Invited Lecture

On People and Chance: the "Hard" Facts about the "Soft" Branches of Fire Safety Science

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ABSTRACT

Science requires falsifiable propositions, preferably assembled in structures that provide non-obvious predictions across a wide scope. The human behavior and probability branches of fire safety science meet this definition. The topic of fire safety science, as distinct from fire science, demands human behavior and probabilistic modeling. In both human behavior and probabilistic modeling applied to fire safety science, there are multiple schools and approaches, often reflecting disputes over how much it is necessary or possible to imitate the structures and elements of the hard branches of fire safety science. A review of these approaches and the state of the art provides a basis for greater understanding of the nature and importance of the soft branches of fire safety science -- and the hard fact that they are worthy of the name "science" and essential to any valid and useful fire safety science structure.

KEYWORDS: Behavior, risk, probability, hazard, evacuation, scenario.

INTRODUCTION

When I was asked to deliver a paper to the International Association for Fire Safety Science on the subject of soft science, my first challenge was to identify what that meant. I made some choices in preparing a title for the paper, identifying soft science with those subjects where human behavior and/or probability play a role. But I also chose the subtitle -- the "hard" facts about "soft" science -- to engage the subtext of the term "soft science."

The further I proceeded into the preparation of this paper, the more I became convinced that my principal contribution would be in clarifying the nature and legitimacy of these essential branches of fire safety science. There is another invited paper at this symposium on human behavior in fire safety science, and there is a third invited paper on performance-based design, which will address some of the basics regarding risk analysis. Those papers, and many others at this and previous symposia, provide considerable detail on the specifics of these branches of fire safety science. My paper will address how the specifics fit together and, more fundamentally, how they fit with our notions of "science" and "fire safety."

Psychology and sociology are two fields often cited in defining "soft science." "Hard science" is usually defined by physics and chemistry. The term "hard" suggests solid results, rigorous thinking, and a firm foundation suitable for calculation and action. The term "soft" suggests work that will not stand up to close examination and an unreliable foundation for calculation.

"Soft science" therefore suggests bad science or even pseudo-science, but that suggestion is wrong. The proof requires a review of the nature of science.

WHAT IS SCIENCE?

From about 1920 on, there have been two principal views of how to define the essential nature of science, as played out in the debates of thinkers in the philosophy of science. [1] The first is an empiricist view, which derives primarily from the work of the English-Austrian philosopher Karl Popper.

To decide whether something is science, Popper asks, is the statement falsifiable through empirical evidence, at least in principle? "Falsifiable" means that the statement makes predictions about phenomena we can observe, and if the observed phenomena are different from the predictions, then the statement has been proven false, or falsified. We can't insist that statements be verifiable in order to be science, because it is not possible to test an equation in every possible application. We cannot insist that direct measurement be possible in practice. No one has seen or ever will see a sub-atomic particle, but we have tested our understanding of such entities through indirect observation using cloud chambers. And we cannot insist on controlled experiments or astronomy is not a science.

What we can reject as non-science is any statement that would be consistent with <u>any</u> possible evidence and is therefore not even in principle falsifiable. According to Popper, we can also reject a statement that has, in fact, been falsified.

Not so fast, says the other principal view of the nature of science. This view, variously called rationalist or constructivist, traces to the thinking of the 19th century French physicist Pierre Duhem. In this view, the essential test is whether a body of statements provide a coherent and consistent basis for wide-ranging, non-obvious predictions. If this sounds too permissive and potentially tolerant of error if it is elegant error, then consider how we test new physical equations. Experiments are run and the resulting data is compared to theoretical predictions. Inevitably, the fit is not perfect. Why is this not taken as falsification of the theory? Part of the reason is legitimate recognition of the variability of measurement, but much of the reason is borrowed confidence in the fundamentals used as a starting point, which have proven over the years to be both elegant and consistent with the most important phenomena, and so close to the truth in diverse settings.

Did many of us reject the claims for cold fusion a few years back because we already knew enough to see the flaws in their experimental procedures or logic? Or did we assume that flaws had to be present in any claim so at variance with a long-standing structure of recognized physical truth?

I would draw an analogy with a statistical procedure known as Bayesian analysis. [2] This is a technique that, in simplified terms, translates the evidence in support of a proposition into an equivalent number of historical experiments. If I run one more experiment, then no matter how it turns out, that one experiment is not enough to overturn a theory based on many previous experiments. But several experiments wildly inconsistent with the proposition would be. In Bayesian analysis, falsification is accomplished cumulatively and is a matter of degree. The constructivist concern with elegance and historical evidence for a theory deserves some weight -- but not absolute deference -- when interpreting the implications of a new experiment.

