execute repairs on the OWT each day.

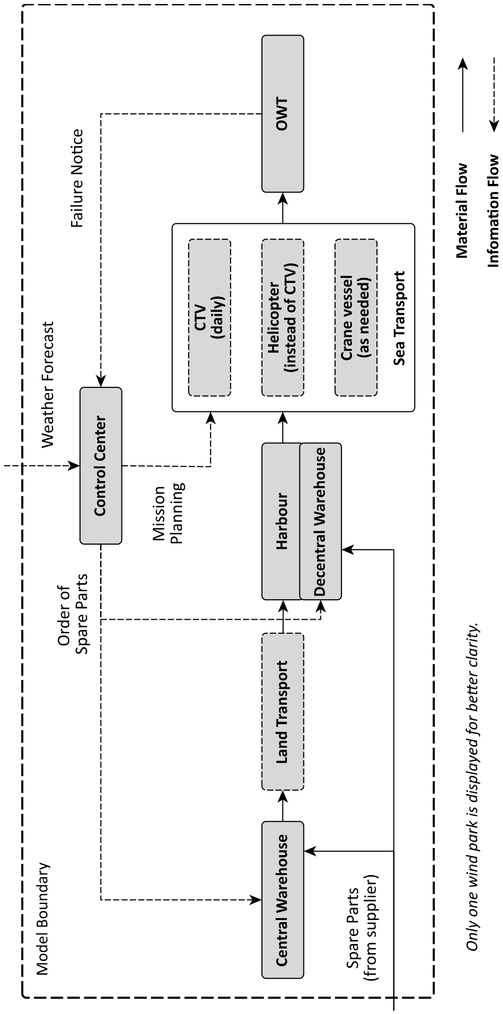

Figure 1: Overview of the Agent-Based Model including Material and Information Flow

For the transportation of the spare parts four different means of land and sea transport a modeled. At land daily pick-ups of spare parts from the central warehouse are assumed e.g. by logistic service providers and modeled by one agent. At sea the means of transport are based on those used by the offshore wind industry in practice for shore-based maintenance (e.g. GL Garrad Hassan, 2013; Münsterberg and Jahn, 2015). They are represented by three different agents (Endrerud, Liyanage and Keseric, 2014). The CTV is the standard mean of sea transportation, and it is assumed that it can carry enough spare parts and personnel to repair on average, three OWT per day. If the CTV cannot operate due to bad weather, but the weather is suited for the helicopter, it shuttles repair crews and spares to two OWT per day. It is assumed that both vehicles are available daily and operate if a window of operation larger than 6 hours is available. The crane vessel, however, has a waiting period of three months after the failure of the wind turbine and leaves the harbour if an operation window of 24h is available (Dalgic et al., 2015).

4.2 Data collection

In total, 16 parameters are needed for the model. Twelve of these are constants since they have no central influence on the land supply chain, which is the central focus of the analysis, and their values can be taken from the literature. Nine of these parameter are listed in Table 1, which define the operation of sea transport.

Table 1: A Key Figures Sea Transport (Münsterberg and Jahn, 2015)

Sea Transport	**Weather Restriction**	**Value**	**Spare Parts**
CTV	Significant wave height	1,5 m	A,B
Crane vessel	Significant wave height	2 m	C
Helicopter	Wind speed	17 m/s	A

The other three concern the different spare parts (see Table 2). The data for these are merged from different sources (Gayo, 2011; Dewan, 2014; Lindqvist and Lundin, 2010). The components with the highest failure rates are identified and chosen for the model. They are assigned a failure rate, which is calculated proportionately of the overall failure rate. The other parameters are the replenishment time and the price which are taken from Dewan (2014) as well as Lindqvist and Lundin (2010).

Table 2: Overview Spare Part Categories

Spare Part Category	**Number of Parts**	**Share of Overall Failure Rate**	**Replenishment Time**	**Spare Part Price [€]**
A	8	0.465	1 or 2 weeks	200 - 1,500
B	7	0.501	1 or 2 weeks	500 - 10,530
C	2	0.034	10 weeks	100,000 - 113,000

The remaining four input parameters are variables which are assigned different values using scenario analysis (see Figure 2). The storage level for the different spare part categories is alternated to enable a comparison of central and decentral storage. Scenarios with a helicopter and without helicopters are run because both supply chain setups are typical in practice. The other two variables: *overall failure rate and delivery time from the central warehouse are varied in the different scenarios to verify the assumptions made. The values for failure rates of OWT vary significantly between the different publications, and it depends on the average wind speed, drive train as well as the climatic conditions* (Faulstich, Hahn and Tavner, 2011; Carroll, McDonald and McMillan, 2016)*. So for the base scenario, overall failure rate per OWT per year is assumed to be 4, and delivery time from the central warehouse to the service harbour with 48h. To be able to determine the influence of this assumption on the results for both variables, high and low scenarios are run increasing or rather decreasing the values by 50 percent.*

