7

Operation and Maintenance Modelling

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CHAPTER MENU

One of the biggest challenges in the development of offshore wind farms is the cost and limited opportunities for maintenance and access. This calls for new solutions when it comes to operation and maintenance (O&M) strategies, condition monitoring and logistics, just to mention some examples. To assess different solutions and to select the best ones, good models for maintenance and logistics decision support are required. This chapter provides an overview of, and a brief introduction to, O&M modelling for offshore wind farms, including transport and logistics for O&M. The main focus of the chapter is on strategic O&M modelling. An O&M simulation model and a model for O&M vessel fleet optimization are presented. The models can be used for analysis and optimization of different aspects of maintenance and logistics and the influence on the costs and availability during the operational phase of an offshore wind farm. Applications of the models are illustrated by examples, among others for cost-benefit evaluation for a new solution for remote inspection of the turbine nacelle. Furthermore, the influence

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of different logistics, maintenance and monitoring strategies on the costs is illustrated in the examples. In addition to these two strategic models, an operational model for routing and scheduling of a fleet of maintenance vessels is presented.

7.1 Introduction

Operational expenditure (OPEX) is one of the major contributions to the levelized cost of energy (LCoE) for offshore wind farms. OPEX includes maintenance and service costs in addition to other variable operational costs. Table 7.1 provides a brief overview of different estimates for the OPEX contribution to LCoE. The estimates are between 12 and 32%, with a typical value around 25%. Some of the variability is due to offshore transmission charges, which in the United Kingdom are payed annually to an offshore transmission operator and, hence, included as OPEX. In other countries, these costs are typically included as capital expenditure (CAPEX) if the wind farm developer owns and operates the offshore transmission system, or are excluded if these costs are socialized and borne by the national or regional transmission system operator. Sometimes the reported OPEX figures also exclude variable operational costs, such as insurance, land lease and so on.

It should be noted that these estimates only consider the contribution of the direct O&M costs to the LCoE. More indirectly, O&M also affects the wind farm availability and lifetime, and, hence, the total levelized energy production entering into the calculation of the LCoE. Consequently, O&M is an important area for improvement in order to reach the goals and ambitions for offshore wind LCoE reduction: from around £140/MWh in 2014 to £100/MWh in 2020, as requested by the UK Department of Energy & Climate Change (The Crown Estate, 2012), or – as estimated by TPWind (2014) – LCoE cost reduction by up to 50% over the next 20 years compared to 2008.

Reduction of O&M costs can be achieved by several measures, such as:

1) increasing the reliability of the components (e.g. by improved component and turbine designs);
2) aiming for maintainability of components (i.e. using components that are easy to maintain);
3) increasing the performance (i.e. the organization's effectiveness) for maintenance support (e.g. through optimized use of resources, and through logistics, transport and using solutions, maintenance techniques and strategies that reduce the downtime when failures occur);
4) optimizing wind turbine and wind farm operation (e.g. reducing loads with improved control systems);
5) getting better control of technical condition and ageing (e.g. new and improved inspection and monitoring methods).

The above list is related to the characteristics of dependability. Dependability is defined as 'ability to perform as and when required' (IEC 60050-192:2015) and includes 'availability, reliability, recoverability, maintainability and maintenance support performance, and, in some cases, other characteristics such as durability, safety and security'.

Some of the measures in the list above are related to design improvements (e.g. 1 and 2) or make changes in the control systems of the turbine or plant (4). Such measures may require considerable technical changes in an existing turbine/wind farm. However, other

Table 7.1 Contribution of OPEX to LCoE.

Source	OPEX contribution to LCoE (%)	Comments
Musial and Ram (2010, p. 117)	13–30	Survey and comparison of eight other sources from 2001 to 2009. Excluding variable costs, these sources report an O&M cost fraction ranging from around 13% to around30 %. Each of the sources built on different assumptions, and some additional assumptions were made in the comparison.
Musial and Ram (2010, p. 71)	20.5	Estimated cost of energy for a typical offshore turbine, based on other sources (cf. above).
Tavner (2012, p. 19)	18–23	'O&M percentage costs for some European offshore wind farms', sources and assumptions not unambiguously stated.
BVG Associates (2012, p. 199)	32	Baseline case 4-B (4-MW turbines) presented in Table C.4 and in Figure 4.4 (BVG Associates, 2012). Includes offshore transmission charges.
BVG Associates (2012)	19	Estimated by subtracting offshore transmission charges from the above, using numbers in Table 4.1 (BVG Associates, 2012).
GL Garrad Hassan (2013, p. 5)	25	'O&M activity accounts for approximately one quarter of the life-time cost of an offshore wind farm' (apparently excluding offshore transmission charges).
Maples *et al.* (2013, p. 13)	12	Baseline scenario for 100 × 5-MW turbines 46 km off the coast of Virginia.
Siemens (2013)	24	Baseline for 2014, based on the SWT-6.0-154 turbine for a 1000-MW offshore wind project.
BVG Associates (2015, p. 11)	16	Illustrative breakdown for typical UK offshore wind project (for 'operation, maintenance and service', excluding offshore transmission costs).
Smart *et al.* (2016, p. 12)	17	Baseline value for 100 × 4-MW turbines 40 km from shore, including contributions from preventive and corrective maintenance (modelled) as well as other fixed and variable OPEX contributions (based on other sources), excluding offshore transmission costs.
Wiser *et al.* (2016)	17	Mean baseline (2014) value across all expert survey respondents.[1]

1 Estimated from Table 2 (Wiser *et al.*, 2016) by using the LCOE calculator at http://rincon.lbl.gov/lcoe_v2/lcoe_calculator.html and setting APEX = 0.

measures contribute to improvements and cost reduction without requiring extensive design and control system changes but by implementing new maintenance strategies and new inspection, monitoring and maintenance methods. To find and select the most cost effective measures, it is necessary to have available models and tools to assess different strategies for O&M.

The use of models and tools supports the development and optimization of asset management plans as part of an asset management system, as described in BSI PAS 55-2 (2008) and ISO 55000 (2014). Furthermore, models are an important and integrated part of the planning activities in a Plan–Do–Check–Act (PDCS) framework (BSI PAS 55-1, 2008) for continuous improvement of asset management. Using models and tools will also help to implement key principles and attributes of asset management as required by BSI PAS 55-2 (2008) and described in Table 7.2.

This chapter presents three O&M models: two strategic models – one simulation model for wind farm availability and O&M cost estimation, and one mathematical optimization model for determining optimal vessel fleet size and mix – and one operational mathematical optimization model determining optimal routes and schedules for a fleet of maintenance vessels servicing turbines at an offshore wind farm. Since these models put special emphasis on the transport and logistics aspects of O&M, the term 'O&M modelling' in this chapter also includes the modelling of transport and logistics.

The rest of this chapter is organized as follows: Section 7.2 provides an overview of O&M modelling for offshore wind farms. Models developed by NOWITECH and related projects are described in Section 7.3. Examples and case studies that illustrate typical applications of the models are presented in Section 7.4. Finally, future trends in O&M modelling, including an outlook on expected development of offshore wind O&M and how this will influence model development, is provided in Section 7.5.

7.2 O&M Modelling for Offshore Wind Farms

7.2.1 Classification of Models

The use of computer models for O&M and logistic activities for offshore wind farms can be divided into two main areas:

1) *Models used as analysis tools to increase the understanding of the systems they are modelling*: the user in this case can, for example, be a scientist interested in the drivers of O&M costs and investigating, say, the effect on the maintenance logistics of wind farms being installed further offshore.
2) *Models used as decision support tools to assist decision makers on specific challenges*: the user in this case will be a decision maker or stakeholder in the offshore wind industry, such as a wind farm developer/owner/operator, maintenance vessel provider/shipping company or an O&M innovation and concept developer.

The primary focus in this chapter will be on the application of offshore wind O&M models for decision support. The terms 'decision support tool' and 'model' are, therefore, used interchangeably.

Decision problems can be classified based on their time scale. A common classification is strategic, tactical and operational decision problems (Shafiee, 2015). Figure 7.1 illustrates how O&M decision problems for offshore wind can be classified

Table 7.2 Key principles and attributes of asset management (BSI PAS 55-2, 2008) and specific contributions to these principles/attributes through O&M models and tools.

Principle/ attribute (BSI PAS 55-2, 2008)	**General description (BSI PAS 55-2, 2008)**	**Specific contribution by using O&M models and tools**
Holistic	Looking at the whole picture, i.e. the combined implications of managing all aspects, rather than a compartmentalized approach.	Taking into account several different aspects of O&M such as different types of maintenance, availability of resources, uncertainties in weather, failure occurrence, electricity prices etc.
Systematic	A methodical approach, promoting consistent, repeatable and auditable decisions and actions.	Using a methodical, consistent and repeatable approach when using models and tools.
Systemic	Considering the assets in their asset system context and optimizing the asset systems value rather than optimizing individual assets in isolation.	Considering the whole wind farm, including the individual turbines, the balance of plant and also the logistics support for offshore wind farm O&M.
Risk-based	Focussing resources and expenditure, and setting priorities, appropriate to the identified risk and the associated cost/benefit.	Taking into account risks due to uncertainties related to future events and illustrate/quantify their effect on performance parameters such as costs and availability.
Optimal	Establishing the best value compromise between competing factors, such as performance, cost and risk, associated with the assets overt their life cycle.	Finding optimal or near optimal solutions and strategies with O&M models and tools.
Sustainable	Consider the long-term consequences of short-term activities to ensure that adequate provision is made for future requirements and obligations.	Strategic models and tools help assessing the long-term consequences of O&M decisions and can consider the full operational phase of the wind farm.
Integrated	Recognizing that interdependencies and combined effects are vital to success. This required a combination of the above attributes, coordinated to deliver a joined-up approach and net value.	Integrating the aspects and properties from above in a model or tool, or by integrating/combining different models and tools.

