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A POSSIBILISTIC APPROACH TO QUALITATIVE MODEL-BASED DIAGNOSIS

Cliff Joslyn

Abstract—The potential for the use of possibility theory in the qualitat model-based diagnosis of spacecraft systems is described. The first section the paper briefly introduce the Model-Based Diagnostic approach to spa craft fault diagnosis, Qualitative Modeling methodologies, and the conce of possibilistic modeling in the context of Generalized Information Theo Then the necessary conditions for the applicability of possibilistic method qualitative model-based diagnosis, and a number of potential directions such an application, are described.

INTRODUCTION

Possibility theory is being developed as an alternative to traditio theories of uncertainty. While possibility is logically independent of probability theo they are related: both arise in Dempster–Shafer evidence theory as fuzzy measu defined on random sets; and their distributions are fuzzy sets. Together these fie compose the new field of Generalized Information Theory (GIT).

Possibility distributions are built from a set of partially overlapping intervals, resu ing in non-additive, possibilistic weights on a set of alternatives. Possibilistic proces generalize both interval arithmetic methods and nondeterministic processes. Possibi tic models provide a Qualitative Modeling (QM) method which is a hybrid of inter and uncertainty distribution methods.

Qualitative methods are appropriate for modeling complex systems, such as spa craft, where the interaction among the large number of parts under varying envir mental conditions results in the possibility of unpredictable behavior and long- departure from established steady-state domains. These methods inherently requ loose representations of uncertainty, and typically involve interval analysis. Therefo it is hypothesized that possibilistic methods may be useful for qualitative model-ba diagnosis and trend analysis of spacecraft systems.

MODEL-BASED DIAGNOSIS

The model-based approach to systems diagnosis (MBD) (Hamscher, Console, & Kleer, 1992) is based on the premise that knowledge about the internal structure o

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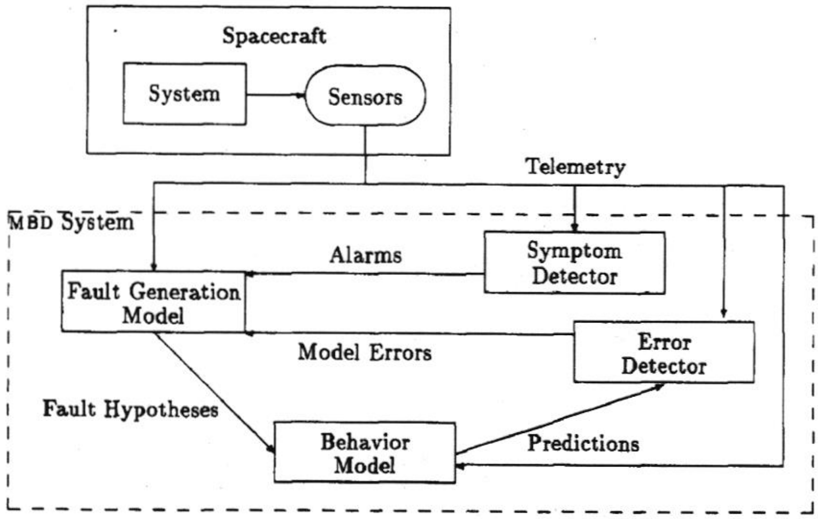

Figure 1. A typical model-based diagnostic system.

system can be useful in diagnosing its failure. In MBD, a software model of the syst
generates and tests various failure hypotheses when given inputs from the real syste

A typical MBD approach (derived from some of the standard literature [Davi
Hamscher, 1992; Dvorak & Kuipers, 1992; Hall, Schuetzle, & La Vallee, 1992])
diagnosing a spacecraft (here described as an internal system whose sensor measu
ments output to a telemetry stream) is shown in Figure 1. An alarm is a report t
some observed system attributes have departed from nominal conditions and ente
error, conditions, usually by exceeding some threshold values. A prediction is a rep
that some system attributes should be in certain states. A fault hypothesis is a list
system components that may have failed. An error is a report of a discrepancy betw
predicted and measured system attribute states.

The overall MBD system then involves two distinct spacecraft models. The Fa
Generation Model (FGM) takes inputs from telemetry, alarms, and errors, and eit
produces new, or modifies existing, fault hypotheses. The behavior model takes inp
from telemetry and fault hypotheses, and outputs predictions. These are then corro
rated against telemetry to produce errors. The fault hypotheses act to modify
behavior model so that it predicts system behavior as if the hypothetical system com
nents had actually failed.

Both models can be difficult to construct, typically requiring delicate enginee
tradeoffs among accuracy, precision, and tractability. But the FGM, as the heart
the MBD approach, is particularly complex and involved. The FGM could be,
example, an inversion of the behavior model (as for Dvorak and Kuipers [1992]) o
decision tree (as for Shen and Leitch [1991]). Through backward reasoning, a var
of subsets of components, failure of any of which is consistent with the given telem
and alarms, can be identified.

Filtering is the process by which error output is used to prune the set of fa
hypotheses. If the prediction of the behavior model as modified by a particular fa
hypothesis produces errors, then that fault hypothesis is not retained. As the syster
monitored over time, further observations narrow the class of viable fault hypothe

Achieving the null set indicates model insufficiency. But if the overall MBD syst stabilizes to a non-empty set of fault-hypotheses, then these are advanced as possil causes of the failure.

QUALITATIVE MODELING

Qualitative modeling, a branch of Systems Science usually considered to be a part the field of Artificial Intelligence, can be broadly described as the attempt to mo systems at deliberately high levels of abstraction. Of course, this approach produ models that are less precise than they might be, but with the tradeoff of potentia greater tractability and accuracy (the less you say, the better your chance of bei right). QM methods can be useful when there is only a poor model of the origi system, or when there are missing or incomplete data. This can happen when syste are incompletely specified, when they have parameters or states that aren't alw known with certainty, or when complexity makes detailed prediction difficult.[1] Th are a variety of broad approaches within QM, which can be known as naive physi qualitative physics, qualitative simulation, qualitative reasoning, qualitative dynami etc. There are also a number of specific methods, including bond graphs, cau loop modeling, natural language modeling, "lumped" state space models and induct approaches.

In this paper, the QM methods of most interest are those that use uncertai distributions on state variables, or mixed interval- and point-valued dynamical s tems. In models using uncertainty distribution methods, the uncertainty about so attribute is represented mathematically by weights on all possible values. The set weights, as a distribution, acts as a meta-state in the space of all such distributio and functional equations relating these meta-states produce predictions about meta-state distribution at future times. Models using probability distributions are miliar as Markov processes and other kinds of stochastic models, and these h correlates in possibility theory (see "Possibilistic Models" below). These methods actually semi-qualitative, because the numerical representation of the distribution a a quantitative component.

