The analysis of vessel operability and downtime

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SYNOPSIS

BMTOPS is a computer program package for analysing operability and downtime. It may be used to evaluate either single-sequence operations, typically involved in offshore drilling, workover or pipelaying, or else multi-sequence operations, describing, for example, floating production systems with loading buoys and shuttle tankers.

Typical results are used to demonstrate the validity of the program itself, comparisons with various simple formulae, sensitivity to changes in the assumptions, and how the program may be used in typical practical applications.

INTRODUCTION

Operability and downtime assessment methods are becoming more widely used to assess the economics of marine and offshore operations. They are particularly useful for comparing different scenarios and systems, and allow uncertainties associated with weather, equipment failure, and possibly such things as human error and the price of oil, to be combined in probability/risk terms and in a rational way.

The computer program package BMTOPS analyses some of the more quantifiable of these factors, especially downtime due to weather. BMTOPS uses Monte Carlo type simulation procedures to generate a typical time-history of sea-states and system operations over a period of several years. Seasonal variations in wave climate may also be modelled. Reference 1 describes the early development of this program.

The program is being extended to analyse dynamically-positioned vessels. Progress is also being made towards incorporating other sources of downtime – such as equipment failure and regular maintenance – working towards a full techno-economic model for assessing different operational scenarios and their relative costs.

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WAVE SIMULATION

Marine operations may be limited by wave height, wind speed, vessel response, etc. In the examples given here it is assumed that the significant wave height H_s is the crucial factor, though we shall see later how empirical relationships between wave height, period and wind speed, together with the response characteristics of the vessel, may be incorporated into the task threshold criteria.

The first task is to provide a sequence of typical values of H_s, over a period of several years. The most obvious source is actual measured data. Measurements are only available for certain specific periods and locations, however. Measurements of wind speed are available over much longer periods of time, and with a wider geographical coverage. This wide availability of wind data has encouraged the development of wave hindcast models, based on empirical relationships between wind speed, wave height, duration, fetch and other parameters. Wave height histories based on hindcast models, in particular the SOWM database, have formed the basis of several downtime analysis programs.[2,3]

A crucial feature is the modelling of wave height persistence statistics. These affect the waiting-on-weather time and the probability of completing a given task in a specified time. Persistence statistics describe the lengths of time when the wave height is above or below a given threshold level.

Both actual wave measurements and wave hindcast models are based on actual storm sequences, and automatically represent wave height persistence in a fairly realistic way. The BMTOPS package is capable of using either type of wave data source.

There is a further way to tackle the problem where time-series records are not available, or where greater control over the data is required. This is to simulate the wave height sequence on the computer. BMTOPS contains two alternative simulation procedures:

1. WASP1, described as a 'building-brick' method, and based on persistence distribution statistics.
2. WASP2, described as a 'Markov' method, and based on wave height exceedance and mean persistence statistics.

If no data other than height exceedance statistics are available, Kuwashima and Hogben (see Ref 4 and the section on the Kuwashima and Hogben model below) have shown how the necessary persistence information may be derived. Their approach opens the way towards using the vast international archive of visual wave data. This database has been assembled over a very long period of time and covers most sea areas worldwide. BMT has already developed a wave climate prediction service, NMIMET,[5,6] by applying quality control and data enhancement techniques to this database.

It should be noted in passing that an alternative procedure, based on auto-regressive moving average (ARMA) modelling, has been developed by O'Carroll.[7] This procedure involves transforming the wave height series into a normalised form. The autocorrelation function of the transformed series was found to be exponential, so that the value X_t at time t could be expressed simply in terms of the value X_{t-3} at a time three hours earlier as follows:

$$X_t = aX_{t-3} + bZ_t \qquad (1)$$

where a, b are constants and Z_t is a standard random normal deviate. This series therefore represents correlation between successive wave heights, but it is not clear whether it realistically models longer-term persistence.

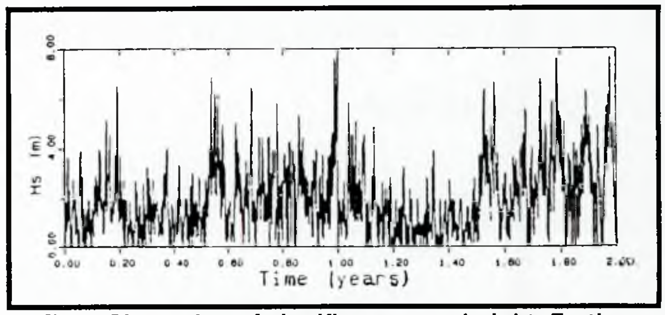

Fig 1: Simulation of significant wave height; Forties, seasonal data

The building-brick method

The basis of this method and a few comparisons with real sea data have been described in Ref 1. The building-brick approach aims to reproduce the entire distribution of persistence durations for heights either greater than or less than given thresholds. It is therefore more ambitious than the Markov approach, described later, which only aims to reproduce the wave height exceedance and mean persistence duration statistics.

It is easiest to understand this model in terms of 'greater than threshold' statistics, though the whole procedure may be inverted for 'less than threshold' statistics.

The first step, as described in Ref 1, is to divide the distribution of numbers of occurrences into duration intervals. Durations τ_n, n = 1 to N are used. The number of intervals during the simulation period when the wave height is less than H_m for durations between τ_n and τ_{n+1} is denoted by ν_{mn}.

What may be described as a 'wall' is then constructed using a population of ν_{mn} 'bricks' of length τ_n (n = 1 to N) at level m. Three rules of construction are assumed as follows:

1. the bricks in the lowest layer are arranged at random along the total available time base;
2. the bricks in succeeding layers are arranged at random, subject to the condition that each must rest on a brick in the previous layer without any overhang;
3. as far as possible, all bricks must be used so as to ensure identical recovery of the required persistence statistics.

In order to satisfy the third condition bricks are chosen to lie in order of descending length – the longest first.

The resulting brick 'wall' could be used immediately to represent a history of wave heights because it has the correct persistence statistics at each of the threshold levels and duration periods specified. Two refinements were, however, incorporated so as to avoid abrupt changes in downtime statistics at these threshold heights and duration periods.

The first refinement makes the exceedance distribution of wave heights continuous between threshold levels. We know that if the 'wall' is m bricks high, then the corresponding wave height lies between H_{m-1} and H_m. The wave height is chosen using a random-walk procedure as follows:

$$H_{m-1} + Z_i \delta H \qquad (2)$$

where δH is the height interval between H_{m-1} and H_m and Z_i is defined by the following equation:

$$Z_i = Z_{i-1} + (Y_i - 0.5)/c$$

where Y_i is chosen from a random uniform distribution between [0,1). The constant c can be used to adjust the amount of correlation between successive values of Z_i. The correlation between successive values of wave height depends mainly on the input persistence statistics, and is fairly insensitive to changes in c. The value c=1.5 was used throughout the present calculations.

The procedure described above allows Z_i to wander outside the required range [0,1), and the distribution is humped rather than uniform. The procedure was therefore modified by incorporating tests on the value of Z_i, the iteration being repeated until Z_i lies in the required range.

The second refinement makes the distribution of persistence durations continuous. It involves using a distribution of brick lengths between τ_n and τ_{n+1} rather than bricks of constant length. This improvement is also intended to reduce a consistent bias in the modelling, mentioned in Ref 1.

The total simulation period, which may last many years, has to be divided into manageable blocks. The fitting process is then applied to each block in turn. Each block consists of 2500 successive height estimates. If separate persistence statistics are available for spring, summer, autumn and winter, then each season can be modelled in turn.

