

9-1977

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Johnson, Duane P., "Nondestructive Evaluation Uncertainty and Inspection Optimization" (1977). *Proceedings of the ARPA/AFML Review of Progress in Quantitative NDE, July 1975–September 1976*. 40.
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Nondestructive Evaluation Uncertainty and Inspection Optimization

Abstract

NDE decisions differ from most other engineering decisions in that the NDE response or responses used in making a decision with regard to the serviceability of a part are often only weakly correlated with the serviceability of the part. The impact of of this weak correlation or inspection uncertainty on inspection errors and the effectiveness of the inspection is discussed. A quantitative methodology for selecting the optimum NDI accept/reject decision thresholds in the face of the inspection uncertainty is outlined. Also discussed briefly is how inspection uncertainty analysis can be used to estimate the inspection reliability from field or production inspection data without the use of a flawed specimen program.

Disciplines

Materials Science and Engineering

NONDESTRUCTIVE EVALUATION UNCERTAINTY AND INSPECTION OPTIMIZATION*

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NDE decisions differ from most other engineering decisions in that the NDE response or responses used in making a decision with regard to the serviceability of a part are often only weakly correlated with the serviceability of the part. The impact of this weak correlation or inspection uncertainty on inspection errors and the effectiveness of the inspection is discussed. A quantitative methodology for selecting the optimum NDI accept/reject decision thresholds in the face of the inspection uncertainty is outlined. Also discussed briefly is how inspection uncertainty analysis can be used to estimate the inspection reliability from field or production inspection data without the use of a flawed specimen program.

What I will discuss with you today is a quantitative approach for selecting the accept/reject levels in nondestructive inspections such that the expected life cycle costs of a part are at a minimum. In the process I hope to illuminate some of the critical factors external to the inspection process itself that influence the cost effectiveness of inspection and how these external factors influence the optimum accept/reject level or the optimum inspection sensitivity. In addition, I hope to identify what it is about the inspection that is critical to its potential to be a cost effective inspection.

Our discussion will apply to the use of non-destructive inspection as a tool for segregating defective parts from sound parts, and will not consider, per se, the other function of NDI which is its use as part of the feedback to the quality control or design functions.

The justification for an inspection is that the additional expenditures for inspection will reduce the total expectant life cycle costs. Here, cost is used in a broad sense, and includes the cost of personal injuries and fatalities. An improved inspection process is not necessarily a more sophisticated process, but is a process which results in a reduction in the total life cycle costs of the product. The cost of the inspection itself is often a very small fraction of the total cost surrounding and associated with an inspection.

Lack of Traceability between Cost and Benefits

The time delay and the lack of traceability between the application of an inspection and the benefits that accrue from the inspection are major barriers to more effective utilization of NDE. Normally, the real downstream benefits in terms of increased product reliability that accrue from an inspection are neither specifically predicted at the time the inspection is instituted, nor evaluated later in the product life.

Normally, a new inspection procedure is introduced because management is convinced that the procedure will decrease the total life cycle costs of

the product or increase sales because of the higher reliability of the product. The first thing that occurs is not a cost reduction, but a cost increase because of the additional cost of this new inspection. The next thing that occurs is not a cost reduction, but an increased manufacturing cost because now the parts have to pass the new inspection. This latter cost may be many times the specific inspection cost. Two, five, ten years later, the benefits of the inspection in terms of more reliable operation occurs, if there are any benefits. It is unlikely that the benefits in dollars of this increased reliability are actually identified; it is even more unlikely that the increase in profitability attributable to the new inspection is identified.

In general, management gives greater weight to the immediate and identifiable costs than the vague and unidentified later date benefits. More accurate estimates of cost trade-offs would result in greater acceptance of inspections that would in fact significantly improve the part reliability and would eliminate many ineffective inspections.

