Sourcing Uncertainty Data by Perception, Experience and Opinion – Methods and Procedures, Advantages and Challenges

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Abstract

Currently, experimental and field data are main sources of estimating uncertainties. When adequate data are not available, engineering and intuitive judgment have been used, which without any rationale, may result in further propagation of error in estimating uncertainties. This paper describes the method of data mining for uncertainty estimation through experts. The method is flexible and can be crafted for a specific application in estimating uncertainties. The data collection is performed in multiple rounds to minimize the bias in responses. Also, the experts can be provided with ample information to refine the process of data mining and bias management. They may be provided with a scenario that replicates, or presents a digital twin of a known case, to bring their thoughts to focus on a specific parameter of concern. Modes of bias relate to an expert’s perception of the problem, their cognitive response in approaching it, and reaction to similar events. Modes of bias are reviewed and strategies to mitigate their effects are presented. This method of uncertainty estimation is useful when the nature of a parameter does not lend itself to conventional methods of data compilation. Thus, the expert opinion can alternatively be used to mine data and estimate the uncertainty. The method is especially applicable when the geometry of a system does not allow tests through experimentation; and field measurements do not provide meaningful data because of low levels of mechanical effects. A procedure for conducting the method is presented along with a discussion on potential challenges.

Keywords: biases, digital twins, expert opinion, probability, uncertainty

1. Introduction

A robust system evaluation analysis depends on an accurate estimation of uncertainties in parameters that influence the performance and function of the system. Currently, experimental and field performance data are considered as the most essential sources of estimating uncertainties. With adequate data, statistical methods (often referred to as Type A) have been used in successfully estimating uncertainties. In a more elaborate method (referred to as Type B), data in addition to some form of distribution function are known and used in estimating uncertainties. A specific example is the method of maximum likelihood, which employs a known probability distribution in finding measures of dispersion in data leading to the estimation of the uncertainty in a specific parameter.

In cases when adequate data are not available or are scares, other means, such as using engineering and intuitive judgement along with certain assumptions, have been used [1]. When conducted without any specific rationale or logic, in most part, these methods result in further propagation of error in estimating a system’s reliability in performing its intended function. In this paper the focus is in methods that rely on engineering judgment and experience. The paper describes the underlying methodology in obtaining the necessary data through experts. The method is rather flexible and can be crafted to suit a specific application in arriving at an adequate estimate of uncertainties. In the simplest form, the data mining can focus on estimating the values of a specific parameter; and as such the opinions of experts are sought and recorded. In a more elaborate method, it can seek an expert’s perception on the value of a parameter, the estimate of its uncertainty as well as the type of function that best describes the parameter’s probability distribution and even in further development of more accurate methods of engineering analysis. In other words, the method is applicable in quantifying both aleatory (data-based) and epistemic (knowledge-based) uncertainties. Another advantage of this type of data collection is that it can also be used in multiple rounds to minimize the bias phenomenon in responses. Furthermore, the experts (sources of data) can be provided with as much information that is possible and reasonable to refine the process of data mining and management of the bias. For example, an expert may be provided with a scenario that replicates, or presents a digital twin of a known case, to bring their thoughts to focus on a specific parameter of concern.

As explained in the paper, one major issue with this method of uncertainty estimation is the bias phenomenon. Different modes of bias often relate to an expert’s perception of the problem as presented to them, their cognitive response in approaching the problem, and reaction to current or past similar events. The paper reviews these modes of bias, as published in the literature, and offers strategies, applicable to engineering problems, to minimize them for more robust results. Specific examples and applications where the method can be used are explained in the paper. The paper further suggests a procedure for conducting this method of uncertainty estimation and outlines challenges to overcome in conducting the method.

2. Overview of the Method

The method of uncertainty estimation through experts is especially useful when a parameter in a system design, decision-making or performance evaluation is of the type that does not lend itself to the conventional methods of data compilation. This can be because of three situations: (1) The parameter is of the type for which laboratory tests or field investigations cannot be performed; (2) The level of load is low and as such no meaningful information for distress conditions can be obtained; and furthermore, non-destructive tests to investigate the system’s performance are not possible because of potential for damaging the system; and, (3) In a problem, it is not clear what may

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trigger the damage or failure since many factors are considered as potential causes of failure. In these situations, the expert opinions can be used to estimate the statistical descriptors of a target parameter (e.g., the mean or variance), the inherent uncertainty in the parameter, and any other desired outcomes, in regard to the system performance.