The Markov method

The Markov approach has been adopted in a number of earlier simulation programs (eg Refs 8, 9). It does not attempt to reproduce the complete distribution of persistence durations, but has the more limited aims of reproducing the wave height exceedance and mean persistence statistics. It manages nonetheless to reproduce distributions of persistence duration quite realistically, and has a number of advantages over the building-brick approach. The main advantages are the comparative simplicity of the input data and high simulation speed. The method also works continuously, rather than dividing the simulation time into fixed length blocks.

The Markov procedure used in BMTOPS is that described in Ref 9. The simulation starts by selecting a wave height randomly from the steady-state distribution of heights. The range from minimum to maximum significant wave height is divided into M intervals, so that class m corresponds to the height range H_{m-1} to H_m. If the wave height at a certain time lies within height class m, it is assumed that at the next time step it may either remain in class m, or else move up or down one class. The transition probabilities for moving up, remaining at the same level, or moving down are a_m, b_m and c_m respectively.

These transition probabilities depend on both the steady-state probability distribution of significant wave height and the mean persistence duration above or below each height class level. The relationships may be expressed,[9] as:

$$a_m + b_m + c_m = 1$$

$$a_m p_m = c_{m+1} p_{m+1} = \frac{P_m \delta T}{\bar{\tau}_{lm}} = \frac{Q_m \delta T}{\bar{\tau}_{gm}} \qquad (3)$$

where p_m is the steady-state probability of being in height

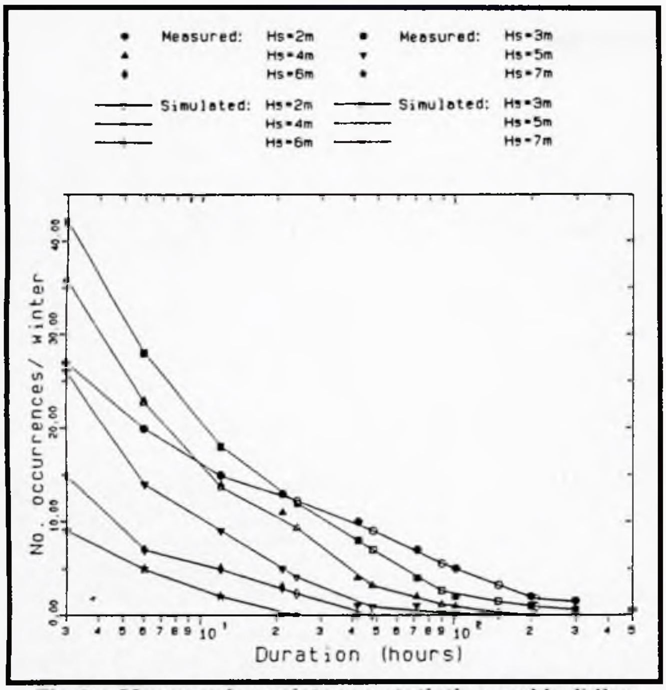

Fig 2a: Measured persistence statistics and building-brick model; Sevenstones, winter, (above thresholds)

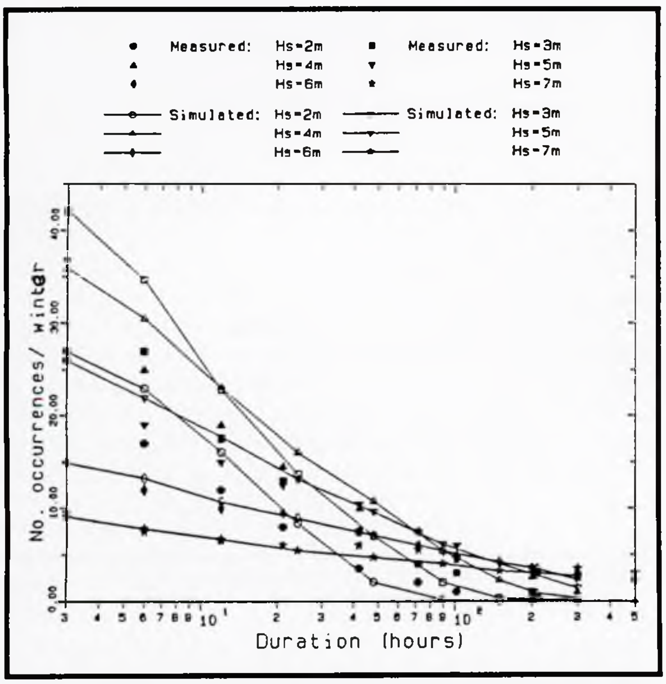

Fig 2b: Measured persistence statistics and building-brick model; Sevenstones, winter, (below thresholds)

class m, and P_m and Q_m are the corresponding cumulative and exceedance probabilities as follows:

$$P_m = \sum_{i=1}^{m} p_i, \quad Q_m = \sum_{i=m+1}^{M} p_i, \qquad (4)$$

where δT is the time interval between successive points in the simulation, and $\bar{\tau}_{lm}$, $\bar{\tau}_{gm}$ are the mean durations of persistence below and above threshold height H_m respectively.

At the upper and lower ends of the range there are additional conditions as follows:

$$P_M = 1.0 = Q_o, \quad a_M = 0.0 = c_1 \qquad (5)$$

These conditions ensure that the simulation remains within the range H_o to H_M.

It is only possible to move up or down one wave height class during each time step δT. Sub-intervals of the basic simulation time-step often have to be used, so that storms can grow and decay within the specified duration times. Numerically, this involves choosing δT such that b_m is always positive, and this is done automatically by the simulation program.

The choice of threshold height classes also involves some skill. If too many height classes are chosen, then not only does the time step δT become very small and the simulation very slow, but the approximations in the above equations become rather poor. The optimum number of classes seems to be about ten in practical cases examined so far.

Once again wave heights have to be interpolated within each class. The procedure adopted is the same as in the building-brick model.

The simulation may proceed either continuously through the entire simulation period, or on a season-by-season basis. It can also work with persistence durations either greater than or less than threshold values.

The Kuwashima and Hogben model

If the only information available is the wave height exceedance distribution (and this is likely to be the case with many older sources of instrumental data or the visual data on which the NMIMET model is based), then the empirical model of persistence, developed by Kuwashima and Hogben,[4] offers a possible way forward. This model starts with a three-parameter Weibull model of wave height exceedance, obtained by fitting the visual wave height data. The three fitting parameters are the minimum wave height H_o, the mean height $\bar{H}_s$ and the decay rate γ_3 describing the exceedance distribution of the significant wave height H_s as follows:

$$Q(\geq H_s) = \exp\left[-\left(\frac{H_s - H_o}{C_3}\right)^{\gamma_3}\right] \qquad (6)$$

where

$$\bar{H}_s = H_o + \frac{C_3}{\gamma_3}\Gamma\,(1/\gamma_3) \qquad (7)$$

and Γ is the gamma function. The three parameters may be obtained by the method of moments, maximum likelihood or other procedures.

Reference 6 provides formulae, derived and validated using measured data, for the mean persistence above and below threshold levels. The persistence distributions are then given in terms of the two-parameter Weibull formula.

By inputting the three parameters H_o, $\bar{H}_s$ and γ_3 it is thus possible to generate either the exceedance distribution and mean duration statistics required by the Markov model, or else the full persistence distribution required by the building-brick approach. All these results are calculated by the WASPO4 module within BMTOPS, and the persistence statistics filed so that they may be used automatically by the Markov and building-brick modules.

