Journal of the Korean Nuclear Society
Volum 19, Number 4, December 1987

On Setting Low-level Performance Criteria and Uncertainty Characterization for a Nuclear Power Plant

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(Received August 28, 1987)

원자력발전소의 저층 성능 기준설정과 불확실성에 대하여

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(1987. 8. 28 접수)

Abstract

This paper addresses the issues in setting performance criteria for safety regulation of nuclear power plants. Since setting criteria at the low level is a much more difficult task than it is at the top level, the low-level performance criteria should be *derived* consistently from the more easily determinable top-level performance criteria. The paper also proposes several approaches to characterizing uncertainties in performance criteria, by extending the reliability allocation methodology that is based on the mean-to-mean mapping to a stochastic multi-objective optimization problem where the state variables are uncertain.

요 약

이 논문은 원자력발전소의 안전성 규제를 위한 성능 기준을 설정하는데 야기되는 몇가지 문제점을 다룬다. 저층 성능 기준을 설정하는 것이 고층 성능 기준을 설정하는 것보다 훨신 더 어려운 과제이기 때문에, 저층 성능 기준은 보다 쉽게 결정될 수 있는 고층 성능기준으로 부터 그와 부합되게 유도 되어야 한다. 본 논문은 또한, 평균치—평균치 mapping에 의거한 신뢰도 할당 방법론을 상태변수가 불확실한 stochastic 다목적 최적화 문제로 적용 확장 함으로써 성능 기준의 불확실성을 규명하는 몇가지 방법을 제안한다.

I. Introduction

Many of the regulatory decisions require that performance criteria be established to be used as standards in judging whether a particular "system" (be it an overall technology or a detail component) subject to decision is acceptable or not. Once the performance criteria are in hand, it is relatively easy to determine whether the system meets the performance criteria. However, determination of the performance criteria itself is a much more difficult problem and thus it becomes a central task in many decisionmaking problems.

This paper addresses some issues in setting performance criteria for safety regulation of nuclear power plants and proposes several approaches to characterizing uncertainties in the derived low-level performance criteria.

The paper is organized as the following. Section II provides a general discussion of the performance criteria setting problem and a brief description of the reliability allocation methodology. Section III presents several approaches to uncertainty analysis for reliability allocation, including selected results obtained by applying a particular approach to a realistic problem. Section IV provides conclusions of the study.

II. Setting Performance Criteria

II.A. Regulation and Performance Criteria

The regulation of a safety-conscious technology such as nuclear power plants is a difficult problem that involves not only technical issues but also nontechnical (political and social) issues, some of which may conflict with each other.

The performance of a "system" is measured by *attributes.* An attribute measures quantitatively the degree of achievement of a performance objective. A specific numerical value that the attribute of a "system" must satisfy is called *criterion.* A criterion is set by the manufacturer (or operator) of the "system" or by the regulatory body. For example, 10^{-4}/year frequency of core damage for a nuclear power plant and 10^{-2}/demand of unavailability for a diesel generator could be performance criteria at an overall technology level and at a detail component level, respectively. Thus, depending on the level where the criteria are defined, they may be called top-level criteria or low-level criteria.

The safety goals related to the operation of commercial nuclear power plants[1~4] that the U.S. Nuclear Regulatory Commission (NRC) has issued represent performance criteria setting at the top level. One of the purposes of the top-level safety goals is to provide an appraisal of acceptable risk easily understandable by the decision makers (regulators or owners of the plants) and the public.

During the last several years, U.S. NRC sponsored various programs to evaluate what form of the safety goals is suitable and whether an allocation of the safety goals into lower levels of function/system reliability requirements is desirable for implementation purposes. Okrent et al.[5] Suggested that such a reliability allocation would provide a set of performance criteria in successive tiers of increasing specificity that could constitute a workable risk management framework that is consistent with the top-level safety criteria and compatible with the needs of reactor designers and operators. A similar argument for the allocation is that the criteria at the plant function/system level would give better guidance to designers of plant systems and operating procedures than the top-level criteria, since the function/system criteria would be more specific. Another argument for the allocation is that from the viewpoint of an experiential data base it is easier to "monitor" and "verify" the lower level safety criteria, e.g., system or component reliabilities, than the top-level safety criteria, e.g., core damage frequency, acute and latent fatalities. The counterarguments against the allocation are variations in the theme of "overregulation." It has been argued that a too detailed prescription would take away flexibility and stifle innovative ideas from reactor designers and operators which would in the long run work against safety of the plant. Table I summarizes the merits and demerits of setting criteria at the top level and at the low level.

