Incorporate Modeling Uncertainty into the Decision Making of Passive System Reliability Assessment

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Abstract: Passive safety features will play crucial roles in the development of the future generation nuclear power plant technologies. However because of the insufficient experiences, researches and validations are still necessary with the aim to prove the actual performance and reliability of the passive systems. Uncertain resources, which will influence the reliability and performance of such systems, can be divided into two groups: modeling uncertainties and parametric uncertainties. Up to now, the researchers have as good as established ways to quantify the effects caused by the parameter uncertainties, e.g. the variation of physical parameters (environment temperature, fabrication error, etc.) and have already got a number of achievements. In addition to the parameter uncertainty, the modeling uncertainty, e.g. uncertain physical phenomenon, uncertainties by different modeling techniques, etc. shall also be an important contributor to the passive system performance. How to take into account the effect caused by this kind of factors, there hasn't any mature approaches. In this paper, a survey of researches about the modeling uncertainty from the open literature is presented. A framework to incorporate the modeling uncertainty into the decision making of passive system reliability assessment will be proposed based on the survey and the discussion.

Keywords: Modeling uncertainty, Passive system reliability, Epistemic Uncertainty.

1. INTRODUCTION

Facing the development of the future generation nuclear power plant, the passive safety features will play crucial roles. At the same time the reliability of passive systems has become an important subject and area under discussion.

A passive component does not need any external input or energy to operate and it relies only upon natural physical laws (e.g. gravity, natural convection, conduction, etc.) and/or on inherent characteristics (properties of materials, internally stored energy, etc.) and/or "intelligent" use of the energy that is inherently available in the system (e.g. decay heat, chemical reactions etc.).

The term "passive" identifies a system, which is composed entirely of passive components and structures, or a system that uses active components in a very limited way to initiate subsequent passive operation [1].

However, the efforts conducted so far to deal with the passive safety systems reliability have raised an amount of open issues to be addressed. The uncertain resources, which will influence the reliability and performance of such systems, can be divided into two groups: modeling uncertainties and parametric uncertainties.

The effects caused by the parameter uncertainties refer to the variation of physical parameters (environment temperature, fabrication error, etc.). Up to now, the researchers have established ways to quantify these kinds of effects, and have already got a number of achievements. Major researchers are from ENEA [2], Bhabha Atomic Research Centre in India [3,4], Polytechnic of Milan in Italy [5-7], European Commission co-funded project under the 5th EURATOM Framework Programme [8], MIT in USA [9], INET in China[10-13] and so on.

In addition to the parameter uncertainty, the modeling uncertainty shall also be an important contributor to the passive system performance. In response to the need for an updated and broader deliberation of the modeling uncertainty issues, this paper provides a summary and discussion of the major approaches from the recent literature that have been used to address the reliability problems. The intent is not to recommend any given model since each requires considerably more analysis than can be conducted here. Rather, the intent is to give a global view of the solving methods, point out its advantages and disadvantages, and identify common issues that should be considered in future development and evaluation studies. The goal is that this framework may be of use when developing new models or when performing comparisons between models.

2. UNCERTAIN FACTORS INFLUENCING THE MODELING OF PASSIVE SYSTEM PERFORMANCE

There are many provisions to support the general judgment that passive systems shall have higher reliability. For example, the simpler structure is one of the very important advantages of passive systems, which is normally translated equivalently to the higher reliability. The working mechanism of the passive systems can be usually explained by the existent theories (e.g. thermodynamic theories for the natural circulation phenomenon), rather than a completely new theory. Although we don't have enough operation experience of passive system, we have tried various ways to collect the experience. For example, proof-of-principle experiments(to demonstrate the theoretical feasibility of the passive system operation) and the scaled experiments (in which the experiment facility is built with a ratio to the real system so that it can be studied in the laboratory scale) are usually required before the system can been used in a real engineering project.

Although most of the experimental results turned out to support the hypothesis that passive systems can have higher reliability, we are still worried about that when we extend the system to the required engineering size, or when we integrate the small passive systems/subsystems into a complex system, whether the actual performance will be the same as what we expected.