As an example of the first situation, suppose we are interested in identifying the significance of human error on the performance of a system. This could be the case, for example, when we investigate the human error effect on the strength of welds used in steel structure connections. For this type of problems, experts, when selected appropriately and with a well-designed set of clear and distinctive questions, offer an alternate data source. An example of the second situation is in performance of an interior gas distribution system (in a house or apartment building, for example) and in evaluating the uncertainties in individual parameters that affect performance of such systems (which generally operate under a low internal pressure). The geometry and location of such systems often do not allow compiling tests through experimentation. Field measurements, on the other hand, do not provide meaningful data because of low levels of mechanical effects. The internal gas pressure is hardly 0.014 MPa – and as such, it does not burden the system with any significant stress condition. At the same time, if we are interested in the significance of interior pressure on the system failure, non-destructive tests are not generally a feasible option. Expert opinion data can effectively be used for such systems [1]. As an example of the third situation, potential causes of failure in system for which a single factor cannot be identified, as the main cause, is mentioned. For example, when a structure unexpectedly fails, without any overloading or natural hazard occurrences, there are many factors that may have contributed to the failure. These factors can be related to the foundation or soil, pre-existing anomalies, changes occurred during construction without being noticed, undetected errors in type of materials delivered at the time of construction, etc. Experts can then be invited to provide their insight into what potentially may have gone wrong. Another example of the third situation is in inspection of bridges. Experts (bridge inspection personnel) examine bridges and express their opinions on bridge conditions. A variety of factors affect bridge conditions including wear and tear, weather conditions, damaged structural components, corrosion, small cracks, fatigue damage, etc. Therefore, experts’ perceptions, judgment and observations are used to arrive at estimates for the structural condition of a given bridge.

3. Features of the Method

The method is rather flexible and can be crafted to suit a specific application in arriving at an adequate estimate of statistical descriptors of a design or decision-making parameter, uncertainties or even the risk of failure of a system. In a more elaborate method, an expert’s perception on the type of function that best describes a parameter’s probability distribution or the probability values for the component failures, or the entire system failure, may be sought. The method can also be used in multiple rounds to minimize the bias phenomenon in responses. The significance of biases and methods to manage them are provided later in this paper. The experts (sources of data) can be provided with as much information that is possible and reasonable to refine the process of data mining and control of the bias. For example, an expert may be provided with a scenario that replicates, or presents a digital twin of a known case, to bring their thoughts to focus on a specific parameter. In special applications where causes of failure are being investigated, the availability of virtual reality images is specifically becoming significant since the digital twin of a specific case can be produced in aiding an expert to better understand the parameters and loading scenarios leading to failure in a system or the significance of variations (uncertainties) in design parameters in affecting the system performance. The application of digital twins in structural engineering and uncertainty analysis is rather new; relevant applications are provided in [2] and [3].

4. Expert Inclusion Criteria

Experts are individuals with experience in a related or similar field to the problem being investigated. Experts are known by their involvement in a pertinent industry and their interest in the problem that is being investigated. Depending on the type of problem, the system involved and the anticipated outcome, expert inclusion criteria are (1) years of experience in general; (2) years of experience directly related to the system being investigated; (3) and familiarity with the type and format of the expected outcome. Since in most cases, experts’ opinions are sought more based on their prediction rather than their recollection, it will be helpful if experts are familiar with probabilistic methods and formulations. Otherwise, the questionnaire will need to be crafted carefully to lead the expert towards probabilistic estimates. And as such, presenting the expert with a scenario and requesting specific answers that translate into probability values will be needed. This method of extracting probabilities is considered as indirect encoding [4].