In an interval-valued dynamical modeling system like QSIM (Kuipers, 1989) precise point-valued dynamical system of differential or difference equations is placed by a homomorphic interval-valued process. Typically, qualitative variables identified within certain intervals, some relatively unconstrained (for example $[0,\infty)$), and some constrained by "landmark" values (for example $x \in [x_{\min}, x_{m}$ where $x_{\min}$ and $x_{\max}$ may or may not be known).

Qualitative variables are then generally related in three ways:

- Functional: For example, if $y = M^{-}(x)$ then y is a monotonically decreasi function of x, so that if $x \in [0,x_{\max})$ then $y \in (-\infty,0]$ or $y \in (M^{-}(x_{\max}),0]$.
- Arithmetic: Standard mathematical operations can also be represented quali tively, for example if $x \in [0,x_{\max}]$ and $y \in (-\infty,0]$, then $xy \in (-\infty,0]$, but x y is unknown. These interval arithmetic methods (Moore, 1979) are closely rela to possibility theory (see "Possibility Theory and Interval Analysis" below).
- Dynamic: Change of state is represented by qualitative magnitude and directi

[1] For more information about QM in general, see the anthologies edited by Bobrow (1985), and Fishv and Luker (1990), and survey articles by Fishwick (1989) and Guariso, Rizzoli and Werthner (1992).

and qualitative differential relations link directions with magnitudes. For exam given $y = dx/dt$, then

$$x \text{ increasing} \rightarrow y \in (0,\infty), \qquad x \text{ decreasing} \rightarrow y \in (-\infty,0).$$

Of course, determinative results may not be available in such qualitative models. example, we saw above that $x + y$ could be any value in $(-\infty,\infty)$. Similarly, existence of potentially unknown landmark values leads to uncertainty as to wheth landmark has been crossed. To account for both possibilities, two alternatives n be considered independently, resulting in a branching nondeterminism. Therefore general, QM systems have a tree of possible system behaviors, and external fac (heuristics or other constraints) may be required to prune that tree.

QM has been applied to MBD to produce qualitative model-based diagnostic tems. For example, in the approach of Dvorak and Kuipers (1992), model predicti are intervals of possible system state values. Stochastic methods, for example Baye networks (Gertler & Anderson, 1992) and Markov processes (Grossman & Werth 1993), have been used extensively in MBD applications. And recently, Shen and Le (1991, 1993) have advanced the FuSim method for qualitative MBD which uses fu arithmetic (see "Possibility Theory and Interval Analysis" below).

POSSIBILITY THEORY

Possibility theory was originally developed in the context of fuzzy systems the (Zadeh, 1978), and was thus related to the kinds of cognitive modeling that fuzzy are usually used for. More recently, possibility theory is being developed as a new fc of mathematical information theory complementing probability theory in the con of GIT. The author is developing mathematical possibility theory on the basis consistent random sets, and is also developing an empirical semantics for possibil including possibilistic measurement procedures and applications to the modeling physical systems.

Possibilistic mathematics in GIT

Table 1 summarizes the primary formulae of probability and possibility theory in context of GIT and random set theory. The mathematical basis of possibility theor the context of GIT can only be briefly introduced here.[2]

Given a finite universe $\Omega := \{\omega_i\}, 1 \leq i \leq n$, the function $m:2^\Omega \rightarrow [0,1]$ is evidence function when $m(\emptyset) = 0$ and $\Sigma_{A\subseteq\Omega} m(A) = 1$. m effectively acts as a pro bility distribution on the *subsets* of Ω, and so a random set generated from an evide function is denoted

$$\mathcal{S} := \{\langle A_j, m_j\rangle : m_j > 0\},$$
$$A_j \subseteq \Omega, \quad m_j := m(A_j), \quad 1 \leq j \leq N := |\mathcal{S}| \leq 2^n - 1,$$

where $\langle\cdot\rangle$ is a vector and each A_j is a focal element. Denote the focal set as $\mathcal{F} := \{$ $m_j > 0\}$ with core and support

[2]See Dubois and Prade (1988), Joslyn (1994c), Klir (1993), and Klir and Folger (1987) for more info tion.

$$\mathbf{C}(\mathfrak{F}) := \bigcap_{A_j \in \mathfrak{F}} A_j, \qquad \mathbf{U}(\mathfrak{F}) := \bigcup_{A_j \in \mathfrak{F}} A_j$$

respectively.

Random sets were first developed in the context of stochastic geometry, deali generally with random compact subsets of $\mathbb{R}^n$ (Kendall, 1974; Matheron, 1975). It only more recently that random sets are being integrated into the formalisms of G (Mahler, 1993; Nguyen, 1978).

In Dempster–Shafer evidence theory (Shafer, 1976) m is called a "basic probabil assignment" and $\mathcal{S}$ a "body of evidence". Given a random set or body of evidence, th the plausibility and belief measures are defined on all $A \subseteq \Omega$ as

$$\mathrm{Pl}(A) := \sum_{A_j \cap A \neq \emptyset} m_j, \qquad \mathrm{Bel}(A) := \sum_{A_j \subseteq A} m_j$$

They establish respectively an upper and lower bound on $\Pr(A)$. Since they are du in that $\mathrm{Bel}(A) = 1 - \mathrm{Pl}(\bar{A})$, in general only plausibility will be considered below.

The plausibility assignment (otherwise known as the trace or one-point cover function) of $\mathcal{S}$ is $\vec{\mathrm{Pl}} = \langle \mathrm{Pl}_i \rangle := \langle \mathrm{Pl}(\{\omega_i\}) \rangle$, where

$$\mathrm{Pl}_i := \sum_{A_j \ni \omega_i} m_j, \qquad ($$

and the summation is over all the A_j containing ω_i.

Since each $\mathrm{Pl}_i \in [0,1]$, therefore $\vec{\mathrm{Pl}}$ can be taken as a fuzzy subset of Ω, where indicates the degree or extent to which ω_i is included in the set. In turn, a given fu set can be mapped to a class of one-point equivalent random sets on Ω (Joslyn, 1994 This provides a key link within GIT between fuzzy theory and both random set a possibility theory (see "Possibility Theory and Fuzzy Theory" below).

