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The Treatment of Model Uncertainties under the Presence of Parametric Uncertainty Sources in Risk and Reliability Analysis

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ABSTRACT

Analyses for complex real-world systems inevitably involve many uncertainties and their analysis is one of the essential processes to address our state-of-knowledge in evaluating performance of these systems. In this point, primary concerns of the uncertainty analysis are to understand why uncertainties arise, and to evaluate how they impact the results of the analysis. In recent times, the uncertainty analysis has focused on parameters of the logical or physical models being used in PSA. As the field of PSA matures, more attention is paid to the explicit treatment of uncertainty sources that are addressed in the models themselves and the accuracy of the models. When the model uncertainties are incorporated into a formal framework of uncertainty analysis, the primary step for evaluating impacts of these uncertainties is to determine sources and types of uncertainty to be addressed in an underlying model itself and in turn model parameters. Depending on the states of knowledge involved in the subject of interest and available evidence, we can choose either a deterministic model or an aleatory model. In addition, uncertainties addressed in parameters of the underlying model can be modeled in a different way, e.g., epistemic, aleatory, or both of them. The foregoing classification of uncertainty sources is related to important practical aspects of modeling for complex technological systems and we have clear advantages of the separation in real applications. The main objective of this paper is to clarify various sources of uncertainty that would often be encountered in the modeling process for the risk and reliability analysis and introduce underlying approaches for handling them quantitatively.

I. INTRODUCTION

In probabilistic safety assessment (PSA) of nuclear power plants, uncertainty is an essential part of formal decision making on the plant safety. Traditionally, the uncertainty analysis has focused on parameters of the logical or physical models used in the PSA (i.e., parameter uncertainty), rather than uncertainty addressed in the models themselves (i.e., model uncertainty). For example, PSA has been performed to obtain a distribution of the different component and system states based on best estimates of the models and parameter values. In that case, the model involves only random or stochastic uncertainties. As the field of PSA matures, more attention is paid to the explicit treatment of sources of uncertainty that are addressed in the models themselves and the accuracy of the assumptions made in the modeling process as well as the parameter uncertainties. When the model uncertainties are incorporated into a formal framework of uncertainty analysis [1-5], our primary concern is to determine whether the underlying model is a deterministic one or an aleatory one and in turn which model parameters are subjected to epistemic uncertainty (called as subjective, reducible, state-of-knowledge uncertainty) or aleatory uncertainty (called as random, irreducible, stochastic uncertainty) [2,6-10]. The aleatory portion of uncertainty deals with the randomness of an event and is not practically reducible since we don't know and understand the underlying reasons and behaviors governing its randomness. Whereas, the epistemic portion of uncertainty deals with our state-of-knowledge about portions of our model and thus as we know more about the underlying problem, epistemic type of uncertainties can be effectively reduced. Thus, the objective of the aleatory uncertainty is to answer the question on 'what might actually happen and with what probability'. Whereas, the objective of the epistemic uncertainty is to answer the question on 'how well we know about a given problem and how much our knowledge about it might change with additional information'.

The foregoing classification of uncertainty sources is related to important practical aspects of modeling for complex technological systems [9,10], including their probabilistic assessment, consistent decision-making under different uncertainty sources (e.g., what we know and how much we know about it), and proper propagation of uncertainties in the evaluation process. However, it should be noted that at a fundamental level, uncertainty is just uncertainty and this type of uncertainty is due to our lack of knowledge [9,10]. In addition, it is well accepted that probability is fundamentally one concept, namely, a measure of degree of belief and uncertainties are always quantified using subjective probabilities. Thus, if we can ever gain precise, accurate and complete knowledge about a subject (e.g., behavior in microscopic level of a physical quantity or time-dependent occurrence of an event) one may eliminate all the uncertainties associated with describing and modeling the behaviors of that subject. In real situation, however, this is neither possible nor practical. In that case, a convenient separation between those sources of uncertainties that are random in nature (i.e., aleatory uncertainty) and those that depend on our state of knowledge (i.e., epistemic uncertainty) is helpful in understanding the nature of the uncertainties, and can guide us in selecting appropriate uncertainty propagation methods. In other words, all uncertainties of the same types can be consistently combined for decision-making purposes, e.g., combination of aleatory (epistemic) uncertainties in case of aleatory (epistemic) inputs. In the computational process, both uncertainties must not be mixed with each other in the final results if they will be used as inputs to the decision-making. This is just because if the effects of all uncertainties of different types are mixed in to a single probability distribution in the prediction level, it is impossible to extract from the distribution the contribution of each type of uncertainty. In real applications, many PSA practitioners would overlook this point in their analysis and as a result they would be confused in interpreting the results of uncertainty analysis.