The experts should also be willing to spend time in training sessions. Providing educational materials such as videos of similar cases and virtual replica of the system by way of digital twin of the case in study are important. And as such, the expert must be aware of these tools and be willing to participate for preparation before start of the data collection survey. In investigating failure of a system, an inclusion criterion may also be based on the expertise of participants and involvement in past failure investigations. Thus, the same experts can be invited to comment on what "may go wrong" in a system based on their experience in evaluating what "went wrong" in previous failure cases. Upon selection of a pool of experts, a screening may be necessary to further focus on a group that has no conflict of interest with the type of problem being investigated and have met the inclusion criteria that are set in the design of the data collection survey.

5. Compiling Data

Experts will need to be provided with ample information to become well familiar with the type of problem being investigated and the type of data being
collected. Any ambiguity in this process will result in misunderstanding and with erroneous outcomes.

5.1 Preliminary preparations

This step is intended to educate the experts with the type of problem and the specific purpose of the survey. Any type of presentation materials that facilitate disseminating information to the experts and clarifying the problem should be considered. At the end of each presentation, experts will need to be invited to ask questions and receive additional information, if still there are areas of ambiguity. As indicated earlier, presentations through videos of similar cases, virtual reality presentation of digital twins of the cases being studied are effective ways of familiarizing experts with the problem (Fig. 1).

Figure 1. Initial training and screening of experts

5.2 Types of outputs

Anticipated outputs from the survey need to be clearly introduced to the experts when recruiting them as well as before the start of the data mining process and the administration of the questionnaire. The outputs can be (1) estimates of the statistical descriptors (e.g., the mean and variance) of one or more parameters in a design, decision-making or performance evaluation of a system; (2) probability distribution models; (3) probability values associated with the performance of a system or its components; and (4) uncertainty estimates of a parameter, whether aleatory or epistemic (see Fig. 2). As explained earlier, depending on the type of outcome and expert’s understanding of the exact nature of the data that are being sought, participants will need to be screened to make sure they are providing data that are meaningful and reasonable. Simplification of questions in a format that can easily be translated into the intended output is very important and facilitates the data mining process. For example, when the purpose of data collection focuses on finding the probability of failure of a component in a system because of a specific cause, a question may be formatted as follows:

“In a case of $n = 1,000$ identical components that are subject to this particular effect within next year, in your opinion, how many ($n'$) will fail within next year because of this particular effect?”

This will result in $p_F = n'n/n$, which is the annual failure probability because of a specific factor. In some cases, experts are more comfortable to express their opinions when questions have a positive tone. For example, the aforementioned question may be presented as follows:

“In a case of $n = 1,000$ identical components that are subject to this particular effect within next year, in your opinion, how many ($n'$) will survive without any damage?”

Again, any visual aids may be helpful to demonstrate what kind of information is being sought when an expert is presented with questions. For example, when questions deal with a type of distribution function for a parameter, the expert may be presented with several types of distribution models and ask to select one that in their opinion best describes the variation in the parameter. Extracting probabilities can be done either directly or indirectly [4]. In extracting probability values, an expert may be presented with a 10x10 lined table and asked to darken the number of boxes corresponding to the possibility of the occurrence of an event in 100 identical situations. This is an example of a direct method; while the example cited above can be regarded as indirect. Extracting information regarding uncertainties associated with estimating values of a parameter is rather complicated, since the perception of what exactly uncertainty is may be different among experts. Ways to facilitate this process is explained later in this paper under a separate heading because of the place of the subject of uncertainty as the main theme of this paper.

Figure 2. Anticipated outputs

5.3 Means of data mining

Data mining is through several means. Among these include (1) face-to-face interviews – whether individually or with groups; (2) questionnaires through mail; and (3) questionnaire through the internet. The face-to-face interview is a very successful method because of its spontaneity. This method allows for better interactions between the expert and the person conducting the survey. If time allows, more than one round of data collection can be conducted in one session, especially if bias phenomenon has been suspected in the data (as explained later). However, as expected, the face-to-face interview is often more difficult to administer compared with other two methods, since experts may not be willing to devote long hours that will generally be needed for this method.
Monetary compensations have shown to be effective in attracting experts to commit to face-to-face interviews. Compiling questionnaires through the Internet is gaining popularity – it is cost effective. Participations increase when there is some kind of rewards associated with it. Some experts prefer this method over others because of (1) the privacy it offers; and (2) the ease it offers in responding to questions.

