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A "Cost-effective" Probabilistic Model to Select the Dominant Factors Affecting the Variation of the Component Failure Rate

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Within the framework of a Probabilistic Safety Assessment (PSA), the component failure rate λ is a key parameter in the sense that the study of its behavior gives the essential information for estimating the current values as well as the trends in the failure probabilities of interest. Since there is an infinite variety of possible underlying factors which might cause changes in λ (e.g. operating time, maintenance practices, component environment, etc.), an "importance ranking" process of these factors is considered most desirable to prioritize research efforts. To be "cost-effective", the modeling effort must be small, i.e. essentially involving no estimation of additional parameters other than λ. In this paper, using a multivariate data analysis technique and various statistical measures, such a "cost-effective" screening process has been developed. Dominant factors affecting the failure rate of any components of interest can easily be identified and the appropriateness of current research plans (e.g. on the necessity of performing aging studies) can be validated.

Keywords: Power Reactor, PSA, Reliabilty, Failure Rate, Component Engineering Parameters, Importance Ranking

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機器故障率変化の支配因子を同定するための
コストエフェクティブな確率論的モデル

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確率論的安全評価においては，機器故障率λは，対象システムの機能喪失確率の現在値及び変化の傾向を予測するために必須の情報を与えるという意味でキーとなるパラメータである。λを変化させる因子は多種多様である（例えば，運転時間，保守の方法，機器の使用環境）。従ってλに関する研究の優先度を検討するために，これらの因子の“重要度付け”の手法が望まれる。そのような重要度付け手法がコストエフェクティブであるためには，モデリングの労力が少なくて済むこと，即ち，λ以外には，特別のパラメータを推定する必要がないことが重要である。本報告書では，多変量解析等の統計分析の手法を用いて，妥当なコストで実施できる重要度付けの手法を開発した。本手法により，注目する任意の機器の故障率を支配する因子を容易に同定することができる。また現在の研究計画の妥当性検討（例えば，経年変化に関する研究の必要性）にも役立つものである。

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1. INTRODUCTION

A Probabilistic Safety Assessment (PSA) includes failure probabilities for all relevant active and passive components of a plant. The derivation of realistic empirical models to describe the variations of the component failure rate λ of components produces analytical tools that allow the monitoring and the control of all failure probabilities of interest and is therefore of key importance to ensure the safety of nuclear power plants. Standard PSA technology, however, averages out almost all dependencies and considers λ as a constant parameter. Further, component failure data availability will usually be insufficient in terms of quality and quantity to formulate significant λ estimates for passive components. In such cases, the estimation of λ will have to be limited to active components only.

In the following, a "cost-effective" empirical model is developed and proposed for application that allows the formulation of component characterizing factors, as retrievable from a given data base architecture, and their quantitative importance ranking versus each other. The model is appropriate to give guidance on the relative importance of certain component-related engineering features or maintenance characteristics of interest and may especially be useful in deciding whether or not certain detailed probabilistic studies have to be performed. The accessibility of a plant-specific component data base is required.

Sections 2 to 4 of this paper deal with the stepwise development of such an importance ranking model, including a numerical example which uses hypothetical component failure rate and engineering data. Possible conclusions from this case study are given in Section 5. Further, an Appendix is included, which presents exemplary component raw failure data as well as component engineering data collection tables, as required to perform the proposed modeling tasks.

2. THE FUNCTIONAL CAPABILITY OF COMPONENTS AS A FUNCTION OF VARIOUS PARAMETERS

Suppose that we are interested in a certain type of component whose failure rate λ shall be monitored and controlled. The detailed probabilistic modeling of component behavior and thus of λ usually requires large modeling, parameter estimation and data collection efforts. Therefore, from an "economical" point of view, it is considered reasonable to develop a simple, "cost-effective" model which gives confidence in the hypothesis that certain underlying "factors" actually have a dominant impact on the variation of λ, while others can be considered quite negligible in that respect. Here, "cost-effective" shall be understood as requiring no estimation of parameters other than standard reliability parameters, like λ.

We start our paper by postulating the existence of various "factors" which could affect the value of the component failure rate, [1,2].

Factors affecting the variation of λ are related to the initial component properties, to maintenance related conditions, to operating conditions ("component environment") and to the cumulative operating time ("component age").

Any number of interactions and dependencies could exist between two or more of such factors resp. subfactors. Therefore, in realistic approaches to model factor topologies for practical applications, many simplifications will become inevitable, such as the renunciation of dealing with interactive factors, the possible time-dependency of some factors, etc. Further, "in reality", the number of component characterizing factors is likely to be an unmanageable large value (in fact, it might even be infinite). Thus, for practical applications, the problem essentially becomes that of determining the most "adequate" subset, where "adequate" refers to those factors which can be quantified from given plant-specific data records and to those which are expected to explain "most" of the components' failure rate variation.

