Analysis of OREDA Data for Maintenance Optimisation

Langseth, H., Haugen, K., Sandtorv, H.
SINTEF Industrial Management
Safety and Reliability

ABSTRACT

This paper provides estimates for the average Rate of Occurrence of Failures, ROCOF ("failure rate"), for *critical* failures when also *degraded* failures are present. The estimation approach is exemplified with a data set from the offshore equipment reliability database "OREDA". The suggested modelling provides means to predict how maintenance tasks will affect the rate of critical failures.

1. INTRODUCTION

OREDA (Offshore REliability Data) [1] is a data collection programme that has been going on since the early eighties. Reliability data has been collected for some 24,000 offshore equipment units comprising approximately 33,000 failures. The project is supported by ten oil companies; AGIP, BP, Elf, Esso, Norsk Hydro, SAGA, Shell, Statoil, and Total. SINTEF has been the main contractor since 1990.

The project is now in its fourth phase ('96). In this phase data is collected by more automatic means, and the data collection specification, and the data collection and analysis software program have been revised in this phase.

The participating oil companies use the data in the development of new oil fields and improving existing facility operation. The reliability data are typically used as input to safety and reliability analysis. Some benefits are: safer operations, increased production availability, and optimised maintenance. Analysis of reliability data is one of several key factors in choosing cost-effective solutions. Two examples recently reported, have shown that savings of about $60 millions can be achieved compared with the cost of the original design. Lately experiences and data from this project are also exchanged with the manufacturers in order for them to improve future designs.

Typical analyses where the data have been applied are: QRA, RAM, RCM, LCC and various maintenance planning assessments. A project on using the data in more advanced reliability analysis has also been undertaken by SINTEF.

The present paper describes a model where OREDA failure event data has been used to predict how maintenance tasks will affect the rate of critical failures, and it is argued that a *model* for the failure mechanisms should be provided. There are two obvious types of such mechanisms:

- the failure occurs immediately (as a "shock"), directly giving a *critical* failure
- the failure is caused by deterioration, so that the item first experiences a *degraded* failure, until finally an essential function is lost and the item is defined to have a *critical* failure.

This modelling of failure mechanisms to utilise the information on the *severity classes* (usually denoted *degraded*/non-critical and *critical*) is the topic of [3] and [4]. These papers, however, focus on *dormant* failures, i.e. failures detected by periodic (functional) testing, only. The present paper considers *all* failure modes and general principles of failure detection.

OREDA failure data on gas turbines are utilised giving estimates for critical failure rates as a function of the preventive maintenance interval τ, and the critical failure rate given that no preventive maintenance is performed (as $\tau \rightarrow \infty$, this is denoted "the naked failure rate").

This paper is a continuation of two papers presented at ESREL 1995 [4] and ESREL 1996 [7] conference. The main features of this paper, apart from applying a new data set, are the focus on qualitative analysis of the data, and presentation of ideas for further work to refine the model.

2. DATA SAMPLE

2.1. Failure classification

The data sample used in this paper origins from the OREDA III Gas turbine database [1]. In the proceeding sections some key concepts of the OREDA database are explained with a discussion of the data adoptions made in this paper.

Failure severity:
The OREDA database classifies the failure severity according to four different categories, viz.:

- Critical
- Degradation
- Incipient
- Unknown severity

A critical failure is one that causes immediate and complete loss of the capability of a system of providing its output. A degradation failure is one that does not cease all function, but compromises that function. Incipient failures have no immediate effect upon function. For simplicity, we have only distinguished between **critical** and **non-critical failures** in this paper. Thus, the non-critical category contains failures classified as **degraded and incipient** in the OREDA III database.

Failure detection method:
In this paper we distinguish between three different types of failure detection:

- **Periodic maintenance**. Failure observed during a scheduled maintenance activity, e.g. periodic service, functional testing, inspection or periodic condition monitoring.
- **Fortuitous observation**. Failure observed during casual operator checks or by production upset.
- **Alarm/monitoring.** Failure revealed by some instrumental monitored value being exceeded, normally observed in the control room by automatic detection.

