International Journal of Advance Industrial Engineering
ISSN 2320 –5539

Available at http://inpressco.com/category/ijaie

Research Article

Fuzzy Logic-based Maintenance Optimization

T.Sahoo[Å*], P.K.Sarkar[Ḃ] and A.K.Sarkar[Ȧ]

[Å]Indian Oil Corporation ltd, India, [B]Indian School of Mines University, India

Accepted 25 March 2014, Available online 30 March 2014, **Vol.2, No.1 (March 2014)**

Abstract

The effective maintenance activities, at relevant frequencies, are designed to maintain functionality and prevent catastrophic failure of process plant equipments thus ensuring that the risk associated with it are limited. To diagnose the unreliable aspects of the machine, root cause failure analysis (RCFA) of the component failure , as a system is carried out by listing all the possible causes related to the machine units . The ability to predict and prevent failures and to make informed decisions based on consolidated equipment health and performance data becomes critical. However such advanced, complex and integrated systems result in complex failure modes, which are more difficult to diagnose and repair, and becoming more complex to operate and maintain. The paper focuses on developing an integrated maintenance management framework to establish „just-in-time" maintenance and to ensure continuous improvements based on maintenance domain experts as well as operational and historic data. To do this, true degradation of components must be identified. True level of degradation often cannot be inferred by the mere trending of condition indicator's level (CBM), because condition indicator levels are modulated under the influence of the diverse operating context. Besides, the maintenance domain expert does not have a precise knowledge about the correlation of the diverse operating context and level of degradation for a given level of condition indicator on specific equipment. Efforts have been made in here to identify the true degradation pattern of a component by analyzing these vagueness and imprecise knowledge. Key question for researchers to address such challenges should be "What is the optimum preventive maintenance time interval?" Too short intervals would lead to unnecessary prevention costs; no preventive maintenance would lead to breakdowns, which may affect production, and inflict money losses on the firm as discussed previously; and too long intervals would result in both inconveniences, as they will involve preventive maintenance actions and would lead to uncontrolled breakdowns. A comprehensive overview helps to overcome unforeseen events and incidents that might lead to catastrophe.

Keywords: *Fuzzy Logic, Maintenance etc.*

Problem Formulation

In practice, the choice of the optimum maintenance strategy is not a simple task. Implementation of such philosophy for complex installations is a difficult and a complex task. Key question to address such challenges should be "What is the optimum preventive maintenance time interval?".

True level of degradation often cannot be inferred by the mere trending of condition indicator‟s level (CBM), because condition indicator levels are modulated under the influence of the diverse operating context (normal, marginal, hostile, operating complexity, etc). Besides, the maintenance domain expert does not have a precise knowledge about the correlation of the diverse operating context and level of degradation for a given level of condition indicator on specific equipment. Advanced software tools, like fuzzy logic, considers these vagueness and imprecise knowledge (better than the conventional statistical modeling) to quantify imprecise and uncertain information.

Maintenance Planning

An overall plan has to be prepared for the production facilities for the conduct of „just-in-time‟ maintenance program .The results from the criticality analysis classification are useful when defining criteria for prioritizing work orders. Prioritization of maintenance (using FMECA or Fuzzy Logic) should be done based on the risk the failure represents, described as consequence and failure impact/probability of failure. Continues improvements on accurate planning can be made by getting updated inputs from improved root cause failure analysis and human-technology-organization (HTO) integration.(Look also Appendix C, prioritization of corrective maintenance recommended by NORSKO-Z008 rev. 3, based on the risk the failure represents, described as consequence and failure impact). Criticality of failures can be classified based on Table 6.

*Corresponding author: **T.Sahoo**

Optimization of Maintenance Interval

By identifying the root cause for the failure, achieving the desired system performance, e.g. reliability, availability, is determined in system design and development, but also through implementation of efficient and effective maintenance strategies. The overall objective of maintenance process is to increase the profitability of the business in a total life cycle cost (LCC) perspective without compromising HSE. The life of a project is extended by improving maintenance performance. Optimization of maintenance strategies is therefore expected to provide a basis for development of cost effective maintenance strategies which minimizes the consequences related to HSE and economy.

There are different types of maintenance, of which the main types are preventive maintenance (PM) and corrective maintenance (CM). Furthermore PM can be grouped in to two.

a) Age/time/condition based; and

b) Opportunistic based

Condition-monitoring is already an integral part of the condition-based maintenance (CBM) strategy of existing production facilities.If potential failures are detected early enough, it is possible to plan for the maintenance action when the component is still on uptime.In order to exploit the information from condition monitoring into maintenance decision making, it is necessary to establish a relationship between the state of the item (or system) and one, or more, condition-monitored state variables, denoted by say, X(t). The relationship between the state of the item and X(t) can be determined by using mathematical models or expert judgments to predict the behavior of the deterioration process. It is often of interest to find the probability of failure based on the value of the condition-monitored state variables.

