Proceedings of the 2014 Winter Simulation Conference
A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, eds.

MARINE LOGISTICS DECISION SUPPORT FOR OPERATION AND MAINTENANCE OF OFFSHORE WIND PARKS WITH A MULTI METHOD SIMULATION MODEL

Ole-Erik V. Endrerud
Jayantha P. Liyanage

Department of Mechanical and Structural
Engineering and Material Science
University of Stavanger
N-4023 Stavanger, NORWAY

Nenad Keseric

Marketing, Processing and Renewables
Department of Operations Strategy and Support
Statoil ASA, Box 3
NO-1033 Fornebu/Oslo, NORWAY

ABSTRACT

The offshore wind industry in Europe is looking to move further from shore and increase the size of wind parks and wind turbines. As of now marine logistics during the operation and maintenance life cycle phase is, besides wind turbine reliability, the most important limitation for wind turbine service, repair and replacement, and pose a large risk for wind park operators and owners. This paper presents a marine logistic simulation model for the O&M life cycle phase based on a combination of the agent-based and discrete event modeling paradigms, currently being tested as a decision support tool by European offshore wind park developers. The model simulates the O&M lifecycle phase of an offshore wind park with all integral components of marine logistic needed. In this paper the simulation model is described together with an application example demonstrating how the simulation model can be applied as a decision support tool.

1 INTRODUCTION

For European renewable energy goals to be met every possible source of renewable energy must be exploited, and offshore wind energy make an important contribution. At the end of 2013 the cumulative installed capacity of offshore wind in Europe was 6,562 MW covering 0.7% of the European electricity consumption (European Wind Energy Association 2014).

Offshore wind energy production carries high financial risk for investors as profit margins are small and dependent on subsidies, production is dependent on uncertain wind speeds, and operation and maintenance depend on uncertain weather for marine logistics.

Marine logistics is necessary to gain access to wind turbines (WT) for service and repairs, and operability of vessels, access solutions and lifting equipment are highly dependent on wave height and wind speed. And to clarify the use of the term logistics it is only the transportation of technicians and equipment that this simulation model is limited to, not warehouse logistics for spare parts for example. In order to minimize downtime of the offshore wind park work management is crucial to maximize utilization of the time available to access and perform work on WTs. In an average offshore wind park with 80 turbines one can expect to have approximately 2-4 failures per day needing marine logistics, which is a considerable work load.

Analytic models have difficulties in incorporating the variability and complexity of a system like this, moreover provide an understanding of how it works. Therefore, a multi method simulation model was developed to provide offshore wind park developers knowledge on how their offshore wind production system will work, incorporating the variability of the marine logistics system beyond statistical distributions and numeric formulas. There exist various other simulation and analytic models (see

978-1-4799-7486-3/14/$31.00 ©2014 IEEE

Hofmann 2011 for a thorough review) and the ECN O&M tool (developed by Energy Research Centre Netherlands – ECN) is regarded as the industry standard in Europe, which is an Excel-based analytic model.

This paper will first introduce how simulation modeling can be used as a business decision tool, followed by an explanation of the simulation model. Finally, an example showing how the simulation model can be applied as a decision support tool in the concept study phase for offshore wind park development is presented.

2 SIMULATION MODELING AS A BUSINESS DECISION TOOL

Notably, the use of modeling as a decision support tool for various applications has gradually grown particularly over the last few decades. The technical nature of modeling efforts based on solid mathematical foundation has evolved gradually to a status today where the physical reality can be replicated in multiple ways for various analytical purposes and inferences (Sawy and Pereira 2012, Pasiouras 2013). The very early efforts to describe various physical or non-physical phenomena through heavy technical approaches have seemingly taken a turn in more modern settings where modeling has become a strategic business tool with a smart combination of simulation capabilities.

In very general terms, the two principal attributes that drive the application of simulation modeling as a modern business decision tool are the *diversity* and *uncertainty* that characterize the nature of complexity associated with modern systems, processes, and concepts. This can provide robust decision support opportunities where the interplay between logics, choices, and rules can be observed as complex behavioral patterns within a simulation domain (Hatfield 2012; van Dam, Nikolic, and Lukszo 2012). Perhaps the biggest impact that the ongoing developments have introduced is the very ability to explain a phenomenon through sharp and clear communication language in terms of risk and value-added by means of visualization processes that are cognitively appealing as almost as real physical events or occurrences.