Failure mechanisms
The calculation method used in this paper distinguishes between two main failure mechanisms:

- **Degradation**. A failure mechanism that evolves over time, and will typically develop to a critical failure in time if not corrected.
- **Shock**. A sudden failure mechanism that is not dependent on time. A typical example of such a failure mechanism is failure of electrical components.

In Table 1, an overview of the relationship between the OREDA III apparent failure causes (called failure descriptors) and the main failure mechanism used in this paper is presented:

Table 1: Failure mechanism overview

Degradation mechanisms	
1.0 Mechanical failures - general	2.1 Material deterioration
1.1 Abnormal process deviation	2.2 Material damage
1.2 Leakage	3.4 Out of adjustment
1.3 Vibration/noise	5.2 Degraded performance
1.4 Mechanical defect	6.1 Blockage/plugged
2.0 Material failures - general	6.2 Contamination
Shock mechanisms	
3.0 Instrument failure - general	4.0 Electrical failure - general
3.1 Control failure	4.1 Short circuiting
3.2 No signal/indication/alarm	4.2 Open circuit
3.3 Faulty signal/indication/alarm	4.3 No power/voltage
3.5 Common mode failure	4.4 Earth fault

The classification presented in this table is a simplification, and deviation from this scheme may occur. In addition to the failure mechanisms listed in Table 1, OREDA comprises codes related to design and operational causes. These codes do not fully fit into the scheme used here, and such events are included in the “degradation” or “shock” category according to the observed distribution between these two failure mechanisms.

2.2. Failure Data

The following data sample has been extracted from the database:

Equipment:	Gas turbines	*Type*:	Aeroderivative
Function:	Electric generation	*Power*:	28 MW

Table 2: Data sample overview

No. of gas turbines	5
Total no. of failures	521
No. of critical failures	81
No. of non-critical failures	440
Total operational time	62.609 hrs (7,1 yrs)
Total surveillance time	104.352 hrs (11,9 yrs)
Total number of demands/starts	1508

The data sample originates from equipment units on the same installation, being of the same make and subjected to the same preventive maintenance program. This, to achieve a homogenous data sample. The number of failures in Table 2 comprises both failures on demand and failure to run. The resulting data set from the OREDA III gas turbine database is presented in Table 3 and Table 4. The results are presented on subunit level, categorised according to the following scheme:

- Critical vs. non-critical failures
- Degradation vs. shock type failures
- Failure detection method

Table 3: Failure classification overview

Failure detection method	#Non-critical failures		#Critical failures		Total
	Degrad. (N_d^{II})	Shock (N_d^{I})	Degrad. (N_c^{II})	Shock (N_c^{I})	
Periodic maintenance	133	16	1	0	150
Fortuitous observation	25	1	0	0	26
Alarm/monitoring	119	143	38	42	342
Unknown	0	3	0	0	3
Total	277	163	39	42	521

In Table 4, the results are further detailed by breaking down the gas turbine into a number of subunits. This is necessary to investigate failure mechanisms on a lower indenture level, and to deal with the situation where the various subsystems have individual preventive maintenance intervals.

Table 4: Input data for the gas turbine subunits.

Subunit	PM interval [months]	Failure detection method	#Non-crit. failures		#Critical failures		Total
			Degr. (N_d^{II})	Shock (N_d^{I})	Degr. (N_c^{II})	Shock (N_c^{I})	
Gas generator	6	Periodic	101	1	0	0	102
		Fortuitous observation	4	0	0	0	4
		Alarm/monitoring	42	6	20	4	72
		Unknown	0	0	0	0	0
Power turbine	6	Periodic	5	1	0	0	6
		Fortuitous observation	0	0	0	0	0
		Alarm/monitoring	2	0	0	0	2
		Unknown	0	0	0	0	0
Lubrication system	12	Periodic	15	0	1	0	16
		Fortuitous observation	15	0	0	0	15
		Alarm/monitoring	32	3	6	1	42
		Unknown	0	0	0	0	0
Control & Monitoring	12	Periodic	1	17	0	0	18
		Fortuitous observation	0	1	0	0	1
		Alarm/monitoring	1	157	0	25	183
		Unknown	0	2	0	0	2
Starting system	Unknown	Periodic	2	2	0	0	4
		Fortuitous observation	3	0	0	0	3
		Alarm/monitoring	10	3	8	11	32
		Unknown	0	0	0	0	0
Total:			233	193	35	41	502

A total of 19 failure records related to the subunit category "Miscellaneous" are not included in the table nor in the analysis.