The question of how to define and estimate different types of uncertainties is particularly critical in the risk and reliability assessment of complex technological systems where little evidence is available. Since a full description of uncertainties addressed in the modeling process of such systems involves various sources of uncertainties such as aleatory, epistemic, and model uncertainties, we also need to consider our thoughts about their treatment. Thus, the need for a consistent discrimination of different uncertainty sources becomes most obvious in the case of risk and reliability analysis. The main objective of this paper is to introduce a recent trend of uncertainty analysis being made in the field of risk and reliability analysis, including the need for clarification of various types of uncertainties that would often be encountered in the risk and reliability modeling process of complex systems and the underlying approaches for handling them. The encoding of uncertainties (or distributions) is one of the essential processes of uncertainty analysis, but the subject is not the main concern of this paper.

II. CHARACTERIZATION OF MODEL UNCERTAINTIES

In the process of a mathematical modeling for the complex problem of interest, we generally decompose the problem by using detailed relevant variables so that available historical and experimental data can be used to help determine the necessary inputs. This sort of decomposition makes it easier for us to think about the required assessments by making assessments separately for more understandable and manageable parts instead of directly for the entire problem. As a trade-off, however, the model decomposition leads to a variety of events or variables about which we are uncertain in an aleatory or an epistemic way. Whenever an assessment question is not described to be fully specific, that is, there is uncertainty on which value to provide as an answer for the question. In this section, the existing two viewpoints in interpreting the two uncertainty sources are introduced to better understand the concept of model uncertainty and consistently interpret the uncertainty analysis results.

II.1 Meaning of Uncertainty and Its Description

Many risk and reliability analyses would include both aleatory and epitemic inputs in their predictive models, and in the literature it is often recommended to divide those uncertainties for a consistent risk communication. While the aleatory uncertainty has been conventionally regarded as a property of the system or activity being studied, the epistemic uncertainty takes into account subjective and perceptional aspects. According to Hofer's definition [8], the aleatory uncertainty arises from the fact that one cannot give a single value for an event, but rather give a population of values with chance. Thus, the value of the event can be thought of as randomly selected from the single true probability distribution that summarizes the variability within the population. Whereas, the epistemic uncertainty is characterized as uncertainty due to knowledge of the single true values of an event and lack of knowledge of a single exact probability distribution summarizing the variability within a population. Since the aforementioned two types of uncertainties become input to different decisions, then their propagation through the model needs to happen separately and presentation has to cater for two uncertainty dimensions. Helton [11] also claims: 'When a distinction between stochastic and subjective uncertainty is not maintained, the likelihood of the deleterious events associated with a system and the confidence with which both likelihood and consequences can be estimated become commingled in a way that makes it difficult to draw useful insights.' Whereas, Winkler

[9] takes another viewpoint about those uncertainties: 'If the problem is not decomposed in a reasonable way, various sources of uncertainties can be commingled in a way that makes it difficult to draw useful insights.'

