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Sensitivity Analysis of O&M Costs for Offshore Wind Farms

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Abstract

The offshore wind farm industry is challenged by high costs related to operation and maintenance (O&M), and a study on how to significantly reduce these costs is essential to make this industry competitive with other energy industries. For this purpose, it is important to understand which factors related to operation and maintenance are influencing the O&M costs. This study is concerned about sensitivity analysis, a common tool used to identify influential input parameters for computer models.

Three Sensitivity analysis methods were implemented and integrated with the computer model NOWIcob that simulates the operation and maintenance of an offshore wind farm. Two of the methods were local, and studied effects in the cost by changing one variable at the time, keeping all other parameters constant at their reference value. The third had a global perspective where all parameter values were selected randomly from a specified range around each parameters reference value. The capabilities of these methods were illustrated by applying them on a case with data for a hypothetical offshore wind farm.

Among the 15 single parameters considered, the local analysis identified a group of five single parameters (three failure rates, the variable cost for the jack-up vessel and the wave access limit for the mother ship) as the most influential on the total O&M cost on this wind farm. The global method confirmed that results from the local method are also valid for a wider range of the parameter values. The results provide suggestions about how to reduce the cost, and the installation of a more robust access system on the mother ship seems to be a possible way to significantly reduce the total O&M cost for the wind farm under consideration.

Sammendrag

Offshore vindindustri møter i dag utfordringer knyttet til kostnader relatert til drift og vedlikehold, og undersøkelser med mål om å redusere disse kostnadene er essensielle for å gjøre denne industrien konkurransedyktig med andre energiindustrier. Denne oppgaven fokuserer på sensitivitetsanalyse, et vanlig verktøy for å identifisere innflytelsesrike input-parametere for et dataprogram.

Tre sensitivitetsanalyse metoder ble implementert og integrert i dataprogrammet NOWIcob som simulerer drift og vedlikehold på en offshore vindpark. To av metodene var lokale, og analyserte endringen i kostnader ved å endre en variabel av gangen, mens alle andre variable ble holdt konstant på deres referanseverdier. Den tredje metoden hadde et globalt perspektiv, der alle parameterverdier ble valgt tilfeldig fra et spesifisert område rundt hver parameters referanseverdi. Evnene til disse metodene ble illustrert ved å anvende dem på et tilfelle, med data for en hypotetisk offshore vindpark.

Blant de 15 valgte parametrene, identifiserte den lokale metoden en gruppe av fem parametere (tre feilrater, kostnaden for kranskipet (jack-up) og bølgehøydebegrensingen til moderskipet) som de mest innflytelsesrike for de totale kostnadene knyttet til drift og vedlikehold på vindparken. Den globale metoden bekreftet at resultater fra den lokale metoden også er gyldige for et større område av parameterverdier. Resultatene gav konkrete forslag til å redusere kostnader. Montereing av et mer robust tilgangssystem for moderskipet ser ut til å være en mulig måte å redusere de totale kostnadene knyttet til drift og vedlikehold på vindparken.

Preface

This Master's thesis concludes my Master of Science degree in Applied Physics and Mathematics, with Applied Physics as the main profile. The work has been done in a collaboration with SINTEF Energy Research and the Department of Physics at Norwegian University of Science and Technology(NTNU).

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Chapter 1

Introduction

1.1 Motivation and objectives

Offshore wind energy is a developing industry. As an example, the total installed offshore wind capacity was around 4 GW in 2011, but is expected to increase to 40 GW by 2020 [1]. The expected benefits of more wind energy and the lower visual impact of the larger turbines, are some of the arguments to install wind farms offshore. However, the offshore wind industry is challenged by higher costs which by 2009 was around 50% higher compared to onshore wind power [2]. An important contribution to the cost for offshore wind power are costs related to operation and maintenance (O&M), which may contribute up to 30% of the total cost of energy [3].

These costs also have a significant variability, for instance due to the randomness of the weather offshore, which for investors put a financial risk in addition to already high costs. Therefore, a study to significantly reduce the O&M costs is important in order to make the offshore wind industry competitive with other energy industries. For this purpose, quantitative computer models that simulates the whole life cycle of an offshore wind farm and estimates both costs and benefits have been developed [4].

One such model is the NOWIcob model (**N**orwegian **o**ffshore **w**ind power life cycle **c**ost and **b**enefit model), currently under development at SINTEF Energy Research [5]. With parameters that define a wind farm and the operation and maintenance strategy at this wind farm as input, this model simulates operation and maintenance of an offshore wind farm over its complete life time. As output the model estimates several performance parameters, such as the O&M costs, and the income from the electricity production.

The intention of this work is to use the NOWIcob model to identify influential parameters for the operation and maintenance costs of a wind farm. More specific, to implement modules that controls the input parameters in the NOWIcob model and performs sensitivity analysis. Sensitivity analysis is a widely used tool for computer models [6], but sensitivity analysis conducted on a simulation model for operation and maintenance of offshore wind farms, is to the author's knowledge rarely used.

1.2 Outline

This thesis is organized as follows: Chapter 2 is a theoretical study about sensitivity analysis methods considered to be applied for the NOWIcob model. A more detailed description of the NOWIcob model follows in Chapter 3. Chapter 4 is divided into two parts. First data for a hypothetical offshore wind farm are presented together with some case specific description of the NOWIcob model. In the second part the implementation of the sensitivity analysis modules are described. Chapter 5 presents the results from the sensitivity analysis applied on the hypothetical wind farm. Discussion about the results together with suggested applications follows in Chapter 6. The conclusions that can be drawn from this study are presented in Chapter 7.

Chapter 2

Sensitivity analysis

Sensitivity analysis (SA) studies the relationship between information flowing in and out of a model [7]. This somewhat non-specific definition is caused by the fact that sensitivity analysis involves a large group of methods with a great range of applications. This chapter introduces some of the many available sensitivity analysis methods which have been considered to be applied for the NOWIcob model. The different methods of sensitivity analysis may be divided into three main categories [7]:

- **Factor screening**, in which the purpose is to identify influential input parameters in a model with many input parameters. These methods can with use of relatively few computational runs identify the subset of input factors that control most of the output variability, and therefore these methods are also recommended for complex models which require long time for a computational run.
- **Local SA**, where the task is to study the models behavior around a nominal point of factors. Local methods often involves estimation of partial derivatives.
- **Global SA**, where the goal is to apportion the output uncertainty to the uncertainty in the input factors. These methods explores the whole space of possible values for the input parameters. These methods are usually the most computationally expensive, but also the most informative.

For all methods the same terminology will be used. A number of k input factors is chosen for the sensitivity analysis. The input factor will be represented as a vector $\mathbf{x} = (x_1, x_2, \dots, x_k)$. The output of the model is denoted $y = y(\mathbf{x})$.

When sensitivity analysis is applied on a computer program, a part of the analysis consists of selecting a set of input parameters for the analysis. Choosing the set of parameters is often denoted as the *design of experiment*. Some common designs will also be presented in addition to some common methodologies of sensitivity analysis.

2.1 Screening methods

The main purpose of a screening method is to identify which of the model factors are most important for the variation in the models output with a relatively low computational cost. These methods can rank the input factors after their importance, but do not give any quantitative measurement of how much more important a given parameter is compared to another. A survey of different screening methods are given in [8], and some of them are presented in the following sections.

2.1.1 One at a time (OAT) designs

OAT designs study effects of perturbing one parameter at the time. In its standard form a base case \mathbf{x}^* of the models parameters is chosen, and each input parameter are evaluated in turn by perturbing its value up and down from this base case. With this approach, $2k + 1$ computational runs is needed (one for the base case and $2k$ for the upper and lower bounds for each factor). The main advantage of this method is its simplicity combined with a low computational cost. The limitation is of course that this method cannot estimate whether interactions among the parameters or non-linear effects are present.

2.1.2 Morris's OAT design

This method was proposed by Morris [9], and denoted as a global sensitive experiment in [8], because the experiments cover the entire space of the input parameters. This method requires more computational runs than the standard OAT, but has the ability to estimate if interaction or nonlinear effects is associated with a parameter in addition to the main effect. The rest of this sub section describes this method.

The k -dimensional input space is characterized by k input parameters, each with p possible values in the set $\{0, 1/(p-1), 2/(p-1), \dots, 1\}$. The region Ω of input parameters is then a k -dimensional p -level grid.

This method involves calculation of *elementary effects* associated with an input parameter. The elementary effect for the i th input parameter is defined by

$$d_i(\mathbf{x}) = \frac{y(x_1, x_2, \dots, x_{i-1}, x_i + \Delta, x_{i+1}, \dots, x_k) - y(\mathbf{x})}{\Delta} \quad (2.1)$$

where \mathbf{x} is in Ω except that $x_i \leq 1 - \Delta$, and Δ is a predetermined multiple of $1/(p-1)$. The elementary effect is a measure of the main effect for the parameter. In general the value of $d_i(\mathbf{x})$ is a function of \mathbf{x} , and Morris distinguishes three ways elementary effects vary with the parameter configuration \mathbf{x} :

1. If $d_i(\mathbf{x})$ is only depended of x_i the parameter has non-linear effects.
2. If $d_i(\mathbf{x})$ is depended on one or more x_j , where $i \neq j$ the parameter is said to have interaction effects.

3. A combination of 1. and 2., which indicates that the parameter is involved in both non-linear and interaction effects.

With the given parameter space a total number of $p^{(k-1)}[p - \Delta(p-1)]$ different elementary effects exists for each input parameter. The discrete distribution of the elementary effects for the i th input parameter is denoted F_i . The main methodology is to select random samples from the k distributions F_i , $i = 1, \dots, k$ and analyze them through their sample mean and standard deviation. A large empirical mean in F_i indicates that the i th parameter has an overall influence on the models output. The sample standard deviation indicates the elementary effects dependency on the parameter configuration, which is a measure of interactions and/or nonlinear effects associated with this parameter.

In its simplest form, selecting a random element from F_i can be done by randomly selecting a parameter configuration \mathbf{x} , increasing the i th parameter with Δ and calculate the elementary effect by Equation (2.1). By repeating this procedure r times, a total number of r elementary effects can be sampled from F_i . This method requires $2r$ simulations for each input factor which results in a total of $2rk$ simulations for all k factors.

However Morris [9] also proposed a more economic method which only requires $(k+1)r$ simulations. For this method it is convenient to assume that p is even and $\Delta = p/[2(p-1)]$ to ensure that each of the $p^k/2$ elementary effects for the i th input parameter has equal probability of being selected [9].

In this method $k+1$ vectors denoted $\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(k+1)}$ of parameter configurations are selected such that two consecutive vectors differ in only one component. It is also required that the actual input factor x_j which is different in the two consecutive vectors is different for each couple of consecutive vectors. With these restrictions for the $k+1$ parameter configurations, a total of k elementary effects (one for each input factor) can be calculated from the vectors by:

$$d_j(\mathbf{x}^{(n)}) = \pm \left(\frac{y(\mathbf{x}^{(n+1)}) - y(\mathbf{x}^{(n)})}{\Delta} \right) \quad (2.2)$$

where j indicates which factor which is different in the two vectors $\mathbf{x}^{(n+1)}$ and $\mathbf{x}^{(n)}$, and $+$ is used if $x_j^{(n+1)} > x_j^{(n)}$ and $-$ otherwise.

In practice one often constructs the $(k+1) \times k$ matrix \mathbf{B}^* whose rows containing the vectors $\mathbf{x}^{(1)} \dots \mathbf{x}^{(k+1)}$. This matrix is called the *orientation matrix*, and corresponds to a trajectory of k steps in the parameter space with $\mathbf{x}^{(1)}$ as starting point. Construction of such a matrix can be done by the following steps [9]:

1. Construct a $(k+1) \times k$ matrix \mathbf{B} , with elements of 1s and 0s with the property that for all columns $i = 1, 2, 3, \dots, k$ there exist two rows of \mathbf{B} that differ in only the i th element. In particular the matrix \mathbf{B} can be chosen to be a strictly lower triangular

matrix of 1s, i.e.

$$\mathbf{B} = \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 \\ 1 & 0 & 0 & \cdots & 0 \\ 1 & 1 & 0 & \cdots & 0 \\ 1 & 1 & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & 1 & 1 & \cdots & 1 \end{pmatrix}$$

2. Let \mathbf{x}^* be a randomly chosen base value for \mathbf{x} . Each element in \mathbf{x}^* is assigned a value from the set $\{0, 1/(p-1), \dots, 1-\Delta\}$, each with equal probability.
3. Let \mathbf{D}^* be a $k \times k$ diagonal matrix where each diagonal element is either +1 or -1 with equal probability, and \mathbf{P}^* a $k \times k$ random permutation matrix, in which each column contains one element equal 1 and all other equal 0, and no two columns have 1's in the same position.
4. The orientation matrix can then be calculated as follows:

$$\mathbf{B}^* = (\mathbf{J}_{k+1,1}\mathbf{x}^* + \frac{\Delta}{2}[(2\mathbf{B} - \mathbf{J})\mathbf{D}^* + \mathbf{J}])\mathbf{P}^* \quad (2.3)$$

where \mathbf{J} is a $k+1 \times k$ matrix of 1s, and $\mathbf{J}_{k+1,1}$ is a $k+1 \times 1$ column vector.

By repeating this procedure r times, r independent orientation matrices \mathbf{B}^* can be constructed. Each of the r elementary effects for a specific input factor is independent from each other such that the standard formulas for sample mean and standard deviation for independent stochastic variables can be used as measures for a factors influence in the output:

$$\bar{d}_i = \frac{1}{r} \sum_{j=1}^r d_i(j) \quad (2.4)$$

$$S_i = \sqrt{\frac{1}{r-1} \sum_{j=1}^r (d_i(j) - \bar{d}_i)^2} \quad (2.5)$$

The main disadvantage of this method is that it does not give detailed information about interactions [7]. Only information about an overall interaction one parameter has to the model can be measured.