Under certain conditions the evidence values m_j and the plausibility assignm values Pl_i are mutually determining. Then $N \leq n$, and $\vec{\mathrm{Pl}}$ is called a distribution of When $N = n$ (there are exactly as many focal elements as there are elements of universe), then the indices j on the focal elements A_j, and the indices i on the unive elements ω_i, are equivalent, and it may be useful to use one or the other interchan ably. This is the case in the two rightmost columns of Table 1.

When $\forall A_j \in \mathfrak{F}$, $|A_j| = 1$, then $\mathcal{S}$ is specific, and $\Pr(A) := \mathrm{Pl}(A) = \mathrm{Bel}(A)$ is additive probability measure with probability distribution $\vec{p} = \langle p_i \rangle := \vec{\mathrm{Pl}}$ and addit normalization $\Sigma_i p_i = 1$ and operator $\Pr(A) = \Sigma_{\omega_i \in A} p_i$.

$\mathcal{S}$ is consonant ($\mathfrak{F}$ is a nest) when (without loss of generality for ordering, and lett $A_0 := \emptyset$) $A_{j-1} \subseteq A_j$. Now $\Pi(A) := \mathrm{Pl}(A)$ is a possibility measure, and $\eta(A)$ $\mathrm{Bel}(A)$ is a necessity measure. Since results for necessity are dual to those of possil ity, only possibility will be discussed in the sequel.

As Pr is additive, so Π is "maximal":

$$\forall A, B \subseteq \Omega, \ \Pi(A \cup B) = \Pi(A) \vee \Pi(B),$$

where $\vee$ is the maximum operator. As long as $\mathbf{C}(\mathfrak{F}) \neq \emptyset$ (this is required if $\mathfrak{F}$ i nest), then $\vec{\pi} = \langle \pi_i \rangle := \vec{\mathrm{Pl}}$ is a possibility distribution with maximal normalizat

Table 1. Summary of probability and possibility in GIT

		Distributions: $i \leftrightarrow j$	
	Random Set	Probability	Possibility
Focal Set	Any	Singletons: $A_i = \{\omega_i\}$	Nest: $A_i = \{\omega_1, \ldots, \omega_i\}$
		$\{\omega_i\} = A_i$	$\{\omega_i\} = A_i - A_{i-1}, A_0 := \emptyset$
Structure	None	Partition	Total order
Belief	$\text{Bel}(A) = \sum_{A_j \subseteq A} m_j$	$\Pr(A) := \text{Bel}(A)$	$\eta(A) := \text{Bel}(A)$
Plausibility	$\text{Pl}(A) = \sum_{A_j \cap A \neq \emptyset} m_j$	$\Pr(A) := \text{Pl}(A)$	$\Pi(A) := \text{Pl}(A)$
Relation	$\text{Bel}(A) = 1 - \text{Pl}(\bar{A})$	$\text{Bel}(A) = \text{Pl}(A) = \Pr(A)$	$\eta(A) = 1 - \Pi(\bar{A})$
Distribution	$\text{Pl}_i = \sum_{A_j \ni \omega_i} m_j$	$p_i := \text{Pl}_i = m_i$	$\pi_i := \text{Pl}_i = \sum_{j=i}^{n} m_j$
		$m_i = p_i$	$m_i = \pi_i - \pi_{i+1}, \pi_{n+1} := 0$
Measure		$\Pr(A \cup B) = \Pr(A) + \Pr(B) - \Pr(A \cap B)$	$\Pi(A \cup B) = \Pi(A) \vee \Pi(B)$
Normalization		$\sum_i p_i = 1$	$\bigvee_i \pi_i = 1$

Nonspecificity	$\sum_{j} m_j \log_2 \lvert A_j \rvert$	0	$\sum_{i=2}^{n} \pi_i \log_2 \left[\frac{i}{i-1} \right] = \sum_{i=1}^{n} (\pi_i - \pi_{i+1}) \log_2(i)$
Strife	$-\sum_{j} m_j \log_2 \left[\sum_{k=1}^{n} m_k \frac{\lvert A_j \cap A_k \rvert}{\lvert A_j \rvert} \right]$	$-\sum_{i} p_i \log_2(p_i)$	$\sum_{i=2}^{n} \pi_i - \pi_{i+1} \log_2 \left[\frac{i^2}{\sum_{j=1}^{i} \pi_j} \right] < .892$
Semiring	$\langle \oplus , \otimes \rangle$	$\langle + , \times \rangle$	$\langle \vee , \sqcap \rangle$
Marginals		$p(x) = \sum_{y} p(x,y)$	$\pi(x) = \bigvee_{y} \pi(x,y)$
Conditionals		$p(x,y) = p(x \mid y) \times p(y)$	$\pi(x,y) = \pi(x \mid_{\sqcap} y) \sqcap \pi(y)$
		$p(x \mid y) = p(x,y)/p(y)$	$\pi(x \mid_{\sqcap} y) \in [\pi(x,y), 1]$
		$\forall y, \sum_{x} p(x \mid y) = 1$	$\forall y, \bigvee_{x} \pi(x \mid_{\sqcap} y) = 1$
		$\mathbf{P} := [p(x \mid y)]$	$\boldsymbol{\Pi} := [\pi(x \mid_{\sqcap} y)]$
Process		$p' = p \cdot \mathbf{P}$	$\pi' = \pi \circ \boldsymbol{\Pi}$
		$p'(x) = \sum_{y} p(y) \times p(x \mid y)$	$\pi'(x) = \bigvee_{y} \pi(y) \sqcap \pi(x \mid_{\sqcap} y)$
Concepts		Division among distinct hypotheses Frequency Chance Likelihood	Coherence around certain hypotheses Capacity Ease of attainment Distance, similarity

$\vee_i \pi_i = 1$ and operator $\Pi(A) = \vee_{\omega_i \in A} \pi_i$. Also define the core and support of the pc bility distribution

$$\mathbf{C}(\pi) := \{\omega_i : \pi(\omega_i) = 1\} = \mathbf{C}(\mathcal{S}), \qquad \mathbf{U}(\pi) := \{\omega_i : \pi(\omega_i) > 0\} = \mathbf{U}(\mathcal{S}$$

Nonspecificity and strife are defined as two uncertainty measures defined on rand sets

$$\mathbf{N}(\mathcal{S}) := \sum_j m_j \log_2 |A_j|$$

$$\mathbf{S}(\mathcal{S}) := -\sum_j m_j \log_2\left[\sum_{k=1}^{n} m_k \frac{|A_j \cap A_k|}{|A_j|}\right],$$

measuring respectively the possibilistic and probabilistic aspects of the uncertainty information, represented in the random set. They achieve the forms shown in Tab for the possibilistic and probabilistic special cases. Note that in the probabilistic ca the uncertainty collapses to stochastic entropy, while in the possibilistic case, the st is bounded above by a small number.