In the following sections, this topic shall be discussed in more detail.

3. CHARACTERIZATION OF COMPONENTS

In PSA studies the detailed component type is usually the lowest hierarchical level for which reliability data are being provided, [2-4]. Components are different in size, design, material characteristics, manufacturer, operational specifications, environmental conditions, etc. Now, a component population to be used in the PSA process shall consist of a well-defined accumulation of "similar" components (i.e. components with certain common characteristics) from the entire recorded component population of the specific plant under investigation and/or of plants considered "similar" versus each other (in the above sense). To each of the N components in the thus-defined component population of interest, unique component identification codes from $(ID)_1$ to $(ID)_N$ can be assigned, denoting the various levels of similarity.

As already mentioned, for each component in the given component population, the existence of various component characterizing factors which could conceivably affect the value of the component's failure rate λ shall be postulated. For practical applications, the condensed component engineering data as symbolically denoted by the component (ID) will usually serve as the most important source of information to establish the topological structures of the abstract factor spaces of interest.

Any set of characterizing factors of interest will therefore entirely classify the component population included in a component reliability data base. Obviously, there is a countless number of possibilities for corresponding data base architectures, and the only restrictions in defining factors of interest will be given by the available man-power and the available (resp. affordable) performance monitoring technology. Thus, "in reality", the number of characterizing factors ϕ_p will always be a manageably small value, e.g.:

$$\lambda = \lambda(\phi_1,\phi_2,\ldots,\phi_p,\ldots,\phi_r : r \leq 15; T) \quad , \tag{1}$$

where T denotes the statistical observation time interval.

The actual selection resp. definition of component characterizing factors of interest will entirely depend on the desired scope of analysis and on the given architecture of the component reliability data base to be used (examples of typical data base architectures are given in reference [1]).

4. MODEL DEVELOPMENT AND NUMERICAL EXAMPLE

In the previous section, we described the abstract architecture of a component reliability data base as a multidimensional topological space of component characterizing factors.

Now, as an illustrative example, the following set of 12 component characterizing factors shall be assumed to define a typical plant-specific component reliability data base:

$\phi 1$ = Country;
$\phi 2$ = Plant Type;
$\phi 3$ = System;
$\phi 4$ = Component Type;
$\phi 5$ = Component Subtype;
$\phi 6$ = Normal Operating Mode;
$\phi 7$ = Component Size;
$\phi 8$ = Periodic Functional Test Interval;
$\phi 9$ = Periodic Check Test Interval;
$\phi 10$ = Periodic Calibration Test Interval;
$\phi 11$ = Overhaul Interval;
$\phi 12$ = Cumulative Component Operating Time (component "age" $(t\text{-}t_0)$).

Recalling equation (1) and taking into account the above-mentioned inevitable modeling simplifications, the component's failure rate λ can here be considered as a function of

$$\lambda = \lambda(\phi_1,\phi_2,\ldots,\phi_p,\ldots,\phi_r \ : \ r = 12; T) . \tag{2}$$

Basically, two types of component characterizing factors ϕ_i have to be distinguished from each other: "easily changeable" and "invariable" factors. For example, the "Normal Operating Mode" and the "Component Size" factors can be considered rather invariable throughout the component's lifetime, while maintenance program characteristics (e.g. the test and the overhaul intervals) are "easily changeable". The "Operating Time" factor of a component and thus it's age "change" of course at each infinitesimal instant of time.

In the above "typical" example, 5 "easily changeable" age & maintenance related factors and 7 "invariable" design, installation & operating mode related factors have been assumed to be retrievable from the given plant-specific data base. Factors 8 to 11 describe the most important quantifiable aspects of maintenance practices performed on a specified component population.

For a certain component population, the above factors could have the following discrete "meanings":

$\varphi 1$ = Japan;
$\varphi 2$ = PWR;
$\varphi 3$ = Auxiliary Feedwater System (AUXFEED);
$\varphi 4$ = Valve;
$\varphi 5$ = Motor Operated Valve (MOV);
$\varphi 6$ = Standby;
$\varphi 7$ = > 200 mm;
$\varphi 8$ = 3 Months Periodic Functional Test Interval;
$\varphi 9$ = 1 Month Periodic Check Test Interval;
$\varphi 10$ = 3 Months Periodic Calibration Test Interval;
$\varphi 11$ = 6 Years Overhaul Interval;
$\varphi 12$ = Component Age of 5 Years.

It shall be noted that, using a real data base, some of the factors in the preceding example may have to be considered "factorial" in their nature; that is, the same factor levels resp. factor values will be used throughout the data base. For example, the factor "Cumulative Component Operating Time" may be treated as being "factorial", since the same age discretizations may be used to classify the "age" of every component included in the data base.