Another uncertain contribution which may be hard to model is that here we raise "the less effectiveness phenomena" but not "zero efficiency". "Zero efficiency" represent the fact that for the active systems, an entire stop of work will occur when there is a serious problem (e.g. loss of power). In other words, active systems act as Boolean variables, i.e. "1" or "0". But here in the case of passive systems, it turned out to be in contrary of "zero efficiency" but a partial working efficiency, which is "the less effectiveness phenomena". It may continue to work but not at an expected rate, or it may work with the delayed responses. This may cause the difficulty to define the success criteria of passive system behavior in Boolean logic as we usually do with the active systems when we talk about the reliability of passive system in Probabilistic Risk Assessment.

The first aspect (hereafter we refer to "integration problem") is not only the problem of passive systems. Active systems do have these kinds of problems too. This is the normal way we produce the product, no matter active systems or passive systems we use. That is to say, we validate the small system or subsystem firstly, and then integrate them into a complex system. If there is certain influence from the integration, e.g. outside environment, interaction among subsystems, the behaviour of the new system can be different from the expected one. Passive systems may be more sensitive to these integration influences than the active systems, because the driven forces are usually small. Because of the insufficient operational experiences of passive systems, we still cannot capture all the possible integration influences, and these influences became uncertain contributions in our models.

The second aspect (hereafter we refer to "less efficiency problem") is a challenge to the traditional probabilistic risk assessment technologies, which are based mainly on binary logics. However these kinds of problems can be hopefully solved by the advanced and dynamic PRA technologies, e.g. DDET (Dynamic Discrete Event Tree), Monte Carlo simulation, CCMT (Cell-to-Cell Mapping Technique) [14] and so on, given the precondition that we can conceive the possible evolution scenarios from the physical viewpoint. For instance, a typical passive system for the future advanced nuclear power plants will be the passive residual heat removal system. If the residual heat cannot be delivered to the atmosphere by 100% due to some reasons (exchanger tube blockages, increased resistance by dirty surface, etc.) in the passive residual system, the temperature feedback may lead the process to another state space, the margins to the thresholds of critical components may be reduced, available mitigation time may be shorter, however the residual heat removal process will not be stopped completely.

To sum up, the modelling uncertainties are caused by something we don't know yet. In the design and implementation of analyses for complex systems, it is useful to distinguish among the types of modelling uncertainty. Different categories of the modelling uncertainties can be found [15, 16], e.g. Aleatory uncertainty, Epistemic uncertainty and Completeness uncertainty.

In EPRI 2008[15], we can find a set of definitions of Aleatory uncertainty, Epistemic uncertainty and Completeness uncertainty. Aleatory uncertainty arises from an inherent randomness in the properties or behaviour of the system under study. Alternative designations for aleatory uncertainty include variability, stochastic and irreducible. Epistemic uncertainty derives from a lack of knowledge about the appropriate value to use for a quantity that is assumed to have a fixed value in the context of a particular analysis. Alternative designations for epistemic uncertainty include state of knowledge, subjective and reducible. Completeness uncertainty relates to contributions to risk that have been excluded from the PRA model. This class of uncertainties may have a significant impact on the predictions of the PRA model and must be addressed.

Here we focus more on the epistemic uncertainty and completeness uncertainty. We'd like to use epistemic uncertainty as the general term to describe the problem we are talking about, because in most of the cases, why we don't include the things into our model just because we don't know them yet. Hence completeness uncertainty is one set of epistemic uncertainty.

3. MODELING APPROACHES SURVEY

According to the open literature review, the methods to quantify the modelling uncertainty are not plentiful. There may be many documents with the keyword of epistemic uncertainty. But, actually they are focusing on the uncertainties caused by parameter variations, not the modelling uncertainties discussed in this paper.

