# Optimization of vibration analysis inspection intervals for an offshore oil and gas water injection pumping system

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**Abstract:** Maintenance is often considered a 'necessary evil' rather than a means of delivering value to owners and operators of physical assets, and means that maintenance seldom has the requisite importance and focus required. Optimal maintenance allows the delivery of maximum productivity and profit at minimum costs, and there are two ways of determining a nominally optimal maintenance solution: qualitative and quantitative optimization. Condition-based maintenance has long been recognized as an effective strategy for maintaining critical plant, and involves the regular inspection of equipment condition to determine the need for remedial maintenance activities. The periodicity at which inspections takes place is often ill-determined and appropriate quantitative analysis seldom takes place. Such an approach often leads to excessive direct costs and can result in significant indirect costs if asset failure is considered. This paper presents a solution to this problem; the quantitative delay-time maintenance model allows the determination of the optimum condition-based maintenance inspection interval. This approach is illustrated by the application of the model to the optimization of vibration analysis intervals for an offshore oil and gas water injection pumping system and demonstrates advantages when compared with conventional qualitative approaches.

**Keywords:** water injection, condition-based maintenance, optimization, vibration analysis

## 1 INTRODUCTION

Industry is increasingly challenged to improve productivity and reduce operational costs whilst meeting health, safety and environmental (H, S and E) requirements. This places significant emphasis on minimizing the cost base of asset ownership to increase profitability. Given this, maintenance can be treated as a cost to be minimized, rather than as a strategic investment. Given that maintenance budgets rival that of defence spending [**1**], it is easy to appreciate the drivers for minimizing maintenance costs; however, when it is considered that the risk of insufficient or inappropriate maintenance can result in production downtime of millions of pounds per day or H, S and E consequences, there is a clear need to balance direct maintenance costs (labour, materials, administration) with the risked costs of not performing maintenance (labour, materials, administration, H, S and E, lost and deferred production, reputation). This is clearly shown in Fig. 1, which demonstrates that, as the direct costs of maintenance increase, there is a general decrease in the risked costs. The sum of the direct and risked costs of maintenance yields the total cost of maintenance, and the optimal condition is satisfied by the total cost minima. The optimal maintenance condition is a target that is difficult to achieve as the optimum condition is ever-changing; economic considerations, performance assumptions, production capability, technology and personnel competence are not fixed but vary with time and mean that maintenance that is regarded as being optimal today may be sub-optimal in the future.

The most common maintenance optimization method is reliability-centred maintenance (RCM), a qualitative approach relying on subjective opinion

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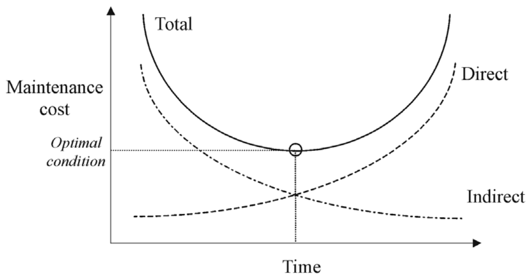


**Fig. 1** Direct, indirect and total maintenance costs

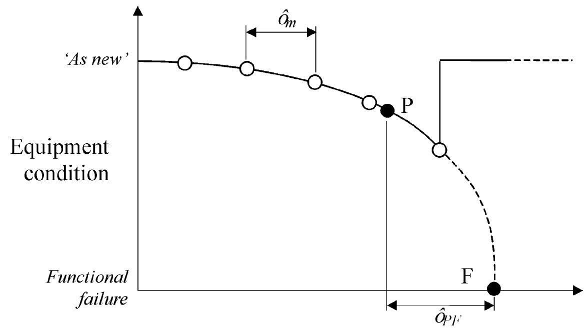


**Fig. 2** Equipment condition varying with time

and experience. An alternative approach is mathematical maintenance optimization, a quantitative analysis requiring reliability data and mathematical models. These two approaches are seldom complimentary; the qualitative approach can be clouded through the rigorous data demands of mathematical modelling and these same models require data that is often unavailable; however, it is increasingly the case that the simpler quantitative approaches can bring benefits to maintenance optimization and it has been recommended **[2]** that it is of value to adopt a simple model, make some well-founded assumptions and derive an approximately optimal solution.