On the other hand, some of the factors may be considered "hierarchical" in nature; that is, the same categories may not be used for all components in the data base. In our above example, the factor "Component Type" with the discrete meaning "Valve" is further classified into the subfactor "Component Subtype" with the discrete meaning "MOV".

Here, it is important to state that the proper categorization of components into classes of components considered similar to each other requires a complete and mutually exclusive set of characterizing factors of the same level. Of course, factors with different hierarchical levels can also be combined into aggregated factors, if necessary, but in such cases it is not possible any more to estimate the relative importances of the therein included hierarchical factors versus each other. In the illustrative example of this paper, the factor "Component Subtype" is only applicable to valves, resulting in three valve subtypes, but not to pumps, wherefore an aggregated factor, "Component (Sub)types", has been formulated. Consequently, it was impossible to estimate the relative importance of the "Component Type" factor versus the "Component Subtype" factor (see example below).

At this point, at the latest, it could be argued that the total number of factors to be used for our further modeling purposes is rather arbitrary and that it may even be impossible to consider "all" relevant impacts on the component failure rate ("hidden factors"). Yet, it shall be recalled that the total number of factors that can be formulated is, by definition, always directly related to and limited by the fixed number of data entries in the given reliability data base. Therefore, the adequacy & appropriateness of the information included in a user-defined set of component characterizing factors is always (at least) the same as the one usually employed in component reliability calculations.

Provided that a corresponding component reliability data collection exists, failure rates can be estimated for each of the possible combinations of the above factors ϕ_i ($i=1,2,\ldots,12$), using the well-known maximum likelihood estimator in a Poisson process,

$$\lambda = \frac{k}{T} = \frac{\#\{\, x_c \ :\ x_c \in \{X_{recorded} \cap X_{unscheduled\ down}\}\}}{\text{Observation Time Interval}} \tag{3}$$

where k denotes the number of failure events in a fixed statistical observation time interval T. That is, the cardinality "#" of the set of recorded events x_C leading to an unscheduled downtime of the selected component(s) of interest (see also Appendix).

To simplify our illustrative example, let us now assume that we are only interested in estimating the modeling task priorities for *"Japanese PWR AUXFEED MOVs in Standby Mode of Operation and 1 Month Periodic Check Test Interval, 3 Months Periodic Calibration Test Interval and 6 Years Overhaul Interval"* (our component population of interest), that means:

$$\{\ \phi_i \ = \ \text{const.} :\ i = 1,2,3,5,6,9,10,11\ \} \ . \tag{4}$$

In other words, the actual configuration of the following four "remaining" component characterizing factors ϕ_i classifies our component population of interest:

ϕ_4 = Component Type,
ϕ_7 = Component Size,
ϕ_8 = Periodic Functional Test Interval,
ϕ_{12} = Component Age.

With that and apart from the trivial contribution of the fixed observation time interval T equation (2) becomes

$$\lambda \ = \ \lambda(\phi_4,\phi_7,\phi_8,\phi_{12}) \ . \tag{5}$$

To further characterize the architecture of the underlying hypothetical data base, discrete descriptive "values" $\varphi_{i\text{-}j}$ shall be assigned to each factor in a way reflecting the given data base structure, for example:

$$\phi_4 = \begin{pmatrix} \varphi_{4\text{-}1} \\ \varphi_{4\text{-}2} \\ \varphi_{4\text{-}3} \\ \varphi_{4\text{-}4} \end{pmatrix} = \begin{pmatrix} \text{Motor Operated Valves (MOVs)} \\ \text{Air Operated Valves (AOVs)} \\ \text{Manual Valves} \\ \text{Pumps} \end{pmatrix} \tag{6}$$

$$\phi_7 = \begin{pmatrix} \varphi_{7\text{-}1} \\ \varphi_{7\text{-}2} \\ \varphi_{7\text{-}3} \end{pmatrix} = \begin{pmatrix} \leq 100\text{ mm} \\ ]100\text{ mm}, 200\text{ mm}] \\ > 200\text{ mm} \end{pmatrix} \tag{7}$$

$$\phi_8 = \begin{pmatrix} \varphi_{8\text{-}1} \\ \varphi_{8\text{-}2} \\ \varphi_{8\text{-}3} \end{pmatrix} = \begin{pmatrix} \text{1 month} \\ \text{3 months} \\ \text{12 months} \end{pmatrix} \tag{8}$$

$$\phi_{12} = \begin{pmatrix} \varphi_{12\text{-}1} \\ \varphi_{12\text{-}2} \\ \varphi_{12\text{-}3} \end{pmatrix} = \begin{pmatrix} \leq 2\text{ years} \\ ]2\text{ years}, 4\text{ years}] \\ > 4\text{ years} \end{pmatrix} \tag{9}$$

