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Fuzzy inference to risk assessment on nuclear engineering systems

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Abstract

This paper presents a nuclear case study, in which a fuzzy inference system (FIS) is used as alternative approach in risk analysis. The main objective of this study is to obtain an understanding of the aging process of an important nuclear power system and how it affects the overall plant safety. This approach uses the concept of a pure fuzzy logic system where the fuzzy rule base consists of a collection of fuzzy IF–THEN rules. The fuzzy inference engine uses these fuzzy IF–THEN rules to determine a mapping from fuzzy sets in the input universe of discourse to fuzzy sets in the output universe of discourse based on fuzzy logic principles. The risk priority number (RPN), a traditional analysis parameter, was calculated and compared to fuzzy risk priority number (FRPN) using scores from expert opinion to probabilities of occurrence, severity and not detection. A standard four-loop pressurized water reactor (PWR) containment cooling system (CCS) was used as example case. The results demonstrated the potential of the inference system for subsiding the failure modes and effects analysis (FMEA) in aging studies. © 2005 Elsevier B.V. All rights reserved.

Keywords: FMEA; Fuzzy logic; Expert opinion; Risk

1. Introduction

Currently, the Nuclear Power Plants (NPP) provide about 18% of the electric power produced in the world. The United States only, at the end of 1989, had 108 reactors in commercial operation. In the last years, the future perspectives for nuclear energy have been analyzed under two antagonizing points of view. The positive aspect is that, in recent studies, some authors have been emphatic to support that the nuclear power plants option does not contributed to the global warming and yet, the new

* Corresponding author. Tel./fax: +55 2121 2209 8231. *E-mail address:* tony@ien.gov.br (A.C.F. Guimarães). pressurized water reactor (PWR) generations possess important intrinsic safety characteristics [1]. These studies suggest that the option for electric nuclear generation would remain as important energy search for at least 50 year. However, the population of commercial nuclear power plants has matured and its main safety and operational components are under aging process. By the year 2014, 48 of these plants will have been operating for 40 years (design life expectance). To solve this problem, researchers and engineers of the nuclear energy area have developed studies to comprehend the causes and effects of aging phenomena. Recently, [2] performed a study about the aging process in Nuclear Power Plant containment cooling systems (CCS). Preoccupied with this

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question, the United States (US) Nuclear Regulatory Commission (NRC), a few years ago, performed an aging assessment of containment cooling systems in nuclear power plants as part of the Nuclear Plant Aging Research (NPAR) program.

The goal of aging analysis in [2] was to determine if aging degradation is a concern for the containment cooling system, and to characterize its effects. To accomplish this, a planned approach was taken. This included: (1) an extensive review of existing Final Safety Analysis Report (FSARs) to identify the different system designs, (2) identification of the operating and environmental stresses imposed on the systems, (3) an analysis of failure data from national databases covering all pressurized water reactors in the USA, (4) an analysis of plant-specific data from one PWR and (5) a system unavailability analysis on one common containment spray system design and one common fan cooler system design to evaluate the potential time-dependent effect of aging on system unavailability. The results of [2] show that aging is a concern for the containment cooling system and should be addressed in plant programs. Failure modes and aging mechanisms were identified for several of the most frequently failed components in each system.

As can be seen in aforementioned work, the traditional safety analysis, specifically the FMEA approach, has been used on aging assessment studies on the nuclear area. Beyond this, in the last years, other important knowledge field, the artificial intelligence, has appointed good solutions for old nuclear engineering problems. Such as: *reactor core design* [3], *fuel reload* [4], *test surveillance planing* [5], *preventive maintenance optimization* [6], *reduced scale experiments design* [7,8], *corrosion on steam generation* [9] and others.

Considering the research lines above mentioned, the goal of this paper is to develop a ranking FMEA using, a direct method with one expert opinion and propose a fuzzy approach to identify implicit information in a very important nuclear safety system.

