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Implications of *Fuzziness* for the Practical Management of High-Stakes Risks

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Abstract

High-stakes (dangerous, catastrophic) risks take on a wider profile as progress unfolds. What are the impacts of technological and social change on the risk landscape? Due to the complexities and dynamics involved, we can only answer these questions approximately. By using the concept of *fuzziness*, we can formalize our imprecision about high-stakes risk, and therefore place their management on a stronger footing. We review here the impacts of fuzziness, i.e., knowledge imperfection, on high-stakes risk management, including its implementation via computationally intelligent decision aids.

Keywords: Risk; fuzziness; risk management; danger.

1. Introduction

High-stakes or *dangerous* risks are those that entail finality, or irreversibility, should they occur. They may affect the existence of the individual, the business enterprise, the community, our entire society, and perhaps even all life on earth as we know it. The last categories, obviously the most potent, have gained considerable attention over the years as it has become obvious that progress may entail at least some potential for global disaster. Among the largest-scale risks we face today are human-induced climate change and other industrial and household pollutants of land, air and water, the threat of global nuclear confrontation, and even financial and economic events that can have extensive physical repercussions.[1]

Understanding high-stakes risk entails a considerable degree of knowledge imperfection. Consider first the distinction between "dangerous" and "not dangerous" events, in terms of annual probability of occurrence. Our knowledge of how small differences in likelihood will affect us are not well known, and perhaps never will be. How can we justify identifying an untoward event whose probability is 10^{-6} (the proverbial "one in a million") as not dangerous and one that has a probability of 9×10^{-5} as causing concern (the difference being one chance in a hundred thousand)? In terms of the measurement of real world probabilities, could we realistically identify such small differences in anything other than a carefully controlled setting? Clearly, both establishing risk acceptability (i.e., distinguishing between "dangerous" and "not dangerous" events), and measuring the probability of high-stakes exposures are often very imperfect exercises in which precision eludes us.

The uncertainties we face due to limitations in our knowledge are different from the variability that defines randomness.[2] In order to identify the uncertainty due to knowledge imperfections we can turn to interval estimates. Intervals suggest a range of possible candidates for the "true" outcome. Intervals can also be generalized in terms of nested segments graded by the degree of confidence. These nested intervals are known as *fuzzy sets*.[3] In this way, the idea of *fuzziness* becomes indispensable to understanding high-stake risks and their treatment.

A fuzzy set A in universe X is the set of ordered pairs,

$$A = \{(x, \mu_A(x))\}, \quad x \in X \tag{1}$$

where $\mu_A(x)$ is called the *grade of membership*, or simply *membership*, of x in A. In this case, $\mu_A: X \rightarrow M$ is a function that maps from X to space M, the *membership space*. We define M here on the closed interval [0,1], with 0 representing the lowest grade of membership, and 1 the highest. When M contains only points, 0 and 1, A is non-fuzzy and reduces to the characteristic function of a non-fuzzy (precise) set.[4]

In terms of fuzzy sets and their associated logic, we can define dangerous situations in terms of the overlap between our definition of danger, and our imperfect assessment of the probability of some event. The degree to which any situation represents danger is then defined by the intersection of the fuzzy concepts of probability of occurrence (P) for the event in question, and our fuzzy risk threshold (T), using the "Min" operator,

$$\mu_{P\cap T} = \mathrm{Min}\,(\mu_P(x), \mu_T(x)), \quad x \in X \tag{2}$$

where universe X is annual probability of loss on the interval [~0,1]. An example is shown in figure 1, where membership in the concept "danger" (i.e., the possibility of disaster) is the envelope of the shaded area. [5]

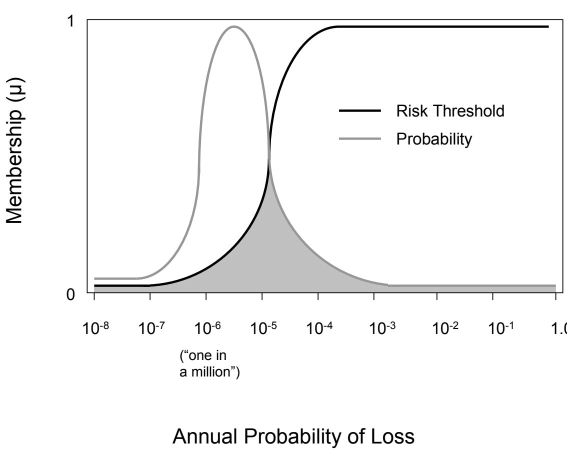

Fig. 1. A Fuzzy Definition of "Danger"

