Title*:* Reliability and O&M sensitivity analysis as a consequence of site specific characteristics for wave energy converters

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Abstract

Cost estimates for the operations and maintenance (O&M) phase of wave energy arrays are difficult to obtain due to the uncertainty surrounding weather windows and failure rates for wave energy converters (WECs). An O&M simulation tool has been used to carry out a sensitivity analysis on WEC failure rates, with the Pelamis P2 device used as a case study. Two different sites at opposite ends of the UK have been characterised and presented in terms of accessibility for marine operations and potential power generation. It was found that a wave farm at one site would incur a higher operational expenditure due to the vessel having to wait longer on average for weather windows suitable for marine operations. This was balanced by higher generated revenue, showing how the tool described can be used to support strategic planning and site selection. The results identify the sensitivity of cost estimates to failure rate estimations for different components, helping users target future work to reduce uncertainties and consequently, LCOE. A key message from the results of the study is that the development of WEC technology requires a close integration of component design for the challenging marine environment in order to obtain more realistic failure rate estimates.

Keywords

Wave energy, failure rates, O&M, reliability, wave farms

Abbreviations

CBA	- Cost-Benefit Analysis
CCO	- Channel Coastal Observatory
EMEC	- European Marine Energy Centre
FMEA	- Failure Modes and Effects Analysis
Hs	- Significant Wave Height
LCOE	- Levelised Cost of Energy
MTBF	- Mean Time Between Failure
O&M	- Operations and Maintenance
OPEX	- Operational Expenditure
OREDA	- Offshore and Onshore Reliability Data
P2	- second generation Pelamis wave energy device
P_{fail}	- probability of failure (per year)
PRIMaRE	- Partnership for Research In Marine Renewable Energy
SPARTA	- System Performance, Availability and Reliability Trend Analysis

Te	- Wave Energy Period
VBA	- Visual Basic for Applications
WEC	- Wave Energy Converter
WES	- Wave Energy Scotland

1. Introduction

The wave power sector has huge potential to be a major contributor to global renewable energy generation. At a national level, the practical installed capacity for wave energy in the UK is estimated to be between 10 to 13GW (Boud, 2012). Globally, a recent estimate for the feasible installed capacity for wave energy worldwide is in the region of 95GW (Gunn & Stock-Williams, 2012). One of the key barriers to commercialisation of the wave energy sector is the high cost of energy relative to other forms of renewables (SI Ocean, 2013; Ocean Energy Systems, 2015). For the developers of wave energy converter (WEC) technology to attract private investment, it is vital that they obtain realistic estimates for the levelised cost of energy (LCOE) based on a holistic engineering approach.

Operations and maintenance (O&M) will account for a significant amount of the total costs of any offshore renewable energy development. In the offshore wind industry, O&M costs account for approximately 20% of the total costs of wind farms (BVG Associates, 2013). Estimates for this operational expenditure (OPEX) are difficult for WECs due to the relatively small amount of experience gained in the sector. However, estimates can be obtained through the use of O&M simulation tools. These have been used widely in the offshore wind industry over the years for both cost estimation and operations planning (Hofmann, 2011; Pahlke, 2007). They can also provide a clear picture of the O&M strategy considerations necessary to ensure smooth operation of wind farms, as demonstrated by Scheu et al. (2012) and Douard et al. (2012). Building O&M simulation tools for wave energy has significant potential in developing wave energy projects (Walker et al., 2013) and providing feedback into the design of devices (Martin et al., 2016).

O&M tools do exist for the marine energy sector. Examples include ForeCoast Marine (JBA Consulting, 2015) and MERMaid (Mojo Maritime, 2016), however, these tools are initially being developed more as real-time operations planning rather than modelling marine energy arrays. A European funded project, DTOcean, is perhaps the closest to producing a useable tool to estimate lifetime costs of a wave energy array (Weller et al., 2015). When completed, this project will produce an open source tool whereby device developers are required to provide their own inputs to analyse and optimise the design of their arrays. The project includes a lifecycle logistics work package which may help assess the O&M strategy of a wave energy farm, if adequate inputs to the tool are provided.

1.1. Failure Rate Data

One of the key inputs required to obtain realistic estimates and scenarios from an O&M simulation tool is failure rate data. This is becoming less of a problem in the offshore wind industry due to the relatively large amount of operational data available to both academics and industrial researchers. Carroll et al. (2015) draw on a population of over 2,000 wind turbines to undertake an analysis on reliability of different generator types. The vast amount of available data for offshore wind turbines has led to the creation of the SPARTA (System Performance, Availability and Reliability Trend Analysis) project; "*a database for sharing anonymised offshore wind farm performance and maintenance data*" (ORE Catapult, 2016). SPARTA was inspired by the OREDA handbook, first created in 1981, which has contributed to improved safety and cost effectiveness in the oil and gas industry (OREDA, 2015). A similar reliability database for wave energy is not possible at present, in part due to the large variety of WEC concepts currently being explored.

Obtaining reliability data for WECs is also challenging due to the lack of full scale testing in open sea conditions (Thies et al., 2012). Destructive testing on generic components such as mooring lines is an extremely useful activity for reducing the uncertainty for failure rates (Weller, et al., 2014). However, many other WEC components are device-specific and therefore require testing to be undertaken by the developer themselves. Such testing can be time consuming and expensive, making WEC developers with relatively low financing backing reluctant to undertake such tasks (Wolfram, 2006). As a result, destructive testing is usually only appropriate for key components such as hydraulic ram cylinders (Rühlicke & Haag, 2013).

Many off-the-shelf components such as hydraulic seals are usually supplied by the manufacturer accompanied by expected failure rates (Voith, 2016). However, this data is generally not very accurate for WECs as the components are being used in a different way and in a different environment than their design specifications (Thies et al., 2012). In reality, the best source of reliability information at this early stage of the wave energy sector's development is open sea testing combined with the expert judgement of those involved. There is a significant amount of uncertainty surrounding failure rates obtained in this manner and this needs to be accounted for when used in O&M tools for estimating OPEX and availability of a wave farm.

1.2. Weather data

Another major input required to make an O&M simulation tool as realistic as possible is weather information. One use of such data is to evaluate the weather windows for the array; periods when the devices can be accessed by vessels and maintenance crew. The weather conditions defining these windows generally come through operator experience as well as vessel specifications (O'Connor et al., 2013). O&M tasks for a wave farm should ideally be scheduled for periods when accessibility is highest and expected revenue is at a minimum (Walker et al., 2013), though this may not always be possible due to unexpected failures. Weather data can also be used to provide yield estimation. Higher temporal and spatial resolution, as well as the proximity of source weather data to a proposed site, will improve the accuracy with which an O&M tool can represent weather conditions. As such, it will offer a more robust estimation of OPEX costs and farm availability.

1.3. Purpose of the Study

This study will address site characteristics affecting accessibility and power performance, and uncertainty surrounding failure rate estimates for wave energy converters. The study will make use of a Monte Carlo-based O&M simulation tool built in Microsoft Excel and VBA, whereby failure rates are used to simulate the occurrence of faults on a machine. This enables a reactive maintenance approach to be taken. This is combined with a proactive maintenance approach of routine inspections taking place once every summer, and a half-life complete overhaul of major components. A case study based on the second-generation Pelamis WEC has been used due to the vast amount of experience gained during a testing programme achieving over 11,000 grid connected hours. The study aims to demonstrate the model as an effective tool for budgeting and planning of a wave energy array. It will also highlight the ability of the tool to support targeting work priorities for developing wave energy technologies.

2. Methodology

The O&M tool used in this study is focused on the Pelamis P2 device (see figure 1), rated at 750kW. The tool was created initially in 2007 by Pelamis Wave Power, the designer and operator of the Pelamis WEC. The software has since been upgraded over the course of a partnership with the Industrial Doctoral Centre for Offshore Renewable Energy (IDCORE). Figure 2 summarises the inputs and outputs of the O&M tool (Gray et al., 2014).

Figure 1: One of the two Pelamis P2 machines operating at EMEC in 2012

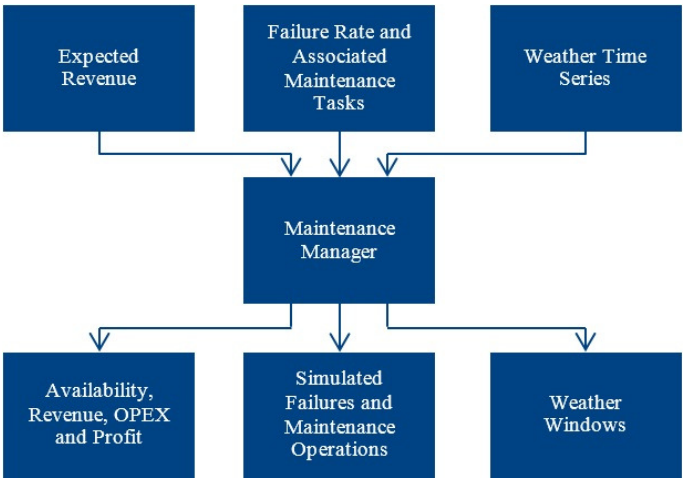

Figure 2: O&M tool flowchart of key inputs and outputs

The P2 device was designed with a 'plug in and play' system, whereby the machine could be installed and removed from its electrical and moorings connection point remotely using a computer on board the installation vessel. The maintenance strategy was to remove the WEC from its offshore location to the safety of a sheltered harbour where spare parts could be readily available and the persistence of weather conditions is not a concern. No maintenance was to be carried out whilst the device was offshore, regardless of weather conditions. A P2 installation operation could be carried out in less than an hour once the machine was on site, using two small, low cost, multi-purpose workboats as shown in figure 3. A removal operation could be carried out '*in a matter of minutes*' (Yemm et al., 2012) and in rougher seas using only one workboat. The inputs to the O&M tool have come from the expert judgement of the engineers involved in the Pelamis endeavour.