There is an infinite range of maintenance activities that can be applied to physical assets; however, this range can be split into three broad maintenance types **[3]**: overhaul, condition-based and on-failure. Of these, condition-based maintenance (CBM) is a cost-effective means of maintaining critical plant **[4]** and involves the measurement of a characteristic equipment parameter, and inference of equipment condition. Remedial maintenance is scheduled according to the condition of the equipment item, minimizing the likelihood of the consequences of unplanned failure. The most common means of implementing CBM is vibration analysis; vibration measurements infer the mechanical condition of rotating equipment and provide information on incipient failure conditions such as misalignment, imbalance, looseness and bearing degradation.

Determination of an appropriate interval at which to conduct CBM activities is difficult; in a qualitative approach practitioners rely on history, experience and original equipment manufacturer (OEM) recommendations. Indeed, the total disregard of quantitative reliability data has been recommended [**5**, **6**] when conducting qualitative analysis because of added complexity. In reality, quantitative data is often disregarded and a maintenance interval selection strategy based on engineering judgement and experience is adopted. For condition monitoring activity interval selection in a qualitative approach, it is considered sufficient that potential failure (PF) intervals are known, as shown in Fig. 2.

Figure 2 shows how the degradation of some arbitrary equipment condition eventually leads to functional failure. The point at which the degrading equipment condition, shown on the vertical axis, can first be detected is point P and is the 'potential' point. Inspections, carried out at ○ are spaced at regular intervals of $\tau_{\mathrm{m}}$ and point F is the point at which functional 'failure' occurs. The time between P and F is termed the PF interval, $\tau_{\mathrm{PF}}$. For condition monitoring to be successful (the defect to be detected and repaired prior to failure), the monitoring interval must be less that the PF interval, otherwise incipient failure may go undetected. Indeed, it is typically **[7]** the case that the monitoring interval is recommended to be set such that $\tau_{\mathrm{m}} \leq \tau_{\mathrm{PF}}/2$. In Fig. 2, the arbitrary equipment condition degrades to point P, after which degradation continues until the next inspection interval. The defect is then detected and repaired, and the equipment condition returned to the 'as new' condition. In this way, functional failure and consequential losses are avoided.

One of the main obstacles to the use of the PF approach is that there is no data on which to base PF intervals; very little by way of published work exists. In Moubray **[7]**, a PF interval of 'weeks to months' is quoted for vibration analysis, giving a monitoring interval of the order of weeks to months. Setting the specific monitoring intervals for particular equipment items is very often left to individual judgement, and can be error-prone. Also, assessing the PF interval is inherently subjective as, if CBM is effective, point F is never reached, hence $\tau_{\mathrm{PF}}$ cannot be measured. A further disadvantage of the PF approach is that the assessment of condition is qualitative; no explicit measurements are attributed to the points 'P' and 'F'. For example, in the case of vibration analysis, the point 'F' could be represented by a vibration level exceeding limits imposed by the equipment manufacturer, the limits stated in vibration standards, or the trip limits of the equipment item, all of which may be different. These deficiencies can be addressed through the adoption of the delay-time optimization model, which uses a different (mathematical modelling) approach to the optimization of inspection intervals. This paper presents the application of the delay-time maintenance model to the optimisation of vibration analysis intervals for an offshore oil and gas water injection (WI) pumping system.

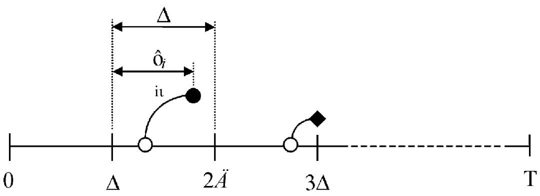


**Fig. 3** Delay-time concept

## 2 DELAY-TIME MODELLING

### 2.1 Overview

The two-parameter delay-time model has been established since 1973 [**8**] and has previously been applied to intrusive inspection situations where the presence of a fault can be determined by physical inspection. A previous example of the application of the delay-time model to vibration analysis interval optimisation has been published in Wang *et al.* [**9**], who investigated the optimum vibration monitoring interval for paper mill bearings. In the paper, a restricted approach was taken and it was assumed that the bearing is a single component with a single, dominant failure mode and that the delay times can be described by the Weibull distribution. Another example [**10**] of modelling of condition-based maintenance examines the usefulness of the delay-time model for modelling the maintenance practices for coal face machinery.