A two-stage experiment (see Table 3) is designed, which includes all relevant scenarios but excludes irrelevant scenarios to reduce the number of overall simulation runs. In stage I, the optimal storage level for the heavy-duty (category C) components is determined and set to this value for all the simulation runs of stage II. This is possible since the supply chain of category C spare parts is independent of the supply chain of the other two spare part categories. In the following section, the results of these simulation runs will be discussed.

Table 3: Input Variables of Different Scenarios

Stage			Storage Level			
	Overall Failure Rate	Delivery Time	A	B	C	Helicopter
I	2, 4, 6 [/OWT/y]	48 [h]	Central/ Decentral	Central/ Decentral	Central/ Decentral	Yes
II	2, 4, 6 [/OWT/y]	24/48/72 [h]	Central/ Decentral	Central/ Decentral	Central	Yes /No

5 Results

In order to enable a comparison of central and decentral storage strategy for spare parts for offshore wind turbines, the profit margins for the two alternatives are first calculated and then compared in this section. Also, the Mean Time to Repair (MTTR) is calculated, which is an essential measure of the efficiency of the offshore wind supply chain and helps to explain the results.

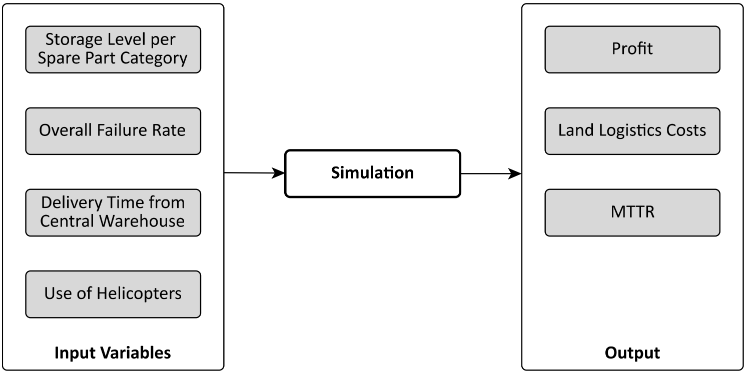

Figure 2: Input Variables and Output of the Simulation

Figure 3 shows the detailed calculation of the profit margin. It is calculated as the difference in revenues during the OWP lifetime minus the land logistics costs. The calculation only takes into account the land logistics costs, since only here are changes made to the supply chain setup. It is assumed that the water-side costs do not change, as the number of OWT failures and, accordingly, the number of repairs do not change. The revenues are calculated as the product of the total energy produced during the lifetime multiplied by the electricity price. The electricity price is set at 10.4 ct/kWh and assumed to be composed of a mixture of subsidized and non-subsidised purchase (Balks and Breloh, 2014). The power generated depends on the wind strength and the power curve of the Siemens SWT 3.6-120. The shortest term forecasts provided from the German Meteorological Service (DWD) for the locations of the two OWPs from 2013-2017 are used (four times during the 20 years of OWP lifetime) as the basis for determining the produced power. Thus, the number of functioning OWTs and the prevailing wind speed per OWP can be queried hourly in the simulation and the power generated can be determined.

The land logistics costs are calculated as the product of *storage costs* plus *transport costs* plus *order costs*. The *transport* and *order costs* are calculated using a fixed cost rate per order. The order cost rate is 400€ for both central and decentral storage. The transport cost rate varies for the different spare part categories: A: 23,11€, B: 42,09€, C: 811€ and is charged individually for every delivery of a spare part to the service harbor (Bundesverband Materialwirtschaft, Einkauf und Logistik, 2015). The storage costs are calculated as the product of the storage cost rate multiplied with the price of the spare part, the average stock level of the spare part and the duration of the simulation. In this case, the storage cost rate is assumed to be 28.7%, which is the usual rate for service providers (Bogaschewsky et al., 2012). All costs are individually determined per simulation run for each spare part category.