Note that neither of the two dominant definitions of "science" require that propositions be stated in terms of matter, energy, and motion. There is no presumption in favor of mechanistic or materialistic frameworks for science. There is only the falsifiability of the propositions and the coherence and scope of the collected body of propositions.

Fire Safety Science is Not the Same as Fire Science

These definitions of science indicate what it takes to study a topic in a manner that deserves to be called scientific. The other part of the definitional fundamentals has to do with what constitutes fire safety science -- the particular branch of science IAFSS is interested in.

"Fire safety science" means a scientific study not of fire but of the phenomena that create threats from fire and safety from those threats. This means not only the phenomena of fire but also the interaction between people and fire, which is how the threat is manifested. Therefore a study of fire safety science does not just permit but actively requires the study of people and fire -- not just fire effects on people but also the ways in which human behavior can increase or reduce the threat of fire and the harm it causes. Also, a study of fire safety requires study of those fires that most threaten safety, which means not only severity of hazard but probability of occurrence.

Every fire safety decision starts as a fire risk decision, because when ordinary people say what being fire safe means to them, they use language so broad and so basic that nothing can capture it but fire risk analysis. We do not say we want a chair that takes 10 minutes to produce a 600°C temperature at eye level or 5 minutes to produce a cloud of poisonous gas at nose level. We don't say we want at least 5 minutes to leave an area. We don't say we want to survive the worst likely fire or whatever term we use for a conservative design fire.

What we say is that we don't want to die. Period.

If you are a researcher in fire physics and you produce and verify elegant models of fire dynamics for fires that almost never happen, your work is great fire science but not of much use in the field of fire safety science. If you work on fire science, any advance in knowledge about any aspect of fire is of interest. But if you work on fire safety science, then what is needed is advances in knowledge about fires that matter. Here's a simple test: If you can't think of five people you can call whose lives are likely to be directly affected by fires of the type you're studying, then you're probably doing fire science, not fire safety science.

And the type of research we most need is in the areas of science where our ability to calculate fire threats and safety requirements is most handicapped by gaps in current knowledge. This is why the soft sciences are not only legitimate branches of fire safety science but may be the branches most in need of greater support, greater usage, and greater familiarity among all fire safety scientists.

THE SOFT SCIENCES OF PEOPLE

Psychology is the study of human behavior. Sociology is the study of collective human behavior, sometimes referred to as the study of people in groups. These are the two principal social and behavioral sciences, and they are what people tend to have in mind when they refer to soft science. [3,4]

Both psychology and sociology were regarded as pseudo-sciences when they first emerged in the 19th century. The term "pseudo-science" refers to a belief system that pretends to be a science but does not use scientific methods, i.e., formulation of well-defined hypotheses and testing of those hypotheses, directly or indirectly, through physical observation.

The psychological theories of early pioneers like Sigmund Freud and Carl Jung were certaintly vulnerable to the label of "pseudo-science". Developers of those theories did not conduct experiments to verify or falsify their propositions, which often were phrased in such a way as to make falsification impossible. And the fact that therapists claiming to act on the basis of those theories had success in alleviating symptoms with many patients does not mean that such therapies constituted experimental tests of the theories themselves.

Both psychology and sociology have produced theories that imitate the look of established concepts in physics but without the requisite substance. Terms are given scientific-sounding names but not operational definitions. Equations are stated linking those terms to each other, but conclusions based on the equations do not go beyond the obvious. And measurement methods tend to either alter behavior by being obtrusive or bypass direct measurement of behavior without verifying that the proxy used is valid. Interviews and questionnaires are valuable but not ideal as proxy measures of actual behavior.

At the same time, many of the objections to psychology and sociology are hard-science snobbery. If Kurt Lewin borrows the term "field theory" from physics to describe his concepts of small-group dynamics, that should not give the theory added credibility, borrowed from its success in physics, but it also should not disqualify the theory. Concepts like the id and superego from Freud may sound like mystical concepts such as the soul or the "chi" or life-force, but if such concepts survive falsification tests and provide non-obvious predictions that prove to be correct across a wide scope of subjects, they qualify as science. Many strange-sounding concepts in psychology and sociology fail the test of science, but many of them pass.

The Soft Science of People and Fire

At IAFSS symposia, people have been studied primarily in terms of their behavior when attempting to escape a fire and, to a lesser extent, in terms of their behaviors leading to initial ignitions. In fact, human behavior has a pervasive effect on every stage of fire development and reaction to fire. For purposes of simplification, though, we can group issues of human behavior into their effects on ignition, evacuation, and reliability.

