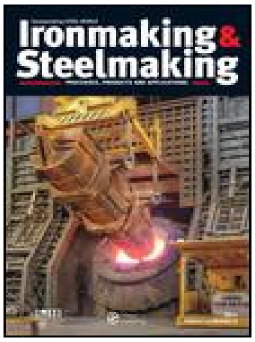


Taylor & Francis
Taylor & Francis Group

Ironmaking & Steelmaking
Processes, Products and Applications

ISSN: 0301-9233 (Print) 1743-2812 (Online) Journal homepage: http://www.tandfonline.com/loi/yirs20

Development of model to predict condition monitoring interval times

K.B. Goode, B.J. Roylance & J. Moore

To cite this article: K.B. Goode, B.J. Roylance & J. Moore (2000) Development of model to predict condition monitoring interval times, Ironmaking & Steelmaking, 27:1, 63-68

To link to this article: http://dx.doi.org/10.1179/030192300677381

Published online: 18 Jul 2013.

Development of model to predict condition monitoring interval times

K. B. Goode, B. J. Roylance, and J. Moore

Condition monitoring intervals are usually set at fixed intervals of length typically set by a mixture of British Standards, manufacturer's recommendations, and personal experience. These rather *ad hoc* methods have little scientific basis. A recently developed condition based maintenance model is described which utilises reliability data combined with condition monitoring measurements. This model provides the necessary basis to optimise condition monitoring intervals. Results obtained using artificial data, based on typical machines found in a hot strip mill, show how the model can be used as part of a condition based maintenance strategy. I&S/1447

Mr Goode was formerly at the EPSRC Engineering Doctorate Centre – Wales, University of Wales Swansea, Singleton Park, Swansea SA2 8PP and is now with Corus, Llanwern Steel Works, Newport, Gwent NP9 0XN. Dr Roylance is in the Department of Mechanical Engineering, University of Wales Swansea, Singleton Park, Swansea SA2 8PP, and Mr Moore is with Welsh Technology Centre, Corus, Port Talbot, SA13 2NG. This paper was presented at the 4th Annual Seminar of the EPSRC Engineering Doctorate Centre – Wales, held at the University of Wales Swansea on 14 September 1998. Manuscript received 30 April 1999; accepted 16 February 2000.

INTRODUCTION

From the mid 1970s organisations primarily dependent on expensive, complex machinery had greater economic demands placed on them to maximise machine life, while at the same time increasing reliability and availability. Customer demands also insisted on consistent product quality, delivered 'just in time' and produced by a safe, environmentally acceptable process. These new challenges are presently being met by new strategies and techniques and a better understanding of maintenance effects. The new strategy being widely exploited is condition based maintenance, whereby a machine is only maintained when it is actually required.[1] Condition based maintenance assumes that a machine will seldom break down without warning.[2] If these warnings can be identified by monitoring some physical parameter, it is argued that it may be possible to assess the condition of the machine, recognise any malfunction, and, hence, identify when a maintenance action is required. The cost of such systems can vary enormously from a few pounds to many thousands.[3] The most complex systems require substantial management support, investment in hardware, appropriate software, and personnel training. Although condition based maintenance is a more complex strategy, it offers the greatest potential financial savings, especially in high maintenance cost industries or where unplanned downtime is financially unacceptable. Dutta states that the adoption of condition based monitoring now forms the backbone of the maintenance strategy at the Bethlehem Steel Co., USA.[1]

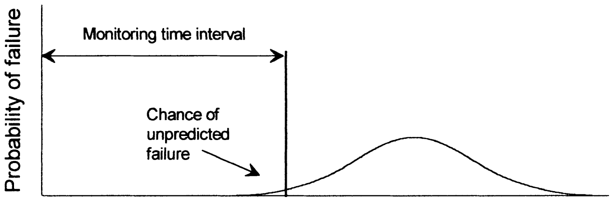
For several years, steel companies in the UK have practised condition based maintenance in strategically vital areas such as hot strip mills. The methods of monitoring utilised cover virtually the whole spectrum of activity; these include vibration analysis, oil and wear debris analysis, and performance monitoring using numerous techniques to measure, e.g. motor current, temperature, etc. Generally, these measurements are collected by operators periodically and stored on a historical database. By comparing the measurements with an original 'fingerprint' measurement, obtained from a correctly operating machine, the current condition of the machine can be assessed and decisions on whether to maintain can be made.