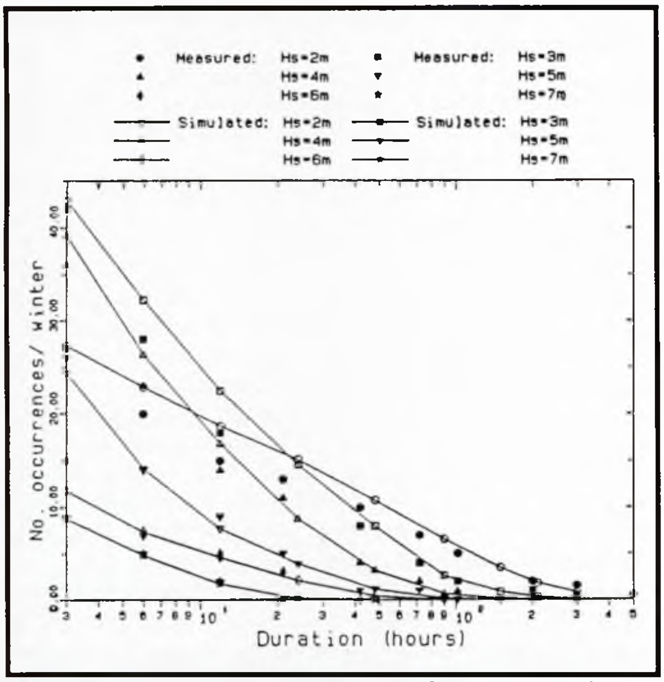

Fig 3a: Measured persistence statistics and Markov model; Sevenstones, winter, (above threshold)

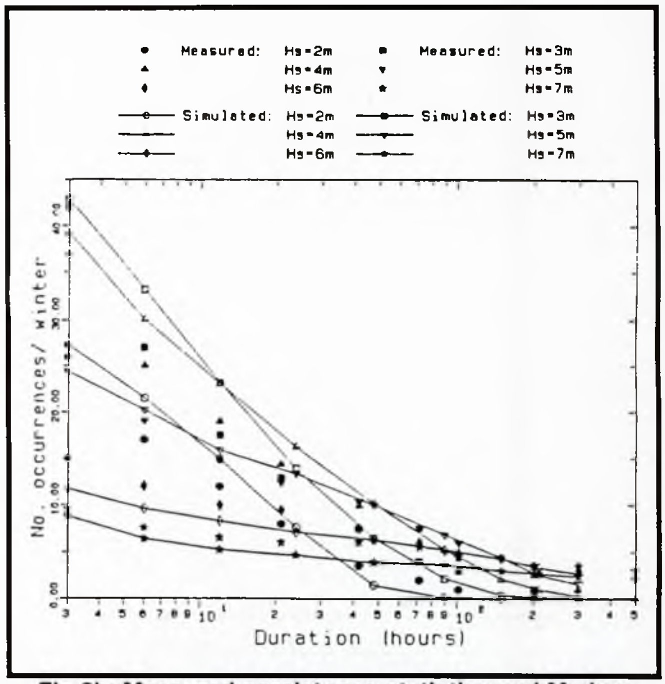

Fig 3b: Measured persistence statistics and Markov model. Sevenstones; winter, (below threshold)

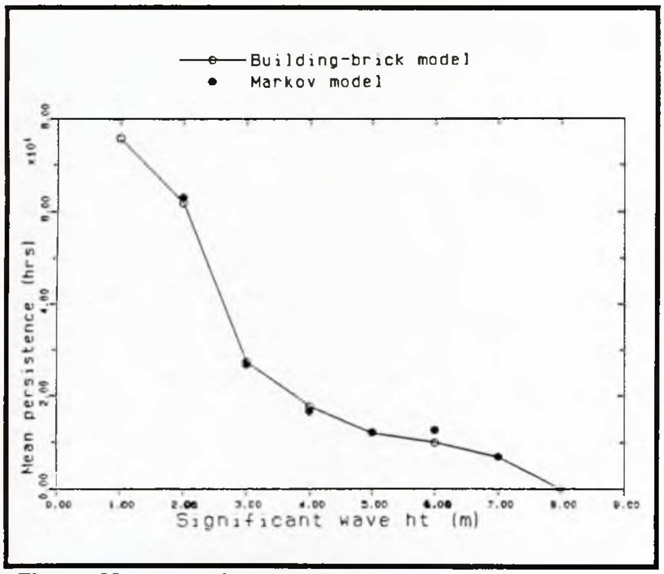

Fig 4a: Mean persistence. Sevenstones; winter, (above threshold)

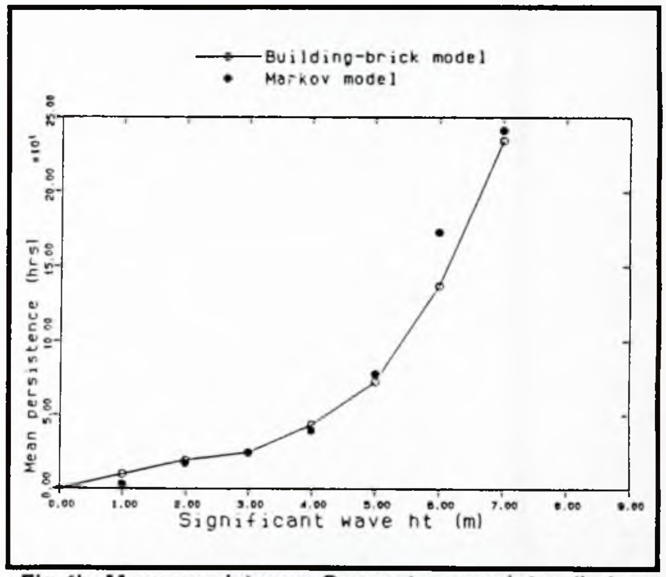

Fig 4b: Mean persistence. Sevenstones; winter, (below threshold)

Sample results

Our first example, Fig 1, shows a typical time-history of simulated wave height, based on persistence statistics for the Forties field in the North Sea.[10] The simulation has been based on the building-brick approach, and includes seasonal variations in the wave height and persistence distributions. The simulation is over a two year period and clearly shows the seasonal changes.

The next results are based on the building-brick model and on persistence data for Sevenstones. Earlier results from this model were included in Ref 1 and these new results incorporate recent refinements.

Figure 2a shows persistence statistics for significant wave heights greater than threshold levels 2, 3, 4, 5, 6 and 7m. The solid points were obtained from measurements at Sevenstones during the winters between January 1968 and June 1974.[11] These statistics were used as input to the building-brick program. The input data values were reproduced exactly when the resulting time-history was analysed (open points).

It is possible to check the realism of this simulation by comparing 'less than threshold' statistics with actual measured values. The two sets of results are overlaid in Fig 2b. Solid points represent the measured data, while the lines and open points represent simulated data. There is broad agreement between the two distributions, and they agree exactly (as they must) when the duration is three hours (the sampling interval for the measurements and simulation). There are, however, some differences for longer durations. The simulation tends to produce slightly too many occurrences over the middle range of durations. One possible explanation is the assumption that