People differ from things in that their behavior is the end result of their acquisition and processing of information, rather than the simple unfolding of the laws of motion and of interaction between physical entities. To fully understand behavior, one must address:

- The quantity and content of external information available to people.
- How external information is acquired, which may introduce gaps and distortions.
- Internal information, including goals and beliefs, that fits, or forces, external information into established frames and contexts.
- Differences in people's abilities to act on their intentions, including physical and mental limitations.

The internal information that frames external information and thus shapes behavior was the subject of an early IAFSS paper by Jones and Hewitt on leadership and group formation in high-rise building evacuations. [5] This paper, from the first IAFSS symposium, was a rare example of research quantifying the role in evacuation of information not connected to the threat or the physical evacuation options. Specifically, the authors showed information unrelated to knowledge of fire safety was processed by people as they sought to identify leaders to guide them in performing fire safety tasks. Your office supervisor might know nothing about fire safety -- or at least far less than you do -- but people are accustomed to following the supervisor's lead and are likely to do so in a fire emergency where more appropriate leadership roles are not already established. This has practical implications. It helps explain the advantage of fire drills using fire wardens in large office buildings. Occupants not only practice effective evacuation behavior but also reinforce a more appropriate and informed leadership structure for dealing with unanticipated decisions in a real emergency.

The Soft Science of People at IAFSS Symposia

The earliest evacuation models did not address information availability or information processing at all. People were treated not as decision-making individuals but as masses in a classic fluid dynamics situation. [6,7] This was equivalent to assuming that each individual had perfect information that was perfectly processed and directed toward a single unequivocal goal of evacuation. These models also ignored differences in people's abilities. Not surprisingly, these models consistently predict performance that is far better than is achieved in practice. In the empiricist sense of science, these models have been repeatedly and conclusively falsified, but in the constructivist sense, they provide ease of analysis, an elegant fit with the physics of fire development, and some valid, non-obvious conclusions, provided you understand their strengths and limitations. They are the easiest models to handle mathematically, and for all these reasons they continue to be widely used. [8]

At the other extreme, there are evacuation models that treat people not as ball bearings but as clairvoyant geniuses. [9] Occupants are provided with complete and accurate information on building layout and location and implications of fire conditions, instantaneously, not only in their immediate vicinity but in remote locations where they could have no realistic access to information. These models can incorporate differences in people's abilities, at least their physical abilities, but in terms of decision-making, every occupant is treated as an omniscient, totally rational actor focused on safety. Not surprisingly, these models also consistently predict performance far better than is achieved in practice.

Both of these types of models have the additional problem that they have no natural basis for addressing behavior prior to the initiation of evacuation movement, such as investigatory behavior designed to confirm early cues and establish that a fire emergency exists. This so-called pre-movement activity has been shown by Proulx and Fahy [10], among others, to far exceed in time the typical requirements of evacuation itself.

The clairvoyant genius approach to modeling human behavior is popular in other fields as well. The so-called "rational expectations" school of economics is constructed along these lines. In these models, economic actors are implicitly provided with perfect information about the past, the present, and even the future. Despite the apparent absurdity of these assumptions, the approach has been elaborated mathematically and applied extensively.

Herbert Simon [11] introduced the concept of "bounded rationality" in a 1955 paper. Limited resources of time, money, and information lead people to search not for optimal choices but for choices that are good enough. This is a particularly good example of established science in the "soft science" fields that has yet to be incorporated into the behavioral models of fire safety science or into the models of economics, for which it was expressly designed.

The dominant approach to evacuation modeling today falls between the mechanistic and the optimizing approaches. People are not treated like ball bearings in a tube or like emotionless clairvoyants who always know the best action to take and execute that action without hesitation or error. Instead, these simulations of behavior operate like video games and move people according to rules. Using small increments of time and either simple or complex collections of rules, these models are able to address human information processing but to do so without unrealistic assumptions about efficiency or consistency. [12,13,14,15,16,17,18,19]

Or at least that is what the rule-based, simulation-format approach permits one to do. In practice, most of these models are still dominated by evacuation movement behavior. They are much better predictors than the fluid dynamics analogue models because they can incorporate crowding, queueing, variant physical capabilities, and other physical phenomena that directly and simply affect movement. But they tend to do a limited job of incorporating pre-movement behavior and ineffective behavior driven by conflicting goals or limited or problematic information.

