Condition Based Reliability, Availability, Maintainability, and Safety (CB-RAMS) model: Improving RAMS predictions by combining condition-monitoring (CM) data with RAMS calculations

Dan M. Shalev[1,2], Joseph Tiran[1], David Katoshevski[2], and Jacob Bortman[1]

[1]*Department of Mechanical Engineering, Faculty of Engineering Sciences, Ben-Gurion University of the Negev, Beer-Sheva, 8410501, Israel.*

dshalev@bgu.ac.il

tiran@bgu.ac.il

jacbort@gmail.com

[2]*The Unit for Management and Safety Engineering, Faculty of Engineering Sciences, Ben-Gurion University of the Negev, Beer-Sheva, 8410501, Israel.*

davidk@bgu.ac.il

ABSTRACT

The goal of this paper is to present a practical method for the enhancement of systems Reliability, Availability, Maintainability, and Safety (RAMS) assessments. During the last decades Condition Monitoring (CM) methods have been improved and extensively implement. A method for integration the CM data with RAMS calculations is suggests. Implementing the method as a practical tool and updating RAMS prognostics assessment according to deterioration condition, is demonstrated by examples that emphasize the method's contribution and advantages. The method is based on conducting correlations between deterioration stages and Remaining Useful Life. Reliability is continuously updated according to pre-calculated Weibull parameters based on historic deterioration stages accumulated data and concurrent CM findings. The updated assessment represents the real system condition along its deterioration stages. The method enables improved decision making operation and maintenance action thus lower the Life Cycle Cost (LCC). The method named "Condition Based-RAMS" (CB-RAMS). Analyzing systems by CB-RAMS in conjunction with Monte-Carlo Simulation software tool, and CM data, is a practical and efficient method to eliminate surprising dangerous and costly events. The paper introduces the method and improvements that are achievable by implementing it. The contribution of the paper is the applicable detailed procedure to use any sort of CM data to enhance his RAMS predictions. The significance of this paper is that presented approach will enhance the importance of implementing CM on systems to lower LCC and increase safety.

1. INTRODUCTION

Forecasting system's behavior and managing an optimal operating and maintenance programs accordingly, is essential to be competitive. The forecasting accuracy is depended on data quality. Usually forecasting are based on failures statistics. Smith (2001) found that the ratio of predicted failure rate (or system unavailability) to field failure rate (or system unavailability) is depended on data source, he distinguishes between generic data, industry specific data and site specific data. By using site specific data, the correlation between calculated reliability and demonstrated reliability is improved[1]. Since data used is based on failures distributions

[1] Smith, D. J. (2001), CONFIDENCE LIMITS OF PREDICTION. The ratio of predicted failure rate (or system unavailability) to field failure rate (or system unavailability) was calculated e and the results were classified in three categories: (a) Predictions using site specific data: strategy and equipment are largely the same). (b) Predictions using industry specific data: (c) Predictions using generic data: Reliability, Maintainability and Risk -The results are: (a) For a prediction using site specific data One can be this confident that the eventual field failure rate will be BETTER than 90% 2.5 times the predicted, and 90% confident that the eventual field failure rate will be in the range: 90% 3.5:1 to 2/7:1. (b) For a prediction using industry specific data

we asked ourselves do we have a better data source to enhance this correlation.

This article presents the contribution of a new method for updating Reliability[2], Availability[3], Maintainability, and Safety (RAMS) assessments along the system's life. The aim of this paper is to present a method based on Condition Monitoring (CM) data and degradation stages and not just on failure distributions. The method provides more information to decision making through all phases of the system life cycle. On earlier work (Shalev & Tiran, 2007) we presented a way to change the failure rate according to degradation rolling bearings deterioration stages (DS) and recalculating an updated Fault Tree Analysis (FTA); we called this process Condition Based Fault Tree Analysis (CB-FTA). In this paper we extend the method to update RAMS predictions for failure distributions different than the exponential distribution function (represented by constant failure rates). By utilizing Monte Carlo Simulation (MCS) the method is generalized for any failure distribution function.

Wesley & Usynin (2008), Heng, Zhang, Tan, & Mathew (2009), Gorjian, Mittinty, Yarlagadda, & Sun (2009) reviewed available RAMS assessment models and emphasized the need for improvement including the integration of condition monitoring (CM) and reliability data.

The aim: a model that will resolve more accurate RAMS predictions based on CM deterioration data. Basic idea is to use instead of "time to failure" a "time to degradation stage" approach, and to enable implementing the model with any sort of CM data collected on any system that undergoes condition monitoring.

By successful Condition Monitoring (CM) actual deterioration is detected; combining CM and RAMS results in more accurate predictions. RAMS predictions are essential knowledge about any system, initially performed during the system design phase. At the beginning, RAMS are based on data derived from available data sources or from component manufacturers. A common method is to use component failure rates for all system components according to failure and repair distributions. Throughout system life, failure data is collected and from time to time RAMS can recalculate and compare these data with the initial predicted RAMS.

Frequently, before actual failures occur, component degradation is detected by CM that obviously affects the system's current RAMS. The moment part deterioration starts, a stopwatch starts to run until the part's End of Life (EOL) is reached, if there is no intervention. On individual operating system degradation, the pace is strongly influenced by a variety of local working conditions, i.e., loads, maintenance quality, environment, and many more individual situations that lead to variances between predicted and demonstrated RAMS values.

Condition Monitoring (CM) is frequently conducted on critical systems; knowledge about the deterioration process is accumulated, components' residual life can be assessed from CM reports. Each time that deterioration is detected by CM, the system's actual RAMS is lowered.

This article suggests a model to combine CM with RAMS to produce Condition Based Reliability, Availability, Maintainability, and Safety (CB-RAMS). The method is based on the assumption that if we already know that deterioration started at a certain time we have to intervene; if not, a failure may occur during a much shorter time than predicted by RAMS. In order to prevent these "supersizing" occurrences, the model offers CB-RAMS, merging CM information into RAMS predictions and using RAMS calculation methods to anticipate the optimal recommended action at each deterioration point.

The presented model suggests options to express detected wear conditions in terms of component reliability and using it to update RAMS calculations and get actual system predictions, rather than retain generic RAMS predictions based on generic data that could be accurate statistically for a group of the same systems but might be erroneous for the individual system that we operate and maintain in our specific conditions.

Using CM one accumulates additional updated knowledge that can be used to update RAMS predictions—a method that quantifies the findings in terms that are suitable for providing an updated RAMS prediction.

The basic idea behind the new method is updating RAMS calculations based on deterioration behavior and distributions as an alternative to the traditional RAMS calculations that are based on failure distributions, failure rate, or Weibull distribution parameters, Dodson (1994), Abernethy (2000). The major difficulty in utilizing the model is that deterioration distributions, and failure rate for each deterioration stage, are not accessible and can be generated from local data accumulated by CM. The deterioration process shortens the component's remaining life. During deterioration, the component becomes less and less reliable. By accumulating deterioration data, distribution can be determined and used in CB-RAMS predictions. When the deterioration rate and distribution are not available we suggest using the exponential function (i.e., constant failure rate) as first order approximation, i.e., the component's

---

One can be this confident that the eventual field failure rate will be BETTER than: 90% 4 times the predicted, and 90% confident that the eventual field failure rate will be in the range: 5:1 to 1/5:1. (c) For a prediction using generic data One can be this confident that the eventual field failure rate will be BETTER than: 90% 6 times the predicted, and 90% confident that the eventual field failure rate will be in the range: 8:1 to 1/8:1

2 "Reliability" is the probability of components, parts, and systems to perform their required, intended functions for a desired specified period of time without failure in specified environments with desired confidence.

3 "Availability" is defined as the probability that the system is operating properly when it is requested for use.

known constant failure rate is altered and accelerated by an empirical growth factor.

The presented model is appropriate to use in conjunction with components that deteriorate over a long duration, Rabinowicz (1981), and for those components where the deterioration is detectable by any CM method (i.e., Vibration monitoring and analysis, Thermography, Oil analysis, Noise monitoring, etc.). Using CM methods, trending is performed over time. The monitored part's condition is updated from the time that initial deterioration is detected until the EOL when a functional break occurs. For those components that break by acute force during a very short time and without any prior detectable signs, the CB-RAMS model is invalid.