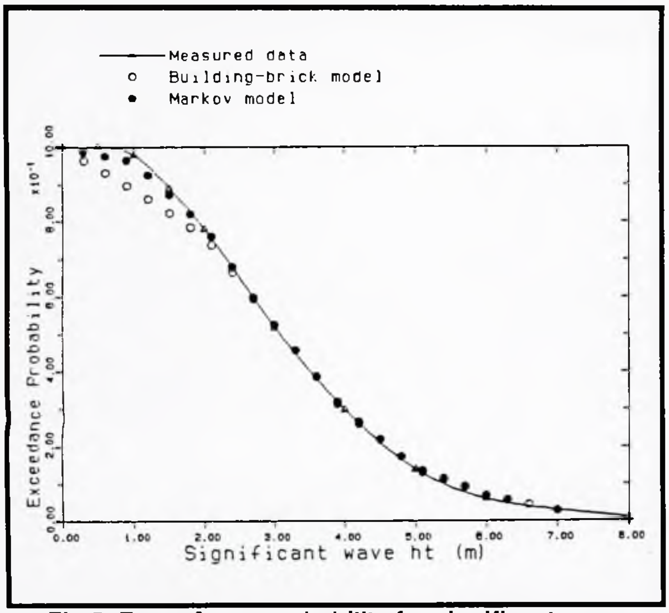

Fig 5: Exceedance probability for significant wave height; Sevenstones, winter

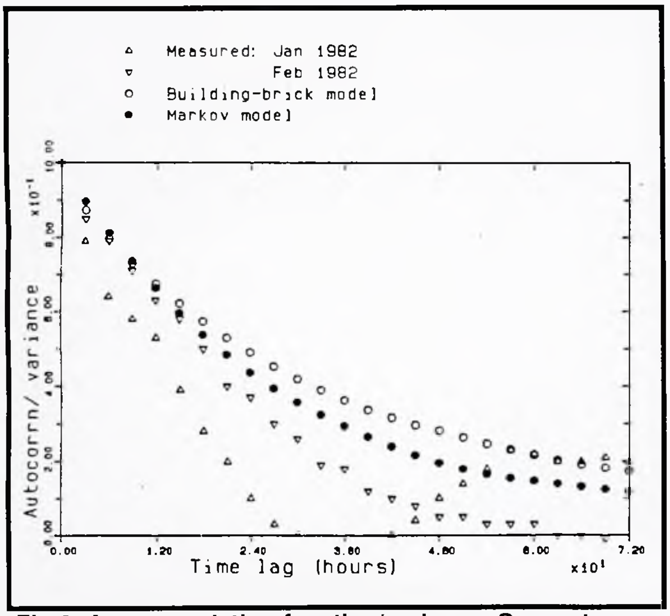

Fig 6: Auto-correlation function/variance; Sevenstones, winter

periods of storm or calm are randomly distributed along the time base. There is no physical reason why this should be true. It seems intuitively likely, in fact, that storms will tend to occur in groups, and the intervening calm periods will tend to be either longer or shorter than assumed.

Another contributory factor is the way in which very rare events with long durations are represented. These appear in the duration statistics as a fractional number of occurrences per winter, and may either be omitted from the input data or lost during the simulation. These 'events' may represent periods of very persistent swell, and tend to affect both the persistence statistics and the exceedance distribution at low wave height levels.

For the purposes of downtime analysis it might seem more appropriate to choose 'less than threshold' statistics as input to the building-brick process, rather than 'greater than threshold' values. The simulation process simply has to be inverted. Difficulties have, however, been experienced because of the different shapes of the two distributions. The program frequently has difficulty fitting in all the required 'bricks' for the 'less than threshold' model, and the resulting model tends to be distorted and untypical.

Figures 3a and 3b show corresponding 'greater than' and 'less than threshold' statistics obtained from a Markov simulation of the same data. These have also been overlaid on top of the actual measured data, using the same notation as in Figs 2a and 2b. The input to this model consisted of the actual measured exceedance distribution of wave height, together with mean 'greater than threshold' persistence statistics obtained from an analysis of the building-brick simulation (measured values not being available). These mean statistics should represent real sea data quite well, because the corresponding distribution of persistence was modelled accurately. It can be seen that both the 'greater than' and 'less than threshold' statistics are modelled quite well, though in this case neither is exactly right. Once again there is a tendency for slightly too many occurrences in the middle range of durations.

Figures 4a and 4b compare the mean persistence used as input to the Markov model (open points) with values obtained by analysing the simulated history (solid points). The input data consisted of mean persistence above threshold (Fig 4a) and wave height exceedance (Fig 5). Corresponding 'below threshold' values are shown in Fig 4b. The input data and simulated results agree well, confirming the adequacy of the Markov approach.

Figure 5 shows exceedance distributions of wave height obtained from both the Markov and building-brick simulations, together with actual measured data from Sevenstones. Both methods reproduce the measured distribution well, though the building-brick model performed less well at low wave heights because the lowest threshold for the input data was 2m.

The autocorrelation function is a further measure of persistence. Figure 6 shows the autocorrelation function, normalised by variance, corresponding to the two Sevenstones simulations. The two curves agree well. Also shown are curves based on measurements at Sevenstones,[12] but each over just one month – January and February 1982. These periods are different from those used in generating the simulation data, and the month-to-month variability is at least as large as differences between the simulated and real sea data.

DOWNTIME ANALYSIS

Basic concepts

Some of the more straightforward statistics that may be calculated using simple methods will now be looked at. These will later be compared with results from the full simulation method.

A distinction is made between the following types of task:

1. interruptible tasks, which may be restarted after a period of downtime, possibly with a delay;
2. single-pass tasks, which have to be completed during a single weather window.

A distinction is also made between:

1. single isolated tasks, started to random times;
2. a sequence of repeated tasks, started one after another, without a break.

If the point of interest is the mean time to complete a sequential task which may be interrupted without incurring any delay, then this statistic depends only on the probability $P(< H_t)$ that the significant wave height lies below the task threshold

H_s. $P(< H_s)$ in fact represents the fraction of time when the task may proceed, so that the mean completion time is simply:

$$T_{min} / P(< H_s) \tag{8}$$

where T_{min} is the minimum time required to complete the task in perfect weather conditions.

The distinction between tasks started at random and in sequence arises because of the persistence of storms and calms. More sequential tasks are completed during periods of calm, and less during storm periods. The start times are therefore not uniformly distributed with time, but tend to cluster during periods of calm, and this affects the task completion statistics.

Persistence affects most of the statistics likely to be required from a downtime analysis. If there is any delay on restarting a task, for example, then the completion time will depend on the number of periods of downtime. The probability distribution of task completion time is also affected by persistence. Examples in the section on single sequential tasks will show the differences between a model which assumes that successive wave heights are uncorrelated, and one which includes realistic persistence statistics.

A simple estimate of 'waiting-on-weather' time may be obtained directly from the persistence distribution. Reference 11 quotes the example of a supply vessel which cannot unload onto a platform when the significant wave height exceeds 3m. Using the measured Sevenstones data of Fig 2a, we see that there will be on average three occasions during the winter when the vessel will have to wait more than 96h to unload.

This simple estimate takes no account of the time required to unload. It assumes that once the wave height goes below the threshold, the vessel may be unloaded immediately. This assumption is likely to work quite well if the unloading time is short or comparable with the time required for changes in sea-state to occur.

This approach is appropriate only for tasks which occur as random events, rather than as part of a repeating sequence. A simple measure of the number of repeated single-pass tasks that may be completed in a given time may be obtained using Kuwashima's,[13] so-called 'potential working time'. This is the time when, on average, the significant wave height is less than a threshold value H_s for durations longer than the minimum task duration T_{min}. The 'potential working time' is expressed by the following equation:

$$P(< H_s) \int_{T_{min}}^{\infty} \tau \, p(\tau \,|< H_s) \, d\tau \tag{9}$$

where $P(< H_s)$ denotes the cumulative probability of significant wave height and $p(\tau \mid < H_s)$ is the probability density function of persistence, with duration τ, for wave heights less than H_s. Results of evaluating this expression will be compared in the section on single sequential tasks with actual working times from the simulation.