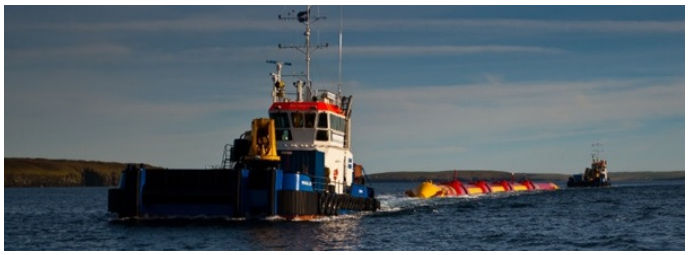

Figure 3: A Pelamis P2 device being towed for installation at EMEC in 2012

2.1. Inputs

Failure rate data is one of the key inputs required to run an O&M simulation tool. Between 2008 and 2014, the two P2 machines achieved over 11,000 hours of grid connection at the European Marine Energy Centre (EMEC) in Orkney. Initial estimates for the P2 device (prior to their deployment) came from four main sources; i) manufacturers' specifications for off-the-shelf components, ii) a US military handbook on reliability prediction (US Department of Defense, 1991), iii) destructive testing on several components (Pelamis Wave Power, 2013), and iv) the limited operational experience with

the Pelamis prototype and P1 devices. These estimates were updated over the course of the P2 testing programme, as staff at Pelamis Wave Power learnt more about their device through operational experience. The failure rate inputs to the O&M tool were last reviewed and updated in October 2014. It should be noted that these failure rate inputs are fixed values, and therefore do not take into account early 'infant mortality' failures or degradation of components over time.

The components and subsystems of the P2 device are represented in the O&M tool by sixteen different failure categories. This allocation was undertaken using a Failure Modes and Effects Analysis (FMEA) to identify the overall consequence of each fault. The categories are classified as either major, intermediate or minor faults. Each category has a failure rate and associated maintenance parameters, such as power loss, parts cost and time to repair. These values are therefore averages of all those components that make up each fault category.

The O&M tool is supplied with a time series of weather conditions containing significant wave height (Hs), wave energy period (Te) and wind speed. A time series of any length can be generated by a Markov-based weather model which has been developed for the O&M tool. It takes an input of hindcast data in order to generate a synthetic time series that displays enough variance to replicate both 'good' years and 'bad' years, yet shows the same seasonal trends as the input data. To achieve this, the three parameters in the hindcast dataset are placed into 'bins' and combined as 'sea states'. The 'bins' range from 0.25m to 9.75m in steps of 0.5m for Hs, from 3s to 15s in steps of 2s for Te, and from 2.5kts to 47.5kts in steps of 5kts for wind speed. The hindcast dataset is then separated by month in order to ensure seasonal variability. At each time step, the next 'sea state' is recorded, enabling a probability transition matrix to be created for each monthly dataset. It is then possible to generate a new time series using the fundamental Markov property that the weather conditions at the present time step depend solely on the conditions at the previous time step. Validation and further details about the functionality of the Markov Chain Model can be found in (Gray et al., 2015). This method has been developed to enable the O&M tool to incorporate the learning gained during real sea testing of the Pelamis P2 device with regards to weather windows. It was found that although significant wave height was the primary factor in accessibility, operational limits of Hs were also dependant on wave energy period (see figure 4). In addition to Hs and Te, wind speed has also been included because it was shown over the course of the P2 testing programme that a wind speed of 20 knots was a constraint for marine operations. This is a typical working limit for multicat vessels and tug boats.

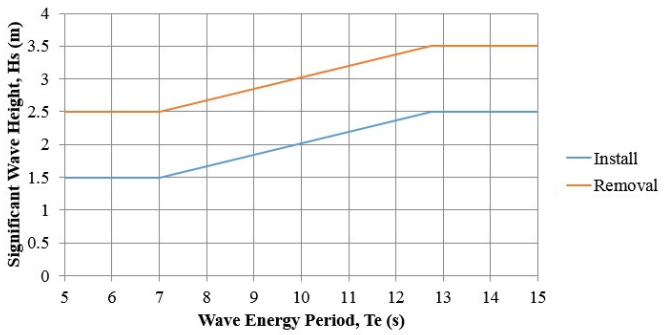

Figure 4: Operational limits defined during the P2 testing programme and used in the O&M tool for this study (Gray et al., 2015)

In order to estimate the annual yield and power loss associated with faults and maintenance, this study also includes an assessment of power generation. A time series of Hs and Te enables the O&M tool to calculate the estimated power generated by each machine in the wave farm. To achieve this, the weather conditions are matched up with values in a power matrix which has been inferred from the contracted targets that Pelamis Wave Power had during the P2 testing programme (figure 5). It should

be noted that this power matrix is not indicative of the true potential of a commercial attenuator WEC. Revenue is then calculated using this power production multiplied by the unit sell price of electricity. The sell price is assumed to be 30.5p/kWh, in line with the UK's 'Contracts for Difference' model.

	Te (s)						
Hs (m)	**3**	**5**	**7**	**9**	**11**	**13**	**15**
0.25	0	0	0	0	0	-	-
0.75	3	11	21	18	9	1	-
1.25	-	14	39	32	12	8	-
1.75	-	42	85	68	36	12	-
2.25	-	57	152	115	69	35	-
2.75	-	91	227	178	111	69	25
3.25	-	-	314	253	159	102	37
3.75	-	-	198	304	217	150	88
4.25	-	-	159	367	280	198	68
4.75	-	-	131	359	318	209	82
5.25	-	-	121	418	367	271	101
5.75	-	-	94	246	413	342	155
6.25	-	-	-	204	413	397	258
6.75	-	-	-	180	388	414	200
7.25	-	-	-	113	201	378	179
7.75	-	-	-	94	215	199	146
8.25	-	-	-	75	208	167	100
8.75	-	-	-	18	164	150	71
9.25	-	-	-	-	150	141	-
9.75	-	-	-	-	113	-	-

Figure 5: Pelamis P2 power matrix inferred from contracted targets during testing programme 2008-2014

2.2. Decision Making

The O&M tool models a reactive maintenance strategy by using a Monte Carlo analysis at every 6 hour time interval. At each time step, a new random number between 0 and 1 is generated for every failure category and compared to the probability of failure for that category (shown in Table A.1, section 9) to determine whether a fault has occurred. The probabilities shown in Table A.1 are adjusted to account for the 6 hour resolution using equation 1.

$$P_{fail\ in\ 6hrs} = 1 - (P_{not\ fail\ in\ year})^{1/(365*4)} \qquad (1)$$

Where 365x4 is the total number of 6 hour time steps in a year. The decision making process of when to remove and repair a device is represented graphically in figure 6. If a device suffers either one major fault or two intermediate ones, then it is retrieved for repair as soon as weather permits. If the device has exceeded the maximum allowable time between two scheduled maintenance events (i.e. September for time-based scheduled maintenance) then it is also retrieved. If none if these conditions are met, then the tool runs through a cost-benefit analysis (CBA) to decide whether or not to send a vessel to remove that machine from site (provided the weather window is open). Groups of an increasing number of machines are assessed in turn to enable multiple devices to be removed in the same window if logistics allow. This analysis weighs up the cost of retrieving and repairing the device/s against leaving it/them to operate at a reduced power output. This becomes quantifiable due to the proactive maintenance strategy of undertaking a routine inspection on each device every summer. Estimates for potential revenue and time spent waiting for a weather window in a given month are provided as an input to enable the cost-benefit calculations to take place.

In undergoing this process at every time interval, the tool can fully analyse the wave farm. The results are presented for each machine, for every year of operation, as well as average values given for the entire array. Outputs such as labour costs, vessel fees, availability, total OPEX and revenue are generated. The sixteen failure categories are assigned portions of the OPEX costs based on the downtime due to the associated faults.

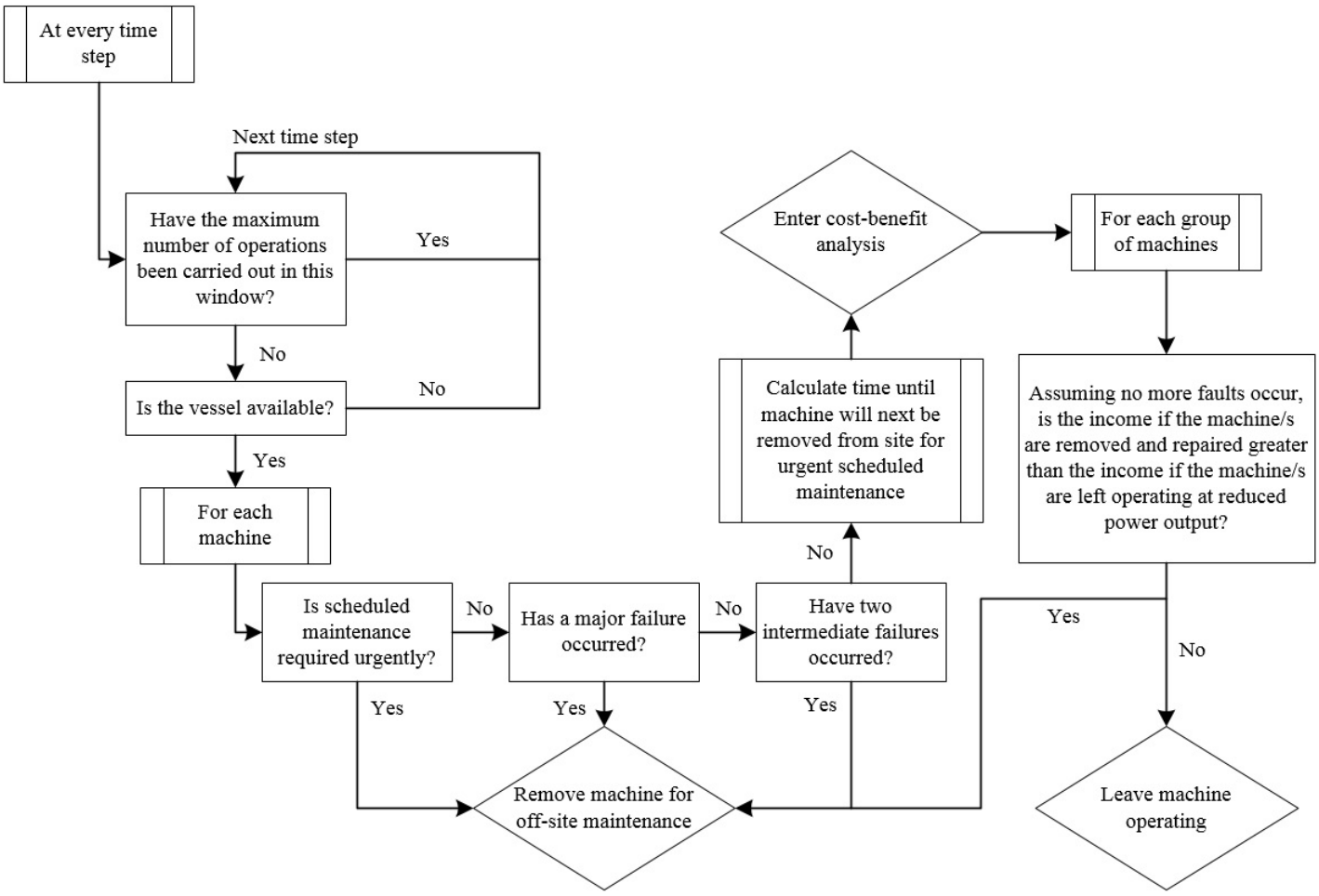

Figure 6: O&M model decision flowchart for marine operations

2.3. Sensitivity Analysis

To undertake the sensitivity analysis presented in this study, the O&M model was ran ten times to obtain the mean values. For each analysis, a base case was simulated once with all fault categories set at the original failure rates (see Table A.1, section 9). For each subsequent run, the failure rate of one fault category was either decreased or increased by a factor of 10. The failure rate information in the model is provided as a probability of failure per year. Therefore, increasing the rate by a factor of 10 means using equation 2:

$$P_{fail:\ increased} = 1 - (P_{not\ fail:\ original})^{0.1} \qquad (2)$$

The exponential value is 10 when decreasing by a factor of 10.