The question how to appropriately "discretize" factors, i.e. how many discrete values have to be introduced for a factor in order to give statistically significant estimates, is an important one; yet, it entirely depends on the given data base and can not be answered in a general way. It shall, however, be noted that a too finely structured factor topology is likely to have many factor combinations that show few or even no failure events. This makes statistical analysis for such cases either very imprecise or impossible. Aggregating failure event data by simply reducing the number of discrete values in a factor will help avoiding such effects, but can, on the other hand, possibly result in severe loss of information, [1]. Therefore, it shall be recommended to quantify the conventional statistical uncertainty bounds around each λ point estimate, which gives a decision criterion whether or not certain factor discretizations result in statistically significant λ estimates.

In a "real" application, to determine the component characterizing factors ϕ_i which have dominant relative importances, we would now have to estimate and further analyze all possible λ-dependencies among the above-defined factors. In our hypothetical example, however, let us now, for the sake of brevity, assume that we are only interested in the pair-wise importances of the component size ϕ_7, the component functional test interval ϕ_8 and the component age ϕ_{12} relative to the four above-defined component (sub)types of factor ϕ_4, i.e. only in the following 3 of $\binom{4}{2} = 6$ possible pair combinations (Cartesian products):

$$\phi_4 \otimes \phi_7 \qquad (10)$$

$$\phi_4 \otimes \phi_8 \qquad (11)$$

$$\phi_4 \otimes \phi_{12} \qquad (12)$$

For each of these Cartesian products, using a given set of hypothetical (however "realistic", when compared to generic failure rate data) reliability raw data, the isomorphic mapping from factor space Ξ^4 to failure rate space Λ^4 results in a set of two-dimensional λ-matrices, as depicted in **Table 1** to **Table 3** (which shall represent our quantitative model input). The λ point estimates in these matrices are in arbitrary units (e.g. per demand).

The question of interest is now, which of the three factors of interest, $\phi 7$, $\phi 8$, $\phi 12$, has the dominant impact on the failure rate of the four component (sub)types, respectively.

In order to estimate the sensitivity of the failure rate value towards variation of certain factors, the following simple importance measure for the failure rate values in the data matrices, **Table 1** to **Table 3**, shall be defined:

$$\Omega = \left(\frac{\textit{maximum } \lambda \textit{ value in a table's row or column}}{\textit{minimum } \lambda \textit{ value in a table's row or column}}\right) . \tag{13}$$

For example, the (mean) "importance" of factor $\phi 7$ is:

$$\Omega_{\phi_7} = \frac{1}{2}\left(\sum_{\left\{\substack{i,j = 4,7 \\ i \neq j}\right\}} \Omega_{\phi_i \text{ varried; } \phi_j \text{ const.}} ; (\phi_8, \phi_{12} = \text{const.}) \right) \tag{14}$$

where,

$$\Omega_{\phi_4 \text{ varried; } \phi_7 \text{ const.}} = \frac{1}{3} \sum_{k=1}^{3} \left(\frac{max\left\{\lambda_{(4\text{-}7)\text{-}1k}, \lambda_{(4\text{-}7)\text{-}2k}, \lambda_{(4\text{-}7)\text{-}3k}\right\}}{min\left\{\lambda_{(4\text{-}7)\text{-}1k}, \lambda_{(4\text{-}7)\text{-}2k}, \lambda_{(4\text{-}7)\text{-}3k}\right\}} \right) \tag{15}$$

and

$$\Omega_{\phi_7 \text{ varried; } \phi_4 \text{ const.}} = \frac{1}{3} \sum_{k=1}^{3} \left(\frac{max\left\{\lambda_{(7\text{-}4)\text{-}1k}, \lambda_{(7\text{-}4)\text{-}2k}, \lambda_{(7\text{-}4)\text{-}3k}\right\}}{min\left\{\lambda_{(7\text{-}4)\text{-}1k}, \lambda_{(7\text{-}4)\text{-}2k}, \lambda_{(7\text{-}4)\text{-}3k}\right\}} \right) . \tag{16}$$

Similar measures can be constructed for the two other factors $\phi 8$ and $\phi 12$ and, using our hypothetical data, be numerically evaluated. The final outcome is then a set of "Relative Importances" $\Omega\phi 7$,$\Omega\phi 8$,$\Omega\phi 12$

for the three selected factors $\phi 7$,$\phi 8$,$\phi 12$ (under the modeling assumption that $\phi 4$ = const.), as summarized in the form of bar plots in **Fig.1**. Again, in a "real" example the estimation of the relative importance of factor $\phi 4$, the component (sub)type, would have to be included in the analysis, which would then have to deal with the complete set of six pair-wise λ-matrices.

