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Managing Uncertainty in Environmentally Benign Design and Manufacture

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Abstract: When making design decisions in environmentally benign design and manufacture, the decision maker is often faced with extreme uncertainty. Due to a lack of understanding of the complex dynamics of environmental and societal systems, it is very difficult to judge the impact different design alternatives have on the environment, the economy and the society, especially in the distant future.
In this paper, two formalisms are illustrated for making design decisions under extreme uncertainty. The formalisms are probability bounds analysis and info-gap decision theory. We introduce the basic concepts for both formalisms, discuss the advantages and limitations, and identify under which circumstances they are useful in the context of design decision making. One can think of both decision methods as having a built-in sensitivity analysis allowing the decision maker to judge whether a decision can be made confidently based on the current information, or whether additional information needs to be gathered.

1. Introduction: Companies are increasingly concerned with the environment as consumers and legislators are realizing that a cost to society results from environmental impact. Interest is therefore growing in Environmentally Benign Design and Manufacture (EBDM), a domain that examines the often competing goals of achieving economic growth and protecting the environment.

All products and processes in some way affect our environment during their entire, and often long, life span. Consequently, an evaluation of all of the loads and impacts has traditionally been addressed with life cycle assessment (LCA) methods. Researchers are starting to recognize that a key characteristic of LCA is that only very limited information and knowledge is available, resulting in large uncertainty, as summarized by Ross [1] and Björklund [2].

In general, multi-criteria evaluations that include environmental performance can be decomposed as depicted in Figure 1. Similar decompositions have been proposed [3, 4], though none are identical in form or scope to the structure presented here. Components are grouped, as indicated by dashed-lines in the figure, using Hofstetter's concept of "spheres" of knowledge and reasoning about environmental evaluation [3]:

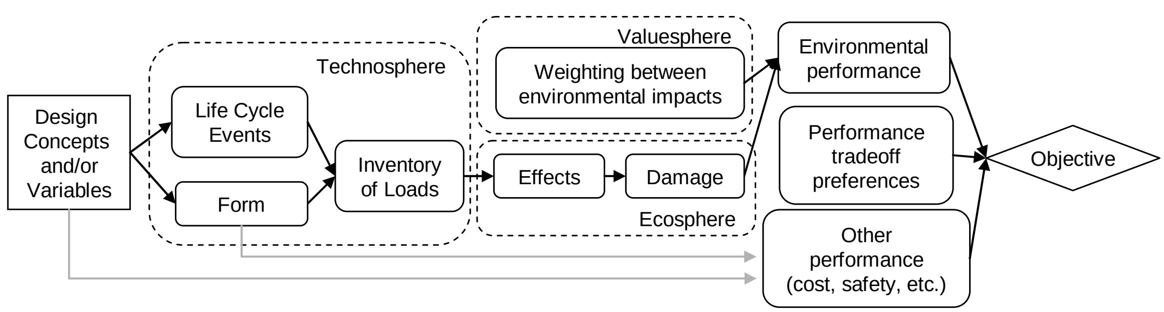

Figure 1: The components of an environmental analysis

- Technosphere: description of the product and its life cycle and an inventory of loads (e.g. emissions)
- Ecosphere: modeling of changes to the environment
- Valuesphere: modeling of the perceived seriousness or importance of changes to the environment

Any of the components in Figure 1 can be a source of uncertainty. Often some of these sources, such as form and inventory, are well characterized, while others, such as environmental damages, are much harder to characterize.

In summary, EBDM is a multi-objective decision problem, pursuing the often competing goals of economic growth and environmental protection, while subjected to multiple sources of uncertainty. This is a rich context in which to explore different methods of representing uncertainty and making engineering design decisions. It also offers an opportunity to contribute to the EBDM and LCA communities by demonstrating practical approaches for uncertainty management in those domains.

2. Decision making in EBDM. When making any design decision, the engineer must predict the uncertain consequences of each alternative under consideration so that the most preferred alternative can be chosen. From a mathematical perspective, this requires the use a formalism in which uncertainty can be expressed and represented, in which one can compute with uncertain quantities to infer information about decision consequences, and based upon which the choice of a particular decision alternative can be justified rationally.