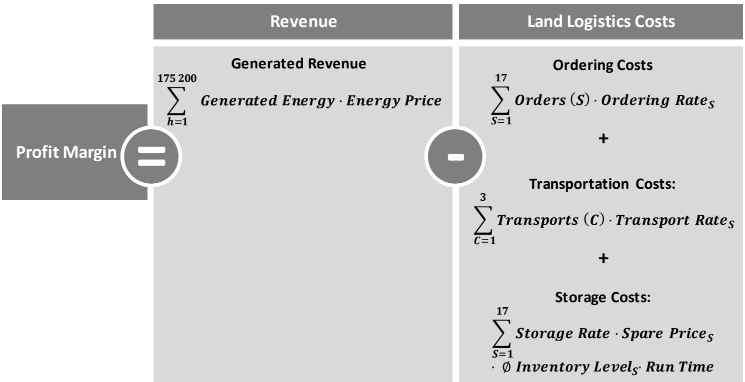

Figure 3: Calculation of Profit Margin

The MTTR is also determined for each spare parts category. It is calculated as the ratio of the sum of the downtime caused by a spare part category over the lifetime divided by the number of faults in this category during the lifetime:

$$MTTR_i = \frac{\Sigma\, downtime_i}{\Sigma\, failures_i} \tag{1}$$

In the following, the results from the two staged experiment are presented. In total, 24 simulation runs were executed during stage I using the input parameters shown in Table 3.

A comparison of the central and decentral storage strategy for the spare parts of category C shows that central storage yields a higher profit margin (see Figure 4). This can be attributed to two effects. First, the land logistics costs are about half as high in the case of central storage compared to decentral storage. A closer look at the costs reveals that this difference can be primarily ascribed to a reduction in inventory. In comparison, the transportation costs that accrue in case of central storage are rather small. The primary effect, however, which explains most of the increased profit margin is the increase in revenue, which is generated by the OWP in case the heavy duty spare parts are stored in a central warehouse. These higher revenues can be attributed to reduced MTTR and higher availability in case of central storage.

For stage II, the storage level for category C spare parts is now set as *central* for all simulation runs. The other input parameters: Overall failure rate, delivery time, stock levels A and B, as well as helicopter deployment, are varied in the different scenarios (Table 3). This means that a total of 72 further simulation runs are carried out.

The results of stage II show that a higher profit margin can be achieved with decentral storage of the small and medium spare parts (Category A&B). Again, the land logistics costs are higher for decentral storage due to increased total inventory levels (see Figure 5). For the spare parts of category A and B, however, the revenue is increased, and the MTTR decreases in case of decentral storage. This increase in revenues is significantly higher than the increase in logistics costs, and therefore, the profit margin increases in the case of decentral storage. A more detailed analysis of the results shows that the profit margin is higher for decentral storage irrespective of the scenario.

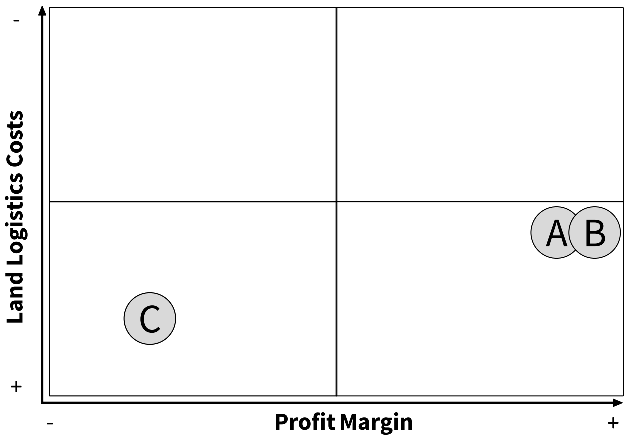

Figure 4: Comparison of Land Logistics Cost and Profit Margin of Decentral Storage compared to Central Storage

The MTTR has a significant impact on the availability of the OWT and therefore, on the profit margin during the O&M phase. Figure 5 shows how the profit margin decreases with increasing MTTR. The MTTR mainly depends on the waiting time for the spare part and the waiting time for a weather window for sea transport.

