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SYSTEM RELIABILITY ASSESSMENT WITH AN APPROXIMATE REASONING MODEL

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System Reliability Assessment with an Approximate Reasoning Model

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Abstract

The projected service life of weapons in the United States nuclear stockpile will exceed the original design life of their critical components. Interim metrics are needed to describe weapon states for use in simulation models of the nuclear weapons complex. We present an approach to this problem based upon the theory of approximate reasoning (AR) that allows meaningful assessments to be made in an environment where reliability models are incomplete. AR models are designed to emulate the inference process used by subject matter experts. The emulation is based upon a formal logic structure that relates evidence about components. This evidence is translated using natural language expressions into linguistic variables that describe membership in fuzzy sets. We introduce a metric that measures the "acceptability" of a weapon to nuclear deterrence planners. Implication rule bases are used to draw a series of forward chaining inferences about the acceptability of components, subsystems and individual weapons. We describe each component in the AR model in some detail and illustrate its behavior with a small example. The integration of the acceptability metric into a prototype model to simulate the weapons complex is also described.

Introduction

Operational requirements and the availability of limited resources often dictate that decisions about the performance, reliability and replacement or refurbishment of important technical systems be made in the absence of complete data and validated system reliability models. Such a situation exists for the United States nuclear weapons complex (NWC). The projected service lives of currently existing nuclear weapons systems will exceed the original design life of their critical components. Extrapolating available reliability and performance data for these weapons systems to cover the now extended component lifetimes will require considerable effort. Major efforts are under way to integrate the available test data – from aboveground experiments and underground nuclear tests, as well as from advanced numerical simulations of weapon performance, into predictive reliability models that will provide a solid basis for such extrapolation. These efforts are part of the Department of Energy's (DOE) Science-based Stockpile Stewardship Program whose goal is to assure the continued reliability and safety of the U.S. nuclear arsenal without nuclear testing. Meanwhile, important decisions about the capacity of the NWC must be made in the near term to allow for long lead-time construction and research and development projects.

As part of a larger effort at Los Alamos to understand this decision process we are developing a prototype NWC simulation model. One element of this project is the search for interim metrics that can be developed rapidly but

that adequately describe the state of a weapon system using currently available evidence. Metrics can provide a useful time-dependent snapshot of the stockpile and will be used to measure how well the NWC of the early twenty-first century operates. Interim metrics should provide enough information to assess the likelihood and potential consequences of crippling maintenance or manufacturing bottlenecks, cost over-runs and other undesirable outcomes in different NWC configurations and operations schedules. Finally, relatively simple interim metrics provide a link between current planning approaches and advanced decision analysis tools that incorporate adaptive modeling methods.

We begin by briefly discussing the principal elements of an AR model. The application of AR in determining the acceptability of a single component is then discussed. We show how different types of data and judgments about their relative quality can be combined. Next the problem of aggregating component acceptability to infer individual weapon acceptability is considered. A numerical example is provided to show how a pilot AR model is being implemented. The subsequent inferences associated with aggregation to the weapon class and stockpile levels are discussed briefly. Finally we describe how the results from this work are being integrated into a simulation model for the NWC.

Overview of the Methodology

In this paper we describe the development of an interim performance metric using the theory of approximate reasoning (AR) (Zadeh 1976) that emulates the inference process used by an expert or group of subject matter experts in making an evaluation. The metric proposed here is the "acceptability" of a weapon to nuclear deterrence planners. We treat acceptability as a linguistic variable whose gradations are expressed by three fuzzy sets into which the weapon states can be classified: nominal (N), marginal (M) and inadequate (I). The nominal acceptability set contains weapons that would be fully capable of performing their design function. Within this set there would be no reason to prefer one nominally acceptable weapon to another. The marginal acceptability set contains weapons for which there is some cause for concern. A nominal weapon is always preferable to one classified as marginal. Finally the inadequate acceptability set contains weapons judged to be seriously deficient and requiring some corrective action.

Although the acceptability of a complete weapon is the first desired output from the AR model, the assignment of a weapon to an acceptability set is based on the states of a selected number of components and subsystems within the weapon. Each of these entities is similarly assigned membership in acceptability fuzzy sets using data on the state of the component or subsystem and an inference rule base that maps a natural language description of component state into acceptability set membership. The overall weapon acceptability is inferred using additional rule bases with individual components and subsystem acceptabilities as antecedents.

The information used to infer component or subsystem acceptability may be quantitative or qualitative. Fuzzy sets are used in AR to provide the capability to "hedge" which acceptability set is to be inferred from this information. This provides a measure of the ambiguity encountered in assigning a component to a particular set and reduces the number of sets needed to accurately describe the features of the data and the inferences drawn from it.

Characteristics of Approximate Reasoning

The theory of approximate reasoning provides a robust and adaptable formalism for emulating a series of expert judgments using both quantitative and qualitative information. We briefly describe the major features of AR below.

Information, Evidence and Uncertainty

The general structure underlying the AR method discussed in this paper is shown in Fig. 1. We begin with some universe of information about a weapon whose acceptability is to be determined. This universe consists of both qualitative and quantitative data. The information may not be in a form that is immediately useful in the inferential process; some processing of the data may be required. We denote the processed data as a body of evidence and only elements within it will be considered in the AR model. Elements of evidence must be related to each other in some definite way in order to draw inferences. This ordering is achieved by way of formal structures with the logical implication operation used to define the inferences. An inference may be related to other elements of evidence or earlier inferences to produce subsequent inferences. In this manner the chain of forward-chaining inferences that is characteristic of an AR model is generated. By carefully constructing this inference chain, a final inference of interest can be obtained. The algorithmic nature of an AR model helps to ensure that the inferential process is traceable and reproducible.

The output from the logic structure is a description of the system called a state vector. The state vector is a concise description of a system, in this case the weapon undergoing the acceptability evaluation. The elements of a state vector are always assumed to include some component of uncertainty that reflects imprecision or imperfect knowledge of the system state. Finally the system state vector is used in a decision model where some definite statement about the system is inferred. Note that as we move through the process the level of abstraction increases.¹

¹ The process can be viewed as a composition of set functions mapping from the universe of information to a set of decisions.

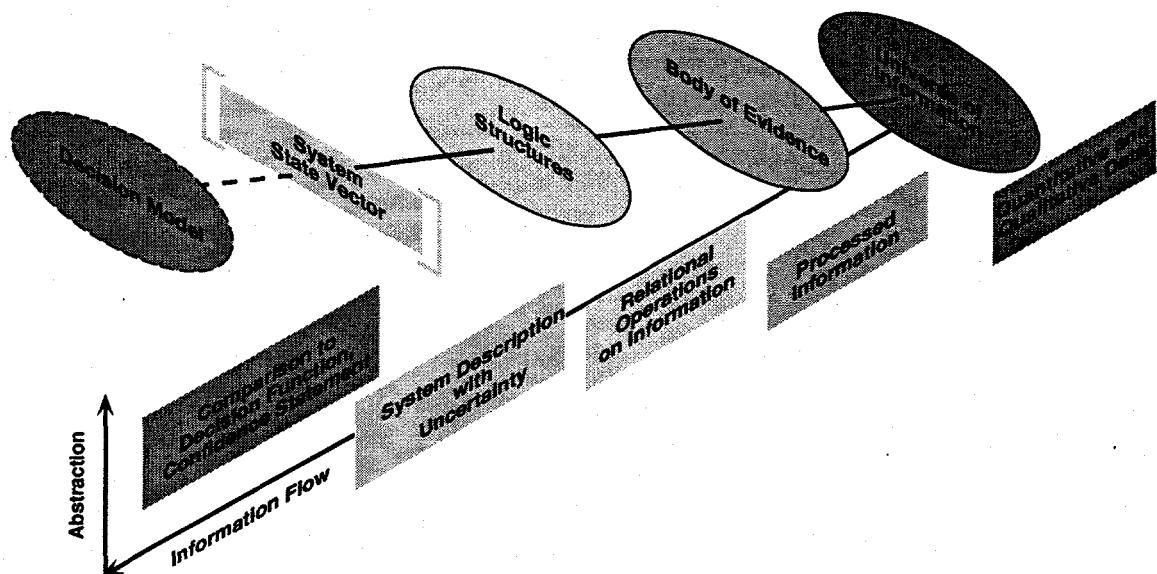


Figure 1. Overall structure for approximate reasoning model. (CP Structure.eps)

