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REVIEW ARTICLE

Measuring reliability under epistemic uncertainty: Review on non-probabilistic reliability metrics

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Abstract In this paper, a systematic review of non-probabilistic reliability metrics is conducted to assist the selection of appropriate reliability metrics to model the influence of epistemic uncertainty. Five frequently used non-probabilistic reliability metrics are critically reviewed, i.e., evidence-theory-based reliability metrics, interval-analysis-based reliability metrics, fuzzy-interval-analysis-based reliability metrics, possibility-theory-based reliability metrics (posbist reliability) and uncertainty-theory-based reliability metrics (belief reliability). It is pointed out that a qualified reliability metric that is able to consider the effect of epistemic uncertainty needs to (1) compensate the conservatism in the estimations of the component-level reliability metrics caused by epistemic uncertainty, and (2) satisfy the duality axiom, otherwise it might lead to paradoxical and confusing results in engineering applications. The five commonly used non-probabilistic reliability metrics are compared in terms of these two properties, and the comparison can serve as a basis for the selection of the appropriate reliability metrics.

1. Introduction

Reliability refers to the capacity of a component or a system to perform its required functions under stated operating conditions for a specified period of time.[1] Reliability engineering has nowadays become an independent engineering discipline, which measures the reliability by quantitative metrics and controls it via reliability-related engineering activities implemented in the product lifecycle, i.e., failure mode, effect and criticality analysis (FMECA),[2] fault tree analysis (FTA),[3] environmental stress screening (ESS),[4] reliability growth testing (RGT),[5] etc. Among all the reliability-related engineering activities, measuring reliability is a fundamental one.[6] Measuring reliability

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refers to quantifying the reliability of a component or system by quantitative metrics. A key problem in measuring reliability is how to deal with the uncertainty affecting the product's reliability. Broadly speaking, uncertainty can be categorized as aleatory uncertainty which refers to the uncertainty inherent in the physical behavior of the system,[7,8] and epistemic uncertainty which refers to the uncertainty that is caused by incomplete knowledge.[7,9]

In the early years of reliability engineering, reliability has been measured by probability-based metrics, e.g., in terms of the probability that the component or system does not fail (referred to as probabilistic reliability in this paper[10]), and estimated by statistical methods based on failure data (e.g., see Ref.[11]). However, in engineering practice, the available failure data, if there are any, are often far from sufficient for accurate statistical estimates.[12] Also, the statistical methods do not explicitly model the actual process that leads to the failure. Rather, the failure process is regarded as a black box and assumed to be uncertain, which is described indirectly based on the observed distribution of the time-to-failure (TTF). From the perspective of uncertainties, the statistical methods do not separate the root causes of failures and uncertainties and therefore, they do not distinguish between aleatory and epistemic uncertainties.

As technology evolves, modern products often have high reliability, making it even harder to collect enough failure data, which severely challenges the use of statistical methods.[13] At the same time, as the knowledge of the failure mechanisms accumulates, deterministic models are available to describe the failure process based on the physical knowledge of the failure mechanisms (referred to as physics-of-failure (PoF) models[14]). An alternative method to estimate the probabilistic reliability is, then, developed based on the PoF models. In this paper, these methods are referred to as the model-based methods. Unlike statistical methods, model-based methods treat the actual failure process as a white box: the TTFs are predicted by deterministic PoF models, while the uncertainty affecting the TTF is assumed to be caused by random variations in the model parameters (aleatory uncertainty). The probabilistic reliability is, then, estimated by propagating aleatory uncertainties through the model analytically or numerically, e.g., by Monte Carlo simulation.[15,16] Compared to statistical methods, model-based methods explicitly describe the actual failure process (by the deterministic PoF models) and separate the root cause of failures (assumed to be deterministic) and the aleatory uncertainty (the random variation of model parameters). The separation of deterministic root causes and aleatory uncertainty allows the designer to implement parametric design for reliability, e.g., the reliability-based design optimization (RBDO),[17,18] tolerance optimization,[19,20] etc., which marks significant advancement in reliability engineering.

From the perspective of uncertainties, only aleatory uncertainty is considered in the model-based methods. In practice, however, the trustfulness of the predicted reliability is severely influenced by epistemic uncertainty. As in today's highly competitive markets, it is more and more frequent to use the model-based method to measure reliability, due to the severe shortage on failure data. To better quantify the reliability with the model-based methods, the effect of epistemic uncertainty should also be considered. Epistemic uncertainty relates to the completeness and accuracy of the knowledge: if the failure process is poorly understood, there will be large epistemic uncertainty.[21–23] For instance, the deterministic PoF model might not be able to perfectly describe the failure process, e.g., due to incomplete understanding of the failure causes and mechanisms.[21,24] Besides, the precise values of the model parameters might not be accurately estimated due to lack of data in the actual operational and environmental conditions. Both of these two factors introduce epistemic uncertainty into the reliability estimation: the more severe the effect of these factors is, the less trustful the predicted reliability is.

In literature, there are various approaches to measure reliability under epistemic uncertainty, e.g., probability theory (subjective interpretation[25,26]), evidence theory,[27] interval analysis,[28,29] fuzzy interval analysis,[30] possibility theory,[31,32] uncertainty theory,[33] etc. In this paper, a critical review on these reliability metrics is conducted to assist the selection of appropriate metrics. Some researchers and practitioners use probability theory to describe epistemic uncertainty, taking a Bayesian interpretation of probability.[25,26] In recent years, problems in dealing with epistemic uncertainty by probabilistic methods have been pointed out.[34,35] Non-probabilistic metrics have, then, been proposed to model epistemic uncertainty. In this paper, we discuss these non-probabilistic reliability metrics.

More specifically, five reliability metrics are discussed in this paper, i.e., evidence-theory-based reliability metrics, interval-analysis-based reliability metrics, fuzzy-interval-analysis-based reliability metrics, possibility-theory-based reliability metrics (posbist reliability) and uncertainty-theory-based reliability metrics (belief reliability). They are classified, based on the mathematical essence of the metrics, as probability-interval-based and monotone-measure-based reliability metrics. The former refers to an interval that contains all the possible reliabilities/failure probabilities, while the latter refers to reliability metrics that are defined based on a monotone measure (or fuzzy measure[36]). A further classification is given in Fig. 1. The probability-interval-based and monotone-measure-based reliability metrics are reviewed in Sections 2 and 3, respectively.

2. Probability-interval-based reliability metrics

Probability-interval-based reliability metrics (PIB metrics) describe the effect of epistemic uncertainty by an interval of values of failure probabilities/reliabilities. The width of the interval represents the extent of epistemic uncertainty: wide intervals represent large epistemic uncertainty. When there is no effect of epistemic uncertainty, the probability interval becomes a single distribution function of the TTFs. We consider three of the most popular non-probabilistic methods for epistemic uncertainty representation, i.e., evidence theory, interval analysis (probability box) and fuzzy interval analysis. We review each of these three methods separately in the remaining of this section.

2.1. Evidence-theory-based methods

Evidence theory, also known as Dempster–Shafer theory or as the theory of belief functions, was established by Shafer[37] for representing and reasoning with uncertain, imprecise and incomplete information.[38] It is a generalization of the Bayesian theory of subjective probability in the sense that it does not require probabilities for each event of interest, but bases the