To identify the danger inherent in any event, we therefore simply assess its fuzzy probability, and match this to our fuzzy definition. In this figure, we show a reasonable degree of overlap, suggesting that the event in question shows the properties of an unacceptable risk. Actionable degree of membership for the combined fuzzy set "danger" is based on a suitable membership threshold, representing a so-called α (alpha)-cut through membership space. Note that if we had simply used some single estimate as best guess, most reasonably the peak of the probability membership function, we would have judged this event as unequivocally *not* dangerous. The fuzzy approach therefore adds a degree of conservatism to the decision. When facing high-stakes risk, this conservatism can be critical.

Fuzziness is not measured directly by data, but is rather identified instrumentally, by how well our assessments let us deal with the real world. The tradeoff then is always between specificity and truth. The more specific we get with inherently imprecise concepts, the less likely our assessment will contain the true value. On the other hand, the more non-specific the estimate, the less useful (e.g., the outdoor temperature tomorrow will be between 0 and 120 degrees Fahrenheit – should I wear shorts?). The "accuracy" of our fuzzy membership assessment depends on how well we balance specificity and truth *based on the information (knowledge) available*.

2. What is "Safe"?

Recognizing the fuzziness in risk thresholds indicates that a strictly zero level of risk, in terms of likelihood, is unobtainable. The laws of physics tell us that there is some positive, albeit miniscule, probability that the molecules within the floor may arrange themselves randomly so as to swallow us whole. Yet no-one takes such likelihoods seriously when making their next step. Instead, we accept some (low) level of probability as natural, as represented by those events that have supported a rather long streak of evolutionary survival on this earth. This background level of risk therefore represents a reasonable, yet fuzzy, safety goal for human activity.[6]

This does not mean that nature is benign to its constituents, nor does this matter. In fact, the survival of the whole may depend on some degree of threat to the existence of those elements that do not promote its wider goals. There is, however, no indication that nature is in fact a danger to *itself*. If it where, we would expect each biological epoch to exist for hundreds or perhaps thousands of years, rather than millions, as our most current one has. In fact, we may utilize the inverse of the time of life's existence on earth in its most recent epoch as a rough guideline for acceptability. More accurate calculations in this regard could help us better identify natural risk thresholds for society as a whole.

The upshot of this discussion is that the management of high-stakes risk is very much an all-or-nothing endeavor. This fact is captured in the *minimax* principle of decision under uncertainty, which suggests that when probabilities are unknown (or irrelevant), we act so as to minimize the maximum loss.[7] When the uncertainties in both the measurement and definition of acceptable risk are considered, we have the so-called *precautionary principle* of high-stakes risk management: *When some action has potentially catastrophic (i.e., terminal) outcomes, we should avoid the action.*[8] The precautionary principle is a linguistic rule for action that can be formalized using fuzzy sets, as described above. Applying the principle to real-world actions involves a *fuzzy pattern matching process* that compares fuzzy probability estimates to the fuzzy definition of natural ("acceptable") risk, as suggested in the formal analysis above.

Practically, this analysis suggests that uncertainty must be considered in making decisions about the safety of modern technological progress. As an example, consider the studies performed early on in the wide-scale development of nuclear power in the United States. These studies included a natural ("background") risk comparison for assessing nuclear safety. Perhaps the most cited (and debated) of these early studies was the 1975 report of the U.S. Nuclear Regulatory Commission (USNRC), *Safety of Nuclear Reactors* (also known as the "Rasmussen Report").[9] As part of its findings, the report compared the likelihood of severe nuclear accidents, computed from extensive probabilistic analyses of component system failures and their outcomes, with the probabilities of natural events. The report proved less than convincing as to the safety of nuclear power *due to its failure to properly account for the great uncertainties involved*. While point estimates suggested a risk profile on par with natural, background risks, reasonable (fuzzy) uncertainty bounds would have placed the risk considerably higher. Failure to properly account for the uncertainties was cited by a number of scientists. Perhaps more importantly, it was also intuited by the general public, who remained generally unconvinced of the safety of such installations.[10]

The responses to the USNRC study, both by concerned scientists and the affected public, suggest that any future risk assessments of alternative energy options need to account for the uncertainties. We may be able to increase acceptability, now and in the future, to the extent that we can reasonably narrow the uncertainty bounds that encompass natural risk levels. The fuzzy formalism provides a method for identifying and communicating these uncertainties, as well as implementing suitably precautionary risk management strategies.