With future increases in condition based monitoring activities coupled with a decrease in available workforce, the need to collect measurements effectively will gain more importance. It therefore follows that a methodology aimed at optimising the collection and processing of condition monitoring measurements is desirable.[1] The model described in this paper aims to introduce a method by which this optimisation can be achieved. It has been developed on the assumption that the failure pattern can be divided into two distinct phases: stable and unstable, which can be distinguished by using the current alarm limits. Depending on the way in which the machinery progresses to failure, one of two methods is employed to predict the chance of failure in a given interval. The first is based entirely on a reliability model, while the second method uses a novel combination of reliability and condition monitoring measurements. If the chance of failure can be predicted, it follows that a condition monitoring time interval can be established provided a criticality or risk factor can be agreed. This criticality assessment will be a function of many factors including the potential lost time after a failure, cost, maintenance time, spares availability, safety, and environmental impact. After describing the methodology used to predict the condition monitoring intervals, the results of a test using artificial data are presented that show how the model can be utilised as part of a condition based maintenance strategy.

CURRENT MONITORING INTERVAL THEORY

Current condition monitoring interval times are typically based on fixed time intervals, empirically dictated by British Standards, equipment manufacturers, and historical operational experience. The major benefit of this approach is the ease of implementation and lack of any other widely used methodology. However, this convenience may seriously compromise the efficiency of the data collection, especially when there exists evidence of time dependent machine failures. If monitoring intervals are too short, valuable man hours will be wasted collecting the data, while, if they are too long, a machine failure may occur without any warning, as shown in Fig. 1.

Inspection models have been developed by Christer[4,5] which, in concept, aim to match more closely real life situations and may be used for establishing condition monitoring intervals. Although numerous practical applications have claimed success,[6] the models are still reliant on the extraction of significant amounts of failure data from historical records, subjective questionnaires, or a combination of both.[7] The inspection evaluation is also limited to that of a pass or fail criterion, restricting the ability of a more



1 Diagram illustrating monitoring interval time constraints

effective health assessment. Although such a fundamental assessment may be adequate in a number of situations, the scenario in which a machine can operate satisfactory with a known defect cannot be so readily modelled.

Moubray[8] examined condition monitoring failure patterns and has highlighted the use of the *PF* interval to solve this predicament. A *PF* interval, as shown in Fig. 2, is the time taken for a machine to reach functional failure *F* from the point at which condition monitoring could have identified a potential problem with the machine *P*.

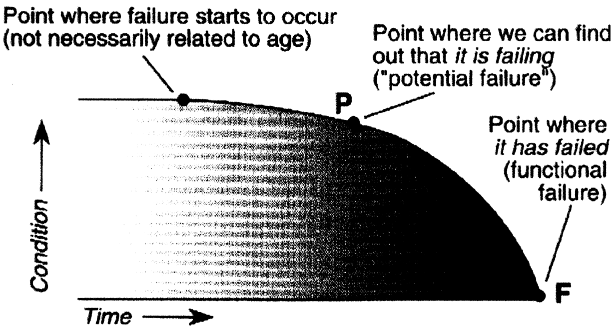
Provided the condition monitoring interval is no greater than the *PF* interval, a functional failure should never occur without warning. In practice, however, the *PF* interval is difficult to quantify and for critical machinery, with a short *PF* interval, continuous monitoring may be justified. This approach described by Moubray will be referred to as 'Moubray's method' in the remainder of this paper.

By setting fixed condition monitoring intervals, current models cannot optimise the monitoring intervals used for identifying time dependent failure mechanisms, such as wear, fatigue, and corrosion. Similarly, fixed condition monitoring intervals are ineffective at 'tracking' a failure once a problem has initially been detected. Within this paper is introduced a new methodology which can define condition monitoring intervals to accommodate such scenarios.

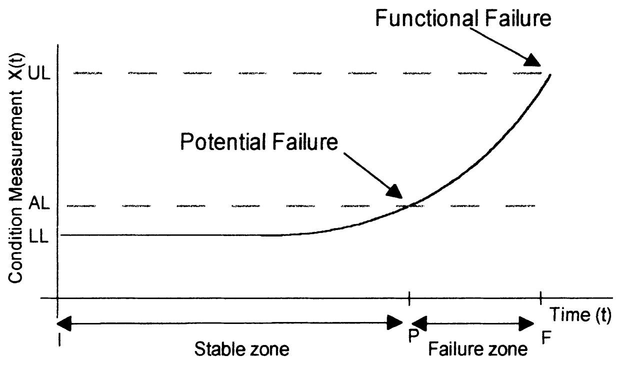
MACHINE LIFE MODEL

In this section, a theoretical solution to the problem of identifying when next to monitor a machine is presented. The theory is based predominantly on the assumption that the life of a machine can be divided into two distinct regions, a stable and a failure zone, that can be distinguished by comparing the observed condition monitored measurements with the alarm limit (Fig. 3). This approach assumes that the machine is initially installed with no defects and, therefore, no infant mortality is present. This approach was initially described by Goode *et al.*[9]