3.1 Quantification of Margins and Uncertainty (QMU)[16]

In 2001, the National Nuclear Security Administration (NNSA) of the U.S. Department of Energy (DOE) in conjunction with the national security laboratories initiated development of a process designated Quantification of Margins and Uncertainty (QMU) for the use of risk assessment methodologies in the certification of the reliability and safety of the nation's nuclear weapons stockpile. Nowadays, the application of QMU is mainly used in the comparison of predictions from a mathematical model against a requirement.

The QMU approach proposed a framework to represent both aleatory and epistemic uncertainties in the model.

A QMU analysis must start with a clear understanding of the conceptual (i.e., mathematical) model used to represent uncertainty. A probabilistic characterization of the uncertainty associated with a quantity **x** is provided by a probability space (X, X_i, p_i), where (i) X is the set of all possible values for **x**, (ii) X_i is a suitably restricted set of subsets of X for which probability is defined, and (iii) p_i is a function that defines probability for individual elements of X_i. Then (X, X_i, p_i) is often represented by a density function $d_{Xi}(\mathbf{x})$, where

$$p_i(\mu) = \int_\mu d_{X_i}(\mathbf{x}) d\mu$$

for $\mu \in X_i$.
In most analyses, the result of interest is a function of uncertain analysis inputs.

$$\mathbf{Q} = f(\mathbf{x})$$

If x is uncertain as quantified by a probability space (X, Xi, pi), then Q is also uncertain, with this uncertainty quantified by a probability space (Q, Qi, pi') that derives from the function $f(\mathbf{x})$ and the probability space (X, Xi, pi) for x.
If **Q** corresponds to a scalar q or q is a component of the vector **Q**, then the uncertainty in q is usually represented by a cumulative distribution function (CDF) or a complementary cumulative distribution function (CCDF) that summarizes the corresponding probability space (Q, Q_i, p_i') for q.

In facing the uncertainties of a complex system, the variable would not be just one. A model that predicts system behaviour corresponds to a function of the form

$$\begin{aligned}&\mathbf{Q}(t|\mathbf{a},\mathbf{e}_M)\\&\quad=[\mathbf{Q_1}(t|\mathbf{a},\mathbf{e}_M),\mathbf{Q_2}(t|\mathbf{a},\mathbf{e}_M),\ldots,\mathbf{Q_{(nQ)}}(t|\mathbf{a},\mathbf{e}_M)]\\&\quad=\mathbf{f}(t|\mathbf{a},\mathbf{e}_M)\end{aligned}$$

where **a** is a vector of the parameters of the probability space of the aleatory uncertainty of the variables, $\mathbf{e}_M$ is a vector that represent epistemically uncertain quantities of the variables used in the modelling of one or more physical processes, t corresponds to time. We assume that for the objective function Q, each group of parameters including the time, the aleatory and epistemic uncertainty of the variables corresponds to a particular value of Q.

So, in fixing one of these terms we can have a curve that represent the correspond changes along with t (Fig .1 example of the curves of Q in given different groups of parameters.) and in giving several groups of parameters we can have a correspond number of curves. If we continue to give a limit bound, the range of the possible solutions will be reduced. The margins can be defined as the difference between the objective function and the given limit bound.

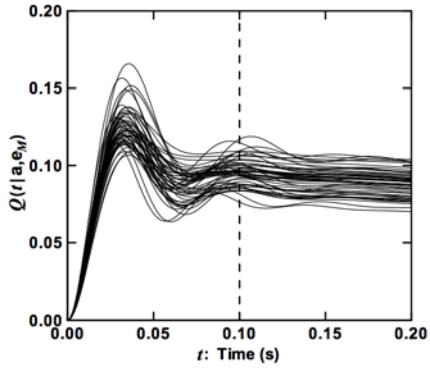

Fig. 1 Solutions Q(t|**a**, $\mathbf{e}_{Mi}$) with the 50 groups of epistemic uncertain elements

In this way, QMU approach estimates the margin of the expected value that contains the epistemic uncertainty.

3.2 Bayesian Methodology for Model Uncertainty Using Model Performance Data [17]

Droguett and Mosleh proposed the Bayesian methodology for model uncertainty by using model performance data in 2008[13]. Main foothold of the approach is that a simple characterization of predictive models in term of model structure and model parameters is very important and useful, because when performing uncertainty analysis, fundamentally one is interested in identifying, at some level of confidence, the range of possible and probable values of the unknown of interest.