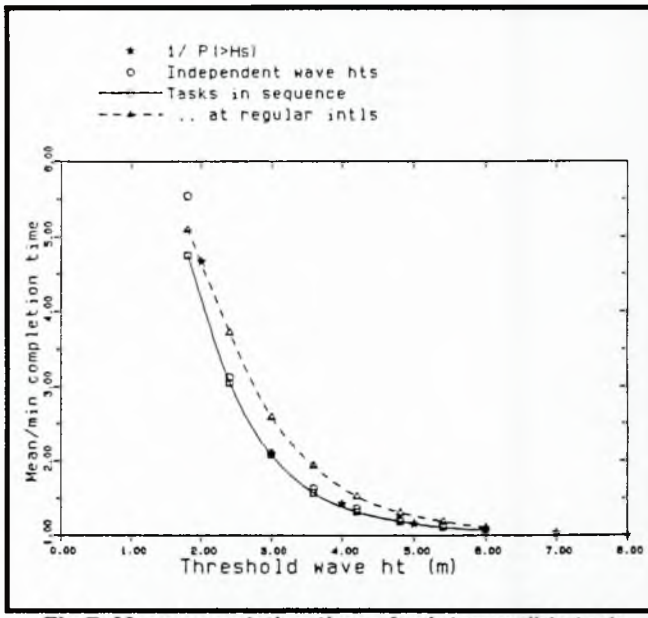

Fig 7: Mean completion times for interruptible task

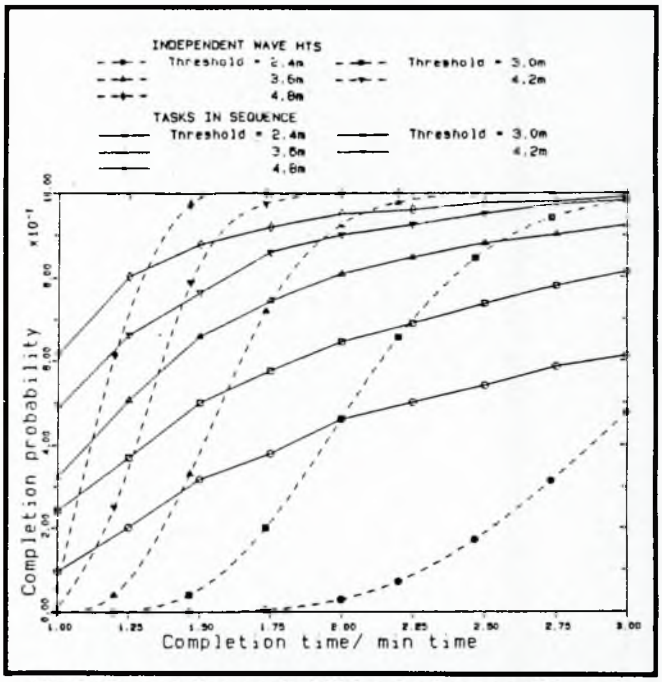

Fig 8: Completion probabilities for interruptible task

Main features of BMTOPS downtime analysis model

The BMTOPS downtime analysis package has a number of unique features. The capabilities of this package will be described and it will then be shown, by means of examples, how the modelling assumptions influence the downtime statistics.

The input to this program consists of two data files. One contains the wave height sequence obtained either directly from measurements, from a hindcast model, or from one or other of the wave climate simulation programs described in the previous sections. The other data file defines the tasks which have to be carried out, the sequence in which they are performed and task threshold levels.

The model can represent either a single sequence of tasks, or else two or more parallel task sequences. A single sequence would be used to represent, for example, the tasks involved in a drilling operation or with a supply vessel. Parallel sequences are needed to represent the operation of a floating production system with one or more shuttle tankers. Examples of both single-sequence and multi-sequence operations will be described in the following sections.

Each task may be interruptible or of single-pass type. The program also allows a third special type of task to be defined – awaiting period with a specified mean duration and coefficient

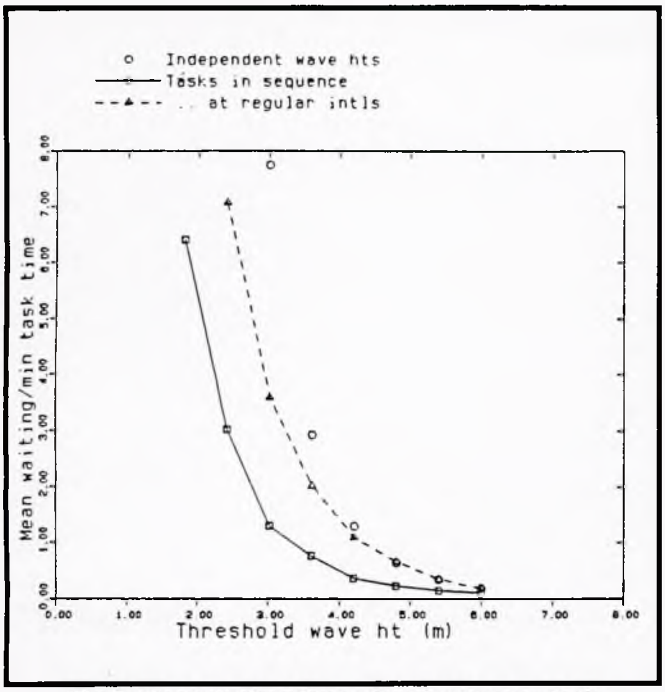

Fig 9: Mean waiting times for single-pass task

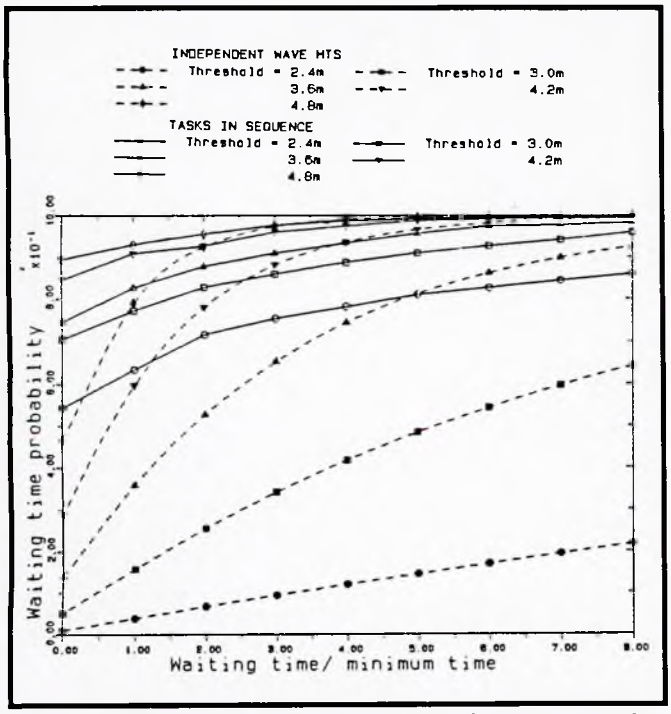

Fig 10: Waiting time probabilities for single-pass task

of variation. This third type of task may be used to represent time spent waiting between contracts, maintenance, etc.

At each time step the program decides whether to continue the task in hand or to cease activity, depending on the significant wave height. Task threshold levels may be based on one of the following:

1. the significant wave height itself;
2. a forecast wave height, based on an extrapolation of recent trends;
3. vessel response motions;
4. station-keeping limits;
5. production or oil transfer limits.

The vessel response motions are defined as a function of wave height, though some statistical variability is allowed. The shape of the response function may be quite complicated, and may define certain bands of wave height within which the task has to stop. A response function may alternatively be used to describe the relationship between wind speed and wave height, in which case the task threshold may be based on wind speed.

The station-keeping limits depend on wind, wave and current forces. This particular module is still under development and no results will be presented here. The general approach being adopted, however, is to treat wind and wind-driven current as strongly correlated with the waves. This tidal current is assumed to be sinusoidal. Mean wind, wave drift and current forces are calculated and the station-keeping ability of the vessel then assessed.