3. The Treatment of High-Stakes Risk is *Unique*

Fuzziness imparts some unique characteristics to the *accumulation* of risk as well. We are not able to rely solely on precise calculations of risk accumulation represented in, for example, the simple application of the additive law of probability. Applying the precise theory to risk accumulation suggests that over repeated trials, *n*, the probability that at least one potentially catastrophic event, with individual probability of loss *p*, will result in disaster is given by the formula,

$$1-(1-p)^n \qquad (3)$$

Precise estimates of p are simply not credible. Nor is simply "fuzzifying" the additive probability enough to capture all uncertainties, as *riskiness* is itself defined by a fuzzy threshold. Instead, the accumulation must be represented by a type 2, or *ultra-fuzzy* set, as shown in figure 2. Type 2 sets represent a second order "fuzziness about fuzziness" that more fully captures the extreme uncertainties of assessing risk accumulation in our complex society.[11]

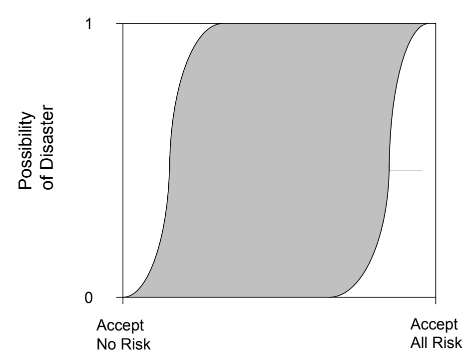

Fig. 2. The Ultra-Fuzzy Accumulation of Risk

Risk accumulation therefore represents the *interaction* of two unknowns: The growing possibility of risk, in terms of imperfectly known individual probabilities, and our imperfect definition of risk acceptability. The result is a distinctly *modal* representation of risk accumulation in terms of impossibility, possibility, and certainty.

In treating this accumulation of risk we face the fundamental *catastrophe problem:* In the long run, there may be no long run. That is, we don't get a second chance to get things right. Combined with the inherent uncertainties of complex and dynamic systems, this observation suggests that the management of high-stakes risk accumulation is itself unique. We can not make treatment decisions using direct statistical techniques that optimize outcomes *over time*.

This fuzzy nature directly impacts the treatment of these risks. First and foremost, proper treatment of uncertain, terminal risks requires application of the *minimax*, in terms of the aforementioned (section 2) *precautionary principle*. We can in this way reduce both the possibility of disaster *and* the uncertainty associated with its growth.

The uncertainty of growth that surrounds high-stakes risks also means that, should we somehow find ourselves in a position of peril, returning to a safer position may not just be a simple matter of "backtracking" along our original path. Complex dynamics may be obscured by the uncertainties. These include the potential for *hysterisis*, or dynamic pathways in which reversal of causes does not guarantee reversal of effects. The potential of unknown dynamics mitigates against a "wait and see" attitude toward the application of precautionary strategies. By the time we are *sure* such strategies apply, it may be too late.

Last but not least, the traditional application of prioritization techniques, or *worst-things-first*, does not make sense when the pathways to risk growth are so obscure. Such rankings are only applicable when there is hope that we might be able to reverse dangerous trends before disaster occurs. Under extreme uncertainty, this approach can only be a matter of faith, or as philosopher Nicholas Rescher has referred to it, "grasping at straws".[12]

The implications of ultra-fuzzy accumulation of risk for risk management are summarized in figure 3. As we can see, all of these suggest a very different approach than we would take when facing statistical risk alone.

1. Fuzzy accumulation suggests the importance of a genuinely precautionary approach. What we don't know, *can* hurt us.

2. Should we find ourselves in a position of concern about growing risk, fuzziness suggests that reducing risk may not be as simple as retracing our steps (i.e., "backtracking").

3. Under fuzziness, the idea of prioritization of risk (lexicographic ordering) does not make sense. How do we know which risk is worse? After all, all it takes is one to end our existence.