It is these very modern features of some of the simulation modeling solutions that have shown great potential for application within the offshore wind energy sector. The growth of the wind energy sector today has the very key features of diversity and uncertainty. It is diverse in terms of business landscape and solutions and at the same time highly uncertain in terms of financial risk exposure and profit margins. It is under these circumstances that the ongoing project in Norway was launched to find a suitable simulation modeling solution for business decision support.

3 DETAILS OF THE OFFSHORE WIND ENERGY O&M SIMULATOR

The simulation model was developed in collaboration with offshore wind park developers to ensure that there exist a common understanding of the model's logic, it's limitations and it's application. Subsequently a verification and validation following the methods described by Sargent (2013) was carried out, using parameter sensitivity analysis, structured walkthrough and testing with extreme values for verification, and comparison with other models and face validity tests for validation. Face validity test were conducted with the same offshore wind park developers that aided in the model development.

AnyLogic, the commercial simulation software, was used as simulation modeling software and hence the simulation model is coded in the Java programming language. AnyLogic was selected and preferred over other simulation modeling software (e.g. NetLogo), and raw coding in Java due to its ease of use for novice modelers, the possibility to read and edit the Java code if necessary, and that it is efficient in terms of time needed to create a model and run simulation experiments.

The model combines agent-based and discrete event modeling, as it was important to capture the individual behavior of vessels, especially in situations where the vessel agent have to deviate from standard procedures. Agent-based modeling is used to model behavior of technicians, managers, vessels, vessel owners, WTs, and wind park operators, and to give these individual characteristics (e.g. failure rates for WTs and weather criteria for vessels). And to model agent behavior statecharts are used. Discrete event modeling is used to model work processes, e.g. planning and diagnosis, mobilization, and maintenance tasks. The discrete event processes are modeled inside every agent that uses them to enable the agent's behavior to be controlled individually by the work process.

Subsequent subchapters will be used to explain briefly the logic behind the different parts of the simulation model, and the theoretical background for this logic where such are applied.

3.1 Wind Turbine Agent and Failure Generation

WTs are modeled with 19 components, shown in Figure 1, and component classification is based on the RDS PP® (Reference Designation System for Power Plants) (VGB Powertech 2014).

The number of failures, $N(t)$, in a time interval between 0 and T of a subcomponent are in the case of minimal repair commonly modeled as a non homogenous Poisson process (Aven 1992, Tavner 2012),

$$P(N(t) = i) = \frac{(\lambda(t) \cdot t)^i}{i!} e^{-\lambda(t) \cdot t}, \qquad i = 0,1,2,\ldots \tag{1}$$

with a time dependent failure intensity $\lambda(t)$ at time t (average number of failures per time unit), which for mechanical components can be expressed as a Power Law process following a Weibull-function,

$$\lambda(t) = \lambda\beta t^{\beta-1} \tag{2}$$

where λ is the annual failure intensity when the wind turbine is new or subcomponent replaced and β is the distribution shape factor representing an increasing ($\beta > 0$) or decreasing ($\beta < 0$) failure intensity. In use λ can be determined based on test data from the wind turbine manufacturer or from analysis of wind turbine failure data, while β is determined either in a qualitative manner based on the decision maker's believed development of new wind turbine components, or by analyzing wind turbine failure data. In the simulation model $\lambda(t)$ is updated for each subcomponent individually whenever the subcomponent is replaced.

The time to failure (TTF) of a subcomponent is assumed to be a random variable following an exponential distribution, as it is assumed that the failure intensity is constant between replacements. After a repair a new TTF is sampled from the exponential distribution with the old failure intensity, whereas after a replacement a new TTF is sampled from the exponential distribution with the updated failure intensity from (2). Failures occur in a wind turbine subcomponent or subsystem in the simulation model when time since last failure exceeds TTF of the respective subcomponent or subsystem. When a failure occurs the wind turbine change to the failed state. Hence, failures are stochastic and wind turbines have 19 different failure modes.

An alternative failure modeling approach is a damage accumulation model applying physics of failure models (e.g. fracture mechanics) instead of statistical models, see e.g. Nielsen and Sørensen (2011).