Cotters design

This design was proposed by Cotter [10] and is denoted as a *systematic fractional replicate design*. This design does not require any assumptions about parameter interactions or nonlinearity. The parameter space is characterized by two distinct values for each of the k input parameters. The following $2k+2$ runs characterize Cotters design:

- One run with all input parameters at their low level.

- k runs with each parameter in turn at its upper level while all other $k - 1$ parameters remain at their lower level.
- k runs with each parameter in turn at its lower level, while all other $k - 1$ parameters remain at their upper level.
- One run with all parameters at their upper level.

From these runs the output denoted $y_0, y_1, \dots, y_k, y_{k+1}, \dots, y_{2k}, y_{2k+1}$ is calculated. Cotter defines $S_o(j)$ and $S_e(j)$ to be the sum of the odd-order and even-order effects involving the j th parameter respectively, which can be estimated by:

$$C_o(j) = \frac{1}{4}[(y_{2k+1} - y_{k+j}) + (y_j - y_0)] \quad (2.6)$$

$$C_e(j) = \frac{1}{4}[(y_{2k+1} - y_{k+j}) - (y_j - y_0)] \quad (2.7)$$

The measure $M(j) = |C_o| + |C_e|$ can be used to estimate the order of importance of the j th input factor. The main disadvantage of this method is the lack of precision. It is also argued in [8] that important parameters may be undetected if a parameter has effects that cancel each other out.

2.2 Local methods

Local sensitivity methods study the models behavior around a set \mathbf{x}^* of nominal values for the input parameters. Usually the *first order local sensitivity coefficients* are calculated and studied. They correspond to the partial derivatives of the models output with respect to its input parameters. For instance:

$$s_i = \frac{\partial y}{\partial x_i} \quad (2.8)$$

corresponds to the *first order local sensitivity coefficient* with respect to the parameter x_i .

The sensitivity coefficient s_i is a linear approximation of the dependency of the output on changes in the parameter x_i . In order to bring the sensitivity coefficients to a common scale it is convenient to multiply them with the corresponding parameter value. The resulting number denoted as *the scaled sensitivity coefficient* is given by:

$$S_i = \frac{\partial y}{\partial x_i} x_i \quad (2.9)$$

These coefficients are useful to compare the importance of the input parameters for variation in the models output around the nominal point.

For computer models, no explicit formula for the models output exist, and the sensitivity coefficients has to be estimated numerically. The most straightforward way is the use of the finite difference approximation, more specific the *central difference* may be applied:

$$s_i \approx \frac{y(x_i + \Delta x_i) - y(x_i - \Delta x_i)}{2\Delta x_i} \quad (2.10)$$

Here a sufficiently small Δx_i should be chosen to ensure a good approximation.

Local methods for sensitivity analysis are discussed in detail in [11]. The following SA methods can be classified as global, because the entire input space are considered.

2.3 Sampling based methods

Sampling based methods have a statistical point of view on the models parameter by assuming that the input factors $\mathbf{x} = (x_1, x_2, x_3, \dots, x_k)$ are uncertain and given by the joint probability distributions $p(\mathbf{x})$. By this definition of the input parameters, the output of the model will be a stochastic variable.

However, if the input parameters are independent from each other, probability theory states that the probability distribution $p(\mathbf{x})$ can be written as the product of the marginal distributions for each parameter. These distributions have to be specified, and the choice of these distributions will affect the results.

When the marginal distributions are chosen the next step is the sampling procedure which consists of a generating a sample \mathbf{x}_n , $n = 1, 2, 3, \dots, N$ of input parameters, where N is the size of the sample (the number of computer runs required). The simplest way of sampling is *random sampling* where each set of parameter values are independently drawn from their marginal distributions. However, other and more sophisticated sampling strategies have been developed, such as *Latin hypercube sampling* which ensures the full coverage of each variable in the sample [12].

When the sample is generated the N outputs from the model $y_n = y(\mathbf{x}_n)$, $n = 1, 2, \dots, N$ is calculated. The sample and the corresponding output from the model are the starting point for the sampling based sensitivity analysis methods.

2.3.1 Scatter plots

Sensitivity analysis by scatter plots is discussed in [6] and [12]. This is a fairly simple approach to sensitivity analysis and the method only involves plotting the output y against each input factor x_i , $i = 1, 2, 3, \dots, k$. More specific the points (x_{ni}, y_n) , $n = 1, 2, \dots, N$ is plotted for each input factor. The plots may give useful information on whether a parameter influences the output and both linear or nonlinear relations can be visualized. In addition it is also possible to calculate the correlation coefficient between each input and the models output as a measure of sensitivity, but as pointed out in [6], these coefficients only indicate the degree of linear relationship between the inputs and outputs, such that scatter plots in general are more informative. A drawback of this method is that interactions between parameters cannot be visualized in scatter plots. However, two-factor interactions can be visualized by tree-dimensional plots.

2.3.2 Regression analysis

A more quantitative method involves *regression analysis* where a linear regression model is fitted to the models output with respect to the inputs. A popular procedure is by use of *standardized variables*. In this case all the sampled input variables and the output are subtracted by their sample mean and divided by their sample standard deviation, before the linear regression model is fitted to the data. For the input parameter x_i with the sampled values as x_{1i}, \dots, x_{Ni} , the standardized values of x_{ni} , $n = 1, \dots, N$ are

$$\frac{x_{ni} - \bar{x}_i}{s_{x_i}}, \quad n = 1, \dots, N \quad (2.11)$$

where \bar{x}_i and s_{x_i} are the sample mean and standard deviation respectively, for the sample x_{1i}, \dots, x_{Ni} .

The regression coefficients obtained from this analysis, denoted as the standardized regression coefficients (SRCs) is a measure of the relative importance for each parameter. For interested readers a detailed description of sensitivity analysis by regression analysis is given in [12].

2.4 Variance-based methods

Variance based methods are a class of global sensitivity analysis methods that use variance as an indicator of importance for the input parameters. More specific, the method involves estimation of the quantity $\text{Var}_{X_i}[E(Y|X_i)]$, denoted as *variance of the conditional expectation* (VCE). This quantity is a suitable measure of the importance of the i th input parameter, since it measures the variation in y caused by the input variable x_i alone. The magnitude of VCE relative to the total variance is measured by

$$S_i = \frac{\text{Var}_{X_i}[E(Y|X_i)]}{\text{Var}(y)} \quad (2.12)$$

and is denoted as the *first order sensitivity index*. This index measures the main effect of x_i on the output. Common variance based methods are the *method of Sobol* and the *Fourier amplitude sensitivity test* (FAST), both presented in [13]. Both methods estimate sensitivity indices given by (2.12), but also provides estimates of higher order sensitivity indices. Higher order sensitivity indices measure interaction effects. For instance, the *second order sensitivity index* S_{ij} , $i \neq j$ measures the interaction effect between parameter x_i and x_j (the part of the variation in $y(\mathbf{x})$ due to x_i and x_j that cannot be explained by the sum of their main effects). In general the n 'th order sensitivity index measures interaction between n parameters.

The *total sensitivity index* (TSI) is a measure of the total effect a parameter has to the models output. For instance: TS_i is defined as the sum of all sensitivity indexes involving the factor x_i (main effect and all interactions). The variance based method typically estimates the first order sensitivity indices and the total sensitivity indices. Different ways of estimating the sensitivity indices distinguish the different variance-based sensitivity analyses.

Chapter 3

The NOWIcob model

NOWIcob is a life cycle cost and benefit model for offshore wind farms, written in MATLAB. The current version of this model is documented and described in [5]. With parameter input that describes the wind farm and the operation and maintenance strategies, the model simulates operation and maintenance of an offshore wind farm over the complete life time with an hourly time resolution. During the simulation the model calculates several performance parameters such as the O&M costs and the income from the electricity production as the result. Offshore maintenance operations are highly weather dependent and therefore weather uncertainty is considered in the model by using a Monte Carlo simulation approach: Several simulations are performed, each with different simulated weather scenarios. The results delivered by the model are therefore given by probability distributions, one for each performance parameter. A simplified flow scheme of the model is shown in Figure 3.1.

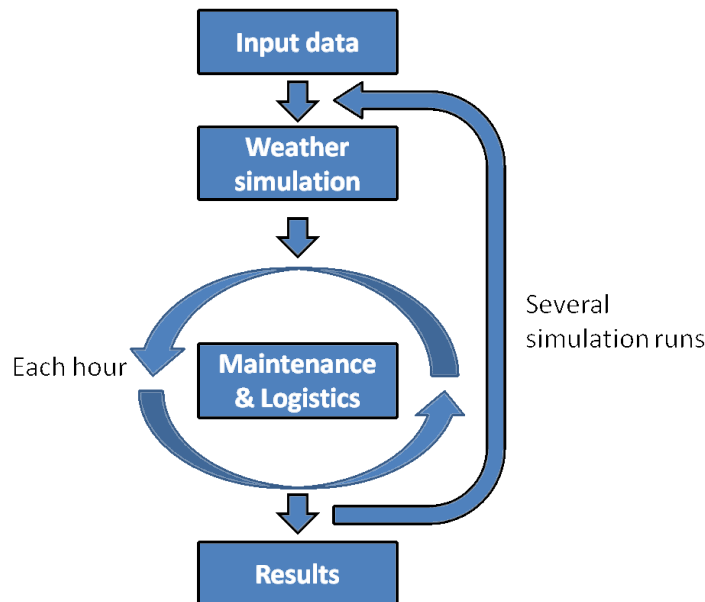


Figure 3.1: Simplified flow scheme of the NOWIcob model. Obtained from [5]

3.1 Parameter input

3.1.1 General input

These parameters contribute to a general description of the wind farm under consideration. Typically parameters are the size and number of different wind turbines, and location and the life time of the offshore wind farm. Different subcomponents of a wind turbine that need maintenance, such as gear box and rotor blade may also be defined.

3.1.2 Operation and maintenance parameters

The operation and maintenance parameters consist of all parameters that have an influence on the maintenance logistics, the O&M costs or the income from the electricity production. The parameter may be divided into two main groups: The controllable options and uncontrollable uncertainties. The controllable options defines the maintenance strategy and all logistics related to it. The uncontrollable uncertainties are not in control of anyone, and are affected by uncertainties. Some examples of operation and maintenance parameters are shown in Figure 3.2. The rest of this sub chapter describes the parameters in more detail.

Vessel data

In the model the resources to perform maintenance activities consist of a fleet of different vessels. A typical vessel is a boat with an access system so the maintenance personnel can access the wind turbine. Some vessels have extra abilities in addition to the access system, such as a crane to lift heavy components. The model also considers future vessel concepts such as mother/daughter ships. A mother ship is a vessel that stays offshore for long durations and carries one or more smaller daughter ships. Accessing an offshore wind turbine is highly weather depended and each vessel has specified weather limits in terms of maximum possible wave height and wind speed possible for accessing a wind turbine. A vessel cannot participate in any maintenance activity if the wave height or the wind speed exceeds its weather limits.

Personnel data

The controllable options related to maintenance personnel consists in defining the number of maintenance personnel at different locations and their working schedule. Maintenance personnel are located at bases, mother ships, or on other vessels that stay offshore for several days. Personnel at a base can use all vessels located at the base. The mother ships have their own dedicated personnel, who can operate the daughter ship and the mother ship itself for maintenance activities. The working time for the maintenance personnel are predetermined and specified by defining a working time per shift combined with the number of shifts per day.

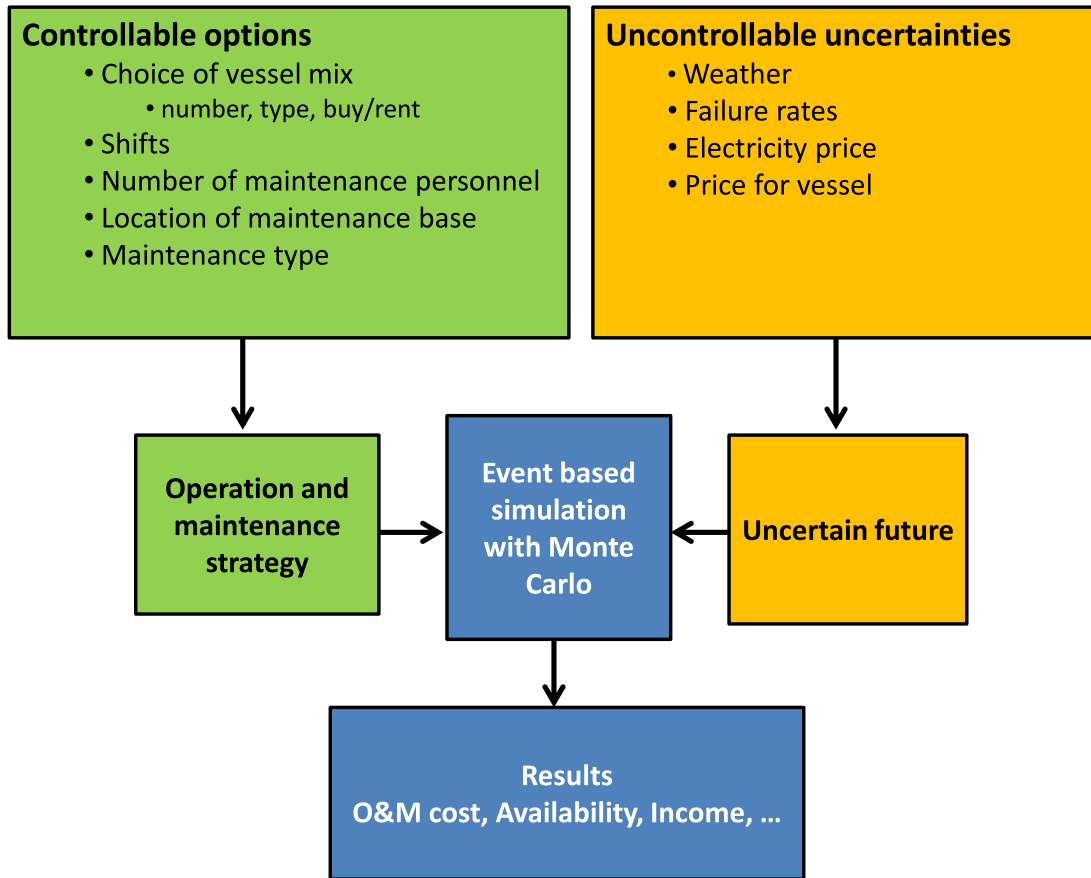


Figure 3.2: Controllable and uncontrollable parameters. Obtained from [5](slightly modified)

Maintenance data

For each component on the wind farm the model considers one or more maintenance tasks. For performing one of these maintenance tasks the model considers three types of resources:

- Spare parts and consumables
- Vessel(s)
- Maintenance personnel

Spare parts and consumables are considered in the model by specifying a lead time and a cost related to it. Otherwise it is assumed that they are always available. All maintenance activities that include traveling to the offshore wind farm need a vessel to transport the maintenance personnel. However some maintenance activities requires extra abilities, such as transport/lifting of heavy components. For these maintenance activities an extra vessel with these abilities is needed. Maintenance personnel is considered in the model by specifying the number of working personnel needed to perform the maintenance task.