Luckily, the majority of component and equipment failures occur due to the wear process. Wear is a general name for deterioration by a contentious process along time and therefore it is potentially detectable by CM. The CB-RAMS model is not valid for equipment that fails because of a sudden occurrence; about 15% of total equipment failures occur very fast, Blanks (1992), therefore trending by CM is not an option. Unluckily for safety, such occurrences can cause surprising events.

RAMS calculation aims to predict what would be the average reliability and availability of a large group of identical systems working under normal conditions. Essentially it does not predict the reliability and availability of one particular specific system, working under specific conditions, and maintained by local procedures, unless local data is used.

Researchers such as Blanks (1992), O'Connor (1991), Smith (2001), Lycette (2005) have shown that in reality, often the correlation between calculated reliability and demonstrated reliability is poor. Mean Time Between Failures (MTBF) is defined as the reciprocal of the failure rate (λ) Logistics Engineering Technology, Branch (1998) and Bazovsky (1961). Blanks (1992) shows the inaccuracy of reliability prediction by comparing predicted and demonstrated MTBFs on real systems representing different technology disciplines. In the majority of studied cases, the demonstrated MTBFs are shorter than the predicted MTBFs. Decisions based on theoretical figures with poor correlation between systems' real MTBFs and predicted MTBFs lead to dangerous outcomes and safety incidents and cause economic losses. Knowing these traditional RAMS calculations' limited accuracy, leads to expensive conservative design with wide safety margins, in order to reduce risk. This fact explains why many analysts are reluctant to use system RAMS figures after passing the system design phase, especially for mechanical systems that are exposed to irregular maintenance. Recommendations and practical conclusions are to use the reliability calculations with great caution. A main benefit of reliability calculation and a good way to implement RAMS is to use the results as relative figures to compare alternatives and to make improvements mainly, but not only, during design or system change.

By implementing CB-RAMS, assessments of RAMS in conjunction with CM findings are improved; the involved personnel can produce more objective recommendations. A major advantage of CB-RAMS is to support system operators and maintenance personnel in real time decisions. CB-RAMS method is also suitable for automated condition-based decision processes. We use MCS by RAPTOR to solve examples and to demonstrate the concept. Thus emphasize the strength of CB-RAMS together with MCS as a practical applicable efficient tool to improve the confidence levels of RAMS assessments on real working systems.

We estimate that in the near future, manufacturers of monitored critical components that undergo CM (e.g., rolling bearings) will have to support CM and provide deterioration progress distribution and reliability data as a function of a component's detected condition. Such data will dramatically improve the accuracy of RAMS predictions.

In reality, working system degradation occurs for many reasons and the pace is not always precisely anticipated. Unpredicted accelerated ageing can be due to ageing accelerators such as: abnormal environmental conditions, excessive usage factors, abnormal temperatures, throughput rate, mechanical stress or vibration, mishandling, and many other factors that are not easy to predict. CM and trending can provide the real system condition.

Some research and earlier works on modeling degradation processes can be found in Stock, Vesely & Samanta (1994), Gorjian et al. (2009). Some early works present methods and models to incorporate degradation into component level reliability and to predict system reliability under a variety of presumed conditions. These models can be used to evaluate different maintenance options. In this work we present a method to use real collected data and incorporate it into reliability calculations, rather than using any presumptions about the degradation process. This article presents the general model and its benefits to produce more accurate reliability predictions than those obtained without using components' real conditions.

The degradation process along time can be of any type; the path from start to End of Life (EOL) can be a decelerated, constant, or accelerated process. The Weibull distribution is the most popular means to describe those behaviors. For simplicity, in introducing the model we start by first presenting an example assuming exponential failure distribution and a constant failure rate.

Using an exponential failure distribution density function with constant failure rate (λ) eliminates the need to use complicated mathematical methods since it can be solved analytically, unlike more general Weibull distribution that MCS has to use (Dubi, 1999, 1986). This constant λ enables performing system fault tree analysis, FTA, a very common and popular reliability prediction technique.

In a previously published paper (Shalev et al.,2007) we presented a method to change the constant failure rate according to degradation stages and to recalculate the updated FTA accordingly; we called this process Condition Based Fault Tree Analysis (CB-FTA).

By extensive Condition Monitoring (CM) with trending, there is a good probability that when a component starts to deteriorate it will be noticed. Identifying the component's concurrent condition and utilizing pre-known deterioration behavior is the basis for assessing the component's residual life at each deterioration stage. This deterioration can be expressed by terms that are used to predict the part's reliability and influence on the whole system's reliability. Since we know the component's state more accurately, we are able to narrow the general generic failure distribution for the specific component. Using CB-RAMS, model recalculation of the whole system's RAMS values is done to produce concurrent predictions that are relevant to the real condition of a particular system; thus the safety predictions become more realistic and measures can be taken well before catastrophe occurs.

During the design phase RAMS predictions help to identify system weaknesses and to improve design by choosing more reliable components or by enhancing redundancy.

The CB-RAMS model is a prognosis process that enables choosing between several alternatives during the operational phase and during the design phase.

CB-RAMS can be a better design tool during the design phase since it enables prediction of availability and reliability of a system after deterioration will be detected, i.e., to choose parts that will result in sufficient residual time to failure. Simulating alternative designs, pre-known values for each deterioration stage, and conducting CB-RAMS calculations result in figures that represent more precisely the anticipated system behaviors. By utilizing the model, we can assign the optimal component during the design process in order to get the needed system availability, to compare redundancy alternatives, and to get the needed maintainability and safety, taking into account the fact that we collect the real deterioration stages and can use the data to make more reliable predictions.

One can change the design to select a more reliable component if additional alarm time is needed before stopping the system, or a less expensive substitute if the projected deterioration will provide sufficient time needed to take action (i.e., time from early warning until scheduled stop); thus, anticipating in advance the system's future behavior assists in improving the system's life cycle cost (LCC), (Berry ,1997).

The models also have the potential to enhance system safety. By detecting degradation on a critical component and updated system CB-RAMS figures, the results represent precisely the system's probability to operate without failure for a certain defined period of time. Surprising failures can be eliminated if we know the limits of RAMS predicted time to fail usually presumed by reliability parameters based on generic failure distribution of those components.

2. CB-RAMS model formulation

The CB-RAMS model is applicable to systems that fulfill all of the following characteristics: 1. Critical component deterioration processes are not random but rather a systematic process. 2. Detection of deterioration processes is possible by any condition monitoring method. 3. Degradation process can be a continuous process or a stage-by-stage process. If the process is continuous it can be divided into stages; we denote each degradation stage by i. Degradation stages can be presented as predefined recognizable stages or as points on a predefined curve made according to previously known data.

Representative figures can be assigned for each degradation stage or monitored condition. New failure rate or narrow failure distribution presents each degradation stage. This figure corresponds to the Residual Time to Total Failure (RTTTF). When all these characteristics are fulfilled CB-RAMS is feasible.

When we deal with the exponential failure distribution, i.e., constant failure rate each time that deterioration is detected, a new higher failure rate is used to calculate the reliability for the residual time.

By conducting CM for each critical component, the degradation stage is detected and a new component failure rate $\lambda_{DSi} = \lambda_{DS1}$ to λ_{DSn} is assigned, where λ_{DSi} stands for failure rate of degradation stage i.

Applying the new λ_{DSi} rate to the system's RAMS or to the system's structured fault tree results in an updated system failure rate and reliability values. This process is the CB-RAMS model.

The upper block diagram in Figure 1 describes the traditional RAMS calculations, while the lower block diagram describes the Condition Based-RAMS (CB-RAMS).

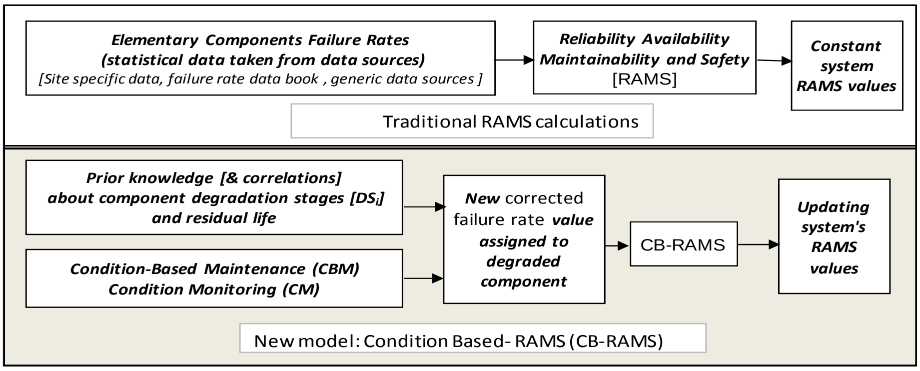

Figure 1. The CB-RAMS model versus traditional RAMS.