In general, setting criteria requires value judgments and preference assessments such as determining what the regulator's views are on the value of human life or on the value of having electric power from nuclear power plants. It requires making value trade-offs among several

Table I. Merits and Demerits of Criteria at Top-Level and Low-Level Measures

	Top-Level	Low-Level
Value Judgment	Easier	Difficult
Guidance to Design and Operation	Vague	More Specific
Flexibility and Innovation	Encourage	Stifle
Compliance and Verification of Regulation	Difficult	Easy
Operating Experience	Indirect	Direct

attributes for which criteria are to be set. As noted in Table I, it will be much more difficult and almost impossible to arrive at agreed-upon value judgments on the attributes at the low level than at the top level. This is because the decision makers and the public are not cognizant of the low-level attributes, e.g., unavailability of certain components or systems. In other words, the low-level attributes do not convey direct meaning to them. In contrast, high-level attributes, e.g., fatalities from the accidents, property damage, cost, and core damage frequency, would have more direct meaning to them. Thus, value judgments based on high-level attributes would be understood and accepted more easily than those based on low-level attributes. Thus, the performance criteria at a low level, e.g., reliability criteria for plant systems and major components, should be derived from the top-level performance criteria, e.g., safety goals. Cho et al.[6,7] developed a methodology for reliability allocation in nuclear power plants: determination of reliability characteristics of reactor systems, components, structures, and operations (low-level criteria) that are consistent with a set of top-level performance goals of the nuclear power plants such as the likelihood of core damage, adverse health effects, and associated economics. The methodology does not require elaborate value judgments in determining the low-level criteria. This is accomplished by the multiobjective programming technique used in a decisiontheoretic approach to dealing with top-level performance goals.[8]

II.B. Low-Level Performance Criteria
(Reliability Allocation)

The fundamental elements of the reliability allocation methodology developed by Cho et al.[6,7] are fourfold:

1. a set of global measures of plant performance (top-level attributes) on which the overall performance of the nuclear power plant is evaluated and which will be subject to a preference assessment by a decision maker
2. a set of specific measures of plant performance (low-level attributes), such as system and component unreliabilities, that characterize each feasible realization of nuclear power plant alternatives
3. a model for relating the set of low-level attributes to the set of top-level attributes
4. a method for deriving specific values (or a range of values) for the low-level attributes that are consistent with expressed preferences in the set of top-level attributes.

II.B.1. Top-Level Attributes

In terms of the risk and economic characteristics of a nuclear power plant, following four attributes are considered as the set of top-level performance measures:

1. core damage frequency C_d $(=Z_1)$
2. acute fatalities A $(=Z_2)$
3. latent fatalities L $(=Z_3)$
4. reliability cost G $(=Z_4)$

The first three attributes are included because they constitute the basis of the various proposed "safety goals" and the final risk measures calculated in current PRAs.

The fourth attribute is included, since economic considerations are important in decision making concerning electric power generation from nuclear power plants. If there were no constraints on the achievability of the various system reliability levels, we would choose the solution with the lowest possible consequences. In the limit, this would imply zero consequences achieved through perfect systems, which are obviously not realizable.

II. B. 2. Low-Level Attributes

The low-level attributes ($\underline{x}$) which compose the top-level attributes are as follows:

1. unavailabilities of safety functions, systems and components, including human errors (affect the elements of $\underline{M}$ in Eq. (1) below)
2. initiator frequencies (vector $\underline{f}$ in Eq. (1) below)
3. containment failure probabilities (affect the elements of $\underline{C}$ in Eq. (1) below)
4. site parameters and emergency planning parameters (affect the elements of $\underline{S}$ in Eq. (1) below)

II. B. 3. Plant Model

The plant model relating the top-level attributes with the low-level attributes consists of a plant PRA model and a reliability cost model, that can be represented concisely as the following:[6,7]

$$C_d = \underline{f}\underline{M}\underline{u} \qquad (1)$$
$$A = \underline{f}\underline{M}\underline{C}\underline{S}(\underline{a})\underline{a}$$
$$L = \underline{f}\underline{M}\underline{C}\underline{S}(1)1$$
$$G = \sum_{1=1}^{n} g_i(x_i)$$

where $\underline{f}$ is the accident initiator (internal and external) frequency vector, $\underline{M}$ the plant damage matrix, $\underline{C}$ the containment matrix, $\underline{S}(\underline{a})$ and $\underline{S}$ (1) the site vectors for acute and latent fatalities respectively. $\underline{a}$ and 1 are the column vectors of the levels of acute fatalities and latent fatalities, respectively, and $\underline{u}$ is the column vector with elements equal to unity. $g_i(x_i)$ is the cost function of component i achieving unreliability x_i and n is the number of components in the PRA model.

II. B. 4. Multiobjective Optimization

The method for deriving specific values of the low-level attributes that are consistent with the top-level performance criteria is mathema-