In our hypothetical example, the resulting set of factor importances, **Fig.1**, clearly indicates the dominant impact of the "Functional Test Interval" factor on the failure rate λ in the case of MOVs as well as the dominant impact of the "Age" factor on λ in the case of AOVs and Manual Valves. The relative importance of the "invariable" size factor exceeds the one for the "easily changeable" age factor in the case of MOVs only, but exceeds the one for the "easily changeable" test interval factor in the cases of both Manual Valves and Pumps. As a conclusion of this hypothetical case study, the necessity for analyzing the appropriateness of the MOVs' test interval as well as for performing "aging" studies for AOVs and Manual Valves could be recommended. It is important to note that the results of such a "relative importances" analysis can only serve as *indications*, depicting possible problem areas(*) and shall thus be understood and used as cost-effective tools supporting decisions on the necessity of conducting further detailed (and more "costly") studies. Reference [2] gives an overview and discussions on the usefulness and applicability of such "costly" models.

Fig.2 to **Fig.4** show the failure rate point estimates for the four component (sub)types (cf. equation (6)) as a function of the three different component size values (cf. equation (7)), the three different test interval values (cf. equation (8)) and the three different age values (cf. equation (9)), respectively.

As can be seen from **Fig.2**, the variation of the size of the components results in a significant change of the λ value only in the case of the pumps. The failure rate of the pumps increases by appr. 7 when the pump size is changed from $\varphi 7\text{-}1$ to $\varphi 7\text{-}2$.

(*) This is, however, true for the results of all importance measures.

In the case of MOVs, the variation of the test interval factor from 3 to 12 months (i.e. from $\varphi 8\text{-}2$ to $\varphi 8\text{-}3$) results in a decrease of λ by appr. 13 (see **Fig.3**).

Eventually, **Fig.4** clearly depicts the great importance of "aging" for AOVs (increase of λ by appr. 10) and Manual Valves (increase of λ by appr. 10) and the very low importance of aging for MOVs (λ remains fairly constant).

Table 1 Failure Rate Point Estimates for $\phi 4$ and $\phi 7$ (e.g. in units/d)

	$\phi 7$		
$\phi 4$	<= 100 mm	]100, 200 mm]	> 200 mm
MOVs	7.3E-03	4.4E-03	3.0E-03
AOVs	1.2E-03	8.0E-04	3.7E-04
Manual Valves	1.0E-04	2.2E-04	4.0E-04
Pumps	3.3E-03	1.8E-02	4.0E-03

Table 2 Failure Rate Point Estimates for $\phi 4$ and $\phi 8$ (e.g. in units/d)

	$\phi 8$		
$\phi 4$	1 month	3 months	12 months
MOVs	3.2E-04	5.0E-04	4.4E-05
AOVs	2.2E-03	1.1E-03	5.2E-03
Manual Valves	2.2E-03	2.2E-03	4.9E-03
Pumps	2.5E-03	3.0E-03	5.8E-03

Table 3 Failure Rate Point Estimates for $\phi 4$ and $\phi 12$ (e.g. in units/d)

	$\phi 12$		
$\phi 4$	<= 2 years	]2, 4 years]	> 4 years
MOVs	1.8E-04	2.0E-04	2.1E-04
AOVs	1.1E-04	5.9E-04	1.3E-03
Manual Valves	4.1E-03	8.8E-03	3.5E-02
Pumps	2.7E-03	3.3E-03	1.6E-02