3.2 Maintenance Planning and Scheduling Process

The simulation model takes into consideration both preventive maintenance (annual service, certification, inspection, etc.) and corrective maintenance (when wind turbines run to failure). Wind turbine failures have different severity from false alarms to full replacement. Severity is classified in the failure type classification (FTC) scale, which is expressed as an integer between 1 and 20, where 1-16 denotes low to high severity and 17-20 denotes service, inspection or certification tasks, which are routine preventive maintenance tasks. When a wind turbine enters one of the failure states an alarm is sent to a maintenance manager agent who will diagnose the alarm and determine the FTC, which, subsequently, determines the resource requirement to resolve the failure causing the alarm. The diagnose and spare part logistic process follows the convention from IEC/TS 61400-26-1 (International Electrotechnical Commission 2010), and is modeled as a discrete event process where the work order created for the failure is the entity flowing through this process, shown in Figure 2. After the alarm is diagnosed there is an average (deterministic) waiting time for spare parts depending on the FTC. When spare parts have arrived the work order created to resolve the failure is delegated to a suitable vessel (some vessels need to be chartered, see section 3.3) that will carry out the work order as soon as there is enough time and a suitable weather window.

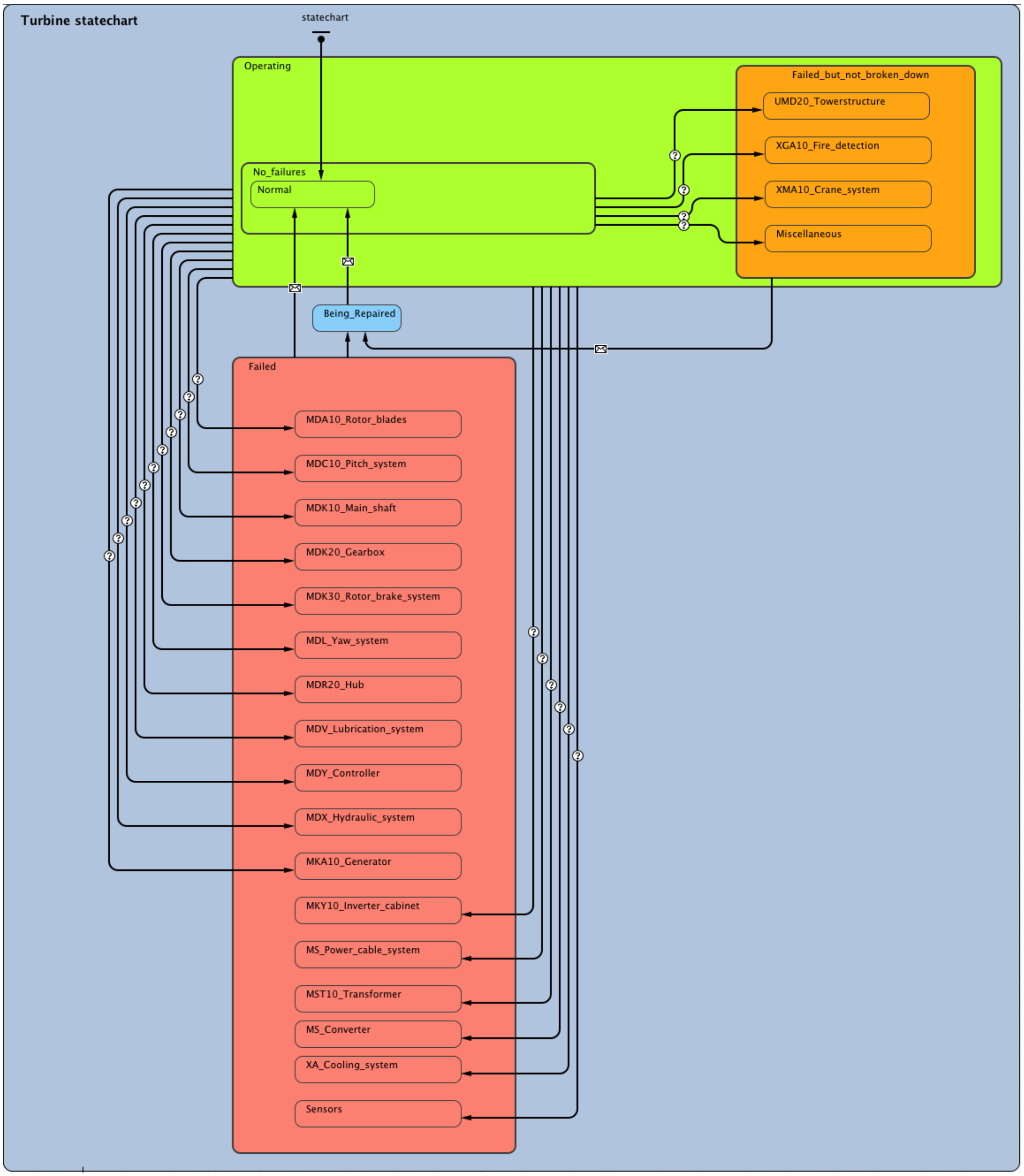

Figure 1: The statechart representing wind turbine behavior. Subcomponents and subsystems can be seen in the red and orange composite states.

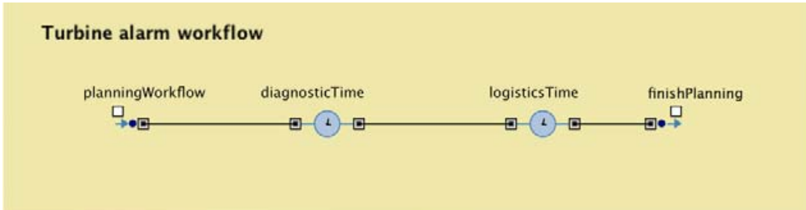

Figure 2: Work process for diagnosing alarm and waiting for spare parts.