In the stable zone, or *IP* interval (*see* Fig. 3), the machinery is functioning correctly and condition measurements, assuming that they reflect the true health of the machine, are randomly varying about an average value. When the condition monitoring measurements deviate outside these alarm limits, a problem is identified and the failure zone, *PF* interval, is entered. In the maintenance model it is assumed that while in the failure zone the machine's health degrades at an exponential rate until functional failure occurs. The machine would then be replaced and assumed to be 'as good as new'. The implementation of the maintenance model is ideally illustrated by the schematic shown in Fig. 4.



2 Diagram illustrating *PF* interval for failing machine[1]



3 Machine life model

Condition monitoring measurements are tested to verify whether or not they are within the alarm limits. If this is found to be true, the machine is considered stable and the chance of failure, in a given interval, is predicted using historical reliability data. If, however, the measurements have exceeded the alarm limits, the machine has entered the failure zone and functional failure is imminent. In this scenario the prediction uses a combination of reliability and condition monitoring data. If these predictions indicate it necessary, the machine will be inspected and maintained. However, if no maintenance is required, then the next monitoring time will be calculated, based on an agreed risk factor and the same failure prediction models mentioned above.

Failure prediction in stable zone

In the stable zone, condition monitoring measurements give little information except to confirm that the machine's health is satisfactory. Therefore, the only information on which to base a machine failure prediction is through historical failures. In this section an approach will be developed which predicts the chance of failure over a period of time, given the machine's age.

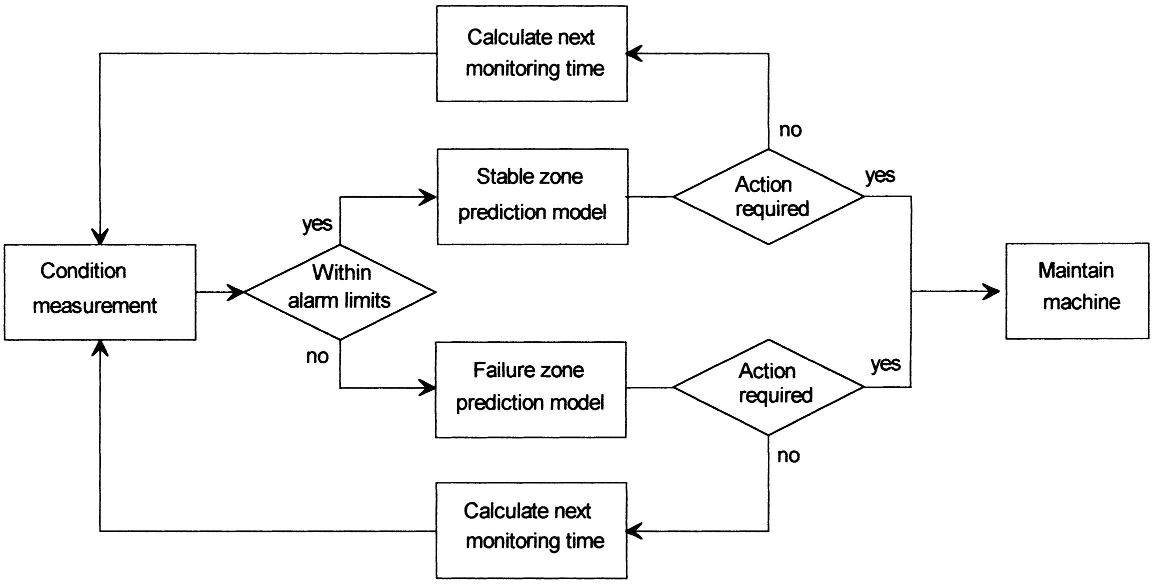
While remaining in the stable zone the chance of a functional failure, in a specified time period, $(n-1)\mathrm{d}t - n\mathrm{d}t$, is simply a function of the probability to reach the potential failure point, P(reaching potential point in time Y), and the probability of reaching the functional failure point in the remaining interval time, P(reaching functional failure in Z), as shown in Fig. 5

$$P(\text{functional failure}) = \sum P(\text{potential failure in } Y) \times P(\text{functional failure in } Z) \quad (1)$$

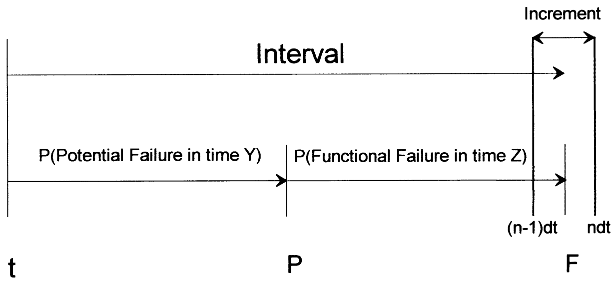
In theory there is an infinite number of possible failure combinations, and, hence, to reduce this number, it is assumed that it takes a small amount of time dt to move from the stable to the failure zone. The first four time increments are shown in Fig. 6.