Whilst the delay-time model has proven useful in these two illustrative examples, the model has yet to be implemented in industrial maintenance optimization, even within the framework of a qualitative approach. This is anomalous as models such as the simple delay-time model have much to offer. Reasons for the lack of application of models such as these include a lack of visibility in the engineering and maintenance arenas, an unwillingness to embrace what is perceived as a complex issue and a belief that the models are difficult to implement and data-intensive [**1**, **2**]. This is especially the case when the use of the model is compared with qualitative approaches which rely on subjective opinion. This paper helps to address these misconceptions through the application of the simple delay-time optimization model to a real-life situation with demonstrable benefits over traditional methods.

As shown in Fig. 3, the delay-time concept [**2**] introduces a failure process that occurs in a two-stage stochastic manner. Suppose an equipment item or component is subject to regularly spaced inspections (such as vibration analysis), with inspections occurring every $\Delta$ in the interval $[0, T]$ where $T$ is some multiple of $\Delta$. A defect (incipient failure) can be detected by inspection at point ○ and is either followed by the inspection and repair of the defect at point ◆, or by catastrophic failure at point ●. There are a total of $n$ defects experienced in the observation period $[0, T]$ and $\tau_i$ is the time to failure at ●, measured from the previous inspection interval. It is assumed that inspections are perfect, i.e. if a defect exists at an inspection the defect is detected and repaired, and that repair times are negligible. The delay-time is the time between a defect becoming apparent and functional failure actually occurring. For example, in discrete interval vibration analysis, the delay-time is the time between a mechanical defect (imbalance, misalignment, bearing wear etc.) being detectable through analysis of the vibration signal and actual functional failure of the mechanical component. Note that functional failure need not be the cessation of component operation, but could equally be excessive vibration when compared with relevant acceptance standards, and depends on the functional specifications that are imposed on the equipment. In the event that the delay-time is shorter than the inspection interval, $\Delta$, the defect may go undetected and failure may result. Clearly, the PF interval concept presented previously and the delay-time model are analogous in that the PF interval is equivalent to the delay-time.

For a Poisson process of defect arrivals of rate $\alpha$ with exponentially distributed delay-times with mean $1/\gamma$ and perfect inspections, the maximum likelihood estimates satisfy the expressions

$$\widehat{\alpha} = \frac{n}{T} \tag{1}$$

$$\sum_{i=1}^{k} \frac{\widehat{\gamma}\,\tau_i}{\mathrm{e}^{\widehat{\gamma}\tau_i} - 1} + \sum_{i=1}^{n-k} \frac{\widehat{\gamma}\,\Delta}{\mathrm{e}^{\widehat{\gamma}\Delta} - 1} = n - k \tag{2}$$

where $k$ failures are observed at times $\tau_i$, $n-k$ defects are found at inspections, and $\widehat{\alpha}$ and $\widehat{\gamma}$ are estimates of $\alpha$ and $\gamma$ respectively. Further, the optimal inspection interval, $\Delta^*$, satisfies the expression

$$(1 + \gamma\Delta^*)\mathrm{e}^{-\gamma\Delta^*} = 1 - \frac{\gamma c_1}{\alpha c_2} \tag{3}$$

where $c_1$ is the cost of inspection and repair, and $c_2$ the cost of failure. Expression (3) has a solution provided that $\gamma c_1 < \alpha c_2$. From expressions (1)–(3) it is clear that, with accurate historical maintenance data (or reasonable assumptions), the delay-time model can be used to determine mean delay-times for equipment times, and can then be used to determine optimal inspection intervals.

### 2.2 Delay-time model assumptions

The applicability of expressions (1)–(3) depends on the following assumptions: the process are Poisson; the delay-times associated with the failures are exponentially distributed with a mean of $1/\gamma$; and maintenance inspections are perfect. The assumption that the process being modelled is Poisson with a defect arrival rate of $\alpha$ implies that defects are independent, as the likelihood of a defect in the near future is not dependent on the occurrence or non-occurrence of a defect in the recent past. This also implies that the failure rate is constant such that defects are not dependent on the age of the item. It is generally believed **[7]** that this assumption holds true for rotating equipment, as the root causes of failure are so diverse that equipment items fail before an age-related failure (wear) will become manifest. Indeed, failure data sources in the oil and gas industry **[11]** assume that defects arise in exactly this manner when compiling databanks.