Different subsystems and components will have different deterioration processes and measures, depending on their construction, materials, usage, and exposure to external adverse conditions. Deterioration may be modeled based on physics of failure and characteristics of the operating environment; i.e., modeling deterioration in terms of a time-dependent stochastic process. Relevant models are, for example, the P-F interval , proportional hazard modeling (PHM)-which is multivariate regression analysis and Markov-processes.

We have taken the case of a reciprocating compressor which is the heart of a Hydro processing plant.it has many components which affect its performance. The most important component which degrades to affect it's performance is the rider ring. The rider ring degradation for a period of two years were taken and it is observed that it follows weibull distribution. So its remaining useful life can be calculated from the weibull plot.

Rider Ring Data

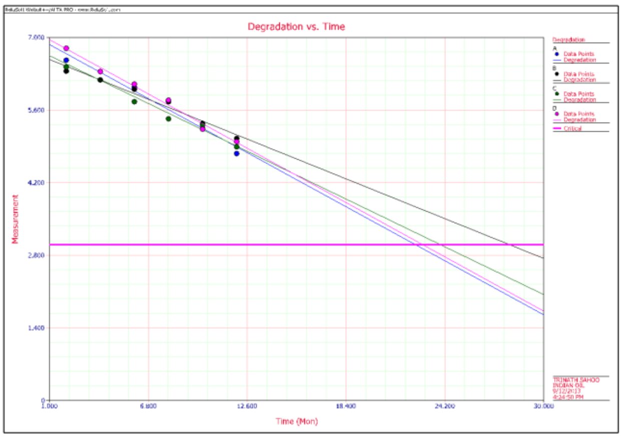
Inspection Time	Degradation	dimension	Unit ID
2	6.56	mm	A
4	6.34	mm	A
6	6.04	mm	A
8	5.76	mm	A
10	5.24	mm	A
12	4.76	mm	A
2	6.35	mm	B
4	6.18	mm	B
6	6	mm	B
8	5.76	mm	B
10	5.34	mm	B
12	5.05	mm	B
2	6.43	mm	C
4	6.34	mm	C
6	5.76	mm	C
8	5.43	mm	C
10	5.31	mm	C
12	4.89	mm	C
2	6.79	mm	D
4	6.34	mm	D
6	6.1	mm	D
8	5.79	mm	D
10	5.23	mm	D
12	4.99	mm	D

The above data shows the rider ring thickness of four cylinders A.B,C,D in a compressor.

The threshold value of the rider ring is 3mm below which it will damage the compressor.

Can we get from weibull when each of the ring will achieve 3mm thickness.

Report Type	Degradation Fit Results			
User Info				
User	TRINATH SAHOO			
Company	INDIAN OIL			
Date	09-12-13			
Parameters				
Unit ID	Parameter a	Std - a	Parameter b	Std - b
A	-0.179714	0.014775	7.041333	0.115084
B	-0.132286	0.011218	6.706	0.087373
C	-0.158857	0.014692	6.805333	0.114437
D	-0.180571	0.01002	7.137333	0.078042



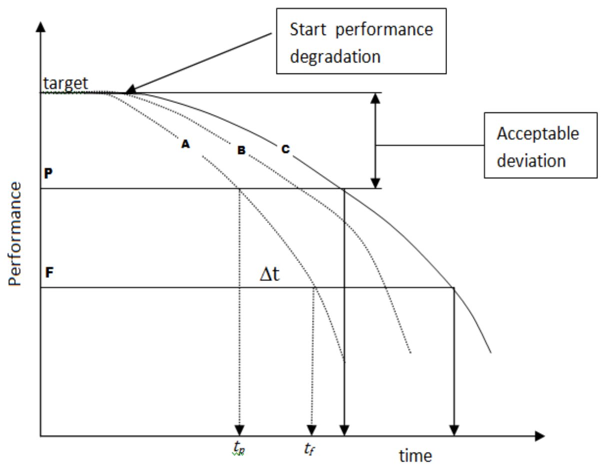
Report Type	Degradation Results	
User Info		
User	TRINATH SAHOO	
Company	INDIAN OIL	
Date	09-12-13	
Parameters		
Distribution:	Weibull-2P	
Analysis:	RRX	
CB Method:	FM	
Ranking:	MED	
Beta	11.661042	
Eta (Mon)	25.263565	
LK Value	-9.293592	
Rho	0.866028	
Fail \ Susp	4 \ 0	
LOCAL VAR/COV MATRIX		
	Var-Beta=18.555180	CV Eta Beta=2.632614
	CV Eta Beta=2.632614	Var-Eta=1.418283

The consequence of component/sub-system failure on a system can be classified into three categories, critical, semi-critical and non-critical based on function criticality, operating context and complexity of the equipment/technology. The equipment‟s true degradation is estimated using condition indicators (or variables) like, vibration monitoring (e.g. belt, gear drive, or surfaces with components with relative motion), temperature (e.g. electrical components, bearing house, hydraulic pumps etc.), lubricant monitoring (transmission components like gears, cams, etc.).