3.3 Repair and Replacement Process, Vessel and Technician Agents

Vessels and technicians carry out repairs and replacements. Depending on the FTC the failure requires different vessels, number of technicians and amount of time to be resolved. A vessel will, after receiving a work order from the maintenance manager, check for available technicians – either on the onshore base or service operation vessel (if used) – and tell the required number of technicians to get on board the vessel. The Agent API provided in AnyLogic enables agent-to-agent communication, and a message from the vessel to a technician will add the technician to a Java collection on the vessel and initiate a transition in the technician's statechart. When there is enough technicians on the vessel, there is a sufficient weather window and time left in the work shift the vessel will start sailing towards the wind park. Locations and movement of agents occur in a GIS map and the model will calculate the shortest distance between its current location and the destination. This distance divided by the vessel's individual speed gives the sailing time to the destination.

The repair and replacement process is modeled as a discrete event process, whereas the vessels' and technicians' behavior is modeled by the agent-based method (see Figure 3) as mentioned earlier. In the work processes shown in Figure 3 work orders are used as entities, and the vessel agent inserts these. When technicians have arrived at a wind turbine a message is sent to the wind turbine agent that fires the transition to move the wind turbine into the being repaired-state (ref. Figure 1). When technicians have finished the work order and transferred back to the vessel a new message is sent to the wind turbine agent in order for it to change to the operating state.