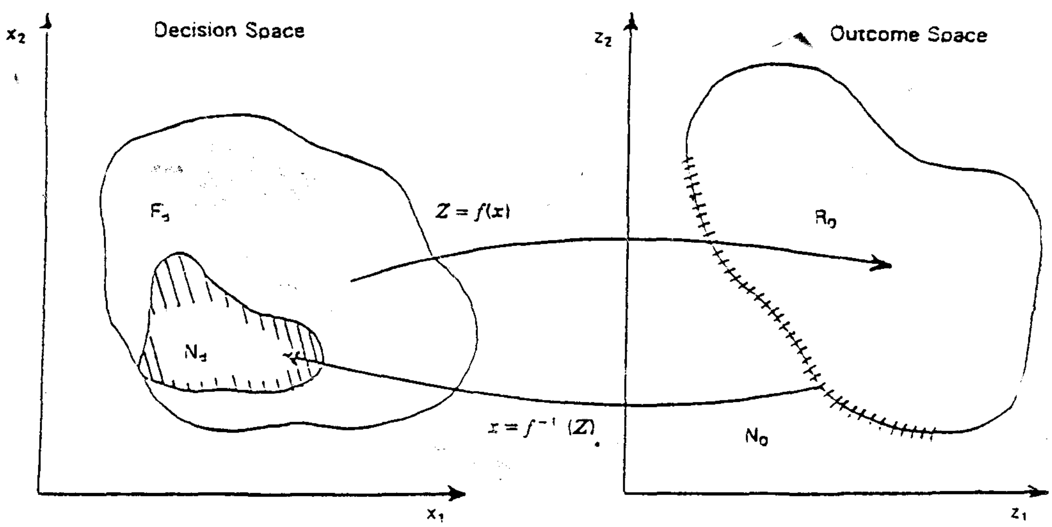

Fig. 1. Mapping of Decision Space into Outcome Space; crosshatched subspaces N_d and N_0 are noninferior solutions.

tically represented by

$$\text{Minimize } \underline{Z}(\underline{X})=[C_d(\underline{X}), A(\underline{X}), L(\underline{X}), G(\underline{X})]$$
$$\text{subject to } \underline{X}\in F_d \quad (2)$$

where $\underline{Z}(\underline{X})$ is a four-dimensional vector composed of the top-level attributes and F_d the feasible region in decision space of the low-level attributes. The notion of "optimality" in single-objective optimization problems must be dropped in multiobjective problems because a solution which minimizes one objective will not, in general, minimize any of the other objectives. The concept called "noninferiority" (or "nondominance") is needed.[9]

Figure 1 represents for the two-dimensional case a mapping of the feasible decision space F_d to the outcome space R_o determined by the plant models, i.e., the PRA model and the reliability cost function. Figure 1 also illustrates the definition of noninferiority. Since, in the formulation of our problem, less in each of the top-level attributes is preferable, the noninferior solutions are shown crosshatched along the "southwest" boundary in the outcome space.

The multiojective programming technique which is a key tool in the reliability allocation methodology considers, in effect, all feasible sets (decision space) of the low-level reliabilities and rejects those that are not consistent with desirable top-level attributes (outcome space). *The rejection is performed, in principle,* by searching the feasible sets and identifying only those whose corresponding top-level attributes are noninferior among themselves (see Fig. 1). The result of this process is the reduction of the feasible sets of low-level attributes into smaller ranges that are consistent with the top-level criteria. These reduced ranges (N_d) of values for the low-level attributes constitute the allocated low-level criteria. Thus, in the methodology, finding N_d is equivalent to setting low-level performance criteria consistently with the top-level performance criteria.

III. Uncertainty Analysis

III. Introduction

It is useful for the purpose of uncertainty analysis to distinguish "state" variables from "control" or "decision" variables in a mathematical model. A "state" variable is a variable which is not under control or not subject to decision, e.g., the elements of the site matrix and the initiator frequencies, the coefficients in the cost models, and in the case of the base allocation model the elements of the containment matrix. It is noted here that the initiator frequencies could be additional decision variables in an extenden allocation model. However, some of the elements of the site matrix could not be decision variables once the reactor site is decided (conceivably parameters referring to offsite protective action policies could be treated as decision variables.)

Note that the methematical model in Eq. (1) is specified to represent a mean value to mean value mapping between the decision space and the outcome space. The mean value property is preserved under the usual assumption of statistical independence in the PRA models, which are usually based on event tree/fault tree analysis.

The reliability cost Gralso represents the mean value with regard to the uncertain coefficients appearing in the cost functions. It is, bowever, evaluated at the fixed mean unavailabilities in the PRA model.

The state variables of the model are, however, characterized by uncertainties themselves. Now, if the state variables $\underline{S}$ are uncertain (random variables), the same is true for the outcome variables $\underline{Z}$. We can state, then, the mathematical problem as a *multiobjective optimization* problem with uncertain state variables. A number of approaches to this problem are briefly described in the remainder of this section, under a variety of conditions. One of the approaches is applied to the base model used in Refs. 6 and 7.

III.B. Approaches

Following the "separation" of the decision variables from state variables, the allocation problem in a multiobjective programming formulation is expressed as

$$(P_o)\ \underset{X}{\text{Minimize}}\ \underline{Z}(\underline{X}, \underline{S})$$
$$=[C_d(X, \underline{S}), A(X, S), L(\underline{X}, \underline{S}), G(\underline{X}, \underline{S})]$$

where $\underline{X}$ is the vector of decision variables as before and $\underline{S}$ the vector of uncertain state variables.

Recall that in Section II. B. 4. minimization of a vector $\underline{Z}$ means finding noninferior solutions.

III. B. 1. Allocation Under Uncertainty

The approaches which belong to this class consider uncertainties before the optimization problem is solved. Thus the uncertainties are imbedded formally in the allocation procedure.

1. Brute-force (Monte Carlo Sampling) Approach

$$(P_1)\ \underset{X}{\text{Minimize}}\ \underset{S}{\text{Sample}}\ \underline{Z}(\underline{X}, \underline{S})$$

where the distributions of $\underline{S}$ are given. The Monte Carlo sampling is straightforward when the s_i's are statistically independent or completely dependent. There also exist Monte Carlo sampling techniques for handling the cases when the s_i's are dependent and distributed according to a joint distribution function. Implementation of these techniques is, however, rather involved.