By looking at the requirements of a successful model for predicting human behavior in response to fire, one can see that the problem is not an absence of science or scientific approach but rather a much greater number of as yet unanswered scientific questions on the topic of human response to fire than in some of the core topics of fire physics.

What is Needed for Useful Science on People and Fire?

Take any phenomenon considered potentially relevant to prediction of behavior. First, one needs an operational definition of the phenomenon that will permit it to be measured and allow testing of whether it makes any difference in behavior. If so, one next needs a specific hypothetical relationship tying this phenomenon to behavior, so that variations in behavior can be shown to vary in predictable and stable ways with variations in the phenomenon. If this is successful, there is both a practical and a theoretical next step. The practical next step is to identify a practical method, preferably using direct measurement, to generate data in specific situations, so you can use the established relationship for analysis and design. The theoretical next step is to develop and confirm more complex relationships showing how this phenomenon interacts with others to affect behavior. Only then can we be said to have a complete and useable model of the relevant behavior.

In fairness, every branch of fire safety science has major areas in which the state of knowledge falls short of this complete picture. You can examine the topics of papers being presented at this symposium to see where the state of the art extends. Studies of evacuation behavior, however, are still at a very early stage across the board.

For example, Proulx has listed a number of phenomena relevant to human evacuation behavior, identified by herself and others, and demonstrated that they influence and can dominate behavior. [20] One example is "commitment," which refers to an individual's involvement in current activity, which must be abandoned if evacuation is to begin.

Commitment is a phenomenon which can be operationally defined and quantitatively measured in terms of the speed and likelihood with which individuals, engaged in certain activities, can be induced to switch their attentions and begin processing information related to a possible emergency requiring evacuation. But we do not have a tool for routine measurement of commitment for particular groups or a way of obtaining or estimating data on commitment that would be appropriate for predicting conditions at the start of a fire emergency. We do not have a mathematical relationship linking commitment to behavior, let alone showing its interaction with other factors and phenomena.

That is not a criticism; it is merely the state of the art, but it applies to a great many behavior-related phenomena. It also is not a disabling flaw in current behavioral models. We know from testing that we can predict the development of fire effects with good accuracy in most situations while ignoring turbulent fluctuations and using default values for heat of combustion. Similarly, we can model human evacuation behavior with good accuracy in most situations while ignoring many second-order phenomena and using default factors, such as time delays, for still other phenomena.

Default values can be reasonably developed from empirical correlations. The early fire evacuation behavior model EXITT [12] by Levin was based on a distillation of simple behavioral rules as a function of individual characteristics, all taken from interview-based reconstructions of behavior in real fires, large and small, and from more controlled evacuation drill experiments. Both of these data sources have significant limitations. Reconstructions of behavior in real fires are subject to biases, gaps, and deficiencies of detail attributable to the limitations of human memory and observation in stressful situations. Evacuation drills tend to be more efficient than real life for a variety of reasons. In this respect, evacuation behavior science is at a stage of development similar to the stage of fire dynamics a quarter or a third of a century ago.

Several papers have identified, and sometimes quantified, relationships and behavioral rules in evacuation. [21,22,23,24,25,26,27,28,29,30,31,32,33,34,35] Some papers have documented behavior in individual fires, which can serve as a basis for calculation of default values. [36,37,38] Some papers have used data from drills or real fires to evaluate -- verify or falsify -- evacuation time predictions from models. [39,40]

It would be a mistake to conclude that our models of fire and fire safety can ignore all of human behavior -- and should do so until we understand it fully. We already know that if we model people as objects in motion, our predictions will be unacceptably far from the truth. We already know that if we model people as perfect information processors, our predictions will be unacceptably far from the truth. We should know that if we try to handle human behavior implicitly and without analysis, for example, by setting criteria or thresholds of safety based on physical phenomena in fire, we have no reason to believe that our models are anywhere near the truth.

Switching now to the link between human behavior and ignition, we find that most IAFSS papers -- and most work in fire safety science -- have started and stopped at the point of quantifying the end-state behavior of interest. Specifically, we have had several papers providing scenario probabilities and other forms of national statistics on the frequency of certain types of ignitions, each of which involves a behavioral component. [41,42] We have done less and seen little regarding models of the factors and phenomena that determine whether those potentially ignition-causing behaviors will occur and will result in ignitions.