It is noted that for each time increment another failure combination is possible and that, due to the assumption that it takes one increment to move from a stable to a failure zone, there is no chance of a failure in the first increment. Hence, to calculate the probability of functional failure in the interval, the probability of functional failure during each incrmeent is calculated and summed, as follows

$$P(\text{functional failure in interval}) = \sum_{n=\text{interval/dt}}^{n=2} P(\text{functional failure in increment}) \quad (2)$$



4 Schematic of maintenance model



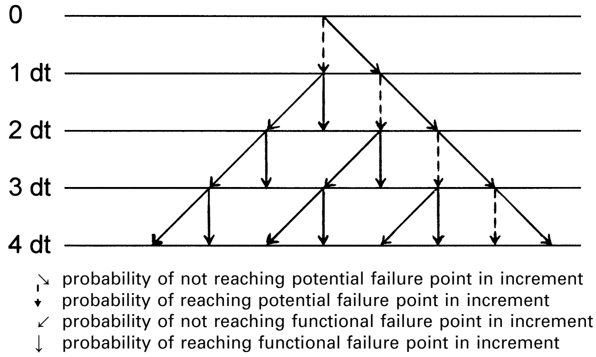
5 Probability of functional failure in increment

To find the probability of reaching a potential failure point, the Weibull distribution hazard rate of the *IP* interval is used. The hazard rate $h(t)$ is defined as the probability of failure over the next time increment dt, assuming no failure has occurred up to current time t. This is expressed as

$$h_{\mathrm{IP}}(t)=\frac{F_{\mathrm{IP}}(t+\mathrm{d}t)-F_{\mathrm{IP}}(t)}{1-F_{\mathrm{IP}}(t)} \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (3)$$

To calculate the probability of functional failure in the time remaining from the potential failure point, the cumulative density function for the *PF* interval Weibull distribution is used

$$P(\text{functional failure in } Z)=F(z\mathrm{d}t)-F[(z-1)\mathrm{d}t] \qquad (4)$$



6 Diagram illustrating multiple failure combinations

Hence, the probability of an overall functional failure between 0 and 1dt is zero, while the probability of functional failure between 1dt and 2dt is

$$=\frac{F_{\mathrm{IP}}(t+\mathrm{d}t)-F_{\mathrm{IP}}(t)}{1-F_{\mathrm{IP}}(t)}\times F_{\mathrm{PF}}(\mathrm{d}t)$$

the probability of functional failure between 2dt and 3dt is

$$=\frac{F_{\mathrm{IP}}(t+\mathrm{d}t)-F_{\mathrm{IP}}(t)}{1-F_{\mathrm{IP}}(t)}\times[F_{\mathrm{PF}}(2\mathrm{d}t)-F_{\mathrm{PF}}(\mathrm{d}t)]$$
$$+\frac{F_{\mathrm{IP}}(t+2\mathrm{d}t)-F_{\mathrm{IP}}(t+\mathrm{d}t)}{1-F_{\mathrm{IP}}(t)}\times F_{\mathrm{PF}}(\mathrm{d}t)$$

the probability of functional failure between 3dt and 4dt is

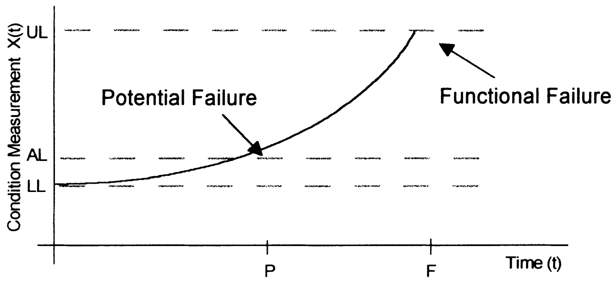
$$=\frac{F_{\mathrm{IP}}(t+\mathrm{d}t)-F_{\mathrm{IP}}(t)}{1-F_{\mathrm{IP}}(t)}\times[F_{\mathrm{PF}}(3\mathrm{d}t)-F_{\mathrm{PF}}(2\mathrm{d}t)$$
$$+\frac{F_{\mathrm{IP}}(t+2\mathrm{d}t)-F_{\mathrm{IP}}(t+\mathrm{d}t)}{1-F_{\mathrm{IP}}(t)}\times[F_{\mathrm{PF}}(2\mathrm{d}t)-F_{\mathrm{PF}}(\mathrm{d}t)]$$
$$+\frac{F_{\mathrm{IP}}(t+3\mathrm{d}t)-F_{\mathrm{IP}}(t+2\mathrm{d}t)}{1-F_{\mathrm{IP}}(t)}\times F_{\mathrm{PF}}(\mathrm{d}t)$$