The model also considers different maintenance strategies, and each maintenance task is assigned a specific maintenance strategy. Time based maintenance are performed at specified times each year. Corrective based maintenance is performed after a component of the offshore wind farm fails. The points in time when failures of a component occur are drawn from an exponential probability distribution with a given failure rate as input. The failure rate denotes the expected number of failures for that specific component per year and is specified for each corrective maintenance task.

3.2 Stochastic components

The weather is in the model represented by a time series of significant wave height and wind speed with an hourly time resolution. As mentioned earlier, both wave height and wind speed are important for the accessibility of an offshore wind farm. In addition the wind speed is needed in order to calculate the electricity production from the wind farm. The weather time series are generated by a Markov Chain model based on historical weather data from the location of the wind farm. The Markov Chain model simulates random weather based on estimated transition probabilities. A description of this weather model is given in [14].

As mentioned at the end of the last section the points in time when failures occur are drawn from an exponential probability distribution with the relevant failure rate as input. Given the failure rate λ for a component on a wind turbine, the probability distribution for the time duration Δt until a failure on that specific component occur is given by:

$$p(\Delta t) = \lambda e^{-\lambda \Delta t}. \quad (3.1)$$

The time duration Δt until next failure are drawn in two cases.

- At the start of the simulation: For all specified components on all wind turbines the point in time when the first failure occur are drawn independently from the exponential probability distribution (Equation (3.1)) with the relevant failure rate as input.
- After corrective maintenance are performed: The point in time when the next failure on the maintained component occur are drawn from the same distribution with the relevant failure for this corrective maintenance task and the current time as input.

The model is therefore able to repeat simulations, each with different and random weather scenarios and random times for failures to account for uncertainty in the weather and times for failures.

3.3 Maintenance and logistics

A typical course of action

An event triggering maintenance activity are typically failures of a component or time based service. A typical course of action after such an event is illustrated in Figure 3.3.

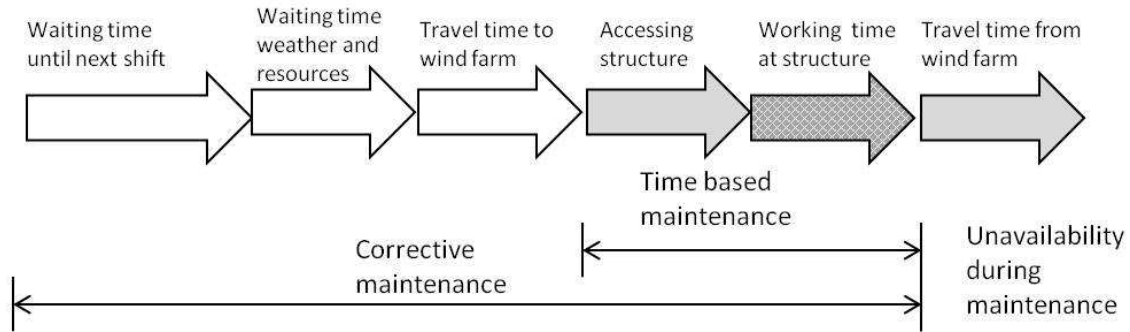


Figure 3.3: Example of a typical course of action for maintenance activity for one maintenance task. The horizontal lines illustrates the unavailability for the maintained component during the maintenance task. Obtained from [5](slightly modified)

Every maintenance task that includes traveling offshore to the wind farm has to be performed at the beginning of a new shift. Additional waiting time can occur in the case of adverse weather or if not enough resources such as vessels or personnel are available. When the maintenance task is scheduled the model calculates the travel time to the wind farm and the access time to enter the structure. The time available for working at the structure is also calculated and is limited by three factors:

- The remaining time left for the current shift.
- Adverse weather. Maintenance activity cannot be performed if the wind speed or the wave height exceeds the vessels weather limits.
- The remaining working time left before the maintenance task is fulfilled.

With the weather and the time left of the current shift as restrictions, the model decides to execute the maintenance activity if the available working time is above a predefined threshold level. In this analysis the minimum working time is 3 hours, unless the time left to fulfill the maintenance task is less than 3 hours. In that case the maintenance task is executed as long as the weather allows it. After the work is finished the maintenance personnel are leaving the structure and traveling back to their location. If the maintenance task were not fulfilled during the shift, the maintenance activity will continue at the next shift.

Also shown in Figure 3.3 is the down time of the component due to the maintenance task. For time based maintenance the maintained component will only be stopped when the personnel works at the structure including the access time. On the other hand corrective maintenance task will lead to a stop when the failure occurs. In this example the maintenance task is fulfilled and therefore the maintained component could be used right after the working personnel left the structure.

Prioritization of vessels and maintenance tasks

It is possible that several different vessels could be used to perform a maintenance task. In such a case the vessel with the most time available for performing this task in the current shift is used. Thereafter, the vessels are sorted by their costs. The cost for use of a vessel for a maintenance task is calculated as the product of the vessels variable cost and the time the vessel has to be used, for the maintenance task in the current shift.

It is also possible that several maintenance tasks are scheduled at the same time. Access vessels can serve different maintenance task in parallel, if the vessels personnel space allows it. In this case the working personnel are transported to the different offshore locations. They work in parallel (at the same time) and are picked up by the access vessel at the latest possible moment. Other vessels with special abilities can only perform maintenance tasks one after each other. It may of course happen that the maintenance tasks are competing for the limited resources. In this case the following priorities are applied. All maintenance tasks that have already started have the highest priority. Thereafter the maintenance tasks that need an extra vessel with special abilities are prioritized. And finally after type of maintenance, where corrective maintenance has highest priority.

3.4 Output

The output from the model consists of several performance parameters, all calculated for each set of weather data and times for failures. In particular the O&M costs, the income and the availability are of interest in this work.

3.4.1 Net present O&M costs

The O&M costs include all the costs related to the operation and maintenance on the wind farm during its life time. In the model the O&M costs are calculated as the sum of the following costs:

- Spare parts and consumable costs (fixed cost per maintenance task).
- Fixed vessel costs (yearly fixed costs per vessel).
- Variable vessel costs (fixed cost per hour in use of a vessel during a maintenance task).
- Personnel costs (yearly fixed costs per maintenance person).
- Costs for using a location, such as a harbor, offshore platform, etc. (yearly fixed cost per location).
- Cost for transporting personnel to locations as mother ship, offshore platforms (yearly fixed costs).

The O&M cost are calculated per year and discounted with a given discount rate to obtain the net present O&M costs, denoted $C_{O\&M}$.

3.4.2 Availability

The electricity production for each wind turbine is calculated considering down time due to failures and maintenance activity at this turbine. In the calculation the model considers the wind turbines power curve and the wind speed time series. The power curve is the relation between power produced by the wind turbine and the wind speed. The total electricity production E_{real} is the sum of the electricity production for all wind turbines. The model also calculates the maximum electricity production E_{max} , where down time due to failures and maintenance is not considered. Thus the availability is defined by

$$A_{el} = \frac{E_{real}}{E_{max}}, \quad (3.2)$$

which is a measure of the efficiency of the wind farm in terms of electricity production.

3.4.3 The net present income from the electricity production

Given the monthly price scenario for electricity production the income from the electricity production is calculated per year and discounted with the specified discount rate to obtain the net present income. In the calculation the model considers losses due to wake effects and electrical infrastructure as constant factors.

Chapter 4

Methodology

4.1 Description of the base case

The sensitivity analysis was performed for a hypothetical offshore wind farm located in the North Sea, approximately 50 km from shore. Data for this wind farm was obtained from one of SINTEF's industry partners. Most of the data are presented in this section, and the remaining data are presented in the appendix.

Table 4.1 summaries some of the general data for this wind farm. The wind farm consists of 60 equal 6 MW wind turbines. All maintenance personnel have one shift per day of 11 hours. A simplified approach for the electricity prices were given with a constant price scenario. A constant price scenario is not very realistic for long time scales, and therefore it was decided to specify the simulation horizon to be one year.

Table 4.1: General data

| Data | Value | Unit |
|-------------------------|-------|---------|
| Number of wind turbines | 60 | |
| Shift duration | 11 | hours |
| Number of shifts | 1 | per day |
| Start of each shift | 06:00 | a.m. |
| Electricity prices | 0.09 | GBP/kWh |
| Simulation horizon | 1 | year |
| Wake loss | 10.7 | % |
| Electrical losses | 1.7 | % |

Data for the vessels to perform maintenance tasks are shown in Table 4.2. The owned vessels consist of a personnel transfer vessel (PTV) and a mother ship with two daughter ships. The PTV is a relatively small boat located at the main base. The mother ship is a bigger boat located offshore, close to the wind farm. At this boat two daughter ships are available in addition to the mother ship itself to perform a maintenance task. The mother ship stays offshore 14 days in a row, and after that time it has to travel back to the main base before it can go offshore again. The variable costs for these vessels are estimated by

data for their fuel consumption. These data are given in Table A.3 in the appendix. The two other vessels are not owned but can be ordered when a maintenance task requires extra abilities such as transporting/lifting a heavy component. The offshore service vessel (OSV) is a ship with one crane and can transport and lift components. The jack-up is a crane vessel with special ability to lift heavy component. The order time defines the time from the ship is ordered until it is available for maintenance activities. After this time the vessel can be used as an owned vessel, until the maintenance task is finished. All costs related to these two vessels are included in their variable costs. More data for all vessels are shown in Table A.1 in the appendix.

Table 4.2: Vessel data

| Vessel name | Number | Wave limit [m] | Personnel space | Fixed cost [GBP/year] | Variable cost [GBP/hour] |
|---------------|--------|-------------------|--------------------|--------------------------|-----------------------------|
| PTV | 1 | 2 | 12 | 1825000 | 30 |
| Mother ship | 1 | 2.5 | 12 | 6570000 | 120 |
| Daughter ship | 2 | 1.2 | 6 | | 9 |
| | Number | Wave limit [m] | Personnel space | Order time [days] | Variable cost [GBP/hour] |
| OSV | 1 | 2.5 | 14 | 20 | 1364 |
| Jack-up | 1 | 2.5 | 21 | 30 | 5454 |

Table 5.4 shows data concerning the maintenance personnel. 12 maintenance persons are located at the main base approximately 80 km away from the wind farm. 12 maintenance persons are also located at the mother ship which usually stays close to the offshore wind farm. This maintenance personnel can be transferred to the wind turbines with the mother ship itself or the daughter ships.

Table 4.3: Maintenance personnel data.

| Location | Distance to wind farm [km] | Number of persons | Fixed cost [GBP/person/year] |
|-------------|-------------------------------|----------------------|---------------------------------|
| Main base | 79.6 | 12 | 105 000 |
| Mother ship | 1.5 | 12 | 105 000 |

Table 4.4 shows the relevant data for corrective maintenance, i.e. maintenance that has to be performed after a failure has occurred. All maintenance activities in this table are related to failures on a component on one wind turbine. Information about which components on the wind turbine the different failures corresponds to was not given, but it is worth to notice that the effect of all failures is that the actual wind turbine has to be shut down. Data for time based maintenance are shown in Table 4.5. This maintenance task has to be performed for all wind turbines and the work begins the first day in May. If weather allows it and enough resources are available, it is planned to work on 8 wind turbines in parallel each shift.

Table 4.4: Corrective maintenance data for a wind turbine

| Maintenance name | Failure rate [1/year] | Access time [hour] | Working duration [hour] | Personnel needed |
|-------------------|--------------------------|-----------------------|----------------------------|---------------------|
| Manual reset | 7.5 | 0.2 | 3 | 2 |
| Minor repair | 3.0 | 0.2 | 7.5 | 2 |
| Medium repair | 0.275 | 0.25 | 22 | 3 |
| Major repair | 0.04 | 0.33 | 26 | 4 |
| Major replacement | 0.08 | 0.67 | 52 | 5 |

Table 4.5: Time based maintenance data for a wind turbine.

| Maintenance name | First inspection [dd.mm] | Access time [hours] | Working duration [hour] | Personnel needed |
|------------------|-----------------------------|------------------------|----------------------------|---------------------|
| Annual service | 01.05 | 0.25 | 60 | 3 |

Two maintenance tasks requires an extra ability, and therefore an extra vessel to fulfill this ability. These data are summarized in Table 4.6. The maintenance activity called major repair need an OSV or a jack-up, while major replacement require lifting of a heavy component, which only the jack-up has the ability to do. These two maintenance tasks are the only one where the OSV or the jack-up are participating in.