Traditionally, the formalism for expressing uncertainty has been probability theory. Dating back to the first half of the twentieth century, probability theory has been shown to support the expression of a DM's beliefs, operationalized as the DM's willingness to bet [5, 6]. Combined with utility theory to express the DM's preferences, a normative decision theory has been established in which the most preferred alternative is determined by maximizing the expected utility [7]. However, in practice, this normative decision theory poses some problems; in order to apply it, one must assume that the DM can express his/her beliefs and preferences accurately and coherently in precise mathematical functions. Even if this were possible, it would require significant resources. Therefore, much of the recent research in decision theory has focused on relaxing the assumptions of precise expressions of beliefs and preferences [8-11].

Many methods have been recommended for representing uncertainty in engineering design, including precise subjective or Bayesian probability theory [6, 12], interval theory [13], imprecise probabilities [11, 14], evidence theory [15, 16], possibility theory [17], and information gaps [18]. Previous work has compared probability theory and possibility theory [19], compared evidence theory and Bayesian theory [20], and demonstrated the potential value of using imprecise probabilities (compared to precise probabilities) in a simple example [14].

In this paper, the focus is on two such alternative approaches for formulating decisions under uncertainty: info-gap decision theory (IGDT) [18] and probability bounds analysis (PBA) [21]. We focus on these because the hold particular promise for decision making under *extreme* uncertainty as is common in EBDM.

Information-Gap Decision Theory. When information is very sparse, a decision maker may want to make a robust decision—that is, a decision that will yield a reasonably satisfactory result over a large range of realizations of the uncertain parameters. One such approach is information-gap decision theory (IGDT), developed by Ben-Haim [18].

In IGDT, it is assumed that a decision maker has available a nominal, but very suspect, estimate of an uncertain quantity. IGDT presents an approach to making design decisions when there is a gap of unknown size between the uncertain quantity's true value (which could be known but is not) and an available nominal estimate. IGDT models the size of this gap as an uncertainty parameter, α. In IGDT, the design decision maker confronts this gap by employing a satisficing decision policy and seeking to maximize robustness to uncertainty. The decision maker must specify a satisficing performance level—a "good enough", minimally acceptable level of performance in a worst case scenario—and accordingly choose the design that, subject to this minimum requirement, allows for the largest information gap, i.e., the largest α.

IGDT is often mentioned in passing in papers on uncertainty in engineering design, but the authors are not aware of any previous detailed discussions of IGDT in environmentally benign design. In this paper, we examine the applicability of IGDT to environmental benign design and LCA when there is severe uncertainty in assessing the loads and impacts that a design has on the environment.

Probability Bounds Analysis. A second uncertainty representation discussed in this paper is Probability Bounds Analysis (PBA) [21] derived from imprecise probability theory [11, 14]. While IGDT uses info-gap models (intervals of unknown size) to represent extremely uncertain information, PBA is a formalism in which uncertainty is represented in probability boxes—a hybrid representation that combines both intervals and probability distributions. In previous work, we have demonstrated that PBA is valuable as compared to traditional decision analysis in cases in which uncertainty is large but quantifiable. In this paper, the comparison of PBA and traditional decision analysis is taken a step farther. In short, the paper begins to answer *when* it is useful to use imprecise probabilities, Specifically, the *process* of using PBA is compared to the process of traditional decision analysis (with sensitivity analysis) [22-24] in the context of EBDM.

In traditional decision analysis, uncertainty is considered in a two step process. First, alternatives are compared based on nominal estimates, or base cases, of uncertain parameters. Second, the sensitivity of this comparison is explored by varying the uncertainty over a specified range. In PBA, the total uncertainty is incorporated into the decision and analysis in one step using a specific sub-class of imprecise probabilities called probability-boxes. We have demonstrated this process in detail in [25]. Here we reiterated the advantages and limitations via a comparison to decision analysis. A theoretical view of PBA as a sensitivity analysis tool was presented by Ferson et al. [26], but to the authors' knowledge, Aughenbaugh *et al.* [25] presented the first practical comparison and demonstration in engineering design and EBDM.

2. LCA Design Example: Oil Filter selection: To investigate the advantages and disadvantages of IGDT and PBA in the context of environmentally benign design and manufacture, we have applied both formalisms to the design of oil filters. The detailed results of these design studies can be found in [27] and [25]

Around 250 million light duty oil filters are discarded (and not recycled) in the United States each year [28]. The environmental impact of these filters can be substantial, as disposable filters contain large amounts of steel, aluminum, or plastic, depending on the style of filter.