Failure mode and effects analysis (FMEA) is an important technique [10] that is used to identify and eliminate known or potential failures to enhance reliability and safety of complex systems and is intended to provide information for making risk management decisions.

Fuzzy logic systems is one of the various names for the systems which have relationship with fuzzy concepts [11], like fuzzy sets, linguistic variables, etc. The most popular fuzzy logic systems in the literature may be classified into three types: pure fuzzy logic systems, Takagi and Sugeno's fuzzy system, and fuzzy logic systems with fuzzifier and defuzzifier [12]. The methodology used in this paper is the fuzzy logic systems with fuzzifier and defuzzifier [9,13–15].

The knowledge-based fuzzy systems allows for descriptive or qualitative representation of expressions such as "remote" or "high", incorporate symbolic statements that are more natural and intuitive than mathematical equations. A direct method with "one expert" [16] was used to aggregate opinion of an individual expert.

This work investigates the potential application of knowledge-based fuzzy systems in a case study. The containment cooling system information was used for this study and system description details can be found in [2].

2. Short description of fuzzy inference system approach

The "pure fuzzy logic system" is the system where the fuzzy rule base consists of a collection of fuzzy IF– THEN rules, and the fuzzy inference engine uses these fuzzy IF–THEN rules to determine a mapping from fuzzy sets in the input universe of discourse $U \subset R^n$ to fuzzy sets in the output universe of discourse $V \subset R$ based on fuzzy logic principles. The fuzzy IF–THEN rules are of the following form:

$$R^{(l)} : \text{IF } x_1 \text{ is } F_1^l \text{ and } \dots x_n \text{ is } F_n^l,$$

THEN y is G^l (1)

where F_i^l and G^l are fuzzy sets, $\underline{x} = (x_1, \ldots, x_n)^T \in U$ and $y \in V$ are input and output linguistic variables, respectively, and $l = 1, 2, \ldots, M$. Practice has shown that these fuzzy IF–THEN rules provide a convenient framework to incorporate human experts' knowledge. Each fuzzy IF–THEN rule of Eq. (1) defines a fuzzy set $F_1^l x \ldots x F_n^l \Rightarrow G^l$ in the product space $U \times V$. The most commonly used fuzzy logic principle in the fuzzy inference engine is the so-called *sup-star composition*, described in detail in [12]. The *mini-inference*

rule and *product-inference* rule are choiced as good from an axiomatic strength point of view, and also because these inferences rules are computationally simple [12]. In our application, we will use the *mini-inference* type of inferences rules in our adaptive fuzzy system application.

In order to use the "pure fuzzy logic system" in engineering systems where inputs and outputs are realvalued variables, the most straightforward way is to add a fuzzifier to the input and a defuzzifier to the output of the pure fuzzy logic system. The fuzzifier maps crisp points in U to fuzzy sets in U, and the defuzzifier maps fuzzy sets in V to crisp points in V. The *fuzzy rule base* and *fuzzy inference engine* are the same as those in the pure fuzzy logic system. In the literature, this fuzzy logic system is often called the fuzzy logic controller since it has been mainly used as a controller. It was first proposed by [13], and has been successfully applied to a variety of industrial process and consumer products. A detailed description of this fuzzy logic system can be found in [12].

The Mamdani fuzzy logic system has many attractive features. First, it is suitable for engineering systems because its inputs and outputs are real-valued variables. Second, it provides a natural framework to incorporate fuzzy IF–THEN rules from human experts. Third, there is much freedom in the choices of fuzzifier, fuzzy inference engine, and defuzzifier, so that we may obtain the most suitable fuzzy logic system for a particular problem [12].

3. Application of the proposed approach to CCS

The containment cooling was selected as example system to permit a comparison with the [2] results. Its function is performed by several different systems, depending on the type and design of the plant. The two systems focused on in that study and also here are the *containment spray system* and the *fan cooler system*. These systems were selected since they are the primary means of removing containment heat during accident conditions.