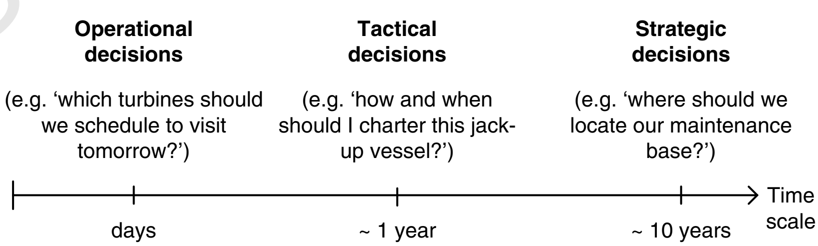

Figure 7.1 Decision problems classified by time scale for offshore wind O&M.

using these three categories. The operational decision problems relate to short-term decisions on a daily basis, the typical planning horizon will be one day and up to a couple of weeks. Tactical decision problems will have a medium-term focus and can include, for example, decisions on which vessels to charter-in on a short-term basis to handle, for example, maintenance campaigns. Strategic decision problems relate to decisions with long-term implications. These decisions are often made in the development or design phase of an offshore wind farm; each decision will often have greater economic implications than decisions made on an operational or tactical level. Partly for this reason, O&M models have, until now, mostly been applied by the offshore wind industry for strategic decision support. Hence, the main focus in this chapter is on the strategic perspective. However, models for operational decision support (routing and scheduling) are also discussed.

O&M modelling tools may also be classified based on type of modelling approach; this chapter considers simulation and mathematical optimization approaches. Modelling tools may also involve approaches comprising elements from both simulation and mathematical optimization methods. Solving a decision problem amounts to selecting the best (optimal) among a set of possible (feasible) decisions (solutions). Decision problems can be formulated as mathematical optimization models with an objective function used to evaluate and find the best solution, and constraints that define the problem's solution space. The objective function can be defined in various ways and depends on the problem and the objectives prioritized by the decision maker. A common objective function for offshore wind O&M is the sum of the (direct) O&M costs and the (indirect costs of) lost revenue due to turbine downtime. This is often referred to as the total O&M cost, and the optimal solution is the one that minimizes this objective function.

When a simulation tool is used to analyse an optimization problem, possible solutions in the solution space are evaluated, as illustrated on the left-hand side of Figure 7.2. The user will then typically specify a set of solutions to consider and the simulation model will analyse each solution one at a time by explicitly calculating the value of the objective function. A comparison of the results for each solution will identify the optimal one. In the example illustrated in Figure 7.3, such a methodology

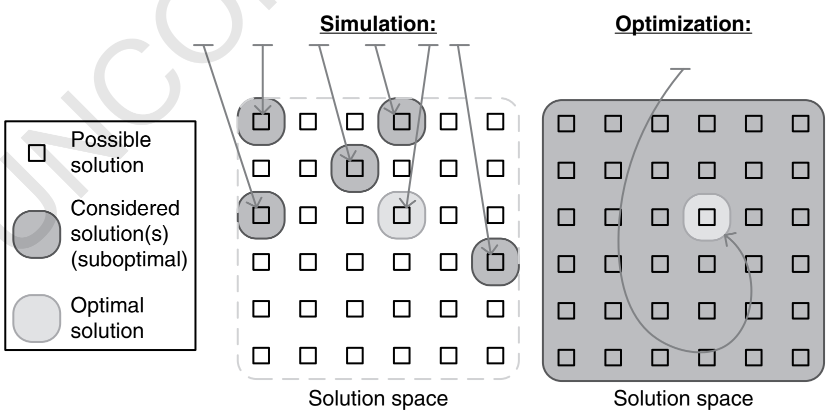

Figure 7.2 Illustration of the distinction between simulation methods and mathematical programming methods for solving an optimization problem.

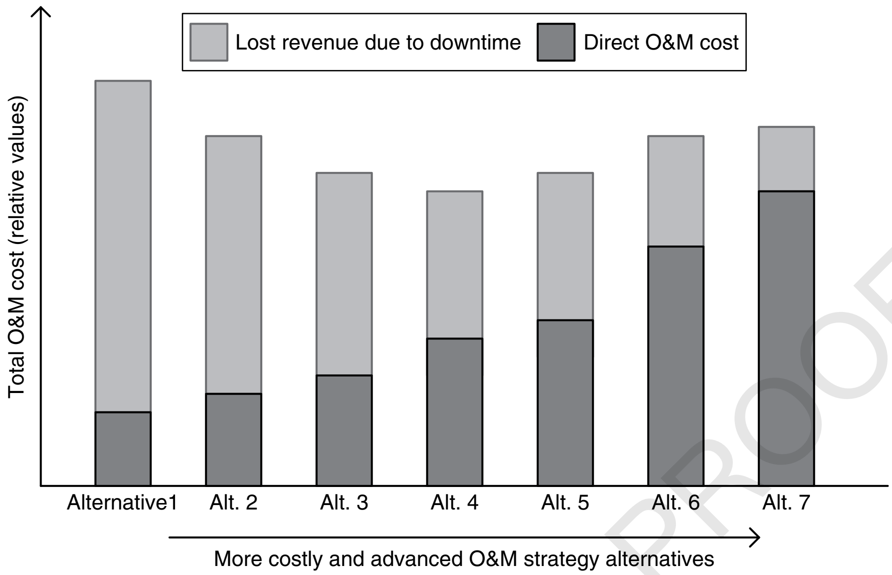

Figure 7.3 Concept sketch of O&M optimization by finding the optimal trade-off between minimizing O&M costs and maximizing turbine availability.

is used to evaluate seven different O&M strategy alternatives (solutions) and alternative 4 is shown to be the one with the best trade-off between low O&M costs and high wind turbine availability.

The solution space, that is the set of potential optimal solutions, may be huge, even infinite, and due to restricted computational resources it will often only be possible to consider a subspace of the solution space by a simulation model. Thus, no guarantee can be given that the global optimal solution is found, since this solution may not be included in the subspace considered in the analysis. By use of mathematical programming techniques, a mathematical optimization model may be formulated and solved directly. The result of such a model will be the optimal solution, that is the model uses efficient techniques to evaluate the whole solution space and find the (proven) optimal solution according to the objective function value. However, depending on the level of detail of the model and size of the decision problem to solve, large computational efforts may be required before the global optimal solution is found and proven to be the global optimum. Hence, to make such a model computationally tractable, a simplified and less detailed representation of the real system is often used in a mathematical optimization model compared with a simulation model.

7.2.2 State-of-the-art in Modelling

An overview of the current status in O&M modelling for offshore wind farms is presented in this section. Findings presented in existing reviews are briefly discussed before results from recent publications are included. The main focus is first on strategic O&M simulation models, before models for selected optimization problems are discussed at the end of the section.

A survey of state-of-the-art in offshore wind O&M modelling was carried out in the initial phase of NOWITECH (Hofmann, 2010). A review of decision support tools for offshore wind farms with special emphasis on strategic decision problems for O&M and on life cycle cost estimation was subsequently presented by Hofmann (2011). A total of 49 models and tools were surveyed, most of them simulation models, although some also include optimization algorithms for parts of the modelled system. 22 of the surveyed models considered the maintenance strategy of the offshore wind farms, but most focused just on some aspects or were not able to consider the full life cycle of the wind farm. Furthermore, the most well developed decision support tools were either commercial software tools or in-house consultancy tools, and almost none of them were available for use by NOWITECH researchers. This led to the conclusion that, in order to have research tools for studying offshore wind O&M, NOWITECH researchers would have to develop their own models (Hofmann, 2010). The results of this development are the models described in this chapter.

Since the publication of the state-of-the-art survey in 2011, the intensity of research efforts on offshore wind O&M modelling has remained high and a number of models and tools have been developed that were not included by Hofmann (2011). Shafiee (2015) has presented an extensive and more recent survey of research in the field of maintenance logistics for offshore wind farms, covering both strategic, tactical and operational issues. However, Shafiee (2015) did not focus on which tools or models are developed for the various publications and does not cover more commercial or nonacademic decision support tools.

To complement Shafiee (2015) and update Hofmann (2011), a simple overview of strategic decision support tools for offshore wind O&M is presented in Table 7.3. Most of the tools in Table 7.3 have been developed after 2011, but some of the tools are older but were not included in the survey by Hofmann (2011). This overview – making no claim to be complete – is based on the experience of the authors from interaction with several research institutes and industry actors throughout the duration of NOWITECH. For instance, the overview excludes decision support tools for operational decision problems and it excludes other special-purpose analysis tools. Furthermore, such overviews are naturally biased towards the kind of models for which information is easily available. Most of the references are, therefore, for models developed through academic and student projects. Information on tools developed by consultancies, owners, operators, developers and so on is typically not that readily available. Partly for these reasons, references cannot always be provided, and the names used to label some of these tools may not be the names used internally or officially. Furthermore, different versions of the same tool may have been described by several references, and references may refer to the same tool by different names. Where this is known to be the case, the most recent names and references are used.

Some of the more notable tools surveyed by Hofmann (2011) that are particularly relevant to mention here are the O2M model of DNV GL (previously Garrad Hassan), the ECN O&M Tool, and the ECN O&M Calculator (previously called OMCE), because these are tools that have been frequently used by the industry. To the best of our knowledge, all the tools mentioned above and in Table 7.3, except for 2OM DSS and the ECN O&M Tool, are based on discrete-event simulation models. Some of the recently developed simulation models, at least the MAINTSYS model and the Fraunhofer IWES Multi Agent System, also employ agent-based simulation methodologies. This overview

Table 7.3 Overview of strategic O&M tools not included in the review by Hofmann (2011) (Reproduced with permission of SAGE publications.).