Table 4.6: Data for maintenance task which needs extra abilities.

| Maintenance name | Extra ability needed | Extra vessel needed |
|-------------------|---------------------------------|---------------------|
| Major repair | Lifting | OSV or jack-up |
| Major replacement | Lifting of a heavy component | jack-up |

4.1.1 Case-specific performance parameters

Some data were missing or not estimated such as lead time and costs for spare parts and consumables. In addition cost for using the location and cost related to transporting personnel at the main base were also not specified.

For the presented case the O&M cost can be written as a sum of three terms represented by fixed vessel cost, variable vessel cost and personnel cost:

$$C_{O\&M} = \sum_{i=1}^2 FC_i + \sum_{i=1}^5 t_i VC_i + 24 \times \text{Personnel Cost}, \quad (4.1)$$

where FC_i is the fixed vessel cost for the i th vessel and VC_i and t_i is the variable cost and the total time in use for maintenance activity, respectively for the i th vessel. Due to the constant price scenario, the income from the electricity production is simply the product of the electricity production, the electricity price and the losses, i.e.

$$I = E_{real} \times \text{Loss}_{wake} \text{Loss}_{el} \times P_{el} \quad (4.2)$$

Since the simulation horizon was specified to be only one year, there is no need to calculate net present values for the O&M costs and the income from the electricity production.

4.2 Performing the sensitivity analysis

4.2.1 Input/Output for the sensitivity analysis

To perform sensitivity analysis a suitable measure for the models output must be chosen. The choice were among the three presented performance parameters, since all of them are related to operation and maintenance. It is often practical to operate with one single number as the models output. Thus the Total cost C , defined as the sum of the O&M costs and losses in the income from the electricity production due to unavailability of the wind turbines were chosen as the output for the sensitivity analysis. Due to constant electricity prices and a simulation horizon of one year one obtain the following formula for the Total cost:

$$C = C_{O\&M} + I\left(\frac{1}{A_{el}} - 1\right), \quad (4.3)$$

where $C_{O\&M}$ is the operation and maintenance costs, A_{el} the availability and I the income from the electricity production.

As the objective of this study is to identify influential parameters for the operation and maintenance costs, it was natural to choose parameters which are expected to influence on the Total cost. The following parameters were chosen for the sensitivity analysis:

- Failure rates (group of 5 parameters)
- Fixed vessel costs (group of 2 parameters)
- Variable costs for all vessels (group of 5 parameters)
- The access vessels wave limit (group of 3 parameters)
- Order time for chartered vessels: (group of 2 parameters)

4.2.2 Quantifying the models stochastic uncertainty

All methods for sensitivity analysis presented in Chapter 2 assumes that the model under consideration is *deterministic*, which means that an equal set of parameters will produce the same output when running the program twice. Because the NOWIcob model takes into account uncertainties such as weather and time for failures of wind turbines the NOWIcob model is considered as *stochastic*. It was therefore decided to have an additional study of the model's stochastic behavior for the base case.

To quantify the stochastic uncertainty a large number of simulations (5000) were performed for the base case. With such a high number of simulations one obtain quite

good estimates for the uncertainty in the Total cost. A histogram based on these simulations is shown in Figure 4.1. A large range of outcomes are shown (approximately $15 - 25 \cdot 10^6$ GBP). The distribution looks fairly symmetric around the midpoint of the distribution, but a fatter tail on the right side of the distribution is observed.

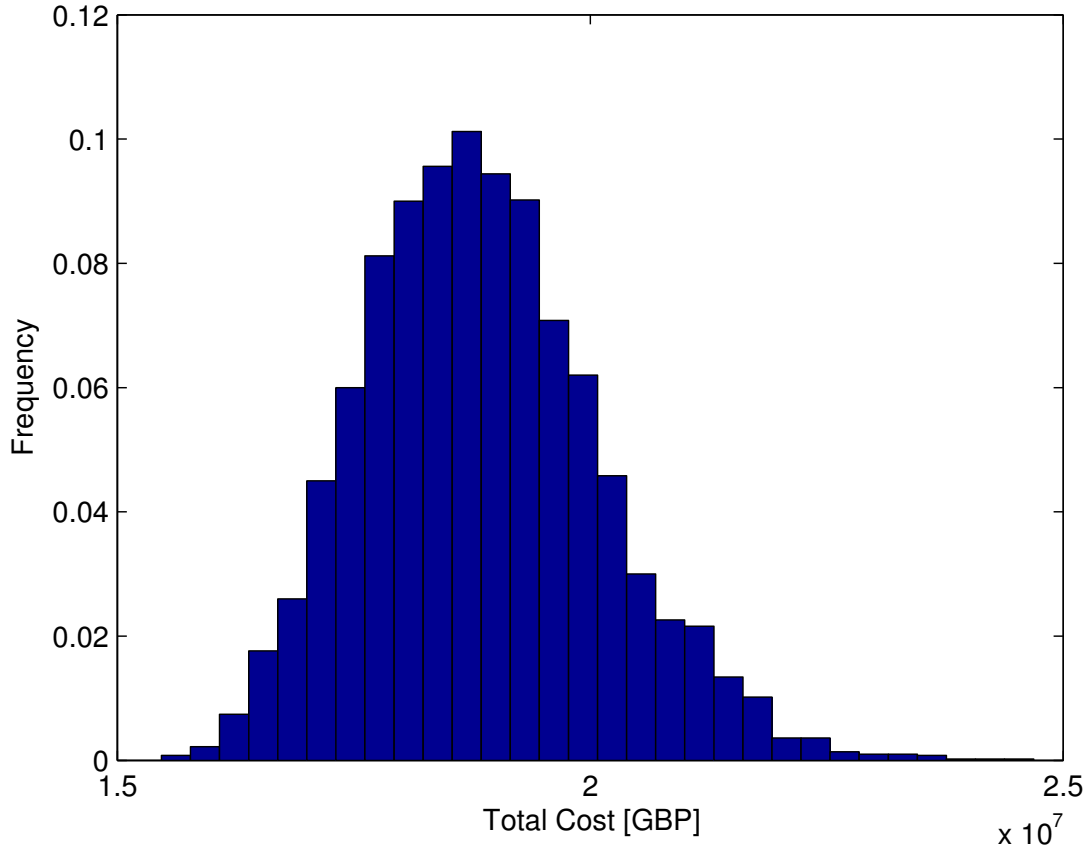


Figure 4.1: Histogram for the Total cost based on 5000 simulations.

It was decided to study this distribution in more detailed by calculating the sample mean \bar{C} and standard deviation S_C of the Total cost based on the 5000 simulations:

$$\bar{C} = \frac{1}{5000} \sum_{i=1}^{5000} C_i = 18.85 \cdot 10^6 \text{ GBP} \quad (4.4)$$

$$S_C = \sqrt{\frac{1}{4999} \sum_{i=1}^{5000} (C_i - \bar{C})^2} = 1.24 \cdot 10^6 \text{ GBP} \quad (4.5)$$

The sample standard deviation of the Total cost and the histogram gives a good illustration of the uncertainty of the models output from the uncertain weather and times for failures. For the sensitivity analysis it was chosen to run the model N times for each parameter configuration to account for this uncertainty. The question left is what the proper value of N is? It is a clear tradeoff between accuracy and computational cost. One

single simulation takes approximately 3 seconds. It was decided to choose the value for N such that the relative uncertainty in the sample mean of the total cost is approximately 1 percent.

Probability theory states that the variance of the sample mean obtained from a sample of N independent random variables is [15]:

$$Var(\bar{C}) = \frac{\sigma^2}{N} \quad (4.6)$$

where σ^2 is the variance the random variables. Since the true variance of the total cost is unknown is was replaced by the sample variance. By taking the square root on both sides of Equation (4.6) one obtain the following estimate for the standard deviation for the sample mean, (often denoted as the standard error [15]):

$$SE_{\bar{C}} = \frac{S_C}{\sqrt{N}}. \quad (4.7)$$

This gives the following estimate for the relative standard error:

$$RSE_{\bar{C}} = \frac{S_C}{\bar{C}\sqrt{N}}. \quad (4.8)$$

Using the restriction of a relative standard error in the sample mean of 1%, i.e $RSE_{\bar{C}} = 0.01$, gives $N = 10000 \frac{S_C^2}{\bar{C}^2} \approx 50$. This size of N resulted in a simulation time of approximately 2.5 minutes which is quite acceptable for performing sensitivity analysis.

In order to visualize this calculation, the sample mean of the Total cost as a function of N compared to the sample mean based on 5000 simulations is shown in Figure 4.2. This plot illustrates that the sample mean is overestimated for small N , but for larger N it fluctuates with small deviations around the assumed true value. Also shown in this figure (the error bars) are the magnitude of the relative standard error of sample mean (Equation (4.8)). At $N = 50$ the relative uncertainty is approximately 1%.

4.2.3 Choosing methods for sensitivity analysis

The base case (the data for the hypothetical wind farm) presented, consists of single values for each parameter. In the terminology of sensitivity analysis this base case corresponds to a single point in the input parameter space. Local methods provide sensitivity measures around such a point and are a very natural starting point for sensitivity analysis.

The local methods have their limitations that their results in general only are valid for small perturbations around the base case. In addition they usually do not assess parameter interactions. It was therefore decided to implement an additional analysis to assess whether the results from the local analysis are restricted to the base case and to assess possible parameter interactions. For this application a bigger part of the input parameter space has to be studied, and the need for global sensitivity analysis occurs.

Sensitivity analysis by linear regression provide estimates for the total effect for each parameter by estimating the standardized regression coefficients, but the quality of the

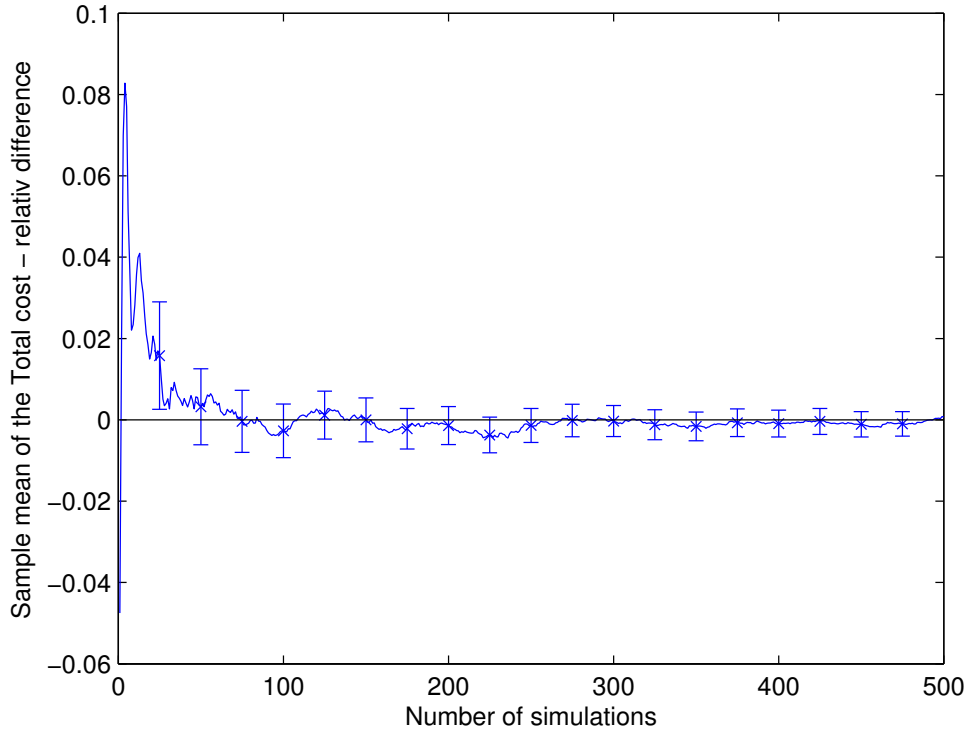


Figure 4.2: The sample mean for the Total cost (relative difference to the sample mean obtained from 5000 simulations) as a function of the number of simulations N . The error bars indicates the relative standard error (Equation (4.8)) in the sample mean for some selected values for N .

methods rely on the assumption of linear dependency of the model to its selected inputs. The linear regression model also fails to measure interaction effects or non-linear effects. For this purpose a higher order regression model is needed [6].

The variance based methods provide quantitative measures of sensitivity by estimation of the sensitivity indices. Parameter interactions can be assessed by the second order sensitivity indices or by the difference between the total sensitivity index and the first order sensitivity index, for each parameter. The variance based methods however, are probably to computationally expensive considering the 15 parameters chosen for the analysis. As an example the variance based sensitivity analysis FAST were performed for $k = 10$ parameters and required 10260 simulation runs [16].

The search for global sensitivity analysis methods were therefore among the screening methods where the Morris method seemed to be the most promising one. This method has the following advantages:

- It is quite similar to usual OAT (here one also studies the effect of changing one parameter at a time, but the parameter configuration is different each time), so the results can be compared with the results obtained from the local analysis (where the effects were measured around the base case).

- It is global since the whole parameter space is explored.
- It has a relatively low computational cost (the number of simulations are linear with the number of parameters).
- It does not have any simplifying assumptions about input-output behavior like regression analysis for instance.

The chosen methods for sensitivity analysis study effects in the Total cost, of changing one parameter at the time. It is therefore natural to study these effects for equal weather time series and if possible for equal times for failures. It was therefore decided to pre-generate the different weather time series, and in the sensitivity analysis to use the same weather time series for each parameter configuration.

As mentioned in Chapter 3 the point in time where the different failures occurs are simulated by drawing random numbers from an exponential distribution with the relevant failure rates as input. They are drawn by use of uniformly distributed random numbers. To produce uniformly distributed random numbers, MATLAB's random number generator *Mersenne Twister* which generates a sequence of random numbers, was applied. For each parameter configuration the seed were set to 0, which implies that same sequence of random number occurs for each parameter configuration.

4.2.4 Case-specific description for local analysis

The local analysis were implemented as MATLAB modules and integrated with the NOW-ICcob model. These modules performs local analysis by perturbing variables around the base case, one at a time. Two separate analysis were implemented, both very similar to the standard OAT design presented in Section 2.1.1.