Since this approach requires one (vector) minimization problem be solved for each realization of the Monte Carlo sampling, the overall computational effort will be highly demanding for reasonable sampling accuracy.

2. α-Confidence Level Approach

Assumptions for this approach are the following:

i) The global attributes are linear in $\underline{S}$, e.g., only the site matrix and the coefficients in the reliability cost models are uncertain and all the other parameters are either decision variables or constant.

ii) Variance of each uncertain variable s_i and, if some of uncertain variables are correlated, Cov (s_i, s_j) are given.

iii) The uncertain variables are normally (or truncated normally) distributed.

Recall the constraint method we can use to solve the multiobjective optimization problem (P_0), i.e.,

$$(P_2)\ \underset{X}{\text{Minimized}}\ C_d(\underline{X})$$
$$\text{subject to } \underline{X} \varepsilon F_d$$
$$A(\underline{X}, \underline{S}) \leq \varepsilon_1$$
$$L(X, S) \leq \varepsilon_2$$
$$G(X, S) \leq \varepsilon_3$$

We now seek the noninferior solution set at the α-confidence level, parametrically in α. Here α is the minimum probability of achieving the constraints on $A, L,$ and G, that is,

$$(P_2')\ \underset{X}{\text{Minimize}}\ C_d(\underline{X})$$
$$\text{subject to } \underline{X} \varepsilon F_d$$
$$P_r[A(\underline{X}, \underline{S}) \leq \varepsilon_1] \geq \alpha$$
$$P_r[L(\underline{X}, \underline{S}) \leq \varepsilon_2] \geq \alpha$$
$$P_r[G(\underline{X}, \underline{S}) \leq \varepsilon_3] \geq \alpha$$

Under the stated assumptions, using the concept of deterministic equivalents, (P_2') can be transformed into:

$$(P_2'')\ \underset{X}{\text{Minimize}}\ C_d(\underline{X})$$
$$\text{subject to } \underline{X} \varepsilon F_d$$
$$A(\underline{X}, \bar{S}) + K_\alpha[A_X^T B A_X]^{1/2} \leq \varepsilon_1$$
$$L(\underline{X}, \bar{S}) + K_\alpha[L_X^T B L_X]^{1/2} \leq \varepsilon_2$$
$$G(\underline{X}, \bar{S}) + K_\alpha[G_X^T B G_X]^{1/2} \leq \varepsilon_3$$

where K_α is a standard normal value such that $\Phi(K_\alpha) = \alpha$ and Φ represents the cumulative standard normal distribution, and B is a symmetric variancecovariance matrix of the uncertain variables S stands. for the mean of $\underset{\sim}{S}$, and A_X for $f\underset{\sim}{M}(\underset{\sim}{X})$ $\underset{\sim}{C}$(similarly L_X and G_X are appropriately defined functions of $\underset{\sim}{X}$).

It is noted in (P_2'') that the second terms in the constraints are perturbations to the first terms, reflecting the effects of uncertainties in $\underset{\sim}{S}$ on A, L, and G and that when $\alpha=0.5K_\alpha$ becomes zero and (P_2'') reduces to the problem we solve in section II. B. 4.

Operationally, (P_2'') would be solved as follows:

i) Choose a specific α from a discrete set of $\alpha's$ (e.g., $\alpha=0.1, 0.2, \ldots\ldots, 0.9$).

ii) Solve the multiobjective problem (P_2'') by varying the $\varepsilon_i's$ as we did in Appendix *B*.

iii) Go to i).

It is noted that this approach allows for incorporation of the uncertainties in the allocation procedure by solving only several deterministic (not stochastic) problems. This is of course possible under the stated assumptions.

The solutions would look like Fig. 2 in a two-dimensional example. The noninferior solutions would be displayed at several confidence levels.

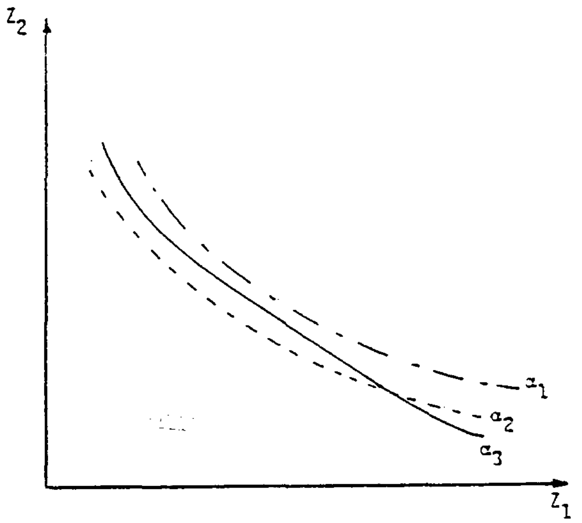

Fig. 2. Noninferior Outcomes at Several Confidence Levels.

III. B. 2. Uncertainty on Allocation

In these approaches we do not consider uncertainties before allocation but first solve the allocation problem using mean values and then examine the variation of top-level attributes due to uncertainties of the state and/or decision variables.