Quantifying and Modeling Human Error Related to Fire

There are relevant bodies of knowledge for such studies. Groner and Chubb delivered one of the few papers on point when they presented some typologies of human error. [43,44] One such typology, taken from Rasmussen, ties in neatly with the view of human behavior as the end result of information availability and information processing. [45,46] Rasmussen identified three types of cognition, each with its own type of error:

- Skill-based cognition involves learned chains of behavior. Error typically occurs because of a lapse in concentration or a random variation in precision of execution. Information processing is not really conscious. This bears on both evacuation and ignition behavior but especially the latter. Imagine the lapse that results in a cigarette being deposited on a couch rather than in an ashtray.

- Rule-based cognition involves behaviors requiring the application of rules to available information. Error typically occurs because the wrong rule is selected or the information used to apply it is flawed. The wrong rule may be judged wrong, in hindsight, because it was wrong as a matter of fact -- e.g., a wet towel placed over an electric lamp will dry quickly but is not close enough to anything hot enough to ignite a fire -- or because it involved a simplified treatment of goals at stake and possible consequences of an action -- e.g., placing a wet towel over an electric lamp will solve my drying needs and will not produce any other effects that I need be concerned about.

- Knowledge-based cognition is rule-based cognition in which the individual also changes the rules or the available information. Error occurs for all the earlier-cited reasons but also because the creative actions of rule-writing and information-generation can be done wrong. In practice, individuals have to go beyond the rules they've previously absorbed and the information that comes to them unbidden, or else they would rarely have a sufficient basis for action. But this dynamic process is almost impossible to model, so evacuation behavior models, for example, are forced to work from a small number of established rules that are expected to govern behavior in most situations.

Behaviors that lead to ignitions tend to be quite rare, which makes them poor candidates for study in controlled experiments. When they are studied, the artificiality of controlled experiments often intrudes and biases the results. People's states of mind are likely to be different in a real emergency evacuation than in a fire drill situation, and even more different if they know that drill is being observed. For studies of behavior leading to ignition, people are likely to be more careful if aware that their behavior is being observed.

Nevertheless, there is a substantial literature, primarily on behavior in workplaces, on behavioral factors and sequences, supporting ergonomic design and programs of education and training. There is untapped data in the literature on evaluation of fire safety education and training programs that can be used to estimate knowledge, behavior, and rules of choice for people with and without training.

This same literature has bearing on the range of issues I would collectively refer to as reliability. [47,48] The modeling of fire, as opposed to the modeling of people exposed to fire, is a time sequence of events predictable by applying established hard-science relationships to situation-specific data on materials, spaces, and the like. That situation-specific data, in turn, will reflect the designer's intent and the relevant codes and requirements, but it will also reflect -- and often be dominated by -- non-standard human actions.

Once the fire begins, codes and designs may state what <u>should</u> be ignitability, proximity, and burning properties of nearby secondary fuel packages, but human actions may deviate slightly or significantly from those intentions, and every point of departure is a form of unreliability. Codes and designs may state the location, durability, and performance of elements of compartmentation, but human actions will block doors open, put holes through walls, and in many other ways create unreliability in structure and compartmentation. Automatic systems can fail for mechanical reasons, but when they do fail, it is usually because people shut them off, interfered with their operation, failed to build and maintain the system as designed, or otherwise introduced unreliability into the design. And so forth.

The late Howard Boyd, a former local US fire marshal, brought the subject of reliability to IAFSS in his paper at the first symposium. [49] His treatment of the subject was more practical than theoretical and did not link to the mainstream of modeling. There has been little attention to the topic at IAFSS or in the fire safety science journals worldwide since then. Interestingly, the subject of reliability is receiving a tremendous amount of attention this year in research conferences and decision-making meetings around the USA within the context of performance-based design and codes. The reasons for this resurgence of interest bear on our discussion here today. Because reliability is mostly human error, you cannot eliminate it; because it is usually significant, you cannot ignore it; and because it is unavoidably probabilistic, you cannot fit it neatly into a deterministic framework.

THE SOFT SCIENCE OF CHANCE

Probabilistic phenomena are not all part of what is usually termed "soft science," a term that usually is reserved for social and behavioral sciences. Reliability may be dominated by human error considerations, but it has a significant mechanical component as well. Quantum mechanics has been a seemingly endless source of examples of indisputable phenomena that can only be expressed probabilistically.

Nevertheless, I included the modeling of randomness in my definition of soft science when I was setting the title and scope of this paper. And my reasons are that the attitudes toward probabilistic modeling, risk analysis, and randomness in general show much the same pattern as the attitudes toward scientific studies of human behavior. Many scientists are skeptical or even hostile, and this attitude is most pronounced among those whose own work falls squarely within the bounds of classic physics and related engineering.