3. CALCULATION MODEL

3.1. Model Assumptions

In the following we restrict consideration to components that have the following properties:

1. Shock failures cannot occur when a component has a critical degradation failure and vice versa.

2. Shock failures occur with a constant rate λ_{Shock} whether or not the component is degraded.
3. Components are as good as new after each failure/repair
4. The non-critical failures are detected either by preventive maintenance, fortuitous observation or alarm, whereas the critical component failures are detected immediately. Hence, there are no "sleeping failures" which are critical to system performance.
5. The MTTRs are assumed to be short and are ignored. Thus, after critical failure or failure detection, the component is immediately brought to state "OK"
6. All shock failures are critical, failures grouped as "non-critical shock failures" are ignored.
7. All calculations are based on operational time. Values given in surveillance years are scaled to their "corresponding" value in operating years.

Assumption 6 is based on the hypothesis that "non-critical shock failures" will not occur to lower indenture components. They appear in our data set, because the critical/non critical classification is performed on system level. Therefore, "non-critical shock failures" are a result of the system configuration, and not the failure mechanisms. As the latter is our main concern in the present paper, we discard these failures.

Assumption 7 implicitly means that in this system, all failures/degradation happens while the machinery is running. This premise can be valid for some failure causes (e.g. "vibration"), but not as appropriate for others (e.g. "corrosion").

Degradation is not assumed to be a continuos process in this system; i.e. we do not measure degree of degradation, as long as the system is degraded. Therefore, the probability of fortuitous detection of a degraded failure will not increase with time spent in the "Degradation, Non-Critical" state.

The failure model is described with a state diagram, based on Markov theory. The states should be understood as described below:

Table 5: Interpretation of system states

State	Interpretation
"OK"	The system is as good as new
"Shock, Critical"	The system has failed due to a shock failure
"Degradation, Non-Critical"	The system is degraded, but still functional
"PM"	A non-critical failure was detected by PM
"Degradation, Critical"	The system has failed due to a degradation failure
"Fortuitous detection"	A non-critical failure was detected during casual operator checks or by production upset

The system states are shown in Figure 1.