Figure 3. High-Stakes Risk Management Under Fuzziness

4. Behavioral Impacts of Uncertainty on Society

Fuzziness has distinct rational implications that are associated with behavioral impacts of decisions as well. Studies have shown that decision-makers react differently to fuzziness than other forms of uncertainty, including probability.[13] Might we not infer that these behavioral aspects could impact an entire society? This leads to the prospect that increasing uncertainty about risk (i.e., fuzziness) may itself act as the ultimate impetus for the radical (fundamental) change necessary to implement a fully precautionary program of risk management. It does so by affecting both the emotional *and* rational mind.

In terms of a theory of revolutionary change, we follow Davies' representation based on the perceived difference between actual and expected need satisfaction (as more fully developed in Hagopian's *Phenomenon of Revolution*).[14,15] This theory is consistent with rising levels of need satisfaction, and not simply levels of absolute deprivation. As shown in figure 4, once actual needs deviate sufficiently from expected needs, revolutionary change ensues.

The need we face with respect to high-stakes risk is safety (in terms of natural risk levels). The increasing uncertainty about our safety corresponds to the widening gap between expectation and actuality – or at least our perception of it. Just as in the case of individual decisions under conditions of fuzzy uncertainty, this aggregated, societal uncertainty will have effects on the choices and actions of the affected population, both rationally and emotionally.

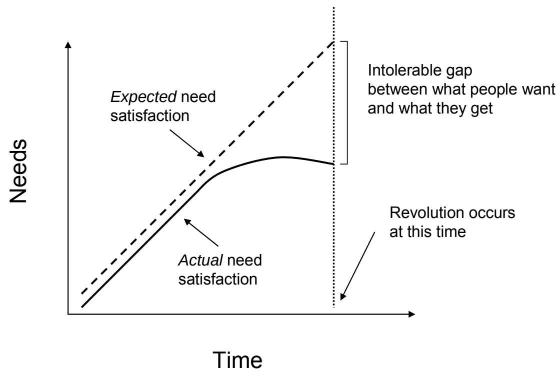

Figure 4. Actual Versus Expected Need Satisfaction as the Trigger for Revolutionary Change (adapted from Davies[13])

The inherent fuzziness in high-stakes risk combined with the need satisfaction theory of fundamental change suggest that the impetus for action will not be that "the end is near", as the doomsayers predict, but rather that *the safety of our future is becoming so uncertain.* Increasing uncertainty about the risks we face may reasonably push society beyond some "tipping point" for action. The hope then becomes that this recognition has not come too late.

5. Implications for Governance

The implications of various forms of uncertainty that go beyond randomness are becoming increasingly recognized in the field of risk governance. Fuzziness, which captures uncertainty due to knowledge imperfection as "degrees of ignorance" can help us extend the governance of high-stakes risk to a more realistic domain. The precautionary principle, as outlined above, recognizes both the need to incorporate extended uncertainty into the decision process for high-stakes risk.[16]

To be truly effective, however, precaution must be applied in a suitably proactive fashion. Otherwise the possibility of *risk dilemmas*, of the "doomed if we do, doomed if we don't" variety, arise. Properly precautionary risk management, therefore, requires *planning on a societal level*. Planning becomes, in effect, an essential component of a new "survival economics that recognizes natural risk levels as absolutes rather than as tradeoffs inherent in simple market economies.[17] While social planning is often characterized as obtrusive, the fact is that all living things plan: *Organism* implies *organization*.[18]

Precautionary governance of risk must therefore go beyond market systems and intervention in such systems in terms of "regulation". As Stirling *et al* note, the institutional changes necessary for a proper appreciation of uncertainty in high-stakes risk management require fundamental changes of framework.[19]

6. Utilizing Computationally Intelligent Systems for Risk Planning

It is likely that systematic planning against high-stakes risks will need to be carried out with the help of large scale electronic computers and communication networks, introducing requirements for the design and implementation of computationally intelligent systems.[20, 21] With respect to the aspects of planning high-stakes risk, the fuzzy formalism described here can be easily incorporated into such systems at a variety of levels, providing a valuable aid to the planning and decision-making process.

From the standpoint of computationally intelligent systems, the use of fuzzy sets allows the construction of automated or hybrid automated-human (i.e., advisory) systems for the management of high stakes risks. With the help of neural and other parallel computing architectures, such systems can be made to handle very large and complex data sets and decision problems. This allows integration into robust local and national planning and decision structures.