In this example, it is assumed that an automobile manufacturer wants to reduce the environmental impact of oil filters from its cars by designing a more environmentally benign filter. Naturally, the company simultaneously wants to make a profit, making this an EBDM problem. We assume that since high-price filters are less attractive to consumers than low-price filters (with all other things being equal), the manufacturer wants to minimize the total cost to the consumer of purchasing oil filters over the lifetime of the vehicle.

In the following, the example is described in more detail. Naturally, some simplifications and assumptions are introduced in the problem. For example, the exact dimensions and parameters for the problem are chosen to be realistic, but are not based on hard, real-world data. Consequently, the emphasis is not on the actual decision outcome (i.e. the chosen filter), but rather on the decision and analysis *process*.

Types of oil filters. In this simplified model, shown in Figure 2, an oil filter is comprised of five components: housing, top cap, filter, inner support, and bottom cap. The housing, top cap, and bottom cap make up the *casing*, and the inner support and filter make up the *cartridge*. Three different types of oil filters are considered, as summarized in Table 1.

Filter	Material	Discarded parts
SEC	Steel	Cartridge and Casing
PEC	Plastic	Cartridge and Casing
TASO	Aluminum	Cartridge only

Table 1. Types of filters

For the steel easy change (SEC) filter, the structural components are made of steel. The entire filter is designed to be replaced at once; it is simply unscrewed from the engine and then discarded or recycled. The plastic easy change (PEC) filter is used exactly as the SEC filter, but its structural components are plastic rather than steel. Finally, the take-apart spin-on (TASO) filter has structural components made of

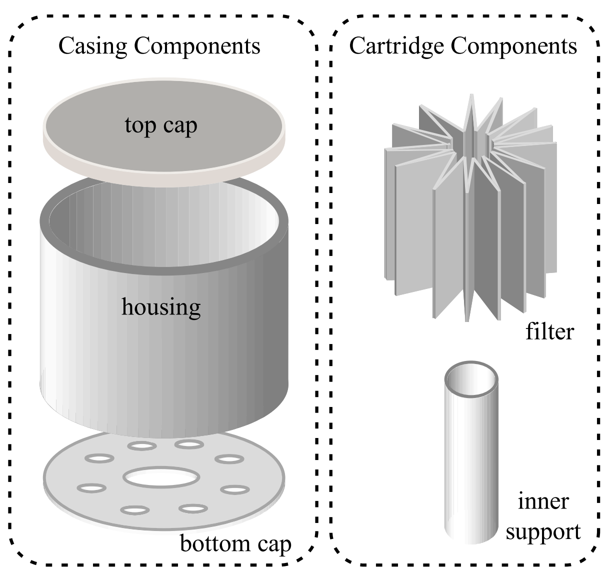

Figure 2. Oil filter schematic diagram

aluminum and when the filter is replaced, only the cartridge is replaced; the casing is reused.

Ecological impact. It is assumed that the primary environmental impact of an oil filter arises due to the construction, transportation, and disposal of the casing and cartridge. These components are constructed of materials such as steel, aluminum, and plastics and are present in large quantities. Other substances, such as the cellulose filter element and oil residue, are present in much smaller quantities and are generally equivalent in all three types of filters.

The Eco-indicator 95 is an impact assessment method for life-cycle analysis in which particular scores (*ecoscores*), measured in eco-points, are assigned to specific materials and processes There is also an updated Eco-indicator 99 available [29], but for illustrative purposes the old database and methodology is sufficient. Since these scores are given for specific materials as points per mass, we will refer to them as Eco-indicator rates, or simply *ecorates* in this paper. For instance, the impact of a filter of material m is computed as:

$$impact_m = ecoscore_m = mass_m \cdot ecorate_m \qquad (1)$$

For a particular material, the ecorate not only captures its environmental effects and damages, but also sets a value on these damages relative to other damages. As such, it combines the ecosphere and valuesphere components of Figure 1. This allows for tradeoffs between different materials and processes with different inherent environmental impacts. These value tradeoffs are fixed within the Eco-indicator model, but in practice, not every society or decision maker will agree with these tradeoffs. Consequently, the valuesphere is a an important source of uncertainty in environmental life-cycle assessment. The effects and damages are uncertain due to the complexity and uncertainty of modeling ecosystems.