Stochastic and possibilistic processes project a probability or possibility distribut forward in time according to a given set of conditional relationships. They are defi on their respective distributions when two operators $\oplus$ and $\otimes$ are available such t $\langle \oplus, \otimes \rangle$ form a semiring ($\otimes$ distributes over $\oplus$), and $\oplus$ is the operator of the distri tion. For probability, $\oplus = +$, and $\langle +, \times \rangle$ is the unique semiring.

For possibility, $\oplus = \vee$, and there are many semirings of the form $\langle \vee, \sqcap \rangle$, where is a triangular norm: a monotonic, associative, commutative operator with identi (Dubois & Prade, 1988). $\wedge$ (the minimum operator) and $\times$ are two of the m popular norms, as is $0 \vee (x + y - 1)$. Conditional possibility is not always uniq depending on the norm used. The formulae for marginal, joint, and conditional pro bility and possibility (which is dependent on $\sqcap$) are then shown in the table, as are next state functions for stochastic and possibilistic processes (see next section).

Possibilistic models

Probability and possibility almost never coincide. It is only when $\exists! \omega_i, \mathfrak{F} = \{\{\omega$ that

$$\vec{\text{Pl}} = \langle 0,0, \ldots, 1, \ldots, 0,0 \rangle,$$

so that $\vec{\text{Pl}}$ is both a probability and a possibility distribution. Semantically, probabi and possibility theory are also related to very different concepts (Joslyn, 199 Probability is inherently additive, and is thus concerned with the dispersal or divis of knowledge over a set of distinct hypotheses, and so with concepts related to quency.

But possibility is inherently *non-additive*. It is concerned with the *coherence* knowledge *around* a set of certain hypotheses (the core $\mathbf{C}(\pi)$), and thus with *ord* concepts related to capacity. Where probability makes very strong constraints on representation of uncertainty (additivity), possibility makes only very *weak* c straints. The maximum relation is a very weak operator, and there is a choice of m norms to use, some of which are strong, and others of which, like $\vee$, are also weak.

So possibilistic models are appropriate where stochastic concepts and methods inappropriate, including situations where long-run frequencies are difficult if not possible to obtain, or where small sample sizes prevail. This is true in reliability an sis, for example, where failures and system entry into non-nominal behavior dom are very rare; and trend-analysis, where even though observations are made over a l time, the state variables of concern change only very slowly, and new domains behavior are only very rarely seen. In these cases, the weakness of the possibili representation is matched by the weak evidence available.

A general modeling relation is shown in Figure 2, where: t and t' are former subsequent times; $W = \{w\}$ is the set of states of the world; $M = \{m\}$ is the se states of the model; o: $W \rightarrow M$ is the measurement function; r: $W \rightarrow W$ is movement of "reality"; and f: $M \rightarrow M$ is the modeling prediction function. I stochastic model, $M = \{\vec{p}\}$, where $\vec{p}$ is a probability distribution of the state of world, while in a possibilistic model, $M = \{\vec{\pi}\}$, where $\vec{\pi}$ is a possibility distribut of the state of the world.

Reality is presumably given, or at least operates on its own without our help. S make a valid model we are required to provide the measurement and prediction fu tions so that the diagram commutes. Measurement is used both to set the ini conditions of the model and to corroborate later measurements against the mc state, while prediction is used to produce the future model state. So a possibili model naturally requires *possibilistic* measurement and prediction procedures.

Possibilistic measurement methods have been developed by the author (Josl 1992, 1993c). The essential requirement is the collection of the frequency of occurre of subsets or intervals that are partially overlapping. If the core of the obser intervals (their global intersection) is nonempty, then Equation 1 yields an empir possibility distribution.

An example is shown in Figure 3. On the left, four observed intervals are sho The bottom two occur with frequency 1/2, while each of the upper two have freque 1/4. Together they determine an empirical random set. The step function on the ri is the possibilistic histogram derived from Equation 1.

There are a variety of well-justified continuous approximations to a possibili histogram. Two examples are shown in the figure. The rising diagonal on the lef common to both. The two falling continuous curves on the right are distinct to ea The trapezoidal form marked π^* is one of the most commonly used continuous proximations, but it must be noted that this is only one possibility among ma including smooth curves. This approach to possibilistic measurement generalizes t intervals and to the continuous case.

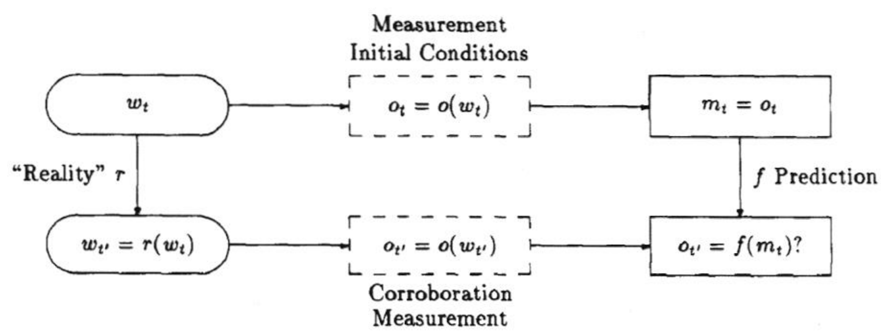

Figure 2. A general modeling relation.

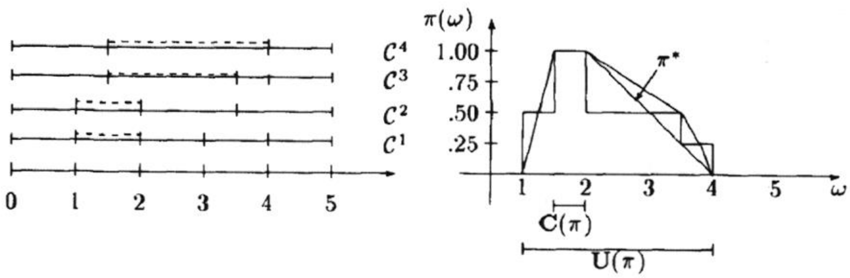

Figure 3. Four example observed intervals (left). The possibilistic histogram and two continuous app mations (right).