3. Case Study

3.1. O&M tool base case

In order to carry out a sensitivity analysis on the failure rate inputs to the O&M tool, it is vital that a base case is established. This study will model a wave farm containing ten Pelamis P2 devices, operating for a lifespan of twenty years. As previously stated, two multipurpose workboats were required for the installation of a P2 device during the testing programme. However, it was always the plan that this level of redundancy would no longer be required in a commercial wave farm. Therefore, the O&M tool assumes that only one multipurpose workboat is required for both installation and removal operations. One workboat is available for the wave farm and is paid for on a 'hire when required' basis. The probability of the boat being available at any given time has been set at 0.9. This accounts for factors such as the vessel being used by the contractor for another job, or undergoing its own maintenance. A mobilisation fee is incurred when the boat is first hired for a period. The vessel stays on hire until all ten devices are back operating in the wave farm. These vessel costs, detailed in table 1, were the typical market rates during the P2 testing programme (2008-2014). The day rate vessel fees are not adjusted for inflation over time in this study. A fuel cost for each operation is also added and is dependent on the distance from the quayside to the wave farm site (discussed in section 3.2). Quayside fees similar to those incurred by Pelamis Wave Power when testing at EMEC are applied. This includes a daily base rate to cover items such as shed rent and insurance, plus an additional fee for each machine that is at the quayside to cover layage costs. An assumption has been made that marine operations could be carried out at night, as it was proven to be beneficial for the profitability of the wave farm by Gray & Johanning (2016). It is also assumed that the quayside could be arranged in such a manner that all ten machines could be stored simultaneously if necessary, and that there are no logistical constraints surrounding which machine can be accessed by the vessel at either the base or the farm.

Vessel Costs			**Quayside costs**			**Labour costs**		
Item	**Costs (£k)**		**Item**	**Costs (£)**		**Technician**	**Number**	**Total annual salary (£k)**
Mobilisation fee	5000		Base rate (shed rent, insurance etc.)	100 per day		O&M base manager	1	45
Day hire rate	4000		Layage	50 per day		Moorings	2	60
Fuel (per operation)	1000					Hydraulic	3	90
						Structural	3	90
						Electrical	2	60
						Apprentice	1	10

Table 1: Cost assumptions in O&M tool

In addition to the fault categories detailed in Table A.1, there are two scheduled maintenance events built into the O&M model (detailed in Table A.2, section 9). A routine service is scheduled to be carried out once every summer, when accessibility is high and lost revenue is minimised. This event includes tasks such as checking bolt tensions and torque, non-destructive testing (NDT) on welded joints, checking oil cleanliness and carrying out minor repainting. One specialist technician from each of the hydraulic, structural and electrical departments, as well as one other team member, are required for this event. A specialist moorings technician is not required as no servicing is scheduled to be undertaken on the moorings. The second scheduled maintenance event is a refit of the major components in each P2 device, to be carried out in the summer of year ten (the half-life of the wave farm). This event was identified as necessary during the design phase of the P2 device because the manufacturers of certain components specified a design life of 10 years. This particularly affected

rubber components such as the bellows seals. Therefore, these components would need to be replaced after 10 years in order for the wave farm to achieve its 20 year design lifetime. The half-life refit event also involves tasks such as changing all hydraulic oil, structural surveying, corrosion analysis and a complete repainting of each WEC. It should be noted that cleaning the underside of the WEC is not included in the scheduled maintenance events as biofouling was proven to not have an effect on power performance during the P2 testing programme. (any reference for this? Ask Beth)

Another input to the O&M tool is the labour details at the operations base. As shown in table 1, this study assumes a total of twelve personnel permanently employed at the base. A multiplier of 1.3 is applied to account for overheads such as travel expenses and laptops. The O&M tool can constrain repairs and maintenance tasks depending on which technicians are available at any given time. However, for this study, it has been assumed that contractors can be hired on a short term basis at a rate of £200 per day to ensure maintenance is not delayed by a lack of technicians. A study by Gray & Johanning (2016) has shown that this has a significant impact on the operability of the array and therefore could be a realistic scenario once wave energy becomes a commercial industry.

3.2. Site Characterisation

This study will look at two specific wave energy sites (see figure 7) using the weather simulation model developed for the O&M tool by Gray et al. (2015). Site A is located off the North coast of Scotland and represents Farr Point; a site previously being developed by Pelamis Wave Power as a potential wave array. Site B is found off the North coast of Cornwall and represents Wave Hub; '*the world's largest and most technologically advanced grid connected site for the testing and development of offshore renewable energy technology*' (Wave Hub Limited, 2015).

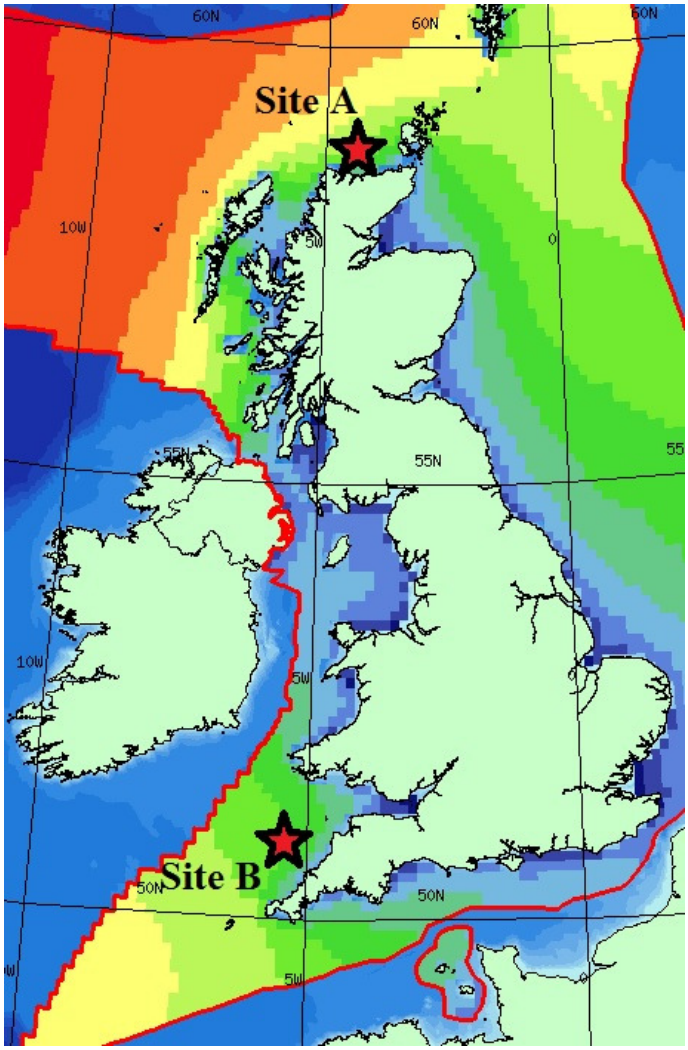

Figure 7: Annual UK wave resource map (ABP Marine Environmental Research Ltd., 2016) showing approximate locations of the two sites analysed in this study

3.2.1. Tow times and marine operations

Port selection is required for both sites in order to define the number of P2 installations and/or removals that can be carried out in a 12 hour weather window. As shown in figure 8, the O&M base for site A would have most likely been located in the natural shelter of Loch Eribol, approximately 30km from the wave energy array.

Figure 8: Map (Google.co.uk) showing distance between Loch Eribol O&M base and site A

When towing a WEC, a multicat vessel is constrained to a speed of 5kts. This means that a vessel could tow a P2 device from the O&M base to site A for installation in approximately 3.5 hours. A

conservative estimate of 1 hour installation time once at the site (Yemm et al., 2012), followed by a quicker journey back to the O&M base (without having to tow a machine) gives the approximatation of 7 hours for a single installation operation. However, experience during the P2 testing programme showed that this time would need to be extended by at least 2 more hours to account for pre-ops work to be undertaken at the wave energy site. This involved attaching a buoy to the mooring line to enable the installation procedure to be undertaken remotely (Pelamis Wave Power, 2012). Therefore, only one device could be installed at site A in a 12 hour window. The remote quick release mechanism of the P2 allowed a removal operation to be undertaken in approximately 15 minutes, making the total retrieval time approximately 6 hours. An assumption has been made that the logistical procedure could be streamlined so that any quayside preparations can be undertaken whilst the vessel is travelling to site to removal a device. Therefore, after one device has been removed from site A and brought to the quayside, the vessel could collect another WEC and carry out an installation operation in the same 12 hour window.

Site B is representative of the Wave Hub commercial scale test site off the North coast of Cornwall. A study by Walker et al. (2013) investigated ports in this area suitable for mobilisation of a WEC. Figure 9 shows the locations of three of the ports considered suitable for access to the Wave Hub site.