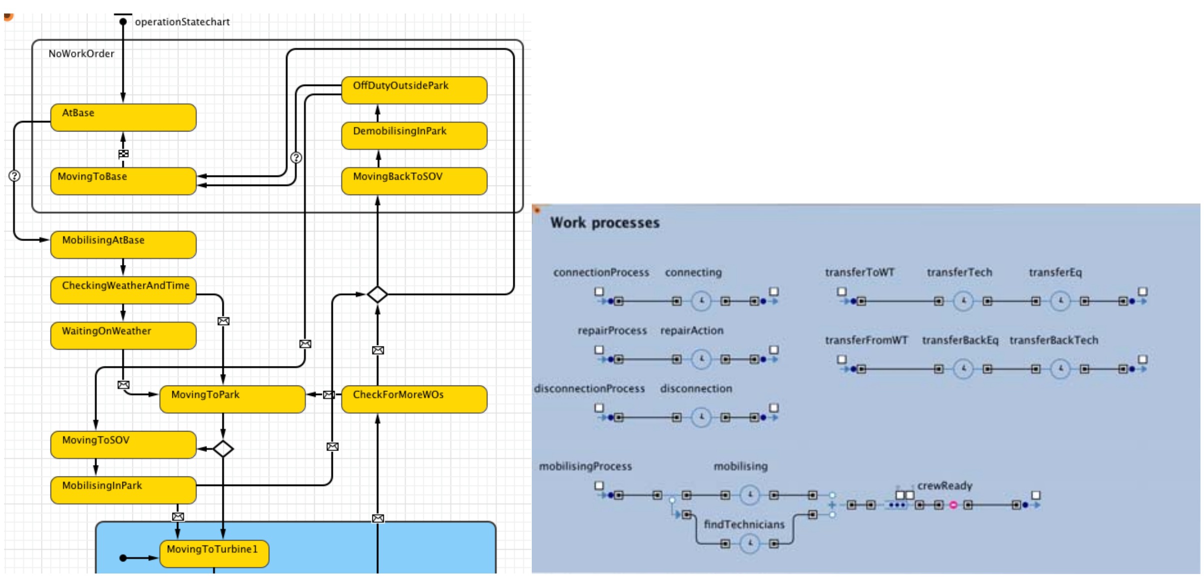

Figure 3: The left figure shows an example of a part of a crew transfer vessel's statechart used to model it's behavior, and the right figure shows the work processes used by the vessel to execute work orders.

Another important part of the model is that technicians are modeled to be adaptive in the sense that they accumulate experience, which in turn contributes to lowering actual repair times. However, it is assumed that there is a diminishing marginal effect of experience on repair times. And furthermore, there are only one category of technicians in the simulation model, hence no distinction between electrical and mechanical technicians.

An interesting aspect of marine logistics for offshore wind parks is the chartering strategy for vessels. It is possible to choose various strategies for vessel chartering, as the strategy varies among wind park operators. In the simulation model it is possible to chose contract type (spot or long term), contract duration and if the charter rate is fixed or variable. Vessel classes available in the model are i) heavy lift vessels (HLV), ii) crew transfer vessels (CTV) and iii) service operation vessels (SOV), illustrated in Figure 4.

Figure 4: The left image shows a HLV, the middle image show a CTV and the right image show two SOVs.

4 SIMULATION AND DECISION MAKING METHODOLOGY

The methodology for decision making, illustrated in Figure 5, consist of the following steps: 1) define the decision alternatives and scenarios together with the decision maker that are tested on each decision alternative, 2) define output metrics that will be used to objectively evaluate the different decision alternatives, 3) run *n* simulation runs, and lastly 4) determine based on hypothesis testing if the alternatives differ and based on the output metrics which decision alternative is the most advantageous one. The advantage of using a simulation experiment approach for decision-making is that it enables the analysis of time dependent and stochastic systems. The intended use of the simulation model explained in this paper is in medium to long-term decisions, e.g. in the initial design phase of an offshore wind park development (long-term) or when reassessing vessel charter contracts or maintenance intervals in the exploitation phase (medium-term).

The preceding subsections briefly describe the input data required in step 1) and the output metrics in step 2).

Figure 5: The simulation and decision making process.

4.1 Input Data Defining Decision Alternatives and Scenarios

The simulation model requires the decision maker to specify several categories of input data; or design basis using engineering jargon. These are 1) weather data, 2) WT and WT park data, 3) vessel data, 4) repair and replacement data, 5) cost and price data, and 6) marine logistic and maintenance strategy data. These input data are used to define decision alternatives and scenarios. Decision alternatives are defined by 2) WT and WT park data and 6) marine logistics and maintenance strategy data, while scenarios are defined by the remaining input data categories.

4.1.1 Weather Data

Significant wave height (H_s) and mean wind speed at hub height (V_w) are the two weather parameters used in the simulation model, and are the main limiting factors for WT access and crane operations. One can either choose to use historic or hind cast weather data, or synthetic time series of weather data can be generated in Matlab e.g. by using a Markov-chain Monte Carlo approach (see e.g. Hagen et al. 2013) for details). Weather data time series must be in hourly resolution. In the application example in this article a historic weather data time series were used.