To start the proposed study, an "expert" with knowledge domain on the analyzed system was adopted. The selected specialist belongs to the reliability engineering and can participate in other domains. A traditional FMEA using the RPN ranking system is carried out in the first moment. Mathematically represented, it will give:

$$RPN = O \times S \times D \tag{2}$$

where O represents the *probability of occurrence*, S the *severity* and D represents the *not detection* probability. The values for O, S and D are obtained by using the scaled values presented in Table 1 [14,15]. The expert in the FMEA analysis was the same in the proposed fuzzy approach. In Table 1, we can see five scales and scores of 1–10 that are used traditionally in FMEA, measuring the probability of *occurrence*, *severity* and the probability of *not detection*.

A failure modes and effects analysis was performed to determine the effects of failure over the major system components. The FMEA analysis for containment cooling system is summarized in Appendices A and B. In [2], the FMEA analysis is presented in detail and the values for O, S and D were evaluated by an expert. For example, considering the PWR operation experience, the CCS seal of valve presents a considerable aging process, consequently, the fail of a seal valve is a relatively common event. So, the occurrence probability to this event is high. However, its consequences to reactor safety and its relative importance to system is moderate (severity index is moderate). Finally, the detection of this event is easily possible with surveillance test performance. So, the non-detection probability is low.

Table 1 Traditional FMEA scales for RPN

Occurrence (O), Severity (S), Not Detection (D)	Rating	Possible failure rate for O (operating days)	Probability of not detection
Remote	1	<1:20,000	0-5/6-15
Low	2/3	1:20,000/1:10,000	16-25/26-35
Moderate	4/5/6	1:2000/1:1000/1:200	36-45 Z46-55/56-65
High	7/8	1:100/1:20	66-75/76-85
Very high	9/10	1:10/1:2	86–100

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To characterize the effects of aging on containment cooling system, several sources of data were analyzed. These include the Nuclear Plant Reliability Data System (NPR-DS) and Licensee Event Reports (LERs), which are national databases. In addition, plant specific data were obtained to supplement and validate the national database findings.

The results of the national database analysis and plant specific data analysis are presented in more details in [2]. Only a summary of aging characteristics will be described here.

The analysis of the national database has identified the major aging characteristics for the containment cooling system components. This information is necessary for understanding the aging process so that it can be properly monitored and managed. Appendices A and B presents the aging characteristics for the most frequently failed components in the containment spray system. The component relative failure frequency represents the relative frequency at which that component fails as compared to other components in the system. Similarly, the sub-component relative failure frequency represents the relative frequency at which that sub-component fails as compared to other sub-components in that specific component. The relative failure mode frequency represents the frequency at which that failure mode occurs when that component fails as compared to other possible failure modes for that sub-component. The frequency ratings of low, medium and high are based on the percentage of total occurrences found in the data analyzed. A frequency was judged to be high if it accounted for 50% or more of the total number of occurrences. A frequency was judged to be medium if it accounted for 25-50% of the total number of occurrences, and low if it represented less than 25% of the total. It should be noted that these ratings may not be representative of any specific plant since there are many factors which can influence these results. These findings should be considered industry averages, which can be used as a baseline for reviewing existing aging management techniques.

As an example of the interpretation of the Appendices A and B, the first entry is for valves in the containment spray system. Their relative failure frequency is medium, which indicates that if a failure occurs in the containment spray system there is a good chance it will involve a valve. Further, if the failure

does involve a valve, there is a good chance that failure will involve the valve packing, and a very good chance this packing problem will manifest itself in the form of external leakage. The predominant aging mechanism leading to this type of failure is wear of the packing, and it can be detected by visual inspection. The Appendices A and B also show that, instead of leakage, there is a chance that the valve packing problem will manifest itself by causing the valve not to open or close, however, the probability of this failure mode is low. This could be caused by binding or distortion of the packing, and can be detected by a valve stroke test. Entries for other component can be interpreted in the same manner.