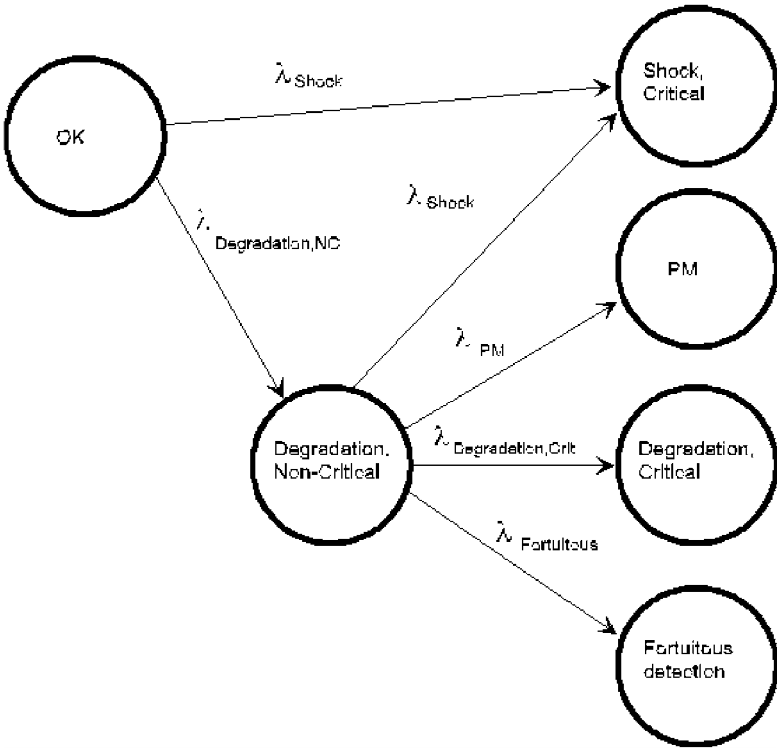

Figure 1: State diagram

3.2. Calculation Formulas

To establish numerical values for the transition rates, the basic assumption is that given a non-critical failure, the time to the next preventive maintenance event is on average $\tau/2$. Here τ is the time (in operation years) between preventive maintenance actions. So, λ_{PM} is estimated equal to $2/\tau$. This is not entirely correct, as the time between each PM equals τ, and the time "a degradation failure must wait to be discovered by PM personnel" is therefore uniformly distributed on $[0, \tau]$. Hence, the exponential distribution is not really suited for this situation. However, as we only are concerned with the asymptotic results, this approximation will be good enough. The other transition rates are found directly by keeping the ratios of the transition rates equal to the corresponding ratios of the observed number of events, see the example below.

Example:
For the gas generators, the calendar time between PM is 6 months. We have a total operational time of 7.15 years and surveillance period of 11.91 years. Therefore, the PM interval (in operating years) equals 0.5 years * 7.15/11.91 = 0.30 years. Number of non-critical failures found by preventive maintenance = 101 and Number of non-critical failures found by fortuitous observation/ alarm / unknown equals 46. Hence, we will use $\lambda_{PM} = 2/\tau = 6.67$ [failures/yr] and the formula

$$\frac{\lambda_{Fortuitous}}{\lambda_{PM}} = \frac{\text{No. non} - \text{critical failures found by fortuitous observation etc.}}{\text{No. non} - \text{critical failures found by PM}}$$

So, we find $\lambda_{Fortuitous} = 6.67 * 46/101 = 3.04$ [failures/yr].

This leaves us with the following set of equations:

$$\lambda_{PM} = \frac{2}{\tau} \quad (1)$$

$$\lambda_{Degradation,Crit} = \lambda_{PM} * \frac{\text{No. critical degradadtion failures}}{\text{No. non-critical failures detected during PM}} \quad (2)$$

$$\lambda_{Fortuitous} = \lambda_{PM} * \frac{\text{No. non-critical failures detected by fortuitous observation etc.}}{\text{No. non-critical failures detected during PM}} \quad (3)$$

With the assumptions 1,2,3 and 5 it follows that the expected number of critical shock-failures is identical to λ_{Shock} multiplied by the total time on test:

$$\lambda_{Shock} = \frac{\text{No. Shock Failures}}{\text{Total Time on Test}} \quad (4)$$

To find the value of $\lambda_{Degradation,\ NC}$ we calculate the mean time for a component in the "OK" state to go through a cycle and return to the "OK" state again. $\lambda_{Degradation,\ NC}$ is selected, so that this value corresponds to that of the data set.

$$\lambda_{Degradadtion,NC} = \frac{1 - \lambda_{Shock} * \frac{\text{Total Time on Test}}{\text{Total No. Failures}}}{\frac{\text{Total Time on Test}}{\text{Total No. Failures}} - \frac{1}{\lambda_{Shock} + \lambda_{PM} + \lambda_{Degradation,Crit} + \lambda_{\text{Fortuitous}}}} \quad (5)$$

Using this approach, all transition rates for a test period identical to that of the data set are found.

The next important assumption is that the components "internal transition rates" will not change because of a change in the preventive maintenance interval. This means that the values λ_{Shock}, $\lambda_{Degradation,\ NC}$, $\lambda_{Degradation,\ Crit}$ and $\lambda_{Fortuitous}$ are independent of PM intervals. Hence, the transition rates we have established for one specific preventive maintenance interval will also apply for other test intervals.

The only transition rate we will change is λ_{PM}. The definition is as before, $\lambda_{PM} = 2/\tau$, but as the preventive maintenance interval is altered, the numerical value of λ_{PM} is changed accordingly. Note that the equations (2) - (5) are only valid for the PM interval observed in the dataset, and used to estimate the transition rates which are *independent* of PM interval. When λ_{PM} is changed, the equations will therefore not be valid.

3.3. Numerical results

We define MTTF to be the time between *critical* failures. By noting that the number of "cycles" the system will go through before it ends in a critical failure follows the geometric distribution, we find the results in Table 6. The present PM intervals of the equipment are indicated as framed areas in the table.