While the two former standpoints focus on a necessity of separation for 'different types of uncertainty' regardless of the decomposition level, the latter one relates it to 'different sources of uncertain information' due to the decomposition as a key motivating factor behind the desire to distinguish among types of uncertainty. According to the latter, the motivation for attempts to make distinctions between them is related to important modeling concerns. While the epistemic uncertainties play a great role when we have little evidence for the question of interest, the aleatory uncertainties do when we have more evidence. In order to get a clearer insight about meanings of the two uncertainty types, let's consider a severe accident sequence with limited resolution or unspecified in many ways. Then, various phenomenological variables contributing to the containment peak pressure (e.g., in-vessel steam explosion, core melt temperature at the occurrence of the event sequence, etc.) are regarded as aleatory variables whose uncertainties are quantified by a probability distribution summarizing the variability within the potential population of relevant values. In that case, there may be two situations by which the aleatory variables may be treated by epistemic uncertainties: The first is when we redefine the above sequence with much more resolution so that the aforementioned aleatory variables can be subjected to epistemic uncertainties. The second is when possible stochastic variation of the aleatory variables is considered to be comparatively negligible in specific aspects of the phenomenological assessment of any event so that the aleatory variables can be treated as deterministic quantities with inaccurately known epistemic uncertainties.

In recent times, most PSA practitioners [9,10] point out that at a basic level uncertainty is just uncertainty and there is only one kind of uncertainty stemming from our lack of knowledge concerning the problem of interest (i.e., epistemic uncertainty). However, the separation between aleatory and epistemic uncertainties is very important for our convenience in investigating complex problem and interpreting the uncertainty analysis results, rather than for basic philosophical reasons. In real applications, a decision for taking either aleatory or epistemic variables depends on the states of knowledge involved in the problem of interest. Although information comes in varying forms and from many sources, involving historical and experimental data, models, or experts, for example, some uncertainties are clearly easier to assess than others. When we are asked for our subjective probabilities, in addition, it seems easier for them to think about probabilities for observable quantities than about unobservable quantities [9,12]. Also, we can make an attempt to distinguish 'reducible uncertainties' (for variables about which we can obtain some additional information) from 'irreducible uncertainties' (for variables about which obtaining further information is impossible or impractical). In that case, it can be useful to think about certain types of distinctions among uncertainties and in complex problems, we typically utilize all forms of information.

The above characterization of uncertainty is very similar to a situation that 'probability' as a mathematical expression of uncertainty is just ‘probability, but we have two different interpretations of it (i.e., relative-frequency and subjective interpretation) [1,4,13]. While the relative-frequency interpretation of probability defines the probability of an event in terms of the proportion of times the event occurs in a long series of identical trials, the subjective interpretation of probability views it as a measure of degree of belief. As for the relative-frequency approach, the issue in practice is the availability of an appropriate data set. In many cases, no objective data may be available bearing directly on the event or variable of interest, but the situation of interest requires a subjective judgment in utilization of available data. Because of the need for this subjective judgment, the relative-frequency interpretation of probability does involve subjectivity and is added to the subjective interpretation. In this sense, the subjective interpretation of probability is considered as an extension of the relative-frequency interpretation. Basically, the subjective probability is probability in the mathematical sense and can be treated according to the rules of a probability theory. However, its use is indispensable for a meaningful interpretation of the analysis results and as such, is essential for the decision-making process based on it. Under the subjective interpretation of probability, there is no desire for objectivity of data or true probabilities. Instead, the subjective probability is a function of the information that is available, including subjective information and relevant evidence, historical data about the problem of interest, and variability in relevant areas. The distinction between evidence and subjective information is useful in identifying sources of probabilistic information in practice, but probabilistic uncertainty analyses, supplementing risk assessments, can only work on the basis of the subjective probability concept.

II.2 Characterization of Model Uncertainty

In description of the real world of interest with a mathematical or predictive model, we are often faced with two different situations: one is that the description of model inputs can be deterministic and another we simply unable to predict their values in a deterministic way.

In the former case, the model output is characterized by magnitudes of the deterministic model inputs and in the probabilistic sense the model outcome becomes always one (i.e., either always possible or always impossible). Like this, a model whose outcome is determined just by the deterministic inputs is characterized as deterministic model. Thus, the deterministic model can be expressed as a simple functional relationship whose output depends in a deterministic manner on various input parameters. In practice, the values of the input parameters are not precisely known and, consequently, some imprecision attaches to the estimate of the model output. Uncertainty about the correct values of input parameters can be quantified by treating the parameters as random variables with appropriate probability distributions. When we develop the deterministic model, moreover, we often have a question on the accuracy of our model itself in predicting the real situation. This question is closely related to the fact that our predictive model itself is an approximation of the real world of interest and its accuracy depends on our knowledge in modeling the real world. In other words, our model itself is always subjected to some degrees of uncertainties, due to our limited knowledge in prediction of the real situation.

