Reliability Engineering and System Safety 125 (2014) 46–53

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

An illustration of the use of an approach for treating model uncertainties in risk assessment

Torbjørn Bjerga [a,*], Terje Aven [a], Enrico Zio [b,c]

[a] University of Stavanger, Norway
[b] Chair on Systems Science and the Energetic Challenge, European Foundation for New Energy-Electricité de France, Ecole Centrale Paris and Supelec, France
[c] Politecnico di Milano, Italy

ARTICLE INFO

Available online 30 January 2014

Keywords:
Risk assessment
Model uncertainty
Subjective probabilities

ABSTRACT

This paper discusses an approach for treating model uncertainties in relation to quantitative risk assessments. The analysis is based on a conceptual framework where a distinction is made between *model error*—the difference between the model prediction and the true future quantity—and *model output uncertainty*—the (epistemic) uncertainty about the magnitude of this error. The aim of the paper is to provide further clarifications and explanations of important issues related to the understanding and implementation of the approach, using a detailed study of a Poisson model case as an illustration. Special focus is on the way the uncertainties are assessed.

1. Introduction

Quantitative risk assessment is largely based on models to represent systems and processes, and provide predictions of defined safety performance metrics. These models are conceptual constructs (translated into mathematical forms) built on a set of assumptions (hypotheses) on the systems and processes: for example, that the occurrence of an uncertain event of interest follows a Poisson distribution in time. The mathematical models include parameters, e.g., the (constant) rate of occurrence of the Poisson distribution: in practice, the values of these parameters are unknown and must be estimated, and the data and information available for that may be more or less precise and complete.

The modeling of a system or process needs to balance between two conflicting concerns: (i) accurate representation of the phenomena and mechanisms in the system or process and (ii) definition of the proper level of detail of the description of the phenomena and mechanisms so as to allow the timely and efficient use of the model. Differences between the real world quantities and the model outputs inevitably arise from the conflict of these two concerns.

In the field of risk assessment, probabilistic models are typically used to describe the (uncertain) future of the quantities characterizing the system or process. From a theoretical viewpoint, these models reflect variation (often referred to as aleatory or stochastic uncertainty) in an infinite (large) population of elements similar to the one (those) studied (i.e. constitutively identical elements but behaving differently because of the intrinsic aleatory character of the properties which rule their behavior). For example, the Poisson model referred to above can be used to represent the variation in the number of events occurring in a system over a period of time, when considering an (hypothetically infinite) population of similar systems. The values of the parameters of the probabilistic models need to be estimated from the information available on the system or process which, as said above, may be more or less precise and complete, and give rise to uncertainty on the values of the parameters (often referred to as epistemic uncertainty, meaning that it results from insufficient knowledge). As such, epistemic uncertainty can be reduced if additional knowledge and information can be acquired; on the contrary, aleatory uncertainty cannot be reduced and for this reason it is sometimes called irreducible uncertainty. The dichotomy of aleatory and epistemic uncertainty is instrumental for its treatment in risk assessment [1,12,25].

In synthesis, the models used in risk assessment are interpreted and simplified descriptions of the real systems and processes of interest, and their accuracy has to be balanced against their efficient use within the characteristic time scale of the assessment. As the value of a risk assessment is in providing informative support to decision making, the confidence that can be put in the accuracy, representativeness and completeness of the models is fundamental.

The concept of model uncertainty is pivotal in risk assessment and has been studied by several authors, see e.g., Zio and Apostolakis [38], Devooght [8], Nilsen and Aven [22], Helton et al. [13], Rosqvist and Tuominen [30,31], Droguett and Mosleh [9,10], Baraldi and Zio [4], Vasseur et al. [35], and Aven and Zio [3], but there still lack consensus on how to treat it in practice and, even on the meaning to be given to it. It comes natural to

* Corresponding author. Tel.: +47 90650576.
E-mail address: torbjorn.bjerga@uis.no (T. Bjerga).

0951-8320/$ - see front matter © 2014 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.ress.2014.01.014

address model uncertainty when there are alternative plausible hypotheses for modeling the specific phenomena or events of interest [26,28], but it can also be evoked in relation to the difference between the actual values of the real world output and the values predicted by the model [15,22,24]. Droguett and Mosleh [9] also talk about model uncertainty in situations where

- a single model is generally accepted but not completely validated,
- a conceptually accepted and validated model is of uncertain quality of implementation,
- a single model covers only some and not all relevant aspects of the problem, and when
- composite models are formed by submodels of differing degrees of accuracy and credibility.