Table 6: Time between critical failure as a function of the PM interval

τ (months)	MTTF (years)	
	Gas generator	Lubrication system
0 [1)]	1.79	7.15
3	0.40	1.32
6	0.30	1.04
9	0.26	0.94
12	0.24	0.89
18	0.22	0.84
24	0.21	0.82
∞ [2)]	0.18	0.74

[1)] τ= 0 means that preventive maintenance is performed continuously. Here, all failures are due to chocks.

[2)] This means no preventive maintenance is performed. Hence, the corresponding MTTF value is identical to $MTTF_{Naked}$, defined in [5]

Graphical presentations of the figures in Table 6 are given in Figure 2 and Figure 3, showing the mean time to critical failure as a function of the preventive maintenance interval for the two chosen subunits.

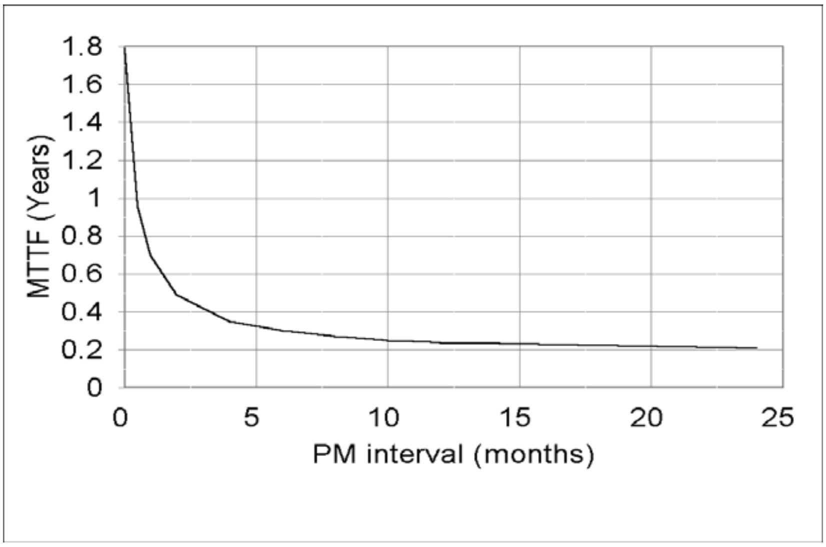

Figure 2: MTTF vs. PM interval, Gas Generator

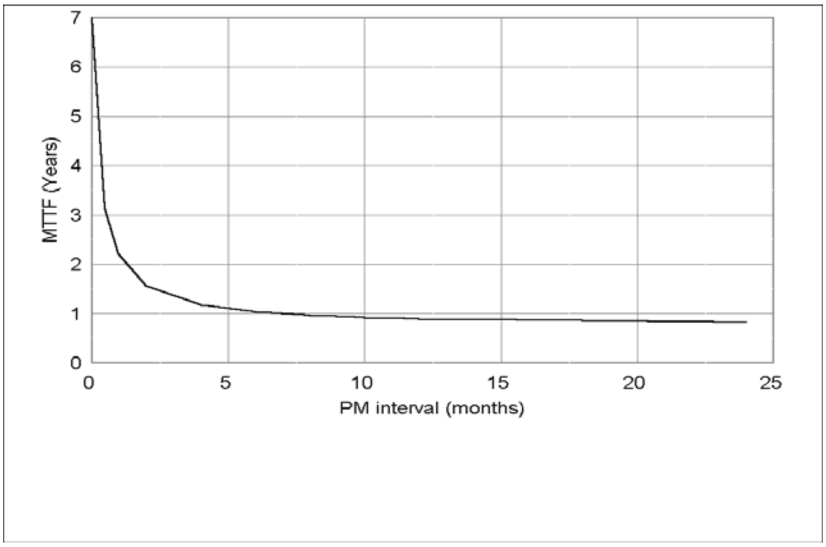

Figure 3: MTTF vs. PM interval, Lubrication system

3.4. Qualitative interpretations

In this section, some simple observations are made based on the data breakdown presented in Table 4. Performing such simple qualitative assessments of the data can provide valuable indicators as to the quality of the PM program and pinpoint areas for further analysis. Examples of such simple indicators are:

- The total ratio of critical versus non-critical failures (i.e. N_c^{II}/N_d^{II}). A high ratio may indicate that the PM program is inadequate, allowing too many failure to develop into a critical failure. Finding the optimal ratio, however, is not completely straightforward and requires that several parameters are considered, e.g. the cost of a critical failure versus the cost of PM activities.