The core, here $\mathbf{C}(\vec{\pi}) = [1.5,2]$, being nonempty, is included in the support $\mathbf{U}(\vec{\pi}$ $[1,4]$. If the core were empty, then $\vee_i \mathrm{Pl}_i < 1$, so that $\vec{\mathrm{Pl}}$ would not be a possibi distribution. In this case, possibilistic normalization procedures, which have also b developed by the author (Joslyn, 1993a), would be required.

Possibilistic prediction procedures can be based on the possibilistic processes in duced in the previous section. For example, the author has defined possibilistic au mata as possibilistic Markov processes (Joslyn, 1994a) which generalize non-detern istic automata.

As an example of a possibilistic process, let $\Omega = \{x,y,z\}$. In Figure 4, each nod a state ω_i. The arcs indicate state transitions, each of which is non-additively weigh with the conditional possibility of the transition. So, for example, $\pi(x|y) = .8$, the entire transition matrix is

$$\Pi = \begin{bmatrix} 0.0 & 0.8 & 0.0 \\ 1.0 & 0.0 & 0.0 \\ 0.2 & 1.0 & 1.0 \end{bmatrix}.$$

Possibilistic transition normalization requires that each node have an out-arc lab 1, so that each column of Π contains a 1. Nodes may have multiple out-arcs, howe so that a unitary weight does not indicate a *necessary*, but rather a *completely poss* transition. For example, from state x, transition to z is .2 possible, but transition is also (completely) possible. z is an absorbing state, with self-transition the c possibility.

Now for $t \geq 0$, let $\vec{\pi}^t = \langle \pi_i^t \rangle^T$ be the state possibility distribution vector, let $\sqcap$ $\wedge$, and assume that at time $t = 0$ the system begins *definitely* in state x. Then $\vec{\pi}^0$ $\langle 1,0,0 \rangle^T$, and $\vec{\pi}^1$ is determined by

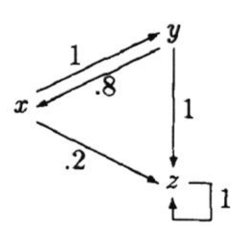

Figure 4. Weighted state transition diagram for a possibilistic process.

Table 2. States of the Example Possibilistic Process.

t	0	1	2	3	4
$\vec{\pi}^t$	1.0	0.0	0.8	0.0	0.8
	0.0	1.0	0.0	0.8	0.0
	0.0	0.2	1.0	1.0	1.0
$N(\vec{\pi}^t)$	0.0	0.2	0.8	0.8	0.8

$$\vec{\pi}^1 = \vec{\pi}^0 \circ \Pi = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \circ \begin{bmatrix} 0.0 & 0.8 & 0.0 \\ 1.0 & 0.0 & 0.0 \\ 0.2 & 1.0 & 1.0 \end{bmatrix} = \begin{pmatrix} 0.0 \\ 1.0 \\ 0.2 \end{pmatrix},$$

where $\circ$ is $\langle \vee, \wedge \rangle$ composition, which is verified by

$$\pi_1^1 = (1 \wedge 0) \vee (0 \wedge .8) \vee (0 \wedge 0) = 0,$$
$$\pi_2^1 = (1 \wedge 1) \vee (0 \wedge 0) \vee (0 \wedge 0) = 1,$$
$$\pi_3^1 = (1 \wedge .2) \vee (0 \wedge 1) \vee (0 \wedge 1) = .2.$$

The system is now *not* unequivocally in one state: Although it is completely poss that y is the system state, z is also .2 possible of being the system state, while . impossible. Transition normalization guarantees that $\vec{\pi}^t$ is always a maximally nor possibility distribution. Other future state vectors (and their nonspecificity values) shown in Table 2.

When

$$\forall i,j,t, \quad \pi_i^t, \pi(\omega_i \mid \omega_j) \in \{0,1\},$$

then "crisp" possibilistic processes, which are equivalent to nondeterministic proces are recovered. In fact, it has been shown by the author (Joslyn, 1994a) that possib tic processes are the valid generalizations of nondeterministic processes, whereas chastic processes are not. The author has also developed possibilistic Monte C methods (Joslyn, 1994c), which are required to select a final outcome based on distribution $\vec{\pi}^t$ for a fixed t.

POSSIBILITY THEORY AS A QUALITATIVE MODELING METHOD

Mathematical possibility, in both theory and applications, is still in the basic resea phase, just out of its infancy. For example, the axiomatic basis for possibility the and the properties of possibility distributions on continuous spaces are still be defined. The semantics of possibility in physical systems has been considered only very few. But there are many reasons why it can be hoped, and even expected, t possibility theory can come to play an important role in QM in general, and in application of QM to MBD in particular.

Hamscher, Console, and de Kleer (1992) have noticed some of the weaknesses stochastic methods for MBD, "it is usually assumed that reliable failure statistics be available, but this is in fact rare in practice. What is needed . . . is a way of work with likelihoods that could be specified ordinally rather than quantitatively" (p. 4 This is *exactly* what possibility theory provides, a non-additive, ordinal approac QM that hybridizes interval-valued dynamics and uncertainty distribution methods

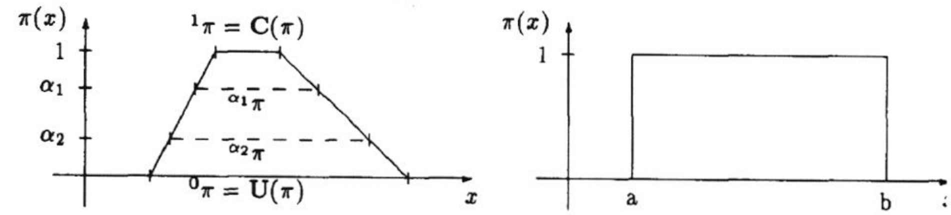

Figure 5. A possibility distribution as a collection of weighted intervals (left). The special case of a c interval (right).

Possibility theory and fuzzy theory

As mentioned above, possibility theory was originally developed by Zadeh (1978) the context of fuzzy sets and fuzzy logic. For Zadeh, a possibility distribution sim *was* a fuzzy set by another name, and thus possibilistic information theory was *stric* related to fuzzy information.

The view presented here, based in GIT, regards possibility theory as analogous probability theory in the context of random sets. Here, possibilistic normalizati ($\bigvee_i \pi_i = 1$) becomes crucial, and both probability and possibility distributions recognized as special cases of fuzzy sets with appropriate special normalization. other words, while it is certainly true that a possibility distribution is a fuzzy set, GIT there are *many* structures that are legitimately fuzzy sets, including *probabil* distributions. The author provides a full discussion elsewhere (Joslyn, 1994c).