Since this type of uncertainty expresses our state-of-knowledge in modeling the real world, the model itself is considered an epistemic model and uncertainty addressed in the model itself is characterized as types of epistemic uncertainties. If there are no uncertainties in our model itself, the model will exactly predict the real values of the specific problem. Due to the model uncertainty, however, our predictions are subjected to either over-estimation or under-estimation. When the epistemic model uncertainty is considered, the overall variability in the resultant model outcome is due to both the uncertainty addressed in the model parameters and the uncertainty due to the model itself.

On the other hand, there is a situation; when we have a limited knowledge on the values of the model parameters and thus we cannot specify single, exact values to the model parameters. This situation requires for us to employ uncertainty on the parameter values in the prediction of model output. In the latter case, the model output is determined by both the occurrence of the event (i.e., aleatory uncertainties) and its magnitude (i.e., epistemic uncertainties). While the model itself is given to be deterministic, that is, different model outcomes occur at random. Since this type of model contains probabilities on the occurrence of the model outcome whose values are evaluated by an aleatory model, it is characterized as *aleatory model or probabilistic model* [2]. In order to characterize the model output we would often employ a probabilistic model for the occurrence of the event and the magnitude of the model parameters characterizing the model output given that the event has occurred. In the deterministic model, our concern is to determine a specific criterion of the model outcome and in turn to evaluate the magnitude of the model parameter (i.e., this is epistemic). On the contrary, our primary concern in the aleatory model is to estimate an occurrence probability of random event addressed in the model or probability distribution (i.e., this is aleatory), and in turn magnitude of the parameter value characterized by the event. To the end, the above descriptions can be summarized as follows: if the model prediction is a fixed event, the underlying model is characterized as a deterministic model; otherwise (if the model prediction is a random event), the underlying model can be characterized as an aleatory model. The aforementioned distinction of models is basically due to our state of knowledge in the modeling process of the problem of interest. Depending on details of the model decomposition, that is, a given model may include epistemic model inputs, aleatory model inputs, or both of them. In addition, our limited knowledge in the model formulations (e.g., structures of physical or logical models), in estimating the exact value of the model parameter, and in formulating the probabilistic model (e.g., an exact type of probability distributions or statistical parameters such as mean and variance) is categorized into epistemic uncertainty. Basically, these epistemic uncertainties are represented by subjective probability distributions that quantify the respective states of knowledge. Figure 1 characterizes measures of these various uncertainty sources that would be often encountered in the risk and reliability analysis.

There are several examples that a given model uncertainty includes both aleatory and epistemic portions in the field of risk and reliability analysis. For example, let's consider the impact of ' impulse load' on a physical system. The behavior of the system does not depend on our knowledge and follows the laws of physics about which we do not have a complete knowledge. In that case, our work is just to evaluate the performance of the system with uncertainty or near uncertainty about all of the conditions imposed to the system. Our uncertainty in a given situation is a function of the information that is available. For this, we first have to determine which type is the impulse event. In one situation, the event can be considered a random event with time and thus an aleatory model is appropriate to characterize uncertainty associated with the occurrence of the event. In another situation, it is considered an always-occurring event (a deterministic event) and thus no uncertainty is imposed to the occurrence of the event. For the both cases, we do not know exactly the magnitude of the impulse load due to our incomplete knowledge and as a result our epistemic uncertainty is addressed when the magnitude is evaluated. Like this, an event is treated as a random variable in the aleatory model, but it is just parameter in the deterministic model. One practical example [10] is a situation that a pipe whose failure is assumed to occur when the capacity of the pipe is smaller than the pressure load imposed on the pipe. The capacity may be time-dependent due to aging mechanism like flow-induced corrosion. The load consists of two parts: normal, steady load and abnormal load due to transients. In the case of the steady-state pressure, there is no uncertainty related to time and thus the failure of the pipe is modeled in a deterministic way. In that case, the load is constant in time, but the failure of the pipe for a given time is determined by the relative magnitude of load and capacity at that time. In the transient pressure load, the occurrence of transients is random in time (i.e., random parameter) and thus the failure of the pipe is also taken into account as a random, aleatory model. In that case, the failure of the pipe for a given time is conditional on both the occurrence of the transients at that time and the relative magnitude of load and capacity given that the transient has occurred. The above example indicates that while quantities such as 'time' are taken into account as aleatory variables in the dynamic model whose inputs are subject to random phenomena, those quantities are just parameters in the static model and thus no uncertainty is imposed to them. As mentioned previously, such a decision for taking either aleatory or epistemic variables depends on our states of knowledge involved in the problem of interest.