1. Local analysis with respect to parameter groups: The parameters were divided into five groups (failure rates, fixed vessel cost, variable vessel cost, wave limit and order time). Each parameter group were analyzed in turn, by simultaneously changing all parameters in the group by the same relative amount, i.e. the reference value for each parameter in the group were multiplied with the same factor. Such an analysis gives information about which parameter group the Total cost is sensitive to.
2. Local analysis with respect single parameters: Each single parameter was evaluated in turn, by changing its value. Such an analysis gives information about which single parameters the Total cost is sensitive to.

Both analysis provided plots for the Total cost as a function of the single parameters and the parameter groups, together with estimates for scaled sensitivity coefficients.

Implementation details

The implementation of local analysis for single and groups of parameters was very similar. To simplify the presentation the term parameter either refers to a single parameter or a parameter group.

In this analysis each parameter was analyzed in turn (the model output were simulated for different values for each parameter), while all other parameters were held constant at their reference values. A large range of parameter values were chosen (50 – 200% of each parameters reference values) with step of 10% of each parameters reference value to assess whether linear or nonlinear effects are associated with each parameter.

The analysis also provided estimates for the scaled sensitivity coefficients by use of the central difference approximation (Equation (2.10)). For each simulation run (each pre generated weather time series), estimates for the sensitivity coefficients was calculated around the base case by perturbing each parameter up and down by the relative the amount $\Delta = 0.1$ of their reference values. The relatively large value for Δ was chosen in order to obtain significant changes in the sample mean of the models output. The sensitivity coefficients were scaled by dividing the difference in the models output with the percentage change in each parameter, which gives the following formula for the scaled sensitivity coefficient:

$$S_{ij} = \frac{C_j(x_i(1 + \Delta)) - C_j(x_i(1 - \Delta))}{2\Delta \times 100\%} \quad (4.9)$$

where S_{ij} is the scaled sensitivity coefficient for the i th parameter obtained from the j th simulation (with the j th pre generated weather time series).

For each of the 50 simulations the sensitivity coefficients were estimated by Equation (4.9) with the Total cost as the models output. Each of the calculated sensitivity coefficients were assumed to be independent from each other (they were calculated for different weather scenarios and times for failures) so the estimate for the scaled sensitivity coefficient S_i were calculated by the sample mean of the 50 sensitivity coefficients, i.e.

$$S_i = \frac{1}{N} \sum_{j=1}^N S_{ij} \quad (4.10)$$

It is also interesting to estimate the stochastic uncertainty for the averaged sensitivity coefficients S_i caused by the uncertain weather and times for failures.

The formula for the standard error of the mean (Equation (4.7)) were used to estimate the uncertainty of the averaged sensitivity coefficients, i.e.

$$SE_{S_i} = \frac{1}{\sqrt{N}} \text{std}(S_{ij}), \quad (4.11)$$

where $\text{std}(S_{ij})$ is the sample standard deviation of the N sensitivity coefficients.

4.2.5 Case-specific description of the Morris method

The Morris method is also a one at a time analysis, since it estimates effect of perturbing one parameter at the time. The difference from the previous methods is that effects for perturbing a parameter (denoted as the parameters *elementary effects*) are computed for different parameter combinations, i.e. several OAT analysis are performed, each for different parameter configurations. This method provide therefore the additional information for the importance of the input parameters: Whether the parameter configuration is important for the effect of a parameter, which is a measure of interactions and/or nonlinear effects associated with a parameter.

All uncontrollable parameters described in section 4.2.1 except the two fixed vessel costs were included in the analysis ($k = 15$ parameters in total). There was no need to study the fixed vessel costs in this global analysis, since their contribution to the Total cost are only one single term without any interactions. The parameter space was determined to consist of $p = 4$ distinct values for each parameter in the range of 80 – 120% for each of the parameters reference values. Since no distribution of the input variables were known it was decided to use equidistant levels for each parameter, which essentially assumes a flat distribution for each input parameter. It was decided to use $r = 10$ replications, i.e. 10 elementary effects were calculated for each parameter, each for different parameter configurations.

Implementation details

As described in Section 2.1.2 this algorithm assumes the parameter values to be in the range $[0, 1]$, in this case with $p = 4$ distinct values (hereafter denoted levels) at $\{0, 1/3, 2/3, 1\}$. The parameter values were adapted to the levels in the algorithm, such that level 0 and 1 represents 80% and 120%, respectively, of the parameters reference value. Table 5.2 compares the parameters values with the levels used in the algorithm.

Table 4.7: Parameter values for Morris design.

| Level in the algorithm | 0 | $\frac{1}{3}$ | $\frac{2}{3}$ | 1 |
|----------------------------------------|-----|---------------|---------------|------|
| Parameter value (% of reference value) | 80% | 93% | 107% | 120% |

As mentioned in Section 2.1.2 the perturbation $\Delta = p/[2(p - 1)] = 2/3$ should be chosen to ensure that the elementary effects for each parameters are selected with equal probability. Therefore $\Delta = \frac{2}{3}(120\% - 80\%) \approx 27\%$ was chosen, which depending on the parameter of interest, corresponds to an amount of approximately 27% of the parameters reference value.

The design of experiment, i.e. the set of parameter configurations used in this analysis was determined by construction of $r = 10$ different *orientation matrices* \mathbf{B}_i^* $i = 1, \dots, r$ by the method described in Section 2.1.2.

One such matrix

$$\mathbf{B}_i^* = \begin{pmatrix} \mathbf{x}_i^{(1)} \\ \mathbf{x}_i^{(2)} \\ \dots \\ \mathbf{x}_i^{(16)} \end{pmatrix}$$

contains 16 rows, each representing a parameter configuration. In addition, two consecutive rows $\mathbf{x}^{(n)}$ and $\mathbf{x}^{(n+1)}$ differ by Δ in only one element. The 15 consecutive rows in \mathbf{B}_i^* provides 15 elementary effects, one for each parameter. A graphical illustration of an orientation matrix for $k = 2$ parameters are shown in Figure 4.3 and one can see that this matrix provide a trajectory in the input parameter space.

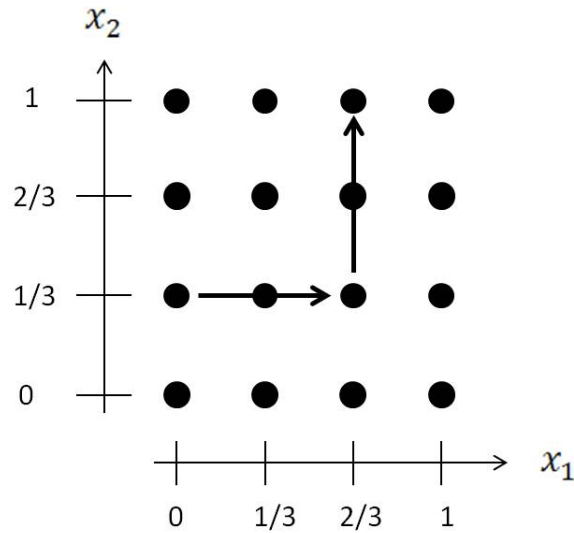


Figure 4.3: An example of a trajectory in the parameter space where each parameter in turn are perturbed by $\Delta = 2/3$. In this example for $k = 2$ parameters and $p = 4$ equidistant levels for each parameter.

The Total costs $C_k(\mathbf{x}^{(n)})$, $n = 1, 2, \dots, 16$ were calculated for each of the $M = 400$ simulations. For each parameter configuration $\mathbf{x}^{(n)}$, the same 400 pre generated weather time series was applied. A larger number of simulations compared to the local analysis was chosen in order to reduce the stochastic error in the estimates. A search to identify which parameter differ in the two vectors \mathbf{x}^n and \mathbf{x}^{n+1} were performed and the i th elementary effect for the j th parameter d_{ijk} was calculated by:

$$d_{ijk} = \pm \left(\frac{C_k(\mathbf{x}_i^{(n+1)}) - C_k(\mathbf{x}_i^{(n)})}{\Delta} \right), \quad k = 1, \dots, M$$

$$d_{ij} = \frac{1}{M} \sum_{k=1}^M d_{ijk} \quad (4.12)$$

for $n = 1, \dots, 15$, where j refers to the single parameter x_j , which is different in $\mathbf{x}^{(n)}$ and $\mathbf{x}^{(n+1)}$, and $+$ were chosen if $x_j^{n+1} > x_j^n$ and $-$ otherwise.

To assess the weather uncertainty in the elementary effects, the standard error for the elementary effects was also calculated, i.e.,

$$SE_{d_{ijk}} = \frac{1}{\sqrt{M}} \text{std}(d_{ijk}). \quad (4.13)$$

By repeating this procedure for all $r = 10$ orientation matrices \mathbf{B}_i^* , the elementary effects d_{ij} , $i = 1, \dots, 10$ were calculated, 10 for each parameter x_j .

Chapter 5

Results

In this chapter the results for the sensitivity analysis are presented. To simplify the presentation, all parameters and their reference values are given in Table 5.1 below. All parameters are labeled with an ID where the letter refers to the parameter group, and a number to indicate the single parameter in a group. For failure rates the number indicates which maintenance task the failure rates belongs to. The other parameters are related to a vessel.

Table 5.1: Parameters for sensitivity analysis

| ID | Parameter Group | Details | Reference value | |
|-----|----------------------|-------------------|-----------------|------------|
| F1 | Failure rate | Manual reset | 7.5 | [1/year] |
| F2 | " | Minor repair | 3.0 | [1/year] |
| F3 | " | Medium repair | 0.275 | [1/year] |
| F4 | " | Major repair | 0.04 | [1/year] |
| F5 | " | Major replacement | 0.08 | [1/year] |
| FV1 | Fixed vessel cost | PTV | 1825000 | [GBP/year] |
| FV2 | " | Mother ship | 6570000 | [GBP/year] |
| VV1 | Variable vessel cost | PTV | 30 | [GBP/hour] |
| VV2 | " | Mother ship | 120 | [GBP/hour] |
| VV3 | " | Daughter ship | 9 | [GBP/hour] |
| VV4 | " | OSV | 1364 | [GBP/hour] |
| VV5 | " | Jack-up | 5454 | [GBP/hour] |
| W1 | Wave limit | PTV | 2 | [m] |
| W2 | " | Mother ship | 2.5 | [m] |
| W3 | " | Daughter ship | 1.2 | [m] |
| O4 | Order time | OSV | 20 | [days] |
| O5 | " | Jack-up | 30 | [days] |

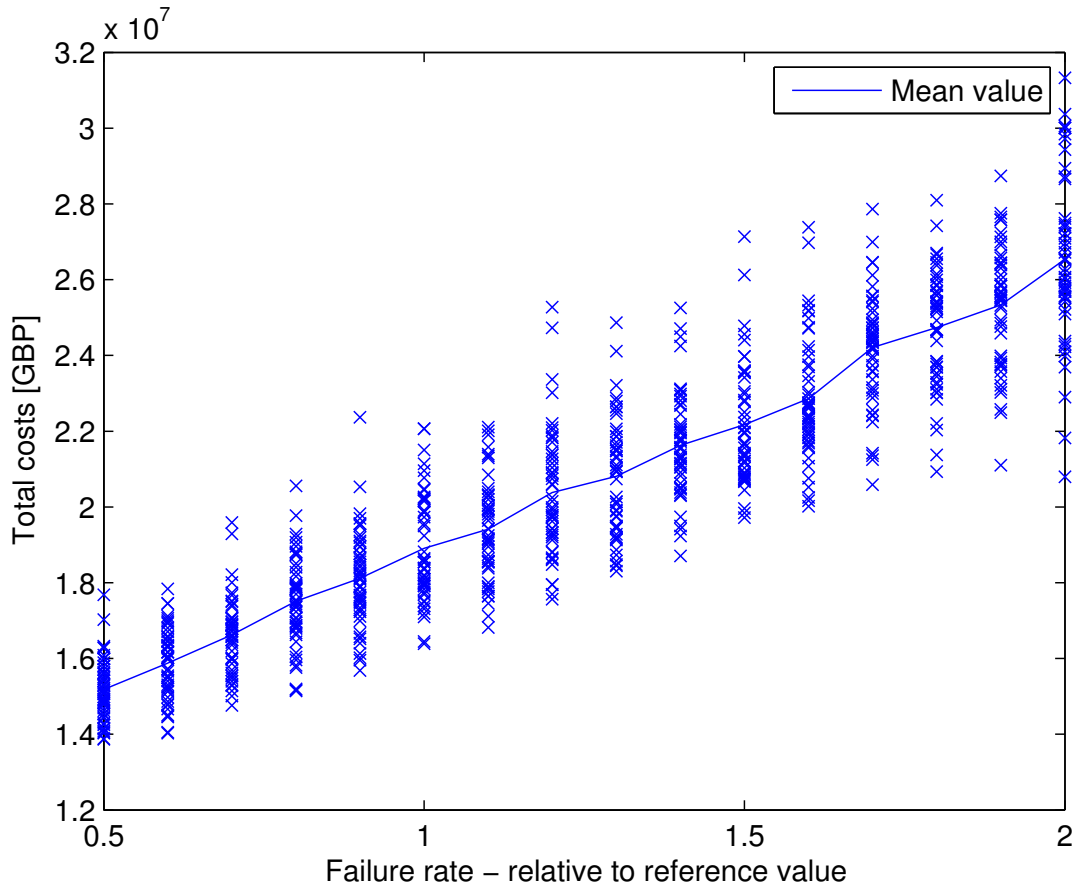


Figure 5.1: One at a time analysis. Total cost to all failure rates (relative to their reference values). All other parameters are fixed to their reference values (Table 5.1).

5.1 Parameters groups

In this section the results from the sensitivity analysis with respect to parameter groups are shown. Each parameter group was analyzed in turn, by simultaneously changing all parameters in the group, with the same relative amount, while all other parameters were held constant at their reference values.