Several different criteria may be applied to a single task, and different criteria may be used when deciding whether to stop a task in progress or to restart a task which has stopped. The efficiency of working may also be reduced when the wave height exceeds a certain level.

Illustrative results – single sequential tasks

Some illustrative examples shall now be looked at, based on a single task repeated many times over during the simulation period. These examples are simple, but helpful in demonstrating sensitivity to the assumptions made in the modelling process. Various task completion statistics for a single-pass task of minimum duration 12h and for an interruptible task of duration 45h will be examined. A single height threshold value is used in each case and there is no delay on restarting. The sensitivity of the following will be looked at:

1. mean task completion time;
2. probability of completing in various times;

with variations in:

3. wave threshold heights;
4. inclusion of persistence or random model of wave height;
5. tasks in sequence or uniformly distributed start times.

The following results will be based on the Markov procedure, representing five years of Sevenstones winter conditions.

The importance of modelling wave height persistence has been stressed. Task completion time statistics calculated in two ways will be compared. In one the persistence is modelled realistically and in the other it is assumed that successive wave heights are uncorrelated. Figures 7 and 8 show mean task completion times, and probabilities of completion in a given time, for the interruptible task. Figures 9 and 10 show corresponding results for the single-pass task, in the form of statistics of waiting time before a suitable weather window occurs.

Uncorrelated results were obtained in two different ways: one using a random sampling technique to generate the wave history, and the other based on analytical expressions for the probability distribution. The two sets of results agreed, thus providing validation of the downtime simulation procedure.

It can be seen that the mean completion time for the interruptible task is the same, regardless of whether persistence is modelled or not. This is because the mean completion time for this type of task depends only on the percentage of time below the threshold. Figure 7 includes an estimate based on equation 8, which agrees well with the result from the full downtime simulation analysis. These results once again confirm that the downtime package is working correctly.

Figures 8 and 10 show completion probability. Solid lines and open points identify results from the downtime analysis which represents persistence. The broken lines and solid points identify results from analytic expressions for the uncorrelated model.

Figure 8 shows the importance of persistence. The range of completion times is much greater when persistence is taken into account, even though the mean time is unchanged. There is a very much higher probability of completing in a very short time, but equally a lower probability of completing in a very long time. This is because the persistence of both calms and storm periods is increased.

Persistence tends to reduce waiting (and completion) times generally for the single-pass task. Mean waiting times (Fig 9) are reduced and the probability of waiting less than a given time (Fig 10) is increased.

The analysis was repeated, taking two or three tasks with different threshold levels in sequence. The probability statistics were found to be affected, to some extent, by the choice of tasks in each group. There was, for example, a higher probability of completing a given task when it was run with tasks with lower threshold levels than when run on its own, or with tasks with higher thresholds. This is a consequence of persistence, because if the lower-threshold task completes successfully, the wave height is already low enough for the higher-threshold task to start.

The results discussed so far were obtained with tasks run in sequence. Figures 7 and 9 also show mean completion times when the tasks were started at regular intervals. This model represents more realistically the completion statistics for an isolated task (which is not part of a sequence, and may start at any randomly chosen time). The mean completion time has increased quite substantially, compared with the sequential model. This difference occurs because the tasks are not distributed uniformly with time in the sequential model. More tasks are completed during periods of relative calm, and less during stormy periods, and this tends to reduce completion times.

Figure 11 shows corresponding completion probability curves for the interruptible task, and again shows a significant difference between tasks in sequence and tasks started at regular intervals. Neither set, however, resembles the results from the uncorrelated wave model (Fig 8).

The effect is exaggerated here because the repeat period of the sequence was very short, and there was some correlation between wave heights over this period. The effect is reduced for several tasks in sequence and longer sequence repeat periods.

Figure 12 shows the fraction of total available time that is spent working actively on a 12h, single-pass task. It has been calculated in three ways. The first is based on the expression for 'potential working time' in equation 9; the other two on time actually spend during a full task simulation with a single task either repeated in sequence or started at regular intervals. These latter two values were calculated from mean waiting time statistics (Fig 9). The fraction of time spent working is simply the ratio of the minimum task time to mean completion time.

The results show good agreement between the 'potential working time' and actual time for tasks in sequence. There is more downtime for tasks started at regular intervals, for the reasons outlined above. The 'potential working time' concept seems to work well for tasks of short duration, as here, where errors due to partial completion of tasks are small. Further calculations for a 24h task showed slightly less good agreement, the 'potential working time' being optimistic.

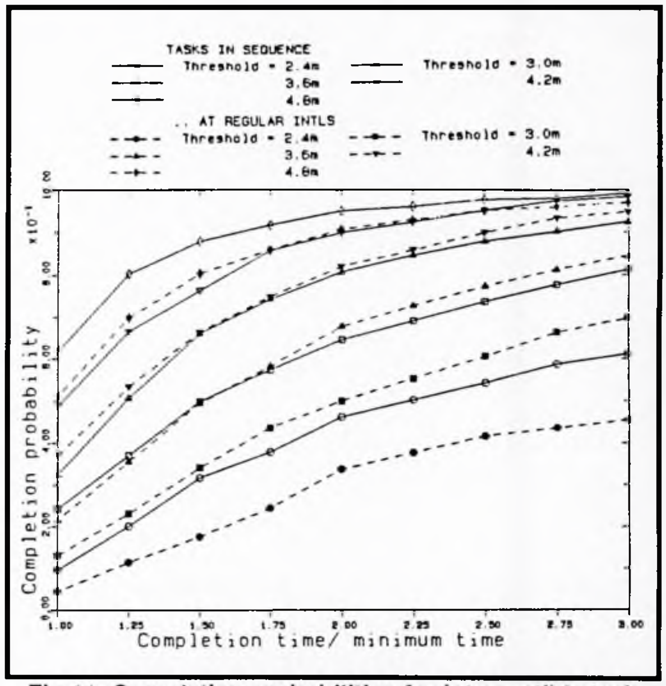

Fig 11: Completion probabilities for interruptible task

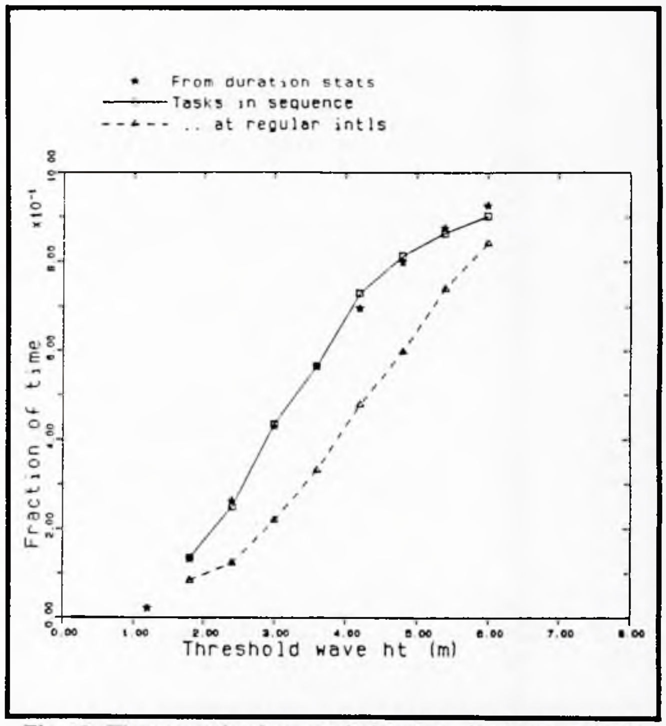

Fig 12: Time required or available for single-pass task

Sequential task modelling

The previous section considered the modelling of single tasks in isolation. The downtime simulation approach is needed to model more complex and realistic task sequences. Sequential modelling programs for predicting downtime have become well-established in the offshore industry, particularly for evaluating different vessels and scenarios for drilling, pipelaying or workover operations (eg Refs 2, 3, 8 and 9).