Figure 9: Map of Cornwall showing three ports suitable for access to Wave Hub (Walker et al., 2013)

This study assumes Hayle port, 25km from site B, can be used as the O&M base for site B. The journey times with and. without towing a WEC would be approximately the same for Hayle-Site B as for Loch Eribol-Site A. Therefore, the O&M model used in this study assumes the same permutations of marine operations, where, in a 12 hour window, the vessel can either:

- remove a maximum of two P2 devices and bring them both to the quayside
- install one P2 device at the farm
- install one P2 device at the farm, then remove another one and bring it to harbour

3.2.2. Weather conditions

Hindcast data has been used to generate time series' for these two sites. As stated by Gray et al. (2015), the hindcast data for Site A (Farr Point) is for an eighteen year period from 1992 to 2010. It contains all three parameters required to define a weather window for the P2 device (Hs, Te and wind speed). Wave Energy Scotland have provided this dataset for the purposes of this study.

A twenty-three year hindcast dataset (1989-2011) for the Cornish coast (Site B) has been provided by the University of Exeter, as part of the PRIMaRE project (PRIMaRE, 2015). This has been validated against buoy measurements by van Nieuwkoop et al. (2013). However, it is only possible to obtain

values for significant wave height and wave energy period from this dataset. In order to match wind speeds to the Hs-Te combinations, data from the Channel Coastal Observatory (CCO) at Perranporth was used (see figure 10). This information is readily available from their website (Channel Coastal Observatory, 2015). Real-time data was chosen for the period 12/3/2014 to 10/11/2015 with values obtained for Hs, Te and wind speed in half hourly intervals. After applying the same resolution found in the weather simulation model to these values, it was possible to calculate a probability for every wind speed matching each combination of Hs and Te. This allowed the completion of the twenty-three year hindcast dataset with the addition of appropriate wind speeds using a Markov-based approach, similar to the method used in the weather simulation model itself (Gray et al., 2015).

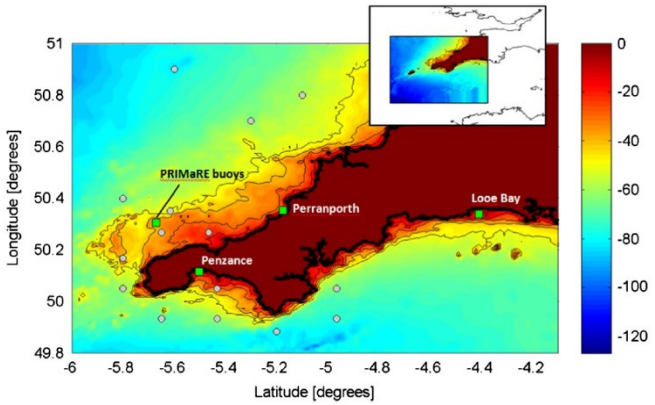

Figure 10: Map of Cornwall showing the approximate locations of data buoys and Perranporth

A comparison between the hindcast data for the two sites in terms of the annual mean values of each of the three parameters can be seen in figures 11-13.

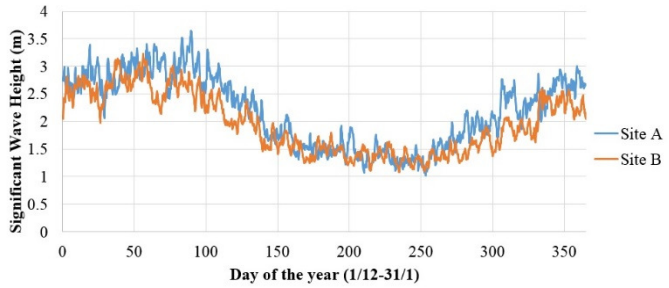

Figure 11: Annual mean significant wave height for the two sites

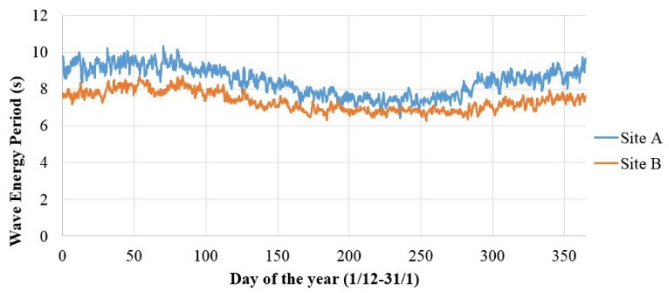

Figure 12: Annual mean wave energy period for the two sites

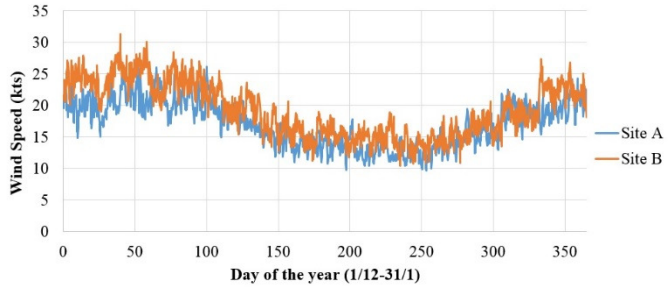

Figure 13: Annual mean wind speed for the two sites

As stated in section 2.1, significant wave height and wave energy period are placed into 'bins' with the resolutions 0.5m and 2s respectively. As a result, the hindcast data used for input to the Markov-based weather model can be represented graphically by occurrence tables (see figures 14 and 15).

	Te (s)						
Hs (m)	**3**	**5**	**7**	**9**	**11**	**13**	**15**
0.25	0%	0%	0%	0%	0%	0%	0%
0.75	0%	1%	7%	5%	1%	0%	0%
1.25	0%	1%	10%	7%	1%	0%	0%
1.75	0%	1%	7%	8%	2%	0%	0%
2.25	0%	1%	5%	8%	2%	0%	0%
2.75	0%	0%	3%	6%	2%	0%	0%
3.25	0%	0%	2%	5%	2%	0%	0%
3.75	0%	0%	1%	3%	1%	0%	0%
4.25	0%	0%	0%	2%	1%	0%	0%
4.75	0%	0%	0%	1%	1%	0%	0%
5.25	0%	0%	0%	1%	1%	0%	0%
5.75	0%	0%	0%	0%	0%	0%	0%
6.25	0%	0%	0%	0%	0%	0%	0%
6.75	0%	0%	0%	0%	0%	0%	0%
7.25	0%	0%	0%	0%	0%	0%	0%
7.75	0%	0%	0%	0%	0%	0%	0%
8.25	0%	0%	0%	0%	0%	0%	0%
8.75	0%	0%	0%	0%	0%	0%	0%
9.25	0%	0%	0%	0%	0%	0%	0%
9.75	0%	0%	0%	0%	0%	0%	0%

Figure 14: Occurrence table for site A

	Te (s)						
Hs (m)	**3**	**5**	**7**	**9**	**11**	**13**	**15**
0.25	0%	0%	0%	0%	0%	0%	0%
0.75	0%	4%	10%	0%	0%	0%	0%
1.25	0%	4%	20%	2%	0%	0%	0%
1.75	0%	1%	17%	4%	0%	0%	0%
2.25	0%	0%	10%	4%	0%	0%	0%
2.75	0%	0%	5%	4%	0%	0%	0%
3.25	0%	0%	3%	3%	0%	0%	0%
3.75	0%	0%	1%	2%	0%	0%	0%
4.25	0%	0%	0%	2%	0%	0%	0%
4.75	0%	0%	0%	1%	0%	0%	0%
5.25	0%	0%	0%	1%	0%	0%	0%
5.75	0%	0%	0%	0%	0%	0%	0%
6.25	0%	0%	0%	0%	0%	0%	0%
6.75	0%	0%	0%	0%	0%	0%	0%
7.25	0%	0%	0%	0%	0%	0%	0%
7.75	0%	0%	0%	0%	0%	0%	0%
8.25	0%	0%	0%	0%	0%	0%	0%
8.75	0%	0%	0%	0%	0%	0%	0%
9.25	0%	0%	0%	0%	0%	0%	0%
9.75	0%	0%	0%	0%	0%	0%	0%

Figure 15: Occurrence table for site B

The O&M tool has the ability to use different 20 year time series' during the sensitivity analysis. However, this would alter the base case for each simulation and therefore only one time series has been used for each site. The cost-benefit analysis part of the O&M tool requires estimates for wait times (i.e. the number of days to wait for a weather window in any given month) and power output. These are obtained by generating a 100 year time series for each site. Therefore, the 20 year time series used for each site in the study was selected based on its similarity to the respective 100 year time series providing estimates to the cost-benefit analysis.

Cumulative probability distribution graphs can be plotted to provide further characterisation of the two sites (figures 16-19). These graphs have been created by analysing the Markov-generated 100 year time series for each site. Firstly, the persistence of non-accessible weather conditions at each 6 hour interval is calculated. The number of occurrences of each persistence time in every month of the year is then recorded, along with the total number of 6 hour intervals in that month. This enables the probability of the non-accessible weather conditions not exceeding each cumulative period of time, up to a maximum of 30 days, to be calculated.

4. Results and Discussion

4.1. Site Characteristics

The site characteristics charts (figures 11-13) show that site A has a greater significant wave height and greater wave energy period on average than site B. The implication from this is that site A will have a higher yield in terms of power output of a wave energy farm. However, this may result in weather conditions suitable for marine operations being more abundant at site B. This effect may be balanced by the wind speed at site A being lower on average than at site B. Figures 16-19 show the cumulative probability distribution functions of the weather window constraints for each season of the year, providing a graphical comparison of wait times for the two sites. This information can be quantified by calculating the average number of days required to wait for a weather window in each month (see figure 20).