In Figure 1 the ecosphere is independent of the technosphere because the ecorates are independent of what effects are present; they are pre-tabulated for all materials. In this problem, the technosphere effects, or inventory, is given by the total mass of material used over a vehicle's lifetime, and are thus incorporated into the problem in Equation (1).

The essential tradeoff that exists in the filter design problem from an ecological perspective is the difference in replacement strategy between the filter options. The TASO incurs a high one-time load whereas the SEC and PEC incur a smaller load every time the filter is changed. When the number of oil filter changes is small, the SEC filter has a smaller impact, but as the number of filter replacements increases, the impact of replacing the casing every time for the SEC filter will exceed the one-time impact of the TASO's casing. The TASO casing has a higher impact because it is contains more material—it is built to last as long as the car's engine—than the SEC filter and because the material is aluminum, which is more resource intensive per unit weight than steel. In contrast, the SEC filter is made of steel (with a lower impact per mass) and contains less material since its lifetime is shorter.

3. Assumptions on available information: It is our hypothesis that the uncertainty representation should be chosen to match the availability and quality of the information. We have therefore considered multiple scenarios in which different problem parameters are more or less uncertain. We have then investigated how these assumptions on the availability of information impact the performance of IGDT and PBA.

Info-Gaps. For IGDT, we have assumed that the decision maker chooses between TASO and SEC filters under the following uncertainty scenarios:

- *One uncertainty that affects both design alternatives.* The number of filters F used over the vehicle's lifetime depends strongly on the behavior of the car's owners. This behavior is very uncertain and warrants a robust design solution.
- *One uncertainty that has the same units and type but a different nominal for each alternative.* The *ecorate* of the casing material for each alternative is considered to be uncertain.
- *Two unrelated uncertainties evaluated first using a combined uncertainty parameter and second using separate uncertainty parameter:* Both the ecorates of the casings and the number of filters F are assumed to be very uncertain.

In each of these cases, the uncertain parameters are assumed to extremely uncertain to the point where an info-gap model is the best characterization.

Probability Bounds Analysis. In the case of PBA, the assumption is that the uncertainty is sufficiently well-understood that it can be characterized as a p-box, but that insufficient data is available to support a precise probability distribution. Specifically, the ecological impact per unit mass is known to be within a stated interval for each material. Interval data is assumed because the uncertainty in the numbers is not probabilistic but rather arises from modeling errors and assumptions about the ecosphere and valuesphere.

Imprecise probabilities are used to represent the uncertainty in the vehicle lifetime and filter change frequencies. The variability arises because the population of vehicle owners contains a variety of individuals, each who has his or her own behavior, but who collectively appear random. For illustration, only one parameter of the distributions is assumed to be known imprecisely, but the methods immediately generalize to multiple uncertain parameters. Several reasons for imprecisely known probabilities include:

- Limited relevant historical data for a new product
- Incomplete characterization of market segment for a new product, e.g. imprecisely known customer population
- Changing behavior due to outside influences, e.g. laws

It is assumed that the vehicle lifetime L and the filter change frequency f are both independent of all eco-rates, and that the weighting w is independent of all other parameters. However, the dependency between L and f is unknown, as are all dependencies between all ecorates.

Why is independence not assumed? L and f are both related to user behavior. It is conceivable that a user who intends to keep a car a long time will change the filter at a higher rate than someone who keeps a car a short time, since the long-time owner would have a greater interest in keeping the engine in good condition. In such a scenario, L and f are correlated. However, this dependence is not known exactly and may not even exist at all, so it makes sense to assume an unknown dependency. A similar argument can be made between the eco-rates; they could be independent since they relate to different material and potentially different environmental effects and damages. However, they could also be correlated if, for example, they share an effect in the ecosphere.

A traditional statistical approach would require perfect knowledge of all joint probabilities, information that is rarely known. Consequently, independence between uncertain parameters is commonly assumed, an assumption that is often unjustifiable given available information. The ability of PBA to handle unknown dependencies, and therefore compute the possible range of results with just the marginal distributions as inputs, is a major advantage over traditional methods.

3. Evaluation of the applicability of Info-Gap Decision Theory: In this section, we discuss our findings with respect to the use of IGDT for decision making under extreme uncertainty in the context of the oil filter design problem.