Model	Developer	Reference
ECUME model	EDF R&D (owner/operator)	Douard *et al.* (2012)
DONG Energy's logistics model for O&M	DONG Energy (owner/operator)	n/a
OPUS/SIMLOX	Systecon (consultancy)	Johansson (2013)
Ecofys O&M Tool	Ecofys (consultancy)	n/a
Strathclyde University offshore wind OPEX model (Strath-OW OM)	University of Strathclyde, also referred to as the Strathclyde University, Centre for Doctoral Training Offshore Wind OPEX Model	Dalgic *et al.* (2015)
MAINTSYS	Shoreline (consultancy) / University of Stavanger (UiS), initially developed through the PhD study of Ole-Erik Vestøl Endrerud within the NORCOWE research centre; also referred to as the University of Stavanger Offshore Wind Simulation Model	Endrerud *et al.* (2014)
MARINA_RAMS_ Executor	Norwegian University of Science and Technology, developed within the MARINA Platform EU FP7 project	Vatn (2014)
AAU OM discrete event simulator for offshore wind turbine blades	Aalborg University, developed through the PhD study of Mihai Florian within the NORCOWE research centre	Florian and Sørensen (2016)
Fraunhofer IWES Multi-Agent-System	Fraunhofer IWES Kassel	Berkhout *et al.* (2015)
2OM DSS	Developed within the 2OM Interreg project by the University of Portsmouth in collaboration with other project partners	Li *et al.* (2016)
University College London O&M Strategy model	University College London, developed through the PhD study of Alexander Karyotakis	Karyotakis (2011)
UCC life cycle cost model	Developed by University College Cork, originated in the MARINA platform project	O'Sullivan (2014)
TU Delft Integrated Decision Support Tool	Developed by Delft Technical University in cooperation with Systems Navigator (consultancy)	Koopstra (2015)
Durham O&M cost model	Developed by Durham University, apparently in cooperation with Romax Technologies	Neate *et al.* (2014)
TU Delft Logistic and Service model	Delft University of Technology, developed in collaboration with Fraunhofer IWES through the master's thesis work of Ashish Dewan	Dewan (2014)
Siemens availability simulator	(A master's thesis prepared in collaboration with Siemens refers to a software for availability simulations provided by Siemens.)	Gustavsson and Nyberg (2014)
NOWIcob	SINTEF Energy Research, developed within NOWITECH and related projects	Hofmann and Sperstad (2013)
Vessel fleet optimization models	MARINTEK, developed within NOWITECH and related projects	Stålhane *et al.* (2016a)

shows that strategic decision support tools are rarely based on mathematical optimization models. In the next two paragraphs, two typical optimization problems are discussed, namely the vessel fleet size and mix problem and the routing and scheduling problem, of which the former is a strategic decision problem and the latter an operational problem.

The problem of determining optimal vessel fleet size and mix for O&M at offshore wind farms has been addressed by NOWITECH with mathematical optimization models and tools. To our knowledge, the models developed in NOWITECH and related projects are the first addressing this problem. Other research communities have recently addressed the same or similar problems (Li *et al*., 2016). However, there exist several studies on other problems related to determining optimal fleet size and mix in the operations research community. These studies all consider the strategic decision of deciding an optimal fleet of vehicles; the problem has been considered for both road-based and maritime transport. Proposed models often include routing decisions, as it will be necessary to also study the underlying structure of the operational planning problem, see, for example, the discussion by Christiansen *et al*. (2007). An extensive literature survey covering fleet composition and routing problems in road-based and maritime transport was presented by Hoff *et al*. (2010). The survey also presented basic mathematical optimization models for the problems found in the literature. Optimization models for maritime fleet composition and routing problems have been presented by Fagerholt and Lindstad (2000), Halvorsen-Weare *et al*. (2012) and Halvorsen-Weare and Fagerholt (2011).

There also exists a little research on mathematical optimization models for the routing and scheduling problem for a fleet of maintenance vessels servicing an offshore wind farm. In addition to the work originating from NOWITECH, Zhang (2014) presents a metaheuristic approach (Duo Ant Colony Optimization) and Irawan *et al*. (2017) present a mathematical optimization model solved by a Dantzig-Wolfe decomposition approach (Dantzig and Wolfe, 1960). The problem can, however, be categorized as generalization of the well-studied pickup and delivery problem; see Berbeglia *et al*. (2007) for a comprehensive survey and classification of such problems.

7.2.3 Decision Problems and Model Application

O&M modelling tools can be used to support many different types of decision problems faced by various stakeholders. Table 7.4 shows a list of typical decision problems these tools can help support.

The examples in Table 7.4 are restricted to typical decisions that can be addressed by the tools developed by NOWITECH and presented in the next section. As shown by the examples in the table, there are a number of stakeholders that will profit from using O&M modelling tools for many different decision problems.

7.3 Decision Support Tools Developed by NOWITECH

The decision support tools and concepts developed in NOWITECH and related projects include models on both the strategic, tactical and operational level. Figure 7.4 shows the tools: NOWIcob, O&M vessel fleet optimization model, TeCoLog, Routing

Table 7.4 Examples of decision problems and decision support by O&M modelling tools.

Stakeholder	Decision	Decision support	Time scale
Wind farm developer, investor	Investment decision: Determining if a wind farm project is expected to have high enough availability to make it profitable.	Calculating expected availability for the future wind farm.	Strategic
Wind farm operator	Choosing vessel fleet for O&M: Which vessel types and how many vessels of each type?	Identification of optimal vessel fleet size and mix – both long-term and short-term charter.	Strategic/ Tactical
Vessel provider	With which vessels, time charter periods and time charter rates should one enter into negotiations with a wind farm operator?	Calculating expected downtime losses for the operator for different charter alternatives.	Tactical
Vessel designer	Which O&M vessel concepts should be built to best serve the offshore wind market?	Identifying optimal vessel fleet for different wind farm scenarios/ markets; calculating expected increase in profitability for an operator using different vessel concepts.	Strategic
Wind farm developer, wind farm operator	What are the best logistics strategies for O&M (e.g. shore-based or investing in an offshore O&M base)?	Calculating costs and availability for different strategies.	Strategic
Wind farm operator, Wind farm O&M innovator	Is it worth investing in new O&M concepts and innovations (e.g. buying or developing an improved condition monitoring system)?	Calculating cost and efficiency and selecting the best of the potential innovations compared with existing technology.	Strategic
Wind farm operator	Determining operational day-to-day maintenance schedule for the maintenance fleet.	Identification of the best routing and scheduling of the maintenance fleet.	Operational
Governmental agencies	Which seabed areas should first be opened for offshore wind development? What policies would be effective in furthering offshore wind development?	Studying different cost drivers of offshore wind O&M and how they vary with, e.g., site characteristics.	Strategic
Insurance agency, investor	What is the possible variation of O&M costs and project profitability depending on assumptions about the wind turbine reliability?	Studying sensitivities of offshore wind farm performance parameters, evaluating the impact of uncertainties in failure rates.	Strategic
Wind farm operator	When should one plan a major replacement campaign to replace major components?	Calculating expected O&M costs and downtime losses for different replacement campaigns.	Tactical

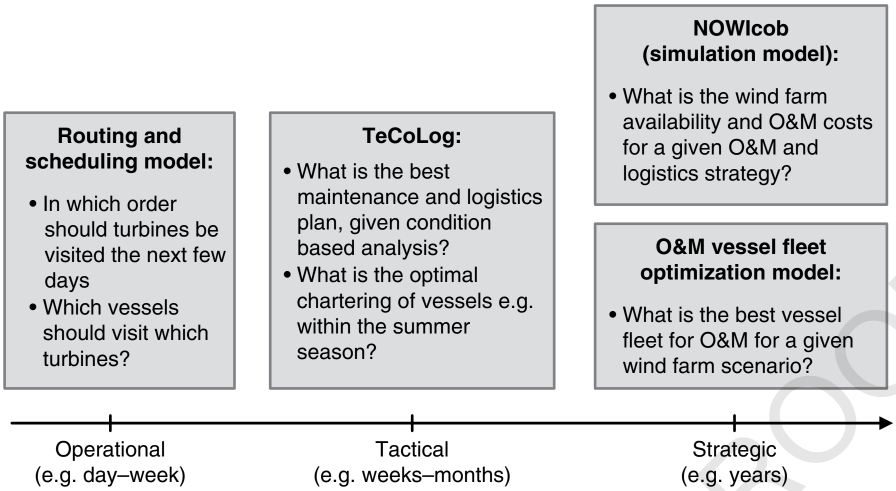

Figure 7.4 Overview over operational, tactical and strategic decision support tools and concepts developed in NOWITECH and related projects, with examples of what problems they can address.

and scheduling model. The figure gives an overview over the timescales of the decision problems the tools are designed for and shows typical decision problems that the tools can help support.

In the following sections, the main models developed by NOWITECH are briefly described. An overview of these models and relevant publications are provided in Table 7.5. More detailed descriptions of TeCoLog are not included here, because the model is still at a conceptual stage. However, TeCoLog will close a gap between operational and strategic modelling, as indicated in Figure 7.4 and described in more detail in Section 7.5. The descriptions presented in this chapter are restricted to an overview level, but the listed publications provide more detailed model descriptions.

7.3.1 NOWIcob

The first version of the NOWIcob simulation model (Norwegian offshore wind power life-cycle cost and benefit model) was created by NOWITECH in 2011 and the tool has since been developed by NOWITECH as well as in the spin-off innovation project FAROFF[2] and in the EU FP7 LEANWIND project.[3] The description of the model given in this chapter is to a large extent based on Hofmann *et al.* (2015) and refers to version 3.2 of the model (dated December 2015). The model simulates the maintenance tasks and related logistics of offshore wind farms over a given number of years to estimate key performance parameters such as wind farm availability and O&M costs.

The model is based on a time-sequential (discrete-event) Monte Carlo simulation technique, where maintenance operations at an offshore wind farm are simulated with

2 FAROFF – Far-offshore operation and maintenance vessel concept development and optimization, innovation project for industry cofounded by the Research Council of Norway.
3 LEANWIND (Logistic Efficiencies And Naval architecture for Wind Installations), EU 7th framework program project funded under the agreement SCP2-GA-2013-614020.

Table 7.5 General overview and relevant publications for the NOWITECH models.