Figures 5.1 and 5.2 shows the Total cost's dependency to the different parameters groups. The scatter points indicate the cost results of the different simulations, and the line indicates the sample mean of the Total cost based on the $N = 50$ simulations.

Figure 5.1 shows an almost linear increasing trend for the Total cost with increasing failure rates. The uncertainty in the Total cost due to random weather and times for failures also seem to increase with increasing failure rates.

Figure 5.2 shows the results for the other parameter groups. An exact linear trend for the sample mean of the Total cost as a function of the fixed and variable vessel costs (upper left and right respectively) is observed. The sample mean of the Total cost dependency to the wave limits (lower left) looks like an exponential decay, which indicates that the

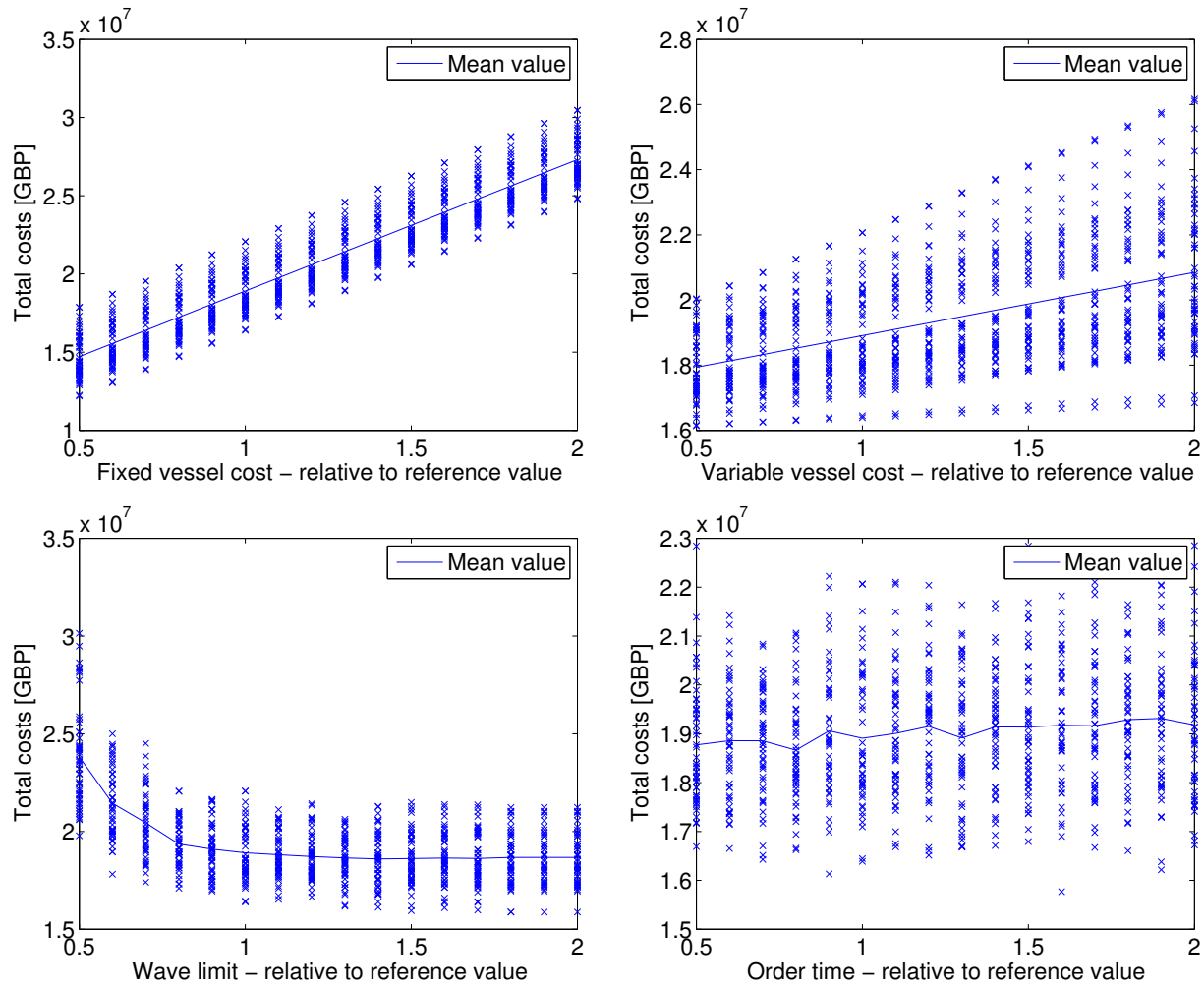


Figure 5.2: One at a time analysis. Total cost's dependency to parameter groups (All parameters in the group are changed relatively to their reference values). All other parameters are fixed to their reference values (Table 5.1).

Total cost is more sensitive for small wave limits. This may be reasonable since small wave limits put serious restriction on when maintenance tasks can be performed, which effects the availability and thereby the loss in income.

These plots gives also a good illustration of the stochastic uncertainty caused by the weather and times for failures compared to the effect of perturbing the parameter groups. Especially for order time (lower right) the fluctuations due to different weather scenarios and times for failures are much larger than the "fluctuations" in the sample mean of the Total cost for different order times.

Figure 5.3 shows the scaled sensitivity coefficients with respect to parameter groups represented as error bars. The center point represent the averaged sensitivity coefficients which essentially are linear estimates for the slope for the lines in Figures 5.1 and 5.2 around the reference point. The sensitivity coefficients were calculated for $N = 50$ dif-

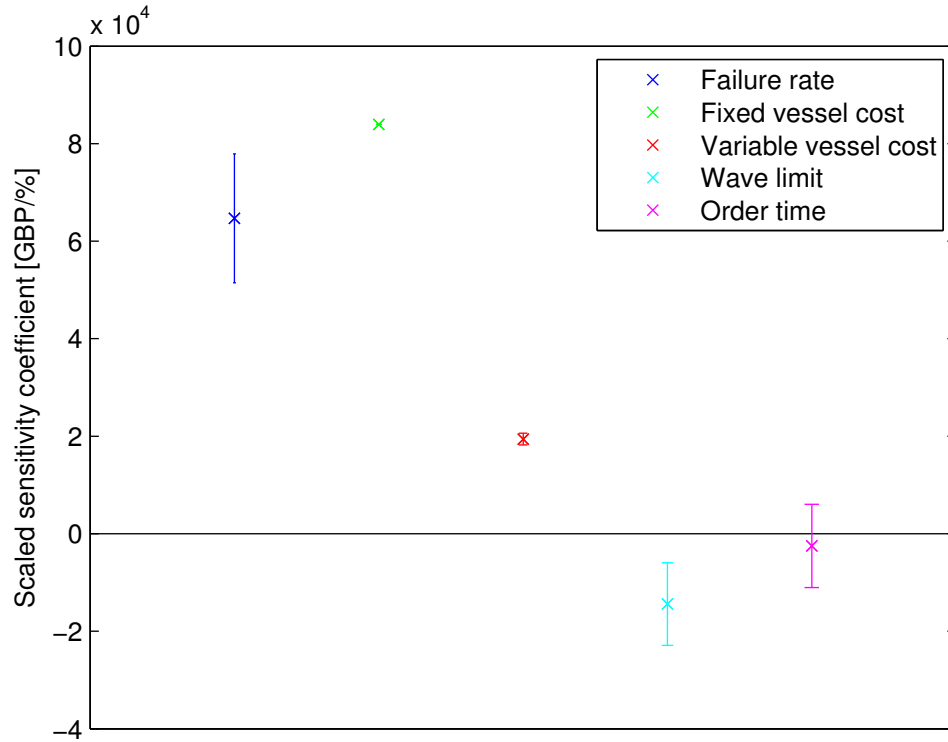


Figure 5.3: Scaled sensitivity coefficients (Equation (4.10)) with respect to parameter groups. The error bars indicate the standard error for the sensitivity coefficients (Equation (4.11)). Based on $N = 50$ simulations.

ferent weather time series and the error bars indicate the standard error of the averaged sensitivity coefficients. Considering the averaged value, the failure rates and the fixed vessel cost clearly have the largest sensitivity.

The fixed vessels costs contribution to the Total cost are only one single term without any weather uncertainty (Equation (4.1)), thus the standard error for the averaged sensitivity coefficients for the group of fixed vessel costs are zero. The variable costs contribution to the Total cost (Equation (4.1)) are a linear combination over all variable vessels costs with the time used by each vessel in hours as coefficients. These coefficients are depended on the weather and times for failures, but seem to be independent of variable vessel costs (according to the linear trend shown in the upper right plot of Figure 5.2). Thus a small standard error are shown for the averaged sensitivity coefficients with respect to the group of variable vessel cost.

The effects of perturbing all failure rates, wave limits or order times are dependent on the weather time series and the times for failures, which are illustrated by relatively large standard errors for the averaged sensitivity coefficients with respect to these parameter groups.

A surprising result is the insignificant sensitivity for order time for chartered vessels, since the order time directly influences the availability, and thereby the loss in the income

from the electricity production. By looking at the lower right plot in Figure 5.2, the effect on the Total cost seems to be small, also on a larger scale for their parameter values.

Table 5.2: Sensitivity coefficients with respect to parameter groups, given as average \pm standard error. The parameter groups are ranked by the absolute value of their averaged sensitivity coefficients.

| Parameter group | Sensitivity [10^4 GBP/%] |
|----------------------|-----------------------------|
| Fixed vessel cost | 8.39 ± 0.00 |
| Failure rate | 6.47 ± 1.32 |
| Variable vessel cost | 1.94 ± 0.12 |
| Wave limit | -1.44 ± 0.85 |
| Order time | -0.25 ± 0.85 |

5.2 Single parameters

5.2.1 Local analysis

Here the results for the local sensitivity analysis with respect to single parameters are shown. In this analysis each single parameter was evaluated in turn. The sample mean of the Total cost based on 50 simulations as a function of the single parameters are shown in Figure 5.4. Each plot considers single parameters from one parameter group. The axes on the plots indicate relative values from the base case value, which implies that for each plot the base case are at the point (1,1). At this point, the magnitude of the relative standard error for the mean of the Total cost (Equation (4.8)) is shown as an error bar, which gives an indication of the uncertainty in the sample mean of the Total cost, also for other parameter values.

The plot for failure rates (upper left) and variable vessel costs (upper right) shows a fairly linear trend of the sample mean of the Total cost. For all failure rates, and the variable cost for the PTV and the mother ship some small fluctuations are observed. These fluctuations are roughly on the same scale as the relative standard error for the base case and may therefore be understood as stochastic error in the sample mean of the Total cost. Similar fluctuations are shown for the three wave limits (lower left) and the two order times (lower right). The lines for the sample mean of the Total cost to the order times are both fluctuating up and down but are still within the magnitude of the relative standard error.

Figure 5.5 shows the scaled sensitivity coefficients with respect to single parameters labeled by their parameter ID. The center points refers to the average sensitivities i.e. the linear estimate for the slopes of the curves in Figure 5.4 around the reference point. The error bars indicates the standard error of the averaged sensitivity coefficients based on the 50 simulations.

Considering the sensitivity coefficients as a measure of importance of a parameter there is no single parameter which clearly has the most influence on the Total cost. It

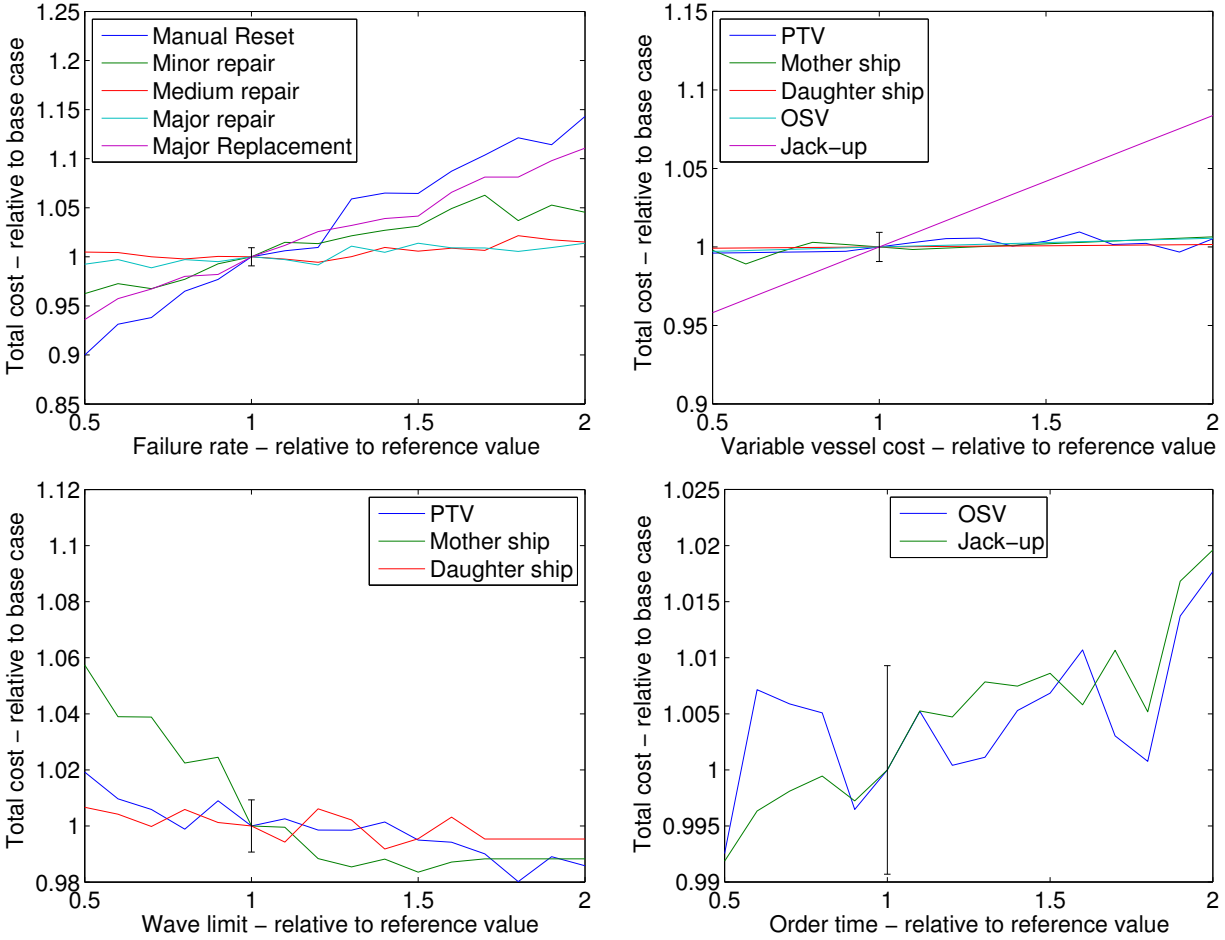


Figure 5.4: Sample mean of the Total cost to each parameter. Each plot refers to one parameter group. Each line represents the sample mean to a parameter while all other parameters are fixed to their reference values (Table 5.1). The error bar indicates the relative standard error of the sample mean the of Total cost for the base case.

seems however that the five parameters (F1, F2, F5, VC5, and W2) are the group of the most influential parameters on the Total cost, with an averaged sensitivity of 20000 – 30000 GBP/%. This means that the linear estimate for the effect of changing one of these parameters by 1% gives an expected change of 20000 – 30000 GBP in the Total cost.