The relationship between the universe of information and a body of evidence is shown in Fig. 2. The universe of information consists of what can be considered "raw" information about the weapon. In the present application these include component ages, surveillance data describing defects and out-of-specification conditions and the results of component testing. Information processing is needed to make this data useful. Processing occurs via phenomenological models, detailed numerical simulation and specific expert judgment. These operations place a piece of information in a useful context for drawing inferences about acceptability. Information of this sort forms the body of evidence.

Fuzzy Sets and Linguistic Variables

In an AR model the elements of evidence are handled as linguistic variables. That is, natural language descriptors are used. For example we can characterize the temperature in a room as "too cold", "comfortable" or "too hot" without actually measuring the temperature. The descriptors are used to define sets in which the variable of interest, in this case the temperature in the room, may belong. The sets used in approximate reasoning are fuzzy. That is, a variable may belong to several sets, which might traditionally be considered to be mutually exclusive.

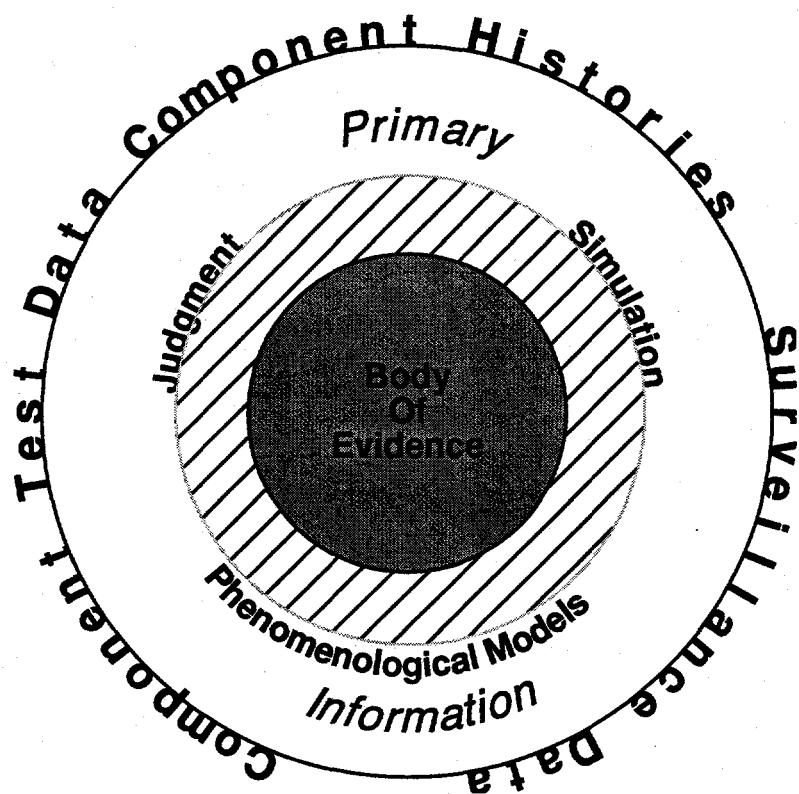


Figure 2. Conceptual relationship between the universe of information and a body of evidence.

For example, the temperature could be assigned membership in all the fuzzy sets {Too Cold}, {Comfortable} and {Too Hot}. Membership in a fuzzy set can vary between zero and one, with one implying full membership and zero non-membership. For quantitative elements of evidence, the degree of membership (DOM) in a set is assigned using membership functions. The numerical value of the degree of membership in a set S_j is determined by $\mu(x, S_j)$, where $\mu(x, S_j)$ is the membership function. One possible set of membership functions for the room temperature is shown in Fig. 3. If the temperature in the room is 70 F then we assign DOMs of 0.5 in {Too Cold} and {Too Hot} and a DOM of 1.0 in {Comfortable}. We denote the three degrees of membership in these sets by the vector $\gamma_T = [0.5, 1, 0.5]$ and membership in {Comfortable} for example, is $\mu(T, \text{Comfortable}) = 1.0$. It is important to note that a small change in temperature will have a similarly small effect on the degrees of membership in the sets. A traditional approach would use threshold values to define the sets. With this approach a particular temperature can only belong to one set. Such sets are referred to as crisp and a small change in temperature could completely change the set to which it belongs. So far we have been dealing with quantitative measures for temperature. However we might chose instead to use subjective judgment to qualitatively define the room temperature. Then the degrees of membership in the sets can be assigned directly. For example the judgment "a little too cold" could be converted directly to a degree of membership vector of

$\gamma_T = [0.3, 0.7, 0]$ without explicit membership functions. Note that when employing either quantitative or qualitative temperature measures, the use of fuzzy sets allows for ambiguity in classification of the temperature.

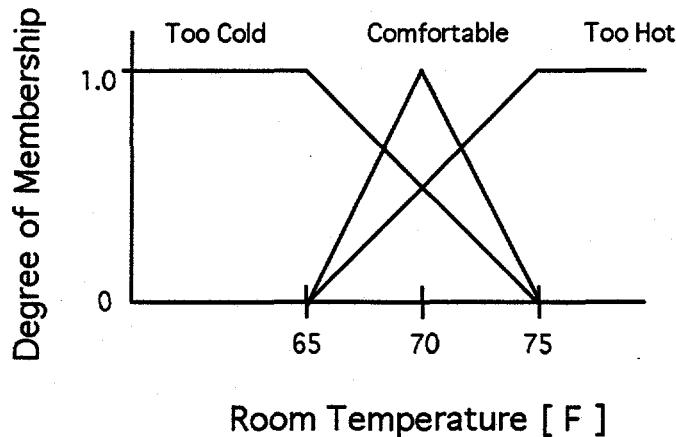


Figure 3. Membership functions for fuzzy sets used to describe room temperature. (FLMF21)

An element of information can be either quantitative or qualitative but it is important to note that in either case it is almost inevitably uncertain. If an element is defined numerically it is treated as a classic random variable characterized by a probability density function. Definition of the parameters in the density function then characterizes the uncertainty. A qualitative element of evidence is always considered to be a linguistic variable. These too can be stochastic.