Probabilistic Economic/Engineering Analysis Methodology

Failure Analysis Associates has developed under Electric Power Research Institute funding, the general methodology required to handle this cost interchange between in-service costs, manufacturing costs and inspections costs. A number of practical means of attaining the required input functions have been established. The methodology has been applied or is being applied to a number of engineering systems including: steam turbines, bearings, nuclear reactors, and railroad track. Failure Analysis Associates has applied aspects of the methodology to one of the world's largest super-tankers, a major freeway bridge here in the state, a major radio tower complex and a number of automobile components.

In the following outline of the methodology, mathematical details will be avoided. These details are given in (1 - 5). Hopefully, a better understanding of the effects of inspection on the life cycle costs will be obtained. Particular consideration is given to the role of inspection sensitivity, inspection uncertainty, the conditional failure probability (that is, the probability of failure if the part contains a flaw), the pre-inspection material quality, the failure costs and inspection costs. Furthermore, the specific functions required to quantitatively describe the total life cycle costs are identified.

The first thing that must be appreciated about a nondestructive inspection is that the accept/reject decision is based on a nondestructive inspection signal response and is not based on the severity of the imperfection. As much as one would like to know, for example, how large the imperfection

is, all one really knows is how large some NDE signal response or combination of responses are.

The second thing that must be appreciated is that given the NDI signal response, there usually exists a significant variation or uncertainty in the actual severity of the imperfection. Because of this inspection uncertainty, a nondestructive inspection decision on accepting or rejecting a part is subject to two types of errors:

- 1) A defective part may be accepted because the response signal from a significant defect is smaller than our acceptance criteria.
- 2) A sound part may be rejected because a benign indication gives a response to the probing agent that exceeds the rejection criteria.

If the acceptance criteria is too sensitive, then an excessive number of sound parts will be rejected by the inspection; if the acceptance criteria are too insensitive, an excessive number of defective parts will be passed by the inspection. The optimum accept/reject criteria has a balance between these two types of errors. In order to establish this balance, some weight must be given to how serious a defective part in the field is versus rejecting a sound part.

Our approach to establishing the optimum accept/reject level and the cost effectiveness of the inspection is summarized in Fig. 1. An average cost is established for a failed part (C_F), for a rejected part (C_R), and for inspecting a part (C_I). These three cost factors are combined with the failure probability and the rejection probability, both as a function of the accept/reject level, to arrive at an estimate of the expectant total life cycle cost of a part as a function of the accept/reject level.

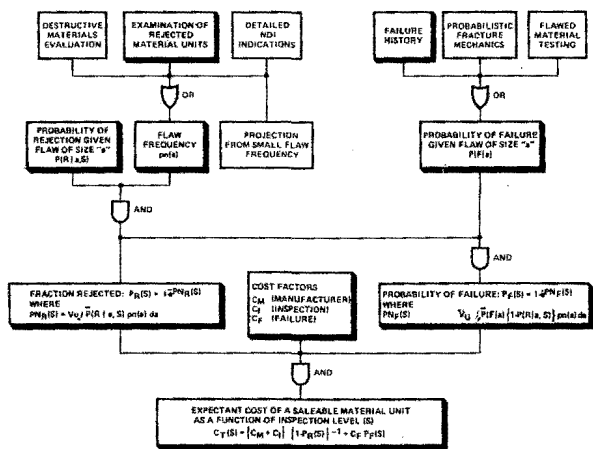


Figure 1. Flow chart summarizing the Engineering/Economic Analysis Methodology

As indicated in Fig. 1, there are three basic engineering functions that are determined in order to predict the dependence of the failure and rejection probability upon the accept/reject levels. One of these functions describes the inspection performance, the second function describes the material quality before inspection, and the third function describes the structural performance of material containing defects.