As shown from the local analysis of parameter groups, failure rates were shown to be one of the most influential parameter group on the Total cost. This contribution seems however to come from F1, F2, and F5. The sensitivity coefficients for the two other failure rates (F3 and F4) show no significant effect. Considering the upper left plot in Figure 5.4, the Total cost seem to be insensitive to these two failure rates, also on a broader scale for these two failure rates.

Among the variable vessel costs the variable cost for the jack-up (VC5) clearly is the most influential on the Total cost. The sensitivity coefficients with respect to the daughter ships and OSV's variable cost (VC3 and VC4 respectively) are small but significantly larger

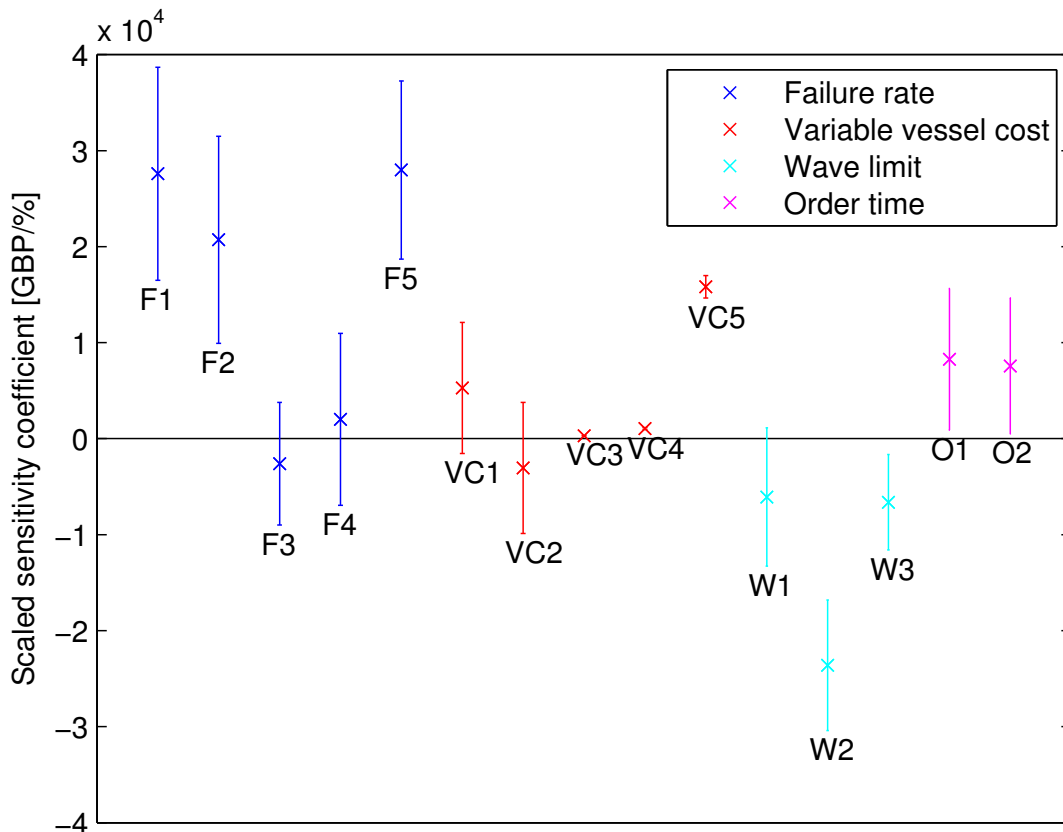


Figure 5.5: Scaled sensitivity coefficients for single parameters labeled by their parameter ID. The error bars indicate the standard error for the sensitivity coefficients based on 50 simulations.

than zero, considering the standard error. What is more interesting is the large standard error for variable cost for the PTV and the mother ship (VC1 and VC2 respectively). Also the plot of the sample mean of the Total cost as a function to these parameters provided not a perfect straight line relationship (upper right plot in Figure 5.4). These results seem to be contradictory to the results from the local analysis of parameter groups, and deserve some extra attention.

To give an idea about this uncertainty/nonlinearity we must have a look at the prioritization rules when vessels are competing to perform a maintenance task in more detail. As mentioned in Chapter 2, if more than one vessel are available to perform a maintenance task, the model decides which vessel to use by the working time available and then by the cost for use of the vessel. The cost for use of a vessel i for a specific maintenance task are calculated by.

$$\text{Cost}_i = (t_{\text{work}} + 2 \times (t_{\text{travel}}^i + t_{\text{access}})) \times VC_i \quad (5.1)$$

where t_{work} are the working time at the structure, t_{access} is the access time to enter the structure and the travel time t_{travel}^i are estimated by the ratio between the distance the vessel has to travel to the wind farm and the vessels speed. By running the NOWIcob

model, searching for a maintenance tasks where the PTV and the mother ship were competing on costs, the following maintenance task was found: The time based maintenance task Annual service (Table 4.5), with only 0.12 hours left of the work before the maintenance task was fulfilled. Due to adverse weather for the daughter ship, but accessible weather for both the PTV and the mother ship, these two vessels were competing for this maintenance task by cost. In this case the PTV was chosen for this maintenance task. By perturbing VC1 the same maintenance task were found again, but now the cost for the PTV was bigger than the mother ships costs, thus the mother ship was chosen. Vessel costs related to this maintenance task (Equation (5.1)) for both values of the parameter VC1, are shown in Table 5.3.

Table 5.3: Example of prioritization of vessels for the time based maintenance task *Annual service* when two vessels are competing on costs. Two cases for the PTVs variable cost (VC1) are considered. All other parameters are fixed to their reference values.

| VC1 [GBP/h] | Cost for use of the PTV [GBP] | Costs for use of the mother ship [GBP] | Chosen vessel by the model |
|----------------|----------------------------------|-------------------------------------------|-------------------------------|
| 27 | 84.24 | 88.80 | PTV |
| 33 | 102.96 | 88.80 | Mother ship |

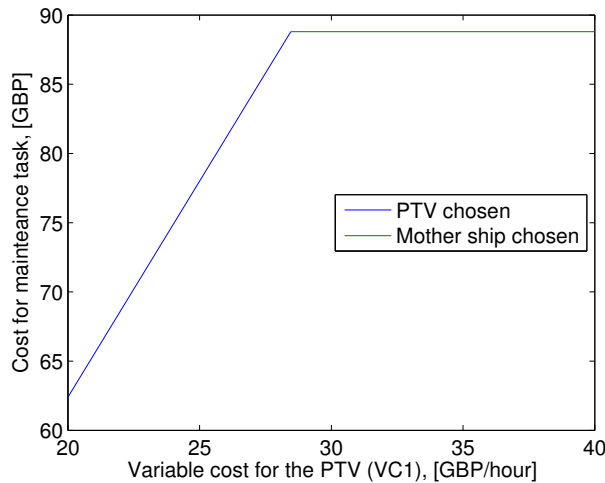


Figure 5.6: Cost for performing the maintenance task *annual service*, when the working time left is 0.12 hours, and the PTV and the mother ship are competing on cost, as a function of the variable cost to the PTV.

The perturbation of the parameter VC1 resulted in an increased cost for this maintenance task from 84.4 GBP to 88.8 GBP. The cost for this maintenance task would have been 88.8 GBP even if VC1 had been increased even more, since the mother ship still would perform this maintenance task and its cost are independent on VC1. A graphical illustration of the cost related to his maintenance task as a function of VC1 are shown

in Figure 5.6. From this figure it is clear that this maintenance task gives a non-linear contribution for the Total cost's dependency of VC1.

This example gives also an indication of the larger standard error in the sensitivity coefficients with respect to VC1 and VC2 compared to VC3, VC4, and VC5, since the circumstances that gave a change in the prioritization of these vessels were depended on the weather. This example also justifies the perfect linear trend observed for the Total cost as a function of the group of variable vessel costs (upper right plot in Figure 5.2). In that study all variable vessel costs were changed simultaneously, with the same relative amount, thus no prioritization change occurred.

About the single wave limits which gives a restriction whether a vessel can perform a maintenance task, the Total cost is more sensitive to the mother ships wave limit (W2) than for the PTV's and the daughter ships wave limit (W1 and W3 respectively). This is reasonable since the mother ship initially has the highest wave limit among the vessels and its wave height limit therefore defines the maximum wave height any vessel can perform a maintenance task. A reduction of the mother ships wave height limit is therefore associated with a reduction in the expected availability and thereby the electricity production.

Other interesting results are the sensitivity coefficients with respect to the order times. In this case they are both positive and significant considering the standard error, while for the analysis of parameter groups, the effect of perturbing both order times resulted in a negative, but insignificant effect. By observing the plot of Total cost's dependency to the order times (lower right in Figure 5.4) around the reference point, the slope seems to be overestimated compared to the trend on a larger scale. To summarize, the 5 most influential single parameters on the Total cost are shown in Table 5.4, ranked by the absolute value of their averaged scaled sensitivity coefficients.

Table 5.4: The sensitivity coefficients with respect to the five most influential single parameters on the Total cost. The sensitivity is given as average \pm standard error.

| ID | Group | Details | Sensitivity [10^4 GBP/%] |
|-----|----------------------|-------------------|-----------------------------|
| F5 | Failure rate | Major replacement | 2.80 ± 0.93 |
| F1 | Failure rate | Manual reset | 2.76 ± 1.11 |
| W2 | Wave limit | Mother ship | -2.36 ± 0.68 |
| F2 | Failure rate | Minor repair | 2.07 ± 1.08 |
| VC5 | Variable vessel cost | Jack-up | 1.58 ± 0.12 |

5.2.2 Morris method

The motivation for implementing Morris method is to assess parameter interactions, and to assess whether the results from the local analysis are restricted to the base case.

The results obtained from the Morris method are shown in Figure 5.7 as distributions of elementary effects, one for each parameter labeled by their ID. For each parameter 10 elementary effects were calculated. Each elementary effect (Equation (4.12)) is a measure of the effect on the sample mean of the Total cost caused by perturbation of one parameter from a random parameter configuration. Their magnitude can be directly be compared to

the averaged sensitivity coefficients in Figure 5.4. As mentioned earlier a dependency of the parameter configuration for a parameter's elementary effect indicates that the parameter is associated with nonlinear effects, interaction effects or a combination of these. In Figure 5.7 the variability of a parameter's elementary effect to the parameter configuration is indicated by a spread of the elementary effects. However, since we are dealing with a stochastic model with uncertain weather and times for failures, the spread may also be caused by stochastic effects rather than different parameter configurations. To indicate the stochastic effect, an error bar showing the magnitude of the standard error of one of the elementary effects to the respective parameter is shown.