Organizing Evidence using a Logic Structure

The connection between the elements in the body of evidence and a logic structure is shown in Fig. 4. The logic structure defines a set of relationships between the elements of evidence. The nature of the individual branch junctions depends upon the particular type of relation used. A relation is a general function that maps multiple inputs into a single output. Many different types of relations, both numerical and logical are possible. However in an AR model the only relation used is formal logical implication. We refer to this as an implication junction. Many of the implications are of the form "If A and B then C", or "A and B implies C", written symbolically as

$$(A \wedge B) \rightarrow C.$$

For example, assume that the acceptability of a weapon is determined completely by two components A and B.

Implication 1: If the acceptability of Component A is *nominal* and the acceptability of Component B is *inadequate* then the acceptability of the Weapon is *inadequate*.

The component acceptabilities are linguistic variables and are the antecedents of the implication. The consequent is "the acceptability of the Weapon". As noted earlier, linguistic variables are allowed to have membership in as many fuzzy sets as are needed so that a reasonably complete description of the quantity is possible. In this case we need $3 \times 3 = 9$ different implications to cover all the possible combinations of the two antecedents. We refer to this set of implications as a rule base. The complete form of the inference rule is

"(A is A_i and B is B_j) and (If A_i and B_j imply C_k) then C_k "

or

$[(A_i \wedge B_j) \wedge ((A_i \wedge B_j) \rightarrow C_k)], C_k$.

This statement is a special logical construct known as the modus ponens tautology and is the basic form of rule base used in all AR models. It can be seen that the combination of Implication 1 above and the statement "the acceptability of A is nominal and the acceptability of B is inadequate" is of exactly this form.

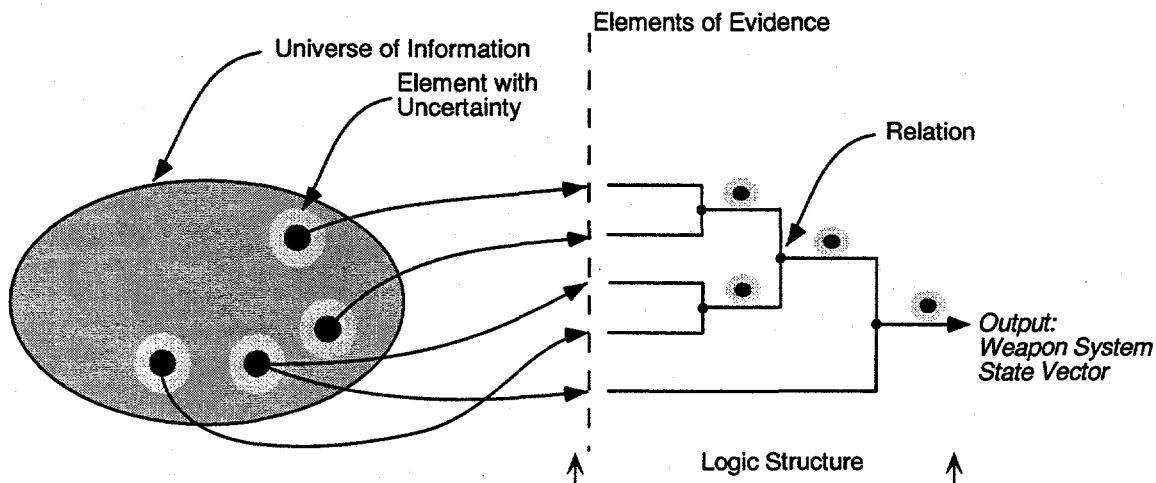


Figure 4. The relationship between a body of evidence and the logic structure used to evaluate it.

Statements of the modus ponens form are evaluated algorithmically in an AR model. We represent the nine implications in the rule base in Table IA. The shaded box is Implication 1. The expert judgment incorporated into this rule base will be discussed shortly. To illustrate how inferences are drawn in practice, let us arbitrarily assign acceptability membership vectors for the two components of $\gamma(A) = [.3, .6, .5]$ and $\gamma(B) = [.4, .7, .5]$. That is, Component A has DOMs of $\mu(\text{Inadequate}) = .3$, $\mu(\text{Marginal}) = .6$, and $\mu(\text{Nominal}) = .5$. Because both components have membership in all of the acceptability sets it is reasonable to expect that all of the implications in the rule base should be considered. The relative strength of these implications is determined using the max-min rule

(Ross 1995). In the first phase of the rule, the minimum degree of membership for the antecedent pair is found for each element in the rule base. This is shown in Table IB. The logic behind this step is that the strength of an individual rule is determined by the *weaker* of the antecedents. In the second phase of the rule, the maximum degree of membership of the consequent sets from phase 1 is found. Referring to Table IB, in the case of the inadequate acceptability set this is $\mu(\text{Inadequate}) = 0.4$ and the membership vector for the weapon is $\gamma(C) = [.4, .6, .5]$. The principle here is that for each consequent set the *strongest* rule should govern. In this particular case no clear-cut performance is possible. This is perfectly reasonable given the assumed degrees of membership for the antecedents. For now we might express the consequent linguistically as "the weapon state is marginal". A rule base to state explicitly how such weapon state vectors should be evaluated will be presented below.

Table IA.

$A \wedge B \rightarrow C$

A	N	I	M	N
	M	I	M	M
	I	I	I	I
		I	M	N
			B	

Table IB.

$A \wedge B \rightarrow C$

A	N .5	I .4	M .5	N .5
	M .6	I .4	M .6	M .5
	I .3	I .3	I .3	I .3
		I .4	M .7	N .5
			B	

AR Model for Reliability Assessment

An overview of the inductive logic structure used for determining weapon acceptability is shown in Fig. 5. The elements of evidence for a NWC system state assessment consist of data about individual components in

individual weapons and judgments about the quality of that data. The desired final output of the AR model for use in modeling the NWC is the acceptability of the nuclear weapons stockpile. To make this final inference it is necessary to make other subsidiary inferences about the acceptability of individual components, subsystems, weapons and weapon types. This series of forward chaining inferences is characteristic of AR models. As noted earlier we focus here on aggregation to the level of individual weapon.

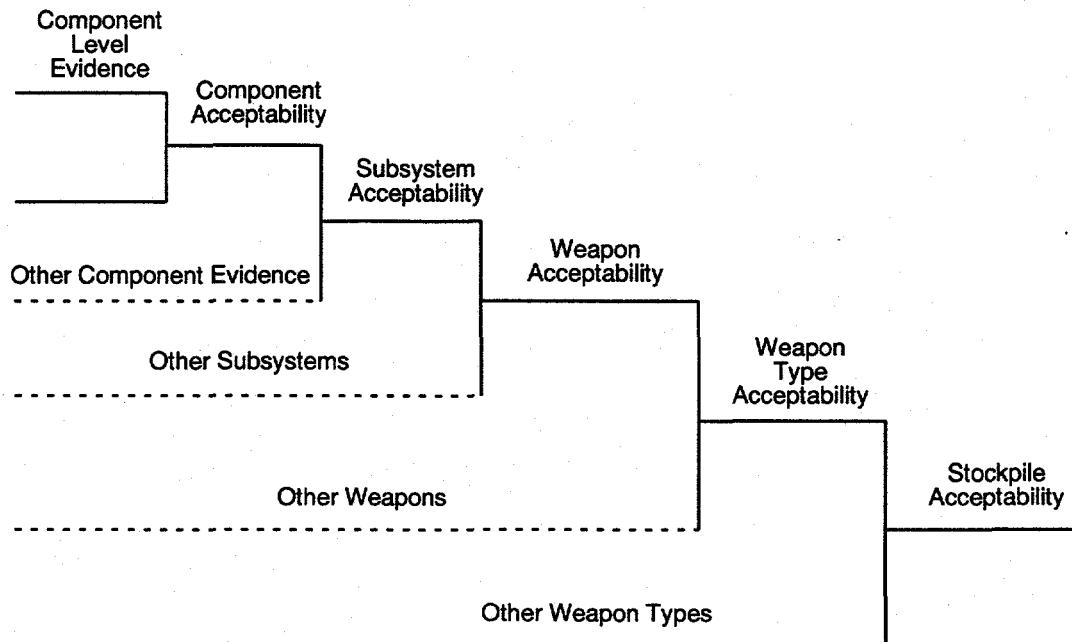


Figure 5. Overall logic structure for determining stockpile acceptability.