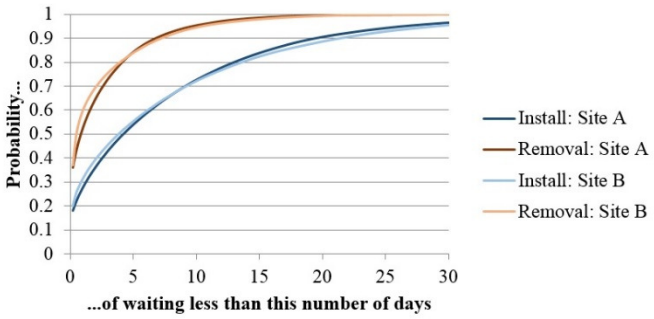

Figure 16: Cumulative Distribution Functions of installation and removal accessibility during winter (December, January and February) for the two sites used in this study

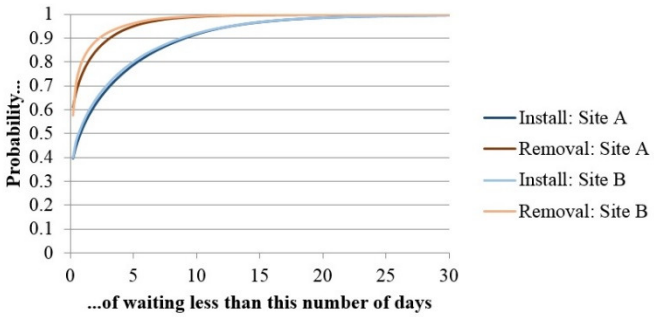

Figure 17: Cumulative Distribution Functions of installation and removal accessibility during spring (March, April and May) for the two sites used in this study

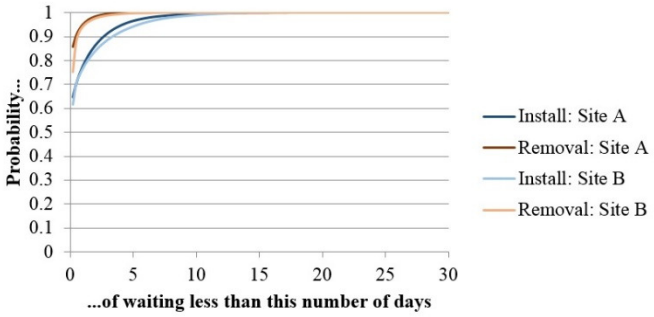

Figure 18: Cumulative Distribution Functions of installation and removal accessibility during summer (June, July and August) for the two sites used in this study

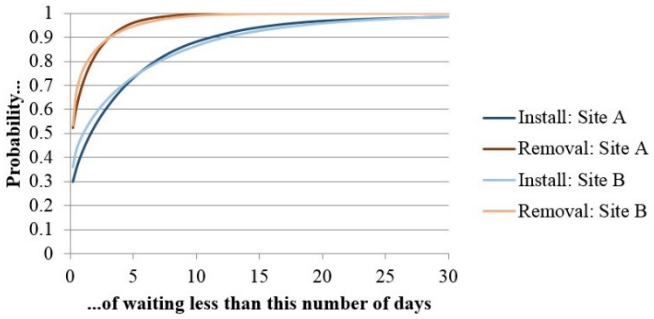

Figure 19: Cumulative Distribution Functions of installation and removal accessibility during autumn (September, October and November) for the two sites used in this study

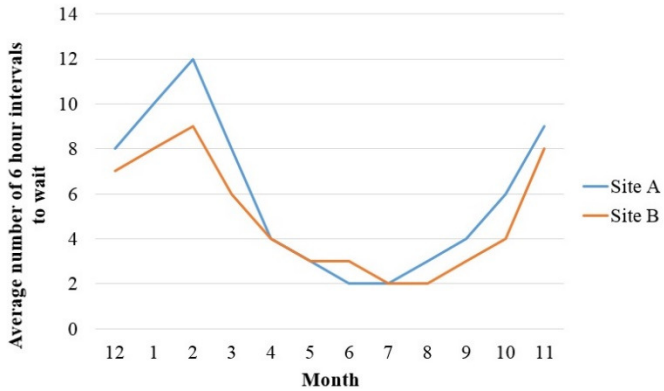

Figure 20: Comparison of the two sites in terms of the average time to wait for a 12 hour weather window suitable for installation of a P2 device in each month

The cumulative probability distribution functions shown in figures 16-19 match up closely for sites A and B. This implies that the time spent waiting for a 12 hour weather window would be approximately equal for the two sites. However, from figure 20 it can be seen that the estimated average number of 6 hour intervals to wait for an open weather window is higher for site A in every month of the year except June. On average, a vessel would need to wait 1.48 days for weather conditions suitable for a 12 hour WEC installation in any given month when the wave farm is located at site A, compared to 1.23 days for site B. This information implies that there may be a slightly higher OPEX cost at site A due to the vessel being kept on hire after its first marine operation if another device is to be installed. This difference between the two sites is demonstrated by the base case results from the O&M tool (see Table A.3, section 9). The average OPEX at site A was calculated to be £1.12m compared to £1.09m for site B, equating to a 2.6% increase.

4.2. Power estimation and base case results

The Pelamis P2 power matrix (figure 5) is matched with the occurrence tables for the two sites (figures 14 and 15) to provide the O&M model with estimates of power generation, thereby enabling the cost-benefit calculations to take place. Figure 21 represents these inputs graphically by comparing the average estimated power generated across a 6 hour period for the two sites in each season of the year, as well as providing the average values for the full dataset.

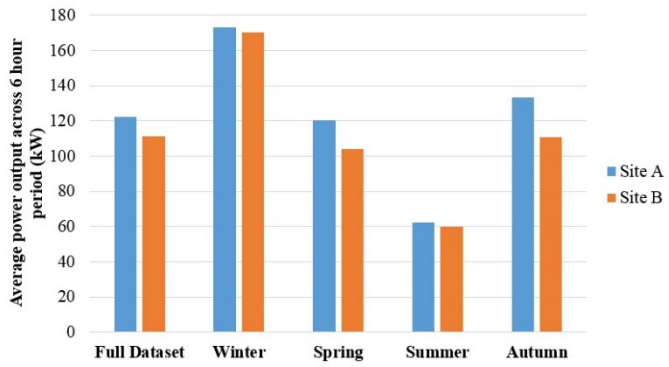

Figure 21: Comparison of the two sites in terms of average power output across a 6 hour period

Figure 21 shows that a wave farm located at site A is estimated to generate more power than at site B. The estimated 6 hourly average power output for Site A is 122.3kW, compared to 111.2kW for Site B. From figures 14 and 15 it can be seen that the conditions at Site A reach beyond 11s Te and 8.75m Hs, and there is a much higher proportion of occurrences in the 9s Te, >1.25m Hs region than Site B. Over 50% of occurrences lie in the 7s Te bracket between 0.75m and 2.25m Hs.

The implication that a Pelamis P2 wave farm located at site A would generate a higher revenue is confirmed by the results of the O&M tool, where the base case annual revenue at site B is £2.57m compared to £2.85m at site A (see Table A.3, section 9). This equates to a 9.8% decrease in revenue if the wave farm was located at site B rather than at site A. The base case results also show that there is a negligible 1% difference between the two sites in availability. This is most likely due to the slightly different inputs in terms of estimated wait times and potential revenue, thereby affecting the cost-benefit calculations within the model.

Using the base case results it is also possible to compare the two sites in terms of Levelised Cost of Energy (LCOE). Equation 3 (Ocean Energy Systems, 2015) has been used for these calculations.

$$LCOE = \frac{CAPEX + \sum_{t=1}^{n} \frac{OPEX_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{AEP_t}{(1+r)^t}} \qquad (3)$$

LCOE – Levelised Cost of Energy

CAPEX – Capital expenditures

$OPEX_t$ - Operational expenditures (at year t)

AEP_t – Annual electricity production (at year t)

r – Discount rate

n – Lifetime of the system

t – year from start of project

The base case results from the O&M model are used for the OPEX and AEP input parameters in this calculation. The annual revenue is divided by the assumed unit sell price of electricity (30.5p/kWh) to give an estimate of AEP. This leads to the AEP being calculated as 9.34GWh for site A and 8.43GWh for site B. A discount rate of 10% has been selected. A manufacturing cost of £6m per Pelamis P2 device has been assumed. Together with an assumed £15m overheads cost for activities such as O&M base development and insurance fees, the total CAPEX for the 10 machine wave farm is taken to be £75m. Using these input parameters, the LCOE is calculated to be £106/MWh for site A and £117/MWh for site B. This shows that the greater OPEX incurred by a wave farm located at site A is outweighed by the higher revenue generated. It should be noted that these values for LCOE have been calculated solely to provide a means of comparison between the two sites. They are not indicative of the true potential of wave energy arrays, and should only be taken in context of the base case described in this study.

The O&M model simulations carried out in this study assume that all maintenance tasks would be undertaken at the ports described in section 3.2.1. However, operators of wave energy arrays would have to consider each maintenance task independently. It is likely that more complex tasks would require specialist equipment, such as a dry dock, meaning that the forward O&M base would need careful planning and significant investment. If such upgrades were impossible due to space or logistical restrictions, WECs would need to be taken to larger ports for some maintenance tasks. For site A, this may involve taking the device to Lyness in the Orkney Islands (see figure 8), or Penzance if the farm was at site B (see figure 9). Both journeys would require a much greater tow time, resulting in longer waits for a suitable weather window and decreased vessel availability for other WECs at the farm. This would have significant knock-on effects on profitability of the wave energy farm. The assumed O&M base location for site B has also not taken into account that access to Hayle harbour is tidal dependant. This would mean that a vessel towing a WEC into the O&M base would have to wait outside the harbour until the tide allows entry, thereby extending the time to carry out the marine operation. An indication of the impact extending the required weather window would have can be seen in figure 22, where a 24 hour window is specified. The same number of marine operations discussed in section 3.2.1 is assumed. The results here show a drop of 4% in availability and 3% in revenue.

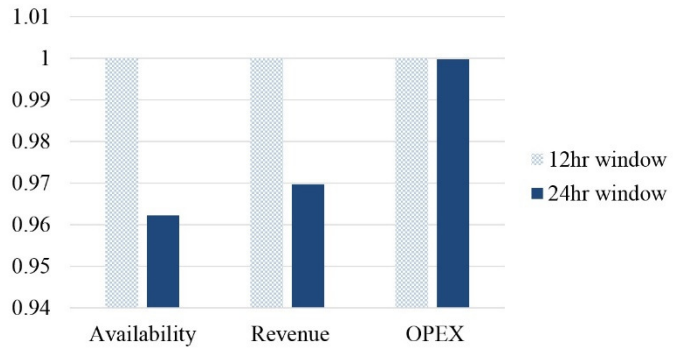

Figure 22: Effects of an increased length of weather window for site B, normalised against the 12hr base case

4.3. Failure rate sensitivity

Table A.3 (section 9) contains the numerical results of the sensitivity analysis and Table A.4 provides the percentage changes from the base case.