Systems consist of several machines working together, in parallel, in series, or both, with or without redundancy. Those machines contain components; machine number *k* will be denoted by m_k, and component number *j* will be denoted by c_j. Some components are more sensitive and degrade faster than others. By condition monitoring we detect sensitive components' wear; component degradation stage will be denoted by DS_i. A component without wear will be denoted as being in degradation stage 0, DS_0. During the degradation process it will move from DS_0 to DS_1, DS_2, in general DS_n until the final stage DS_f, when a functional failure occurs and the component is at End of Life (EOL).

System theoretical reliability R_{sys} is a function of all its machines' and components' failure rates. In reality, the components' conditions and related degradation stages determine the system's actual reliability:

$$R_{sys}(t) = f\left(m_k, c_j, DS_i\right) \tag{1}$$

The terms m_k, c_j, DS_i mean that component number j in machine number k is in degradation stage i.

All system components are classified by their inherent sensitivity and their criticality to the machine function. For each component in the whole system a monitoring policy is assigned. Methods for condition monitoring are assigned especially for all critical components. The monitoring frequency for each component is based on number of cycles, operation hours, previously known condition, etc. For those critical components that are more sensitive than others, or less approachable, the monitoring is done continually by on-line sensors; we then get the component's condition as a function of time, while for less critical components the monitoring is done by off-line systems (e.g., hand-held instruments). Individual Monitoring is performed at a certain time interval or at a certain number of accumulated working cycles. As a result of the condition monitoring (CM) procedure, the component can be at the same stage that was detected at the previous round or in an inferior degraded condition that will be represented by degradation stage DS_i.

Each time that any deterioration change is found, the system is presented with a new reliability value.

Therefore, we can express system reliability at time t as a function of $\left[m_k, c_j, DS_i\right]$. If any of measured $\left[m_k, c_j, DS_i\right]$ at time t_i, changed to $\left[m_k, c_j, DS_{i+1}\right]$ at time t_{i+1}, then new system's reliability is calculated.

$$\widetilde{R}_{sys,(k,j,i+1)}(t_{i+1}) = f\left(m_k, c_j, DS_{i+1}\right) \tag{2}$$

This updated reliability value represents the system condition at time t_{i+1} at a higher confidence level and enables making better quality decisions.

A procedure with three steps is describe to explain the method: <u>First step</u>: Calculating system reliability according the usual/traditional way, assuming the known failure distributions and failure rate parameters for all components. <u>Second step</u>: Determining which are the most sensitive components and assigning CM policy including monitoring procedures and techniques to those components, which will be monitored and trended along the system's life. <u>Third step</u>: Calculating a series of system reliability figures starting from the baseline, and presuming that the most sensitive component is undergoing a deterioration process, from DS_0 to DS_f. At each time t that degradation is detected in the real working system, we get $R_{sys(t)}$ corresponding to this situation and we know what the $R_{sys(t+1)}$ will be when the next deterioration will be detected at t+1, if the system continues to work as is or if any other operational alternative will be in place.

When analyzing a redundant system, at each time t when we get new evidence that any component c_j has deteriorated from stage DS_i to DS_{i+1} we are facing branching in the decision tree. The immediate question is what the recommended optimal reaction is. We have to choose at each branching whether to continue to operate the same machine or to change the operating machine and to switch to the standby machine.

The decision function maximizes the system reliability R_{sys} between operational alternatives for the next deterioration step. For simplicity of the model explanation, we use an assumption that at each time step the most critical component on the system will deteriorate to its next deterioration stage. Maximizing the R_{sys} reliability is done by recalculating R_{sys} for each alternative, and comparing the alternatives.

Alternative 1: R_{sys1} is the system predicted reliability if we do not change from primary operating machine m_1 to standby machine m_2, and assume that the most sensitive component c_j in m_1 will deteriorate to $\left[m_1, c_j, DS_{i+1}\right]$.

Alternative 2: R_{sys2} is the system predicted reliability result if we decide to stop machine m_1 and to start machine m_2 and assuming that the most sensitive component c_j in m_2 will deteriorate to $\left[m_2, c_j, DS_{i+1}\right]$.

If change in deterioration is detected, an operational decision is made by comparing R_{sys1} at $t+\Delta t$ to R_{sys2} at $t+\Delta t$. The system will be set to operate in the alternative that will result in maximal reliability.

$$MAX \begin{pmatrix} R_{sys}1(t+\Delta t)=f\left(m_1, c_j, DS_{i+1}\right) \\ R_{sys}2(t+\Delta t)=f\left(m_2, c_j, DS_{i+1}\right) \end{pmatrix} \quad (3)$$

In general, we calculate system reliability for all next deterioration alternatives, for all components, and for all possible deterioration stages and $\left[m_k, c_j, DS_{i+1}\right]$. The optimal operation scheme will be the one that has the best probability to result in maximum reliability at time $t+\Delta t$ when the next monitoring procedure will be done.

$$Max \left\{R_{sys}(t+1)=f\left(m_k, c_j, DS_{i+1}\right)\right\} \quad (4)$$

CB-RAMS method is applicable to systems analysis if the described three characteristics are fulfilled:

Deterioration process is Repeatable and not random; it can be Continuous or a Step-by-step process (i.e., deterioration of rolling bearings, majority of bearings deterioration is a four-stage process as described in Figure 2).

Detection of each stage is possible: Detection of the bearing deterioration stage is done by vibration measurement and FFT spectral analysis as detailed in Figure 2.

For each failure stage, the residual time to total failure is definable or can be calculated from previous accumulated data.

For many critical components (such as rolling bearings), the degradation can be translated to a new failure rate, which is the degradation stage failure rate (λ_{DSi}).

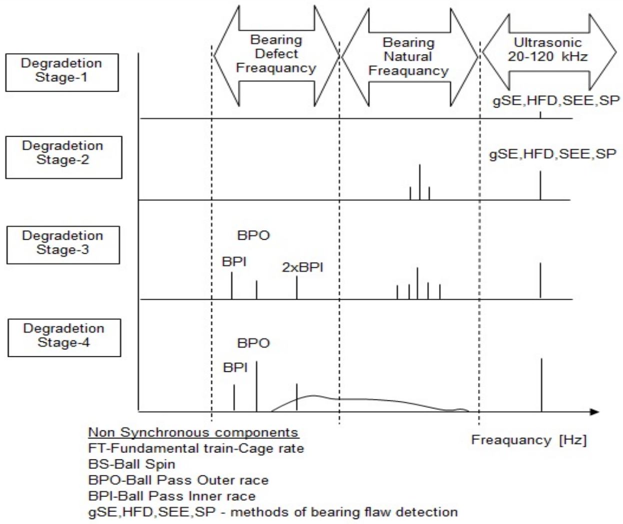

Figure 2. Typical Vibration spectrum for rolling bearing failure stages

(Berry,1991, 1997, 1999), (Berggren, 1988), (Shreve, 2010)

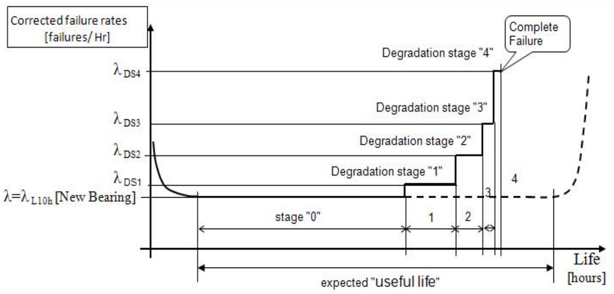

Figure 3. Theoretical expected useful life as predicted by regular RRMS, and shortened life after component wear is detected by CM and bearing is in degradation stages.

The common traditional reliability calculations that presume exponential failure distribution are based on constant failure rate; this simplifies the reliability calculations but does not always accurately describe the real failure behavior. For lot of real cases the optimal choice to describe the failure distribution is the Weibull distribution, Sung (1996).