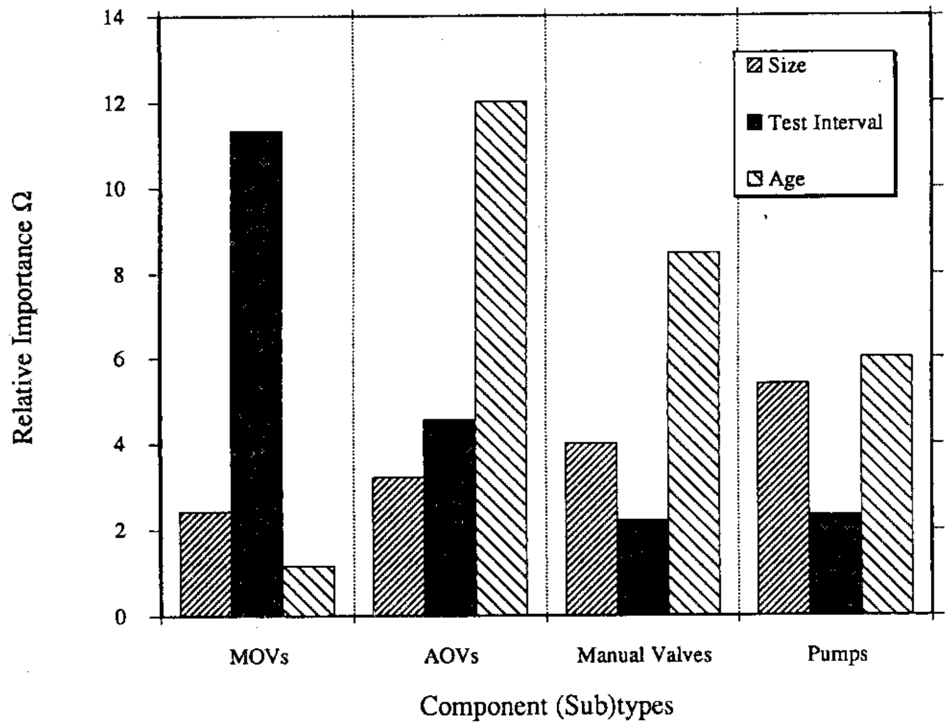

Fig. 1 Relative Importances of Selected Factors

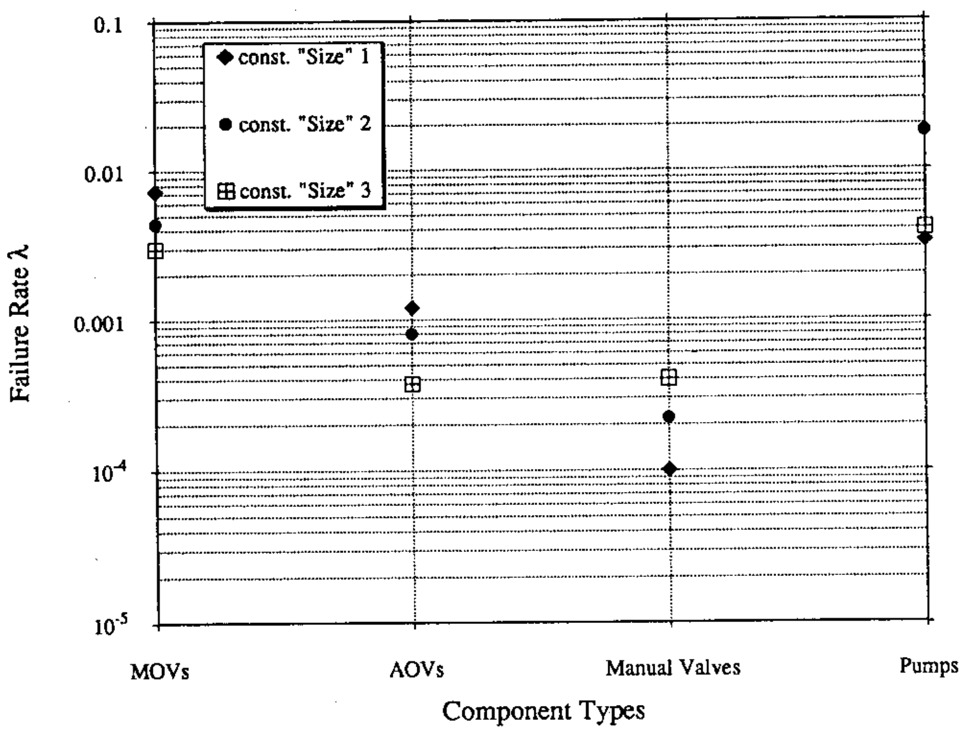

Fig. 2 Variation of the "Size" of the Components

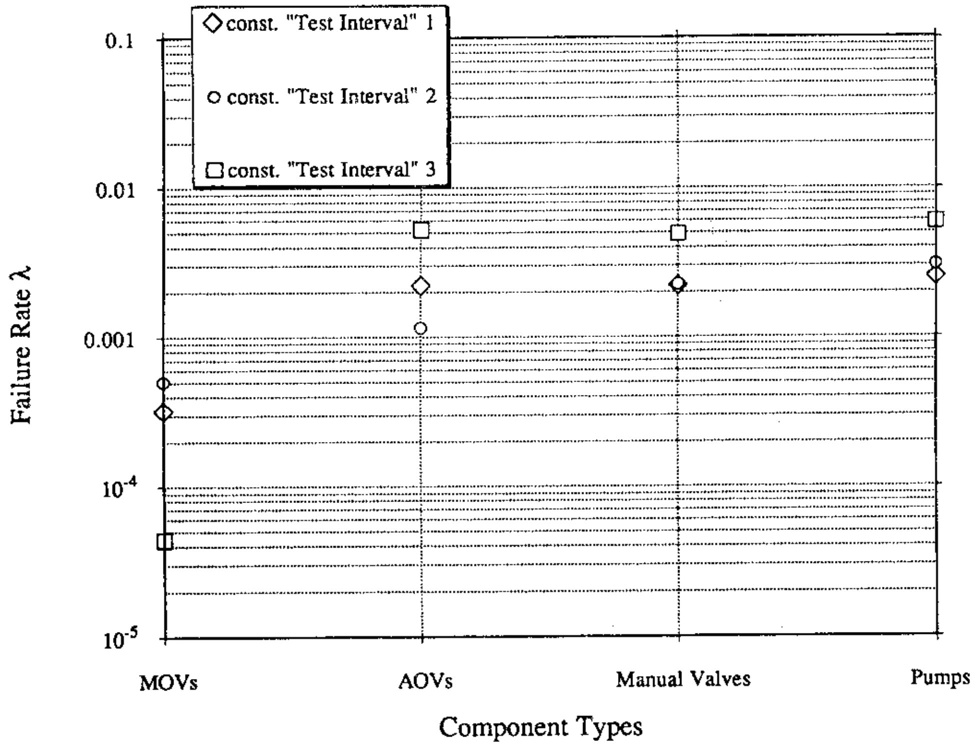

Fig. 3 Variation of the "Test Interval" of the Components

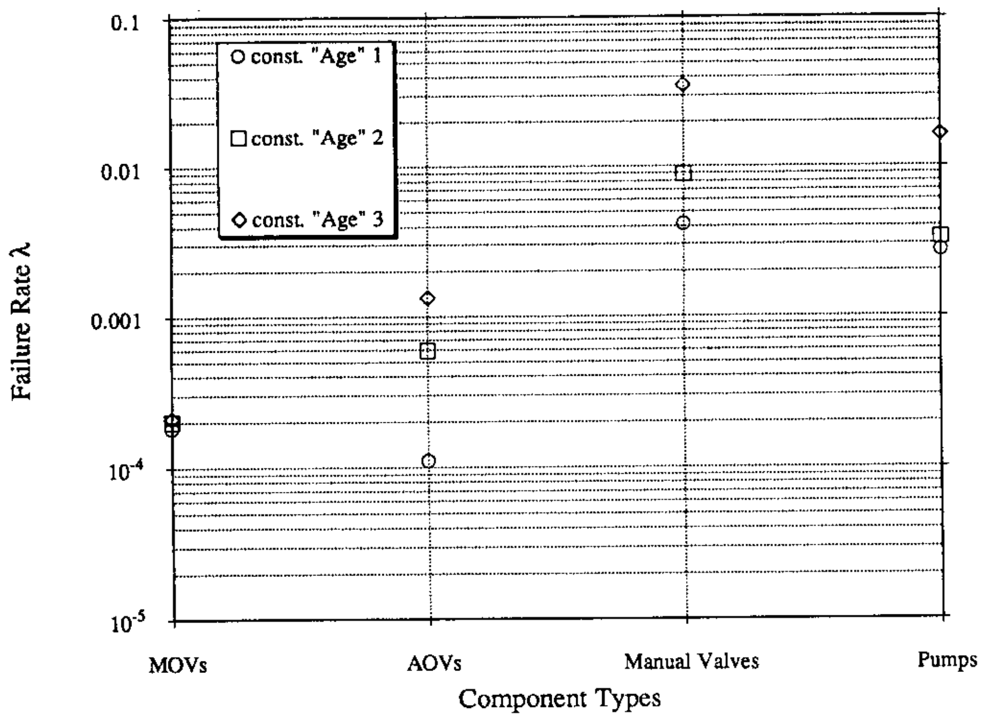

Fig. 4 Variation of the "Age" of the Components

5. SUMMARY AND CONCLUSIONS

Using basic component classification schemes, a multivariate data analysis technique and various elementary statistical measures, a "cost-effective" screening process has been developed to calculate relative importance values for all quantifiable component characterizing factors of interest directly from active components' failure report and engineering data. The only parameter to be estimated is λ, the point estimate component failure rate. Suppose, Ξ^m represents the topological space of all m discretized factors $\{\varphi 1, \varphi 2, \ldots, \varphi i, \ldots, \varphi j, \ldots, \varphi m \ : \ i,j = 1,2,\ldots,m \ ; \ i \neq j\}$ that have been formulated from the given data records. The corresponding failure data collection can be considered as the mapping from Ξ^m to Λ^m. Now, for each possible Cartesian product subset $\Xi^{\varphi_i \otimes \varphi_j}$, a two-dimensional matrix $\Lambda^{\varphi_i \otimes \varphi_j}$, consisting of failure rate point estimates can be constructed, taking over the pattern of the corresponding factor space and using the given raw failure data. The order of these matrices be $(r_i \times c_j)$, respectively. Calculating the arithmetic mean of all (r_i+c_j) permutated statistical range fractions of the failure rate point estimates gives a simple measure for the relative importances of the component characterizing factors among each other with regard to the underlying failure rate measure.