4.2.1. Minor primary hydraulic faults

From the results of the sensitivity analysis, it can be seen that the biggest drop in profitability of the wave farm occurs when the failure rate for fault category 13 ('minor primary hydraulic') is increased by a factor of 10. The percentage changes from the base case are represented graphically for the two sites in figures 23 and 24.

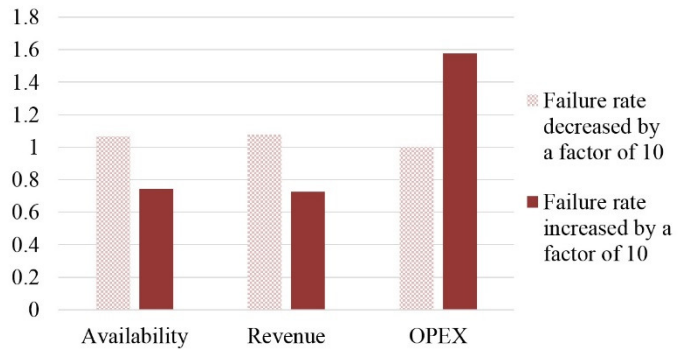

Figure 23: Sensitivity analysis results for 'Minor primary hydraulic' faults at site A, normalised against the base case

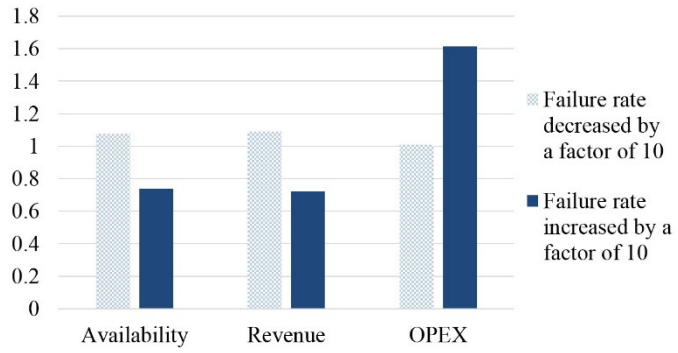

Figure 24: Sensitivity analysis results for 'Minor primary hydraulic' faults at site B, normalised against the base case

Availability decreases from the base case by approximately 22.2% for each of the two sites, whilst revenue decreases by 27.4% and 27.8% for sites A and B respectively. Operational expenditure also increases significantly in this case by 57.7% and 61.5% for sites A and B respectively. As shown in Table A.1 (section 9), the base failure rate for category 13 is a probability of failure per year (P_{fail}) of 0.9375. Increasing this rate by a factor of 10 leads to a probability of failure of 0.9938 per year. Therefore, a minor primary hydraulic failure is almost guaranteed to occur at least once per year on each machine in this scenario. On the other hand, the values for associated parameters such as power loss, time off site and repair costs are minimal when compared to other fault categories. However, the results from the sensitivity analysis show that the increased failure rate of minor primary hydraulic faults has a significant impact on operability of the wave farm. This indicates that an increase in the number of minor primary hydraulic faults leads the cost-benefit analysis (CBA) part of the O&M tool to set affected devices for retrieval more than in the base case, regardless of the low-impact associated parameters.

Conversely, when the failure rate for category 13 is decreased by a factor of 10, the results show the largest increases in availability and revenue. This increase stems from the fact that there are less minor primary hydraulic faults occurring in the farm, and thus the cumulative impact of power loss is reduced compared to the base case. However, this scenario does not lead to an equally significant decrease in OPEX. An explanation for this could be that the reduced number of minor primary hydraulic faults does not have enough of an impact on the cost-benefit calculations to lead to a decrease in either the average number of marine operations or the time a machine spends off site over the lifetime of the farm.

It is possible to look into the fault category at a component level by investigating the P2 FMEA spreadsheet. From this, it can be seen that the component with the biggest influence on the minor primary hydraulic fault category is the hydraulic valves within the ram manifolds. There are 8 such valves within a single ram manifold, with a total of 16 manifolds in a Pelamis P2 device. Each of these 128 hydraulic valves has a manufacturer's target Mean Time Between Failure (MTBF) of 100 years. This equates to a total probability of failure of 0.7313 per year, making up the majority of the 0.9375 base failure rate for the minor primary hydraulic fault category. As with many components within a WEC, these hydraulic valves are being used in a different environment from the one they were designed for. As a consequence, it is not unfeasible that the manufacturer's specified MTBF could be an underestimate of the true failure rate when deployed in a WEC. The results from this sensitivity analysis show that an increase of the number of failures in the minor primary hydraulic fault category could have a significant impact on profitability of the wave farm. Therefore, developers of WECs should work closely with manufacturers to design components specifically for the marine environment, and carry out testing accordingly for more realistic failure rate estimates.

4.2.4. Half circuit failure

The biggest increase in OPEX occurs when the failure rate of category 7 ('half circuit failure') is increased by a factor of 10. This is a 64.5% increase for site A and 63.1% for site B, as shown in figures 25 and 26. There are also decreases in availability and revenue in the region of 4-5% and 6-8% respectively for both sites. There are also minor increases in availability and revenue, and a slight decrease in OPEX, when the failure rate for the half circuit failure category is decreased by a factor of 10.

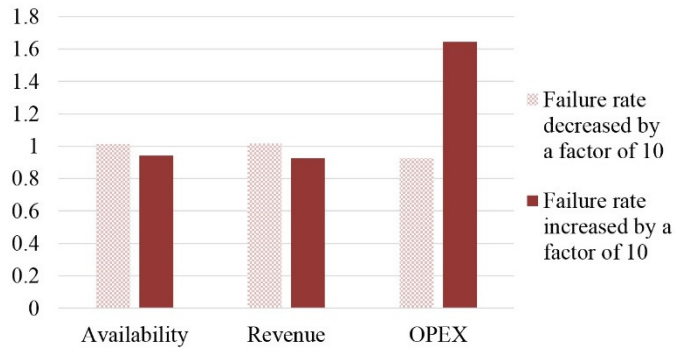

Figure 25: Sensitivity analysis results for 'Half circuit failure' at site A, normalised against the base case

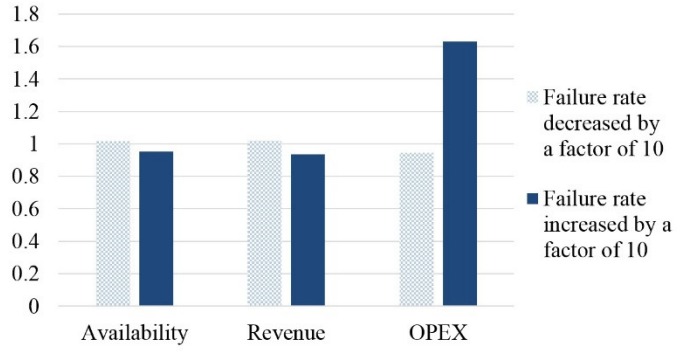

Figure 26: Sensitivity analysis results for 'Half circuit failure' at site B, normalised against the base case

A Pelamis P2 device was made up of four articulating joints called modules, each housing a hydraulic power take off unit. A half circuit failure is defined as any mechanical or hydraulic fault, such as an oil leak or ram manifold crack, which leads to one half of a module becoming incapable of power generation. This category has the second highest base failure rate (P_{fail} = 0.36) due to the sheer number of potential faults that could contribute to a half circuit failure. In the O&M model, this is classed an intermediate failure where the associated power loss, time off site and repair costs are not particularly large when compared to the major faults. Therefore, it can be assumed that the results of the sensitivity analysis for this category come from the high probability of failure in the base case.

This assumption can be confirmed when compared to the results for category 9 ('data communications'). Here, the power loss and repair parameters are similar to the half circuit failure but with a much lower base failure rate (P_{fail} = 0.0139). The sensitivity analysis for data communications faults shows virtually no impact on operability of the wave farm. This information highlights that in subsystems where many individual faults lead to the same overall failure, those components must be over engineered and thoroughly tested to ensure minimal impact over the lifetime of the wave farm.

4.2.5. Control system faults

The results of the sensitivity analysis are also quite significant for fault category 11 ('control system'), as shown in figures 27 and 28. When the control system base failure rate (P_{fail} = 0.2604) is increased by a factor of 10, availability and revenue drop by approximately 7% and 9.5% respectively for both sites. There is some variation between the two sites in terms of the increase in OPEX; 27.4% for site A and 30.8% for site B. It has been discussed previously that the two sites do not differ significant in accessibility, so this variation is perhaps due to the presence of other faults. A control system failure is classed as a minor fault and therefore most likely requires other faults to have occurred before the CBA deems it beneficial to repair the affected P2 machine. Again, minor impacts are seen when the base failure rate is decreased by a factor of 10.