Much of the resistance to probabilistic treatments of subjects is similar to the resistance to empirical correlations or artifical constructs like index numbers. A variable that corresponds to no observable, directly measureable phenomenon is that much harder to subject to falsification tests. A relationship that permits several possible outcomes with no insight into the why or how of the outcome that occurs is a black box.

Probabilistic models are not built up from mechanistic fundamentals or first principles of physics. They often are not built up from anything more fundamental than their own elements, so they provide limited insight. Nevertheless, they provide testable, falsifiable, non-obvious propositions in a consistent and coherent framework of great scope. As such, they are within the bounds of what science is.

What Are Probabilities?

Within the field of probability theory, there are two schools of thought regarding the nature of probability. [2] One school sees probabilities always rooted in the reality of frequencies of actual events. It may not be obvious how to directly measure these frequencies or to use them without alteration to describe or predict future events, where some factors may have changed. It may be necessary to estimate the probability values -- or, if you are feeling less generous, to guess at those values. Sometimes, it is possible to develop, verify, and then use a probabilistic model to infer needed probability values from other probabilities that can be calculated from measured frequencies of observable events. But even if the only data is guesswork, the parameters themselves are understood to correspond to something real.

The other school sees probabilities as the quantification of degrees of belief. [50] The mathematics of probability works perfectly well no matter where the probability numbers come from. But is the result science?

This probability-as-degree-of-belief school also tends to dismiss the notion of shared, objective truth, believing instead that every individual has his or her own personal truth. This basic belief may sound mystical and unscientific, but that is not enough by itself to declare it outside the bounds of science. Even if Person A regards a set of propositions as part of a personal truth, if the rest of us can agree on falsification evidence relevant to those propositions, we can treat the propositions as science if they pass that test.

But why should we bother? If all truth is personal, then so is any notion of verification or falsification. If the author of the probabilistic model claims it as an expression of his or her personal truth, then the evidence to dispute it is only the evidence that one person accepts. The problem comes if a probabilistic model is put forward as a scientific tool useful in the pursuit of shared truths but immune by definition from any requirements for falsification or any need to respond to apparently contradictory empirical evidence. This is a classic case of trying to have your cake and eat it, too. I would not accept such a model as fire safety science until or unless it was subjected to the tests that science by definition requires.

Therefore, my remaining discussion of probabilistic modeling and the relevance and use of probabilities in fire safety science favors my preference for the underlying frequency definition of probability. And from that vantage point, I would assert that Nature is full of phenomena that can only be understood and validly studied with the use of probabilities.

What is Needed for Fire Safety Science Using Probabilities?

As with human behavior studies in fire safety science, so with probabilistic models, most of the state of the art leaves a great deal still to be done. When my colleagues and I estimate probability parameters from historic fire experience, those values constitute a candidate model, a set of propositions to be verified. Only by comparing actual to predicted values for fire experience from another place or another time can we describe the model as verified. And then, the next step is to construct and verify a model of the determinants of those probability parameters. This model may contain nothing but probability parameters or it may include empirical correlations to physical phenomena, but either way the model should provide a basis for predicting how changes in physical entities or human behavior will translate into changes in the original probability parameters.

The same literature cited earlier on reliability shows that studies at this level of detail do exist for probability parameters applicable to fire safety science. Both the strengths and the weaknesses of our current state of knowledge regarding probability parameters may be traced to the fact that we have extensive data regarding circumstances at fire events but typically much less data regarding those same circumstances in everyday life.

For example, we can estimate the probability, given fire, that a particular product or behavior was associated with that event. We usually cannot as easily estimate the probability that that particular product is in use generally or the probability that that behavior occurs in a given period of time in the general population. And so we usually cannot estimate the probability that the use of that product or the occurrence of that behavior will lead to an unwanted ignition.

The problem is not that we do not know how to observe and measure behavior, although unobtrusive measurement that does not alter the behavior it observes can be difficult or impossible to arrange. But fire is a very rare event. In a year's time, only one US household in 4,000 will suffer a fire serious enough to involve the fire department, and at most one in five will suffer any kind of unwanted fire whatsoever.

Many of the behaviors that lead to unwanted ignitions or create a greater danger if fire occurs also are rare events. We can collect data on the probability that stairway doors in high-rise office buildings are blocked open at a particular moment in time, but it is much more difficult to collect data to estimate the probability of occurrence of an act of blocking open a door or the distribution of the duration times during which the door is blocked open. Yet this more complex set of data may be necessary to accurately model the probability of effective vs. ineffective compartmentation of stairways in a risk analysis.