3.1. Fuzzy membership function

Making use of the fuzzy logic toolbox simulator of MatLab [17], the expert was invited to define each membership function and the values in the universe of discourse using the interpretations of the linguistic terms described in Table 2 [14]. The expert chose the triangular membership function defined by fuzzy number (a, b, c) expressing the proposition "close to b" [16]. After that, the following question may be answered by the expert: "Which elements x (a, b, c)have the degree of membership $\alpha_a = \text{zero}, \alpha_b = \text{one}$ and α_c = zero". Direct methods with one expert [16] were used. The linguistic terms describing the input are Remote (R), Low (L), Moderate (M), High (H) and Very High (VH), and for output are Unnecessary (U), minor (mi), very-low (vl), low (l), moderate (mod), high (h), M-high (Mh), V-high (Vh), n and A-n. After receiving the feedback from the expert, the membership function of the five linguistic terms, are generated. Fig. 1, show occurrence (identical for severity and not detection) and the membership function for the linguistic variable for risk is determined and graphically represented in Fig. 2.

3.2. Fuzzy rule base application

The membership function derived from the expert is used to generate the fuzzy rule base. The total number of rules, equal to 125, in the fuzzy rule base, is reduced when these rules are combined. The Rule Viewer of the MatLab that opens during the simulation can be used to access the "Membership Function

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Linguistic term Probability of occurrence Detection Severity Remote It would be very unlikely for these A failure that has no effect on the system Defect remains undetected failures to be observed even once performance, the operator probably until the system performance will not notice degrades to the extent that the task will not be completed Low Likely to occur once, but unlikely A failure that would cause slight annoyance Defect remains undetected to occur more frequently to the operator, but that cause no deterioration until system performance is to the system severely reduced Moderate A failure that would cause a high degree of Likely to occur more than once Defect remains undetected operator dissatisfaction or that causes noticeable until system performance but slight deterioration in system performance is affected High Near certain to occur at least once A failure that causes significant deterioration Defect remains undetected in system performance and/or leads until inspection or test is to minor injuries carried out Very high Near certain to occur several times A failure that would seriously affect the ability Failure remains undetected, to complete The task or cause damage, such a defect would almost serious injury or death certainly be detected during inspection or test

Table 2 Interpretations of the linguistic terms for developing the fuzzy rule system

Editor" and the "Rule Editor". Through "*Simulator*" many results can be evaluated and rules can be removed. For example, consider these three rules:

- Rule 1: if Occurrence is M and Severity is H and not Detection is M then Risk is M-h.
- Rule 2: if Occurrence is H and Severity is M and not Detection is H then Risk is M-h.

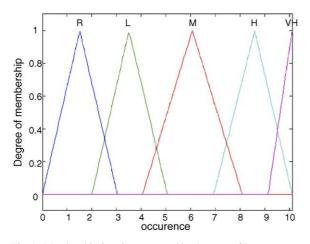


Fig. 1. Membership function generated by the expert for occurrence (identical for severity and not detection).

Rule 3: if Occurrence is H and Severity is H and not Detection is M then Risk is M-h.

Rules 1, 2 and 3, can be combined to produce:

"if Occurrence is M and Severity is H and not Detection is M then Risk is M-h" or any combination of the three linguistic terms assigned to these variables, then Risk is M-h.

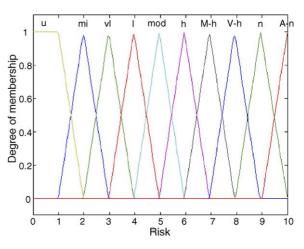


Fig. 2. Membership function for the Risk generated by expert.