1. Uncertainty Propagation Approach

The variation of top-level attributes can be examined by using the various uncertainty propagation methods, e.g., response surface technique, method of moments, and Monte Carlo sampling. Two approaches using the Monte Carlo sampling technique are the following:

(P_3) i) $\underset{X}{\text{Minimize}}\ \underset{\sim}{Z}(\underset{\sim}{X}, \bar{\underset{\sim}{S}})$

ii) $\underset{\underset{\sim}{S}}{\text{Sample}}\ \underset{\sim}{Z}^*(\underset{\sim}{X}^*, \underset{\sim}{S})$

where $\underset{\sim}{Z}^*$ and $\underset{\sim}{X}^*$ are the noninferior solution from i).

(P_4) i) $\underset{X}{\text{Minimize}}\ \underset{\sim}{Z}(\underset{\sim}{X}, \bar{\underset{\sim}{S}})$

ii) $\underset{X,\underset{\sim}{S}}{\text{Sample}}\ \underset{\sim}{S}^*(\underset{\sim}{X}^*, \underset{\sim}{S})$

where $\underset{\sim}{Z}^*$ and $\underset{\sim}{X}^*$ are the noninferior solution from i).

2. Mean-Variance Approach

Assumptions for this approach are the same with the first two assumptions i) and ii) for the α-confidence level approach.

(P_5) i) $\underset{X}{\text{Minimize}}\ \underset{\sim}{Z}(\underset{\sim}{X}, \bar{\underset{\sim}{S}})$

ii) Calculate $\underset{\underset{\sim}{S}}{\text{Var}}\ \underset{\sim}{Z}^*(\underset{\sim}{X}^*, \bar{\underset{\sim}{S}})$

where $\underset{\sim}{Z}^*$ and $\underset{\sim}{X}^*$ are the noninferior solutions from i).

III.C. Application

As an example of uncertainty analysis, the uncertainty propagation approach (P_4) described above is applied to the base allocation model used in Refs. 6 and 7. The base allocation model constructed from a PRA model[10] of a boiling water reactor consists of three accident initiators that are most dominant contributors to

Table II. List of Decision Variables

x_h	Name	Event Description
1	RPS(M)	Mechanical failure of reactor protection system
2	SLCSH	Hardware failure of standby liquid control system
3	LOSP	Transient-induced loss of off-site power
4	EDC	Loss of all dc (loss of all ac for >4h or other failures in dc power supply system)
5	WSW	Loss of service water
6	FWPCS	Hardware failure of the feedwater and primary coolant system (PCS)
7	ARC	Operator failure to provide alternate room cooling to frontline system rooms
8	RCICH	Hardware failure of reactor core isolation cooling system
9	HPCIH	Hardware failure of high-presure coolant injection system
10	ADSH	Hardware failure of automatic depressurization system (ADS)
11	LPCIH	Hardware failure of low-pressure coolant injection system
12	LPCSH	Hardware failure of low-pressure core spray system
13	RECOV	Failure to recover the support system
14	RHRH	Hardware failure of residual heat removal system
15	FWPCSL	Hardware failure of feedwater and PCS system for long-term containment heat removal
16	DG	Failure of diesel generator system
17	X	Operator failure to actuate the ADS
18	D	Operator failure to inhibit ADS actuationin ATWS events
19	FWPCSL (RECOV)	Failure to recover feedwater and PCS hardware in 20h given that it failed in early phase ($\underline{Q}$)

core damage and health consequences. The three initiators turn into 15 accident sequences which are classiffied into four plant damage states.

The reliability cost functions used for illustration purposes are, for all components.

$g_i(x_i)=a_i(1/x_i-1)$.

Table II defines the low-level attributes (decision variables) that are considered in the model. Table III shows the initiators and associated frequencies. The approach (P_4) first solves the allocation problem using mean values and then propagates uncertainties of the state and decision variables through the model by using the Monte Carlo sampling techniques.

Table III. Uncertainties in Initiator Frequencies

Initiator	Mean (Events/ Reactor Year)	EF*
LOFW/MSIV Closure	1.23	2.3
LOSP	0.17	4.4
Turbine Trip	8.17	1.5

* 90% error factor under the lognormal distribution in Ref. 10.

Tables III through VI show the input data used in the uncertainty analysis, and Table VII and Fig. 3 through 6 provide the results. A modified version (to handle multiple outputs in a single run) of the SAMPLE program in WASH-1400 was used assuming all uncertain variables follow the lognormal distributions with

Table IV. Uncertainties in Containment and Site Matrices*

Accident Class	α_i		β_i	
	Mean**	EF***	Mean**	EF***
I	2.132(−1)	2.8	1.709(+3)	23.5
II	4.277(−1)	2.1	1.381(+3)	16.3
III	2.132(−1)	2.8	1.709(+3)	23.5
IV	8.071(+1)	34.4	1.308(+4)	27.0

* α_i is the expected acute fatalities given Accident Class i and β_i is the expected latent fatalities given Accident Class i since $\underline{\alpha}=\underline{C}\underline{S}(\underline{a})\underline{a}$ and $\underline{\beta}=\underline{C}\underline{S}(1)1$.