Another example [14] that a given model can be characterized as both aleatory and epistemic portions is a fault tree model of the AFW system failure. While the fault tree model itself is a deterministic model, the epistemic portions of the model uncertainty may arise when assumptions are made under out lack of precise knowledge about the system functionality. Typical sources of the epistemic model uncertainty contain modeling of only active components, application of different success criteria, and modeling of only perfect component failures. Once one of those models (e.g., model success criteria) is incorporated in the system fault tree model, weighting factors are assigned to each of various elements of the underlying model and in turn parametric (epistemic) uncertainty is accounted for via the component data. The aleatory uncertainty is accounted for by separating component-level basic events into two parts: one part represents an aleatory uncertainty characterized as the underlying probability model for component failure rate (with specific mean and standard deviation) and the other part represents an epistemic uncertainty characterized as the "applicability" of the underlying probability model.

For the second part, we simply assign the subjective weight on the failure probability of the component. While the foregoing weighing factors (assigned to each element of different success criteria and different probability models of the component failure) may be viewed as the epistemic uncertainty, the underlying probability model itself of the component failure may be viewed as the aleatory uncertainty of the fault tree system.

III. FORMAL TREAMENT OF MODEL UNCERTAINTIES

On the other hand, we can think of a problem that includes the individual models and associated uncertainty about the models themselves (e.g., via different decompositions of the analysis model or submodel elements resulting in different predictions for parameters or variables addressed in the analysis model or different probability distribution models). Many of model uncertainties have been taken into account implicitly though an aggregation of expert opinions. The uncertainty distributions obtained in such way, however, do not give a full spectrum of uncertainties explicitly, but a mix of aleatory, epistemic, different hypotheses made in the modeling process. Instead, modeling uncertainties can be quantified by using the weighting information assigned to each model (e.g., self-weighting of experts on their own individual models of how good their work was or indirect weighting by the analyst to importance of each model). The method also makes it possible to separate parametric and modeling uncertainty in their quantification process. When the model uncertainty is treated explicitly as such, it does add another layer of uncertainty to the problem of interest. Regarding the modeling uncertainty, two different situations are often faced in real applications: one is when there is only one single model available and a variety of actual evidence for a given problem, and another is when there are multiple models, but there is no evidence available.

III.1 When there is just a single predictive model, but evidence is available

In order to describe the former situation, let's consider a population of "circumstances" that lead to different actual values for each output calculated by a model. Then this "circumstance variability" may be characterized by *aleatory uncertainty* of the model, i.e., the particular circumstances of interest will be one of the many circumstances for the same model parameters. In order to express our uncertainty in the model predictions under the assumption of circumstance variability, Kaplan employs the Bayesian approach [15]. Whereas, Siu et al. [10,16], employ the 'adjustment-factor approach', and according to their approach the factor is defined as the ratio of the actual value over the calculated value by a deterministic reference model of the specific quantity. Then, the relative frequency of the values with the same calculated values of the specific quantity determines the likelihood the specific quantity will have the corresponding values. As a result, the uncertainty of the adjustment-factor accounts for the uncertainty in the calculated value on the actual specific values. The uncertainty is due to the approximation made to develop a predictive model for the quantity. In the case of a problem, they proposed an approach to estimate the distribution of the factor when evidence becomes available, by utilizing both aleatory uncertainties (e.g., lognormal distribution with parameters m , s) and epistemic uncertainties (e.g., probability density function over the vector of the parameters). Then each value of this vector specifies one aleatory distribution for the adjustment factor. The average of these aleatory curves is used in the second stage as the epistemic distribution of the factor for a specified set of circumstances.