The assumption that delay times are exponentially distributed with mean $1/\gamma$ implies the same independence and failure rate criteria as for defect arrivals, and initially would appear to be unfounded, as it could be reasonably be expected that a constant degradation process would apply. In practice this is not the case; delay times associated with equipment failure vary significantly, with figures of weeks to months quoted **[7]**, predominantly because of varied construction, operations and maintenance vagaries and environmental factors. The perfect inspection criteria assume that all defects that are able to be detected by inspection are actually detected and repaired prior to failure. This assumption is difficult to validate in practice as root causes of failure are hard to establish, hence identifying those defects that should have been detected prior to failure, but were not, is problematic. Similarly, ensuring that those defects that have been identified and remedied would have eventually led to failure is equally difficult to validate. Given these difficulties, and in the absence of evidence to the contrary, the perfect assumption criteria is assumed.

## 3 APPLICATION OF THE DELAY-TIME MODEL

### 3.1 System description

Canadian Natural Resources Limited (CNRL) operates the Ninian fields in the UK northern North Sea. The Ninian fields' production is declining and WI is required to boost reservoir pressure and maximize recovery; WI duty is performed by the system shown in Fig. 4.

Figure 4 shows a schematic diagram of the CNRL Ninian Central WI system. Seawater is extracted using seawater lift pumps and is then treated (filtration and the removal of corrosive oxygen). Seawater is then delivered to the seawater injection booster pumps via the pressurization drum. The seawater injection pressure of 290 Bar is then achieved in a two-step process using batteries of booster pumps and injection pumps. The pressurized seawater is delivered to the periphery of the reservoir using specific seawater injection wells and significantly aids in maximizing reservoir recovery. In total, the WI system is designed to pump 308 000 barrels of seawater per day into the reservoir. Each of the seven WI pumps delivers 44 000 barrels of seawater per 24 h day, and all units are required continuously. The pumps are 'cartridge'-type, multistage centrifugal units and are driven by induction motors via a speed-up gearbox. Although the financial consequences of a loss of WI capability varies depending on the reservoir into which the water is delivered, it is estimated that the average 'value' of lost WI capacity to CNRL is of the order of £0.30 per barrel. Hence, the unavailability of one of the WI pumps is estimated to be £550.00 per hour. Historically, a wide range of CBM activities have been undertaken on the Ninian assets, the programme of CBM activities comprising vibration analysis, lubricating oil analysis, operator watchkeeping and hydraulic performance monitoring. Vibration analysis is provided to the platforms on a monthly basis and the vibration programme on the platform constitutes 58 driven equipment items, associated drivers, power transmission, and ancillary equipment.

Vibration data collected for the WI pumps include measurements taken from both installed instrumentation and measurements collected manually from the equipment items. Measurements taken from installed instrumentation are those where there is an installed vibration monitoring system (predominantly measuring relative shaft motion via proximity probes), usually provided as part of the equipment protection system. This instrumentation typically has connections from which vibration data can be collected manually using a portable data collection device, the data being intended to provide more detailed information (spectral analysis) than the overall measurements used by alarm and shutdown functionality offered by the protection systems. Manually collected data refer to measurements taken directly from the equipment item, typically using a portable accelerometer mounted on a bearing cap. Again, a portable instrument is used to

 