3. Implementing the CB-RAMS method

Weibull distribution is used for the reliability calculations:

$$F(t) = 1 - R(t) = 1 - e^{-\left(\frac{t-t_0}{\eta-t_0}\right)^{\beta}} \quad (5)$$

Parameters:
$F(t)$: Failure Probability
$R(t)$: Reliability (or Survival Probability)
t: Statistical variable (load time, load cycle, act.) > 0

η: Scale parameter, Scale factor, Characteristic lifetime, For t=T, F(t)=63.2%, R(t)=36.8%, T>t_0

β: Shape parameter, Shape factor, Failure slop. Determines the curve shape > 0

t_0: Location parameter, Failure free time. Point in time that failures starts. Shifting of the failure behavior along time axis, if $t_0 > 0$ then $t > t_0$

In order to explain the method, we examine how a change in typical rolling bearings' Weibull parameters will influence the reliability. By looking at the graphs (Figure 4) we can understand how a change in each of the parameters will influence the reliability and the failure rate.

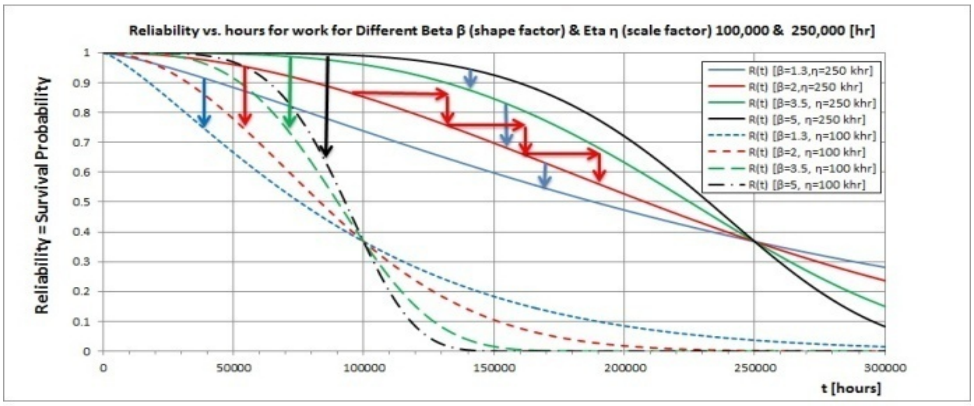

Figure 4. The influence of changes in Weibull parameters on the reliability.
This graph is based on arbitrary generic parameters.

The blue vertical arrows represent lowering the β parameter value while leaving the value of parameter η constant. The red horizontal arrows represent changing location t_0-factor (location parameter) while leaving values of η and β constant.

The black vertical arrow represents lowering the value of the parameter η while leaving the β parameter value constant. A change can also be any combination of change of these parameters. A method to determine Weibull parameters for each DS_i by using CM accumulated data is presented. This is done by the following steps: The CM historic data for each part is organized according to working hours and detected deterioration stages DS_i.

Operation hours until each DS_i is detected are calculated from operation log, or, if available, directly from working hours counter.

The time span from initial deterioration findings until failure is divided into intervals, DS_i. The intervals are according to known deterioration steps (e.g., in rolling bearings) or a value defined by the machine manufacturer or known from local experience (such as an initial warning threshold, the value of alerts, and an unacceptable value requiring an immediate halt).

An updated reliability calculation is carried out based on known Weibull parameters corresponding to the DS_i; at each time that a new or worsening deterioration is diagnosed the result is updated component reliability.

Based on known Weibull parameters for each DS_i, reliability and availability calculations are done for the component, the machine, and the whole system. Calculation process and determining Weibull parameters is based on the graphic solution of the Weibull equation, Dodson (1994), Abernethy (2000): Weibull equation failure probability, Equation (5), is transformed to a form that is suitable for graphical solution.

$$\ln\left[\ln\left(\frac{1}{1-F(t)}\right)\right] = \beta\ln(t) - \beta\ln(\eta) \tag{6}$$

This equation looks similar in form to a straight line equation (y=ax+b), where the dependent variable (y) is:

$$\ln\left[\ln\left(\frac{1}{1-F(t)}\right)\right] \tag{7}$$

The free variable (x) is: ln(t). β is the line slope and ln(η) β is the intersection (b) with the y-axis. We present a method based on local equipment CM to determine the Weibull parameters for each deterioration stage DS_i. And further, recalculating updated RAMS based on known adjusted parameters for each DS_i.

4. Applications

Some practical applications of CB-RAMS method is presented and demonstrated by 3 examples:

Example 1: **Bearing reliability-** Calculating Weibull parameters according to historic CM data and calculating bearing reliability at each degradation stage DS_i.

Example 2: **Pump reliability** - Calculating the individual pump (Figure 9) reliability and availability at each degradation stage DSi in each of the pump's bearings.
Example 3: **Two-pump system reliability** - Calculating reliability and availability for a system (Figure 10) for each degradation stage DS_i in each of the pumps' bearings.

The source of this data is based on preformed CM on redundant six feed pump system, which supplies pressurized hot water to steam boilers. Same completion of missed points was done by extrapolation. All pumps are interchangeable and working in the same operation and maintenance conditions. All pump bearings are CM on a frequent basis. Data is collected along several years and documented according to pump serial number and summarized in Table 1.

Example 1: Bearing reliability at each degradation stage:

Calculating Weibull parameters according to historic CM data and calculating individual bearing reliability at each degradation stage DS_i.

The method consists of fitting Weibull parameters for each DS_i separately as explained. The time parameter t [hr] is defined from the beginning of DS_i to total failure (TF).
Calculation steps are: calculation of time data (Table 1) and calculating the Weibull parameters by building a linear trend line (Figures 5 and 6) for each degradation stage

Table 1. Cumulative operation hours from initial start until diagnosing each DS_i.

Monitored component	cumulative hours from initial start to detecting each DSi				Hours from new to total Failure t_{TF}	Elapse hours from detection each DS_i to total failure (TF) $\Delta t = t_{TF} - t_{DSi}$			
Bearing	t_{0DS1}	t_{0DS2}	t_{0DS3}	t_{0DS4}		Δt_{DS1}	Δt_{DS2}	Δt_{DS3}	Δt_{DS4}
Pump 1	2664	3672	4080	4200	4296	1632	624	216	96
Pump 2	11136	11856	12480	12960	13920	2784	2064	1440	960
Pump 3	3168	4200	5136	5160	5760	2592	1560	624	600
Pump 4	4848	7392	8400	8904	9624	4776	2232	1224	720
Pump 5	8496	10104	11088	11784	12480	3984	2376	1392	696
Pump 6	9672	12120	13440	14496	15288	5616	3168	1848	792
Pump 7	14904	16992	18216	18864	19032	4128	2040	816	168
Average	8704	9476	10405	10909	11485	3644	2009	1080	576
STD	3891	4398	4579	4828	4873	1277	722	516	299

First we calculate the bearing reliability using the traditional way, from new to total failure. The data for this calculation is presented in Table 2 and the results in Figure 5 and Table

Table 2. The values used for the least mean square Weibull parameters calculations.

New to Failure, [hr]	Ascending order, [hr]	Rank	Reverse Rank	h(t)= 1/Reverse Rank	H(t)	ln(t)	ln H(t)
4296	4296	1	7	0.14	0.14	8.36	-1.95
13920	5760	2	6	0.17	0.31	8.66	-1.175
5760	9624	3	5	0.2	0.51	9.17	-0.675
9624	12480	4	4	0.25	0.76	9.43	-0.28
12480	13920	5	3	0.33	1.10	9.54	0.09
15288	15288	6	2	0.5	1.60	9.63	0.47
19032	19032	7	1	1	2.59	9.85	0.95

By graphical presentation of the calculated results and linear trend line, we get the Weibull parameters for each deterioration stage.

$$\ln H(t-\delta)=\beta\ln(t-\delta)-\beta\ln(\eta)$$

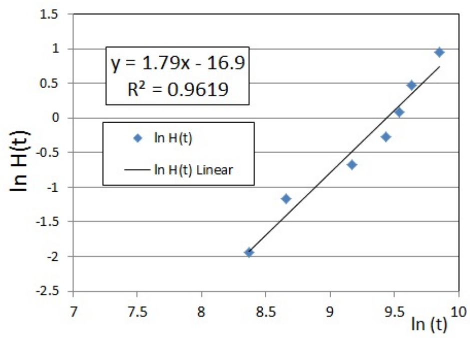

Figure 5. Graphical presentation of calculation of Weibull parameters, from new to Total Failure.