Model	General overview and examples of applications	References
NOWIcob	Discrete-event Monte Carlo simulation model for estimating the long-term average wind farm availability, O&M costs and other performance parameters. The model can be used to support strategic decisions relating to the profitability of a certain wind farm project and to select the logistics solutions for O&M and other aspects of the O&M strategy.	Hofmann and Sperstad (2013) Netland *et al.* (2014) Hofmann and Sperstad (2014) Sperstad *et al.* (2016a)
Vessel fleet optimization model	Mathematical optimization models for determining optimal number and types of vessels to charter for a long term or a short term to support maintenance tasks. Also determines optimal mix of maintenance bases (ports, offshore installations etc…). The models can be used to support strategic decisions (e.g. which maintenance logistic infrastructure should be invested in) and tactical decisions (e.g. when to short-term charter jack-up type vessels and which vessels to short-term charter for maintenance campaigns).	Halvorsen-Weare *et al.* (2013) Gundegjerde *et al.* (2015) Stålhane *et al.* (2016a) Stålhane *et al.* (2016b)
Routing and scheduling model	Mathematical optimization models for determining the optimal routing and scheduling of a fleet of maintenance vessels to support a given set of maintenance tasks. The models can be used to support operational day-to-day planning: Which turbines should be visited when by which maintenance vessel and which technician team?	Dai *et al.* (2015) Stålhane *et al.* (2015)

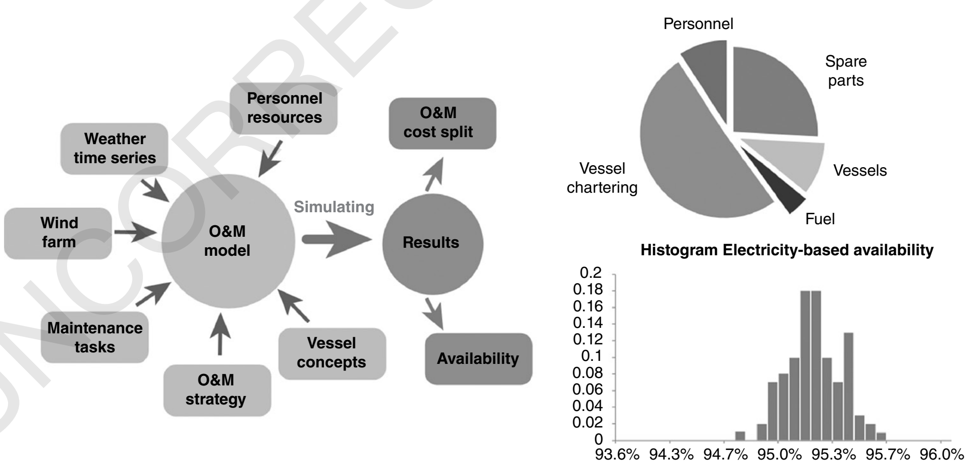

Figure 7.5 Schematic of inputs and outputs for the NOWIcob model.

an hourly resolution. The user chooses whether to carry out a simulation of the full lifetime of the wind farm (e.g. 20–25 years) or to focus on just one or a few years (e.g. a typical year or a year of special interest). The inputs and the outputs of the model are illustrated schematically in Figure 7.5.

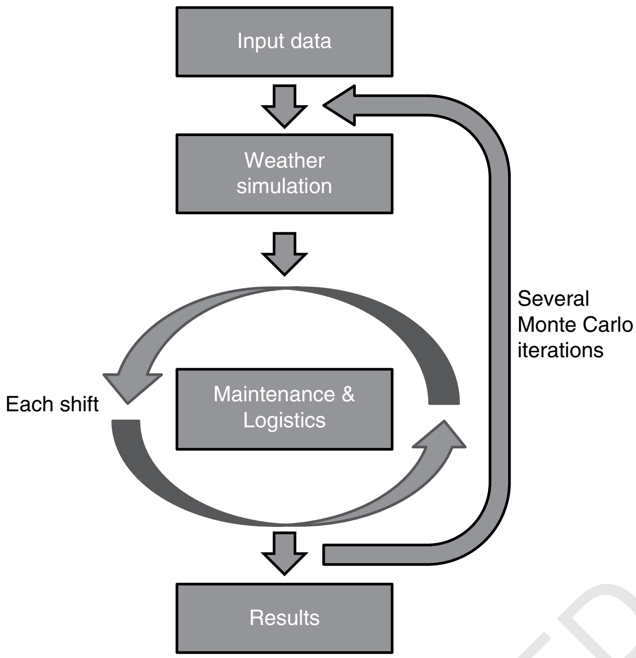

Figure 7.6 Simplified flow scheme of the model (Hofmann *et al.*, 2015. Reproduced with permission of SINTEF.).

Several input parameters, both decision variables (e.g. the number of technicians and crew transfer vessels) and uncontrollable variables (e.g. weather or failure rate scenarios), can be changed to assess their impact on performance parameters, such as the availability of the wind farm and the O&M costs. Offshore maintenance operations are highly weather dependent and, therefore, weather conditions and weather uncertainty are considered in NOWIcob by using a Monte Carlo simulation approach with a weather model generating new, representative weather time series for each Monte Carlo iteration (simulation run). To handle uncertainties, the model can run several Monte Carlo iterations for each case (Figure 7.6) and present the results as histograms estimating probability distributions (Figure 7.5).

Before running the model, input data must be specified, imported and preprocessed. Then the weather is simulated for the whole lifetime of the wind farm. Maintenance tasks and related logistics are simulated throughout the predefined simulation period. Maintenance tasks are scheduled for one work shift at a time and the number and length of work shifts can be specified by the user. Although the resulting wind turbine availabilities are calculated with a time resolution of one hour, the time resolution of the logistics simulation is less than one minute. After all Monte Carlo iterations are executed, the results are collected, processed and presented to the user.

The stochastic model variables in this Monte Carlo simulation methodology are primarily the weather time series and the times of failures for corrective and condition-based maintenance tasks. In addition, other model variables can also be stochastic when a probability distribution is specified for the corresponding input parameter. Probability distributions can be specified for the mobilization time of chartered vessels, the lead-time of spare parts, the active maintenance time of maintenance tasks and the prewarning time of condition-based maintenance tasks.

7.3.2 Vessel Fleet Optimization Models

Experience from the oil and gas industry has shown that supply vessel cost is a major cost element in the logistic chain. Keeping an optimal fleet of supply vessels is, therefore, essential to reduce the logistics costs. In the same manner, one of the most expensive resources for maintaining an offshore wind farm is the vessels used to transport technicians and spare parts to the wind turbines when maintenance tasks are to be executed. Some of these vessels also need to be capable of carrying out heavy lifting when major components (e.g. turbine blades) need replacement.

To achieve cost-effective O&M strategies it is essential to find an optimal, or close to optimal, vessel fleet. Hence, optimization models for determining optimal fleet size and mix to execute the maintenance tasks are considered to provide valuable support for decision makers concerned with offshore wind farm O&M and logistics. Through various projects (NOWITECH, FAROFF, LEANWIND) vessel fleet optimization models have been proposed. In cooperation with NOWITECH, a deterministic and stochastic version of a first model type was developed (Halvorsen-Weare *et al.*, 2013; Gundegjerde *et al.*, 2015). Later, another stochastic mathematical model was proposed by Stålhane *et al.* (2016b). A decision support tool was developed based on a more efficient mathematical optimization model approach than the previous proposed models, and in close cooperation with industry partners (Stålhane *et al.*, 2016a). This tool was developed through the NOWITECH, FAROFF and LEANWIND projects, and there exists three versions with different solution methodology:

1) Deterministic mathematical programming model
   - all input parameters are considered known
2) Stochastic mathematical programming model
   - weather data and occurrence of failures are treated as stochastic input parameters
3) Model version with heuristic solution method (i.e. method that cannot guarantee to find the global optimal solution)
   - weather data and occurrence of failures are stochastic input parameters.

The problem considered by the vessel fleet optimization models is to select the best combination and number of different vessel types that should be available to execute maintenance tasks at an offshore wind farm. Typical tasks and operations that are carried out at an offshore wind farm by vessels are:

- transfer of equipment, spare parts and technicians to wind turbines;
- fuel transfers;
- emergency responses;
- standby;
- accommodation;
- heavy lift operations.

Vessel types used for these operations can be, for example, smaller speed boats for transporting maintenance technicians, larger supply vessels and mother vessels, or jack-up barges. Helicopters can also be used to transport technicians and smaller spare parts and equipment to the wind turbines and are, therefore, also considered as ‘vessels’ by the vessel fleet optimization models.

The objective of the vessel fleet optimization models for maintenance operations at offshore wind farms is to determine the minimum cost fleet and maintenance infrastructure that can execute all, or most of, the maintenance tasks during the planning horizon. The maintenance tasks are divided into preventive (planned maintenance) tasks and corrective tasks (necessary, unplanned maintenance due to failures). Execution of preventive and corrective maintenance tasks incurs costs due to downtime and the need for maintenance and logistics resources (maintenance technicians, vessels, crew, spare parts, tools etc.). When preventive maintenance tasks cannot be executed or completed (e.g. due to weather restrictions or lack of necessary vessel capacity), the model assumption is that a penalty cost applies which represent, for example, the potential cost of failures that could be avoided if maintenance was not delayed. There are a number of other assumptions that are either built into the optimization models implicitly, or that must be provided as input data before the optimization models can be run. Examples of assumptions and input are how maintenance tasks are executed, how vessels are operated and which restrictions they have (weather/waves, speed, lifting capacity, number of technicians, availability: seasonal/whole year etc.), cost data and weather data. More detailed overviews of input data and assumptions can be found elsewhere (Halvorsen-Weare *et al*., 2013; Gundegjerde *et al*., 2015; Stålhane *et al*., 2016a, 2016b).

The objective function of the optimization models minimizes all the fixed costs of vessels and vessel bases, variable costs of using the vessels at the wind farm, expected downtime costs of delayed preventive maintenance tasks and corrective maintenance tasks, penalty costs for maintenance tasks that are not executed and transport costs. The output of the models includes total cost, the optimal solution (number and type of vessels/transport resources used, maintenance bases) and expected wind farm availability of the solution. Costs are further split into the different elements: vessel cost (time charter cost of vessels in the fleet), maintenance base costs, preventive maintenance costs, corrective maintenance costs, downtime costs and penalty costs.

An overview of the vessel fleet optimization tool is provided in Figure 7.7. Input parameters are provided in an Excel workbook, in addition to weather data input that is read from separate files; one set of weather data for the deterministic version, and several sets for the stochastic and heuristic versions. A C# (for the deterministic/stochastic versions) or Java application (for the heuristic version) is then run to solve the vessel fleet optimization problem, and when the optimal solution is found, or the current program execution is aborted by the user, the solution will be reported back to the Excel workbook.

The deterministic and stochastic versions of the vessel fleet optimization model have been implemented in the optimization software FICO® Xpress Optimization Suite.[4] These models are run from an application coded in C#. To run the application, the user needs to have a software licence for the Xpress optimization software. The heuristic version of the model is coded in Java, and does not require for the user to invest in additional software licences. As for the deterministic and stochastic version, the model is run by the user from an application.

7.3.3 Routing and Scheduling

The routing and scheduling problem for O&M at offshore wind farms is a short-term operational problem that considers how to execute planned maintenance tasks (the next day – and up to a couple of weeks) by routing and scheduling the vessels in the available fleet of maintenance vessels.