The problem of model uncertainty is, then, fundamental for the accreditation of the model itself, for its use in practice. We take the understanding of accreditation as the objective of reaching a required quality level of a model by validation, for its certified use. Clearly, this requires that model uncertainty be sufficiently small, for confidence in the use of the outputs produced by the model. What is sufficiently small is of course dependent on the purpose for which the model is to be used. In practice, model accreditation stands on the evaluation of the comparison of the model predictions with the corresponding true values of the predicted quantities, for establishing the level of confidence in the model predictive capability needed for the intended use of the model: the accreditation must demonstrate that in correspondence of given input values the model produces predictions of the true values of the output quantity with the sufficient level of accuracy and the confidence required for taking decisions. In the case of accreditation, then, the evaluation of the model uncertainty serves the purpose of verifying the level of accuracy achieved so as to have the confidence required to make decisions informed by the outcomes of the model.

In the case that experimental data are available, there exists a wide range of statistical methods that can be used for validation in order to accredit a model. These methods include both traditional statistical analysis and Bayesian procedures, see e.g., Bayarri et al. [6], Jiang et al. [14], Kennedy and Hagan [16], Meeker and Escobar [21], Xiong et al. [36], and Zio [37]. However, these methods are not within the scope of the present paper, in which we consider situations with lack of data.

Model validation is often linked to model verification (and is often referred to as Verification and Validation, or simply "V&V."), which is commonly understood as the process of comparing the model with specified requirements [17,20,23,27,29]. The verification part is obviously important in many contexts to produce a model that meets the specifications.

For the treatment of model uncertainty in the case of scarce data, both Bayesian and non-Bayesian approaches can be undertaken. Classic examples of Bayesian approaches are the alternate hypotheses and adjustment factor approaches [38]. In the former, alternate hypotheses approach, a plausible set of models based on alternate hypotheses are used. These hypotheses are then assigned individual probabilities reflecting the analyst's relative confidence in the alternate hypotheses to be true. Differently, the adjustment-factor approach uses the output of a single-best model which is then adjusted by a multiplicative or additive factor to account for the uncertainty directly. Since this factor is generally unknown, probability distributions are introduced to provide a measure of confidence for different values of these factors. As for non-Bayesian approaches, an example is that of Rosqvist and Tuominen [30] which is based on a qualitative score assessment of direction of bias toward risk, where each modeling assumption is given a score: no bias, conservative or optimistic. For instance, if an assumption is deemed to represent the physical or social phenomena truthfully without any bias, then it is given the score 'no bias'.

One structured way for addressing the problem of model uncertainty in risk analysis is that described in the NUREG 1855 report (issued in 2009) by the US Nuclear Regulatory Commission [33] and related documents (a draft of a revised version open for comments was issued in March 2013; the draft is basically identical to the 2009 version on the issues here discussed [34]). What we find in the report mainly relates to the sources of model uncertainty ([33], p. 14):

Model uncertainty arises because different approaches may exist to represent certain aspects of plant response and none is clearly more correct than another. Uncertainty with regard to the PRA results is then introduced because uncertainty exists with regard to which model appropriately represents that aspect of the plant being modeled. In addition, a model may not be available to represent a particular aspect of the plant. Uncertainty with regard to the PRA results is again introduced because there is uncertainty with regard to a potentially significant contributor not being considered in the PRA.

The statements quoted above are not sufficiently unambiguous to confidently treat model uncertainty in risk assessment. The sentence "uncertainty exists with regard to which model appropriately represents that aspect of the plant being modeled", in practice is not necessarily meaningful for all cases. If you are considering two models, one model may give more accurate output for some inputs, and the other for others: what is, then, the model that "appropriately represents those aspects … being modeled"? And what is the uncertainty about it?

In another part of the NUREG 1855 report ([33] p. 7), it reads:

In developing the sources of model uncertainty, a model uncertainty needs to be distinguished from an assumption or approximation that is made, for example, on the needed level of detail. Although these assumptions and approximations can influence the decision making, they are generally not considered to be model uncertainties because the level of detail in the PRA model could be enhanced, if necessary. Therefore, methods for addressing this aspect are not explicitly included in this report, and Section 5 discusses their consideration.

It seems, then, that assumptions and approximations on the level of resolution of the model are not included as contributors to model uncertainty. On the contrary, we believe that they are key contributors and need to be included in the analysis.

The present paper is based on the framework for model uncertainty analysis introduced by Aven and Zio [3] with the aim of clarifying how to interpret and treat model uncertainty. From the above discussion it appears that such clarifications could be important for the risk field, and risk regulation in particular. In Bjerga et al. [5], an application of the framework has been presented within a risk assessment related to hydrocarbon releases in an LNG (Liquefied Natural Gas) plant in an urban area. Here, we extend the work by considering a probability model (the Poisson model) for describing the variation in the occurrences in time of a specific event. Through the example, we clarify the meaning of the various concepts of the model uncertainty framework and show how they can be described and measured in practice using different approaches, including subjective probabilities and interval probabilities. We also deal with the decision on accreditations or remodeling. Before we introduce the Poisson model and study its uncertainties, we give a short presentation recall of the framework. To help the reader understand the concepts used in this case study and the framework in general, we first provide some fundamentals related to probability models.

2. Some fundamentals related to probability models

Let N be the number of events occurring stochastically in a specific system for an interval of length l, and assume that the