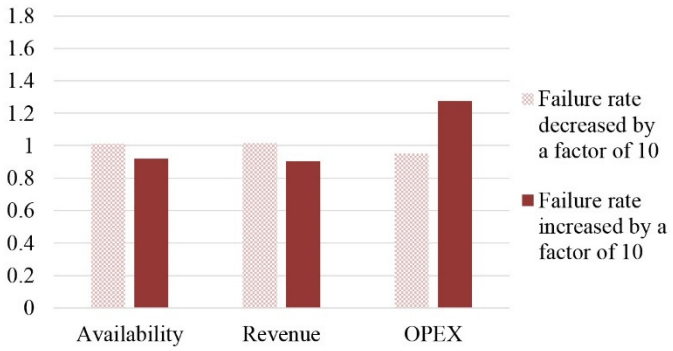

Figure 27: Sensitivity analysis results for 'Control system faults' at site A, normalised against the base case

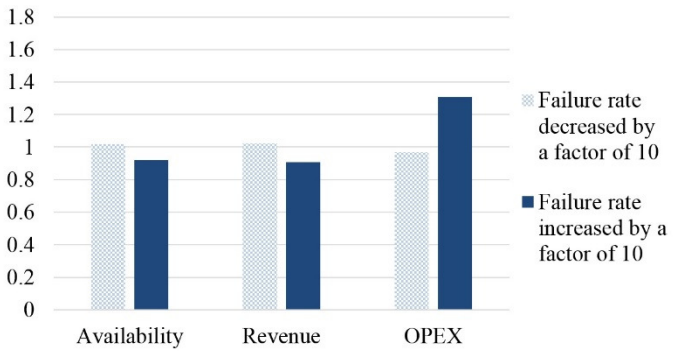

Figure 28: Sensitivity analysis results for 'Control system faults' at site B, normalised against the base case

Similar to category 7, a control systems failure can arise from several sources such as the pressure sensors in a ram manifold. This cumulative effect leads to the control systems failure having the third largest base failure rate of all 16 fault categories. Obtaining the failure rate for this category is made difficult due to different specifications of pressure sensor having very different failure rates, and also because pressure sensor failure rates are highly dependent on the operating environment. When comparing categories 7 (half circuit failure) and 11 (control systems), it can be seen that they have the exact same values for power loss (0.2), time to fix (2 days) and repair costs (£3,000 in total). The three differences that may contribute to the variation in the sensitivity analysis results are the base failure rate (P_{fail} = 0.36 for half circuit failure versus P_{fail} = 0.2604 for control systems failure), classification (intermediate versus minor) and labour requirements (two technicians versus one). Although a previous study has shown labour logistics to have a significant effect on the operability of the wave farm (Gray & Johanning, 2016), the simulations in this paper do not delay repairs to a lack of technicians. The much larger increase in OPEX when the base failure rate for category 7 is increased by a factor of 10 compared to the same scenario for category 11 (63-65% versus 27-31%) must be attributed to the greater base failure rate. However, this does not explain the variation in availability and revenue. With the half circuit failure having the greater base failure rate, it was expected that the scenario of increasing it by a factor of 10 would lead to a greater decrease in availability and revenue than for the control systems category. The reverse has been shown in the results which could perhaps be explained by the different classifications of the two faults. As stated in the methodology (section 2), if a device suffers either one major fault or two intermediate ones, then it is retrieved for repair as soon as weather permits. Therefore, the fact that a half circuit failure is classed as an intermediate fault could mean that the O&M model sets devices for immediate retrieval more when the base failure rate is increased, thus avoiding the complexities of the CBA.

Another fault category with similar parameters to the control systems one is category 15; secondary hydraulic failure (see Table A.1, section 9). It has the fourth highest base failure rate at P_{fail} = 0.2256, has total repair costs of £3,500, takes one technician two days to carry out the repair and is also

classed as a minor fault. The biggest difference between the two categories is the associated power loss; 0.2 for control systems and 0.06 for secondary hydraulic. The results from the sensitivity analysis show that changing the base failure rate of category 15 has less of an impact than category 11 (figures 29-30). This indicates that the power loss associated with a control systems failure is a significant factor. Therefore, redundancy needs to be built into WEC subsystems in order to minimise the power loss and improve the profitability of the wave farm.

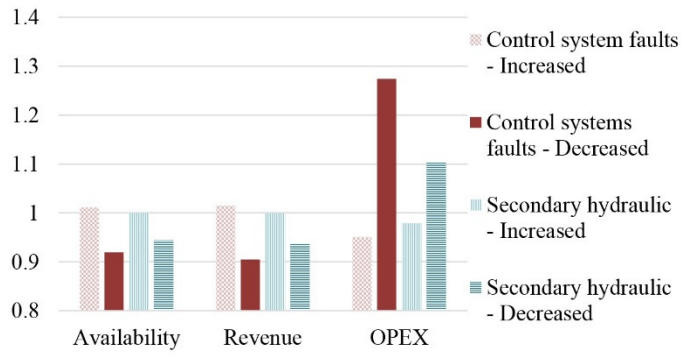

Figure 29: Comparison of sensitivity analysis results at site A for 'Control system faults' and 'Secondary hydraulic' failures, normalised against the base case

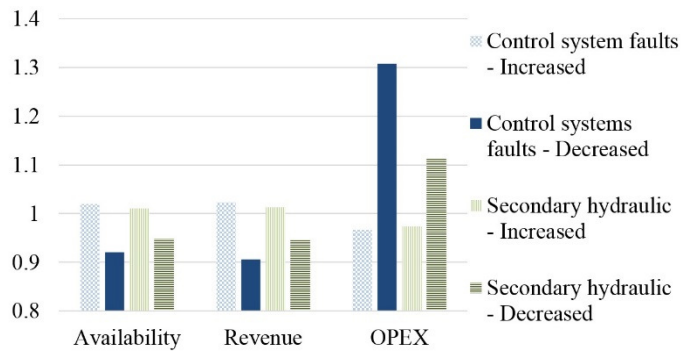

Figure 30: Comparison of sensitivity analysis results at site B for 'Control system faults' and 'Secondary hydraulic' failures, normalised against the base case

4.2.6. Faults leading to immediate recovery

Category 2 ('major structural – no warning') shows the third largest increase in OPEX when the base failure rate is increased by a factor of 10 (see Table A.4), at 54 % and 56.4% for sites A and B respectively. However, the decrease in availability (~1%) and revenue (~1.5%) is negligible in comparison. This difference is due to the classification of category 2 as a major failure. The O&M tool does not enter the cost-benefit analysis calculations when a major failure occurs, instead it sets the affected machine for removal and repair as soon as a weather window is open. This effect can also been seen to a lesser extent in the results for categories 1 ('major mooring') and 3 ('major structural – identified'). Category 2 sees the largest impacts because it has the highest failure rate of the three and requires the longest time off site for repair (see Table A.1, section 9). This decision making process also occurs when power output on a machine drops to zero, which is why similar results are produced for category 10 ('electrical unions & tieback'), even though it is classed as intermediate. The base failure rates for these four categories are already so minimal that similar impacts do not occur when the failure rate is decreased by a factor of 10.

5. Conclusion

This study has seen an Operations and Maintenance (O&M) simulation tool used to address the two issues of site characteristics affecting accessibility and power performance of wave energy arrays, and uncertainty surrounding failure rate estimates. The Monte Carlo-based O&M tool uses failure rate data that has been obtained for the Pelamis P2 device to model the operations and maintenance activities undertaken on a 10 machine wave farm over a lifetime of 20 years. The tool uses the Pelamis approach of using low cost vessels for rapid installation and removal of devices, with repairs taking place offsite at a sheltered quayside. The majority of the inputs to the model, including the failure rate data, have been informed by the P2 testing programme undertaken at the European Marine Energy Centre (EMEC) from 2008 to 2014. One key input is a weather time series containing values for significant wave height, wave period and wind speed. Two sites at different ends of the UK have been analysed in this study.

Characteristic analysis of the two sites initially showed that there was very little difference in terms of accessibility. However, some variation in power performance was identified when the occurrence tables for the two sites were matched to the power matrix for the Pelamis P2 device. The outputs of the O&M tool confirmed the expected variation in power performance, where a 10% difference in revenue was identified between the two sites, based on device performance in different wave climates. These results suggest that a wave energy converter (WEC) should be designed for the weather conditions at a specific site in order to maximise revenue. Despite the differences between the two sites in terms of revenue and OPEX identified in the base case results, the relative trends in terms of fault category sensitivity align perfectly. This was to be expected as the failure rates remain constant for each simulation and are not affected by changes in weather conditions. A more comprehensive assessment of the site differences could be achieved by having the failure rate inputs of certain components dependent on weather conditions. Further real sea testing by WEC developers is required before this level of data becomes available.

The sensitivity analysis on the failure rate inputs to the O&M tool has identified hydraulic valves as the component most sensitive to changes in estimated failure rate in the Pelamis P2 device. To minimise the uncertainty surrounding failure rates of these valves, as well as other components, WEC developers should collaborate with manufacturers to design and test components for the marine environment. In cases where several individual faults can cause the same overall failure within a WEC, the associated components must be over engineered and tested to reduce the impact on operability of a wave farm. In addition, redundancy of components must be built in to WEC subsystems to minimise the power loss associated with faults. It is vital that major failures, such as a structural breach, are considered are planned for in order to deal with such occurrences in a rapid and co-effective manner.

This study has demonstrated how an O&M simulation tool can enable effective budgeting and planning of a wave energy farm. It has highlighted how the tool can assist in strategic decision making such as port location and farm design. In addition, by using an O&M model to undertake a sensitivity analysis, a technology developer will be able to prioritise the design of certain components and subsystems to ensure that the WEC achieves its full potential when deployed in a wave farm.

6. Further Work

At present, the failure rate data is given to the O&M tool as constant values throughout the lifetime of the wave energy array. This is a flawed assumption as some components within a WEC would be likely to degrade over time, as well as being affected by changes in weather conditions. It is also true that the failure rates presented in this study are likely to be more representative of early ‘infant mortality’ failures, given that the values have been inferred from the experience gained during the

Pelamis P2 testing programme. Future O&M tools should be more realistic in this regards, perhaps by applying a Weibull distribution model to replicate component degradation. This would also pave the way for incorporating a predictive maintenance strategy, whereby WECs are scheduled for inspection when certain components have reached a certain level of risk in terms of potential failure. Increased application of condition monitoring systems in real-sea wave energy testing programmes is vital for this type of failure rate modelling.

In order to obtain realistic outputs, a wave energy O&M simulation tool must be device specific due to the complexity of the inputs and variables involved. There is no such thing as a *realistic* and *generic* O&M tool for WECs because of the lack of convergence on a single device design. Many of the inputs contain a level of uncertainty which can be addressed through further sensitivity analysis. An example is the vessel costs where, for this study, a day rate has been assumed and unaltered for inflation over time. Further work will involve assessing different vessel hire or purchase arrangements to identify the optimal strategy for wave farm logistics. The O&M tool is also a 'living' software tool in that real sea testing will improve the inputs to the model and therefore provide more confidence in the outputs. Further work will involve identifying the development steps required to build the O&M tool around another wave energy device. Such a process will be extremely useful for developers of WEC technology at an early stage of development because the O&M tool outputs can provide feedback into the design of their device, thus enabling iterative improvements. Once a WEC developer has achieved a level of operational experience with their device, the O&M tool could be used for due diligence and cost estimation, thereby making projects more attractive for commercial investment.