- The ratio of critical versus non-critical failures detected by alarm/monitoring. A high ratio may indicate that the protective instrumentation configuration is not optimal. This may be improved by changing the instrument set points or by altering the configuration.

Other observations:

1. 99% of the failures related to the control and monitoring system are caused by a shock mechanism. This is as expected as the subunit mainly comprises electronics/ instrumentation. This could be a starting point for further studies to investigate whether the PM interval could be extended.
2. 94 % of all failures related to the gas generator are caused by a degradation mechanism. This underlines the importance of preventive maintenance.
3. For the gas generator, 33% of all failures detected by alarm/monitoring are critical. This may be an indication that the instrument configuration should be improved, e.g. by lowering the limits for activation.

4. FUTURE ENHANCEMENTS OF THE MODEL

4.1. Preventive maintenance (PM) induced failures

The data from OREDA IV will include the failure causes “Maintenance error” and “Operator error”. In the current model, the possibility for PM induced failures are discarded, and the MTTF is strictly decreasing as τ increases. However, if estimates for failures induced during PM are added to the model, we would expect to find a “failure rate” similar to the sketch below:

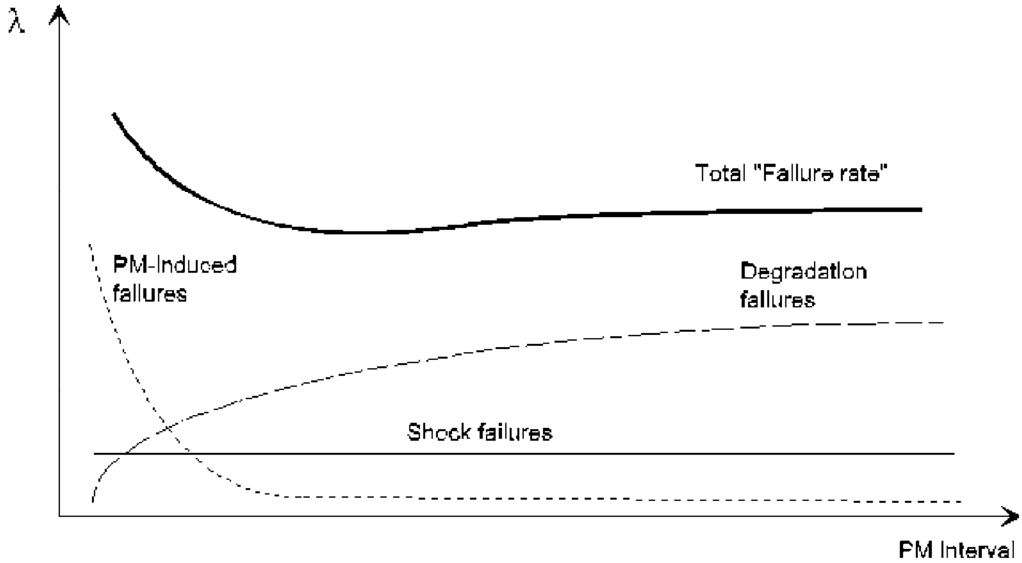

Figure 4: Average ROCOF when PM induced failures are included

4.2. Improved estimation techniques

More sophisticated methods can be used when estimating the parameters of the model. The estimators in the current paper are based on the five components in question only. A more well-bred approach would include Bayesian estimation techniques, where the parameters' prior distributions were founded on a broader range of the data gathered within in the OREDA project. This Bayesian approach is described in further detail in [6].

4.3. Operational time vs. Surveillance time

All calculations in the present model are based on operational time (ref. Assumption 7). This implies that we assume that all failures are due to the operation of the equipment, and the equipment unit will not fail during standby. This is, of course, not a correct assumption, although it may be appropriate for some failure mechanisms.