the probability of functional failure between $(n-1)$dt and ndt is

$$=\frac{F_{\mathrm{IP}}(t+\mathrm{d}t)-F_{\mathrm{IP}}(t)}{1-F_{\mathrm{IP}}(t)}$$
$$\times\{F_{\mathrm{PF}}[(n-1)\mathrm{d}t]-F_{\mathrm{PF}}[(n-2)\mathrm{d}t]\}$$
$$+\frac{F_{\mathrm{IP}}(t+2\mathrm{d}t)-F_{\mathrm{IP}}(t+\mathrm{d}t)}{1-F_{\mathrm{IP}}(t)}$$
$$\times\{F_{\mathrm{PF}}[(n-2)\mathrm{d}t]-F_{\mathrm{PF}}[(n-3)\mathrm{d}t]\}$$
$$+\frac{F_{\mathrm{IP}}(t+3\mathrm{d}t)-F_{\mathrm{IP}}(t+2\mathrm{d}t)}{1-F_{\mathrm{IP}}(t)}$$
$$\times\{F_{\mathrm{PF}}[(n-3)\mathrm{d}t]-F_{\mathrm{PF}}[(n-4)\mathrm{d}t]\}$$
$$+\ldots$$

until there are $n-1$ expressions.

Once the probability of functional failure for each individual increment has been calculated, they are plotted cumulatively against time to indicate the probability of failure in any time interval, using equation (2).



7 Failure zone model

Hence, by using such plots it is possible to predict the likelihood of a functional failure given any time interval over which the machine is required to run. For each new condition measurement which indicated the machine was operating correctly, a new plot must be produced. However, if the condition monitoring measurements indicate a problem, i.e. the potential failure point has been reached, a new approach must be used which makes use of the condition monitoring information in the failure zone.

Failure prediction in failure zone

When the condition monitoring measurements have exceeded the alarm limit, it is assumed that a problem has developed with the machine, the failure zone has been entered, and a functional failure is approaching.

It follows, therefore, that an improved prediction model will utilise the condition monitoring information to track the progression of the problem until the functional failure occurs. To achieve this improvement, a model of the failure zone pattern must first be developed. Figure 7 shows an ideal failure zone pattern.

The failure begins at the lower limit LL, the average condition measurement while in the stable zone. The condition monitored measurement $X(t)$ increases until it is detected passing through the alarm limit AL, where the potential failure point P is identified. Eventually, the condition deteriorates so seriously than the upper limit UL is reached and a functional failure occurs. If it is assumed the failure pattern can be approximated by an exponential function, a model of the failure zone can be defined as

$$X(t) = LL + (AL - LL)\exp\left[\frac{\ln\left(\dfrac{UL-LL}{AL-LL}\right)}{PF} \times t\right] \quad (5)$$

The point of functional failure UL may be set using a number of parameters including British Standards, manufacturer's recommendations, or an operator's past experience. The value of the PF interval must also be estimated and is best done using a Weibull probability distribution function. If equation (5) is rearranged, an expression for t with respect to the measured condition $X(t)$ is obtained, as follows

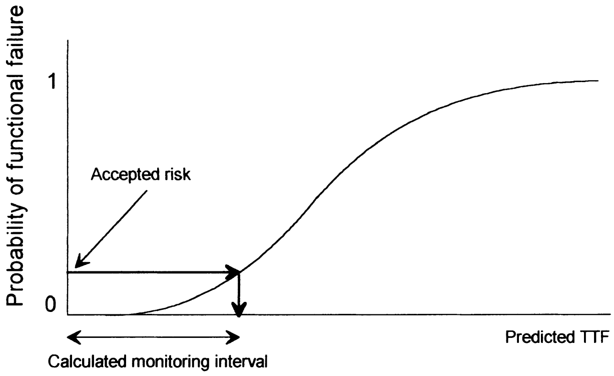
$$t = PF\left[\ln\left(\frac{X(t)-LL}{AL-LL}\right)\bigg/\ln\left(\frac{UL-LL}{AL-LL}\right)\right] \quad . \; . \; . \; (6)$$