III.2 When different predictive models are available, regardless of evidence

When various models are available for the prediction of a given problem and each of them is base on the underlying assumptions, most PRA practitioners have accepted that it is appropriate to represent degrees of belief in different hypotheses using subjective probability. While the combination of such degrees of belief to provide some overall measure of uncertainty is relatively straightforward, it has been argued that in many cases it may more informative to adopt an approach to uncertainty analysis which more explicitly displays the effects of different hypotheses while still associating some measure of the degree of belief in each hypothesis. When various models are available, there are two different approaches for quantifying impacts of those models to the final outcome: one is an integration of all modeling uncertainties into the overall uncertainty by analytically or statistically (i.e., integration of model uncertainties), and another a sensitivity analysis of different models (i.e., model sensitivity analysis).

<u>Integration of Model Uncertainties</u>

In many PSAs, the integration of modeling uncertainties into the overall uncertainty has indeed been less complete than that of parameter value uncertainty. This is fundamentally due to the lack of formal methodologies for the explicit treatment of modeling uncertainty. More specifically, there is no clear consensus on how to define modeling uncertainties (e.g., mutually exclusive and independent models), how to characterize quantitatively modeling uncertainties, and how to incorporate these uncertainties into the framework of quantitative. If we assume that modeling uncertainties are given in the form of submodels and they are probabilistically independent of each another, a possible approach is to utilize a statistical integration of modeling uncertainties through the analysis model. In that case, the treatment of modeling uncertainties is similar in principle to uncertainty about the parameters of a given model [1,13-14]. As a result, we can assign our degree of belief to each hypothesis (using relative weights or probabilities), and probability distributions for the model parameters can be evaluated conditionally upon the model being appropriate. To this end, we can propagate those uncertainties (both different submodels and parameter uncertainties) through the analysis model analytically or statistically. The Bayesian aggregation model [1-5,17] can analytically combine the effects of parameter uncertainties and model uncertainties by explicitly incorporating available evidence, but its practical implementation is not so simple and there is little guidance to the practitioners on the selection of parameter values for the aggregation model. The statistical approach is based on the Monte Carlo simulation. As long as both modeling and parametric uncertainties are involved, a practical implementation of the statistical approach must be based on a two-stage propagation of uncertainty [5,18,19] by which model uncertainty is taken in the first stage and parameter uncertainty in the second stage. By the approach, different types of uncertainties are kept separated in the analysis. The resulting uncertainty distributions are then summarized by a composite uncertainty distribution that folds all the modeling and related parameter uncertainties (one uncertainty curve). For instance, let's a fault tree model for a system failure whose basic events are characterized by aleatory uncertainties. Also, we have a set of different submodels characterizing different possible states or occurrence criteria for some basic events and subjective probabilities are assigned to each of alternative submodels. For each combination of different submodels, the effects of aleatory uncertainties addressed in the basic events on the failure prediction of the system are then represented by conditional probabilities. The epistemic uncertainty curves of the system failure probability distributions can be obtained by statistically combining epistemic uncertainties addressed in the submodels and aleatory uncertainties addressed in the fault tree basic events.

On the other hand, there may be two essential difficulties in implementing the model uncertainties by the integrated way. The first is that there is no generally accepted, robust approach for handling quantitatively the impacts of the both types of uncertainties on the final outcome of the model because models do not always have a simple, intuitively appealing interpretation. The second is that it is necessary to make an appropriate selection of a combination of different model alternatives in a reasonable way and use that combination to get some insight into what the uncertainties are. If all possible combinations are taken, we can get some strange physical situations because some are non-physical, even though the computer codes would allow them. This is, in part, because we do not really understand the processes that are occurring.