4 http://www.fico.com/en/analytics/optimization

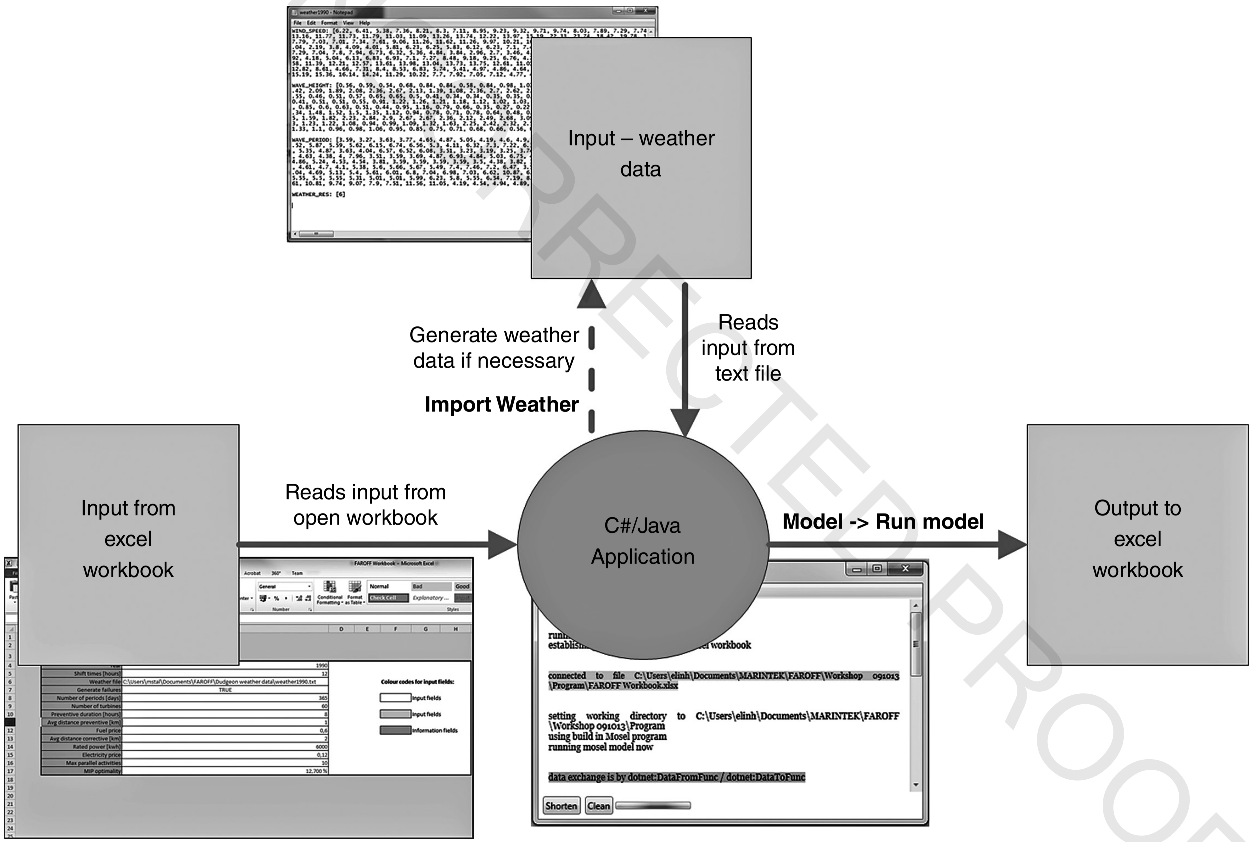

Figure 7.7 Overview of vessel fleet optimization tool.

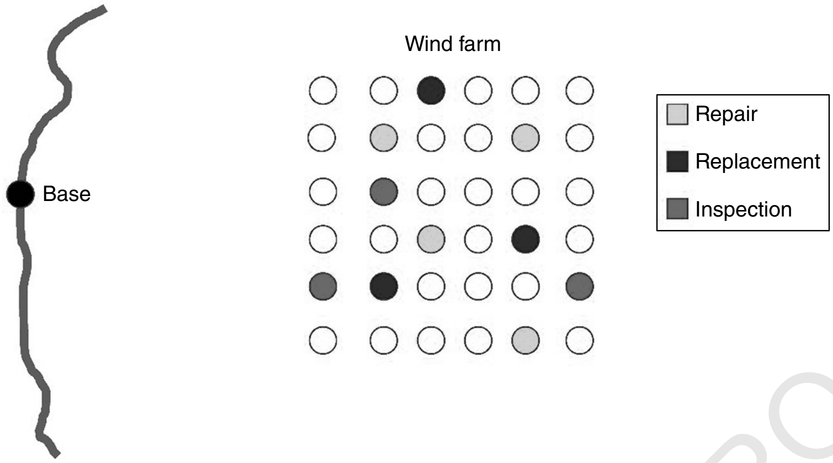

Figure 7.8 Overview of a small offshore wind farm O&M routing and scheduling problem.

A small example problem is illustrated in Figure 7.8, where there are 10 turbines that require maintenance visits the next planning period. For this small example, there will be a huge number of options for routing and scheduling of the maintenance fleet: as a pickup and delivery problem (Savelsbergh and Sol, 1995, where technicians are to be dropped off and picked up at the turbines, there are around $20! \approx 2.4 \times 10^{18}$ different options. This number can, however, be substantially reduced but there will still be an unmanageable number of options to evaluate. Hence, an optimization model to aid in the decision making process will be very useful.

In collaboration with NOWITECH, two different mathematical optimization models for this routing and scheduling problem have been developed: an arc-flow formulation (Dai *et al.*, 2015) and a path-flow formulation (Stålhane *et al.*, 2015). The problem considered consists of finding the optimal set of routes and schedules for a fleet of maintenance vessels to support a number of maintenance tasks at an offshore wind farm. The fleet of maintenance vessels needs to transport technicians and spare parts/equipment from a maintenance base out to the turbines that require maintenance and then return the technicians and parts/equipment to the maintenance base after the maintenance tasks are finalized (or after the end of a work shift).

The objective of the models is to minimize the total cost of performing maintenance tasks at the offshore wind farm. All maintenance tasks need to be executed within the planning horizon, or can be postponed to the next planning horizon at a (high) penalty cost. Maintenance tasks are allowed to be postponed to ensure that the optimization model(s) will find a feasible solution also when the fleet of maintenance vessels cannot support all the maintenance tasks within the given planning horizon.

Maintenance tasks are given the following properties:

- expected duration of task;
- number of technicians needed;
- weight/volume of necessary spare parts and tools;
- whether vessels need to be at turbine during maintenance or not;
- penalty/expected lost income per day until maintenance task is executed.

Vessels are characterized by the following:

- fuel costs – fuel consumption rate;
- transfer speed;
- weight/volume capacity;
- access and transfer time for technicians;
- number of hours of operation on a given day calculated based on:
  - wave criteria and weather forecast;
  - work shift length.

Based on these inputs, the overall goal is to create one vessel route and schedule for each vessel each day during the planning horizon while minimizing total cost (transport costs, downtime costs and penalty costs). From this, the maintenance task schedule (which maintenance tasks to execute on which day) and the technician schedule (how many technicians are to be delivered and picked up on which turbines when) will also be known.

A possible solution for the small example illustrated in Figure 7.8 is shown in Figure 7.9. Here there are two vessels available at the maintenance base. One vessel (stippled line) drops off a team of technicians at a turbine for inspection, then sails to next turbine and drops off a new team for a repair operation, before sailing to a turbine that needs a replacement. Then it sails to pick up the team at the first drop-off turbine, before picking up the teams at the other turbines and returning to the maintenance base. The second vessel (solid line) drops off a team of technicians at a turbine needing inspection, then sails to a turbine needing repair before it visits two turbines in need of replacement and repair, respectively. On these turbines the vessel is required to stay by the turbine during maintenance, and hence waits at the turbine before sailing to the next. Once these two maintenance tasks are finalized, the vessel picks up the teams on the two other turbines before returning to the maintenance base. Three maintenance tasks could not be executed during the work shift by the two maintenance vessels and hence are postponed to next work shift.

The mathematical optimization models are implemented in FICO® Xpress Optimization Suite, and, hence, a licence for this software is required to run the models.

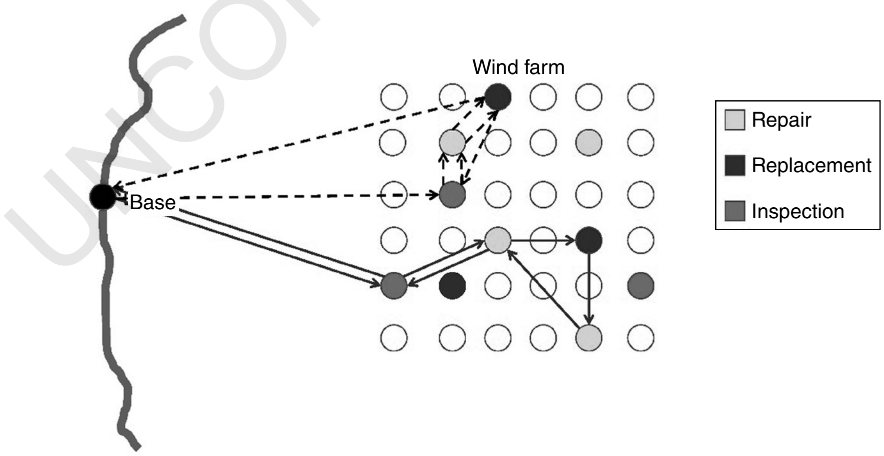

Figure 7.9 Possible solution for the small routing and scheduling example.

7.3.4 Use of Different Models and Synergetic Interactions

The general differences between optimization and simulation models outlined in Section 7.2.1 also imply a difference in how the models developed by NOWITECH are used. As optimization models, such as the vessel fleet optimization models, are designed to identify the optimal solution, using an optimization model for this purpose is less time consuming for the user than manually evaluating potential optimal solutions with a simulation model like NOWIcob. The differences between NOWIcob and the vessel fleet optimization models and their intended use are summarized in Table 7.6.