Weibull parameters according to bearing time to failure are: β =1.79, y_0 = -16.9, and $\eta = \exp(-y_0/\beta) = 12598$.

According to those parameters, the bearing reliability is calculated. These results are bearing reliability Weibull parameters. The results are the calculated traditional bearing reliability, without considering the deterioration stages. Results are shown in Figure 5.

Table 3. Traditionally calculated bearing reliability without deterioration stages, denote as $R(t)DS_0$.

t(hr)	1000	2000	3000	4000	5000	6000	7000	8000
$R(t)DS_0$	0.99	0.96	0.93	0.88	0.83	0.77	0.71	0.64

Note: Reliability value obtained at t = η corresponds by definition to default of 63.21% of the population. The value t = L_{10} corresponds by definition to failure of 10% of the population. It is generally assumed that the ratio between L_{10} and η is about five, Barringer (2001).

Pump bearings whose data in the example above were designed to be L_{10} = 25 khr, given the results of the actual η, a bearing wears out if the design was based on the value of L_{10} = 12598/5 = 2520 hr. One possible explanation for this situation is problematic working conditions. Feed water pumps work at high temperatures, ball bearing cooling is performed by flow from a cooling tower. By this calculation we can see that the cooling system is not effective, it is clogged by lime scale deposits and not always able to maintain the required temperature in the bearings, so the actual bearing life is shorter than originally planned.

According to actual failure distribution, correction alternatives must be considered. Enhance reliability and reduce maintenance activities by: using cooling water treated better, selecting pump bearings housing where cooling is more efficient, purchase of a more expensive pump characterized by better reliability level.

Decision should be made by comparing the LCC life cycle costs of each alternative system. A second possible explanation for this situation is the quality of maintenance: Quality replacement bearings while overhauling the pumps.

Weibull parameters for each DS_i are calculated according to CM records. Determining the Weibull parameters for each DS_i based on the total time t [hr] from beginning of DSi until part reaches total failure (TF), or very close to this point.

Table 4. Calculated Weibull parameters according to hours from detection of each DS_i to total failure (TF), data taken from Table 1.

Δt_{DS1} [hr]	Δt_{DS1} [hr] arranged in ascending order	Rank	Reverse Rank	h(t) =1/Reverse Rank	H(t)	ln(t)	ln H(t)
1632	1632	1	7	0.14	0.14	7.40	-1.95
2784	2592	2	6	0.17	0.31	7.86	-1.17
2592	2784	3	5	0.20	0.51	7.93	-0.67
4776	3984	4	4	0.25	0.76	8.29	-0.28
3984	4128	5	3	0.33	1.09	8.33	0.09
5616	4776	6	2	0.50	1.59	8.47	0.47
4128	5616	7	1	1.00	2.59	8.63	0.95

By repeating the same procedure, we calculate Weibull parameters for DS_2, DS_3, and DS_4. The results are presented in Figure 6 and summary Table 5.

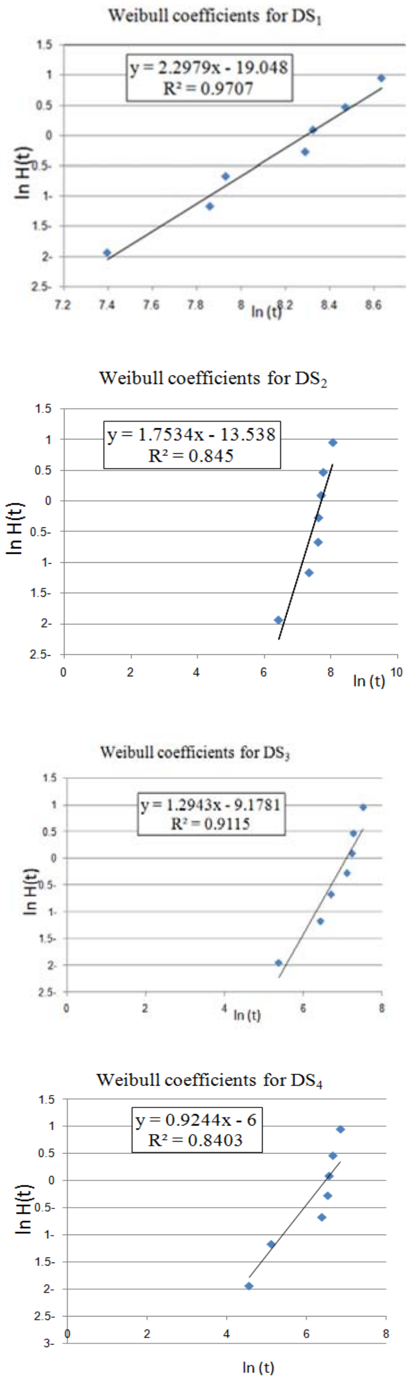

Figure 6. Weibull parameters β and η for each Degradation Stage DS_i.

Table 5. Calculated Weibull parameters β and η for each DS_i.

DSi	DS_0	DS_1	DS_2	DS_3	DS_4
Weibull parameter β	1.79	2.30	1.75	1.29	0.97
Weibull parameter y_0	-16.9	-19.4	-13.53	-9.18	-6
η=exp(-y0/β)	12599	4655	2249	1203	501

Bearing reliability for a bearing found to be in DS_1 will be according to time when DS_1 is detected until total failure: R(t) @ DS_1: t(DS_1) to t(TF).

Table 6 shows the difference in the bearing reliability values with and without repair by the mode to corrected values for bearing detected and found at DS_1 by CM. By using those parameters, we calculate the bearing's reliability at each DS_i. After we know the updated Weibull parameters for the individual deteriorated part, we perform updated RAMS calculations for the machine and for the whole system. Those system values remain relevant until a new deterioration stage is detected by CM.

Table 6. Bearing Reliability values for each DS_i detected by CM.

t	Bearing's reliability without compensating to DS_i	R(t) @ DS_1: $t_{(DS1)}$ to $t_{(TF)}$	R(t) @ DS_2: $t_{(DS2)}$ to $t_{(TF)}$	R(t) @ DS_3: $t_{(DS3)}$ to $t_{(TF)}$
1000	0.989	0.971	0.785	0.455
2000	0.964	0.866	0.443	0.145
3000	0.926	0.695	0.191	0.038
4000	0.880	0.494	0.064	0.009
5000	0.826	0.308	0.017	0.002
6000	0.767	0.167	0.004	0.0003
7000	0.705	0.078	0.001	5.7E-05
8000	0.642	0.0312	9.6E-05	9.1E-06

$$R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{8}$$

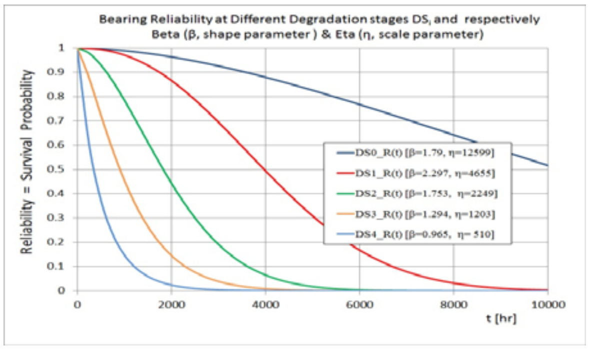

Figure 7. Bearing Reliability values as a function of DS_i.

When diagnosing DS_1, level of reliability will reduce only at t = 1100 hr to below a value of 0.95.

When diagnosing DS_2, the reliability level at t = 1100 hr will drop to below about 0.8.

That is, the probability of a bearing at DS_1 to survive 1000 hours without failure is much greater than that of the bearing that was diagnosed at condition DS_2.

This is also clear intuitively, but by utilizing the model, reliability values can be obtained depending on the hours of work and degradation and using the calculated figures to compare various alternatives.

Comparing these reliability results to analytical calculation of a component's reliability and Monte-Carlo simulation shows that the difference is less than one percent (Table 7).

Table 7. Bearing Reliability and Availability at a detected degradation stage DS_i. Reliability values obtained by Raptor; MCS are similar to those calculated analytically.