We can observe people for a period of time and estimate the probability per unit time that one will drop a cigarette into a particular combustible location. The more detail we want on the particular fuel source exposed to a cigarette or the risk factors contributing to unsafe behavior, the more people we must observe and the more observation time we will need.

It is possible to collect this data in a sufficiently closely supervised environment, where most of the behaviors of interest occur often enough to be observed repeatedly in a reasonable period of time. Data bases on probabilities of human error in dealing with equipment were developed in complex industrial environments. These are places where human-machine interaction is frequent, even constant, so that the lapses and events that form the building blocks of poor equipment performance, failure of equipment to perform, or harm to people, can be measured and frequency-based probabilities derived.

For every probability value like this, however, there are a multitude of probabilistic phenomena relevant to fire occurring in settings where close supervision is not common and often not possible, and where event frequencies are too low for simple, direct observation to support frequency calculation. Consider how many of the types of probabilities required to describe fire development and the effects of fire fall outside the scope of the settings where easy direct measurement of frequencies is possible:

There are not only the probabilities of ignition for particular type of fires but also probabilities that various protective systems will be present and will operate; probabilities that construction features of the building or product were designed properly, manufactured and assembled properly, installed properly, and maintained properly; probabilities that people, property, or essential elements in operations are present to be endangered by fire or to act so as to increase or diminish the danger of fire; and probabilities that people's behavior is or is not effective for safety.

The Soft Science of Probabilities in IAFSS Symposia

Research on probability in past IAFSS papers and related publications broadly fall into four categories. [51,52,53,54]

First, there are the large risk analysis packages like Canada's FireCAM. [55] In these modeling packages, risk is calculated as the sum, over all studied scenarios, of the probability times the severity of the scenario, where severity is calculated by deterministic models. Probabilities of ignition are factored into scenario probabilities, as are reliability probabilities, which determine the status of the building and its fire defenses when fire occurs. Probabilities of occupant loadings, locations, and conditions are also pulled forward into scenario probabilities, so that probabilities are used solely as weights on a series of deterministic models. The output is usually stated as the expected, or average, risk, but it can be stated as the probability that severity will exceed a threshold. [56] The latter can be useful if the risk of interest is solely the risk in very severe fires. [57]

This approach to the use of probabilities addresses one of the concerns of the hard science school. It uses physics, chemistry, and the other hard sciences to the maximum degree possible, using probabilities only to choose which fires to study and how to interpret results when multiple fires lead to conflicting evaluations of a building design.

Misunderstandings about this approach seem mostly to involve the concept of "average." You cannot validly calculate the average risk by modeling the severity of one average fire or a small number of typical fires. Average risk will reflect extreme, high-severity situations, and it is possible that these scenarios will dominate the overall average. The calculation of risk assumes that you are approximating a sum over all possible scenarios. Because such a summation is impossible, scenarios are grouped for probability estimation, but that requires some procedure for selecting a representative fire for severity calculation in each scenario group. The sensitivity analyses and uncertainty calculations that are frequently invoked as necessary, but less frequently performed, not only address the uncertainties inherent in the probabilities but also address the error potential in the rules used for grouping scenarios.

The second major approach to probabilities is in a fault tree, success tree, or event tree. This is the format of probabilistic model most often used in the major applications of risk analysis, which are in environmental and other health impact policy issues. Where the first approach might be said to showcase its use of deterministic methods, while walling off the probabilities at the front end of modeling, this second approach showcases its use of probabilities and walls off any deterministic calculations at the very end of the modeling. The output of such a model can be average risk, if an event tree is used, but is more likely to be an overall probability of acceptable or unacceptable performance.

The first approach seems to be used more for analysis of national policy options, such as the impact on risk if sprinklers were universally used in some property class where they are now rare. The average risk measure generated by the first approach is more readily converted to a cost equivalent and so supports risk/cost evaluation. Again, Canada's FireCAM is a highly visible example.

The second approach seems to be used more as an aid to the structuring of engineering analysis on individual design projects. Here, the use of the approach may be more informal than formal, more qualitative and conceptual than quantitative, and premised on the notion of probabilities more as measures of degrees of belief than as frequencies. [58,59] For all these reasons, the second approach is not often used as the basis for evaluation or analysis of designs but is used rather as support, at the engineer's discretion, for review and design leading to conclusions that rest entirely on the engineer's professional authority.

A notable exception is in the industrial arena, exemplified by nuclear power facilities, where failure probabilities of complex equipment are pervasive and severities can be extreme. [60,61] In these settings, decision-makers are more likely to demand a formal analysis that is open and transparent enough to be examined and approved by a wide range of stakeholders, and a fault tree format is the only way to deal explicitly with the reliability and equipment failure probability issues that are unavoidable in design.