As a concrete example, for each run of the simulation model it is necessary to specify which vessels should be used by the wind farm operator and from which maintenance bases or ports these vessels should operate. In contrast, when running the optimization models, these variables are treated as decision variables rather than input parameters. This means that the optimization models select the maintenance bases and vessels that constitute the optimal solution, and the user only specifies the range of possible values as input to the model. Differences in the input parameters between the simulation and the optimization models are summarized in Table 7.7.

Even though the efficiency of an optimization model may come at the cost of a less accurate representation of reality, running a simplified optimization model may be very

Table 7.6 General differences and intended use of NOWIcob and vessel fleet optimization models.

Vessel fleet optimization models	NOWIcob simulation model
Determine the optimal vessel fleet	Requires simulation of many different cases to find a (near) optimal solution → Time consuming to use for optimization
Built to evaluate only optimal solution – can be used also to evaluate given, user specified, solutions	Straightforward to evaluate any solution
Require a lower level of detail and shorter planning horizon to be able to run optimization	Allows for high level of detail and long planning horizon
Stochastic approach – find optimal fleet over multiple realizations of weather and failures	Stochastic approach – statistical output over multiple realizations of weather and failures

Table 7.7 Differences in input parameters.

Vessel fleet optimization models	NOWIcob simulation model
Possible maintenance bases (and mother vessels)	Maintenance bases in use
Maximal number of vessels available from each base for each vessel type	Number of vessels available from each base for each vessel type
Penalties for not completing maintenance within a given time period	N/A
Options for optimization algorithm	N/A
Number of scenarios	Number of Monte Carlo iterations

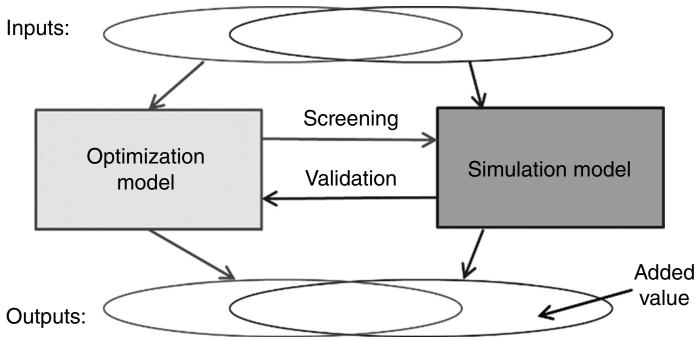

Figure 7.10 Illustration of possible synergetic interaction between vessel fleet optimization models and simulation model (NOWIcob).

useful for screening purposes. Especially when the solution space is large and it is not evident in which part of the solution space the optimal solution (or even good solutions) can be found, using the solution found by the optimization model as a starting point helps narrowing down the search. One can then explore the neighbourhood of the solution chosen by the optimization model and evaluate different promising solutions using a more detailed and time-consuming simulation model. The simulation model can thus add value to the optimization model if it captures and can study the impact of additional system features or effects (e.g. the impact of condition-based maintenance). A simulation model can also add value to the results of the optimization model if it can provide additional, more detailed output parameters (e.g. estimates of the probability distribution of wind farm availability). If one knows that the simulation model has a more accurate representation of reality, one can use such a simulation model to validate the optimization model by checking whether the simplifications made significantly affect its conclusions. Such interactions between a simulation model and an optimization model and how they can be used together are illustrated in Figure 7.10. The example presented in Section 7.4.2 illustrates the combined use of the two different models.

7.3.5 Model Validation and Verification

Verification and validation (V&V) are essential parts of the development of computer models and contribute to building credibility for the users and decision makers using them for decision support. Based on the definitions of Sargent (2013), verification of a simulation model is here understood as ensuring that the *computerized model* is implemented according to the specifications of an underlying *conceptual model* of the system. Validation of the computer model is understood as ensuring that the model is sufficiently accurate for its intended applications. Whereas verification often is an internal process that can be carried out by the model developers themselves, validation typically involves the users of the model and external experts. Models can undergo *conceptual validation* by having the underlying assumptions scrutinized by domain experts. So-called *operational validation*, on the other hand involves running the models with real, historical input data and comparing the results with the performance of the same real system (Sargent, 2013).

The strategic decision support tools developed by NOWITECH have conceptually been validated through discussion with industry partners in NOWITECH and various spin-off projects. NOWIcob has been used by Statkraft, Statoil and Kongsberg, and both NOWIcob and the vessel fleet optimization model were used in a project for Statkraft for its investment decision for the Dudgeon Offshore Wind project. NOWIcob was also used extensively by Statkraft in its development of other offshore wind projects. In addition, NOWIcob has been licensed to three European research institutes, used by a European wind farm operator and used by a number of Norwegian and European masters' students for their thesis work. Through these use cases, the applicability and accuracy of the NOWITECH O&M models have been tested and improvements have been made accordingly. However, validation is a continuous process and, in practice, one can never expect any model to be validated absolutely (Sargent, 2013), so these validation activities in NOWITECH and related projects are still continuing at the time of writing.

For operational validation of an offshore O&M model, one would need real, historical data including spare part costs, vessel costs and statistical information on component reliability, as well as wind farm performance measures such as O&M costs and availability. Developers of offshore wind O&M models typically do not have access to such data, hence a full operational validation is difficult to achieve. Even for model developers collaborating closely with offshore wind farm owners and operators, parts of the data are often very uncertain. Often such data are only fully known and understood by the wind turbine manufacturers, or they may be nonexistent for new wind turbine models.

To meet the challenges outlined above, the so-called 'offshore wind O&M modelling group' was formed in early 2013 as an informal forum for comparing and discussing models and data for O&M at offshore wind farms. This collaboration eventually included model developers and users from SINTEF Energy Research, MARINTEK, the University of Strathclyde, the University of Stavanger, EDF and NREL. Table 7.8 gives an overview of the participants and models involved in the collaboration. As a means towards the goal of verifying and validating the models involved, a set of reference cases for benchmarking O&M models was developed. This reference data set was then used for a so-called *code-to-code comparison* or *cross-validation* of the O&M models involved in the collaboration. Although such a comparison is not an operational validation of the

Table 7.8 Overview of participants and models in the 'offshore wind O&M modelling group'.

Model developer/user	Model	Comment
SINTEF Energy Research	NOWIcob	Simulation model
MARINTEK	Vessel fleet optimization model	Optimization model
University of Strathclyde, Centre for Doctoral Training	Strathclyde University offshore wind OPEX model (Strath-OW OM)	Simulation model
University of Stavanger / Shoreline	MAINTSYS / UiS Sim model	Simulation model
EDF	ECUME	Simulation model
NREL	ECN O&M Tool	Spreadsheet-based model developed by ECN

models, the approach is an alternative given the lack of a data set from a real wind farm.. These reference cases were the first publically available data sets with reasonable and representative O&M data for an offshore wind project.

The reference data set and a process for using it for verification and benchmarking of O&M models were published in Dinwoodie *et al.* (2015). This paper also presents results from a comparison between four different simulations models; the input data and results for these reference cases have since been used by several other model developers and users for testing and benchmarking of their models. In this way, the collaboration has aided model development and verification and has contributed to increased understanding and confidence in the modelling of offshore wind O&M. The reference data set has also been used as a starting point for a more detailed data set and LCoE calculation involving multiple OPEX and CAPEX models (Smart *et al.*, 2016). Building on the work and the reference data set, the offshore wind O&M modelling group has also carried out a comparison and benchmarking of O&M models as applied as decision support tools for O&M vessel fleet selection (Sperstad *et al.*, 2016b). The main contribution of this work is to show that the uncertainties associated with such decision support are still considerable, implying that decision makers should use such tools with caution and not rely upon solutions from a single decision support tool.

7.4 Application of Models – Examples and Case Studies

In the following, two examples of applications of the O&M simulation and optimization tools are presented. The examples are:

1) Remote Inspection – cost-benefit analysis of a remotely controlled robot for inspection of the components in a nacelle;
2) O&M vessel fleet optimization – use of optimization and simulation tools to find optimal fleet of maintenance vessels for an offshore wind farm.

7.4.1 Cost-Benefit Evaluation of Remote Inspection

An important cost driver for O&M of offshore wind turbines is frequent manned maintenance visits to the turbines. Thus, solutions for maintenance and inspection that would reduce the number of turbine visits could result in a significant economic benefit, especially for offshore wind power installations. Hence, a remote presence concept was developed and investigated by NOWITECH. This section describes how O&M modelling and NOWIcob can help to estimate quantitatively the benefits of such O&M innovations as the NOWITECH remote presence concept. Parts of the content is based on the PhD thesis by Netland (2014); the cost-benefit analysis has also been presented in Netland *et al.* (2014).

Within the scope of NOWITECH, the remote presence system mainly focused on remote inspection, meaning the ability to observe the equipment within a turbine nacelle for decision support. The remote inspection system consists of a remotely controlled robot installed on a monorail inside the nacelle of the wind turbine (Figure 7.11). The goal is to provide a service that allows a wind turbine operator to look and listen inside a wind turbine nacelle for improved decision support without having to transport technicians to the turbines.

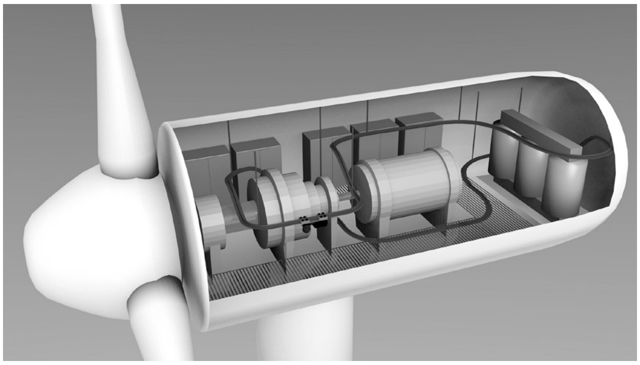

Figure 7.11 Concept drawing of remote presence system in a wind turbine nacelle.