6. Uncertainty Estimation

Sourcing uncertainties through experts’ opinions requires a more elaborate process, since respondents may have totally different perceptions regarding what exactly uncertainty is. The training phase of the process plays a very critical role in attaining meaningful outcomes. Aleatory uncertainties inherent in a system’s parameters are those expected to be driven as a result of their random nature. Although direct questions asking experts to provide their opinion on the estimate for a particular uncertainty may be crafted, a simpler method can be based on compilation of “raw data.” For example, in estimating the uncertainty in the randomness in a material property, the focus can be placed on the uncertainty in the estimation of the mean. And as such, the experts may simply be asked to provide their estimates for the material property. With n responses compiled, and the estimates of the mean and variance computed as \( \bar{x} \) and \( \sigma^2 \), respectively, a measure of uncertainty can be computed, upon data compilation using Eq. 1, which includes the significance of the variation \( \delta_1 = \sigma/\bar{x} \) and \( \delta_2 = (\sigma/\bar{x})/\sqrt{n} \), i.e., the standard error of the mean [5].

\[
\Delta = \sqrt{\delta_1^2 + \delta_2^2} = \left( \frac{n+1}{n} \right)(\sigma/\bar{x}) \tag{1}
\]

An alternate method is to ask experts to provide a ± variation or upper and lower bound estimates for a parameter based on their perception of the changes that can be expected for the parameter. With the upper and lower bound values defined as \( x_2 \) and \( x_1 \), respectively and a uniform distribution, the estimate of the uncertainty (based on data from an individual expert) is [6]

\[
\Delta = 0.58 \frac{x_2/x_1-1}{x_2/x_1+1} \tag{2}
\]

An overall estimate of the uncertainty can then be obtained by averaging the responses received from individual experts.

When uncertainties are epistemic, their estimation using expert opinion involves a more in-depth process and requires experts who (1) have an advanced knowledge and experience in understanding the problem and (2) understand well what kind of knowledge deficiency exists in the estimation of a particular parameter through mathematical formulations and modeling.

As an example, let’s consider the deformation patterns of a floor system made up of wood joists and planks when the floor is subject to occupants’ rhythmic activities. Using conventional methods, the basic theories of structural dynamics are used along with elastic material properties and cross section dimensions of structural members. The current knowledge uses an idealized modulus of elasticity which assumes elastic behavior within reasonable ranges of load applications using “clear” wood specimens [7]. However, there is an uncertainty associated with recommended value of the modulus, since it can be different because of a variety of factors, see for example, [8] and [9]. Factors that affect the modulus can be (1) the dynamic effect of loading; (2) site conditions (temperature effect); (3) moisture effect; (4) variation between the type of wood used versus those used in the lab for estimating the modulus; (5) significance of system behavior as an assemblage rather than an individual structural component; and (6) span lengths. The expert’s opinion on the significance of these factors individually or integrally can be sought through specific questions and explanation of the situation. In even a broader application, experts can also be invited to (1) identify what factors actually may affect the modulus of elasticity significantly; and (2) rank these factors according to their importance, if there are no prior data available.

The main trust of the process for data mining in areas where the uncertainty is due to lack of knowledge is in providing adequate information, in whatever form possible, to potential experts. One simple method is to provide them with very precise questions highlighting clearly the significance of factors that have caused errors in arriving at a value for the target parameter. For example, in regard to the significance of the dynamic load on the modulus of elasticity of wood structural members, an example question may be crafted as follows:

“Several references have indicated changes in the modulus of elasticity when wood structural members are subject to dynamic load applications. Examples of these references are provided for your information. In light of this notion, please offer your opinion by indicating how much the modulus of elasticity may be different from those used in design. Provide your response with a ± margin of difference as perceived by your judgment based on your experience.”