The imperfection rejection probability ($P(R|a,S)$) gives the probability of rejection of a part, given that the part contains an imperfection of size a and the inspection level is S . This function describes the inspection performance and is the only term that is dependent upon the accept/reject level S . Three techniques have been identified for determining the inspection performance. Two techniques involve defective specimen inspection programs and the third involves the use of results from field or production inspections. In the most common approach, specimens containing known defects are inspected at various imperfection levels and the number of rejected and nonrejected imperfections are counted.⁶ More detailed information on the inspection performance can be obtained from a defective specimen program if an uncertainty analysis of the results is conducted to determine the correlation between the imperfection size and the NDI response parameters used to make the accept/reject decision.³ The advantage of inspection uncertainty analysis over conventional counting analysis of defective specimen inspection programs are illustrated in detail in (4). The third approach is to record the NDI responses obtained in production or field inspection and remove a sampling of the parts for metallurgical evaluation in order to establish the correlation between the imperfection size and the NDI response parameters used to make NDI accept/reject decisions. This inspection uncertainty analysis of field or production data is discussed in detail in (3).

The material quality in this case is described by the flaw frequency $pn(a)$. Here $pn(a)da$ is the probable number of imperfections per unit volume with size between a and $a+da$, prior to inspection of the part. Four techniques have been identified for determining the flaw frequency. One is simply to metallurgically examine a sufficient amount of material to establish the frequency of imperfection at the size of interest. A second approach is to metallurgically examine a sufficient number of rejected parts, and knowing the imperfection rejection probability, the flaw frequency can be determined. The third approach is to keep track of the frequency and strength of the NDI indications. If the inspection uncertainty (correlation between the indication strength and imperfection size) is known, the flaw frequency can be determined. A final technique that is used is to project the large-flaw frequency from the more easily determined small-flaw frequency using an assumed log normal distribution.

The conditional failure probability $P(F|a)$ describes the probability a part will fail given that it contains an imperfection of size a . Three technologies have been identified for determining these functions. One simply uses failure history and will be illustrated later. The second approach uses probabilistic fracture mechanics⁷ and the final approach involves defective material testing. A

combined analysis using failure history and fracture mechanics analysis has been particularly successful in situations where only limited data are available.⁸

The imperfection rejection probability, the flaw frequency and the conditional failure probability are combined to give the probability of failure and rejection as follows:

$$P_R = 1 - e^{-PN_R(S)}$$

where

$$PN_R(S) = V_U \int_0^{\infty} P(R|a,S) pn(a) da,$$

$$P_F = 1 - e^{-PN_F(S)}$$

where

$$PN_F(S) = V_U \int_0^{\infty} P(F|a) [1 - P(R|a,S)] pn(a) da.$$

Here, V_U is the material volume of the part.

Illustrative Example: Turbine Blades

Consider a hypothetical situation that is representative of quality assurance questions that may be encountered with certain turbine blades. This example shows:

- A. The use of failure history and the result of examining rejected blades to select the inspection level that will minimize the expectant cost to the turbine manufacturer.
- B. The effect of a significant increase in failure cost on the optimum inspection level.
- C. The use of the methodology to select the best of three inspection methods and to optimize the inspection level.

First, consider the failure history. Assume that 10^5 blades have been used for their design life and 100 of the blades have failed prematurely. The fraction failed is then $F_F = 10^{-3}$. The total cost of these 100 failures to the manufacturer, including indirect costs such as bad will with certain customers, is estimated to be 10 million dollars. This gives an average cost per failure $C_F = \$100,000$. The 100 failed blades were analyzed to determine the size of defect which initiated the failure, and the results are summarized in Table 1.

Table 1 - Number of Failure Initiating Flaws per 0.1 cm Interval in 100 Failed Blades

Flaw Size Interval in cm	Number of Flaws	$pn_0(F,a,S_0)$ in cm^{-4}	Flaw Size "a" in cm
0.00 - 0.10	0	0×10^{-6}	0.05
0.10 - 0.20	0	0×10^{-6}	0.15
0.20 - 0.30	0	0×10^{-6}	0.25
0.30 - 0.40	0	0×10^{-6}	0.35
0.40 - 0.50	1	2×10^{-6}	0.45
0.50 - 0.60	7	14×10^{-6}	0.55
0.60 - 0.70	25	50×10^{-6}	0.65
0.70 - 0.80	36	72×10^{-6}	0.75
0.80 - 0.90	22	44×10^{-6}	0.85
0.90 - 1.00	7	14×10^{-6}	0.95
1.00 - 1.10	2	4×10^{-6}	1.05
1.10 - 1.20	0	0×10^{-6}	1.15