When IGDT is warranted. In certain situations, the info-gap design analysis approach can eliminate the need for further data collection by facilitating decision making under extreme uncertainty. For instance, if a switch in design choice (e.g., from SEC to TASO) requires a small sacrifice in guaranteed performance yet affords a reasonably large amount of extra robustness to error in a nominal estimate, one could decide to switch choice without collecting more information. An item for future work is to quantify the cost savings that such IGDT analyses generate by requiring less information to support simple, clear choices.

Although info-gap models are meant for use when less information is available than is required by other uncertainty representations, it seems possible that there are still “gray areas” where, given the available information, it is difficult to know which approach will produce the best results. For example, when assuming that the uncertainty in the number of filters is extreme. A strong argument could be made that this uncertainty could be bound with an interval, such as $F = [5, 40]$. Which is a better approach, IGDT or interval analysis? Future work will include experiments comparing IGDT results to those of other approaches with different information, assumptions, and values, with an aim towards eventually developing guidelines for when IGDT would be more appropriate or less expensive to apply.

Intuitiveness of evaluating severe uncertainty and satisficing performance. The IGDT approach requires that the decision maker be able to evaluate the acceptability of some satisficed level of critical performance in light of the corresponding gain in robustness to an info-gap of unknown size. In the example in this paper, we assumed that the decision maker could state a preference for some acceptable size in the Eco-indicator 99 measure of environmental impact. Although Eco-indicator points are grounded in reality, with one “point” corresponding to 1/1000 of the environmental load of a European citizen over 1 year, the Eco-indicator 99 construct was primarily developed to compare options relatively, not absolutely [29]. Whether or not it is reasonable to state one’s preference for an absolute millipoint score with that reference point in mind is left to future study.

Similarly, IGDT requires a decision maker to have a relative sense for the magnitude of deviation around an uncertain quantity’s nominal estimate, but not all uncertainty severities are equally easy to assess. In this example, it is probably easier to understand the severity of error in the number of lifetime filter changes than to understand the severity of particular errors in an ecorate. This problem is further compounded when there are uncertain ecorates for different materials with different nominal values. Difficulty assessing the severity of an uncertainty makes trading off performance to gain robustness difficult, perhaps prohibitively so. A discussion of calibration and judgment of tradeoffs is considered in an entire chapter by Ben-Haim [18], but more experimentation is needed to determine the efficacy of such techniques in environmentally benign design problems.

Considerations when using IGDT for multiple uncertainties. In general, analyzing the relationships between satisficing reward, info-gap robustness, and the robust-optimal design increases in difficulty whenever any of them have multiple dimensions. In [27] it was shown that having multiple uncertainties made visualizing and understanding tradeoffs more involved. The established technique of parameterizing all uncertainties with a single α was shown to be feasible but restrictive, as all errors had to be defined as normalized by their nominals as well as all growing at the same rates.

The novel technique of assigning a separate uncertainty parameter α_i to each uncertain quantity revealed that there are possible ranges of indeterminacy that are not identified when uncertainties are lumped into a single α [27]. However, a more complicated three-dimensional viewing method was needed to facilitate and understanding of relationships. This multi- α method may be inapplicable for examples with decisions that are more complicated than the simple selection problem explored in this paper. Future work is needed to determine how large the ranges of indeterminacy are, as well as whether or not a designer could successfully tradeoff robustnesses between different uncertainties.

Other future areas for IGDT-related investigation. There are other opportunities for future work besides those mentioned in previous sections. With the goal in mind to integrate economic assessments into environmentally benign design, support for multi-objective problems is necessary. The existing multi-criteria techniques used in info-gap decision theory [18], which involve defining goals preemptively, may have practical limitations similar in nature to those found when designing for multiple uncertainties. Also, the implications of IGDT need to be considered across a wider variety of the uncertainties across the components originally laid out in Figure 1; in this paper, only life cycle events and proxies for real environmental impact were explored. Finally, it is the expectation of the authors that more careful and structured experiments comparing uncertainty formalisms can move us towards a framework for systematic treatment of the typical uncertainties encountered in environmentally benign design.

5. Evaluation of the applicability of Probability Bounds Analysis: In this section, we discuss our findings with respect to the use of PBA as compared to traditional decision analysis, focusing on four areas: veracity, acuity, complexity, and flexibility.