Figure 5 shows a simple neural architecture for assessing fuzzy probabilities from inputs. These inputs may be identified by experts, or through fuzzy data processing techniques (e.g., fuzzy clustering). For a large dam facility, for example, these inputs may be age of the dam, condition assessments, and the type of construction. Outputs are the associated fuzzy membership functions, here assessed using a simple Gaussian form that is completely specified by numerical shape, center and spread parameters. The network is trained using human expert associations, or fuzzy data. The result is various connection strengths between nodes, including a processing, or hidden, layer that matches inputs to outputs based on training data. A fully trained network can be used to implement very fast computational assessments of fuzzy probability.[22]

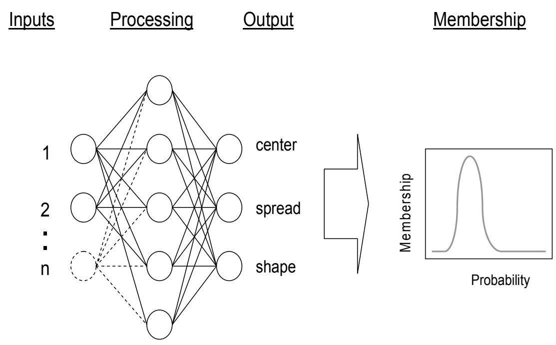

Figure 5. A Simple Neural Architecture for Assessing Fuzzy Probabilities

Once the probability membership function is identified, it can easily be matched to fuzzy acceptance criteria, to determine the need for precautionary action. Input parameters can also be manipulated, as well as connection strengths evaluated, to assess how changes in inputs parameters might change the results. In this way, a fully automated system of safety assessment can be implemented.

Proper interfaces allow direct input and observation of results by all interested parties, making the process more transparent. These interfaces can also simplify the process of achieving consensus of inputs and goals. Democratic participation in risk decisions requires that all assumptions be made plain.

Combined with wider socio-economic planning systems, fuzzy assessments allow for an integrated functioning of societal decision systems that pays proper respect to the overall goals in a multi-criteria fashion. These systems maintain a true community sense of purpose, or shared *teleology*, that supplants atomistic decision processes that could lead to globally disastrous outcomes.[23] The result of their implementation is a safer pathway to progress.

7. Summary and Conclusions

"Danger" is an inherently fuzzy concept. Considerable knowledge imperfections surround both the probability of high-stakes exposures, and the assessment of their acceptability. This is due to the complex and dynamic nature of risk in the modern world.

Fuzzy thresholds for danger are most effectively established based on natural risk standards. This means that risk levels are acceptable only to the degree they blend with natural background levels. This concept reflects an evolutionary process that has supported life on this planet for thousands of years. By adhering to these levels, we can help assure ourselves of thousands more. While the level of such risks is yet to be determined, observation suggest that the degree of human-made risk we routinely subject ourselves to is several orders of magnitude higher.

Due to the fuzzy nature of risk, we can not rely on statistical techniques. The fundamental problem with catastrophe remains, in the long run, there may be no long run. That is, we can not rely on results "averaging out" over time. With such risks, only precautionary avoidance (based on the minimax'ing of the largest possible loss) makes sense. Combined with reasonable natural thresholds, this view allows a very workable approach to achieving safe progress.

What might be the impetus for the changes needed to realize a more fully precautionary approach to progress? It is likely that growing uncertainty about the risk we face may be the strongest motive for fundamental change. The growing disparity between the safety we feel we are entitled to, and the risk we may be exposed to, can push society beyond the "tipping point" and into action. Whether this action will come soon enough, is an open question.

The impacts of uncertainty surrounding high-stakes threats to our existence suggest a more inclusive, and powerful, form of risk governance is needed. The proactive approach required to make precaution truly effective will require that more detailed *risk planning* replace market interaction in the form of regulation. This planning will require, in turn, efficient computational systems to both warn us of, and manage, potentially high-stakes risks.

In terms of computationally intelligent systems, the fuzzy risk management process can be easily computerized. We have identified here a simple neural architecture for assessing fuzzy probabilities. Other such advancements are possible. All in all, such systems can become an indispensable component of an overall structure of social and economic planning that helps assure safe progress.

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