Acceptability for an Individual Component

Figure 6 shows the logic structure used to draw an inference about the acceptability of a single component. Here F denotes fraction of service life, D denotes a measure of defects or out of specification conditions and R is a quantitative reliability estimate for the component.² All of these elements of evidence are time-dependent. Q is a linguistic variable used to evaluate the quality associated with an element of evidence. We start by discussing the characteristics of each element of evidence and then explain how they are combined to draw the necessary inferences.

² The actual component lifetimes, defect rates and reliability metrics for nuclear weapons are classified. All numerical values used in this paper are for illustration purposes only.

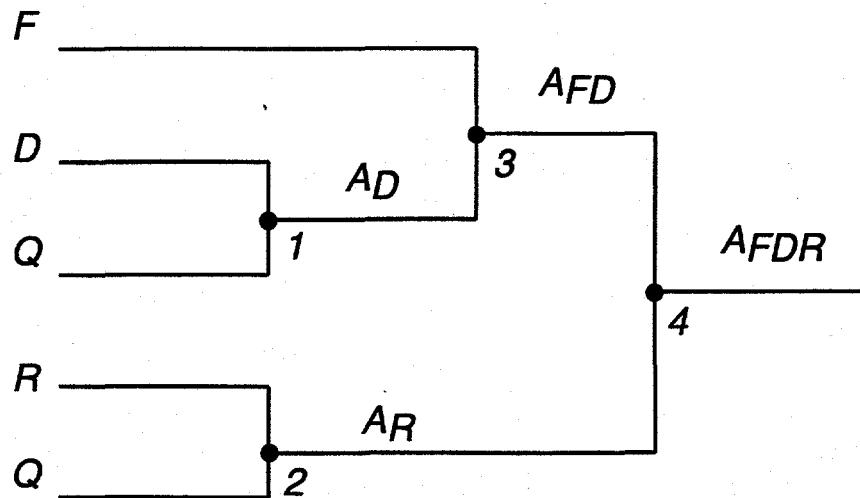


Figure 6. Logic structure used to determine component acceptability.

Fraction of Service Life, F

The fraction of service life for a component at time t is just

$$F = (t - t_0) / t_s$$

where t_0 is the time of manufacture and t_s is the specified service life of the component. The service life is determined primarily during initial design testing and for nuclear weapons reflects the results of underground tests as well as evaluations of accelerated aging units. Service life therefore incorporates implicitly the judgments of the weapon designers and component engineers. Service life may change as a result of the surveillance of weapons over time. Finally service life is component-based so to infer weapon acceptability it will always be necessary to define intermediate rule bases that allow this evidence to be combined.

In order to use F in the AR model it is first necessary to decide upon the natural language expressions that describe it sufficiently. One obvious set would be "small", "medium" and "large" and that therefore any value of F will be a member of one or more of these sets, $F \in \{\text{Small, Medium, Large}\}$. Three straightforward inferences that could be drawn immediately are

If F is small then the component acceptability is nominal.

If F is medium then the component acceptability is marginal.

If F is large then the component acceptability is inadequate.

In fact an inference of this form is always the first step in the consideration of F for any component. Therefore we chose to characterize these linguistic variables immediately using the expressions for acceptability. That is, $F \in \{\text{Inadequate, Marginal, Nominal}\}$.

Numerical values of F must be converted into degrees of membership in these sets before the information can be processed in the AR model. This is done using membership functions such as those shown in Fig. 7. These membership functions must be defined for each component and can vary in shape (subject to certain consistency constraints) and in the locations where full membership in a particular set occurs. Referring to Fig. 7, if $F = 0.5$ for Component C_i , then at this particular time it has degrees of membership in {Inadequate}, {Marginal} and {Nominal} of 0, 0 and 1.0 respectively, $\gamma_F(C_i) = [0, 0, 1]$. Similarly, if $F = 1.6$, then $\gamma_F(C_i) = [0, .75, .25]$. Note that in the latter case F has membership in two of the acceptability sets. Although we have defined all of the membership functions in this paper so that a specific element of evidence will have non-zero membership in at most two fuzzy sets, this is not an AR requirement. If for example in Fig. 7, the intercept with the abscissa for {Inadequate} were moved leftward from $F = 1.5$ to 1.0, then for values of F in the interval $[1.0, 1.5]$, non-zero membership in all three sets would occur. A set of membership functions for F must be defined for each component in the system.

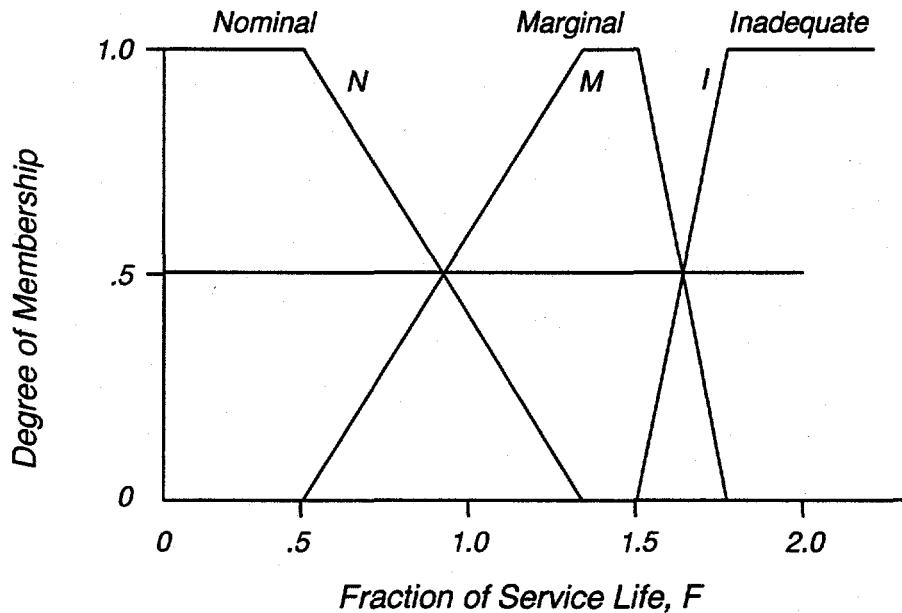


Figure 7. Example membership functions for fraction of service life, F .