Therefore, it is proposed to classify all failures in one of two groups:
1) Failures are initiated mainly during operation
2) Failures are initiated mainly during standby/downtime

The failures within "Group 1" is properly treated with the current model. For the other failures, however, a more sophisticated model based on calendar time will be necessary. This new model should be able to predict the probability for a component to fail with the "Fail to Start" failure mode after a period in standby. A "first layout" of the corresponding state diagram is displayed in Figure 5 below, which may be compared with the original model in Figure 1.

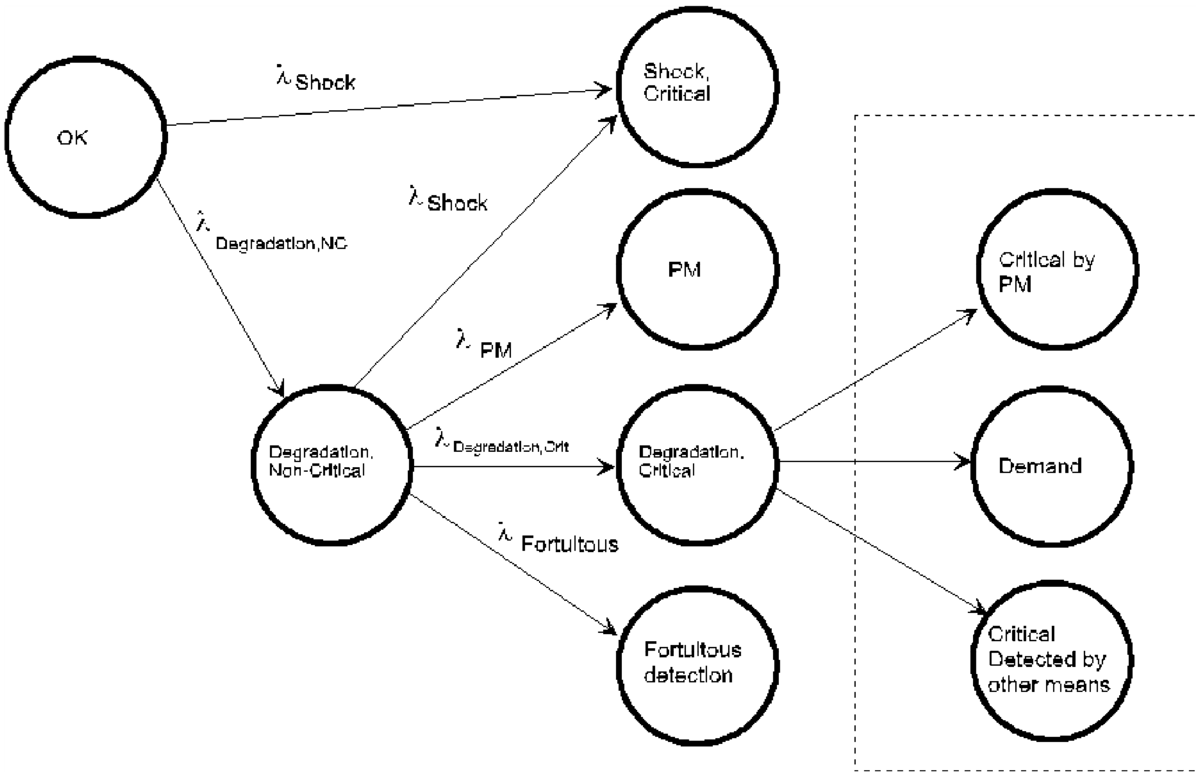

Figure 5: Enhanced model

The extension allows critical degradation failures to be found either during PM, by a demand (resulting in a “Fail to start” failure mode) or by some other means (i.e. alarm and monitoring, fortuitous observation etc.).

5. SUMMARY AND CONCLUSIONS

- The estimated model shows what is the real pay-back for doing preventive maintenance (in terms of critical failures). For the gas generator, MTTF will decrease from 0.30 years at present to 0.18 years if no PM is performed. Similar values for the lubrication system are 0.89 and 0.74 years.
- The estimators we have found are not very robust.
- The main advance for this method, is that we can pinpoint the effect of PM for a component that is subject to random inspection (such as alarm/monitoring or some type of fortuitous observation).

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