The use of BMTOPS will be illustrated for a typical sequence of workover operations. These have been taken from Ref 14 and are defined with the threshold levels shown in Table I.

All significant responses are quoted as double-amplitude values. The exact nature of the operations, and the choice of limiting criteria, are not important. The purpose is simply to show how these limiting criteria are incorporated into the BMTOPS analysis – and to show how downtime is affected by the choice of vessel.

Table I: Limiting criteria for typical workover operations

Task	Signif heave (m)	Signif roll (deg)	Signif wave ht (m)	Wind speed (kn)
Wireline ops	1.7	6.0	–	50
Logging	2.0	7.0	–	50
Cementing	2.0	7.0	–	–
Run and land wireline BOP	1.0	3.0	2.0	35
Pull wireline BOP stack	2.0	5.0	3.0	40
Disconnect wireline BOP lower riser	4.5	8.0	5.0	60
Diving ops	3.0	–	–	–

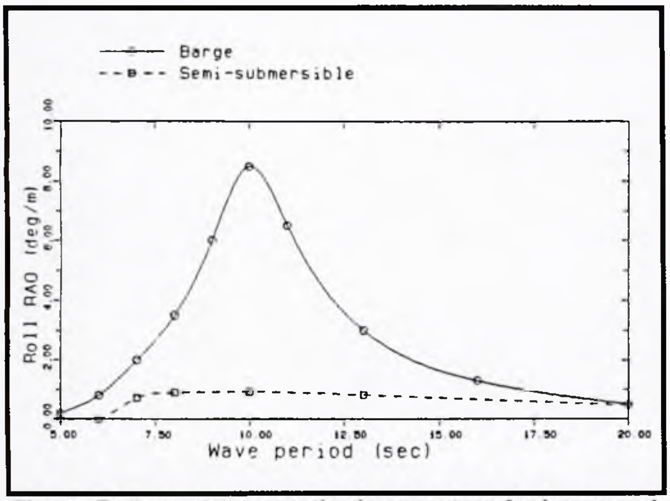

Fig 13: Roll response amplitude operators for barge and semi-submersible

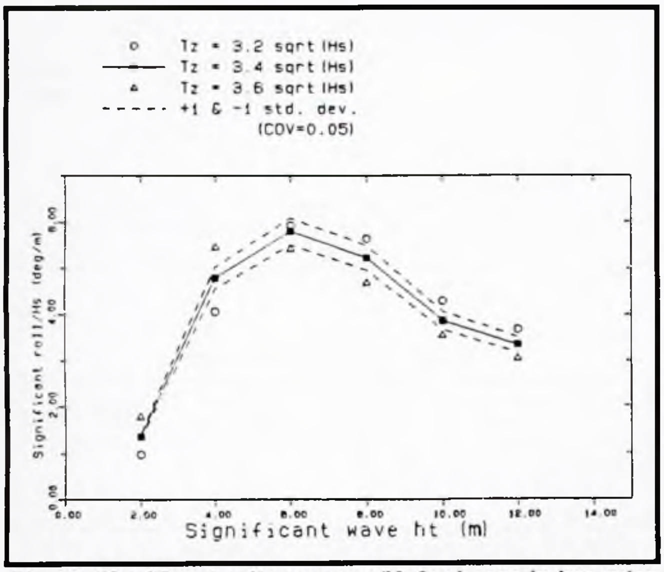

Fig 14: Significant roll response/H_s for barge in irregular beam waves

The wave height limits may be applied directly to the simulated history, in order to decide at each step whether the task is to proceed or stop. The response criteria are treated on the basis that heave and roll motions, also wind speed, are correlated with wave height. We characterise the relationship in each case in terms of the mean and standard deviation of the response as a function of the wave height.

In the present example two alternative vessels for use as a workover rig will be considered: one a semi-submersible, the other a barge. The pessimistic assumption that the vessel has to operate beam-on to the waves will be made. The response amplitude operators for these vessels in roll are shown in Fig 13. These curves show how the response varies with regular wave period. It is assumed that the response varies linearly with regular wave height.

Standard spectral superposition methods may then be used to estimate the significant response in an irregular wave spectrum. In this case it has been assumed that the waves may be described as mean Jonswap spectra. The Jonswap formula requires both the significant wave height H_s and the zero up-crossing period T_z to be specified. These two parameters are correlated and we shall consider the following range of values:

$$T_z = \alpha\sqrt{H_s} \tag{10}$$

where α = 3.2, 3.4, 3.6. The upper and lower bounds are based on limits given in section 3.1.8 of Ref 15. The significant roll response of the barge, as functions of H_s and T_z, are shown in Fig 14.

The two parameters describing the relationship between significant roll response and H_s may now be estimated. The 'mean' response is taken to be the curve with α = 3.4. The response also varies with T_z, and this is treated as statistical variability about the mean, and characterised in terms of a coefficient of variation (COV = standard deviation of response 0 divided by the mean for each value of H_s). It is not clear how to relate one standard deviation to results for α = 3.2 and 3.6. It will be assumed, however, for present purposes that they are roughly the same. The results are not, in any case, very sensitive to the amount of variability so introduced, which tends to average out during the course of the simulation. In this case a COV equal to 0.05 is chosen, and the dashed curves in Fig 14 then represent $\pm 1\sigma$ either side of the mean.

Similar procedures were used to calculate heave and roll response curves for both the barge and semi-submersible, and for the relationship between wave height and wind speed.

At any time step, with significant wave height H_s, the response is then calculated as:

$$R_m(1 + Z_i \times \text{COV}) \tag{11}$$

where R_m is the 'mean' response corresponding to H_s and Z_i is a standard random normal deviate.

The wave height simulation was based on seasonal data for the Forties field (see next section for further details), and, for the purpose of this comparison, all tasks were assumed to take the same minimum time (24h) and to be of single-pass type.

The results are summarised in Tables II and III, which are reproduced from the BMTOPS output. The first four columns contain the mean, standard deviation, minimum and maximum task completion times for the simulation. The next four columns contain corresponding statistics of downtime. Next comes the fraction of time when the task was proceeding actively; this statistic is the best single-number indicator of efficiency.

The superiority of the semi-submersible over the barge (at least in beam-sea conditions) is immediately apparent. The differences arise through the heave and roll characteristics. The heave response of the semi-submersible was about half that of the barge. Its roll response, however, was about $^1/_7$ that of the barge, and this was where the main improvement arose.