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This type of reduction consider that the probability of *Occurrence, Severity and not Detection* have the same importance.Fuzzy inference functions, such as the defuzzification method, used in this application are:

name: 'FMEA_CCS' type: 'Mamdani' andMethod: 'min' orMethod: 'max' defuzzMethod: 'centroid' impMethod: 'min' aggMethod: 'max' input: $[1 \times 3 \text{ struct}]$ output: $[1 \times 1 \text{ struct}]$ rule: $[1 \times 15 \text{ struct}]$

4. Results

"RPN" and "FRPN" are the risk numbers by the FMEA. *Ranking_RPN* and *Ranking_Fuzzy* are the ranking of RPN and fuzzy methodology. The RPN is the product of $O \times S \times D$ and fuzzy is the proposed approach in this paper.

Using the same data from the traditional FMEA, and expressing the three variables considered linguistically with aid of the membership function in Fig. 1 and the fuzzy rule base, gives the results of the modified FMEA. These results are then defuzzified using the centroid method to obtain the *Fuzzy* Risk results for ranking, expressed in variable *Ranking_-Fuzzy*, as shown in Table 3.

The most critically debated disadvantage of the traditional FMEA is that various sets of Occurrence (*O*), Severity (*S*) and not Detection (*D*) may produce an identical value of RPN, however, the risk implication may be totally different. For example, consider two different events having values of 3, 1, 6 and 1, 9, 2, for *O*, *S* and *D*, respectively. Both these events will have a total of RPN of 18 (RPN₁ = $3 \times 1 \times 6 = 18$ and RPN₂ = $1 \times 9 \times 2 = 18$), however, the risk implication of these two events may not necessarily be the same.

Table 3 Ranking comparison

	6 1			
ID	RPN	Fuzzy	Ranking RPN	Ranking Fuzzy
1	135	2.9705	24	24
2	252	7.8406	14	10

Table	3 (Contin	nued)		
ID	RPN	Fuzzy	Ranking RPN	Ranking Fuzzy
3	210	7.7627	19	11
4	168	3.9597	22	23
5	252	7.8406	14	10
6	60	0.8530	29	27
7	343	7.9320	5	7
8	294	7.9221	10	8
9	378	8.0071	4	5
10	252	7.8406	14	10
11	252	7.8406	14	10
12	252	7.8406	14	10
13	196	4.9504	20	22
14	196	4.9504	20	22
15	168	4.9504	22	22
16	288	6.9915	11	18
17	288	6.9915	11	18
18	343	7.9320	5	7
19 20	294 420	7.9221	10 2	8 2
20 21	420 420	8.9651 8.9651	2	2
21	420 294	7.9221	10	8
22	294	7.6683	10	13
23 24	210	4.9504	18	22
24 25	175	7.5027	21	16
26	243	4.9504	16	22
20	70	1.9813	28	26
28	392	8.7839	3	3
29	150	7.5027	23	16
30	105	2.8039	26	25
31	245	7.5489	15	15
32	175	7.5027	21	16
33	294	7.9221	10	8
34	252	7.8406	14	10
35	315	7.7735	9	11
36	163	4.9504	22	22
37	224	4.9504	17	22
38	120	4.9504	25	22
39	270	6.9306	13	20
40	320	6.9664	8	19
41	324	7.9194	7	9
42	75	2.8039	27	25
43	294	7.9221	10	8
44	294	7.9221	10	8
45	294	7.9221	10	8
46	336	7.1226	6	17
47	288	6.9915	11	18
48	288	6.9915	11	18
49 50	336	7.1226	6	17
50 51	294 432	7.9221	10 1	8
51 52	432 320	9.4291 8.3659	8	1 4
52 53	320 320	8.3659	8	4
55 54	320 280	8.3639 6.8459	8 12	21
54 55	336	7.9353	6	5
55 56	245	7.5489	15	15
50 57	243	7.5609	12	13
<u>~ · · · · · · · · · · · · · · · · · · ·</u>	200			

Other disadvantage of the RPN ranking method is that it neglects the relative importance among *O*, *S* and *D*.