Veracity of the analysis. The oil filter example problem (details in [25]) revealed that a one-way sensitivity analysis can lead to the conclusion that the decision is insensitive to the uncertainty, while the PBA analysis of the same problem can indicate that the solution is very sensitive to the uncertainty. An obvious question to ask is *which one gives the right result*? Unfortunately, this question has no straightforward answer.

Due to repeated variables in the interval calculations, PBA gives bounds that may be overly conservative (too broad). On the other hand, one-way sensitivity analysis ignores dependencies and higher order interactions and can lead to results that are non-rigorous, i.e., that are inconsistent with the truth. If the selection problem is recast as a hypothesis testing, the types of errors made with the PBA and sensitivity analyses can be discussed in standard statistical terms [30].

Consider the null hypothesis that either the PEC or the SEC filter is the best choice. The alternative hypothesis is that the TASO filter is the best. A sensitivity analysis may underestimate the true uncertainty and indicate that there is enough evidence to reject the null hypothesis in favor of the alternative when there really is not sufficient evidence to do so. In this situation, the null hypothesis could be rejected when it is true, a Type I error.

Conversely, PBA may overestimate the uncertainty and lead to the failure to reject the null hypothesis when it is false, a Type II error. A Type II error is an error in the sense that an opportunity to make a decision is lost; the null hypothesis could have been rejected, but was not. Consequently, a decision maker may waste resources or make an arbitrary decision trying to reduce indeterminacy that does not exist in the actual problem.

Which is preferable, a Type I or Type II error? A Type II error may be preferable in high-risk applications; when the cost of failure is high, one is often more willing to be conservative and spend additional resources to reduce uncertainty further. In other applications, the cost of delaying a decision or collecting more information may exceed any potential benefit from waiting. There is no general answer; the analyst must assess the situation and make his or her own choice.

We are currently collaborating with applied mathematicians in the interval arithmetic community to improve our ability to compute with p-boxes without generating overly conservative results [31]. This would eliminate the concern for Type II errors and leave only the consideration of increased computational cost.

Acuity of analysis. One goal of sensitivity analysis is often to determine what additional information could best improve the decision. To this end, the breakout of uncertainty and sensitivity into individual parameters in one-way sensitivity analysis is an advantage. By considering each parameter independently, the decision maker gains insight into the sensitivity of the decision to each parameter.

PBA considers all uncertainties simultaneously, accounting for all interactions and dependencies, but it does not identify the individually important sources of the sensitivity. If the PBA analysis determines that the decision is not sensitive to the overall uncertainty, this is not a problem. However, in a case in which there is indeterminacy, a decision maker would benefit from guidance into resolution of the indeterminacy.

For example, based on the sensitivity analysis in Figure 3, there seems to be no need to increase knowledge about vehicle lifetime. On the other hand, the difference between SEC and TASO filter is very sensitive to the ecorate of steel, though not enough (as a one-way effect) to change the decision. The sensitivity analysis suggests that any additional information collection focus on characterizing the environmental effects. The basic PBA analysis does not provide this insight.

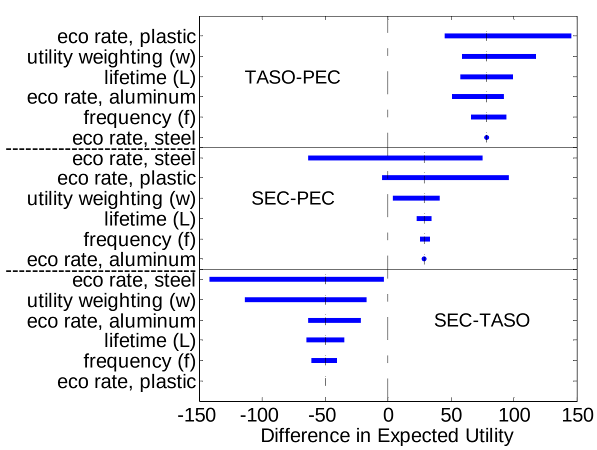

Figure 3. Tornado plot comparing multiple alternatives (uncertain objective weight)

Ferson et al. [26] have suggested using a meta-sensitivity analysis with PBA. Traditional sensitivity starts with the base values and systematically varies one parameter at a time to its extremes. Since PBA can capture all of the uncertainty at once, the opposite approach can be taken. The "base" case becomes the results with all of the uncertainty considered, and then each uncertain parameter is "pinched" down to a zero-variance interval, a precise probability, or even a point value and the reduction of uncertainty in the result is observed.