		R(t) = exp [-(t/η)^β)]				
		Without DS_i correction	DS_1	DS_2	DS_3	DS_4
		R(t)[DS_0]	R(t)[DS_1]	R(t)[DS_2]	R(t)[DS_3]	R(t)[DS_4]
β, Shape parameter	β	1.79	2.297	1.753	1.294	0.9653
	y0	-16.9	-19.4	-13.53	-9.1	-6
η, Scale parameter	η=exp(-y0/β)	12598	4655	2248	1203	500
R(t), Reliability (analytically computed)	t=1000 [hr]	0.989	0.971	0.785	0.455	0.142
	t=2000 [hr]	0.963	0.866	0.443	0.145	0.022
	t=3000 [hr]	0.926	0.694	0.191	0.038	0.003
R(t), Reliability (Results by MCS) (n=2000)	t=1000 [hr]	0.987	0.971	0.786	0.463	0.149
	t=2000 [hr]	0.960	0.861	0.461	0.151	0.0175
	t=3000 [hr]	0.924	0.686	0.195	0.034	0.0025
A(t) Availability Results by MCS (n=2000)	t=1000 [hr]		0.990	0.919	0.730	0.436
	t=2000 [hr]		0.954	0.764	0.507	0.250
	t=3000 [hr]		0.897	0.616	0.365	0.169

Without the use of aggregated CM data, it was not possible to determine the corresponding Weibull parameters for each DS_i. Table 5 shows the adjusted Weibull parameters for this example. β and η values are fitted according to CM data for each DS_i.

Weibull failure rate calculation, Instantaneous failure rate, h(t) (also called hazard rate), for each DSi are as follows:

$$h(t)_{t_0=0} = \lambda(t) = \frac{f(t)}{R(t)} = \frac{\beta}{\eta-t_0}\left(\frac{t-t_0}{\eta-t_0}\right)^{\beta-1} = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{9}$$

$$\lambda(t)=\frac{f(t)}{R(t)}=\frac{\beta}{\eta-t_0}\left(\frac{t-t_0}{\eta-t_0}\right)^{\beta-1},(t_0=0) \tag{10}$$

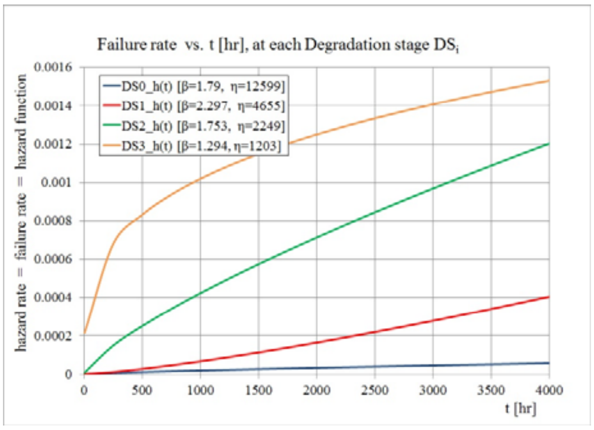

Figure 8. Failure rate calculation for each DS_i versus time.

Results in the area where the main wear occurs, up to 4000 hr, are shown in Figure 8, and presents the change in failure rate at DS_2 and the steep jump at DS_3, in which practically the bearing reaches unacceptable reliability of 0.7 in about 500 hours, leaving only a few days before total failure.

Table 8. Failure rate versus time at each degradation stage DSi.

	Weibull hazard rate=failure rate=hazard function			
Time t [hr]	DS_0_h(t) [β=1.80, η=12599]	DS_1_h(t) [β=2.30, η=4655]	DS_2_h(t) [β=1.75, η=2249]	DS_3_h(t) [β=1.29, η=1203]
5	2.9E-07	6.9E-08	7.8E-06	0.0002
250	6.4E-06	2.6E-05	5.7E-05	0.0008
500	1.1E-05	5.1E-05	0.00014	0.0008
750	1.5E-05	7.4E-05	0.00024	0.0008
1000	1.9E-05	9.7E-05	0.00035	0.0008

It can be seen from Figure 8 and Table 8 that failure rate at DS_3 of 500 hours comes to a value 16 times the failure rate at DS_1 for 500 hours.

Note: values at DS_4 have no practical significance; reliability decreases rapidly at this stage and when it is diagnosed, in practice the machine must be stopped immediately.

Calculations by Weibull failure distribution result in failure rate values that vary depending on the time; this reflects the reality of bearing wear better than the approximation of using a fixed failure rate.

Example 2: Pump reliability at each combination of bearings degradation stages:

Calculating the individual pump reliability and availability at each degradation stage DS_i in each of the pumps' bearings. Once we calculate the adjusted Weibull parameters for each stage of a pump's bearing, we can calculate the reliability and availability of the whole pump as a function of bearing deterioration. For all other less-critical pump components we will use typical reliability values, Logistics Engineering Technology Branch, (1998).

We will concentrate on the decision process between alternatives where reliability and availability values have practical significance. Situations where reliability values fall below 0.8 are not acceptable.

Table 9. Input data for Raptor MCS of pump reliability for DS_0; no deterioration is detected.

Block Name	Fail Distro	Param1	Param2	Param3	Repair Distro
Beaing_1	Weibull	1.790	12598.0	0.0	None
Bearing_2	Weibull	1.790	12598.0	0.0	None
Casing	Exponential	200000.0	0.0		None
Fluid_Driver	Exponential	333333.0	0.0		None
Seals	Exponential	125000.0	0.0		None
Shaft	Exponential	125000.0	0.0		None

Param1=β, Param2=η

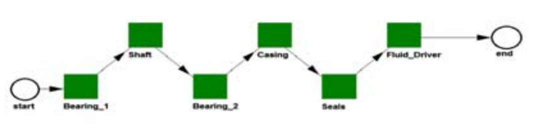

Figure 9. The MCS scheme for single pump reliability.

MCS results for one pump reliability and availability are shown in Table 10

Table 10. MCS results for pump reliability and availability as a function of its bearings' DS_i (n=3000 runs) [values are presented in format: R(t)/A(t)].

Bearing Weibull parameters		DS_0	DS_1	DS_2	DS_3	DS_4
Shape parameter	β	1.79	2.297	1.753	1.294	0.9653
Scale parameter	η=exp(-y0/β)	12598	4655	2248	1203	500
Reliability/Availability		$R(t)[DS_0]$	$R(t)[DS_1]$	$R(t)[DS_2]$	$R(t)[DS_3]$	$R(t)[DS_4]$
Reliability/Availability One bearing is in DS_0, Other bearing degrades from DS_0 to DS_4	t=500	0.98/0.99	0.98/0.99	0.91/0.97	0.71/0.86	0.36/0.62
	t=1000	0.95/0.98	0.93/0.98	**0.75**/0.9	**0.44**/0.715	0.14/0.43
	t=1500	0.92/0.97	0.87/0.95	0.56/0.82	0.25/0.59	0.07/0.32
Reliability/Availability One bearing is in DS_1, Other bearing degrades from DS_0 to DS_4	t=500		0.97/0.99	0.91/0.96	0.71/0.86	0.36/0.62
	t=1000		**0.92**/0.97	0.74/0.89	0.43/0.71	0.14/0.43
	t=1500		0.82/0.94	0.54/0.81	0.24/0.59	0.06/0.32
Reliability/Availability One bearing in DS_2, Other bearing degrades from DS_0 to DS_4	t=500			0.84/0.94	0.65/0.84	0.33/0.61
	t=1000			**0.59**/0.83	0.34/0.66	0.11/0.41
	t=1500			0.35/0.71	0.15/0.52	0.04/0.30

Conclusions from this example:

The results indicate that a pump with **two bearings in DS_1** ($R_{t=1000}$ = **0.92**) is **superior** in terms of reliability and availability compared to a pump where **one bearing is in DS_2** ($R_{t=1000}$ = **0.75**). Results indicate that a **pump with two bearings in DS_2** ($R_{t=1000}$ = **0.59**) is superior in terms of reliability and availability compared to a pump where **one bearing is in DS_3** ($R_{t=1000}$ = **0.44**).

These results are valuable in order to predict the optimal operation alternative. Even for this simple example for one machine reliability, those results are available only by the new CB-RAMS model.

Example 3: Two-pump system reliability:

Calculating reliability and availability for a system, a set of several machines (Figure 10) for each degradation stage DS_i in each of the pumps' bearings.