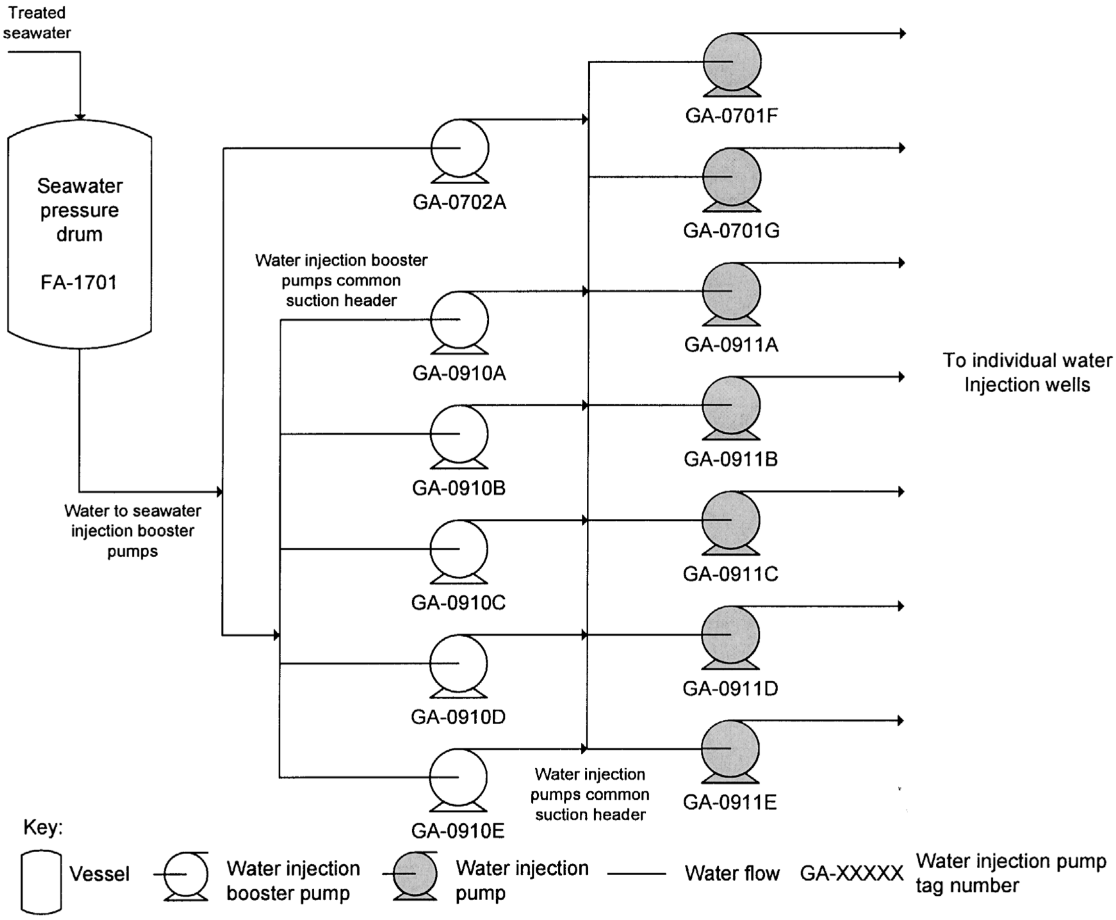


**Fig. 4** Schematic diagram of CNRL Ninian Central Water Injection system

capture relevant measurements. As routine vibration analysis is generally conducted on 'packages' of equipment (driver, power transmission, driven unit and ancillaries) rather than on individual equipment items, this paper will focus on all equipment items comprising the WI package, thereby providing a more comprehensive analysis. For convenience, the term 'WI pump' should be taken as referring to the WI pump, gearbox and driver motor.

### 3.2 Data collation and comparison

#### *3.2.1 Data collation*

Maintenance data pertinent to the WI pumps were extracted from the CNRI computerized maintenance management system (CMMS) for the period 1994–2003 inclusive. A total of 786 individual work orders (WOs) were assessed and it was determined if the maintenance referred to planned or unplanned (corrective) activities. In the event that the maintenance WO referred to a planned activity, the WO was discarded; however, if the WO referred to unplanned activity it was further analysed. Further analysis consisted of interrogating the WO to identify (as far as was possible) the nature of the corrective work and the defect which had arisen that necessitated maintenance. All unplanned WOs that described maintenance activity relating to a mechanical defect of the WI pump were collated and sorted according to WI pump, date and the equipment item that the maintenance activity pertained to.

Vibration analysis reporting for the analysis period was also reviewed. The seven WI pumps were identified in a total of 185 instances over the 10-year period. Each of these instances was analysed to determine the nature and content of incipient failure detected, and the content of the remedial maintenance activity initiated. These data were then cross-referred with the collated CMMS data and a total historical record of the WI pump maintenance derived. This record is shown in Table 1, which details the collated results and defines the defects that have been recorded for the WI pumps over the 10-year period. Each defect is recorded along with the date of the defect (or failure) and the respective inspection interval, $\Delta$ or time to failure, $\tau_i$. These data are termed 'observed' data. From Table 1 it is