Measure of Defects or Out-of-Specification Conditions, D

Components in nuclear weapons follow the familiar bathtub curve for occurrence of defects: birth defects are seen at early time, followed by a long period where defects occur rarely and a final stage where defects appear at an increasing rate. In the past, weapon systems have been retired from the stockpile before this final stage was reached so little data exists on how rapidly the defect rate may increase. Observations of defects or out-of specification components are made as part of an extensive surveillance program that includes both non-destructive and destructive testing. Statistical models are then employed to predict the probability of a number of defects as a function of time. D is also either component or subsystem based so some aggregation method is required to

evaluate an individual weapon. How does the presence of a number of defects or out of specification conditions affect the acceptability of a component? If a reliability model does not exist for the component then we might infer that as the number of defects increases the likelihood of a condition that could affect weapon performance – a lethal defect would increase. We can express this likelihood as a linguistic variable by assigning membership to the fuzzy sets {Extremely Unlikely}, {Very Unlikely}, {Unlikely}, {Likely} and {Very Likely}. Modifiers such as "extremely" and "very" are referred to as hedges and are used in AR to represent the qualifiers often employed by subject matter experts. Figure 8 shows notional membership functions for assigning numbers of defects or out-of-specification conditions to the likelihood metric sets. It is important to note that we use the expression "likelihood" in the sense that it "supplies a natural order of preference among the possibilities under consideration" (Thomas 1995). That is, something that is said to be "very likely" is understood to have a more realistic chance of happening or to occur more frequently than something that is "likely" or "extremely unlikely." However it must be emphasized that the likelihood linguistic variable is not to be confused with quantitative probability nor do we intend our use of likelihood to be associated directly with the likelihood function of probability theory.

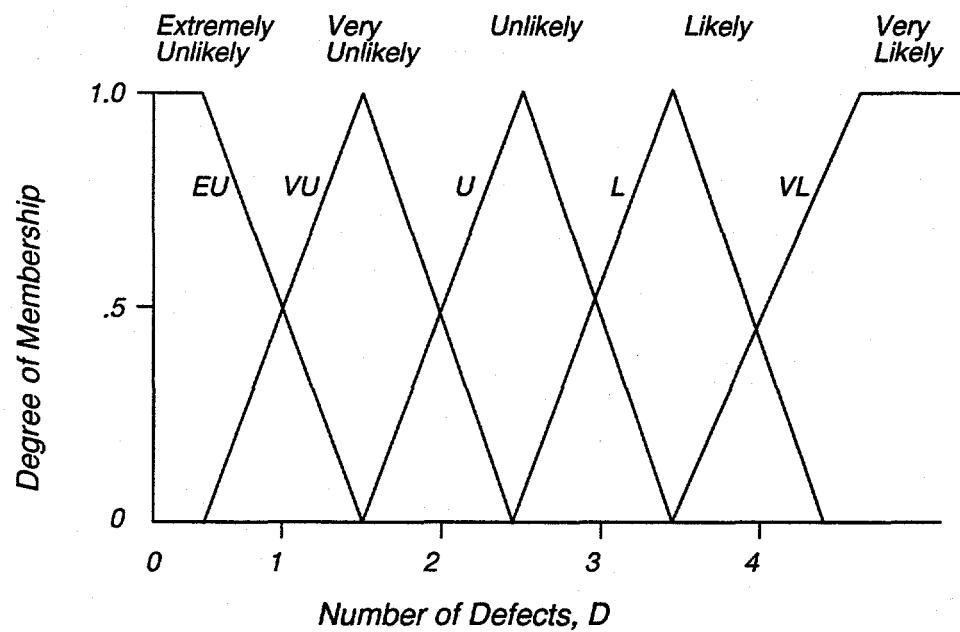


Figure 8. Example membership functions for number of defects, D.

Both defect rate and reliability are explicitly model-based. Therefore it is necessary to incorporate some judgment about the quality of the data and model that are being used. This evaluation is done by incorporating a linguistic variable, Q that represents an expert judgment about the quality of the prediction. The sets used for Q are $Q \in \{\text{Poor}, \text{Fair}, \text{Good}\}$. Several approaches for assigning degrees of membership in these sets using expert elicitation are

discussed in (Eisenhower 1998). We will discuss a rule base that uses D and Q shortly.

Reliability, R

Reliability estimates for weapon systems beyond their original design life are not currently available. However, for certain components sufficient accelerated aging data and validated reliability models exist so that beyond-design life reliability can be predicted. For such components this metric naturally is very useful. Additionally, as the results of Science-Based Stockpile Stewardship appear, reliability models for other components and subsystems will become available and will be incorporated into the AR model. Figure 9 shows a set of notional membership functions for R. Here we use the natural language expressions ranging from very high to very low to describe the fuzzy sets to which numerical values of R are to be assigned. For very high performance systems it would be reasonable to expect that $1 - R \ll .01$ for an assignment to {Nominal} and this would be incorporated into the membership functions accordingly. As noted above, the quality variable Q is also used with this metric.

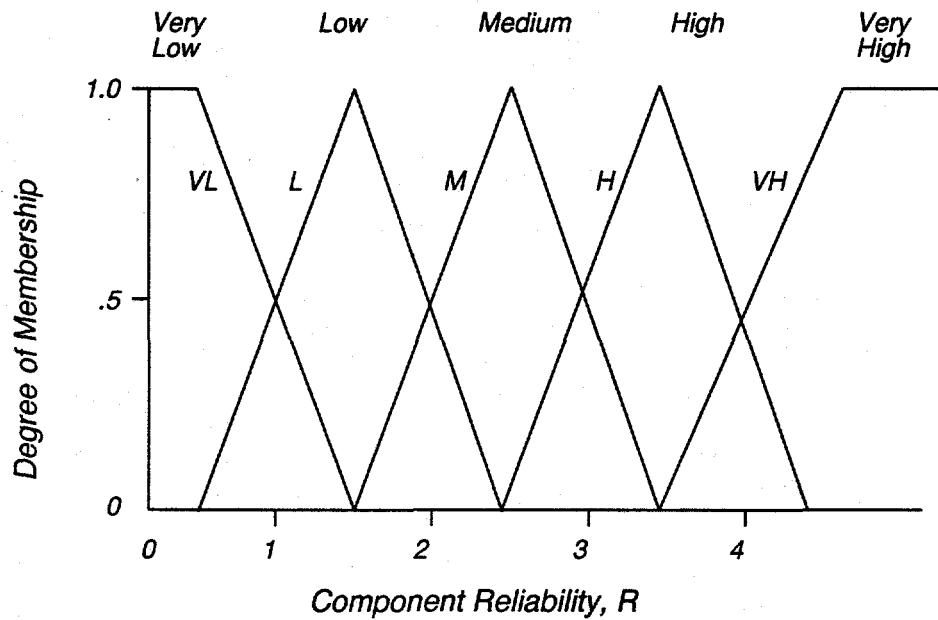


Figure 9. Example membership functions for reliability, R.

Figure 10 shows all three of the elements of evidence as a function of time. It is evident that the three are closely related. Service life is initially determined before the component or system goes into service. In some cases the determination of service life may be derived from a reliability model. As surveillance data becomes available, realistic estimates for numbers of defects become possible. This may result in modifications of service life or changes in reliability estimates. For the case considered here, it is realistic to assume that the AR model must initially operate with very little defect and reliability evidence.