The number of factors that can be formulated is limited by the scope of the analysis itself (user input) and the given number of data entries in the underlying data base. Thus, depending on the user's requirements, the quality and quantity of information included in the factors will always be (at least) the same as the one in "conventional" reliability calculations.

The relative importances of the "easily changeable" factors (e.g. factors related to a component population's age & maintenance) can be compared to those of the more "invariable" factors (e.g. factors related to the component's environment, design & normal mode of operation). In the case that the "easily changeable" factors dominate the pattern of importance values, further component performance studies, e.g. on aging and maintenance effects, are considered necessary. In such a case, the "typical" failing component has been identified as a component with a certain (too long) age or with certain inappropriate periodic maintenance characteristics. The relative importance of both of these factor types can consequently be decreased by either introducing shorter overhaul intervals or more appropriate maintenance intervals.

However, it has to be mentioned that the developed model does not allow the importance ranking between components. For a pre-selected and clearly specified component population of interest, sets of component characterizing factors can "only" be ranked versus each other. Obviously, the user's definition which components are "currently of interest" will heavily depend on their estimated contribution to overall plant risk.

Further, it shall be recalled that the results of such a model can only serve as indications depicting possible problem areas and shall thus be understood and used as cost-effective tools supporting decisions on the necessity of conducting further studies.

To give an impression how to actually conduct such a ranking process of component characterizing factors and how to interpret the results, a simple case study example has been included in this paper, using hypothetical component failure rate and engineering data.

By means of this approach it shall be possible to detect the current plant-specific priorities for conducting necessary research on (active) component performance studies. Thus, utilities as well as research institutions having access to plant-specific data could thereby prioritize their research planning and validate the appropriateness of current research plans.

Considering the specific characteristics of Japanese plants, equipment designs, maintenance practices and programs, the application of this model shall be proposed to such organizations in order to determine future Japan-specific strategies in the field of necessary probabilistic component performance studies.

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APPENDIX

THE NECESSARY ANALYSIS INPUT DATA

This includes the "Component Failure Data Sheet", **Fig.A1**, and the "Component Specification Sheet", **Fig.A2**, which have both been developed to exemplarily support the suggested importance ranking process of component characterizing factors. The format of both data sheets has been designed in a way that enables the user to directly perform the importance calculations proposed in the previous sections.

"Failure Events" of components shall thereby always be understood as events recorded in the data base, directly or indirectly affecting the components with consequences requiring a maintenance act (preventive or corrective maintenance) and therefore leading to an unscheduled downtime of the component (see equation (4)). Thus, a "failure" does not necessarily result in an inoperable state of the component, wherefore degradation events may also be considered and counted as "failure events". Since the date of failure discovery and the date of actual failure event occurrence may (and usually will) differ from each other, an estimate of the date of failure event happening shall always be included in the "Component Failure Data Sheet", **Fig.A1**.

In order to specify the characterizing factors of a certain component in detail, the "Component Specification Sheet", **Fig.A2**, has been developed.

Component Code (ID)	(Estimated) Date of Failure Event	Date of Failure Discovery
1AUX001MV	*1989-01-01*	*1989-02-15*
	1989-08-22	*1989-08-22*
	1991-11-01	*1991-11-01*
1AUX002MV	*1985-07-06*	*1985-07-06*
	1992-02-01	*1992-03-01*
2AUX001MV	*1984-08-01*	*1984-08-01*
	1988-01-15	*1988-01-15*
	1988-02-01	*1988-02-01*
2AUX002MV	*1987-09-01*	*1987-10-01*
	1988-12-01	*1988-12-30*
.....	.....	.....

Fig. A1 Example of a Component Failure Data Sheet

Component Code (ID):	*1AUX001MV*
Country:	*Japan*
Plant Type:	*PWR*
System:	*AUXFEED*
Component Type:	*Valve*
Component Subtype:	*Motor Operated Valve*
Normal Operating Mode:	*Standby / Closed*
Component Size/Flow Rate:	*200 mm diameter*
Periodic Functional Test Interval:	*3 Months*
Periodic Check Test Interval:	*1 Month*
Periodic Calibration Test Interval:	*3 Months*
Overhaul Interval:	*5 Years*
Installation Date:	*1988-03-01*
Out-of-Operation Date:	*still in operation*
Start of Observation (Date):	*1989-01-01*
End of Observation (Date):	*1992-04-30*

Fig. A2 Example of a Component Specification Sheet