Model Sensitivity Analysis

Fundamentally, the aforementioned integration approach obscures the differences between the models under consideration and does not explain the reasons for the differences. When we want to know the impact of each model to the final results explicitly, we can utilize the model sensitivity analysis by which parametric uncertainty analysis is made conditionally upon each of the model elements (i.e., reference model element). In fact, there are many situations that model sensitivity analysis may be particularly helpful in several regards. For example, we often have situations that differences in probability estimates assigned to each of different models do not affect final results very much, in which case the approach has little influence on conclusions. Also, it may be important for the decision maker to appreciate the degree of disagreement among the different models and its effect on the results. If the degree of sensitivity is very high, the aforementioned integration approach should be avoided since they may tend to obscure critical differences of model. In the aforementioned cases, it is preferable to retain separate models for each sensitivity analysis.

When the input uncertainty distributions are not definitive due to scarcity of available data and varying experts' opinions, on the other hand, the impact of the input distributional uncertainty (i.e., a kind of model uncertainties) on the output uncertainty must be assessed through a distributional sensitivity analysis. Then, the distributional sensitivity analysis quantifies the sensitivity of output uncertainty distributions obtained by the analysis model to the uncertainty distributions assigned to the input parameters. The output distributional sensitivity analysis may be made through either the establishment of relationships between alternative input distributions and the corresponding output distributions. Two references [19,20] provide various methods to quantify the sensitivity of deterministic model uncertainties.

IV. SUMMARY AND CONCLUSIONS

In this paper, we have clarified various types of uncertainty sources that can be encountered in evaluating the uncertainty analysis of PSA model and addressed the underlying approaches for incorporating their impacts into the formal framework of uncertainty analysis. Associating with the uncertainty type, our particular concern was the distinction between aleatory and epistemic uncertainties. Although discussions in the literature are often unclear with respect to this distinction, most PSA practitioners seem to accept the fact that different sources of uncertainties must be kept separated in the uncertainty analysis. That is, all uncertainties of the same types should be mutually combined for the purposes of decision-making, e.g., combination of aleatory (epistemic) uncertainties in case of aleatory (epistemic) inputs. The selection of appropriate uncertainty types greatly depends on our knowledge about the prediction of the system behavior and available evidence. At a fundamental level, uncertainty is just uncertainty and conceptually there is only one type uncertainty that is due to our lack of knowledge, Nevertheless, the reason why we clarify them into more detailed types is related to important practical aspects of modeling for complex technological systems and as pointed in this paper we have clear advantages of the separation in real applications. That is,

- In connection with risk analysis and communication it is common to divide uncertainty into at least two dimensions of aleatory and epistemic, and the formal separation of uncertainty sources allows to summarize the variability of a population of values of interest and to quantify how this summary is influenced by our lack of knowledge. When both aleatory and epistemic uncertainties are already mixed up in the course of the analysis without a clear separation, it would not be possible to identify the resulting combined effect of the uncertainties of either type.
- The formal separation of uncertainty sources facilities decision-making under uncertainty, allows for proper propagation of uncertainties in the computational process, and leading to a more realistic quantitative assessment of the risk and reliability.
- The foregoing two types of uncertainty would be input to different decisions. While the aleatory uncertainty is considered as a measure of inherent variability addressed in the estimated risk, improved knowledge of the epistemic quantities and the associated narrowing down of their ranges of uncertainty always do not mean changes of the risk.