The monitoring frequency could be periodic/ continuous. The operating context is important factor, which influences degradation. The adverse operating context in the offshore can also be classified into three operating regimes (Edwin and Chaturvedi, 2006), namely; normal, marginal and hostile operating contexts.

Under the influence of operating context, condition indicator levels are modulated, thereby true level of degradation cannot be inferred by the mere trending of condition indicator‟s level. Hence, operating context needs to be considered while using condition indicator level to understand the true state of equipment. On the other hand, the maintenance domain expert does not have a precise knowledge about the correlation of the operating context and level of degradation for a given level of condition indicator on specific equipment. Expert System theory (e.g. Artificial Intelligence) considers these vagueness and imprecise knowledge (i.e. by integrating quantitative and qualitative knowledge) to come up with possibilities of failure degradation modes and hence improving our decision making to improve maintenance performance

The uncertainty between initiation of degradation and reaching to unacceptable levels is shown in the Figure below. As shown in the figure, the performance decreases over a period of time and drops down to an unacceptable level (potential failure, tp) and leads to a functional failure at a later time (tf). The degradation of a component/system may vary widely due to above mentioned factors. Owing to this variation and associated randomness, the potential and functional failure times are also not precise. Hence, the frequency of monitoring decided on the basis of P-F interval (PF Interval = tf - tp) is also a variable. Some say PF interval itself is hard to define.



uncertainty in the PF interval (modified from Edwin and Chaturvedi, 2008)

(tp =potential failure time, tf =functional failure time)

Since this interval is uncertain and degradation is a random event (it could be pattern A, pattern B, pattern C. etc), predicting an impending failure is highly probabilistic. Therefore, the probability of detecting a failure in advance is not a crisp event and fuzziness (uncertainty) is associated with it. This uncertainty can be better handled with fuzzy logic using appropriate membership function to arrive at estimating appropriate possibility level. Fuzzy logic uses to reflect the dispersion of data adequately. The dispersion includes variation in human performance, vagueness in adverse operating/environmental conditions and vagueness in the system performance due to age.

Rule-based fuzzy logic can be integrated into the maintenance program to determine the times for the periodic PM actions, considering maintenance imperfections. Indeed, considering human factors in maintenance programs is indispensable to assure more accurate results. However due to the difficulty to handle by their modeling, most theoretical maintenance models do not consider these factors.

Therefore, fuzzy logic can be an important tool to include them. We modify the maintenance program at every maintenance action according to the duration of maintenance actions and the technician‟s experience seeking to optimize the maintenance program („just-in-time‟) so as to minimize the cost or maximize the availability of the system to compensate for high maintenance cost. Fuzzy Inference System (FIS) on a hardware platform can be developed for a real-time application.

Fuzzy Logic theory approach proposes to estimate the "Possibility of failure mode detection". For offshore, three fuzzy variables are important to be considered in the fuzzy inference System i.e.: level of condition indicator; frequency of monitoring; and operating context.

Table 1 Level of condition indicator

Catastrophic	Complete mission failure,	**9,10**
Critical	Major mission degradation,	**6,7,8**
Moderate	Minor mission degradation,	**3,4,5**
As new	Less than minor mission degradation	**1,2**

Table -2 Operating context

hostile	**Very fast** failure due to operating context or loss of system	**9,10**
Marginal	Major mission degradation, , or major system damage due to operating context.	**5,6,7,8**
Normal	Less than minor mission degradation, or minor system damage due to operating context.	**1,2,3,4**

Frequency of monitoring

Table 3 Probability categories

Rank	**occurrence**	**meaning**
9,10	**online**	**continuous**
7,8	**frequently**	**Repeated**
4, 5, 6	**Occasional**	**Occasionally taken**
12,3	**Unlikely**	**Never taken**

Create the Fuzzy Membership Functions

Fuzzy control systems are “expert” systems, meaning they’re modeled on the expert experience of real people. The next step is to incorporate such experience in defining the fuzzy membership functions for each input and output.

Fuzzification process

The fuzzification process converts the occurrence and severity inputs into their fuzzy representation which can be then matched with the premises of the rules into the rule base.In the fuzzification subprocess, the membership functions defined on the input variables are applied to their actual values, to determine the degree of truth for each rule premise too.