Possibility theory and interval analysis

Nevertheless, fuzzy theory and possibility theory do share a number of points common. In particular, $\langle \vee, \wedge \rangle$ matrix composition is a common operation in fu systems in general.

A fuzzy interval is a fuzzy set on $\mathbb{R}$ that is also a convex possibility distribution, that

$$\forall x,y \in \mathbb{R}, \quad \forall z \in [x,y], \; \pi(z) \geq \pi(x) \wedge \pi(y).$$

When $\exists! x \in \mathbb{R}, \pi(x) = 1$, then π is a fuzzy number. Fuzzy intervals and numbers a in fact maximally normalized possibility distributions, and all possibilistic histogra and their continuous approximations are fuzzy intervals (Joslyn, 1993c). As illustra in Figure 5, under these conditions, π can be represented as a set of nested interv weighted by their possibility values, where ${}^{0}\pi := \mathrm{U}(\pi)$ as a special case, and

$$\forall \alpha \in (0,1], \; {}^{\alpha}\pi := \{x \in \mathbb{R} : \pi(x) \geq \alpha\}, \; \alpha_1 \geq \alpha_2 \rightarrow {}^{\alpha_1}\pi \subseteq {}^{\alpha_2}\pi.$$

A standard interval $[a,b] \subseteq \mathbb{R}$ is a special case of a fuzzy interval, where

$$\pi(x) = \begin{cases} 1, & a \leq x \leq b \\ 0, & x < a \text{ or } x > b \end{cases}, \quad \forall \alpha \in [0,1], \quad {}^{\alpha}\pi = [a,b].$$

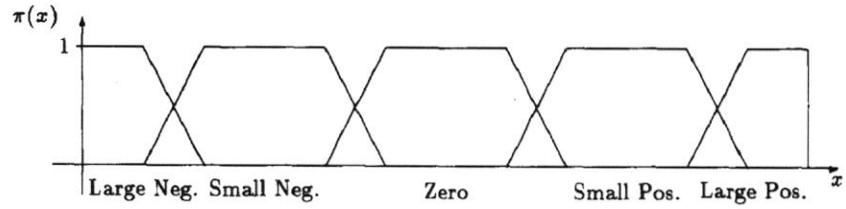

Figure 6. Traditional use of fuzzy intervals as linguistic variables.

Fuzzy arithmetic (Kaufmann & Gupta, 1985), where mathematical operations sı as addition and multiplication are defined on fuzzy intervals and numbers, is a dir generalization of interval arithmetic (Moore, 1979). In this way, possibility theory c be used as a generalization of interval analysis, and QM methods that use fu: arithmetic are essentially possibilistic.

Fuzzy arithmetic is also very popular and common in applications, and has be used as a QM method both generally (Sugeno & Yasukawa, 1993) and for M] (Fishwick, 1991; Shen & Leitch, 1993). Here the standard methods of fuzzy cont systems are used, where a set of overlapping fuzzy intervals divide a quantity spa into a few linguistic, qualitative values like "large positive" and "small negative" (Figure 6). These fuzzy sets are almost never *measured* properties of the system bei modeled, and are instead heuristically specified by the system modeler. Thus they a essentially modeling the cognitive state of some human expert, rather than direc modeling the system in question.

This contrasts sharply with possibilistic processes and models. First, possibilistic moc are cast strictly within the context of mathematical possibility theory specifically, ratl than fuzzy theory generally. They, thus, always imply strict possibilistic normalizati Also, they are based on measurement, in the form of possibilistic histograms and th continuous approximations, of the attributes of the system being modeled.

A POSSIBILISTIC APPROACH TO MBD

At both the general level and in some specific ways, there are areas of MBD for wh it is appropriate to consider a possibilistic approach.

Possibilistic symptom and error detection

Symptom and error detectors in a typical MBD system simply compare the measu value against a crisp interval of nominal or predicted values (Dvorak & Kuipers, 199 This is inadequate because the resulting cutoff from nominal to error condition essentially arbitrary. It is natural to use a fuzzy interval to generalize this, measuri either prediction errors or fault symptoms as the possibilistic distance of the teleme from the predicted or nominal system state respectively.

Consider a measured value x compared against an error fuzzy interval of the fo shown in Figure 5. Such a possibility distribution could be the output of the behav model, for instance, and would then serve as input to the error detector. Then $\pi(x$ the strength of the error or alarm raised. When $x \in \mathbf{C}(\pi)$, then $\pi(x) = 1$ and there no alarm. When $x \notin \mathbf{U}(\pi)$, then $\pi(x) = 0$ and the alarm is complete. In between, intermediate alarm is raised.

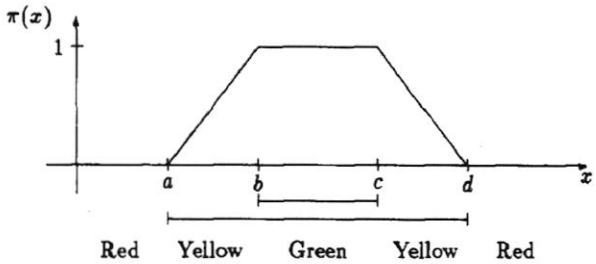

Figure 7. Degrees of alarms as a fuzzy interval.

A simple hypothetical example is illustrated in Figure 7. Here two crisp error thr olds $[b,c] \subseteq [a,d]$ are provided, where $[b,c]$ represents a conservative and $[a,c$ liberal judgment as to the nominal system state x. It is natural to let $x \in [b,c]$ indi the full "green" range, while $x \in [a,b) \cup (c,d]$ indicates "yellow" status, grow "redder" as $x \rightarrow a$ or $x \rightarrow d$. Finally, $x \in (-\infty,a) \cup (d,\infty)$ indicates a full "r status.

This is fully in keeping with the possibilistic approach, as indicated by the trape dal continuous approximation (shown in the figure) to the possibilistic histog generated by the two crisp intervals. Here $\pi(x)$ is the degree of "greenness" of system state, and $\pi(x) \in (0,1)$ indicates an intermediate degree of "yellow".

Even in situations where crisp thresholds are acceptable, they may be dynar varying as a result of changing system and environmental conditions. Doyle, Sell and Atkinson consider the situation of an earth-orbiting spacecraft as it proce through sunlight and shadow.