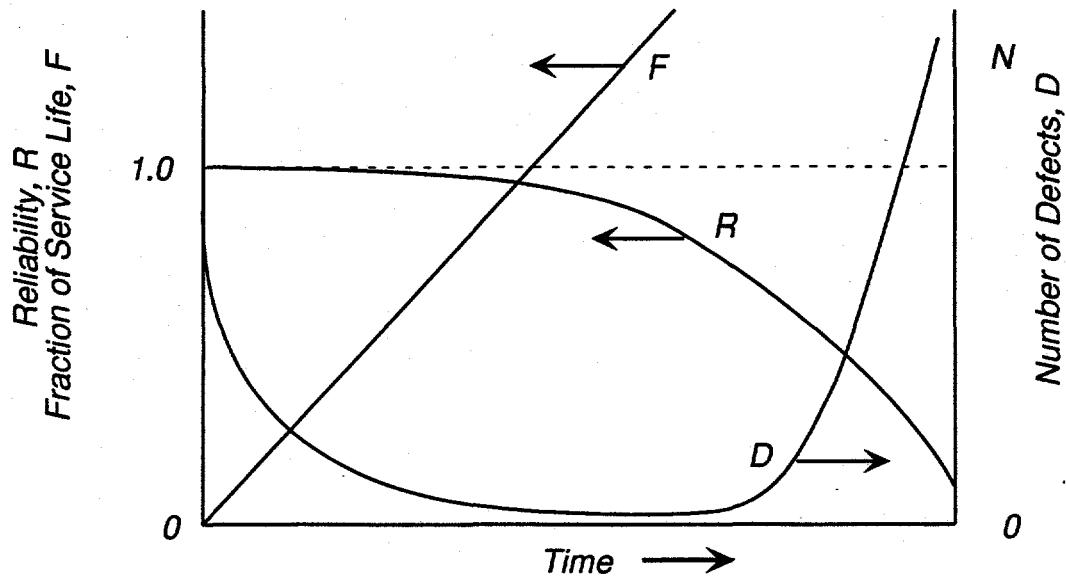


Figure 10. Relationship between the three elements of evidence used to measure component state.

Inference Chain for a Single Component

Each node in Fig. 6 is an inference of the form discussed earlier. We consider first Node 1 associated with D and Q_D . The importance that we attach to the likelihood of a lethal defect certainly depends upon some consideration of the quality of the data and model used to estimate it. We incorporate this weighing of the evidence into the AR model by explicitly defining how component acceptability will be inferred from D and Q . One possible rule base to do this is shown in Table II. This rule base reflects a positive bias towards weapon function. Good data is required to convince an expert that there is a problem with a weapon. Otherwise the weapon is assumed to be functionally nominal.

Table II.

$$D \wedge Q \rightarrow A_D$$

D	EU	N	N	N
	VU	N	N	M
	U	N	M	M
	L	M	M	I
	VL	M	I	I
		P	F	G
		Q		

The shaded box corresponds to the rule: "If the likelihood of a lethal defect is *unlikely* and the quality is judged *good*, then the component acceptability is *marginal*." In this version of the rule base the inference that the acceptability is nominal can occur when the quality is judged good only if the number of defects is assigned to {Extremely Unlikely}. However if Q is poor then even an assignment of D to {Unlikely} will yield in a nominal acceptability. Underlying this rule base is a perspective that poor evidence should not be given too much influence.

A similar inference must be drawn for the reliability evidence. Here the reliability estimate is placed into context by considering how confident one feels about the surveillance data and the statistical model being used. A rule base similar to Table II that allows this assessment is given in Table III.

Table III.

		$R \wedge Q \rightarrow A_R$		
		N	N	N
		N	N	M
R	VH	N	M	M
	H	M	M	I
	M	M	I	I
	L			
	VL			
		P	F	G
		Q		

Node 3 in Fig. 6 is an example of aggregation. Here two acceptability measures must be combined to infer a joint acceptability. The rule base for this is shown in Table IV. The structure of this rule base is identical to that in Table II and the actual inferences are the same as those discussed earlier in the discussion of modus ponens rule bases and the max-min rule (Tables I). Only the linguistics used to describe one of the antecedents has changed. The shaded box corresponds to the rule: "If the defect rate acceptability is *marginal* and the fraction of service life is *nominal* then the aggregate acceptability is *marginal*." Several characteristics of this rule base should be noted. First, both antecedents are given the same importance in the inference. Therefore the rule is symmetric about the right diagonal. If the expert judgment were that defect evidence should be given more importance then the rule base would be changed to reflect this judgment. Secondly if either acceptability is "inadequate" then so is the aggregate. Finally, if there is no defect evidence then when using this rule base A_D is given full membership in {Nominal}. In this case the aggregate acceptability reflects the judgment based upon the service life evidence only.

Table IV.

$$A_D \wedge F \rightarrow A_{FD}$$

A_D	N	I	M	N
	M	I	M	M
	I	I	I	I
		I	M	N
			F	

A rule base of the same form is used for Node 4 to obtain the inferred acceptability for a component. This is shown in Table V. Again if there is no reliability evidence then the other antecedent that uses the F and D evidence alone determines the inference.

Table V

$$A_R \wedge A_{FD} \rightarrow A_{FDR}$$

A_R	N	I	M	N
	M	I	M	M
	I	I	I	I
		I	M	N
			A_{FD}	

Aggregation of Component Acceptability

The inductive logic structure for inferring weapon acceptability is designed to allow for the evaluation of several alternatives

- 1) all components are equally important
- 2) certain components are especially important
- 3) the acceptability of subsystems must be considered.

Note that these considerations arise because of the absence of a system reliability model. The AR structure therefore must incorporate logic that represents subject matter experts' judgments about how to evaluate these possibilities. In this paper we consider only the first and third cases. Nuclear weapons systems are

not highly redundant and therefore all major components can be considered to be of equal importance.

If all components are equally important then aggregation to the weapon level proceeds as follows. First find the maximum degree of membership in each acceptability set over the set of all components. For example if $\gamma(C_1) = [0, 0, 1]$, $\gamma(C_2) = [.2, .5, .4]$, and $\gamma(C_3) = [.8, .2, 0]$ then this operation yields $\max \gamma = \gamma(C_1, C_2, C_3) = [.8, .5, 1]$. The process of converting this vector into a definite natural language expression is a form of defuzzification (Ross 1995). We currently use the rule that if the degree of membership in {Inadequate,} is greater than 0.5 then the weapon state is inadequate. If the weapon state does not satisfy this criterion then it is tested in the same way to determine if the acceptability is marginal. If it is neither inadequate nor marginal then the weapon state is nominal. In the example here the result would be "the weapon state is inadequate". Similarly if $\gamma(C_1, C_2, C_3) = [.0, .4, .7]$ then the weapon state is nominal. The defuzzification rule is described compactly in Eq.1.

- If $\mu(\max \gamma, \text{Inadequate}) \geq 0.5$ then the weapon state is Inadequate
- If $\mu(\max \gamma, \text{Inadequate}) < 0.5$ and $\mu(\max \gamma, \text{Marginal}) \geq 0.5$ then the weapon state is Marginal
- If $\mu(\max \gamma, \text{Inadequate}) < 0.5$ and $\mu(\max \gamma, \text{Marginal}) < 0.5$ then the weapon state is Nominal

(1)

If subsystems must be considered then the concern involves how to treat situations where multiple components that are "marginal" occur. We illustrate the general approach by example. Suppose that two components C_1 and C_2 form a subsystem as do components C_3 and C_4 . The two subsystems are then combined into a higher level subsystem. Table VI shows the possible outcomes. M_{123} denotes that all three components C_1 , C_2 and C_3 have been independently assigned to the marginal set. At this stage expert opinion is required to determine which of these marginal possibilities should be considered to represent an inadequate state. Suppose for illustration that all multiple marginal possibilities greater than pairs are considered to be inadequate weapon states. That is, we infer that if three or four components in a subsystem are marginal considered singly then the subsystem itself should be considered inadequate. Table IV then becomes Table VII. It is important to note that the order in which the components are grouped is important because of the way in which the inference rule bases are evaluated. That is, to apply this rule base to make an inference about sub-system acceptability, the components must actually be members of a distinct subsystem.