An immediate conclusion is therefore that the variable cost for the daughter ship

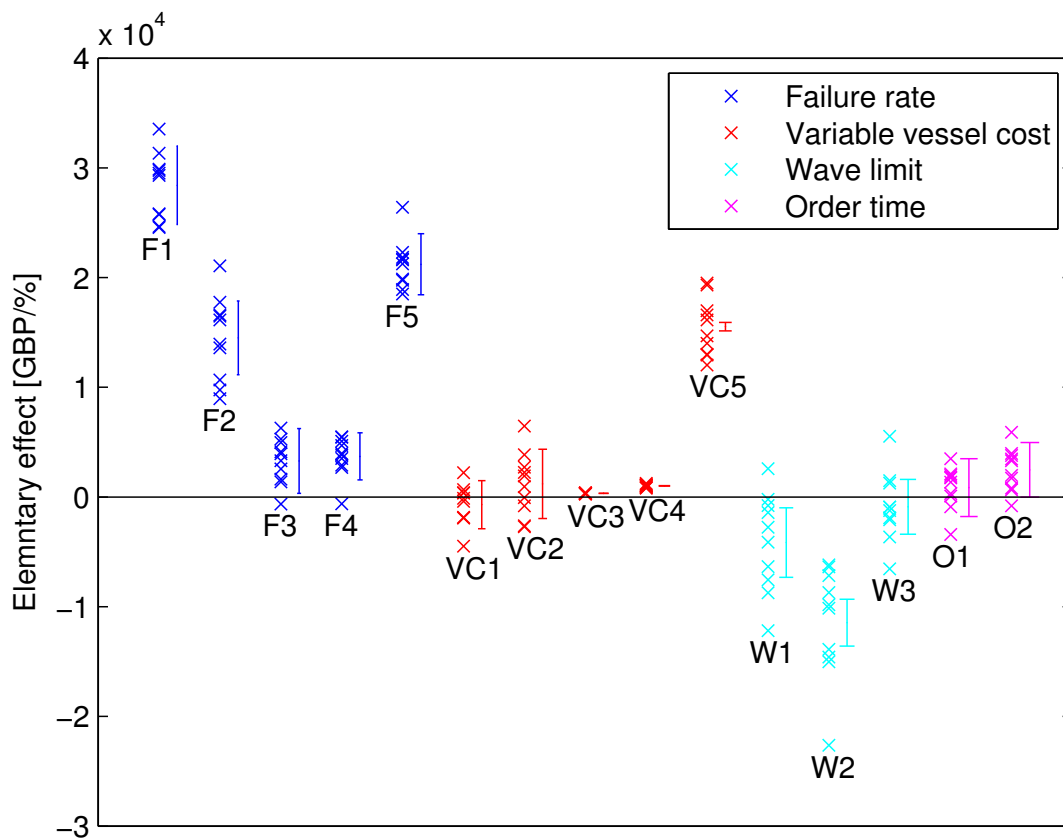


Figure 5.7: Results from the Morris method represented as distributions of elementary effects (Equation (4.12)) on the Total cost (sample mean from $M = 400$ simulations), for $k = 15$ single parameters labeled by their ID. For each parameter, $r = 10$ elementary effects were calculated, each by perturbing the parameter by an amount $\Delta = 27\%$ of the parameters reference value from a random parameter configuration (each parameter were randomly assigned a value from the $p = 4$ levels in the range of $80 - 120\%$ of the parameters reference value). To assess the stochastic uncertainty in the elementary effects, the standard error for one of the parameter's elementary effects are displayed as an error bar.

and the OSV (VC3 and VC4 respectively) is not involved in any important interactions. Their elementary effects are all almost equal and at the same magnitude as the averaged scaled sensitivity coefficients with respect to the same parameters. The standard error for their elementary effects is also small, which indicates that their elementary effects are almost independent on the weather and times for failures. A larger spread in the elementary effects is present for the other parameters, but also a larger standard error for their elementary effects. However, for the variable cost for the jack-up (VC5) the variability of the elementary effects are large compared to the standard error. This indicate a significant measure of parameter interactions or non-linear effects associated with the parameter VC5. Considering the linear trend for The total cost as a function of VC5 in the upper right plot Figure 5.4, the variability the elementary effects for the VC5 are probably due to interactions involving VC5. Also the variability in the elementary effects for the three wave limits (W1, W2, and W3) are larger than the standard error which indicates that these parameters also are involved in interactions or non-linear effects. For the other parameters it is hard to conclude anything about interactions/nonlinear effects since the variability of the elementary effects are at the same order of magnitude as the standard error. A drawback of the Morris method is that it does not give any information about what parameters interact with each other. The jack-up is only used for the two corrective maintenance tasks major repair and major replacement, whose failure rates are F4 and F5 respectively. It is therefore likely to believe that VC5 interacts with one or two of these failure rates.

By comparing the magnitude of the elementary effects with respect to different parameters rather than the distribution for one single parameter, the group (F1, F2, F5, VC5 and W2) seems to be the group of the most influential parameters on the Total cost. This is the exactly same group of parameters found to be the most influential on the Total cost in the local analysis of single parameters. This means that the Morris method confirms the main results from the local analysis. Other results that are obtained from the local analysis and that are confirmed by the Morris method, are that VC5 is clearly the most influential variable vessel cost, the two failure rates F3 and F4 are not influential compared to the other failure rates, and that the mother ships wave limit (W2) are the most influential parameter among the access vessels wave limits. There are also some differences. Now the effect for F3 is positive, as expected. The elementary effects for the lead times are distributed around zero, which further indicates the insensitivity of the Total cost to these parameters. To summarize, the five most influential parameters on the Total cost are shown in Table 5.5, ranked by the absolute value of the average of their elementary effects.

Table 5.5: The subgroup of the most influential single parameters. Ranked by the absolute value of the average of their elementary effects.

| ID | Group | Details | Elementary effect [10^4 GBP/%] |
|-----|----------------------|-------------------|-----------------------------------|
| F1 | Failure rate | Manual reset | 2.84 |
| F5 | Failure rate | Major replacement | 2.12 |
| VC5 | Variable vessel cost | Jack-up | 1.55 |
| F2 | Failure rate | Minor repair | 1.45 |
| W2 | Wave limit | Mother ship | -1.14 |

Chapter 6

Discussion

The goal of this work has been to identify influential parameters on the cost related to operation and maintenance at an offshore wind farm by sensitivity analysis. The work resulted in three sensitivity analysis modules, conducted with the NOWIcob model with data for a hypothetical wind farm as input.

The local methods with respect to parameter groups identified the failure rate and the fixed vessel costs as the most influential parameter groups on the Total cost. The local method with respect to single parameters identified a subgroup of 5 single parameters as the most influential on the Total cost. The global analysis further confirmed that this subgroup also are the most influential for other parameter configurations, i.e., that the main results from the local analysis, also are valid when a wider range of input parameter values was considered.

The results provide a good starting point for discussions about the accuracy in the estimates of the Total cost delivered by the NOWIcob model. The stochastic uncertainty has already been demonstrated by different weather and times for failures, but taking the sample mean value with respect to many simulations provides an estimate for the expected cost. For instance, three failure rates (F1, F2 and F5) and the variable cost for the jack-up (VC5) are all in the subgroup of the five most influential parameters for the Total cost. Accurate estimates for these parameters are therefore important to obtain realistic cost estimates delivered by the NOWIcob model. It is therefore recommended to have an additional study of these parameters' uncertainty. Such a study may provide:

1. A more accurate parameter value: In this case the cost estimates will be more realistic.
2. If the uncertainty in one of these parameters is quantified, for instance by a relative standard deviation σ_i , an estimate for this parameters contribution to the uncertainty in the cost estimates delivered by the NOWIcob model can be computed. The first order approximation for the parameters contribution to the variance of the expected cost is $(S_i \times \sigma_i)^2$ [11], where S_i is the scaled sensitivity coefficient for the parameter.

On the other hand, it is not so important with accurate estimates for parameters with a little influence on the Total cost. For instance, the order time for chartered vessels has a

very little effect on the Total cost. Therefore there is no need to put big efforts into estimating these parameters accurately, even though the order times obviously are uncertain and in practice probably not constant during the life time of the wind farm. The variable costs for the access vessels (VC1, VC2 and VC3) were based on rough estimates based on data for their fuel consumption (Table A.3), and are obviously affected by uncertainties. Considering the low sensitivity for these parameters, it is probably not so important to estimate vessels fuel use accurately to obtain significantly better Total cost estimates.

The results may also give tips on how to reduce the operation and maintenance costs on this hypothetically wind farm, and where there is potential to obtain the largest cost reduction. For instance, the mother ships wave height limits showed a significant negative effect for the Total cost, larger than for the other access vessels. If possible, a cost reduction is therefore possible by increasing the mother ships wave limit. This may not be so unrealistic, since the size of mother ships provides sufficient deck space and stability to mount heave-compensated access systems which are generally too large for standard work boats [1]. It is also possible to obtain cost reduction by trying to cost optimize the three corrective maintenance tasks manual reset, minor repair and major replacement, since their failure rates (F1, F2 and F3 respectively) were shown to influence the Total cost. The failure rate is a measure of the expected number of failures that require corrective maintenance. Therefore, the sensitivity of the failure rate is a measure of costs related to its corresponding corrective maintenance task.

The accuracy of the sensitivity coefficients should be discussed. They are essentially linear estimates for the partial derivatives of the Total cost with respect to parameters. The fairly linear trend for the Total costs as a function of the selected parameters in Figures 5.1, 5.2 and 5.4, probably justifies the approximation of central difference even with the relative large perturbation of $\pm 10\%$. The main sources of inaccuracy are therefore from the weather and times for failures estimated by standard errors for the averaged sensitivity coefficients. As shown in Figures 5.3 and 5.5, the standard error for sensitivity coefficients with respect to failure rates, order times, wave limits and for the variable cost for the PTV and the mother ship was relatively large. As a consequence the calculated average sensitivity coefficients are not accurate estimates for the Total costs sensitivity to these parameters.

Obviously, increasing the number of simulations N will provide more accurate estimates. However, using more of the calculated costs results shown in Figures 5.1, 5.2 and 5.4, to estimate the sensitivity coefficients is probably a more computationally efficient approach. For instance, the scaled sensitivity coefficient S_{ij} with respect to the i th parameter, can be calculated with the central difference approximation for different perturbations Δ . With the cost data calculated, $S_{ij}(\Delta)$ can be computed by Equation (4.9) with $\Delta = 10, 20, \dots, 50\%$ for $j = 1, \dots, 50$, representing the 50 simulations. In this work, only $S_{ij}(10\%)$ have been calculated. If the Total cost is linear with respect to the i th parameter, a simple average $S_{ij} = \frac{1}{5} \sum_{\Delta} S_{ij}(\Delta)$ can be used to estimate the sensitivity coefficient with respect to the i th parameter. Or if a non linear-trend is observed S_{ij} can be computed by extrapolating the function $S_{ij}(\Delta)$ towards $\Delta = 0$, which gives a more local approximation of the derivative. When the calculation is done the averaged sensitiv-

ity coefficient and the standard error can be calculated with Equation (4.10) and (4.11) respectively. It would be interesting to compare the results done in the analysis with the two new suggested methods.

With the relatively simple approach to estimate the sensitivity coefficients done in the analysis, the actual effect for the model response caused by perturbation of parameters was assessed. The large standard error for the sensitivity coefficients indicates that the change in the Total cost calculated by the NOWIcob model, caused by changing input parameter values, are highly depended on the weather and times for failures.

The simplifications done in the analysis should also be discussed. Neglecting the yearly fixed costs for harbors and personnel transport costs reduced the estimates for the Total cost, but the sensitivity measures are all unaffected. A more serious simplification are the missing data for lead time and costs for spare parts and consumables for each maintenance task. As a consequence the model has a systematic underestimation of the costs related to the maintenance tasks that requires consumables or spare parts. It is therefore most likely that the sensitivity coefficients for some of the failure rates were underestimated, since they have a direct impact on the expected number of failures (corrective maintenance tasks).

The sensitivity analysis modules implemented in this work have been demonstrated to identify the group of parameters with the most influence of the O&M costs. Their main advantage are their low computational costs and that their only simplifying assumptions about input/output behavior are local linearity. Therefore, they can be easily be applied to analyze even more parameters than what have been done in this work.

Chapter 7

Conclusion

Three sensitivity analysis modules have been integrated to the computer model NOWIcob that simulates the operation and maintenance of an offshore wind farm.

The sensitivity analysis modules were applied on a case with data for a hypothetical wind farm. Among the 15 selected input parameters, the sensitivity analyses identified five parameters as the most influential on the O&M costs calculated by the NOWIcob model: The three failure rates related to the maintenance tasks manual reset, minor repair and major replacement, the variable cost for the jack-up and the wave access limit for the mother ship.

Depending on the parameters chosen for the analysis, the results from the sensitivity analysis can give advise on how to obtain better estimates delivered by the NOWIcob model, or give advise for reducing the costs. For the presented wind farm, searching for more accurate values for the three most influential failure rates and the jack-up vessels variable cost, may improve the accuracy of the cost estimates. Installing a more robust access system for the mother ship seems to be one way to significantly reduce the costs related to operation and maintenance at the wind farm.

For further work it is suggested to improve the method of estimating the local sensitivity coefficients to obtain more accurate estimates for the parameter's influence on the O&M costs. The sensitivity analysis modules can easily be applied for other offshore wind farms, and depending on the purpose of the study other parameters may also be chosen.

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Appendix A

More case data

Here the rest of the data for the hypothetical wind farm are presented.

Some more data for the vessels are shown in Table A.1. The term days offshore indicates how long a vessel stays offshore, as long as the weather allows it, before it has to return to the main base. The weather limits for a vessel to stay safely offshore are determined by their offshore wave and wind limits respectively.

Table A.1: More Vessel data

| Vessel name | Travel speed [knots] | Wind limit [m/s] | Days offshore | Offshore wave limit [m] | Offshore wind limit [m/s] |
|---------------|-------------------------|---------------------|------------------|----------------------------|------------------------------|
| PTV | 35 | 16 | 0 | 4 | 30 |
| Mother ship | 14 | 16 | 14 | 5 | 30 |
| Daughter ship | 16 | 16 | 14 | 2 | 30 |
| OSV | 14 | 16 | 14 | 5 | 30 |
| Jack-up | 5 | 10 | 21 | 5 | 30 |

Weather data was given as an observed time series over 20 years for significant wave height and wind speed, from the location of the wind farm, with an hourly time resolution.

Data related to maintenance tasks that require pre inspection are shown in Table A.2. For these maintenance tasks, pre inspection has to be performed before the maintenance activity can start.

Table A.2: Maintenance task where pre inspection is needed

| Maintenance name | Time needed for inspection | Access time [hour] | Personnel needed |
|-------------------|-------------------------------|-----------------------|---------------------|
| Medium repair | 8 | 0.2 | 2 |
| Major repair | 8 | 0.2 | 2 |
| Major replacement | 8 | 0.2 | 2 |

The variable costs for the access vessels were estimated by the product of the vessels fuel consumption and the fuel price. These data are shown in Table A.3.

Table A.3: Fuel consumption and fuel price for the access vessels.

| Vessel | Fuel consumption [liters/hour] | Fuel price [GBP/liter] | Variable vessel cost [GBP/hour] |
|---------------|-----------------------------------|---------------------------|------------------------------------|
| PTV | 50 | 0.6 | 30 |
| Mother ship | 200 | 0.6 | 120 |
| Daughter ship | 15 | 0.6 | 9 |