The next chosen example will emphasize one of the benefits of the CB-RAMS method for systems. According to CM findings and bearing DS_i and known Weibull parameters for each DS_i, update of the **whole system reliability** and availability is performed. By stipulating the next degradation stage of each critical part, reliability and availability calculation of **any operational alternatives** can be compared.

This is done for systems by CB-RAMS in conjunction with Monte–Carlo simulation (MCS). In this example we choose to analyze a small redundant two-pump system shown in Figure 10 (m/n=1/2). Note: For simplicity of presenting the results we do not present the more multipart system (m/n=3/6).

This pump-redundant system has two identical pumps; we will use the same pumps as were analyzed in the previous examples. Only one pump is needed for the system's purposes; therefore, one pump is operating while the second pump serves as a stand-by. This arrangement is a typical subsystem used in countless industries and services, and is critical to safety. Each pump has sensitive rolling bearing components whose failures are common reasons for the system's premature failure.

Using the CB-RAMS model and calculating RAMS for the whole system for several conditions:

Nomenclature: P1-B1-DS_1 means that on pump No. 1, bearing No. 1 deteriorated at stage DS_1. We will solve and compare two basic conditions:

Condition 1: One bearing only has deteriorated to DS_2 in one pump, P1-B1-DS_2, and all other bearings are in DS_0.

Condition 2: In each pump, one bearing has deteriorated to DS_1, P1-B1-DS_1, P2-B1-DS_1, and all other bearings are in DS_0.

One benefit of the CB-RAMS method is to make operationally optimal decisions. By comparing the results of option 1 and option 2, the operator can decide what the optimal action is after the first bearing deterioration is detected. If he decides to switch between the operating pump and the standby pump the next deterioration will be in the second pump and the total system reliability will be according to option 2 results.

System reliability can be calculated analytical or by MCS. For Weibull distribution we have to MCS is used. System reliability for a component in series:

$$R_{sys} = 1 - (1 - R1) * (1 - R2) * ....(1 - R_n) = 1 - \prod_{i=1}^{n} (1 - R_i) \quad (11)$$

System reliability for a component in parallel:

$$R_{SYS} = R_1 * R_2 * \dots R_n = \prod_{i=1}^{n} R_i \qquad (12)$$

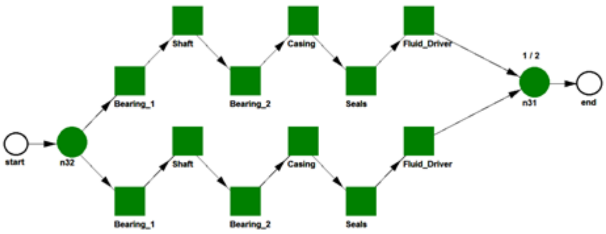

Figure 10: The MCS scheme for two-pump redundant system.

Table 11. Condition 1 input: one bearing has deteriorated to DS_2 in 1 pump, P1-B1-DS_2, and all other bearings are in DS_0.

Block Name	Fail Distro	Param1	Param2	Param3	Repair Distro
P1-Bearing_1	Weibull	1.7530	2248.0	0.0	None
P1-Bearing_2	Weibull	1.790	12598.0	0.0	None
P1-Casing	Exponential	200000.0	0.0		None
P1-Fluid_driver	Exponential	333333.0	0.0		None
P1-Seals	Exponential	125000.0	0.0		None
P1-Shaft	Exponential	125000.0	0.0		None
P2-Bearing_1	Weibull	1.790	12598.0	0.0	None
P2-Bearing_2	Weibull	1.790	12598.0	0.0	None
P2-Casing	Exponential	200000.0	0.0		None
P2-Fluid_driver	Exponential	333333.0	0.0		None
P2-Seals	Exponential	125000.0	0.0		None
P2-Shaft	Exponential	125000.0	0.0		None

Table 12. Condition 2 input: each pump, one bearing has deteriorated to DS_1, P1-B1-DS_1, P2-B1-DS_1, and all other bearings are in DS_0.

Block Name	Fail Distro	Param1	Param2	Param3	Repair Distro
P1-Bearing_1	Weibull	2.2970	4655.0	0.0	None
P1-Bearing_2	Weibull	1.790	12598.0	0.0	None
P1-Casing	Exponential	200000.0	0.0		None
P1-Fluid_driver	Exponential	333333.0	0.0		None
P1-Seals	Exponential	125000.0	0.0		None
P1-Shaft	Exponential	125000.0	0.0		None
P2-Bearing_1	Weibull	2.2970	4655.0	0.0	None
P2-Bearing_2	Weibull	1.790	12598.0	0.0	None
P2-Casing	Exponential	200000.0	0.0		None
P2-Fluid_driver	Exponential	333333.0	0.0		None
P2-Seals	Exponential	125000.0	0.0		None
P2-Shaft	Exponential	125000.0	0.0		None

Results of this example:

Table 13: MCS results for system reliability and availability

	condition 1		condition 2	
	P1-B1-DS_2, all other bearings in DS_0		P1-B1-DS_1, P2-B1-DS_1, all other bearings in DS_0	
t (hr)	R(t)	A(t)	R(t)	A(t)
1000	0.9920	0.9983	0.9960	0.9992
1500	0.9690	0.9926	0.9786	0.9958
3000	0.8126	0.9449	0.8353	0.9598
5000	0.6193	0.8523	0.4050	0.8275
8760	0.2833	0.6757	0.0120	0.5307

R(t)=System Reliability, A(t)=System Availability, n=3000 runs

From results we see that up to t=3000 hr, system reliability and availability will be higher if the next deterioration step will be on the second pump, and lower if the same pump will continue to work and the bearing will reach degradation stage 2. i.e., $R_{(t)SYS}$ (P1-B1-DS_1+ P1-B1-DS_1)) > R_{SYS} (P1-B1-DS_2). CB-RAMS model assists operation decisions and eliminates confusing intuitive decisions. In this example RAMS values will be superior if one bearing in each pump will be in degradation stage 1, rather than if one bearing in one pump will be in degradation stage 2.

The operational practical decision in this case will be to change between the operating pump to the stand-by pump when DS_1 is detected. This will result in maximum reliability and availability.

Even this simple case is not solvable without the method. In practice, operators decide when to change between redundant pumps by personal preferences and intuition. This example emphasizes the benefits of the CB-RAMS model to predict behaviors of multipart systems. Decisions will be more efficient based on CB-RAMS.

The CB-RAMS model is a tool to make optimal LCC decisions, enabling more precise results to maximize production. As shown by the example, based on local CM data, always on this particular system, system availability will be greater if one bearing in both pumps will be in degradation stage 1 than if one bearing in one pump will be in degradation stage 2. Or: A_{SYS} (P1-B1-DS_1+ P1-B1-DS_1)) > A_{SYS} (P1-B1-DS_2).

Lower availability means loss of working hours. This may cost a huge amount of revenue on a production plan.

5. Discussion

Initial RAMS predictions are calculated during system's design phase. Condition Based RAMS (CB-RAMS) is recalculating RAMS according to CM findings along the system's operational life.

Using accumulated local CM historical data, the basic known components' parameters (e.g. Weibull parameters) are calculated to represent each one of degradation stages DS_i. Once obtaining the corresponding Weibull parameters of each DS_i, system reliability and availability is recalculate along system live according to CM findings.

Thus CB-RAMS model take into account the local operation and maintenance conditions. Updated CM-RAMS describe accurately the current deteriorated system. CB-RAMS model assist to reduce intuitive decisions about optimal timing for components replacing, shutdown and maintenance.

CB-RAMS enable to simulate and anticipate the system's RAMS along parts deterioration, as a consequence of parts and redundancy alternatives during system's design phase. The simulation is based on the component's degradation stages detected by CM during a system's real life. This process enables the designer to choose optimal cost benefit design to achieve adequate reliability levels and optimal maintenance shutdown intervals. As demonstrated in the example, by CB-RAMS simulation the influence of chosen component degradation on system reliability can be predicted.

The method extends the use of RAMS beyond the system design phase and makes it useful tool throughout system's life. CB-RAMS enable to decide operation and maintenance activities based on the whole system's reliability, thus preventing unnecessary maintenance work and downtime to get optimal LCC decisions. Implementing CB-RAMS by simulating degradation situations create methodical plan to guide the operation reactions as an alternative to typical on spot intuitive decisions.