> Impingement solar radiation changes the thermal profile of the spacecraft, as does the configuration of currently active and consequently, heat-generating subsystems on board. Thresholds on temperature sensors should be adjusted accordingly. A particular temperature value may be indicative of a problem when the spacecraft is in shadow or mostly inactive, but may be within acceptable limits when the spacecraft is in sunlight or many on-board systems are operating. (Doyle, Sellers & Atkinson, 1989: 1231)

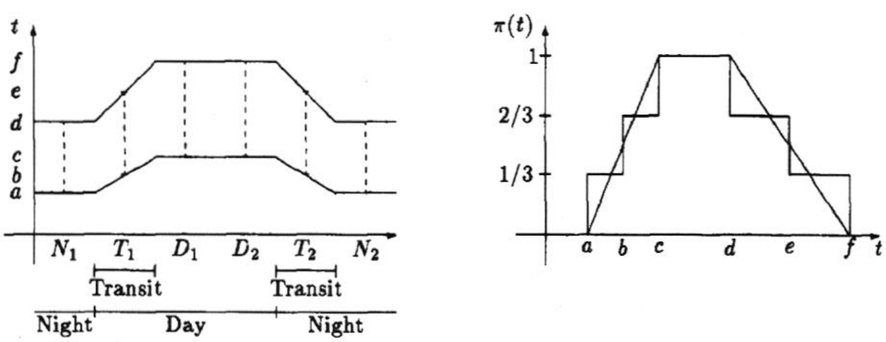

Figure 8. Variable critical range of a component through a day-night cycle (left). Its possibilistic histog and a trapezoidal approximation (right).

This situation is shown in Figure 8. Assume a variable, say the temperature t o given component, must be kept in a critical range as the spacecraft moves in and ‹ of daylight. As it does so, the range shifts as shown in the upper left of the figu where the transition periods begin at a change in sunlight, and continue to therr equilibrium. For simplicity, assume that that interval is sampled uniformly six tir during the orbital day, twice each for daylight D_i, night N_i, and transition period for $i \in \{1,2\}$. The possibilistic histogram for the possibility $\pi(t)$ of t holding a va at any given time and a trapezoidal approximation are shown on the right of the figu

A combination of these two approaches is also possible, where instead of a cr interval changing over time, a whole possibility distribution as a generalized inter changes with time.

Sensor modeling

Although the MBD system contains two models, the behavior model and the FGM, a whole, it is itself also a model of the spacecraft. As such, it is dependent on its inp from measurement, and thus on the sensor output of the spacecraft. Thus, there modeling issues in MBD concerning the sensors themselves.

When modeling complex systems, sensor data may be sparsely distributed, w missing observations, and sometimes very small samples sizes. As argued elsewhere the author (Joslyn, 1993b), these are important conditions for the inapplicability stochastic methods, and when they hold, possibilistic methods should be considered

In this respect, there is strong support in the literature for the idea that possibili as distinct from probability, has a role to play in QM. For example, Luo and K observe

> When additional information from a sensor becomes available and the number of unknown propositions is large relative to the number of known propositions, an intuitively unsatisfying result of the Bayesian approach is that the probabilities of known propositions become unstable. (Luo & Kay, 1989)

While Durrant-Whyte's (1987) approach is statistical, he also notes, "a robot syst uses notably diverse sensors, which often supply only sparse observations that can be modeled accurately." Dvorak and Kuipers (1992) make a similar observation in context of model-based monitoring, "all measurements come from sensors, which ‹ be expensive and/or unreliable and/or invasive. Monitoring is typically based o small subset of the system parameters, with limited opportunity to probe other parar ters."

Data fusion

Possibilistic measurement, as outlined above, is predicated on the observation of s sets or intervals that are partially overlapping. It is, therefore, imperative to consi the source of these intervals. But traditional measurement methods do not in gen yield overlapping intervals. Rather, the purpose of designing a good sensor is to p duce distinct outcomes, perhaps intervals with some uncertainty, but still disjoi forming equivalence classes.

Random set theory in general and possibility theory in particular is significant wl considering the problem of data fusion in MBD (Hackett & Shah, 1990; Luo & K 1989). This is because overlapping intervals *may* result from the combination of d from *different* instruments that measure the same system attribute, either directly indirectly. This can be seen in Figure 3, where each $\mathcal{C}^k$ is a different measuring devi While each $\mathcal{C}^k$ produces disjoint intervals, any two intervals taken from two differ $\mathcal{C}^k$ may or may not overlap.

Hackett and Shah (1990) discuss data fusion in general, including indirect measu ments, as well as the Dempster–Shafer (that is, random set) approach, "every senso sensitive to a different property of the environment; in order to sense multiple prop ties, it is necessary to use multiple sensors. A system using multiple sensors that sens single property can be used." Dubois, Lang, and Prade (1992) have considered data fusion problem using possibilistic logic, as has Mahler (1993) using random se

Indirect measurements. First, consider the situation where measurements of a com nent are not made directly, but rather knowledge of the state of the component is o gained indirectly by inference from the outputs of sensors attached to other com nents. Doyle, Sellers, and Atkinson (1989) offer an example from jet aircraft: L engine thrust can be indicated by either low exhaust temperature, low turbine rotat speed, or both.

This situation is illustrated in Figure 9. Here component A is not monitored. state can only be inferred from the sensors D and E, which monitor components B a C, and which, in turn, are causally connected to A. All of the intervals that can reported by either D and E individually are distinct from each other and disjoint. I since the knowledge of A provided by D and E is mediated by B and C, together tl may indicate that A exists in two different, possibly overlapping, intervals. So as amount of sensor "penetration" (sensor/component ratio) drops, standard measu ment methods yielding frequency distributions may become less tenable, leaving o observations at the random set level.

Redundant measurements. Alternatively, a system component may be monitored dundantly by multiple instruments, as shown in Figure 10. If these sensors are ide cal, and identically calibrated, then the result will simply be as if there was a time-se of observations from a single instrument. But if they are mutually discalibrated, eit out of phase, or scale, or both, then the intervals reported from each instrument n overlap.