This is obviously a rather lengthy question. However, it is emphasized that the data mining in this case is unique and requires a more elaborate information-question type of format to appropriately educate the respondents and bring them to focus in understanding the type of issues involved.

An alternative method is to present the respondents with visual presentations describing what is already available as information on the significance of factors that have been reported in causing dramatic changes in a target parameter involved in design, decision-making or
performance of a system. The respondents are then informed that this significance effect has not yet been considered in the prescribed values for the parameter due to the lack of knowledge. This is in fact a preparation phase in educating the respondents and explaining to them why their input is being sought. Figure 3 suggests several methods as the necessary steps in preparation phase of the process. There is no limit in regard to the amount of prior information that can be supplied to experts. The idea presented in this paper advocates the notion that the more the expert is familiar with the problem, the more robust results are obtained.

Figure 3. Estimation of epistemic uncertainty

The response from each expert can be quantified as a "correction factor" \( u_i \) applied to the estimate of the mean \( \bar{x} \) of a target parameter \( X \). Usually, this factor is considered as the ratio of the exact value of the mean of the parameter (as perceived by the expert) to the known estimate that being used in design, decision-making or system performance investigations. This is to say that per opinion expressed by the \( i \)th expert, the mean of \( X \) should be taken as \( u_i \bar{x} \). With \( n \) experts and \( u_1, u_2, ..., u_n \) responses, the mean for the correction factor and the corresponding uncertainty are

\[
\bar{u}_E = \frac{(u_1 + u_2 + \cdots + u_n)}{n} \tag{3}
\]

\[
\delta_E = \sigma_E / \bar{u}_E \tag{4}
\]

where

\[
\sigma_E^2 = \frac{\sum_{i=1}^{n}(u_i - \bar{u}_E)^2}{n-1} \tag{5}
\]

The corrected mean value for the parameter (\( \mu_X \)) uses the average of all correction factors (\( \bar{u}_E \)). The uncertainty associated with this correction (\( \delta_E \)) is then accounted for in the total uncertainty in the parameter using the first order approximation. The following equations summarize these operations [6].

\[
\mu_X = \bar{u}_E \bar{x} \tag{6}
\]

\[
\Delta_X = \sqrt{\delta_E^2 + \delta_1^2 + \delta_2^2 + \cdots} \tag{7}
\]

Where \( \delta_1 \) are uncertainties associated with the randomness in the parameter \( X \) as explained earlier.

7. Biases in Data

One major issue with this method of data collection is the bias phenomenon. Different modes of bias often relate to an expert’s perception of the problem as presented to them, their cognitive response in approaching the problem, and reaction to current or past similar events. Thus, it is important to recognize these modes of bias and offer strategies to manage them for more robust results. As demonstrated in Fig. 4, biases can be categorized as either motivational or cognitive [4].

Figure 4. Types of bias

7.1 Motivational bias

This mode of bias is intentional and is primarily based on experts’ desire to change the outcome to their own favor. In engineering applications, this kind of bias may happen when an expert finds a question in direct conflict with their interest. Experts from certain groups or industries may not feel comfortable with the notion that there are uncertainties in parameters involved with the system they are affiliated with, thinking that the public may perceive this as a problem with the system. Accordingly, they may intentionally provide answers that are skewed compared with those by others. In an uncertainty estimation, depending on the desire by an expert to move results in one or other direction, the estimated value provided may contain nearly zero or a very large variation.

7.2 Cognitive biases

Cognitive biases depend on the expert's modes of judgment. This type of bias is systematically introduced by the way the expert responds. The expert may be influenced by most recent occurrences of the event of interest and thus would respond accordingly. In engineering problems, this type of bias can shift the response distribution to either left or right depending on the expert’s perceptions. For example, recent failure cases may cause the expert to produce an unusually low rate of failure for a structural system only to pretend that, despite the recent failure cases, the system is safe and thus to influence the outcome of the
survey skewed more to the lower value side. On the other hand, another expert might think quite differently and produce an unusually high rate of failure only because of being influenced by the most recent occurrences thinking that these recent failure cases represent the real risk of failure involved in the given system.