Construct the Rule Base

Now we write the rules that will translate the inputs into the actual outputs. After the fuzzy input set have been defined, the conceptual model for the fuzzy criticality system is completed by writing the rules that describe the riskiness of the system for each combination of input variables. Several rules are described in the next table.

Table -4

Rule	**occurrence**	**severity**	**risk**
#1	Low	Moderate	Moderate
#2	Low	high	important
#3	Low	Very high	important
#4	moderate	moderate	important
#5	moderate	high	Very important

The characterization of the fuzzy system is based on expert knowledge and usually appears in the form of If-then rules, which can be easily implemented by fuzzy conditional statements. The collection of fuzzy rules, as in the previous table, gives the rule base. Fuzzy rules are often formulated in linguistic terms than in numerical terms. The proper choice of variables is fundamental in characterizing the operation of a fuzzy system and their selection has a significant effect on the accuracy of the system.

Inference

In the inference sub process, the truth-value for the premise of each rule is computed, and applied to the conclusion part of each rule. This results in one fuzzy subset to be assigned to each output variable for each rule. In our example only there is only four logical rules, which are practically used. On the basis of the Risk Assessment Matrix they are the following ones:

Rule (A): If severity is critical and probability is occasional then risk is high;
Rule (B): If severity is moderate and probability is occasional then risk is medium;
Rule (C): If severity is critical and probability is seldom then risk is medium;
Rule (D): If severity is moderate and probability is seldom then risk is low

It is very interesting that, using the given rules, the risk – a result of a rule – can be high, medium and low.

The most frequent techniques for the fuzzy inference processor called “min-max inference” to calculate numerical conclusion to linguistic rules based on the system input values. The result of this process is called “fuzzy conclusion”. The rule evaluation consists of determining the smallest (minimum) rule antecedent, which taken to be truth value of the rule, then applying this truth value to all consequences of the rule. We will present in our example the following rules

Rule (B): If severity is moderate and probability is occasional then risk is medium;
Rule (C): If severity is critical and probability is seldom then risk is medium

Optimized Method of Maintenance

In order to locate the weak link of the compressor and its components , the first stage to be realized at the time of the study of the reliability of the compressor is the determination and the analysis of risk of each of its components.

Fuzzy logic study mainly allows optimizing the direct costs .Indeed it is a clever method of diagnosis to the extent that it predicts a number of weaknesses, defects, anomalies and failures at all the elements that contribute to system availability

Conclusion and Future Research Directions

Integrated maintenance management framework in the Oil and Gas Industries helps to explore the use of sophisticated technical solutions. The application of such sophisticated technologies in maintenance of complex production facilities can bring huge benefits in terms of reducing risk. To utilize such sophisticated technologies, it is important to understand the interconnected issues and challenges. Some of the potential benefits of the use of such integrated maintenance management include:

- Enhancement in terms of better and effective control of potential events and incidents that may lead to functional failures.
- Model, analyze and predict the behavior of systems in more realistic manner (removes vagueness in maintenance planning).
- Helps in a quick review of ranking of numerous maintenance tasks to plan suitable maintenance practices /strategies for improving system performance

Reference

Ben-Daya, M., & Raouf, A. (1996). A revised failure mode and effects analysis model. International Journal of Quality & Reliability Management, 13(1), 43–47.

Bowles, J. B. (2004). An assessment of PRN prioritization in a failure modes effects and criticality analysis. Journal of the IEST, 47, 51–56.

Bowles, J. B., & Pela´ez, C. E. (1995). Fuzzy logic prioritization of failures in a system failure mode, effects and criticality analysis. Reliability Engineering and System Safety, 50, 203–213

Braglia, M., Frosolini, M., & Montanari, R. (2003a). Fuzzy criticality assessment model for failure modes and effects analysis. International Journal of Quality & Reliability Management, 20(4), 503–524.

Braglia, M., Frosolini, M., & Montanari, R. (2003b). Fuzzy TOPSIS approach for failure mode, effects and criticality analysis. Quality and Reliability Engineering International, 19, 425–443.

Chang, C. L., Wei, C. C., & Lee, Y. H. (1999). Failure mode and effects analysis using fuzzy method and grey theory. Kybernetes, 28, 1072–1080.

Chang, C. L., Liu, P. H., & Wei, C. C. (2001). Failure mode and effects analysis using grey theory. Integrated Manufacturing Systems, 12(3), 211–216.

Chin, K. S., Chan, A., & Yang, J. B. (in press). Development of a fuzzy FMEA based product design system. International Journal of Advanced Manufacturing Technology, doi:10.1007/s00170-006-0898-3.

Dong, W. M., & Wong, F. S. (1987). Fuzzy weighted averages and implementation of the extension principle. Fuzzy Sets and Systems, 21, 183–199.