If the sensors measure distinct modalities of a single component, for example pr sure and temperature, then a process of registration (Hackett & Shah, 1990) is requi

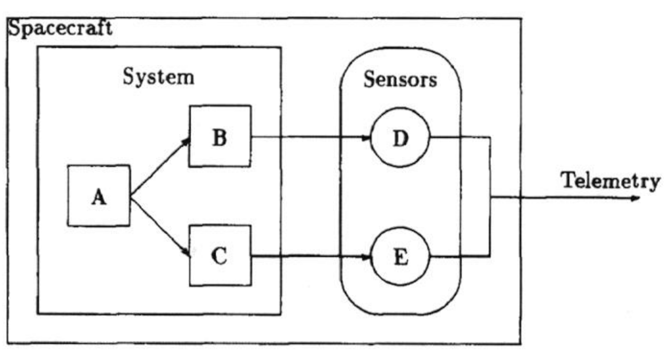

Figure 9. Indirect measurements of the state of a spacecraft component.

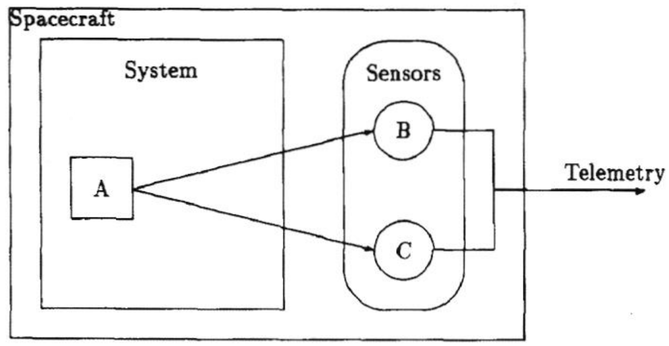

Figure 10. Redundant measurements of the state of a spacecraft component.

to derive a report from one in the modality of the other, or two new reports from ea
in a third modality. In any event, the argument here is very similar to the one above
the case of indirect measurements, and possibly overlapping intervals may result.

Sensor failure modeling

As mentioned above, in MBD data are not only combined from disparate sensors, th
are also sometimes incomplete, degraded, or missing altogether. Even when standa
(disjoint) observations are made, under these conditions there is the potential for t
application of GIT and possibility theory.

First, in GIT standard measurements are represented as singleton sets $\{\omega_i\}$, wh
each $\omega_i \in \Omega$ may indicate a disjoint interval. In a Bayesian or stochastic approa
sensor failure is represented by a uniform distribution over each of the $\{\omega_i\}$, aga
dividing our ignorance among a set of disjoint choices.

But in GIT, a missing observation is represented, more accurately, as an observati
of the *entire* universe Ω. While this does not result in a specifically possibilistic situ
tion, neither does it result in a frequency or probability distribution. This is discuss
more fully by the author elsewhere (Joslyn, 1994c).

For a simple example, assume that a system with three states $\Omega = \{a,b,c\}$ is o
served at ten uniformly distributed times, with a and c each seen twice, b seen th
times, and three cases where the sensor made no report. These final three cases m
be recorded as observations of Ω, and the specific observations replaced with obser
tions of the singleton sets $\{a\}$, $\{b\}$, and $\{c\}$ respectively. The overall empiri
random set is then

$$\mathcal{S} = \{\langle\{a\},1/5\rangle,\langle\{b\},3/10\rangle,\langle\{c\},1/5\rangle,\langle\Omega,3/10\rangle\}.$$

The plausibility assignment is then $\vec{\text{Pl}} = \langle 1/2,3/5,1/2\rangle$, which is neither an addit
probability distribution nor a maximal possibility distribution.

When sensor data are not missing, but rather degraded, compromised, or suspect
some way, a confidence weighting on each sensor's output is naturally not additi
our confidence about the sensors is not divided among them, since all could be perf
or any number of them could be in any state of degradation. Instead, it is natural
represent this confidence as a possibility distribution (or general fuzzy set) on ea
sensor's output. Again, an observation in the core indicates complete confidence, wh
one outside the support indicates complete sensor failure.

Representation of a graduated degree of sensor failure allows a corresponding gra uated degree of confidence in model predictions. The need for this has been noted Fulton (1990), "when we detect a broken sensor, great difficulty arises if we contin diagnosing other failures, because typical rule-based systems do not degrade gen when sensors fail (because the mapping is dependent on a complete and accurate set sensor data)."

Possibilistic models proper

In the sequel, the term "system model" will refer to the FGM or the behavior mo generally. So finally, it is useful to consider possibilistic methods applied directly the system models themselves, constructing them as possibilistic processes such possibilistic automata, and not as fuzzy arithmetic systems as discussed above.

Input to these systems (telemetry, alarms, and errors) may or may not be *pro* possibility distributions, since both crisp (standard) intervals and point values special cases of possibility distributions. But if they are, then it was discussed how th can be possibilistically weighted. A possibilistic FGM then would be responsible producing as its output a set of fault hypotheses that are possibilistically weighted input to the behavior model. This would, in turn, generate model prediction err with possibilistic weights.

A system model that is a possibilistic automaton can also be cast as a possibilis Markov process. As such, its key component is its transition matrix Π, essentiall vector of conditional possibility distributions as discussed above. Each conditio possibility distribution represents the possibility, for a given input, of transiting fr one system state to another.

The semantics of this transition matrix in a system model is understood in terms o subsystem-level model where the conditional possibilistic weight indicates a no additive coupling or relatedness among subsystems. This could be, for example, efficiency of the subsystem, as in the approach of Doyle, Sellers, and Atkinson (198 Or, when considering the system model as a causal graph, as in the approach of Ha Schuetzle, and La Vallee (1992), the weights indicate the degree of causal connectiv between subsystems.

Thus in the possibilistic approach a system model is essentially a possibilistic n work, where nonadditive, possibilistic weights are placed on the arcs of a causal gra The corresponding network appears similar to a Bayesian network, but the mathem ics is possibilistic, not stochastic.

CONCLUSION AND FUTURE DIRECTIONS

We have considered possibility theory as a qualitative modeling method in the cont of GIT (probability theory, Dempster–Shafer evidence theory, random set theory, a fuzzy theory). We have also defined the key concepts of model-based diagnosis, a have considered, in the context of spacecraft diagnosis, the potential for the appli tion of possibility theory to MBD in terms of symptom and error detection, da fusion, sensor failure modeling, and nonadditive causal graphs.

It should be emphasized that this work is still in the basic research phase. Mathema cal possibility theory is still being developed, and most of the key concepts in possibil tic modeling (for example, possibilistic measurement and automata) have only be defined in the past year or so. The application of possibility theory to the modeling physical systems and the semantics of possibility in empirical contexts is being cons ered only by a few.

This work points to many future directions for research, including computer-bas implementation of possibilistic models proposed by the author (Joslyn, 1994b), a continued exploration of the conditions for the applicability of possibilistic modeli to spacecraft systems.

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