Calculating CB-RAMS data by MCS makes this method applicable to multipart systems that are impractical to solve analytically.

Reliability calculations are based on total failure statistical data gathered from a large quantity of failures of the same components, while CB-RAMS is based on degradation detected by CM on individual components in a real operating system, and statistical knowledge about the component's degradation stages.

6. CONCLUSIONS

CB-RAMS can be implemented with any detection method. It can be implemented in conjunction with built-in sensors. Furthermore, data in real time can be analyzed to control system operation. Implementing CB-RAMS is applicable to automating safety measures based on built-in sensors Bond (2003).

More research is required to support and to improve the proposed method. Suggested techniques necessarily need to be evaluated with care in practice.

CB-RAMS connect condition monitoring with reliability, thus improvement in prediction accuracy and better forecasting enhance system's safety.

REFERENCES

Abernethy, R. B. (2000). *The new Weibull handbook*. 4th edition. North Palm Beach, FL: R. B. Abernethy.

Berggren, J. C. (1988). Diagnosing faults in rolling element bearings. *Assessing Bearing Condition*,*4*(1), 5–13.

Barringer, P. H. (May, 1998). *Life cycle cost and good practices*. NPRA Maintenance Conference, San Antonio, Texas.

Barringer, P. H. (2001). Problem of the month, April 2001–Weibull beta slopes for ball bearings. Barringer & Associates. . Retrieved from:http://www.barringer1.com/apr01prb_files/apr01prb.pdf

Bazovsky, I. (1961). Reliability theory and practice. Englewood Cliffs, N.J: Prentice-Hall.

Berry, J. E. (1991). *Tracking of rolling element bearing failure stages using vibration signature analysis*. Charlotte: Technical Associates of Charlotte.

Berry, J. E. (1997). *Tracking of rolling element bearing failure stages using vibration and high frequency enveloping and demodulation spectral techniques. Analysis II - Concentrated Vibration Signature Analysis and Related Condition Monitoring Techniques*. 2nd Edition. Charlotte, NC: Technical Associates of Charlotte, P.C.

Berry, J. E. (1999). Technical associates of charlotte: Good vibes about oil analysis. *Practicing Oil Analysis Magazine*. November/December, 31–39.

Blanks, H. S. (1992). *Reliability in procurement and use*. Chichester: John Wiley & Sons.

Bond, L. J. et al. (June, 2003). *On-line intelligent self-diagnostic monitoring system for next generation nuclear power plants*, Final Project Report for the U.S. Department of Energy. Retrieved from: http://www.pnl.gov/main/publications/external/technical_reports/pnnl-14304.pdf

Dodson, B. (1994). *Weibull analysis*. Milwaukee: Amirican Society for Quality_QASA.

Dubi, A. (1986). Monte-Carlo Calculations for Nuclear Reactor. in Y. Ronen (Ed.), *Handbook of nuclear reactor calculation*. Boca Raton, Fla: CRC Press.

Dubi, A. (1999). *Monte Carlo applications in systems engineering.* New York: John Wiley & Sons Ltd.

Gorjian, N., Ma, L., Mittinty, M., Yarlagadda, P., & Sun, Y. (2009). *A review on degradation models in reliability analysis*. Proceeding of the 4th world congress on engineering asset management, Athens, Greece.

Heng, A., Zhang, S., Tan, A. C., & Mathew, J. (2009). Rotating machinery prognostics: State of the art, challenges and opportunities. *Mechanical Systems and Signal Processing*, *23*(3). 724–739.

Logistics Engineering Technology Branch, (1998). *Handbook of reliability prediction procedures for mechanical equipment: NSWC-98/LE1, NSWC*. West Bethesda, Maryland: Naval Surface Warfare Center, Carderock Division. Retrieved from: https://www.raytheoneagle.com/asent/downloads/NSWC-98-LE1.pdf

Lycette, B. (2005). Practical considerations in calculating reliability of fielded products. *The Journal of the RAC, Second Quarter 2005*, 1–6.

O'Connor, P. D. T. (1991). *Practical reliability engineering*. 3th edition, Chichester: John Wiley & Sons.

Rabinowicz, E. (1981). *Why equipment fails*. ASLE Bearing Workshop: M.I.T.

RAPTOR version 4.0s and RAPTOR 7.

Shalev, D. M. & Tiran, J. (2007). Condition-based fault tree analysis (CB-FTA): A new method for improved fault tree analysis (FTA), reliability and safety calculations. *Reliability Engineering & System Safety, 92*(9), 1231–1241.

Shreve, D. H. (2010). Rolling-element bearing analysis (reba) techniques and practices. Retrieved from: http://reliabilityweb.com/ee-assets/my-uploads/docs/2011/dshreve_doc.pdf

Smith, D. J. (2001). *Reliability, maintainability and risk: Practical methods for engineers*. 6th edition, Burlington, MA: Elsevier Butterworth-Heinemann.

Stock, D., Vesely, W., & Samanta, P. (1994). *Modeling the degradation of nuclear components*. New York: Brookhaven National Laboratory.

Sung, K, (1996). How to evaluate fan life. *Electrics Cooling*. Retrieved from: http://www.electronics-cooling.com/1996/05/how-to-evaluate-fan-life/

Wesley, J., & Usynin, A. (2008). Current computational trends in equipment prognostics. *International Journal of Computational Intelligence Systems*, *1*(1). 94–102.

BIOGRAPHIES

Dan m. Shalev received his B.Sc. degree in Mechanical Engineering from Ben-Gurion University (BGU), Beer-Sheva, Israel in 1974. And his M.Sc. in Nuclear Engineering from BGU in 1992, his M.Sc, Industrial Engineering & Management from BGU in 1994, and his M.Sc, in Management & Safety Engineering from BGU in 2004. Currently he is a Ph.D, student on Interdisciplinary Studies in Kreitman School of Advanced Graduate Studies, at BGU. He directed and performed predictive maintenance (PdM) programs, including component and plant fault detection, mainly spectral vibration analysis, machinery monitoring, & diagnostics, prognostics and condition-based and reliability based maintenance.

Joseph Tiran, Ph.D, is a Senior Lecturer at the Department of Mechanical Engineering, BGU at the BGU (Emeritus). Research Interests: Design and theory of Air Conditioning and Energy systems and control, Mechanics of flight, Safety Engineering, Biomedical Engineering systems and control.

David Katoshevski is a full Professor and the Head of Safety Management and Engineering Environmental Engineering Unit, BGU, Israel. Education: Aerospace Engineering B.Sc, & M.Sc, Applied Mathematics Ph.D, 1995. Post-Doc. RWTH-AACHEN in 1995-96 & Environmental Engineering, California Institute of Technology, CALTECH, USA in 1996-98. Since 1998 at BGU. Deals with dynamics of particles and droplets in various systems, and air pollution control.

Jacob Bortman joined the academic faculty of BGU in September 2010 as a full Professor. He spent thirty years in the Israel Air Force (IAF), retiring with rank of Brigadier General. In the IAF he held the following positions: Head of the Fatigue and Damage Tolerance Lab; Head of the UAV (unmanned aerial vehicle) and Space Department; Head of the IAF's Engineering Laboratories; Head of the Aircraft Department, and finally Head of the Material Directorate, a senior position which reports directly to the chief commander of the IAF. Prof. Bortman received all his three academic degrees in Mechanical Engineering. He received his D.Sc. degree from Washington University in 1991. His thesis was on "Nonlinear Models for Fastened Structural Connection Based on the p-Version of the Finite Element Method" and the Finite Element Method has remained as one of his areas of expertise. His areas of research in the Dept. of Mechanical Engineering include: Health usage monitoring systems (HUMS), Conditioned based maintenance (CBM); Usage and fatigue damage survey; Finite Element Method; and Composite materials. Professionally, He is a board member for several companies, The Van Leer Technology Ventures Jerusalem Ltd (hi-tech incubator), Blades Technology International, Inc., Precision Components International, Inc., Blades Technology Ltd, Turbine Jet Ltd, Gema Medical Ltd, Keren Medical Ltd. He is also the co-founder of, 3F - Fracture, Fatigue, Finite elements. In 2008 he won the Israeli Prime Minister National Prize for Excellency and Quality in the Public Service.