This t is an estimate of the elapsed time since the potential failure point. Hence, to predict the remaining time to functional failure, estimates of t and PF are substituted into

$$TTF = PF - t \quad . \; . \; . \; . \; . \; . \; . \; . \; . \; . \; . \; . \; . \; (7)$$

to give

$$TTF = (\gamma_{PF} + \eta_{PF}\{-\ln[1-F(t)]\}^{1/\beta_{PF}}) - (\gamma_{PF} + \eta_{PF}\{-\ln[1-F(t)]\}^{1/\beta_{PF}}) \times \left[\ln\left(\frac{X(t)-LL}{AL-LL}\right)\bigg/\ln\left(\frac{UL-LL}{AL-LL}\right)\right]$$



8 Graphical calculation of condition monitoring interval

or

$$TTF = (\gamma_{PF} + \eta_{PF}\{-\ln[1-F(t)]\}^{1/\beta_{PF}}) \times \left\{1 - \left[\ln\left(\frac{X(t)-LL}{AL-LL}\right)\bigg/\ln\left(\frac{UL-LL}{AL-LL}\right)\right]\right\} \quad (8)$$

The solution to equation (8) can be obtained using a Monte Carlo mathematical technique. The form of the prediction can be converted into a probability density function, i.e. simply transformed into a cumulative density function. It is noted that the prediction does not rely on the accurate identification of the potential failure point, but on the condition monitored measurement and an estimate of the PF interval distribution.

MONITORING INTERVAL TIMES

In the previous section, two models were developed which predicted the chance of failure using cumulative probability functions. It is feasible to use these same plots to predict the condition monitoring interval times, provided an acceptable functional failure risk value is determined, as shown in Fig. 8. This risk is simply the probability of functional failure acceptable between each condition monitoring measurement. This will obviously depend on the importance of the machine and the consequences of its failure, specifying a smaller risk for critical machines and vice versa.

To calculate the condition monitoring interval time while in the stable zone, the accepted risk must be compared with the cumulative incremental probability of functional failure. However, in the failure zone, equation (8) can be modified with $F(t)$ equal to the accepted risk

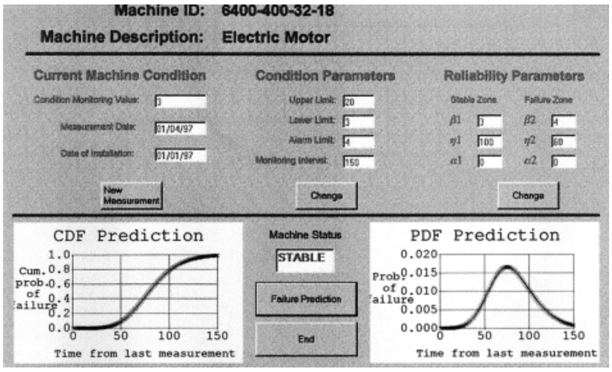
$$\text{interval} = \{\gamma_{PF} + \eta_{PF}[-\ln(1-\text{risk})]^{1/\beta_{PF}}\} \times \left\{1 - \left[\ln\left(\frac{X(t)-LL}{AL-LL}\right)\bigg/\ln\left(\frac{UL-LL}{AL-LL}\right)\right]\right\} \quad . \; . \; . \; . \; . \; . \; . \; . \; . \; . \; (9)$$

If it is required to increase the monitoring intervals, the increased chance of an undetected functional failure can be calculated. Hence, a better understanding of the consequences of altering monitoring intervals can be gained and used to optimise measurement collection.

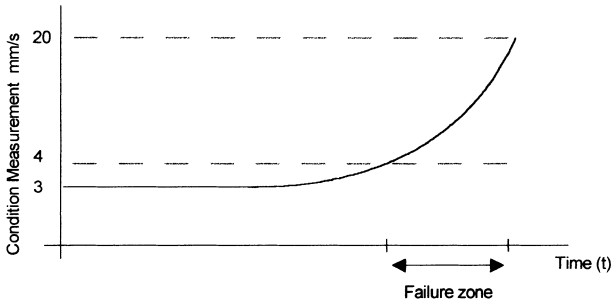
MAINTENANCE MODEL IMPLEMENTATION

To implement the maintenance model, a user friendly, Windows based computer package was developed. After historical reliability data and condition monitoring limits have been entered, current condition monitoring values are introduced. The chance of failure, in a given time period, will then be predicted and illustrated graphically as a cumulative and probability density functions, as shown in Fig. 9