The three factors are assumed to have the same importance. This may not be appropriate when considering a practical application of FMEA process. An approach using fuzzy rule base is proposed to address these failures. A fuzzy rule base is used to rank the potential causes identified within the FMEA, with identical RPN values but different risk implications. The approach extends the analysis to include importance factors for O, S and D using defuzzified linguistic terms.

Based in comments presented before, fuzzy approach produces, for example, Ranking_Fuzzy value of 6 for event 55 and Ranking_Fuzzy value of 17 for event 49. In another case, events 13, 14 and 15, the defuzzified ranking was 4.9504. So, these three events obtained the same fuzzy priority number. In the RPN method, however, produces a result of 196, 196 and 168 for events 13, 14 and 15, respectively. This denote that event 15 has the lowest priority number. This ranking could be misleading; especially when the safety data is accompanied with a high level of uncertainty. This shows that a more accurate ranking can be achieved by the application of the fuzzy rule base to FMEA.

aging degradation exists in containment cooling systems and is a significant contributor to failures. Since these systems play an important role in *accident mitigation*, plant programs should specifically address the proper management of aging in containment cooling systems. Each of the aging mechanisms identified in this study should be addressed by at least one monitoring technique.

This article extends the use, in the nuclear area, of a capable methodology to subsidize new reactor projects through the fuzzy identification of critical systems and components and possible failure modes.

This fuzzy approach can be used for systems where safety data is unavailable or unreliable and may to combine expert knowledge and operational experience for use in an FMEA study.

Fuzzy approach have identified the priorities for the containment cooling system components and implicit information is necessary for better understanding of the aging process so that it can be properly monitored and managed in a effective NPP usefulness span extension program.

Acknowledgments

5. Conclusions

In accordance with [2], the results of Nuclear Plant Aging Research program (NPAR) study show that To Mr. Eugenio Rangel Marins and the Sponsors: Fundação de Amparo à Pesquisa do Estado do Rio de Janeiro – FAPERJ and Conselho Nacional de Desenvolvimento Científico e Tecnológico – CNPq.

Appendix A. Aging characteristics for components of the containment spray system

Component	Component relative failure frequency	Sub- component	Sub-component relative failure frequency	Component failure mode	Relative failure mode frequency	Aging mechanisms	Detection methods	0	S	D
Valves ID: 1–6 Medium	Medium	Seals/packing	High	External leakage	High	Wear	Visual inspection	9	5	3
			Does not open/close	Low	Binding Distortion	Valve stroke test	6	1	6	
		Seats	Medium	Internal leakage	High	Wear Corrosion Erosion Dirt/crud buildup	Valve leakage test	7	5	6
				Does not open or close	Low	Binding Dirt/crud buildup	Valve stroke test	4	7	6
		Stem/linkage	Low	Does not open or close	High	Wear Binding Poor lubrification	Stroke test	6	7	6
				External Leakage	Medium	Galling Nicking	Visual inspection	4	5	3

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Appendix A (Continued)