Some of the potential uses of remote inspection, both as a standalone system and together with condition monitoring systems (CMS), are:

1) Inspections can be performed at almost no cost, allowing inspections to be performed frequently.
   a) Each inspection increases the probability that an error is detected.
   b) Frequent inspections increase the probability that an inspection is performed after a symptom of an error becomes visible and before it causes a failure.
   c) Can be used to investigate a failure and plan corrective maintenance. Getting correct information early can reduce downtime if spare parts have to be ordered. The technicians can also be better prepared when they have studied the failure beforehand.
2) Verify diagnoses from the CMS.
   a) False positive diagnoses (i.e. false CMS alarms) can be identified with remote inspection, before they cause an unnecessary maintenance action.
   b) If a diagnosis is confirmed, that is the requirement of a preventive maintenance task is confirmed by remote inspection, then remote inspection could furthermore be used in the planning of this task.
   c) Since the consequence of false positives can be reduced with remote inspection, the CMS can lower its thresholds for giving diagnoses, thus reducing the probability that a failure will go unnoticed.
3) The sensors on the remote inspection device can supplement the sensors of a CMS.
   a) CMS can use information from the sensors on the mobile inspection robot, and possibly reduce the number of sensors installed in the turbine. An example is that a thermographic camera could replace a large number of temperature sensors.
   b) Sensors on the inspection robot can be used as an alternative for a failed sensor. Although the sample time and accuracy likely will be lower, it can at least reduce the urgency of replacing the sensor.

7.4.1.1 Simulation Cases in NOWIcob

NOWIcob has been used to simulate an offshore wind farm with different strategies for inspection and condition monitoring, and the resulting performance parameters have been compared. Three simulation cases have been defined for cost-benefit evaluation of remote inspection. These share the same set of possible failures, their failure rates and what type of maintenance that is required. For larger maintenance tasks, a pre-inspection task is required as part of the planning.

In the base case, there is neither condition monitoring nor remote inspection. Preventive maintenance is performed yearly and corrective maintenance is performed when there has been a failure.

The second case includes a state-of-the-art condition monitoring system that provides warnings about potential future failures. If condition-based maintenance is performed before the failure occurs, the task will be less expensive and time consuming. However, the condition monitoring system is not perfect and it will not detect all failures. It is also assumed that half of the alarms are false positives and that the sensors of the condition monitoring system can fail and need repair.

The third case has a remote inspection system in addition to the condition monitoring system. This means that pre-inspections and investigations of false alarms can be done remotely. However, since remote inspections are considered more time consuming than on-site inspection, these tasks take twice as much time to complete than traditional on-site inspection tasks. There are also other potential benefits to remote inspections, for example reduction of failures due to inexpensive, frequent inspections. Since these effects are uncertain and difficult to quantify they have not been included in the simulations. A remote inspection system failure has also been added to the list of potential failures.

The investment cost of the turbines has been estimated to 2 250 000 EUR/MW, with an addition to the cost of 120 000 EUR for a condition monitoring system and 60 000 EUR for a remote inspection system. A wind farm with 100 3-MW turbines was used for the simulation. The wind farm was located 40 km from an onshore maintenance base, a reasonable distance for future wind farms. Each case was simulated with two crew transfer vessels equipped with advanced systems for accessing the turbines. A jack-up vessel was available and could be chartered for periods of two weeks when operations that include heavy lifting were required.

7.4.1.2 Results of the Cost-Benefit Analysis

For each case, a 20-year simulation was run 20 times. The results are shown in Figure 7.12, as the improvement in availability and cost of energy compared to the base case. Relative values have been used to minimize any bias in the assumptions for the simulations, especially the parameters regarding cost are considered preliminary. The availability results are likely more reliable than the results for cost of energy, as these performance parameters do not rely on any assumptions about the costs.

Both condition monitoring and remote inspection show significant improvements compared with the base case. This is as expected, as relying on corrective maintenance alone is not considered a viable strategy. The results show that the improvements are larger for the case where remote inspection is included also than for the case where only condition monitoring is included. When some maintenance tasks are performed remotely, even trivial ones such as checking for false alarms and pre-inspections, there is more time available to do other tasks, thus reducing the total downtime. The reduced cost of energy is mostly due to less downtime but there was also a small reduction in the use of both crew transfer vessels and chartering of the jack-up vessel, which reduces the O&M cost.

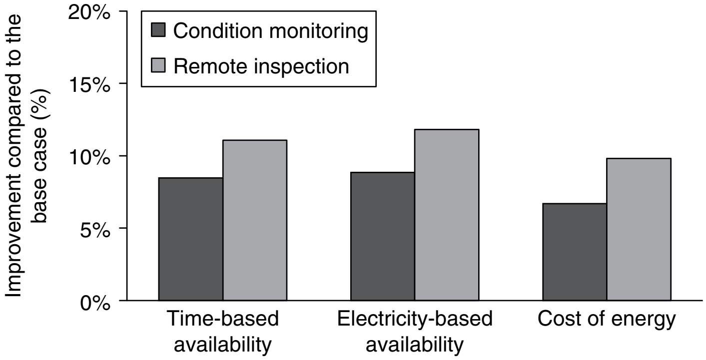

Figure 7.12 Results from NOWIcob cost-benefit analysis.

7.4.1.3 Laboratory Evaluation

During NOWITECH, two smaller pilot experiments and two larger tests of remote inspection were performed, with up to 30 participants (Netland *et al.*, 2015). The tests were performed in a laboratory that consisted of generic industrial equipment as shown in Figure 7.13. The equipment is there to be observed, not used, so it only needs to be visually similar to industrial equipment to be a sufficiently realistic mock-up of a wind turbine. The participants performed both manned and remote inspections, allowing for a direct comparison between the two inspection methods.

The participants were given the task of searching for *targets*. Some targets resembled actual errors and were intended to be as realistic as possible, and others were paper clips hidden in the laboratory equipment. The experiments consisted of several inspections performed in sequence, each with different error markers and paper clips visible.

The prototype (Figure 7.13) was used throughout the user tests, with iterative improvements in the control software and the user interface. The prototype moved along the rail installed in the laboratory and was equipped with a pan and tilt Creative 1080p web-camera for inspection. Pan and tilt for the camera of a telerobot have been found to be beneficial in several experiments. As the prototype moves on a rail, the pan and tilt becomes even more important as the robot cannot turn itself.

The main results from the last experiment are shown in Figure 7.14. The left-hand diagram shows the detection rates for the error markers and paper clips for remote and

Figure 7.13 Left: Prototype used in usability tests, Right: Laboratory with mock-up industrial equipment used in usability tests.

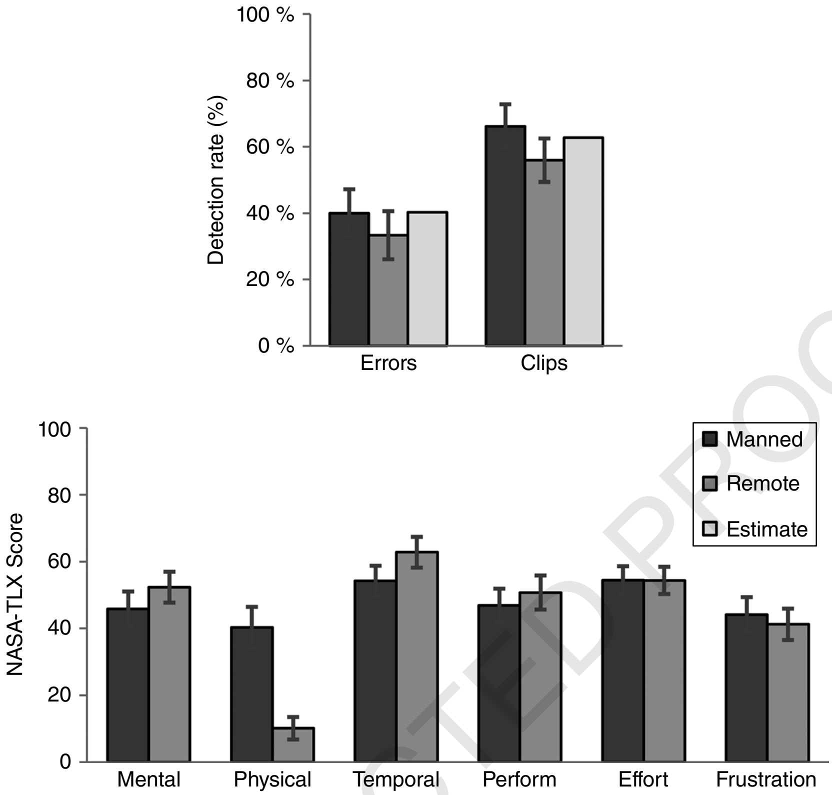

Figure 7.14 Results from the last laboratory usability test. Top: Detection rates of error markers and paper clips for manned and remote inspections. Bottom: NASA-TLX workload assessment results, where lower values indicate an advantageous low workload.

manned inspections. As expected, the results for manned inspections are better, but not by a large margin. Also, the main problem identified with remote inspection was that it took more time, and the participants were often not able to investigate the whole laboratory within the allotted time. The 'Estimate' columns are estimated results for remote inspection if the participants had enough time to investigate the whole laboratory. The estimated results are almost identical to the manned inspections. Provided that the longer inspection time is accepted, the results indicate that the effectiveness of remote inspection can be similar to that of manned inspections.

The right-hand diagram shows the participants subjective assessment of their workload based on a NASA-TLX test (Hart and Staveland, 1988). NASA-TLX is a commonly used questionnaire for subjective evaluation of the workload experienced by users of a system. The test results show that the participants found remote inspections to be more mentally demanding and much less physical demanding, which is as expected. The temporal workload is also higher for remote inspections, which reflect that many did not have enough time to complete.

The results from the usability tests indicate that remote inspection is a viable method and worth considering for applications where manned inspections are difficult or expensive, as at offshore wind turbines.

Figure 7.15 Left: Latest high fidelity prototype. Right: Sample image from pilot installation.

7.4.1.4 Remote Inspection after NOWITECH

NOWITECH's industrial partner Norsk Automatisering AS (NAAS) has continued the development of remote presence towards a commercial product. Part of this work has been part of the LEANWIND project. A near final product prototype is shown in Figure 7.15 (left).

A prototype has also been installed and run for six months in an older turbine at Brekstad outside of Trondheim, Norway. A sample image from the information gathered there is shown in Figure 7.15 (right). More pilot installations are currently under planning, as of September 2016.