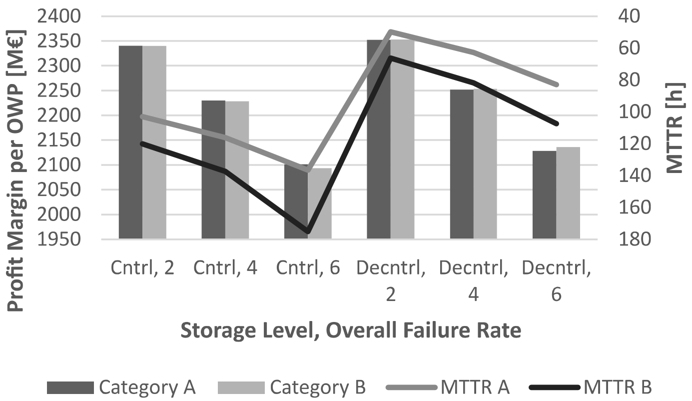

Figure 5: Profit Margin and MTTR for Spare Parts of Category A&B depending on Storage Level and Overall Failure Rate (averaged from 12 simulation runs)

In the model, the waiting time for sea transports does not change, but the waiting time for a spare part varies between the different scenarios. The analysis of the results shows that all the four input variables influence the MTTR. First, the MTTR increases if the spare parts are stored in a central warehouse as the spare parts have to be delivered to the service harbour. Second, the MTTR increases with the failure rate. This can be explained with longer waiting periods for sea transport as its capacity is limited. Additionally, the Figure shows that the MTTR of category A components is always shorter than that of category B, as these spare part can be transported by helicopter in addition to the CTV. Third, the deployment of the helicopter does influence the overall MTTR because it allows for additional repair missions in the OWP compared to only using a CTV. Fourth, increased delivery time from the central warehouse leads to an increased MTTR.

In order to verify the assumptions made about logistics and spare parts costs, a sensitivity analysis is carried out. This shows that the results are stable as even a doubling of costs does not influence them. The evaluation of the different scenarios also shows that an increase and decrease of the delivery time from the central warehouse and the overall failure rate by ± 50% does not influence the result.

6 Discussion of results

The results show that the MTTR is a moderator between the spare part strategy used and the revenue of the OWP. If the MTTR increases, the availability of the OWT decreases, and so does the revenue from the OWP. Other authors have also stressed the relevance of this parameter in the past, for example, in connection with the accessibility of the OWT (e.g. Dalgic et al., 2015). The results show that the causes of the MTTR changes vary depending on the characteristics of the spare parts.

For spare parts transported with the helicopter or CTV, the MTTR decreases in the case of decentral storage, since in this case the spare parts are directly available at the service port and the availability is not delayed by a delivery from a central warehouse. Spare parts transported with a crane vessel, on the other hand, are subject to an increase in MTTR due to increased stock shortages in decentral warehouse scenarios. Due to the higher storage costs and lower failure rates, inventories for of the heavy-duty components are only minimal, and the central storage allows for better absorption of peak demands while at the same time reducing storage costs. Since these components have a long replenishment time, shortages have a particularly drastic effect on MTTR. Also, the waiting time for a crane vessel is longer than the delivery time from the central warehouse, so the extension of the delivery time if stored at a central warehouse does not affect the MTTR.

For spare parts transported by CTV or helicopter, it can be seen that the increase in profits due to higher availability outweighs the higher logistics costs. This trend becomes particularly apparent with an increasing number of turbine failures, as the MTTR gains significance with a larger number of failures. In the future, this effect will gain even more relevance by increasing the power of the individual WTGs, since a more significant power potential remains unused in the event of a WTG failure. This shows that it is essential for the operators to ensure the high availability of spare parts because resulting in additional costs are outweighed by the increase in revenues.

The developed model assumes a local separation of service ports of the two OWPs. If, however, several OWPs are supplied from one service port, cost savings can be achieved by merging the warehouses without negative influences due to a longer delivery period.

The results are limited due to the characteristics of the model and the poor availability of data. The model includes only a reduced number of spare parts without reducing the number of defects per WTG. This means on the one hand that the failure rate per component is increased, on the other hand, that the number of spare parts in stock is reduced. The reduction in the number of components also means a reduction in the total stock. An increased number of components with the respective safety stock in the warehouse also means an increase of the total stock and thus of the storage costs. The average land logistics costs calculated are only about half as high as values from the literature. However, doubling these costs does not alter the results presented.

The reduction in the number of spare parts in the model also means that no components with a lower error rate than the C components and high storage costs are included in the model. After evaluation of the results, this type of spare parts appears to be suited for central storage.

Future research on spare part management for OWP could use other criteria for the division of the spare parts. The most fitting seems to be failure rate and storage cost of the spare parts. Nevertheless, the model showed that it was suitable to answer the research question.