Component	Component relative failure frequency	Sub- component	Sub-component relative failure frequency	Component failure mode	Relative failure mode frequency	Aging mechanisms	Detection methods	0	S	D
Valve operator ID: 7–12	Medium	Torque switch	Medium	Does not open/close	High	Set point drift Short/ground Wear Dirt/dust intrusion	Valve stroke test Valve leakage test	7	7	7
		Gears	Low	Does not open/close	High	Wear Poor lubrification Fatigue Fracture/cracking	valve stroke test Visual inspection	6	7	7
		Motors	Low	Does not open/close	High	Short/burnout Wear Dirt/dust intrusion	Valve stroke Motor current signature analysis Motor insulation resistance test	6	7	9
		Limit switch	Low	Does not open/close	High	Deterioration of insulation Wear Out of adjustment Dirt dust intrusion Short/ground	Valve stroke test	6	7	6
		Solenoid	Low	Dots not open/close	High	Binding Dirt/dust intrusion Short/burnout	Valve stroke test	6	7	6
		Diaphragms	Low	Does not	High	Wear Deterioration	Valve stroke test	6	7	6
Instrumentation/ Controls ID: 13–17	Medium	Transmitter	Medium	open/close Incorrect Signal	High	Calibration drift Short/ground Deterioration Dirt/dust intrusion	Visual Inspection. Functional test	7	4	7
		Indicator/ Recorder	Medium	Incorrect signal	High	Calibration drift Short/ground Deterioration Dirt/dust intrusion	Visual inspection	7	4	7
		Computer	Medium	Incorrect signal	High	Calibration drift Short/ground Deterioration Dirt/dust intrusion	Functional test	7	4	7
		Relays/bistables/ switches	Low	Low	High	Wear Deterioration Dirt/dust intrusion Short/ground	Functional test	6	8	6
		Power Supply	Low	Low	High	Short/burnout Wear Dirt/dust intrusion Deterioration	Functional test	6	8	6
Circuit breakers ID: 18–22	Medium	Contacts	Medium	Does not open/close	High	Wear Out of adjustment Dirt dust intrusion Binding Corrosion Burnout/pitting	Visual inspection Functional test	7	7	7
		Gears	Low	Does not open/close	High	Binding	Visual inspection	6	7	7

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Appendix A (Continued)

Component	Component relative failure frequency	Sub- component	Sub-component relative failure frequency	Component failure mode	Relative failure mode frequency	Aging mechanisms	Detection methods	0	S	D
						Out of adjustment Fatigue Fracture/crack Wear	Functional test			
		Overload Relays	Low	Breaker trip	High	Wear Deterioration Fatigue Dirt/dust intrusion	Visual inspection Functional test	6	10	7
		Delay timer	Low	Failure to trip when required	High	Calibration drift Short/ground Deterioration Dirt/dust intrusion Wear	Visual inspection Functional test	6	10	7
		Handle/control switch	Low	Does not open/close	High	Wear Fatigue/cracking Binding Deterioration Poor lubrification Short/burnout	Visual inspection Functional test	6	7	7
Pumps ID: 23-27	Low	Shaft seals	Medium	Leakage	High	Wear Dirt dust intrusion Deterioration	Visual inspection Functional test	6	5	7
				Does not run	Low	Binding Out of adjustment Distortion Wear	Visual inspection Functional test Shaft torque measurement	3	9	8
		Gaskets	Low	Leakage	High	Wear Deterioration	Visual inspection Functional test	5	5	7
		Bearings	Low	Does not run	Medium	Deterioration Dirt/dust intrusion Wear Poor lubrification	Visual inspection Functional test Vibration measurements Excessive noise	3		9
				Leakage	Low	Binding Wear Deterioration Poor lubrification	Lube oil analysis Visual inspection Functional test	2		7

Appendix B. Aging characteristics for components of the fan cooler unit

Component	Component relative future frequency	Sub- component	Sub-component relative future frequency	Component future mode	Relative Future Mode frequency	Aging mechanisms	Detection methods	0	S	D
Valves/dampers ID: 28–32	Low	Stem/linkage	High	Does not open/close	High	Wear Binding Poor lubrification	Valve stroke test Visual inspection	8	7	7
		Seals	Low	Internal leakage	High	Wear Corrosion Erosion Dirt/crud buildup	Valve leakage test	5	5	6

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Appendix B (Continued)