** Best-estimate in Ref. 10.

*** 90% error factor assuming the lognormal distribution.

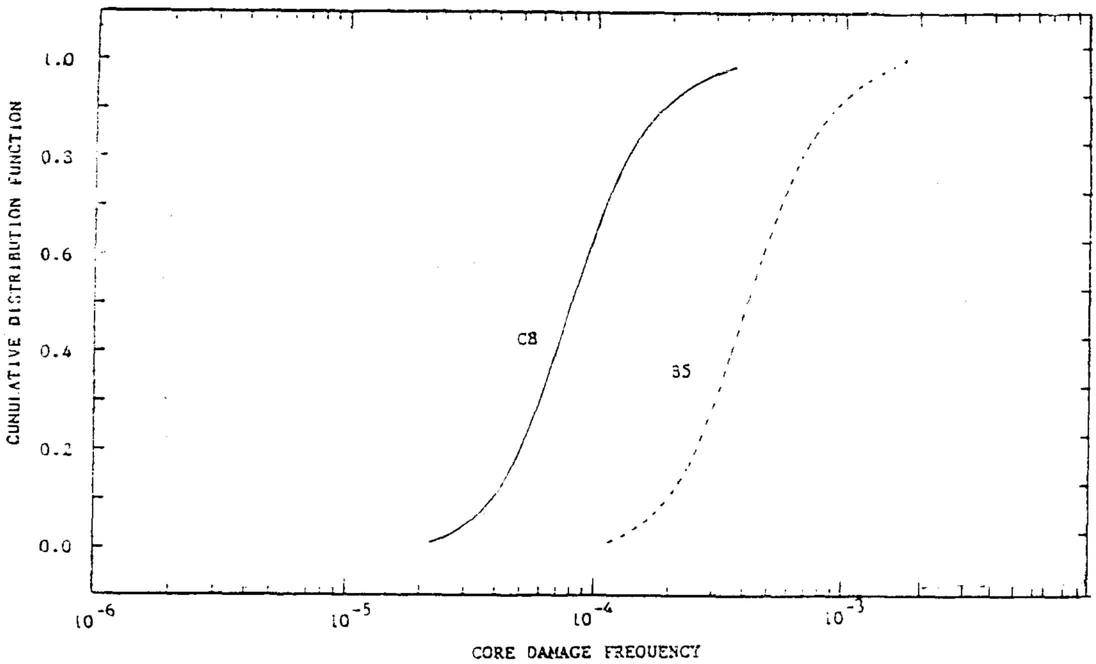

Fig. 3. Cumulative Distribution of Core Damage Frequency for Noninferior Solutions B5 and C8.

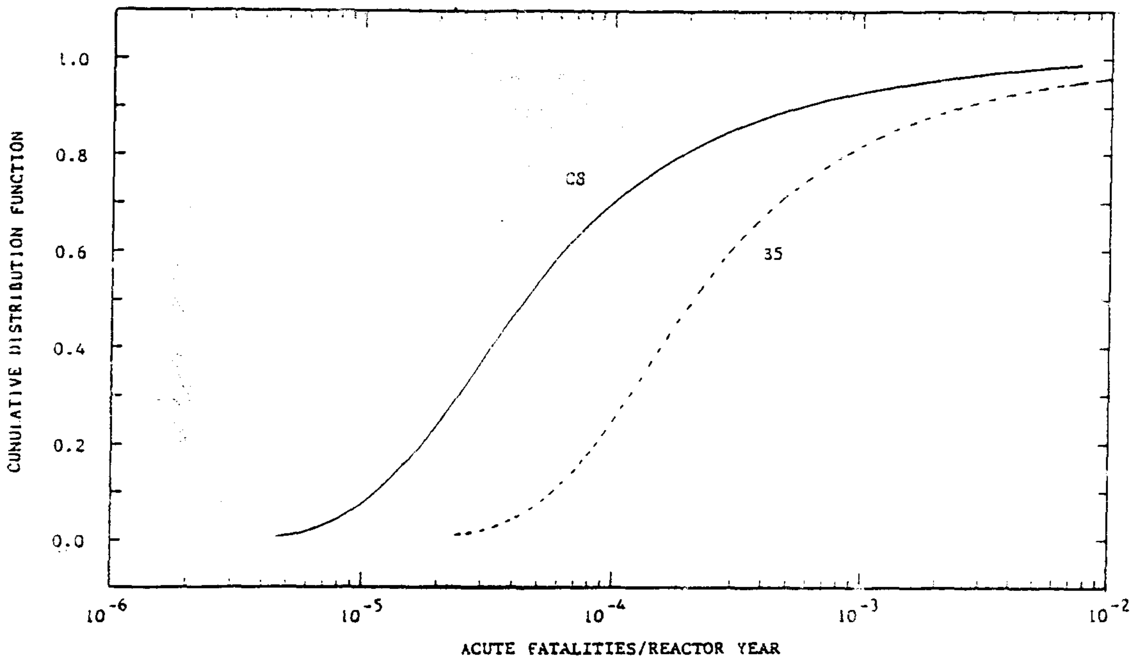

Fig. 4. Cumulative Distribution of Acute Fatalities/Reactor Year for Noninferior Solutions B5 and C8.