When the model uncertainty is treated explicitly, on the other hand, it does add another layer of uncertainty to the problem of interest. Similarly with the parametric uncertainties, the essential steps for the analysis of modeling uncertainties are to find sources of modeling uncertainty in view of aleatory or epistemic uncertainties (i.e., discrete sets of possible models or hypotheses), to provide a proper method for quantitatively handling them, and finally to make a consistent interpretation of the uncertainty analysis results. Most of the existing applications deal with model uncertainty probabilistically by assigning subjective probabilities as a measure of the relative importance of one model over another model under consideration. This is due to the fact that the model uncertainty is a kind of epistemic uncertainties and the subjective probability is a means for expressing them. Then, the final result of model uncertainty analysis allows the presentation of uncertainties about alternative hypotheses of a given proposition by a family of uncertainty distributions. The dispersion in the spectrum uncertainty distributions obtained through their computational propagation represents the effects of model uncertainties in the presence of aleatory or the other epistemic uncertainties on the final predictions of the analysis model. For some decision-makers, the final uncertainty distributions can be averaged over aleatory or epistemic space of uncertainty to give a single type of uncertainty. Even though the essential questions about how and whether probabilities for models can be interpreted and how to encode them may arise from the adoption of the aforementioned approach, it has clear advantages for purposes of a comprehensive decision-making.

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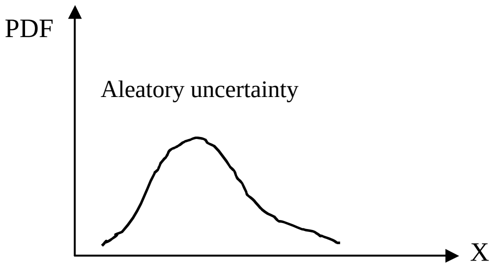
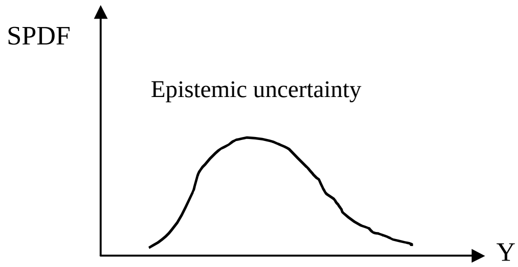
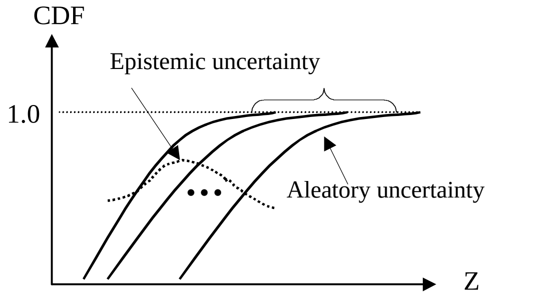


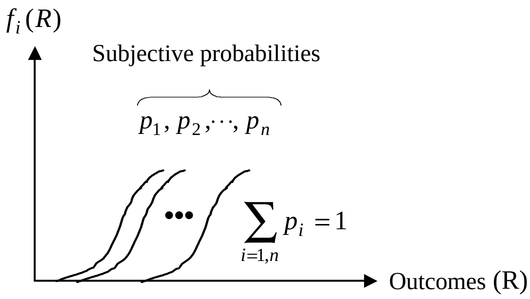
(a) Uncertainty of aleatory variable



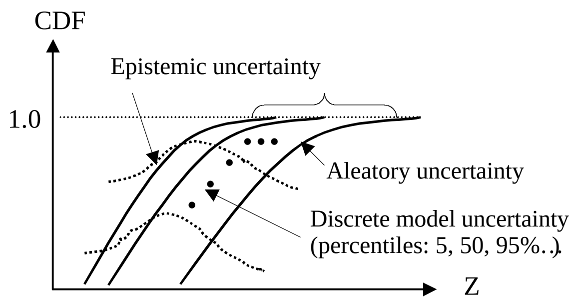
(b) Uncertainty of epistemic variable



(c) Epistemic uncertainty of aleatory variable



(d) Discrete Model uncertainty



(e) Model uncertainty in the presence of
aleatory and epistemic uncertainties

Note: (S)PDF: (subjective) probability density function, CDF: cumulative distribution function
p_i : subjective probability for i -th model, R: output variable, $f_i(R)$: model prediction for R

Figure 1. Characterization of Different Uncertainty Sources in Risk and Reliability Analysis