Five different modes of judgment are identified to explain cognitive biases (see for example, [4], [10] and [11]). These are: availability; adjustment and anchoring; representativeness; unquoted assumptions; and, coherence. These modes in an engineering application involving uncertainty and reliability prediction in interior gas distribution networks are also discussed in [1]. The "availability" and "adjustment and anchoring" modes of judgment are mainly concerned with occurrences the expert recalls. "Availability" deals with the occurrences the expert recalls in general; whereas the "adjustment and anchoring" mode deals with the most recent occurrences. The "unquoted assumptions" mode of judgment deals with expert's assumptions on which the response is based. For example, in a bridge component's modes of failure, the expert may ignore the environmental effects such as salt and humidity on corrosion and loss of components' effective cross-sections and merely consider vehicular loads as damage-causing possibilities. In the "representativeness" mode of judgment, the expert's response is on a specific issue based on the similarity or the representativeness of the raised issues to the general population it belongs to (see for example [11] and [12]). In the bridge example cited above, the expert may think the salt effect and the corrosion issue is only an occasional and rare representative of the bridge component's damage and thus bias the response by only focusing on the perception that damage is solely represented by vehicular effects. The "coherence" deals with the reasonability and coherence of the occurrence of a series of events that lead to the development of the event of concern (or a target event). In engineering problems, the system analysis and identification of scenarios leading to the occurrence of the target event influence this mode of judgment. Since the types of problems civil engineers deal with are made of limited and often well-defined and analytically-proven scenarios leading to the target event, this mode of judgment is expected to influence the bias to a much lesser extent than the other four [1].

Biases can be identified by observing the responses from an expert’s that consistently appear at extremes when plotted and compared with responses from others. Biases in a subgroup of experts often result in a skew in plotted data. Often a commonality element can be detected among members of this subgroup such as, for example, representing the same segment of the industry.

Methods that may be used to abate the significance of bias in the outcome may consider (1) Assuring the anonymity of the responses; (2) Conducting data gathering in more than one round; (3) Showing the data after Round 1 to participants and asking them if they wish to change their opinions, if they are way off in their responses; (4) Changing the way questionnaire was designed; and (5) Making sure respondents understand what information is being gathered to reduce possibilities in providing responses that do not relate to the main focus of the problem.

8. Illustrative Example

This example presents the estimation of risk of natural and man-made hazard occurrences as perceived by experts taking an advanced system risk and reliability analysis course at Illinois Institute of Technology. This type of expert opinion survey is useful in decision-making and planning for emergency preparedness and allocation of budget for implementation of needed actions when necessary. The inclusion criteria were (1) having taken a course in probabilistic applications in engineering; (2) having taken an advanced graduate level course in system risk and reliability analysis; and (3) a two-hour lecture, as an information session, on the type of man-made and natural hazards that may trigger an area, past occurrences and significance of each occurrence in disrupting essential services and causing casualties and property losses. Seventeen events were identified (Table 1) based on information provided by experts in risk management and system reliability and hazard analyses. For each event, “risk” is defined as the product of the probability of occurrence of the event and the severity of the event.

Risk = Probability × Severity

The “severity” is defined as a factor that is affected by the magnitude of the event in causing casualties and service disruption and mitigation measures that are available to respond to the event. Experts were asked to provide their estimates for the probability of occurrence of each event within next year. For the severity data, three factors are included in the magnitude effect: possibility for human loss of life and injury; possibility for property loss; and possibility for service disruption. Experts’ opinions were sought on these factors by asking them to provide scores on the scale of 0 to 1; where 0 means no possibility for these effects; while 1 means severe possibility. In regard to mitigation measures, also, three factors were included: availability of preparedness planning; availability of internal response (e.g., campus task force available for emergency help); and availability of external response (e.g., community police and medical help). Experts were asked to express their opinions on these factors by providing scores - low scores (0 to 0.33) when these mitigation factors are available; and high scores (up to 1), when these mitigation measures are not available. The estimate of severity from each expert’s response is then computed as

Severity = [(hi + pi + bi) + (pp + ir + er)]/6
Where hi, pi, and bi are the scores for magnitude factors; and pp, ir, and er are scores for the mitigation measures (Fig. 5). Notice that severity reduces with less dramatic impact and better mitigation measures.