**Table 1** Observed data

| Equipment item | Component | Tag number | Date of defect | Inspection interval $\Delta$ (months) | Time to failure $\tau_i$ (months) |
|---|---|---|---|---|---|
| Motor | Bearings | GA0701F | 24 January 1999 | 1 | |
| | | GA0911B | 26 September 1995 | 1 | |
| | | GA0911C | 31 December 2002 | 1 | |
| | | GA0701F | 5 August 1998 | | 0.5 |
| Gearbox | Bearings | GA0701F | 22 April 1994 | 1 | |
| | | GA0911C | 22 August 1995 | 1 | |
| | | GA0911E | 10 June 2000 | 1 | |
| | | GA0701F | 27 March 1999 | | 0.1 |
| | | GA0911B | 17 January 1994 | | 0.9 |
| Pump | Bearings | GA0701F | 22 April 1994 | 1 | |
| | | GA0911C | 20 February 1995 | 1 | |
| | | GA0911D | 13 January 1998 | 1 | |
| | | GA0911A | 22 December 1995 | | 0.2 |
| | | GA0911B | 17 January 1994 | | 0.9 |
| | | GA0911B | 7 October 1996 | | 0.4 |
| Pump | Impeller | GA0701G | 27 November 1998 | 1 | |
| | | GA0911A | 15 March 1996 | 1 | |
| | | GA0911B | 22 April 1994 | 1 | |
| | | GA0911B | 8 September 1998 | | 0.4 |
| | | GA0911B | 24 June 1999 | | 0.8 |
| | | GA0911D | 13 December 1995 | | 0.9 |
| | Shaft | GA0701F | 3 May 1997 | 1 | |
| | | GA0911B | 17 September 1996 | | 0.9 |
| | | GA0911C | 1 October 1995 | | 0.1 |
| | | GA0701G | 16 October 1997 | | 0.7 |

clear that, for the data analysed, only a single dominant failure mode was demonstrated for the WI motor and gearbox: bearing failure. However, the WI pumps demonstrated three clear failure modes; bearing failure, impeller failure, and shaft failure.

### 3.2.2 *Data comparison*

In order to ensure that the observed data was broadly consistent with other reference data, the failure rates of observed and reference data were compared. Reference data was sourced from an industrial reliability databank **[11]** and their comparison with observed data is shown in Table 2. In Table 2, both observed and reference data have been converted to a common base, the mean time between failure (MTBF). For the observed data, the MTBF is calculated in two steps; firstly expression (1) is used to estimate a failure rate, $\alpha$, given a value for $T$ of 70 equipment-years or 840 equipment-months. This failure rate is then converted to an MTBF. For the reference data, failure rates are initially expressed per $10^6$ h and are then converted to a MTBF assuming continuous equipment operation, as is the case with the equipment analysed. The failure rates for the reference data were selected by attributing a percentage of the overall mean failure rate to the applicable equipment component. For example, the mean overall failure rate for centrifugal WI pumps in **[11]** is given as 541.320 per $10^6$ h and the proportion of the total failure rate that is attributed to bearings (all types) is 3.48%, giving a proportionate failure rate of 18.840 per $10^6$ h.

From Table 2 it may be seen that the failure rates for the observed and reference data are comparable; however, with the exception of motor bearings and pump impellers, the observed data failure rates are greater (and the MTBF shorter) than those of the

**Table 2** Comparison of failure rates

| | | Observed data | | Reference data | |
|---|---|---|---|---|---|
| Equipment item | Component | Failure rate $\alpha$ (per month $\times 10^{-3}$) | MTBF (years) | Failure rate (per $10^6$ h) | MTBF (years) |
| Motor | Bearings | 4.762 | 17.500 | 9.740 | 11.720 |
| Gearbox | Bearings | 5.952 | 14.000 | 1.949 | 58.579 |
| Pump | Bearings | 7.143 | 11.667 | 18.840 | 6.060 |
| Pump | Impeller | 7.143 | 11.667 | 2.057 | 55.500 |
| Pump | Shaft | 4.762 | 17.500 | 3.789 | 30.126 |

**Table 3** Mean delay times and dominant failure modes

| Equipment item | Component | Mean delay-time $1/\gamma$ (months) |
|---|---|---|
| Motor | Bearings | 1.580 |
| Gearbox | Bearings | 0.808 |
| Pump | Bearings | 0.560 |
| Pump | Impeller | 0.663 |
| Pump | Shaft | 0.209 |

reference data. There are a number of reasons for the differences between the failure rates; the reference data is an amalgam of data from a number of difference equipment items, manufacturers, organizations and installations, whereas the observed data is from a single installation of WI pumps and different operations, maintenance and data reporting practices all serve to affect the failure rates. It should be noted that the observed data represent a total operational time of 70 equipment-years spanning seven equipment items on one installation, while the reference data represents a total operational time (pumps only) of 131 equipment-years, spanning 44 equipment items on eight installations. Also, the interpretation of historical maintenance records can also affect the way in which failure rates are represented as it is typically the case that facilities such as accurate failure coding are not used.