4.1.2 Wind Turbine and Wind Turbine Park Data

The decision maker needs to specify the wind turbine power curve with cut-in and cut-out speeds, reliability data for the wind turbine, and wind park layout. The power curve determines power production at various wind speeds, and is the basis for calculating actual and lost production. Reliability data in the form of average annual failure rates must be specified for all of the 19 components that are present in the wind turbine model used in the analysis. There exist very little reliability data for offshore wind turbines but some analyses have been done by Tavner, Xiang, and Spinato (2007); Faulstich, Hahn, and Tavner (2011); and Faulstich, Lyding, and Tavner (2011).

Wind park layout is defined by specifying the geographical location of each wind turbine in longitude and latitude. This information is important to enable calculation of travel distance and time for vessels. The wind park developer should provide this information.

4.1.3 Vessel Data

Vessel data required as input are operational limits (H_s and V_w), transit speed and speed with dynamic positioning (DP), DP activation time, connection and disconnection time, transfer time for technicians and equipment, technician capacity, and vessel failure rate.

There are some differences between vessel classes, and HLVs require input on jacking speed (if it is a jack-up vessel) and operational limitations for jacking.

4.1.4 Repair and Replacement Data

Detailed data on cost of spare parts, time required to carry out the work order, number of technicians needed and vessel type required. Generic data are provided as default input, but it is recommended that the decision maker provide more accurate data. For generic data on spare part costs see e.g. the NREL Wind Pact project (Malcolm and Hansen 2006).

4.1.5 Cost and Price Data

In order to compare operation and maintenance cost items (marine logistics cost, spare part cost, etc.) it is necessary to specify day rates for the different vessels, salary costs, warehousing costs, overhead costs, insurance, land rent and tax. Generic numbers are provided as default, but it is recommended that the decision maker provide such cost data.

Some sort of support mechanism often supports offshore wind parks in Europe financially. For example in the UK there are the Renewable Obligation Contract (ROC) and Contract for Difference (CfD) support mechanisms. In order to compare revenue it is important to specify the correct support mechanism. In the simulation model it is assumed that the electricity price is constant, and should be interpreted as the average electricity price over the simulation period.

4.1.6 Marine Logistic Strategy Data

The decision maker will need to decide on the marine logistic strategy by providing input on the desired number of technicians and vessels, and the desired type of vessels. It is also necessary to state how different maintenance tasks should be handled; e.g. shall a CTV be spot chartered for service tasks (i.e. FTC 17-20) or shall the SOV prioritize corrective tasks over preventive tasks. An onshore supply base also needs to be defined, and the input is the base's geographical location in longitude and latitude. These are normally the input data defining the decision maker's decision alternatives.

4.2 Output Data

A set of standard key performance indicators is used as output metrics, and the decision maker for a specific simulation experiment can choose a subset of these. The mean, standard deviation, min and max are all collected for statistical analysis and hypothesis testing after all *n* simulation runs are completed. The standard output metrics are:

1. Time-based availability (available time/total time)
2. Energy-based availability (actual production/theoretical possible production)
3. Technical availability (available time/theoretical available time)
4. Lost production
5. Marine logistics cost
6. Vessel utilization (days used/days chartered)

5 DECISION MAKING EXAMPLE

The decision-making example is inspired by a real case where the simulation model is currently being applied. The scenario consists of a generic wind park with 67 wind turbines with a rated capacity of 6 MW at a distance of approximately 40 kilometers from shore and a pool of 30 technicians. The question at hand is whether an SOV is more suitable than two CTVs for marine logistic in the operation and maintenance life cycle phase of this offshore wind park. Hence, there are two decision alternatives: 2 CTVs or 1 SOV.

The output metrics that will be compared are time and energy based availability, lost production, marine logistics cost, and vessel utilization, and the results are presented in Table 1. A total of 5 simulation runs were carried out for each of the two decision alternatives with the one scenario defined above, and the simulation length was two years (typical charter length). The number of simulation runs is defined as the minimum required number of simulation runs needed for the standard deviation of the output metric sample to be less than 3-5% of the sample average (for all output metrics). In the hypothesis testing comparison a confidence level of 95% was chosen, and the Student's *t*-distribution was chosen as test statistics. This confidence level gives a critical *t*-value of 2.7764, from which the confidence interval in Table 2 is created.

Table 1: Simulation results (mean μ, standard deviation σ and standard error S) for decision alternatives.