Using this package, the model's performance can be compared with Moubray's method. Two scenarios will



9 Prediction model user interface



10 Failure zone parameters

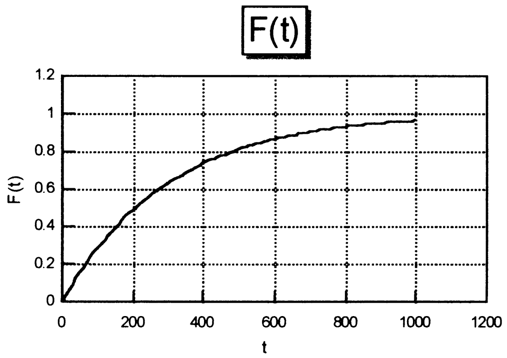
be tested, based on observed condition monitoring failure patterns. The first assumes a random failure pattern in the stable zone followed by a time dependent failure zone pattern. The second assumes time dependent stable and failure zone patterns.

Model testing

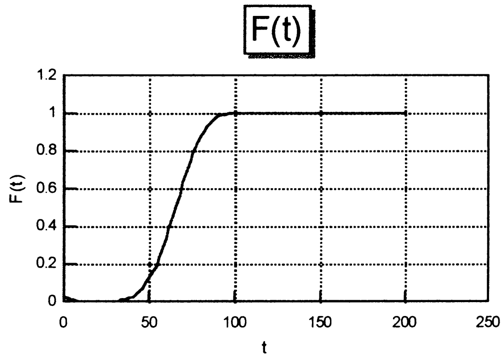
The artificial machine used in these tests is assumed to be condition monitored using overall vibration monitoring and has a failure pattern of the kind illustrated in Fig. 10. In the stable zone the condition monitoring values vary randomly around a value of 3 mm s^{-1}. Measurements exceeding 4 mm s^{-1} will trigger an alarm, indicating a potential problem, which becomes a functional failure when 20 mm s^{-1} is reached.

In the first scenario, random failure in the stable zone is observed, followed by a time dependent failure zone; this may be typical of many mechanical failures. The reliability data used to describe the stable and failure zones are illustrated graphically in Figs. 11 and 12.

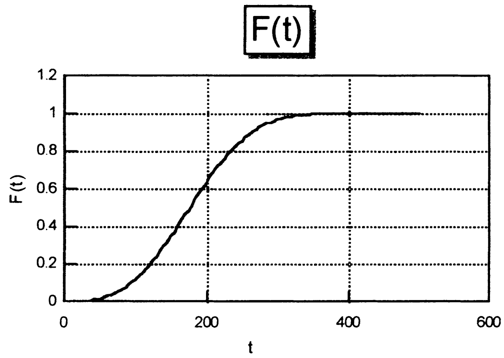
Estimating the *PF* interval for use in Moubray's method is difficult with a failure zone distribution. Hence, a 1% chance of functional failure, in the failure zone, will be used. This results in a *PF* interval of 26 days. Therefore, applying



11 Random stable zone



12 Time dependent failure zone



13 Time dependent stable zone

Moubray's method, condition monitoring measurements would be taken every 26 days from the point of machine installation, until a potential failure was identified.

However, if the new model is employed, again with a 1% chance of functional failure, while in the stable zone the condition monitoring intervals are a constant 57 days apart.

The second scenario looks at time dependent stable and failure zones. This is a common failure pattern when fatigue, wear, or corrosion problems affect the health of a machine. The reliability data used to describe this scenario are illustrated graphically in Figs. 13 and 14.

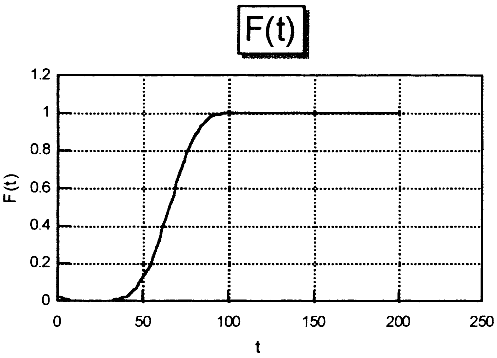
Once again, Moubray's method, based solely on the *PF* interval, results in a constant monitoring interval of 26 days.

With a time dependent stable zone pattern, the maintenance model is able to predict varying monitoring intervals, depending on the age of the machine. At initial installation the next predicted monitoring time is after 65 days. When the machine is 65 days old, provided all is still stable, the next predicted monitoring measurement is in a further 21 days time. Again after these 21 days, provided the machine is still stable, the next monitoring measurement is predicted in 17 days time. Clearly, as the age of the machine increases, the monitoring intervals reduce to reflect the higher chance of failure. These results are summarised in Table 1.