7. Acknowledgements

The lead author would like to thank the co-authors for their support in proof reading the paper and providing vital feedback. Thanks must also go to the Pelamis engineers who undertook the P2 testing programme and provided the inputs for the O&M tool used in this study. Wave data for site B was provided by the University of Exeter, and the matching wind speed data was obtained from the Channel Coastal Observatory's MET station, installed by the University of Plymouth. The lead author would also like to thank Wave Energy Scotland, the IDCORE programme and its funding bodies, in particular the ETP (Energy Technology Partnership), for their support. IDCORE is funded by the Energy Technology Partnership and the RCUK Energy Programme; Grant number EP/J500847/1.

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9. Appendix

ID	Full name	Classification	Probability of failure per year	Power loss	Parts cost (£k)	Other costs (£k)	Days off-site
1	Major mooring	Major	0.01594	1	20	30	5
2	Major structure (no warning)	Major	0.0624	0.5	15	30	15
3	Major structural failure (identified through monitoring system)	Major	0.03017	0.5	15	20	10
4	Major primary hydraulic	Major	0.00997	1	10	5	5
5	Loss of GPS comms & main comms	Major	0.004	1	2	2.5	2
6	Major sealing	Intermediate	0.03174	0.33	1	2	5
7	Half circuit failure	Intermediate	0.36	0.2	1	2	2
8	Minor mooring	Intermediate	0.03371	0	2.5	5	3
9	Data communications	Intermediate	0.01395	0.33	1	2	2
10	Electrical unions/ tieback	Intermediate	0.0396	1	25	5	2
11	Control system	Minor	0.2604	0.2	1	2	2
12	Minor structural	Minor	0.02621	0	2	2	2
13	Minor primary hydraulic	Minor	0.9375	0.05	0.15	1	1
14	Minor sealing	Minor	0.19	0	0.25	2	2
15	Secondary hydraulic	Minor	0.2256	0.06	1.5	2	2
16	Generator or switchgear	Minor	0.0396	0.06	1	2	2

Table A.1, part i: O&M tool fault categories and associated parameters

ID	Full name	Moorings specialists required	Hydraulic specialists required	Structural specialists required	Electrical specialists required	Other technicians required
1	Major mooring	2	0	0	0	1
2	Major structure (no warning)	0	0	3	0	1
3	Major structural failure (identified through monitoring system)	0	0	2	0	1
4	Major primary hydraulic	0	1	0	0	1
5	Loss of GPS comms & main comms	0	0	0	1	1
6	Major sealing	0	0	3	0	1
7	Half circuit failure	0	0	0	1	1
8	Minor mooring	2	0	0	0	1
9	Data communications	0	0	0	1	1
10	Electrical unions/ tieback	0	0	0	1	1
11	Control system	0	0	0	1	0
12	Minor structural	0	0	1	0	1
13	Minor primary hydraulic	0	1	0	0	0
14	Minor sealing	0	0	1	0	0
15	Secondary hydraulic	0	1	0	0	0
16	Generator or switchgear	0	0	0	1	0

Table A.1, part ii: O&M tool fault categories and associated parameters

Full name	Type	Interval if machine in for another repair	Interval if vessel is on hire	Maximum allowable time	Parts cost (£k)	Other costs (£k)	Inspection costs (£k)	Days off-site	Moorings specialists required	Hydraulic specialists required	Structural specialists required	Electrical specialists required	Other technicians required
Routine service	Time	May - every year	July - every year	September - every year	2	1	3.25	7	0	1	1	1	1
Half-life refit	Time	May - year 10	July - year 10	September - year 10	100	3	47.25	30	0	2	2	2	1

Table A.2: O&M tool scheduled maintenance categories and associated parameters

Base Case	Site	Availability (per year)	Revenue (£k per year)	OPEX (£k per year)
	A	0.868	2848.9	1116.3
	B	0.857	2570.0	1087.7

Category		Pfail > Site	Availability (per year)		Revenue (£k per year)		OPEX (£k per year)	
			Decreased	*Increased*	Decreased	*Increased*	Decreased	*Increased*
1	Major mooring	A	0.867	*0.870*	2842.1	*2854.6*	1101.1	*1227.7*
		B	0.859	*0.863*	2573.3	*2591.0*	1080.5	*1212.9*
2	Major structure (no warning)	A	0.863	*0.857*	2829.2	*2807.0*	1046.0	*1718.5*
		B	0.858	*0.848*	2574.3	*2534.0*	1030.9	*1701.2*
3	Major structural failure (identified through monitoring system)	A	0.867	*0.865*	2843.1	*2834.1*	1068.2	*1338.3*
		B	0.857	*0.859*	2571.4	*2577.9*	1047.8	*1317.6*
4	Major primary hydraulic	A	0.866	*0.871*	2838.9	*2857.7*	1103.0	*1152.4*
		B	0.855	*0.860*	2559.6	*2581.3*	1065.0	*1137.8*
5	Loss of GPS comms & main comms	A	0.863	*0.870*	2830.7	*2856.7*	1088.2	*1101.3*
		B	0.858	*0.859*	2570.4	*2574.6*	1096.9	*1103.8*
6	Major sealing (ram bellows seals etc)	A	0.866	*0.855*	2841.4	*2795.8*	1092.0	*1187.9*
		B	0.860	*0.843*	2581.1	*2515.6*	1088.0	*1151.6*
7	Half circuit failure	A	0.880	*0.820*	2895.8	*2635.9*	1033.4	*1836.7*
		B	0.871	*0.816*	2622.4	*2400.6*	1028.0	*1774.2*
8	Minor mooring	A	0.864	*0.873*	2829.2	*2866.4*	1108.3	*1181.4*
		B	0.859	*0.866*	2576.0	*2600.1*	1090.0	*1144.0*
9	Data communications (NB GPS OK)	A	0.868	*0.859*	2849.3	*2813.5*	1071.0	*1138.8*
		B	0.856	*0.859*	2565.6	*2579.1*	1080.2	*1117.8*
10	Electrical unions/ tieback	A	0.865	*0.868*	2838.6	*2836.5*	1086.8	*1327.1*
		B	0.859	*0.864*	2578.1	*2583.4*	1056.1	*1330.4*
11	Control system	A	0.878	*0.799*	2890.5	*2577.6*	1061.1	*1421.7*
		B	0.874	*0.789*	2629.2	*2328.8*	1051.5	*1423.1*
12	Minor structural	A	0.866	*0.868*	2840.7	*2850.4*	1113.7	*1090.3*
		B	0.858	*0.857*	2571.2	*2571.3*	1082.3	*1103.4*
13	Minor primary hydraulic	A	0.925	*0.646*	3065.0	*2067.9*	1118.2	*1760.0*
		B	0.923	*0.634*	2801.3	*1855.1*	1096.1	*1756.5*
14	Minor sealing	A	0.868	*0.853*	2845.4	*2804.6*	1097.5	*1155.0*
		B	0.865	*0.853*	2597.6	*2564.1*	1090.7	*1151.7*
15	Secondary hydraulic	A	0.869	*0.820*	2847.6	*2671.6*	1092.9	*1233.1*
		B	0.866	*0.813*	2601.8	*2431.1*	1058.5	*1211.8*
16	Generator or switchgear	A	0.864	*0.856*	2829.2	*2801.5*	1087.9	*1128.3*
		B	0.861	*0.850*	2584.4	*2545.3*	1087.1	*1095.8*

Table A.3. Results from O&M tool sensitivity analysis

Category		Pfail > Site	Percentage Increase from Base Case (%)					
			Availability		Revenue		OPEX	
			Decreased	*Increased*	Decreased	*Increased*	Decreased	*Increased*
1	Major mooring	A	-0.2	0.2	-0.2	0.2	-1.4	10.0
		B	0.2	0.6	0.1	0.8	-0.7	11.5
2	Major structure (no warning)	A	-0.6	-1.2	-0.7	-1.5	-6.3	54.0
		B	0.1	-0.9	0.2	-1.4	-5.2	56.4
3	Major structural failure (identified through monitoring system)	A	-0.1	-0.3	-0.2	-0.5	-4.3	19.9
		B	0.1	0.2	0.1	0.3	-3.7	21.1
4	Major primary hydraulic	A	-0.3	0.3	-0.4	0.3	-1.2	3.2
		B	-0.2	0.4	-0.4	0.4	-2.1	4.6
5	Loss of GPS comms & main comms	A	-0.5	0.2	-0.6	0.3	-2.5	-1.3
		B	0.1	0.2	0.0	0.2	0.8	1.5
6	Major sealing (ram bellows seals etc)	A	-0.3	-1.3	-0.3	-1.9	-2.2	6.4
		B	0.3	-1.4	0.4	-2.1	0.0	5.9
7	Half circuit failure	A	1.1	-4.9	1.6	-7.5	-7.4	64.5
		B	1.5	-4.1	2.0	-6.6	-5.5	63.1
8	Minor mooring	A	-0.5	0.5	-0.7	0.6	-0.7	5.8
		B	0.2	0.9	0.2	1.2	0.2	5.2
9	Data communications (NB GPS OK)	A	0.0	-0.9	0.0	-1.2	-4.1	2.0
		B	0.0	0.2	-0.2	0.4	-0.7	2.8
10	Electrical unions/ tieback	A	-0.3	-0.1	-0.4	-0.4	-2.6	18.9
		B	0.2	0.7	0.3	0.5	-2.9	22.3
11	Control system	A	1.0	-6.9	1.5	-9.5	-4.9	27.4
		B	1.7	-6.8	2.3	-9.4	-3.3	30.8
12	Minor structural	A	-0.2	-0.1	-0.3	0.1	-0.2	-2.3
		B	0.1	0.0	0.0	0.1	-0.5	1.4
13	Minor primary hydraulic	A	5.7	-22.2	7.6	-27.4	0.2	57.7
		B	6.6	-22.2	9.0	-27.8	0.8	61.5
14	Minor sealing	A	0.0	-1.5	-0.1	-1.6	-1.7	3.5
		B	0.8	-0.4	1.1	-0.2	0.3	5.9
15	Secondary hydraulic	A	0.1	-4.8	0.0	-6.2	-2.1	10.5
		B	1.0	-4.4	1.2	-5.4	-2.7	11.4
16	Generator or switchgear	A	-0.5	-1.2	-0.7	-1.7	-2.5	1.1
		B	0.4	-0.7	0.6	-1.0	-0.1	0.7

Table A.4. Results of sensitivity analysis in terms of percentage increase from base case