Table II: Completion and downtime statistics for barge with OWV criteria

Program Down 1: Summary of task completion statistics
Wave height data source: Forties persistence data
Task data: Barge/OWV criteria

	Total completion times (h)				Lost times (h)				%Active time
	Mean	St–Dev	Max	Min	Mean	St–Dev	Max	Min	
Wireline W/O	49.2	65.1	540.0	24.0	25.2	65.1	516.0	0.0	48.7
Logging	40.3	47.6	411.0	24.0	16.3	47.6	387.0	0.0	59.5
Cementing	43.0	62.0	606.0	24.0	19.0	62.0	582.0	0.0	55.8
R&L W/L BOP	108.2	183.2	1332.0	24.0	84.2	183.2	1308.0	0.0	22.2
Pull W/L BOP	39.7	51.0	474.0	24.0	15.7	51.0	450.0	0.0	60.5
Disc W/L LRA	36.4	43.9	375.0	24.0	12.4	43.9	351.0	0.0	66.0
Diving	27.7	16.8	207.0	24.0	3.7	16.8	183.0	0.0	86.6
Totals for sequence: 1	**342.7**	**246.0**	**1710.0**	**168.0**	**174.7**	**246.0**	**1542.0**	**0.0**	**49.0**

Table III: Completion and downtime statistics for semi-submersible with OWV criteria

Program Down 1: Summary of task completion statistics
Wave height data source: Forties persistence data
Task data: Semi-submersible/OWV criteria

	Total completion times (h)				Lost times (h)				%Active time
	Mean	St–Dev	Max	Min	Mean	St–Dev	Max	Min	
Wireline W/O	25.3	6.8	96.0	24.0	1.3	6.8	72.0	0.0	94.9
Logging	24.3	2.2	51.0	24.0	0.3	2.2	27.0	0.0	98.9
Cementing	25.1	6.4	111.0	24.0	1.1	6.4	87.0	0.0	95.5
R&L W/L BOP	75.1	106.0	1188.0	24.0	51.1	106.0	1164.0	0.0	31.9
Pull W/L BOP	28.9	18.7	177.0	24.0	4.9	18.7	153.0	0.0	83.1
Disc W/L LRA	24.1	1.8	51.0	24.0	0.1	1.8	27.0	0.0	99.5
Diving	24.2	2.2	54.0	24.0	0.2	2.2	30.0	0.0	99.2
Totals for sequence: 1	**226.1**	**110.5**	**1332.0**	**168.0**	**58.1**	**110.5**	**1164.0**	**0.0**	**74.3**

These results are, of course, not surprising, and were chosen as an illustrative example. This technique is capable of showing much more subtle differences between different vessels, and of identifying which type of limit is most critical, and where improvements need to be sought.

Modelling of a floating production and offloading system

The last illustrative example is a floating production and offloading system. The model is based on the BP Buchan CALM system and some of the results will be compared with actual operating experience.

The Buchan system consisted of a Pentagone-type semi-submersible production vessel, with no on-board storage, together with a CALM loading buoy and two dedicated shuttle tankers. A detailed description of the Buchan system, together with operational and downtime statistics, is given in Ref 16. The present simulation is based on later experience with the vessel, described in Ref 17.

A production system of this type cannot easily be described in terms of a single sequence of tasks. In this case there are essentially three sequences as follows:

1. oil production, via the production riser assembly to the process plant on the platform, then via a subsea line to the CALM loading buoy;
2. oil transfer to each of two tankers, moored to the CALM buoy, which then have to return to port and unload.

The following operating criteria were assumed:

1. oil production rate in good weather conditions = 21 000 b/d (1987 rate, from Ref 17) with no on-board storage;
2. shuttle tanker capacity is 450 000 barrels (based on 60 000 dwt tanker, from Ref 17). At the above production rate, this corresponds to about 20 days production;
3. tanker may return to port if disconnected in bad weather and more than 75% full (also based on assumptions in Ref 17);

Table IV: Oil production downtime for Buchan

	Total downtime	Weather downtime	Other delays
Case A:			
BMTOPS	8.7	4.9	3.8
Marex	6.2		
Case B:			
BMTOPS	28.2	4.7	23.5
Actual	22.2		

The Marex prediction and actual operating value were taken from Ref 17.

Table V: Tanker downtime

	Total downtime	Weather downtime	Other delays
BMTOPS:			
Case A	46.9	3.3	43.6
Case B	58.0	22.7	35.3

4. tanker turn-round time is 72h;
5. remooring time on returning to CALM buoy or after disconnection is 6h;
6. delay on reconnecting the production riser is 24h (assumed in Ref 17).

Two different sets of wave height threshold levels were used. Both come from Ref 17. One set was based on the original Marex study of the Buchan system, while the other set was based on actual operating experience (1981). These two sets of criteria were as follows:

riser disconnect level – H_s = 6.5m
riser reconnect level – H_s = 1.5m

Case A (Marex): tanker disconnect level – H_s = 5.5m
tanker reconnect level – H_s = 3.5m

Case B (actual): tanker disconnect level – H_s = 3.22m
tanker reconnect level – H_s = 2.15m

The difference between these two cases, therefore, is the much lower actual thresholds for tanker disconnection and reconnection. The reconnection threshold is particularly crucial.

Wave conditions for Buchan were not readily to hand and the simulation was based on statistics for Forties.[10] Spring, summer, autumn and winter conditions were simulated in sequence, for a period of 10 years using the building-brick model.

The total amount of lost time was divided into weather downtime and other delays. Weather downtime for oil production was caused solely by having to pull the riser. Other sources of delay include riser reconnection delays, tanker disconnected or not available to collect oil. The mean calculated downtimes, expressed as a percentage of total time, for oil production are given in Table IV.

BMTOPS has predicted slightly more downtime than Marex or actual operating experience had indicated. The difference is, however, well within the range of uncertainty associated with defining the sea-states and operating limits. The Forties wave conditions, in particular, may have been worse than those at Buchan, because Forties is slightly further from the Scottish coastline – and did in any case cover different periods of time. The simulation is, moreover, likely to be less reliable for modelling the persistence of very low wave heights around the tanker reconnect threshold.

Table V shows corresponding downtimes for one of the tankers.

There was a marked increase in weather downtime when the tanker connection thresholds were reduced (Case B in Table V). 'Other delays' are quite large in both cases, because they included waiting time offshore while the other tanker loaded.

These examples were then rerun to see the effects of: reducing tanker turn-round time to 48h, increasing the tanker remoor time to 12h, using two CALM buoys instead of one, allowing both tankers to be moored simultaneously. These changes made only minor differences to downtime for oil production, changing it by at most 3% of the total time.

The system was insensitive to turn-round time because of the large storage capacity of the shuttle tanker relative to the oil production rate. The lost oil production time arose largely as a result of having to disconnect the tanker and then wait until conditions improved. The riser was disconnected relatively infrequently and the resulting downtime was quite small.

Once again these results are intended mainly as an illustrative example. The program could also be used to show sensitivity to production rate, shuttle tanker capacity and to the choice of production vessel (for example, whether on-board storage is worthwhile using a SWOPS-type system). Response limits on the production process itself can also be included very easily. The oil/gas separation equipment may, for example, be sensitive to vessel roll motions. Response limit criteria may then be set using the approach outlined in the section on sequential task modelling.

This model takes account of downtime due directly or indirectly to weather. A large part of the downtime actually occurring offshore seems to be associated with equipment failure and waiting-on-weather for repairs. Reference 16, for example, shows that nearly 50% of the total available production time was lost at Buchan during 1981/82, much of this due to mooring arm damage, broken hawsers or general repairs to the buoy. Where such effects are quantifiable, they can be included quite readily in the computer model. This then allows planning decisions to be made in as well-informed a manner as possible.

CONCLUDING COMMENTS

BMT has developed a downtime analysis computer package, known as BMTOPS, which includes two alternative wave height simulation routines. These simulation routines make use of wave height persistence data.

The programs are very efficient and fast, enabling many different scenarios to be evaluated. Typical run times on a MicroVAX II were about 3 min for a 10 year downtime analysis of the Buchan data, involving three tasks sequences in parallel. The building-brick simulation of wave height took slightly longer; a Markov simulation would be faster.

BMTOPS is a sophisticated and flexible package, allowing simulation of either single-sequence or multi-sequence operations. Task thresholds may be defined in terms of wave heights, response motions, wind speed and in various other ways.

Typical results from the two wave simulation and downtime analysis modules have been used to demonstrate the validity of the program, to show the sensitivity of results to modelling assumptions, and to show how BMTOPS is used in practice.

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