### 3.3 Mean delay time calculation

The observed data presented in Table 1 was then used with expression (2) to determine the mean delay-times, $1/\gamma$, for each of the dominant WI failure modes. The results are shown in Table 3.

It is interesting to note that the mean delay-times shown in Table 3 are significantly less than those normally assumed when determining vibration inspection intervals; typically, a delay-time (PF interval) of around 3 months is assumed and an inspection interval of one month implemented. There is also a range of mean delay-times demonstrated for similar components of different equipment items; bearings of the motor, pump and gearbox demonstrate a range of 0.560–1.580 months. This is reasonable, as the environmental conditions of the bearings in the three equipment items are different, the bearing arrangements are particular to the equipment item, and the rate of propagation from a defect becoming apparent to eventual failure will be different in all cases. The delay-time for the pump shaft is also significantly less than that of the other dominant failure modes with a mean of 0.209 months. This is expected, as by the time a shaft defect (typically a crack in the analysis conducted) becomes evident through vibration analysis the crack is well propagated, and the residual time to failure short.

### 3.4 Optimal inspection intervals

Following the determination of the mean delay-times, the optimal inspection interval, $\Delta^*$, was calculated using expression (3). Tables 2 and 3 detail the appropriate rate of defect arrival, $\alpha$, mean delay-times, $1/\gamma$, and the costs of inspection and repair, $c_1$, and costs of failure, $c_2$, are shown in Tables 4 and 5 respectively. The costs of inspection and repair have been estimated by calculating the labour and materials costs of detecting and repairing the defect to an as new condition. In all cases, an inspection cost of £100 has been assumed, and this figure includes the costs of contract labour, transportation, accommodation, data collection, data analysis and reporting. Labour costs have been estimated by assuming that each repair activity requires two maintenance personnel for the duration of the work, and that the internal costs of labour are £100 per hour. Attempts to cross-refer the costs of inspection and repair to the CMMS data were made but these data did not contain sufficient information to allow a direct correlation. Note also that the repair activities have also been assumed to be such that the repair can be affected in a planned manner coincident with other planned equipment outages, i.e. the equipment item is not required during the maintenance period, and concomitant production deferral is averted.

**Table 4** Costs of inspection and repair

| | | Repair | | | Costs (£) | | | |
|---|---|---|---|---|---|---|---|---|
| Equipment item | Component | Activity | Materials | Duration (h) | Inspection | Labour | Materials | Total $c_1$ |
| Motor | Bearings | Replace bearings | Bearings | 6 | 100 | 1200 | 1000 | 2300 |
| Gearbox | Bearings | Replace bearings | Bearings | 6 | 100 | 1200 | 1000 | 2300 |
| Pump | Bearings | Replace bearings, seals | Bearings, seals | 24 | 100 | 4800 | 5000 | 9900 |
| Pump | Impeller | Replace impeller | Impeller, bearings, seals | 36 | 100 | 7200 | 30 000 | 37 300 |
| Pump | Shaft | Replace shaft | Shaft | 240 | 100 | 48 000 | 20 000 | 68 100 |

**Table 5** Costs of failure

| Equipment item | Component | Repair: Activity | Repair: Materials | Repair: Duration (h) | Production deferral (h) | Costs (£): Labour | Costs (£): Materials | Costs (£): Deferred production | Costs (£): Total $c_2$ |
|---|---|---|---|---|---|---|---|---|---|
| Motor | Bearings | Replace motor | Motor | 24 | 168 | 4800 | 250 000 | 92 400 | 347 200 |
| Gearbox | Bearings | Replace gearbox | Gearbox | 96 | 360 | 19 200 | 300 000 | 198 000 | 517 200 |
| Pump | Bearings | Replace cartridge | Cartridge | 120 | 1680 | 24 000 | 100 000 | 924 000 | 1 048 000 |
| Pump | Impeller | Replace cartridge | Cartridge | 120 | 1680 | 24 000 | 100 000 | 924 000 | 1 048 000 |
| Pump | Shaft | Replace cartridge | Cartridge | 120 | 1680 | 24 000 | 100 000 | 924 000 | 1 048 000 |

The costs of failure were estimated by calculating the labour, materials and deferred production costs of a defect which had turned into a catastrophic failure (as opposed to being detected through inspection and repaired). Labour and materials associated with the maintenance activities have been calculated as previously, except that a component failure results in significantly more damage than in the case of detection and repair, and in the case of the offshore oil and gas industry, normally results in a replacement equipment item being installed, rather than a repair taking place and in all instances a 'worst case' scenario has been presumed. Deferred production costs have been estimated as the product of the costs of production deferral for one hour for one machine (£550) and the likely production deferral duration. Optimal inspection intervals were then calculated and the results are shown in Table 6 along with the relevant data. From Table 6 it may be seen that optimal inspection intervals can be derived for both the motor and the gearbox; however, there are no solutions to expression (3) for the pump for any of the dominant failure modes. This is because the $\gamma c_1 < \alpha c_2$ condition cannot be satisfied, and it is therefore optimal to never inspect the unit.