	2 CTV			1 SOV		
	μ	σ	S	μ	σ	S
Time based availability [%]	97.03	0.21	0.09	93.51	0.62	0.28
Energy based availability [%]	94.27	0.22	0.10	90.95	0.60	0.27
Lost production [kWh]	8.99E7	8.45E6	3.78E6	16.6E7	9.81E6	4.29E6
Marine logistics cost [mill £]	8.395	2.06	0.92	19.08	1.32	0.59
Vessel utilization [%]	32.74	0.76	0.34	46.88	0.80	0.36

Table 2: Hypothesis test with the CTV-alternative as base case to determine if the results are statistically significant from each other. Confidence intervals are created from the base case.

	Time based availability	Energy based availability	Lost production	Marine logistics	Vessel utilization
Lower limit	96.77%	93.99%	7.94E7	£5 838 981	31.80%
Upper limit	97.29%	94.55%	10.0E7	£10 951 019	33.68%
t-value	39.111	33.997	8.476	41.718	92.217
p-value	~ 0%	~0%	~0%	~0%	~0%
Reject with	~100%	~100%	~100%	~100%	~100%

From the results in Table 1 one can see that the two decision alternatives differ quite a lot, with the SOV being the least efficient vessel in terms of availability and lost production. However, the SOV is the most utilized vessel of the two alternatives. Another interesting aspect of the results is that the CTV is a smaller vessel with lower weather limitations and longer distance to travel between shore and wind park, but still – by far – outperforms the SOV in cost-benefit ratio (marine logistics cost over lost production).

To verify that the results above is not due merely to chance a hypothesis test is conducted. And from the results from the hypothesis test in Table 2 one can arrive at the conclusion that the two decision alternatives are statistically significant from each other, with a confidence of approximately 100%. What it means is that the differences are due to other factors than chance; in other words, there is a statistically significant difference in using the two types of vessels. It is therefore safe to say that the preferred decision alternative is to charter two CTVs, and discard the SOV-alternative for now. Alternatively, neither of these alternatives is satisfactory and a new or modified solution has to be found.

6 CONCLUSION AND FURTHER WORK

Current status of offshore wind energy sector calls for innovative solutions to manage its principal business influence factors and cost drivers. Marine logistics plays a critical role in this context, and thus is crucial for wind park operators to operate their assets successfully with high availability and positive returns. This paper focused on marine logistics as a domain that bear major risks for offshore wind park operators and owners under the current business conditions, and hence made an effort to improve the underlying decision making process with respect to the configuration and operation of this dynamic system. The principal contribution of this paper is a novel simulation model that can be used as a decision support tool by wind park developers to make decisions on vessel fleet configuration, supply base location, wind turbine technology (e.g. direct drive versus gearbox driven based on wind turbine reliability), staffing and work processes.

This simulation model is based on a combination of agent based and discrete event modeling. Wind turbines, technicians, vessels, maintenance managers and other living agents were modeled in the agent based paradigm with individual decision making and attributes, while work processes such as repair and replacement are modeled in the process oriented discrete event paradigm. Discrete event work processes were modeled directly inside the agent that uses it so that the agent can be controlled individually by the work process. This approach helped largely in limiting the set of assumptions and add-ons needed to represent the marine logistics system in such a detailed manner. The model was validated with domain experts through face validity and comparison with other models.

Finally, the use of the simulation model for decision making was shown through an application example where there was a decision to be made regarding the vessel type to be used for maintenance for a large offshore wind park, a “what if” analysis of two decision alternatives under one scenario. The analysis showed, through hypothesis testing, that it is possible to say that the two alternatives are statistically significant from each other, and therefore confidently select the vessel with the most desired output metrics.

The work presented in this paper is part of an ongoing project on simulation modeling applied on offshore-unmanned production assets. In the next phase the model will be extended to be able to investigate the effect of condition based maintenance on wind park performance. And of special interest is how work processes and the maintenance organization should be configured to take full advantage of the information one gets from machine prognostics. In addition, the model still lacks a robust weather data module for creating weather time series of future weather and this will be investigated together with the project partners. It is highly unlikely that future weather will be identical to historic measurements, especially due to climate change.

ACKNOWLEDGMENTS

The authors would like to thank the Norwegian energy company Statoil for providing valuable inputs to this paper, and development and validation of the application example. This project is a part of the Norwegian Research Centre for Offshore Wind Energy (NORCOWE).