7 Conclusions

In this paper, the influence of the spare parts strategy on the LCOE of Offshore Wind Parks is investigated. For this purpose, an agent-based model of a supply chain for spare parts for two offshore wind parks is developed including three spare part categories and the possibility of central and decentral storage. The results show that the correct spare parts strategy can help to reduce the LCOE of Offshore Wind. The main effect of the right spare part management, however, lies in the maximization of revenues through an increase of the Mean Time to Repair rather than in the reduction of costs. This increase in revenues leads to higher economic feasibility of offshore wind projects. The study highlights again how essential the O&M phase of the OWP is since it is the only phase during the lifetime of an OWP where revenues are generated.

References

Astariz, S., Vazquez, A. and Iglesias, G., 2015. Evaluation and comparison of the levelized cost of tidal, wave, and offshore wind energy. Journal of Renewable and Sustainable Energy, 7(5), p.053112.

Balks, M. and Breloh, P., 2014. Auswirkungen des neuen Erneuerbare-Energien-Gesetzes auf Offshore-Wind-Investitionen. Wirtschaftsdienst, 94(7), pp.520–523.

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

Besnard, F., 2013. On maintenance optimization for offshore wind farms. Doktorsavhandlingar vid Chalmers Tekniska Högskola. Göteborg: Chalmers Univ. of Technology.

Bogaschewsky, R., Eßig, M., Lasch, R. and Stölzle, W., 2012. Supply Management Research: Aktuelle Forschungsergebnisse 2012 ; Wiesbaden: Gabler Verlag.

Borshchev, A. and Filippov, A., 2004. From System Dynamics and Discrete Event to Practical Agent Based Modeling: Reasons, Techniques, Tools. p.23.

Bundesverband Materialwirtschaft, Einkauf und Logistik, 2015. BME-Preisspiegel Stückgut & Teilladungen: Frachten von 50 kg bis 15 Tonnen deutschlandweit. Frankfurt.

Carroll, J., McDonald, A. and McMillan, D., 2016. Failure rate, repair time and unscheduled O&M cost analysis of offshore wind turbines. Wind Energy, 19(6), pp.1107–1119.

Dalgic, Y., 2015. Development of Offshore Wind Operational Expenditure Model and Investigation of Optimum Operation and Maintenance Fleet. University of Strathclyde.

Dalgic, Y., Lazakis, I., Turan, O. and Judah, S., 2015. Investigation of optimum jack-up vessel chartering strategy for offshore wind farm O&M activities. Ocean Engineering, 95, pp.106–115.

Datta, P.P. and Christopher, M.G., 2011. Information sharing and coordination mechanisms for managing uncertainty in supply chains: a simulation study. International Journal of Production Research, 49(3), pp.765–803.

Dewan, A., 2014. Logistic & Service Optimization for O&M of Offshore Wind Farms: Model Development & Output Analysis. Delft.

Dinwoodie, I., 2014. Modelling the operation and maintenance of offshore wind farms. University of Strathclycde.

Endrerud, O.-E.V., Liyanage, J.P. and Keseric, N., 2014. Marine logistics decision support for operation and maintenance of offshore wind parks with a multi method simulation model. In: Proceedings of the Winter Simulation Conference 2014. pp.1712–1722.

Faulstich, S., Hahn, B. and Tavner, P., 2011. Wind turbine downtime and its importance for offshore deployment. Wind Energy, 14(3), pp.327–337.

Ferdinand, R., Monti, A. and Labusch, K., 2018. Determining Spare Part Inventory for Offshore Wind Farm Substations based on FMEA Analysis. In: Proceedings - 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe, ISGT-Europe 2018.

Gallo, G., Ponta, L. and Cincotti, S., 2012. Profit-based O&M strategies for wind power plants. In: 9th International Conference on the European Energy Market. Florence, Italy: IEEE.pp.1–7.

Gayo, J.B., 2011. Results of Project ReliaWind: Project Final Report.

GL Garrad Hassan, 2013. A Guide to UK Offshore Wind Operations and Maintenance.

Halvorsen-Weare, E.E., Norstad, I., Stålhane, M. and Nonås, L.M., 2017. A metaheuristic solution method for optimizing vessel fleet size and mix for maintenance operations at offshore wind farms under uncertainty. Energy Procedia, 137, pp.531–538.

Jin, T., Tian, Z. and Xie, M., 2015. A game-theoretical approach for optimizing maintenance, spares and service capacity in performance contracting. International Journal of Production Economics, 161, pp.31–43.

Karyotakis, A., 2011. On the optimisation of operation and maintenance strategies for offshore wind farms. University College London.

Kost, C., Shammugam, S., Jülch, V., Nguyen, H.-T. and Schlegl, T., 2018. Levelized Cost of Electricity- Renewable Energy Technologies. p.42.