When a problem has been identified, either by Moubray's method or the maintenance model, it is assumed that the machine has entered the failure zone. If it is decided to monitor the machine deterioration inside the failure zone, a maintenance engineer has to decide at what frequency should the condition measurements be taken. The Moubray method cannot offer any advice on how to make this

Table 1 Comparison of Moubray's method and new maintenance model in stable zone

Machine age, days	Moubray's method	New maintenance model
0	26	65
65	26	21
86	26	17



14 Time dependent failure zone

decision. However, a scientific solution can be calculated through the use of the new maintenance model. Consider the failure zone used in Fig. 14 with the monitoring parameters given in Fig. 10.

Table 2 gives the results of comparing the current condition monitoring values and the predicted monitoring interval with a 1% chance of failure, obtained from the maintenance model. It is observed that, as the condition monitoring measurements increase, thereby indicating the increased deterioration of the machine, the predicted monitoring intervals decrease.

DISCUSSION

There are a number of limitations with setting monitoring intervals using current methodologies. Reliability based inspection models require significant amounts of failure data, notoriously difficult to obtain, while the Moubray method is based on the analysis of the failure zone and does not take into account stable zone effects. These methods generally result in equally spaced monitoring intervals that may not necessarily be efficient at optimising the collection of monitoring data. Such methods are also restricted to the identification of problems. If a problem has already been identified and the machine is still required to operate, no advice can be obtained on the subsequent setting of monitoring intervals in this scenario.

The new maintenance model attempts to solve these problems. Given a risk factor, the model predicts the time a machine can operate before the risk is exceeded; this time then becomes the condition monitoring interval time. For random failures, the monitoring intervals predicted by the model are equally spaced. For time dependent failures, the model biases the amount of monitoring towards the highest failure risk area. Intuitively this approach appears to be correct.

Table 2 Comparing condition measurements and predicted monitoring intervals

Condition monitoring value, mm s^{-1}	Next monitoring interval, days
6	33
11	17
17	4

Using this model, it is envisaged that maintenance planning engineers will be able to conduct their work with greater focus on critical machinery and with an improved realisation of the failure risks. It is believed therefore that this new maintenance model could lead to the improved efficiency of condition monitoring data collection.

CONCLUSIONS

1. In this paper the current difficulties of applying condition monitoring intervals are discussed.
2. A new approach to predicting the optimum monitoring interval times is introduced.
3. The model offers a scientific basis on which to base variable monitoring interval times that reflect the increased chance of failure.
4. Monitoring interval times can be predicted even when a machine problem has been identified, enabling the failure of a deteriorating machine to be 'tracked'.
5. The model will improve the efficiency of condition monitoring measurement collection by providing a better understanding of relative failure risk.

ACKNOWLEDGEMENTS

The authors would like to thank Dr B. J. Hewitt, Director Technical and E. F. Walker, Manager Technical Coordination, Welsh Technology Centre, Corus, for permission to publish this paper and acknowledge the support of the Engineering and Physical Sciences Research Council. They also thank Port Talbot's PCM department and Llanwern's FMMS department for their help and contribution to this project.

REFERENCES

1. A. K. DUTTA: *Mech. Eng. Bull.*, 1986, **17**, (2), 43–54.
2. A. DUBEY: *Mech. Eng. Bull.*, 1986, **17**, (3), 114–123.
3. M. J. NEALE and Assoc.: 'A guide to the condition monitoring of machinery', 1979, London, HMSO.
4. A. H. CHRISTER and W. M. WALLER: *J. Oper. Res. Soc.*, 1984, **35**, 967–984.
5. A. H. CHRISTER: *J. Oper. Res. Soc.*, 1982, **33**, 723–732.
6. A. H. CHRISTER, W. WANG., J. SHARP, and R. A. BAKER: 'A pilot study on maintenance strategy of finishing mill roll change equipment at Llanwern, British Steel', Report, University of Salford, 13 November 1995.
7. R. D. BAKER and W. WANG: *IMA J. Math. Appl. Business Ind.*, 1991, **3**, 259–281.
8. J. MOUBRAY: 'Reliability centred maintenance', 144–149; 1991, London, Butterworth Heinemann.
9. K. B. GOODE, B. J. ROYLANCE, and J. MOORE: in Proc. JOAP Int. Condition Monitoring Conf., Mobile, AL, 1998, 203–212.