Component	Component relative future frequency	Sub- component	Sub-component relative future frequency	Component future mode	Relative Future Mode frequency	Aging mechanisms	Detection methods	0	S	D
		Bolts/ fasteners	Low	Does not open/close	High	Vibration Fatigue Fracture/cracking	Visual inspection	5	7	3
		Louvers	Low	Does not open/close	High	Fatigue Wear Fracture/cracking	Visual inspection Functional test	5	7	7
		Seals	Low	External leakage	High	Wear Deterioration	Visual inspection Functional test	5	5	7
Valve operator ID: 33–35	Low	Diaphragm	Medium	Does not open/close	High	Deterioration Wear	Valve stroke test Valve leakage test	6	7	7
		Solenoids	Medium	Does not open/close	High	Wear Deterioration Short/ground	Valve stroke test	6	7	6
		Motors	Low	Does not open/close	High	Short/burnout Wear	Valve stroke test Motor current	5	7	9
						Dirt/dust intrusion Deterioration of insulation	signature analysis Motor insulation resistance test			
Instrumental ion/ controls ID: 36–39	Low	Transmitter	Medium	Incorrect signal	High	Calibration drift Short/ground Deterioration Dirt/dust intrusion	Visual inspection Functional test	6	4	7
		Indicator/ recorder	High	Incorrect signal	High	Calibration drift Short/ground Deterioration Dirt/dust intrusion	Visual inspection Functional test	8	4	7
		Integrator/ computer	Low	Incorrect signal	High	Calibration Short/ground Deterioration Dirt/dust intrusion	Functional test	5	4	6
		Controllers	Low	Loss of function	High	Wear Deterioration Dirt/dust intrusion Short/ground	Functional test	5	9	6
Cooling coils ID: 40–42	Low	Tubes	High	External leakage	High	Wear Fracture/cracking	Visual inspection Eddy current testing	8	5	8
				Fouling/ plugging	Medium	Dirt/crud buildup	Visual inspection Functional test Differential pressure/temperature	6	6	9
		Gaskets	Low	External leakage	High	Wear Deterioration	Visual inspection	5	5	3
Circuit breakers ID: 43–50	Medium	Contacts	Low	Does not open/close	High	Out of adjustment Corrosion Burnout/pitting	Visual inspection Functional test	6	7	7
		Gears	Low	Does not open/close	High	Binding Out of adjustment Fracture/crack Wear	Visual inspection Functional test	6	7	7

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Appendix B (Continued)

Component	Component relative future frequency	Sub- component	Sub-component relative future frequency	Component future mode	Relative Future Mode frequency	Aging mechanisms	Detection methods	0	S	D
		Overload relays	Low	Breaker trip	High	Wear Deterioration Fatigue	Visual inspection Functional test	6	7	7
		Fuses	Low	Loss of function	High	Short/ground Deterioration Fatigue	Functional test	6	8	7
		Coils	Low	Loss of function	High	Out of adjustment Short/burnout Deterioration	Functional test	6	8	6
		Starters	Low	Loss of function	High	Wear Short/burnout	Visual inspection functional test	6	8	6
		Springs	Low	Loss of function	High	Wear Fatigue Binding Distortion	Visual inspection Functional test	6	8	7
		Handle/ control switch	Low	Does not open/close	High	Wear Fatigue/cracking Binding Deterioration Poor lubrification Short/burnout	Visual inspection Functional test	6	7	7
Blowers ID: 51–54	Low	Bearings	Medium	Does not run	High	Deterioration Dirt/dust intrusion Wear Poor lubrification Binding	Visual inspection Functional test Vibration measurements Excessive noise	6	8 8 8	9
		Shaft	Low	Loss of function	High	Wear Fatigue Fracture/cracking	Functional test Disassembly inspection	5	8	8
		Rotors/blades	Low	Loss of function	High	Wear Fatigue Fracture/cracking Vibration	Visual inspection Functional test Disassembly inspection	5	8	8
		Belts	Low	Loss of function	High	Wear Deterioration	Visual inspection Functional test	5	8	7
Motors ID: 55-57	Low	Bearings	Medium	Does not start	High	Wear Dirt/dust intrusion Poor lubrification	Functional test Vibration measurement	6	7	8
		Leads/connectors	Low	Does not start	High	Dirt/dust intrusion Vibration	Visual inspection Functional test	5	7	7
		Insulation	Low	Does not start	High	Wear Deterioration	Disassembly inspection Functional test Resistance measurement	5	7	8

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