The turbine blades before being admitted to service had to pass an inspection** in which the inspection uncertainty $\delta = (0.2S + 0.1)$ cm, and the inspection size $S = S_0 = 3/4$ cm. The rejection rate has historically been $FR_0 = 4.5\%$. A sample of 100 rejected blades was destructively examined, and the imperfections in these blades which caused rejectable indications are summarized in Table 2.

Table 2 - Number of Rejectable Indications per 0.1 cm Interval in 100 Rejected Blades

Flaw Size Interval in cm	Number of Rejectable Indications	$pn_0((a,S_0) R)$ in cm^{-4}	Flaw Size "a" in cm
0.00 - 0.10	16	32×10^{-3}	0.05
0.10 - 0.20	19	38×10^{-3}	0.15
0.20 - 0.30	19	38×10^{-3}	0.25
0.30 - 0.40	17	34×10^{-3}	0.35
0.40 - 0.50	13	26×10^{-3}	0.45
0.50 - 0.60	9	18×10^{-3}	0.55
0.60 - 0.70	5	10×10^{-3}	0.65
0.70 - 0.80	3	6×10^{-3}	0.75
0.80 - 0.90	1	2×10^{-3}	0.85
0.90 - 1.00	1	2×10^{-3}	0.95

The cost of manufacturing a blade is \$100 plus an additional \$10 to inspect the blade. The question arises as to whether the total cost to the manufacturer could be reduced by selecting a different inspection size. Using the data above as input into the methodology, the dependence of the expectant cost of a saleable blade upon inspection size can be determined. The expectant cost to manufacture a turbine blade that passes the historical inspection method as a function of inspection size is summarized by Fig. 2, along with the expectant failure cost.

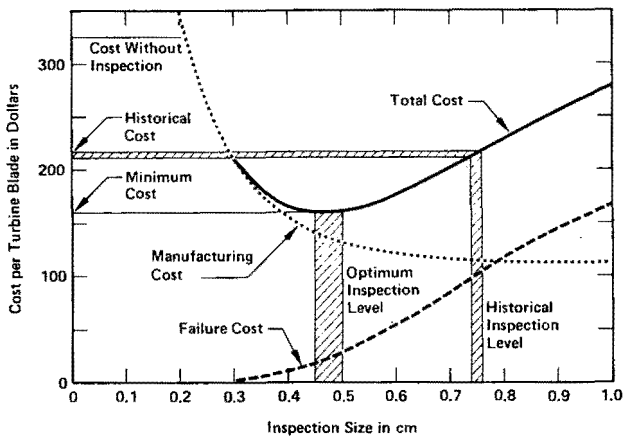


Figure 2. Cost per turbine blade as function of inspection size.

The total expectant cost of an acceptable turbine blade is the sum of expectant cost to manufacture a turbine blade that passes the inspection and the expectant cost due to the finite probability that the blade will fail. The total expectant cost per saleable blade is also illustrated in Fig. 2. The total expectant cost of a turbine blade if no inspection is conducted is \$328. It is evident from Fig. 6 that the historical inspection reduces the total cost of a saleable blade to \$215, which represents a total savings of over 11 million dollars for the 10^5 blades. The total expectant cost of a blade can be further reduced from the present cost of \$215 per blade to \$159 per blade by reducing the inspection size from the historical 0.75 cm to an optimum 0.45 cm. Over 10^5 blades, this represents a potential additional savings of approximately 6 million dollars.