Law, A., 2007. Simulation Modeling & Analysis. New York: McGraw-Hill.

Lindqvist, M. and Lundin, J., 2010. Spare Part Logistics and Optimization for Wind Turbines: Methods for Cost-Effective Supply and Storage. Uppsala.

Lütjen, M. and Karimi, H.R., 2012. Approach of a port inventory control system for the offshore installation of wind turbines. p.8.

Macal, C. and North, M., 2014. Introductory tutorial: Agent-based modeling and simulation. In: Proceedings of the Winter Simulation Conference 2014. pp.6–20.

Münsterberg, T. and Jahn, C., 2015. Offshore-Windenergie: Kostensenkung durch Logistiksimulation. In: Simulation in Production and Logistics 2015. pp.585–594.

Münsterberg, T., Jahn, C. and Kersten, W., 2017. Simulation-based evaluation of operation and maintenance logistics concepts for offshore wind power plants. Innovations for maritime logistics / Fraunhofer Center for Maritime Logistics and Services CML. Stuttgart: Fraunhofer Verlag.

Nielsen, J.J. and Sørensen, J.D., 2010. Risk based maintenance of offshore wind turbines using Bayesian networks. In: 6th PhD Seminar on Wind Energy in Europe. Norwegian University of Science and Technology.pp.101–104.

Nnadili, C.D., 2009. Evaluation and comparison of the levelized cost of tidal, wave, and offshore wind energy. Massachusetts Institute of Technology.

Poulsen, T., Hasager, C. and Jensen, C., 2017. The Role of Logistics in Practical Levelized Cost of Energy Reduction Implementation and Government Sponsored Cost Reduction Studies: Day and Night in Offshore Wind Operations and Maintenance Logistics. Energies, 10(4), p.464.

Rauer, R., Jahn, C. and Münsterberg, T., 2013. Quantity and Type Forecasting Tool for Offshore Wind Power Plant Spare Parts. in: Birgitt Brinkmann and Peter Wriggers (Ed.): Computational Methods in Marine Engineering. Digital copy. MARINE 2013. Hamburg, 29-31.5.2013. International Center for Numerical Methods in Engineering, 1. Ed. Barcelona.

Reimers, B. and Kaltschmitt, M., 2014. Kostenentwicklung der Offshore-Windstromerzeugung – Analyse mithilfe der Erfahrungskurventheorie. Zeitschrift für Energiewirtschaft.

Rinne, A., 2014. After Sales Service in der Offshore-Windenergiebranche. Ein Vergleich von Ersatzteilversorgungsstrategien. Universität Bremen.

Sahnoun, M., Baudry, D., Mustafee, N., Louis, A., Smart, P.A., Godsiff, P. and Mazari, B., 2015. Modelling and simulation of operation and maintenance strategy for offshore wind farms based on multi-agent system. Journal of Intelligent Manufacturing.

Schrotenboer, A.H., uit het Broek, M.A.J., Jargalsaikhan, B. and Roodbergen, K.J., 2018. Coordinating technician allocation and maintenance routing for offshore wind farms. Computers & Operations Research, 98, pp.185–197.

Shafiee, M., 2015. Maintenance logistics organization for offshore wind energy: Current progress and future perspectives. Renewable Energy, 77, pp.182–193.

Stålhane, M., Christiansen, M., Kirkeby, O. and Mikkelsen, A.J., 2017. Optimizing Jack-up vessel strategies for maintaining offshore wind farms. Energy Procedia, 137, pp.291–298.

Stålhane, M., Vefsnmo, H., Halvorsen-Weare, E.E., Hvattum, L.M. and Nonås, L.M., 2016. Vessel Fleet Optimization for Maintenance Operations at Offshore Wind Farms Under Uncertainty. Energy Procedia, 94, pp.357–366.

Tracht, K., Westerholt, J. and Schuh, P., 2013. Spare Parts Planning for Offshore Wind Turbines Subject to Restrictive Maintenance Conditions. Procedia CIRP, 7, pp.563–568.

Wind Europe, 2018. Offshore Wind in Europe - Key trend and statistics 2017.

Wooldridge, M.J., 2009. An introduction to multiagent systems. 1. ed. Chichester: John Wiley & Sons.

Zhang, K., Feng, Y., Cui, Y., Wang, Z. and Yang, F., 2018. Quantity Optimization of Spare Parts For Offshore Wind Farm Based on Component Updating. IOP Conference Series: Earth and Environmental Science, 186, p.012024.