The basic logic structure, generic membership functions and rule bases described here are sufficient to allow evaluation of a system of arbitrary size. In the next Section we consider a small system that illustrates the operation of an AR model.

Table VI

A_{C1C2}	N	I	M_{34}	M_4	M_3	N
	M_1	I	M_{134}	M_{14}	M_{13}	M_1
	M_2	I	M_{234}	M_{24}	M_{23}	M_2
	M_{12}	I	M_{1234}	M_{124}	M_{123}	M_{12}
	I	I	I	I	I	I
		I	M_{34}	M_4	M_3	N

A_{C3C4}

Table VII

A_{C1C2}	N	I	M	M	M	N
	M_1	I	I	M	M	M
	M_2	I	I	M	M	M
	M_{12}	I	I	I	I	M
	I	I	I	I	I	I
		I	M_{34}	M_4	M_3	N

A_{C3C4}

Illustrative Results

For our example problem we consider the fictitious three component weapon system shown in Fig. 11. Components 1 and 3 have only service life elements of evidence associated with them while for Component 2 there exist service life and defect rate information. Further, Components 2 and 3 comprise a single subsystem. All components are assumed to be of equal importance. For some time t , the membership functions for the components yield the degrees of membership for F_1 , F_2 , D_2 and F_3 shown. Also the quality associated with D_2 is judged to have degrees of membership of $\gamma_Q = [0, .6, .4]$ in { Poor, Fair, Good }. Such a situation might occur if Component 1 had been replaced before time t and the other components were becoming increasingly marginal as judged by service life or an estimate of the number of defects present.

Also shown in Fig. 11 are the results of the evaluation of the implication rule base for each node. For reference Node 1 corresponds to the rule base in Table I, Node 2 uses Table II, the rule base for Node 3 is a two component version of Table VI and Node 4 uses the rule defined in Eq. 1. We discuss each node briefly below.

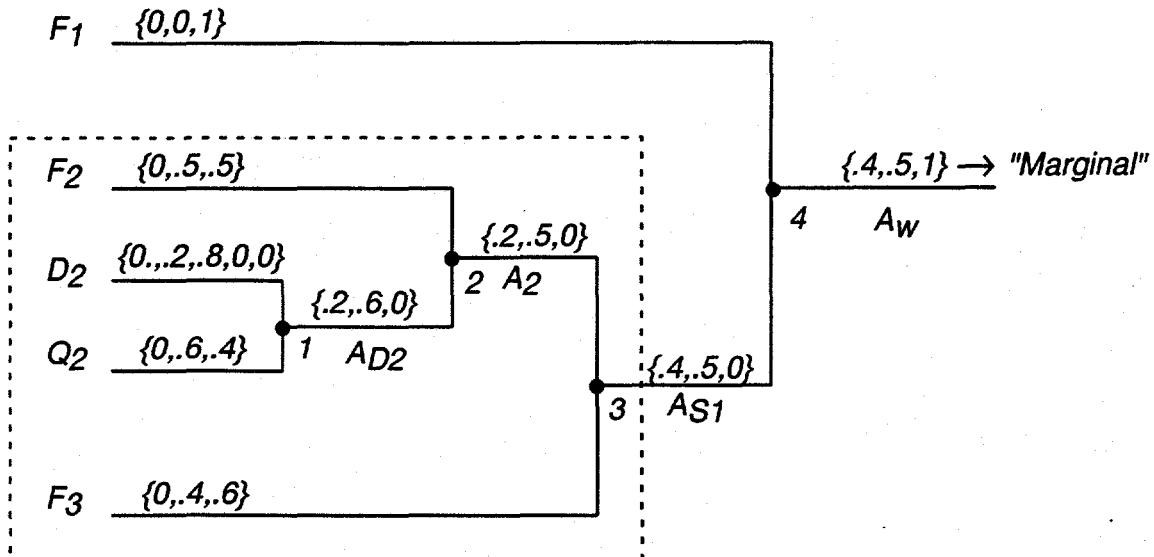


Figure 11. Logic structure for illustrative weapon acceptability AR model.

As noted earlier, evaluation of a rule base proceeds according to the max-min rule. Table VIII shows the evaluation for Node 1. The shaded boxes are those that correspond to the maximum of the minima for each consequent set with non-zero membership. In this case the degrees of membership for the acceptability of Component 2 based upon the defect rate evidence is [.2, .6, 0]. Linguistically this corresponds to "the acceptability is marginal tending toward inadequate." Node 2 evaluates in a similar fashion to $A_{FD} \rightarrow [.2, .5, 0]$. This may appear somewhat surprising since F has a degree of membership in {Nominal} of $\mu(F_2) = 0.5$. However the consequent cannot have a non-zero membership in this set because A_{D2} has no membership in {Nominal}.³

Table VIII

		$D \wedge Q \rightarrow A_D$		
		N (0, 0)	N (0, .6)	N (0, .4)
		N (0, 0)	N (0, .6)	M (0, .4)
D	U .8	N (.8, 0)	M (.8, .6)	M (.8, .4)
	L .2	M (0, .2)	M (.2, .6)	I (.2, .4)
	VL 0	I (0, 0)	I (0, .6)	I (0, .4)
	P 0		F .6	
	Q		G .4	

³ The only numerical values for degrees of membership that appear anywhere in an AR model are those associated with the elements of evidence. The sets to which these numbers apply change as the chain of inferences is drawn.

Node 3 is an aggregation inference for a subsystem. The condensed version of Table VI is shown in Table IX. For this example we assume that the multiple marginal M_{23} (shaded in the Table) is judged to be of particular concern and add the internal inference that $M_{23} \rightarrow I$. Note that by concluding that multiple marginal components in this subsystem are unacceptable the degree of membership in {Inadequate} has increased from 0.2 to 0.4.

Table IX.

$A_{C2} \wedge A_{C3} \rightarrow A_{S1}$		
A_{C2}	N - 0	$I - (0, 0)$
	M - .5	$M_{23} - (0, .4)$
	I - .3	$M_3 - (0, .6)$
	I - 0	$I - (.5, 0)$
		$M_2 - (.5, .6)$
		$I - (.3, 0)$
		$I - (.3, .4)$
		$I - (.3, .6)$
	M - .4	N - .6
	F_{C3}	

Finally, at Node 4 the complete weapon acceptability is inferred. The calculation of $\max \gamma$ produces an acceptability vector for the system of $\max \gamma = [.4, .5, 1]$ and according to Eq. 1 this evaluates to "Marginal". That is, for the notional elements of evidence presented, the corresponding AR model produces a final inference that the state of the weapon is marginal. Given the nature of the membership functions discussed above it is clear that the degree of membership in {Inadequate} will increase as a function of time and that this particular weapon will become increasingly unacceptable unless some corrective action is taken.