REFERENCES

Aven, T. 1992. *Reliability and risk analysis.* Hampshire, England: Elsevier Applied Science.

European Wind Energy Association. 2014. “The European offshore wind industry - key trends and statistics 2013.” European Wind Energy Association.

Faulstich, S., B. Hahn, and P. J. Tavner. 2011. “Wind turbine downtime and its importance for offshore deployment.” *Wind Energy* 14(3): 327-337.

Faulstich, S., P. Lyding, and P. Tavner. 2011. “Effects of Wind Speed on Wind Turbine Availability.” In *Proceedings of the 2011 European Wind Energy Conference*.

Hagen, B., I. Simonsen, M. Hofmann, and M. Muskulus. 2013. “A Multivariate Markov Weather Model for O&M Simulation of Offshore Wind Parks.” *Energy Procedia* 35:137-147.

Hatfield, M. 2012. *Game Theory in Management: Modelling Business Decisions and their Consequences*. Gower.

Hofmann, M. 2011. “A Review of Decision Support Models for Offshore Wind Farms with an Emphasis on Operation and Maintenance Strategies.” *Wind Engineering* 35(1): 1-16.

International Electrotechnical Commission. 2010. “Wind Turbines - Part 26-1: Time based availability for wind turbines.” International Electrotechnical Commission. IEC/TS 61400-26-1.

Malcolm, D. J., and A. C. Hansen. 2006. “WindPACT Turbine Rotor Design Study.” National Renewable Energy Laboratory.

Nielsen, J. J., and J. D. Sørensen. 2011. “On risk-based operation and maintenance of offshore wind turbine components.” *Reliability Engineering and System Safety* 96(1): 218-229.

Pasiouras, F. 2013. *Efficiency and Productivity Growth: Modelling in the Financial Services Industry*. Somerset, NJ, USA, Wiley.

Sargent, R. G. 2013. “Verification and validation of simulation models.” *Journal of Simulation* 7(1): 12-24.

Sawy, O. A. E. and F. Pereira. 2012. *Business Modelling in the Dynamic Digital Space: An Ecosystem Approach*. Springer.

Tavner, P. 2012. *Offshore wind turbines reliability, availability and maintenance*. London: Institution of Engineering and Technology.

Tavner, P. J., J. Xiang, and F. Spinato. 2007. “Reliability analysis for wind turbines.” *Wind Energy* 10(1): 1-18.

van Dam, K. H., I. Nikolic, and Z. Lukszo. 2012. *Agent-Based Modelling of Socio-Technical Systems*. Springer.

VGB Powertech. 2014. “RDS-PP Application Guideline Part 32: Wind Power Plants.” VGB Powertech e.V. VGB-S-823-32-2014-03-EN-DE.

AUTHOR BIOGRAPHIES

OLE-ERIK ENDRERUD is a Doctoral Research Fellow at the Department of Mechanical and Structural Engineering and Material Science at the University of Stavanger in Norway. He holds a B. Sc. in Mechanical Engineering, a M. Sc. in Industrial Asset Management and a M. Sc. in Marine- and Subsea Engineering all three from the University of Stavanger. His email address is oleerik@endrerud.no.

DR. JAYANTHA P. LIYANAGE is a Professor of Industrial Asset Management at the University of Stavanger (UiS), Norway. He is the Chair of the Centre Industrial Asset Management (CIAM) and serves on the Board of Directors of the Society of Petroleum Engineers (Stavanger Chapter). He is a Co-organizer and Coordinator of the European Network for Strategic Engineering Asset Management (EURENSEAM), Honorary Founding Fellow of the ISEAM (International Society of Engineering Asset Management) and the Editor-in-Chief of the International Journal of Strategic Engineering Asset Management (IJSEAM). He has more than 100 publications in various books, international journals and conferences over the last few years, and has received a number of awards for his professional achievements. His email address is j.p.liyanage@uis.no.

DR. NENAD KESERIC is the Head of Operations Strategy and Support Department and Asset Manager within Statoil Wind Energy. He is Statoil's representative in UK for Sheringham Shoal offshore wind park. He holds a M. Sc. in Electrical Engineering and a Ph. D. in Energy Economics from Vienna University of Technology. His email address is nenk@statoil.com.