The third approach I've seen to the use of probabilities is in component models limited to particular phenomena and incorporating both probabilistic and deterministic elements directly into the model. Ling and Williamson's paper on fire growth with emphasis on barrier breach is perhaps the best example in the IAFSS symposium and related literature. [62,63] Their network model permitted deterministic time-based modeling to alternate with probabilistic steps in a combination that reflected the realities of barrier breach more realistically and more completely than any purely deterministic or purely probabilistic model could have done. It is perhaps a commentary on the mutual suspicion and discomfort between the deterministic hard-science camp and the probabilistic soft-science camp that so few researchers in either group have embraced Ling and Williamson's work in a larger analysis package or pursued network approaches, though there have been some. [64,65] There has also been considerable discussion, though to date very little actual model-building, of the use of alternating probabilistic and deterministic steps in a network model format for evacuation.

In both the second and third approaches, there is the problem of obtaining appropriate, defensible parameter values for the probabilities. Both approaches require probabilities that are particularly difficult to estimate directly from empirical frequencies, because the events in question are both rare and well outside the range of what is recorded in any ongoing data base. Subjective estimates may be necessary, and there is an extensive literature on methods to organize the process of developing and testing such estimates to try to improve their accuracy. The so-called Delphi method, named for the ancient Greek oracle, is perhaps the best known of these formal methods, but the Delphi method is very painstaking, and many estimation exercises referred to as quasi-Delphi are really just Delphi exercises with unverified short cuts. You can, of course, avoid all these questions by declaring the probabilities to be only degrees of belief, but the price for doing so is to remove any valid claim of being science applicable to a group decision-making process.

This last point leads directly to the fourth common approach to probabilities in IAFSS and related papers, and that is papers with data, methods, or findings useful in the estimation of needed probabilities. These papers are valuable even if they are not new basic science, because they enable better, more valid applications of existing probabilistic models to more problems and cases, but quite often, these papers also point to changes in the models themselves, thereby qualifying as new basic science.

A recurring misconception in this area, perhaps because the researchers do not always make the point explicitly, is that Monte Carlo simulation is a method for estimating unknown probability values. It is not. Monte Carlo is a method of calculating risk values from a tree model without having to calculate severity for every scenario having a distinct probability, but the scenario probabilities still must be provided externally. [66] Monte Carlo chooses cases to calculate so that the frequency of cases matches their probabilities. Default approaches of using equal probabilities for all scenarios or estimating scenario probabilities from a standard probability function are not an inherent part of Monte Carlo simulation and must be independently verified.

SUMMARY COMMENTS ON "SOFT" FIRE SAFETY SCIENCE

1. Classic definitions of the nature of science do not require materialistic or mechanistic models. Much of the work on human behavior with respect to fire and probabilistic modeling of fire and fire safety easily meets the definitions of science.

2. All fire safety decision problems are presumptively fire risk analysis problems. Such problems require proper attention to human behavior and probabilities if they are to be appropriately addressed. Therefore, fire safety science without the soft branches is either incomplete, misleading, or not useable.

3. Dealing with uncertainty through conservative or "worst case" assumptions can be expensive and may not be truly conservative. This is because of the tendency to rush past assumptions on matters that are seen as "soft," such as assumptions about human behavior and reliability.

4. Researchers in the soft branches of fire safety science need to realize how much further they have to go before many of their propositions will have been quantified enough to be useful and tested enough to be trusted. However, the limitations of the state of the art are no excuse for researchers in the hard branches to ignore the findings that are established or to try to study real problems while excluding the roles of people and chance.

5. There is much for us to learn and apply from the soft science research outside the core recognized as part of the IAFSS community. We have often been too inbred, a condition all too common in every branch of pure and applied science. At the same time, we do not need any visiting experts with all-purpose models from other disciplines if they cannot listen to what is unique about fire and fire safety and will not modify their models to properly reflect those unique realities.

6. If you believe, then so must you act. As the great English mystery writer P.D. James said, "Once you have discovered what is happening, you can't pretend not to know, you can't abdicate responsibility. Knowledge always brings responsibility." Our responsibility is to create better science in the soft branches of fire safety science, while also better recognizing their importance in the overall picture and incorporating their findings in our current practices. The key to all these necessary steps is more and better conversation -- between the hard and soft camps of fire safety science, between the soft scientists and the users of fire safety science, and between the soft scientists inside and outside fire safety science. Let us begin those conversations today.

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