Now assume that there is an additional loss, on the average, of \$900,000 that results from the fact that a blade failure forces the unit to be out of service for an extended period of time and, due to a new contract with the users, these consequential costs are also passed on to the manufacturer. Hence, under the new contract, the average failure cost to the manufacturer will increase from \$100,000 to \$1,000,000. Figure 3 illustrates the new expectant costs of a saleable blade as a function of inspection size. If the inspection size is left at the historical level, the expectant cost of saleable blade will increase from \$215 to \$1,115 per blade. A change in inspection size from the historical level to the level of 0.35 cm will reduce the cost impact of the contractual change to a \$19 increase per blade (\$234).

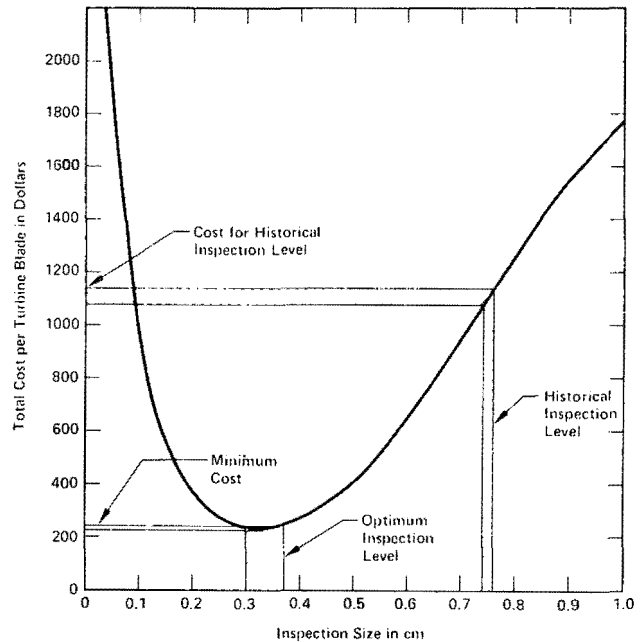


Figure 3. Total cost of a saleable blade as a function of inspection size when the average cost of a failure is a million dollars.

Even at the optimum inspection level the cost of failure and blade rejection (\$234 per blade) still represents a major increase over the base manufacturing and inspection costs of \$110 per blade. Let us suppose that two alternative inspection methods, A and B, are available, which are reported to be better than the historical inspection method. The direct inspection cost for each of these methods is projected to be essentially the same as the historical inspection method. Both inspection A and B have been used to inspect material specimens that are somewhat similar to the blade material. The results of examining 100 material units rejected by inspection method A and method B, along with the results given in Table 2 for the historical inspection, are summarized in Fig. 4. Inspection method A rejected a significantly greater fraction of the material units than did inspection B. Inspection method A has an inspection uncertainty (width of the correlation function between the imperfection size and the NDI response amplitude) which is twice as large as that characteristic of the historical inspection, while method B has an inspection uncertainty which is half the historical method.

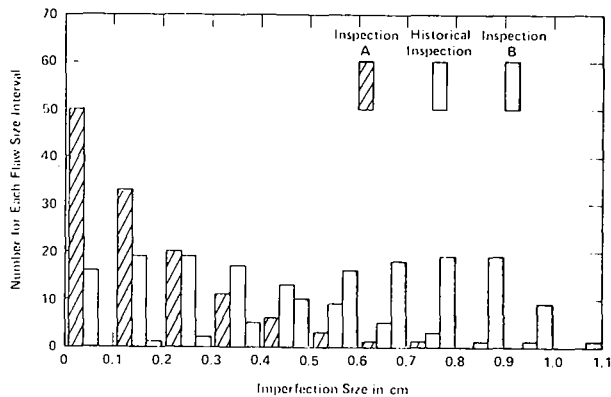


Figure 4. Number of rejectable indications for each flaw size interval for 100 rejected material units observed for inspection A, the historical inspection and inspection B.