If no defect evidence were available then, for all other evidence the same, $\max \gamma = [0, .5, 1]$, which evaluates again to marginal. In this case however, the state vector has zero membership in {Inadequate} and the interpretation of the severity of the situation would be different. The state vector contains information about how the acceptability metric is changing.

Discussion

The weapon state vector and the weapon acceptability are time-dependent because F , D and R for the components are functions of time. Therefore the AR model must be run for a number of different times in order to understand how the weapon state evolves. Figure 12 shows how the components of the state vector can change and weapon acceptability degrades from nominal through marginal to inadequate according to Eq. 1.

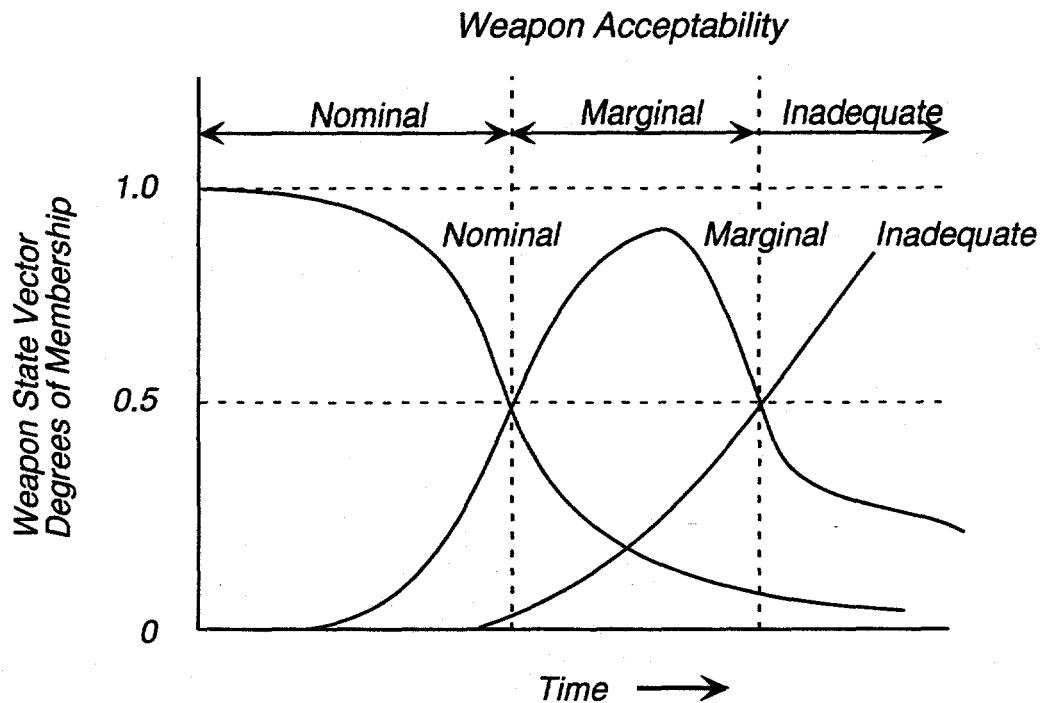


Figure 12. Time-dependent behavior of the weapon state vector elements and the acceptability metric.

It is also the case that the elements of evidence are stochastic. We expect for example that the number of defects as a function of time is a random variable characterized by a probability density function. The underlying distribution or the parameters defining it may also be uncertain. This means of course that the outputs of the AR model are stochastic as well. Thus rather than express the acceptability as simply "marginal", we now must make a statement such as "at the 90th percentile the weapon state is marginal". We treat this situation by using Monte Carlo simulation. This introduces additional considerations beyond the scope of this paper that are discussed in Eisenhower (1998). One can view the addition of Monte Carlo sampling to AR as the analog of an expert's expression of confidence in his judgment.

As part of our research efforts at Los Alamos National Laboratory, we have developed system-level tools based on the concepts of virtual manufacturing for assessing the capability of the NWC to perform its mandated mission. Los Alamos is studying the science and developing the concepts and methods for a new generation of "enterprise" modeling technologies to address long-term planning options.

A comprehensive system model will be used to assess the performance of future NWC manufacturing alternatives with the intent of identifying production configurations that are best capable of achieving the goals and objectives of the Department of Energy. It is during the process of searching many alternatives that the intuition we seek about the real system performance begins to emerge as a formal product of the computational experiment.

Applying the weapon acceptability metric is an essential element that enables us to understand how well possible NWC alternatives actually meet expectations.

To maintain the weapon stockpile, DOE must decide when, where, and the extent of intrusion required to upgrade and/or refurbish weapon components. The weapon maintenance job is remarkably constrained by the limited capability of the downsized NWC manufacturing infrastructure. The present maintenance process relies on engineers, designers, and various subject matter experts to produce schedules intended to extend the service life of nuclear weapons. These schedules are referred to as Lifetime Extension Options (LEO). Current LEO planning is a manually executed process – essentially a guess and test methodology. Use of the Los Alamos NWC model will enable us to rapidly develop globally optimal, component-by-component maintenance strategies.

The ability to develop maintenance schedules using weapon acceptability measures to optimize overall NWC system performance will be a significant improvement in how business is conducted by DOE. A model-based approach can significantly reduce the cost and time it takes to produce LEOs and will increase the overall effectiveness of the NWC manufacturing system.

At this time we are in the early stages of evaluating acceptability for a stockpile of several thousand individual weapons of seven different types. Each weapon in this model has seven individual components that in several cases are actually subsystems themselves. The acceptability for various proposed LEOs will be determined subject to infrastructure constraints imposed on NWC performance.

We anticipate that this is only the initial application for the approach discussed here. We are working on incorporating AR into advanced, adaptive models for the NWC and industry. In these models AR will be an important tool in evaluating the fitness of solutions found by the adaptive search algorithms. We expect to see enterprise models that incorporate AR and adaptive search used to evaluate other manufacturing-related issues within government operations and, eventually, throughout all of industry. The fact that a model of the NWC can now quantitatively address an enterprise-level task of this magnitude is a direct result of the development of the AR methodology discussed in this paper.

Conclusions

In this paper we have proposed an approach based upon the theory of approximate reasoning for assessing the state of a system in the absence of a complete reliability model. Such an approach is needed now for modeling the NWC. Our approach is centered around an inductive logic structure that specifies how the evidence on individual components and subsystems can be used to draw inferences about the state of individual weapons and aggregations of weapons up to the level of the national stockpile. The metric used to describe the state of entities from components up to aggregations of weapons is acceptability. Acceptability is a linguistic variable defined in terms of the fuzzy sets {Nominal}, {Marginal} and {Inadequate}. Inferences about acceptability are drawn using rule bases that describe how specific antecedents are related by

logical implication to a consequent. The sequence of forward-chaining inferences emulates the evaluation process used by subject matter experts.

We have developed logic structures that allow different kinds of evidence about a component to be combined. This logic also allows for the assessment of evidence quality. Several possibilities for component aggregation have been proposed, in particular a method for treating the case where components must be treated as part of a subsystem.

Through the use of an illustrative example, the application of this methodology to the assessment of a small fictitious system is described. The time-dependent nature of the assessment is easily treated with the AR model and the extension to a system where the evidence is stochastic is straightforward.

The acceptability metric has proven to be a useful metric in the development of a NWC simulation model. We are encouraged by the results to date and are working on incorporating approximate reasoning into an advanced, adaptive model for the Complex. We suggest that the approach used here may be applicable to other systems where decisions related to system performance must be made without detailed reliability data.

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