Consider that we are interested in assessing u_t, the true state or value of an unknown U. In assessing the uncertainty about U, information can be available in two main forms. (1) Information from models: quantitative or qualitative estimates of U. (2) Information about models, including: (i) performance data, i.e., evidence on a model's past performance (benchmark data), which can be in the form of a set of model predictions and actual observations; (ii) other information, including any qualitative or quantitative evidence on model credibility and applicability other than performance data. Furthermore, we may also have the information regarding the unknown U from one or several models, u*, and possibly information about the models themselves, D. To this set of evidence we refer as IM = (u*, D). In assessing the uncertainty about U, the ultimate goal is to ensure that the true value u_t falls within some uncertainty range characterized by a probability distribution π (u), i.e., u_t is bracketed by π (u).

From the problem statement, it is natural to apply Bayes' theorem as the framework for assessing and expressing the uncertainty. In particular, a general Bayesian framework for dealing with model and parameter uncertainties in an integrated fashion can be formulated as follows. The available models are treated as sources of information that can be used to estimate the unknown U, through the application of Bayes' theorem:

$$\pi(u \mid IM) = \pi(u \mid \underline{u}^*, D) = \frac{L(\underline{u}^* \mid D, u)\pi_o(u)}{\int_u L(\underline{u}^* \mid D, u)\pi_o(u)\, du},$$

where $\pi(u \mid IM)$ is the posterior distribution of U; $\pi_o(u)$ is the prior distribution, and $L(u^* \mid D, u)$ is the likelihood function.

In this way, once we have another new method or new data come out, we can add it into the existent function and optimize our model. The more we considered the less the modelling uncertainty will remain.

4. OUR PILOT CASE

The two methods presented in Section 3 need a very important precondition that we should have enough information that can describe the working rules of the system. That is to say, we should know either the exact physical model of the system (i.e. QMU) or enough working data (i.e. Droguett's approach) to engender one.

While in the case of the epistemic uncertainty talked in this paper, the cognition of the system is always not complete, neither the mechanism nor the data. When we use the above methods to describe and analyze the system, there may have some variables or intra-relations that we have not discovered. It seems that at least QMU approach cannot work well for our cases.

What we actually propose is similar to the second approach, because both of them are simulating the process of how a human being makes decision. When we have a decision to make, it is a question to us. We first have an expected value as an answer to the question. We then list all the choices and compare them with the aim. We can't always have a choice that coincides perfectly with our expectation. So we take the one that approach the most to the wanted value as higher priority and the worse ones as the lower ranking. And if there is a clear veto of certain parameters for a choice, we should eliminate it.

Given the background of passive system reliability, especially for the nuclear facility applications, we fall into the knot of lacking of mechanism and data. However, we have to deal with this situation. Generally there are two ways. One is to create, maybe based on the knowledge that we have had, a new model that is more complete than the previous ones. The other way is to use what we already have as methods or data to eliminate some of the possibilities/impossibilities in our old model. It is to say that we are trying to make our cognition more complete by reducing the uncertainty gradually.

In case of passive system reliability, the choices might refer to judgment choice of the uncertain phenomena. For example, when we integrate some small passive system into a new complex system, we are not sure about the interaction among these subsystems. The set of possible combinations will be enumerated, i.e. no interactions, some of them have intersections, and all of them have intersections and so on. Our approach is a process to rebuild the belief likelihood value of the choices. Different from the second approach, the belief likelihood values for the choices in our approach are based on the Bayesian theorem but not directly calculated.