Although Fig. 4 shows that inspection method A is more sensitive than either the historical inspection or inspection B, this does not necessarily mean that A is the better of the three methods. Which inspection method should be introduced to produce the minimum total cost blade and at what level the inspection size should be set requires a cost-risk analysis. Figure 5 summarizes the expectant total cost of a saleable turbine blade utilizing the historical inspection method, inspection method A and inspection method B. It is evident from Fig. 5 that the introduction of inspection method A, which appeared most sensitive in Fig. 4, would result in a minimum cost of \$494 per turbine blade, or \$160 more than minimum cost possible with the historical inspection. With inspection method B, a saleable turbine blade can be manufactured with a total expectant cost of \$146 per blade. The introduction of inspection method B with an inspection size $S = 0.35$ cm would result in a potential savings of 9 million dollars over the minimum cost blade if the historical inspection method is used.

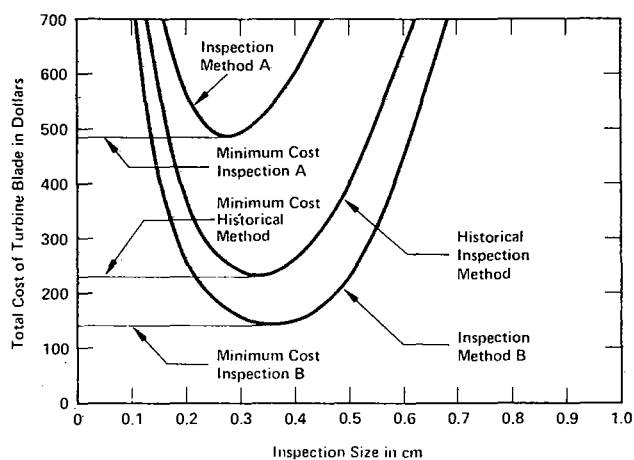


Figure 5. Comparison of turbine blades total costs for three inspection methods.

This example clearly shows the potential impact of this inspection optimization methodology. In situations involving a number of inspections and failure modes, Monte Carlo computer algorithms are used to predict the expected life cycle cost.

In summary, the better the correlation between the signal parameter that is used in the decision and the actual severity of the imperfection; that is, the smaller the inspection uncertainty, the greater the potential cost effectiveness of that inspection.

Secondly, having selected an inspection and having determined what the inspection uncertainty is, there exists an optimum accept/reject criteria or inspection sensitivity which is dependent upon pre-inspection material quality, the inspection uncertainty, the stress and environment the part is subjected to, the cost of failure and the cost of rejecting the part. These factors can be quantitatively determined and combined to establish the cost effectiveness of the inspection and to select the optimum accept/reject level or levels.

* This work was supported by the Electric Power Research Institute under contracts Nos. RP217-1 and RP700-1.

** Here the imperfection rejection probability is taken to be a normal cumulative distribution function with standard deviation δ and mean S .

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DISCUSSION

- DR. RICHARD CHANCE (Grumman Aerospace Corp.): How would you propose to utilize a system like this where the manufacturer is not charged with the failure cost by the user?
- DR. JOHNSON: In most cases, there is some expectant failure cost assigned to the manufacturer, even if it is only lost profits due to loss of future sales. If a manufacturer is interested in maximizing profits and there are no possibilities of failure cost being charged to him, then he should not conduct an inspection. Seldom are all the failure costs charged to the manufacturer, hence, based on this analysis, the optimum inspection for the manufacturer will be less restrictive than the optimum inspection as seen by the user. As can be seen by comparing Figs. 2 and 3, the optimum inspection size is not strongly dependent upon the perceived failure costs.
- MR. JACK NICHOLAS (Naval Ship Engr. Center): Does the total cost of failure include the cost of lost revenues, or is that the cost to repair the failure?
- DR. JOHNSON: The total cost of failure depends upon whose point of view you are taking. Certainly from a user's point of view, possible loss of revenue is part of the total expectant cost associated with failure. Possible fatalities or personal injury must also be included in the total expectant cost.