7.4.2 O&M Vessel Fleet Optimization

To illustrate how a simulation model and an optimization model can be used together for an offshore wind O&M decision problem, namely the problem of selecting the vessel fleet for O&M at an offshore wind farm, a simple case study is presented here. Providing decision support for this problem is the primary application of the vessel fleet optimization models and is also one of the main applications of the NOWIcob model and similar decision support tools. Since vessels and offshore logistics are major contributors to the O&M costs (GL Garrad Hassan, 2013; Smart *et al.*, 2016) and are decisive factors in ensuring high wind farm availability, this is a highly relevant decision problem in the offshore wind industry.

The case study is based on Sperstad *et al.* (2016b), which, in turn, is based on the offshore wind reference data set published in Dinwoodie *et al.* (2015). Here, a reference wind farm is defined to consist of 80 3-MW wind turbines at an offshore location with given metocean conditions and a distance of 50 km from an onshore maintenance base. The problem is to select the combination of O&M vessels that constitutes the optimal trade-off between low O&M costs and high wind farm availability. For simplicity, the case study is restricted to two types of O&M vessels: 'CTV' represents a standard crew transfer vessel, and 'SES' (surface effect ship) represents a faster and more robust, but more costly crew transfer vessel. Even with just two types of vessels, allowing a fleet of up to five vessels in total gives a solution space of 20 possible vessel fleet combinations to consider.

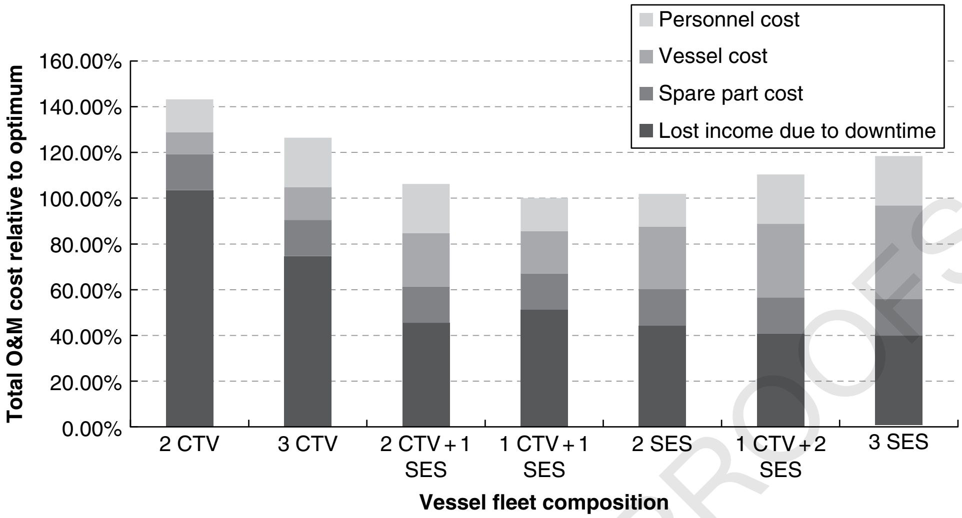

Figure 7.16 O&M cost contributions and lost revenue due to downtime for different O&M vessel fleets as estimated by NOWIcob.

Applying the vessel fleet optimization model to this problem, it implicitly considers all the vessel fleet combinations and returns the fleet '2 SES' as the optimum. Using this as a starting point for further investigations, the NOWIcob simulation model is then used for analysis of a number of similar vessel fleets consisting of two or three vessels. The results for the O&M costs and the lost revenue due to turbine downtime are shown in Figure 7.16. Here one can observe that '2 SES' is, indeed, a competitive vessel fleet with a lower total O&M cost than most of the alternatives. However, according to NOWIcob, the vessel fleet '1 CTV + 1 SES' performs at a slightly lower total O&M cost. A likely reason for the difference between the models is that, in order to make the problem computationally tractable, the optimization model operates with a time resolution of six hours when considering weather windows, using the worst-case metocean conditions during each six-hour period. This may give somewhat less optimistic estimates for the performance of each vessel compared to NOWIcob, which consider metocean conditions with a time resolution of one hour. It should be noted that vessel fleet '1 CTV + 1 SES' is not very robust, and hence slightly more pessimistic input data will return a solution where not all preventive maintenance can be executed within the planning horizon.

What this case study illustrates is that (ii) an optimization model can be useful for screening the solution space and (ii) a simulation model can be useful for validating the results from the optimization model.

7.5 Outlook

General trends for offshore wind farms relevant for the maintenance logistics are that both the power rating of the turbines and the number of turbines are increasing and new wind farms are often located further away from shore. Furthermore, the extensive development of offshore wind power will lead to clusters of neighbouring wind farms, so it becomes more relevant to coordinate the maintenance tasks of wind turbines within a cluster. These developments have justified the use of larger and more costly O&M vessels (service operation vessels, or SOVs) in the offshore wind industry. The need to optimize the use of these and coordinate with smaller CTVs lead to new and more complicated operational patterns for the O&M vessel fleet. The complications are compounded by more frequent use of helicopters; this is becoming a cost-effective option for large distances and tasks of high priority.

The increasing number of options to consider increases the solution space for the maintenance logistics strategy, and thus also increases the value of mathematical optimization for selecting the best strategy. In the vessel fleet optimization example in Section 7.4.2 there were only some tens of potential solutions to consider, but this number easily becomes many orders of magnitudes larger for the next generation of offshore wind farm projects. In addition, the increasing size of individual turbines typically increases the distance between neighbouring turbines. Larger distances within the wind farms (or wind farm clusters) and larger distance from shore will, in particular, result in greater benefit of tools for optimal routing and scheduling of routine maintenance and minor corrective maintenance tasks that are carried out frequently.

Targets for O&M in 2020, 2030 and 2050 were suggested in a study by TPWind (2014) (Table 7.9). In the same study, the three main O&M research priority areas are given as (i) versatile service fleets and safe access, (ii) improving reliability and availability and (iii) asset management. Both as part of the research priority areas (ii) and (iii), and as a mean to reach several of the O&M targets, improved O&M models and tools will play a decisive role.

The trends and developments described above will influence modelling of offshore wind farm O&M. In addition, as the offshore wind industry becomes more mature, decisions will increasingly be based on structured decision support using objective and

Table 7.9 Operation and maintenance – Targets for 2020, 2030 and 2050 (TPWind 2014).

2020	2030	2050
• Enabling easy and safe access for maintenance and service works on wind turbines under a broad range of relevant site and sea conditions • Shareable failure database for modelling the reliability behaviour and benchmarking • Implementation of a standardized reference system for components, failures and measures for offshore wind turbines • Introduction of condition and risk-based maintenance systems	• Reliability characteristics for key components used for load-dependent O&M strategies and concepts • O&M strategy will include experience based decision support methods for optimizing service routines • Reduction of planned maintenance visits by 50% through probabilistic planning methods	• Technologies and procedures that lead to energy based availability of 100% • Technologies and procedures that minimize unplanned maintenance. Planned maintenance will be scheduled in low wind periods to minimize production losses and thus maximize energy yield

quantitative analysis. This is a trend that has been seen in mature industries as, for example, for aviation logistics or power production scheduling. Furthermore, availability of more and better data will also enable the use of decision support tools with a higher level of detail than is currently utilized. Increasing use of, for example, probabilistic modelling and stochastic optimization will allow decision support tools to represent and take into account the uncertainties of real-life offshore wind O&M. More detailed, accurate and reliable models and input data also facilitate the use of models for more operational decision problems. Compared to more long-term decisions, operational decisions typically put even greater requirements on the decision support in terms of robustness and efficiency, and the decision maker needs to have great confidence in a decision support tool to put it to operational use. This is the main reason why the state-of-the-art overview in Section 7.2.2 is more focused on decision support tools for strategic decision problem than operational decision problems, as tools for operational decisions, such as, for example, routing and scheduling have not yet been adopted by the industry.

Another trend in offshore wind O&M modelling is the move towards more integrated analysis, in the sense that one takes into account multiple timescales, multiple life-cycle phases and multiple supply chain segments when analysing the O&M strategy. Although integrating everything in a single holistic decision support system may become unwieldy for the decision maker, one would still want to avoid suboptimizing the O&M strategy by considering, for example, the vessel fleet selection in complete isolation from, for example, the scheduling of preventive maintenance tasks. An example that illustrates the ideas of integration is presented below, where the strategic decision support tools NOWIcob and the vessel fleet optimization model interact with the (operational) routing and scheduling model via a tactical model (TeCoLog). TeCoLog, as briefly mentioned in Section 7.3, has conceptually been developed in the LEANWIND project based on a technical condition monitoring system (TeCoMan) (MARINTEK, 2011) and the vessel fleet optimization model. For TeCoLog, the principles of TeCoMan has been adapted to offshore wind turbines, and will provide input to a logistic module in terms of the need for (condition-based) maintenance at the turbines. The logistic module will then determine which maintenance tasks (preventive, corrective, and condition-based) to prioritize for the next tactical planning horizon that can be e.g. one week and up to a few months.

The integration illustrated in Figure 7.17 shows the indented use of the models on the three planning levels:

- Strategic: use vessel fleet optimization model and NOWIcob to determine the optimal fleet of maintenance vessels and overall O&M strategy. Use of models can be, for example, yearly or whenever new strategies need to be assessed/made.
- Tactical: use TeCoLog to prioritize maintenance tasks based on the O&M strategy and number of preventive, corrective and condition-based maintenance tasks that should be planned within the next planning period. Use of model can be, for example, weekly.
- Operational: use the routing and scheduling model to determine daily plans for operation of the fleet of maintenance vessels and teams of technicians. Use of model will typically be on a daily basis.

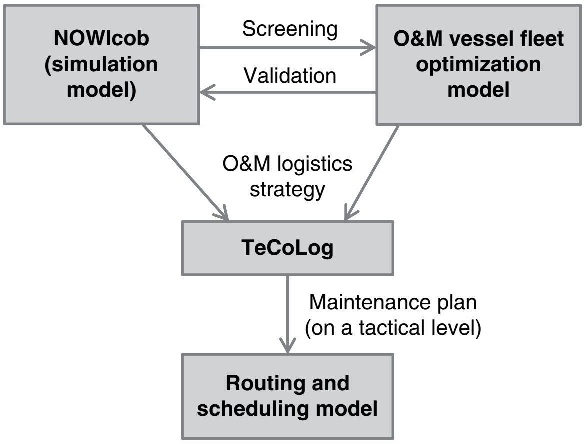

Figure 7.17 Illustration of possible synergetic interaction between different decision support tools.

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