We take a system consist of three identical machines (A, B, C) in series as an example. We can get the independent failure probabilities of A/B/C by small or scaled experiments, e.g. 0.01 for each one. When they are integrated to a complex system, is there any influence among them? For instance, the vibration aggravation may increase the failure probability of the machines. We can have following choices. Choice No.1 might be the first thought that comes to our mind, that there isn't any dependence among them and the belief likelihood values are (1, 0, 0, 0). But with a second thought, we might find that there are possible interactions. Eventually there can be four possibilities as shown in the schema below:

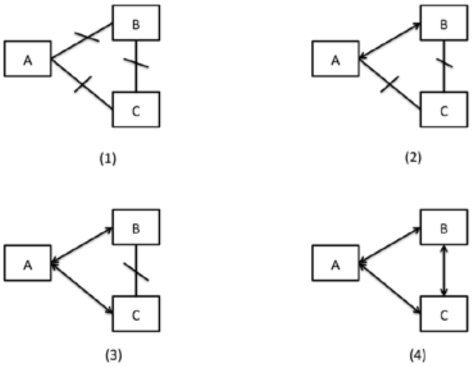

Fig.1 Different types of dependency among three machines

For each of the modeling choices, we can estimate the expected values of system failure probabilities in applying the Bayes' theorem.

Choice 1:

$$p_1 = p(A+B+C) = p_A + p_B + p_C - p_A p_B - p_B p_C - p_A p_C + p_A p_B p_C = 2.9706\times10^{-2}$$

Choice 2 assumes that A and B has interaction.

$$p_2 = p(A+B+C) = p_A + p_B + p_C - p_{AB} - p_A p_C - p_B p_C + p_{AB} p_C = 2.98\times10^{-2} - 0.99 p_{AB}$$

Choice 3 assumes the interaction failures for AB and AC respectively.

$$p_3 = p(A+B+C) = p_A + p_B + p_C - p_{AB} - p_{AC} - p_B p_C + p_{ABC} = 2.99\times10^{-2} - 2p_{AB} + p_{ABC}$$

Choice 4 assumes interaction failures for AB/AC/BC

$$p_4 = p(A+B+C) = p_A + p_B + p_C - p_{AB} - p_{AC} - p_{BC} + p_{ABC} = 3\times10^{-2} - 3p_{AB} + p_{ABC}$$

We have several unknown value of the relations, i.e. p_{AB}, p_{ABC}. There is no way but adding extra information to improve our confidence to the four choices. If new operational data, i.e. the integrated system failure probability can be measured as 2.88×10^{-2}, obviously choice 1 shall be eliminated and the belief likelihood value of choice 1 is set to 0. Choices 2/3/4 are still valid choices, because the equations can have valid solutions.

$$p_2 = 2.98\times10^{-2} - 0.99 p_{AB} = 2.88\times10^{-2}$$

$$p_{AB} = 1.01\times10^{-3}$$

$$p_3 = 2.99\times10^{-2} - 2p_{AB} + p_{ABC} = 2.88\times10^{-2}$$

$$2p_{AB} - p_{ABC} = 1.1\times10^{-3}$$

$$p_4 = 3\times10^{-2} - 3p_{AB} + p_{ABC} = 2.88\times10^{-2}$$

$$3p_{AB} - p_{ABC} = 1.12\times10^{-3}$$

We don't have further information to rank choice 2~4 up to now, but the belief likelihood values are now changed into (0, 1/3, 1/3, 1/3). We have already reduced some of the modeling uncertainties. If we can have more information from the small or scaled experiments, for example, the interaction behaviors of two machines, we can use it to update the above equations continually till we approach to the true situation.

This proposed method haven't resolved all the problems, because usually we will meet many terms we don't know if we apply this to describe the real passive system performance. The most important thing we've learnt from this pilot study is that this thought shows us a way of thinking and simulating, but we still have a long way to go to make it practicable enough for well analyzing most of the systems with modeling uncertainty.

5. CONCLUSION

Currently the majority of the existing models do not yet adequately address the epistemic uncertainties. Bayesian based methodology seems to be a promising way to reduce and quantify the modelling uncertainty. In regard to future approaches, however, it will be important that a larger set of issues is considered than has typically been the case in the models discussed here. The integration problem and less efficiency problem of passive system reliability are not the same kinds of issues, and can be treated by different techniques.

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