From the results presented it is clear that the optimal inspection interval for the WI pumps is different to that currently being implemented; the delay-time model suggests that intervals of 5.790, 3.425 and $\infty$ are optimal for the motor, gearbox and pump equipment items, respectively. For the pump specifically, the requirement that the $\gamma c_1 < \alpha c_2$ condition be satisfied before it is optimal to perform any inspections means that, with $\alpha$, $c_1$ and $1/\gamma$ remaining as in Table 6, the costs of failure, $c_2$, are required to be £$1.250 \times 10^6$, £$6.335 \times 10^6$ and £$20.095 \times 10^6$ before the inspections become of value for the bearings, impeller and shaft respectively. For the results presented it is clear that there are potential opportunities for cost savings in the current inspection regime; for the seven WI pump examined, each item is subject to inspection at a monthly interval, giving annual direct costs of £25 200 for inspection only. Assuming that nominally optimal inspection intervals of 6, 3 and $\infty$ months were chosen for the motor and gearbox (the pump not being inspected at all), those annual direct costs would reduce to £4200.

## 4 CONCLUSIONS

This paper has presented the delay-time mathematical maintenance optimization model, and has used the model to optimize the vibration analysis inspection intervals of an offshore oil and gas WI pumping system. Industrial data pertaining to the WI system has been sourced from the CMMS and CBM reports and have been collated to form a 'picture' of the failure history of the WI pumps. These data have been compared with an existing industry-standard databank and shown to be reasonable. The delay-time model has been used to generate a series of mean delay-times for each of the WI pump dominant failures and these delay-times are significantly smaller that have been previously

**Table 6** Optimal inspection interval $\Delta^*$

| Equipment item | Component | Total failures, $n$ | Failure rate $\alpha$ (per month $\times 10^{-3}$) | Mean delay-time $1/\gamma$ (months) | Inspection cost $c_1$ (£) | Failure cost $c_2$ (£) | Optimal inspection interval $\Delta^*$ (months) |
|---|---|---|---|---|---|---|---|
| Motor | Bearings | 4 | 4.762 | 1.580 | 2300 | 347 200 | 5.790 |
| Gearbox | Bearings | 5 | 5.952 | 0.808 | 2300 | 517 200 | 3.425 |
| Pump | Bearings | 6 | 7.143 | 0.560 | 5000 | 1 048 000 | No solution |
| Pump | Impeller | 6 | 7.143 | 0.663 | 30 000 | 1 048 000 | No solution |
| Pump | Shaft | 4 | 4.762 | 0.209 | 20 000 | 1 048 000 | No solution |

assumed when initially determining inspection intervals. The model has then been used with estimated costs of inspection, repair and failure to determine optimal inspection intervals for vibration analysis. It has been shown that the current vibration analysis inspection schedule is sub-optimal and incurs excessive costs and it has been shown that it is sub-optimal to ever inspect the WI pump equipment item. The delay-time maintenance model has been shown to have clear applicability in the optimization of vibration analysis inspection intervals and reduces the subjectivity often associated with determining suitable periods between inspections. The use of the model does depend on having access to accurate data pertaining to defects and failures, or the ability to make reasonable assumptions that can be validated. In this paper data was extracted from a CMMS and a manual 'filtering' process was required to validate data. In the absence of an appropriate failure coding system, failure data will require manual validation. Further, it is clear that the volume of actual data required to perform the analysis is small; only a total of 25 instances of $\tau_i$ and $\Delta$ were required over 70 equipment-years; however, these data must be representative of equipment performance. Therefore it seems reasonable to suggest that a well-populated CMMS is a prerequisite for practical application of the technique. This methodology is sufficiently general that it can be applied to any asset that employs physical assets and where CBM is applied, providing that sufficiently accurate failure data are available.

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