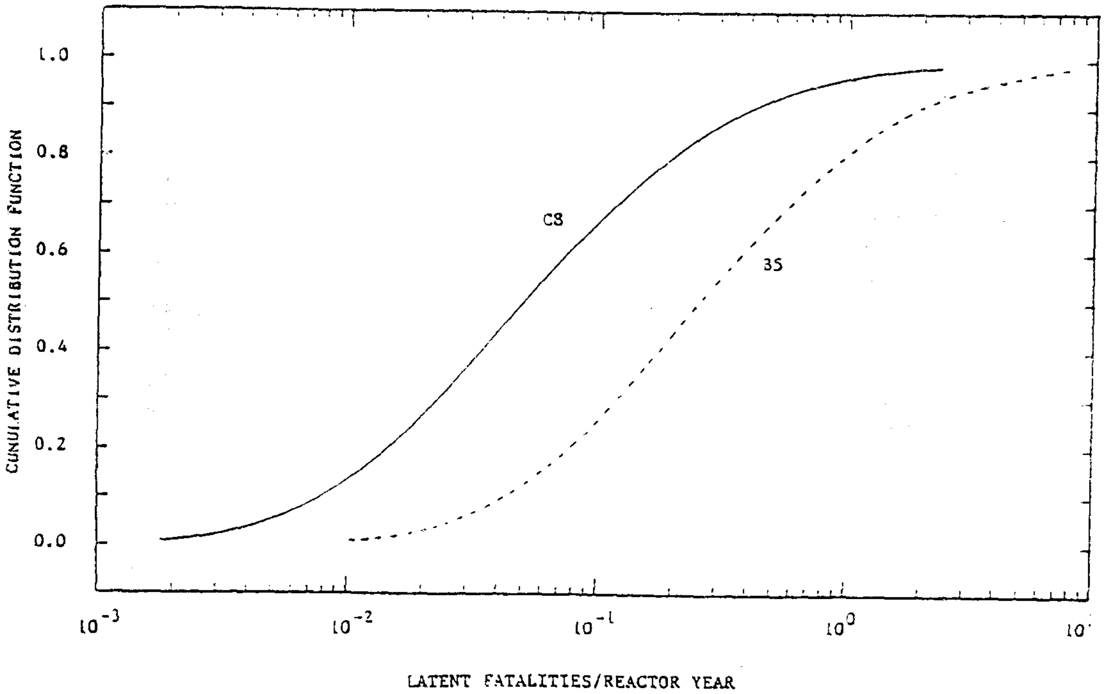

Fig. 5. Cumulative Distribution of Latent Fatalities for Noninferior Solutions B5 and C8.

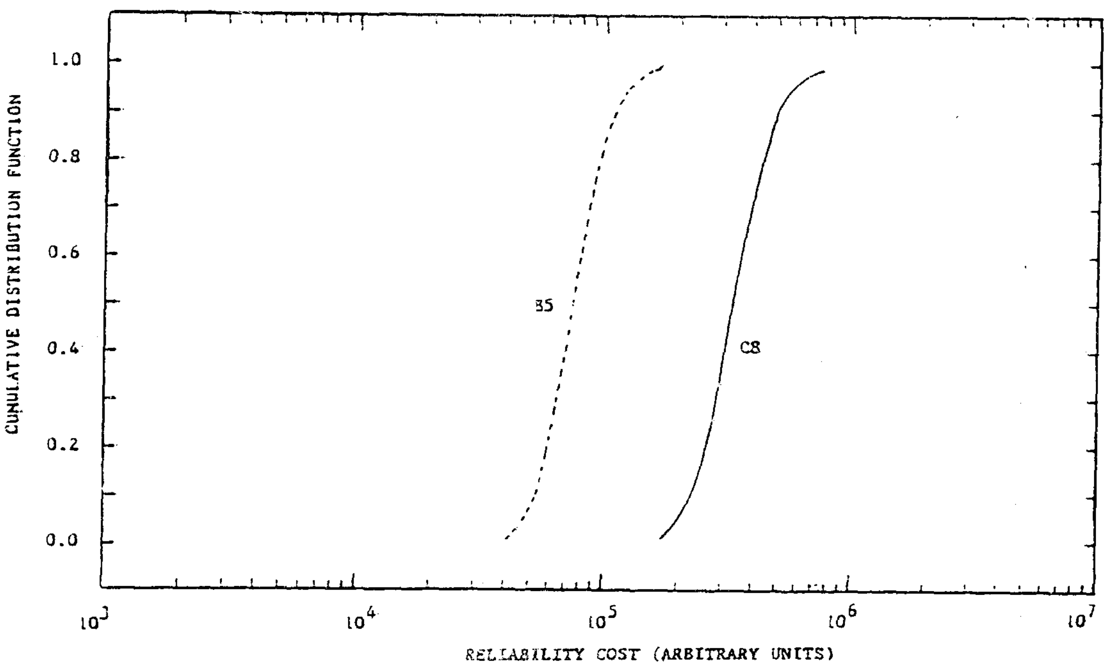

Fig. 6. Cumulative Distribution of Reliability Cost for Noninferior Solutions B5 and C8.

Table V. Uncertainties in a_i of Reliability Cost Functions Assumed in Uncertainty Analysis

Component	Mean	EF*
X (1) RPS(M)	10.	3
X (2) SLCSH	1.	3
X (3) LOSP	1.	5
X (4) EDC	1.	2
X (5) WSW	1.	3
X (6) FWPCS	10.	5
X (7) ARC	1.	3
X (8) RCICH	1.	3
X (9) HPSIH	1.	3
X (10) ADSH	1.	5
X (11) LPCIH	1.	3
X (12) LPCSH	1.	3
X (13) RECOV	10.	2
X (14) RHRH	10.	3
X (15) FWPCSL	10.	3
X (16) DG	10.	10
X (17) X	1.	2
X (18) D	1.	5
X (19) FWPCSL(RECOV)	10.	2

* 90% error factor assuming the lognormal distribution.