As an example, the responses from one of the 18 experts participated are summarized, and the corresponding severity and risk estimates are provided in Table 2. For the event “Extreme Temperature, (Cold),” which is Event #13, the expert provided the following estimates:

Magnitude factors: Death and Injury: 1; Property Damage: 0.16; Service Disruption: 0.33. For mitigation measures and preparedness factors, the expert provided the following scores: Preparedness: 0.33, Internal Response: 0.67, Community Response: 1. The severity for this event is

\[
\text{Severity} = \frac{(1+0.16+0.33+0.33+0.67+1)}{6} = 0.582
\]

And with the probability for the event as 0.67

\[
\text{Risk} = \text{Probability} \times \text{Severity} = 0.67 \times 0.582 = 0.39
\]

In other word, based on this expert’s opinion, there is 0.390 risk involved with an extreme temperature (cold) striking the area with considerations for its magnitude impact and all potential mitigation measures in place. For Event #13, the estimated risk values from experts are plotted in Fig. 6.

<table>
<thead>
<tr>
<th>Hazard Number</th>
<th>Probability</th>
<th>Severity</th>
<th>Risk = Probability × Severity</th>
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<tr>
<td>1</td>
<td>1.00</td>
<td>0.193</td>
<td>0.19</td>
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<tr>
<td>2</td>
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<tr>
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<td>0.19</td>
</tr>
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<td>0</td>
</tr>
<tr>
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<tr>
<td>17</td>
<td>0.33</td>
<td>0.500</td>
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</tbody>
</table>

1 Probability measures: Not Possible=0; Low=0.33, Moderate=0.67; High=1.00
2 This survey was done pre-COVID 19. A more recent survey by a group in 2021 resulted in unanimous 1 for the probability of an epidemic/pandemic event, which indicates a cognitive bias resulting from COVID 19.

9. Summary, Discussion and Conclusions

This paper presents an overview of uncertainty estimation by perceptions, experience and opinions. Since the data collection using this scheme requires experts, the
paper suggests directions in identifying, screening and including experts in a study – referred to as “inclusion criteria.” The method is especially applicable in design, decision-making and system performance evaluation problems, where quantification of certain target parameters cannot be done by conventional means. The paper also discusses the bias phenomenon, that is often expected in this type of data mining process.

In addition to the bias phenomenon, another major challenge in data mining through expert opinion is the result verification. As reported in [1], there have been some efforts to compare the expert opinion data with data obtained through conventional means. However, generally, the type of problems for which the expert opinion data mining process is used are versatile and each one is unique in its driving parameters. And as such, unless a specific validation can be done for a given problem, one cannot rely on the verifications used for other applications as a way of supporting the validity of the results. Since data from conventional means are under extreme conditions, they often appear as an upper bound when compared to the data from expert opinions in failure investigation problems [1].

The following are a few distinctive points that can be mentioned as the highlights of this paper.

(1) In addition to parameter quantification, the expert opinion method is especially helpful in estimating uncertainties in design and decision-making parameters and in the investigation of a system’s performance.

(2) As explained in the paper, both levels of uncertainties (whether aleatory or epistemic) can be estimated through experts; however, epistemic uncertainty estimation will require a more elaborate process that involves educating experts by providing them with adequate background knowledge to get them acquainted with the type of data that need to be obtained.

(3) As suggested in this paper, among different methods that can be used to manage the bias phenomenon, one may consider conducting the survey in multiple rounds and providing respondents with the assurance of anonymity of responses.

(4) In light of the shortcoming of the method in offering a possibility for result verification, a reasonable method to assure robust results from the expert opinion data mining appears to be one that considers (a) crafting a careful design for the questions in the survey to avoid confusion on the part of respondents; (b) providing the experts with as much information as possible to educate them about the parameters for which the data are being collected; and (c) using visual presentations through any means including virtual reality case studies and digital twins of the case in question to familiarize experts with the case.

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