The one-way nature of the meta-sensitivity analysis is actually beneficial. When deciding whether to spend resources collecting information about a particular parameter, the decision maker is specifically interested in effect on the overall uncertainty of reducing the uncertainty in that particular source. This type of information is not available in traditional sensitivity analysis. It thus appears that the most accurate identification of sensitivity is achieved by a hybrid approach. Additional research into such approaches is underway.

Complexity of analysis. A one-way sensitivity analysis is computationally inexpensive. In addition to the solution with the base values, each uncertain parameter requires just two calculations—one for the upper bound and one for the lower bound. Each of these calculations may involve one Monte Carlo loop to calculate expected values, although in many cases this is unnecessary. Either way, the computational complexity is generally less than with PBA.

The advantage quickly switches to PBA if two-way (or higher) sensitivity analysis is performed, especially when nested Monte Carlo loops are used. PBA computations using dependency bounds convolutions [32] are generally much faster than traditional sensitivity analysis [26, 33]. However, dependency bounds convolutions require an open, operationally defined model (e.g. algebraic) of the problem. Consequently, they cannot be used to analyze models such a differential equations, simulations, and finite element analysis. Current research establishes methods for propagating p-boxes through "black box" models, or models with unknown or complicated structure [31], and a comparison of these methods of PBA with sensitivity analysis is an area of future work.

Flexibility of the analysis. Another advantage of PBA is its inherent flexibility. We have already discussed PBA's flexibility in terms of assumptions of independence or unknown dependence within the context of the EBDM example. Recent algorithms also handle the pairwise dependencies of maximal or minimal correlation, correlation, linear relationship and correlation within a specified interval, and signed (positive or negative) correlation [26].

In [25], the flexibility with regard to imprecisely known distribution *parameters* was demonstrated, but PBA can also handle cases of unknown distribution *type* [34]. For example, a p-box can be constructed and propagated with only knowledge of the mean and variance; no assumption of distribution type (e.g. normal, lognormal, gamma, or Weibull) is necessary. This would be useful in the filter selection if, for example, the decision maker had an estimate of the mean and variance of filter change frequencies, but no theoretical or empirical evidence about the distribution family.

Sensitivity analysis ignores dependencies and higher order interactions, and it requires a known distribution type. Consequently, the types of problems that can be accurately explored with sensitivity analysis are more limited than PBA.

6. Summary: In this paper, we introduced an example EBDM decision of an oil filter selection problem with multiple objectives and multiple sources of different types of uncertainty. The selection problem is was used the evaluate the suitability of IGDT and PBA under a variety of different uncertainty scenarios.

Information-gap decision theory (IGDT), developed by Ben Haim [18], seeks to assist a decision maker in making decisions that yield satisfactory performance and are robust, despite the presence of severe uncertainty. The examples examined in [27] have shown that IGDT has promise for expanding decision making capabilities under severe uncertainty in EBDM problems. However, assessing one's preference for robustness versus critical satisficing reward becomes more complex as the nature and number of uncertainties increase. A clearer demarcation of the effectiveness of info-gap in practical situations, as well as closer examination of the method with respect to other robustness approaches, is left to future work.

Similarly, PBA analysis provides the decision maker with an ability to make decisions that are robust to epistemic uncertainty by incorporating a gobal sensitivity analysis in its formulation. Traditional sensitivity analysis in decision making can identify important sources of uncertainty, but it can also lead to an incorrect selection because it neglects dependencies and interactions. PBA can compute with unknown distributions types, unknown dependencies, and uncertain parameters. It also provides a rigorous and global sensitivity analysis. However, PBA may yield overly conservative results (bounds that are bigger than necessary), and it is computationally more complex than simple one-way sensitivity analysis. PBA also requires meta-analysis to identify the important sources of uncertainty, but this meta-analysis is more valuable than standard sensitivity analysis.

In short, both IGDT and PBA are both useful in certain engineering design scenarios. While both approaches have their own limitations, they clearly reveal more information in some scenarios than traditional decision analysis. As such, we believe that IGDT and PBA should receive continued attention and development in the design community.

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