Table VI. Uncertainties in Achieved Unavailabilities Assumed in Uncertainty Analysis for the Noninferior Solutions B5 and C8

	B5		C8	
	Mean*	EF**	Mean*	EF**
X (1)	1.65(−3)	3	3.66(−4)	3
X (2)	7.27(−4)	3	3.15(−4)	3
X (3)	5.20(−4)	5	5.20(−4)	5
X (4)	2.73(−5)	3	5.57(−6)	3
X (5)	6.10(−5)	5	1.25(−5)	5
X (6)	5.31(−3)	5	5.00(−3)	5
X (7)	1.50(−1)	3	1.50(−1)	3
X (8)	1.00(−2)	5	1.00(−2)	5
X (9)	1.00(−2)	5	1.00(−2)	5
X (10)	6.79(−3)	5	1.43(−3)	5
X (11)	3.75(−2)	5	1.31(−2)	5
X (12)	3.56(−2)	5	1.23(−2)	5
X (13)	5.00(−2)	10	5.00(−2)	10
X (14)	2.05(−3)	5	5.40(−4)	5
X (15)	3.52(−3)	5	1.40(−3)	5
X (16)	1.65(−3)	5	3.36(−4)	5
X (17)	7.44(−3)	10	1.43(−3)	10
X (18)	2.00(−3)	10	2.00(−3)	10
X (19)	5.00(−2)	5	5.00(−2)	5

* Noninterior solutions obtained from the base model.
** 90% error factor assuming the lognormal distribution.

appropriate mean values and error factors.

It is noted from Fig. 3 through 6 that, if only one attribute is considered in isolation of the other attributes, the noninferior solution C8 stochastically dominates the noninferior solution B5 in the core damage frequency, acute fatalities and latent fatalities, while the noninferior solution B5 stochastically dominates the noninferior solution C8 in the reliability cost. (C8 and B5 are the extreme noninferior solutions for $C_d=1\times10^{-4}$/reactor-year and $C_d=5\times10^{-4}$/

Table VII. Cumulative Distributions* of Core Damage Frequency Acute Fatalities, Latent Fatalities, and Reliability Cost for the Noninferior Solutions B5 and C8

		5th Percentile	Median	95th Percentile	Mean
Core Damage	B5	1.57(−4)	4.08(−4)	1.15(−3)	5.00(−4)
Frequency	C8	3.10(−5)	8.13(−5)	2.32(−4)	1.00(−4)
Acute	B5	4.19(−5)	2.08(−4)	7.35(−3)	2.56(−3)
Fatalities	C8	8.24(−6)	4.32(−5)	1.63(−3)	5.65(−4)
Latent	B5	2.51(−2)	2.53(−1)	3.50(+0)	1.17(+0)
Fatalities	C8	4.71(−3)	5.03(−2)	7.32(−1)	2.46(−1)
Reliability	B5	4.77(+4)	7.56(+4)	1.25(+5)	7.98(+4)
Cost	C8	2.02(+5)	3.34(+5)	5.73(+5)	3.54(+5)

* Using Monte Carlo sampling size of 4800.

reactor-year, respectively.) Clearly, the attribute of reliability cost conflicts with the other three attributes in choosing one from the two alternatives B5 and C8. Thus, in this situation, choosing one alternative requires a decision maker's preference assessment. It may also happen that none of the alternatives exhibits stochastic dominance in any of the attributes if the alternatives are "close" enough. In any case, uncertainty analysis around the noninferior solutions should facilitate preference assessment of a decision maker because it reveals more relevant information about the problem.

IV. Conclusions and Recommendations

The performance criteria (either at the top-level or at the low-level) are used as standards for many regulatory decisions. The problem of setting the performance criteria is, however, a difficult one and it is a fundamental element in many decisionmaking problems. In particular, setting criteria at the low level is a much more difficult and almost impossible task than it is at the top level. Thus, the performance criteria at a low level should be derived in a consistent fashion from the more easily determinable top-level performance criteria.

The investigation of the uncertainty characteristics is facilitated by distinguishing state variables from decision variables in the plant mathematical model. Since the state variables are characterized by uncertainty, the outcome variables (top-level attributes) are also uncertain. The reliability allocation methodology based on the mean-to-mean mapping can be extended to a stochastic multiobjective optimization problem where the state variables are uncertain. The extended reliability allocation methods formulated in the paper are the following:

(i) Brute-force (Monte Carlo Sampling) Approach
(ii) α-Confidence Level Approach
(iii) Uncertainty Propagation Approach
(iv) Mean-Variance Approach.

The primary motivation of the uncertainty analysis is to give a full exposition of the criteria setting problem to those who determine or accept the criteria. The basic premise here is, following the value theory of information, that uncertainty analysis around the noninferior solutions should facilitate making value judgments (and thus setting performance criteria) because it reveals more relevant information about the problem.

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