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Probability box as a tool to model and control the effect of epistemic uncertainty in multiple dependent competing failure processes

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ABSTRACT

Engineering components and systems are often subject to multiple dependent competing failure processes (MDCFPs). MDCFPs have been well studied in literature and various models have been developed to predict the reliability of MDCFPs. In practice, however, due to the limited resource, it is often hard to estimate the precise values of the parameters in the MDCFP model. Hence, the predicted reliability is affected by epistemic uncertainty. Probability box (P-box) is applied in this paper to describe the effect of epistemic uncertainty on MDCFP models. A dimension-reduced sequential quadratic programming (DRSQP) method is developed for the construction of P-box. A comparison to the conventional construction method shows that DRSQP method reduces the computational costs required for P-box constructions. Since epistemic uncertainty reflects the unsureness in the predicted reliability, a decision maker might want to reduce it by investing resource to more accurately estimate the value of each model parameter. A two-stage optimization framework is developed to allocate the resource among the parameters and ensure that epistemic uncertainty is reduced in a most efficient way. Finally, the developed methods are applied on a real case study, a spool valve, to demonstrate their validity.
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1. Introduction

Engineering components and systems are often subject to multiple processes that lead to their failures. Usually, these processes compete to cause failures and are dependent in various ways. Hence, they are referred to as multiple dependent failure processes (MDCFPs) [1]. In practice, most MDCFPs involve both degradation processes and random shocks [2]. MDCFPs have been well studied in literature and various models have been developed to predict the reliability of MDCFPs. A typical example is [3], in which Peng et al. considered a MDCFP where failure can be caused by either a degradation process or a random shock process. The two failure processes are dependent since when a random shock arrives, an abrupt increase to the degradation process is caused. A similar model can be found in [4], where degradation is modeled by a diffusion process and the random shocks are assumed to follow a Poisson process. Wang and Pham [5] modeled MDCFP in a similar way, within a framework for defining the optimal imperfect preventive maintenance policy. Li and Pham [6,7] developed a reliability model and an inspection-maintenance model for multistate degrading systems, considering two degradation processes and a shock process. Keedy and Feng [8] applied Peng's approach ([3]) to model a stent, where the degradation process is modeled by a Physics of Failure (PoF) model. In a recent paper by Lin et al. [9], the degradation process is modeled by a continuous-time, semi Markov process and the shock process is modeled using a homogeneous Poisson process.

Most existing MDCFP models assume that the precise values of the model parameters are known to the modeler. In practice, however, due to the limited resource, it is often difficult to precisely estimate the model parameters. Hence, the reliability predicted by the MDCFP models are affected by epistemic uncertainty [10]. The effect of epistemic uncertainty should be accounted for in MDCFP models.

In literature, there are various approaches to describe epistemic uncertainty, e.g. Bayesian theory [11], evidence theory [12,13], possibility theory [14], fuzzy theory [15], probability box (P-box) [16], etc. The major differences among these theories are the way

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that the incomplete knowledge is interpreted and mathematically described. For example, applying Bayesian theory implies that one can represent our incomplete knowledge as prior probability distributions [17,18], evidence theory expresses incomplete knowledge by identifying basic probability assignments (BPA) [12,13], possibility theory relies on possibility distributions (or membership functions) to describe the state of knowledge [19,20], probability box (P-box) expresses the incomplete knowledge based on intervals or bounds of probability distributions [21,22]. Among them, P-box is natural to engineers and easier to implement in practice. Therefore, in this paper, we use P-box to describe epistemic uncertainty in MDCFP models.

A P-box comprises a pair of upper and lower cumulative density functions (CDFs), in which the real CDF is bounded. P-boxes have been widely applied in many fields to solve the problems associated with epistemic uncertainty, such as engineering [23], biology [24], environmental science [25], etc. An early implementation of P-box can date back to the work of Walley and Fine [26], where they constructed a probability box to model the imprecision in probability estimations. Wolfenson and Fine [27] used upper and lower probabilities to support Bayesian-like decision making. Ferson et al. [16] used P-boxes to handle both variability (aleatory uncertainty) and ignorance (epistemic uncertainty) in safety assessments. In the field of reliability, Karanki et al. [21] applied P-box to evaluate the probability of system failure under the influence of epistemic uncertainty. Xiao et al. [28] proposed a unified method to perform sensitivity analysis reliability for structural systems by combining the P-box, first-order reliability method (FORM) and Monte Carlo simulation (MCS). Luis et al. [29] applied P-box to the analysis of polynomial systems subject to parameter uncertainties. Zhang developed interval Monte Carlo Simulation (IMCS) method [22], interval importance sampling method [30] and quasi-Monte Carlo method [31] for finite element-based structural reliability assessment based on P-boxes. In order to reduce the calculation cost of IMCS method, Yang et al. [32] introduced a hybrid method based on P-box, where the true limit state equation is approximated by a surrogate model, to evaluate the reliability of structures.

In existing P-box method, the epistemic uncertainty is propagating by calculating the Cartesian products of the input parameters and their P-boxes (see [21] for example). More specifically, to calculate the reliability of a time-varying system which is described by P-boxes, the time interval under investigation is discretized into several subintervals and the maximum and minimum reliability is searched using numerical optimization methods in each subinterval [33]. A major drawback of these uncertainty propagation methods is that their computational costs grow as the number of model parameters increases. In this paper, we develop a dimension-reduced SQP method, which uses gradient information to reduce the required computational costs.

Since epistemic uncertainty reflects the unsureness in the predicted reliability, a decision maker might want to reduce it by investing resource to more accurately estimate the value of each model parameter. In this paper, a two-stage optimization framework is also developed to allocate the resource among the parameters and ensure that epistemic uncertainty is reduced in a most efficient way. The contribution of this paper is summarized as follows:

- probability box is used as a tool to describe epistemic uncertainties in multiple dependent competing failure processes (MDCFPs);
- a dimension-reduced-SQP (DRSQP) method is developed to construct the probability box;
- an optimization model is developed to control the effect of epistemic uncertainty in MDCFP.

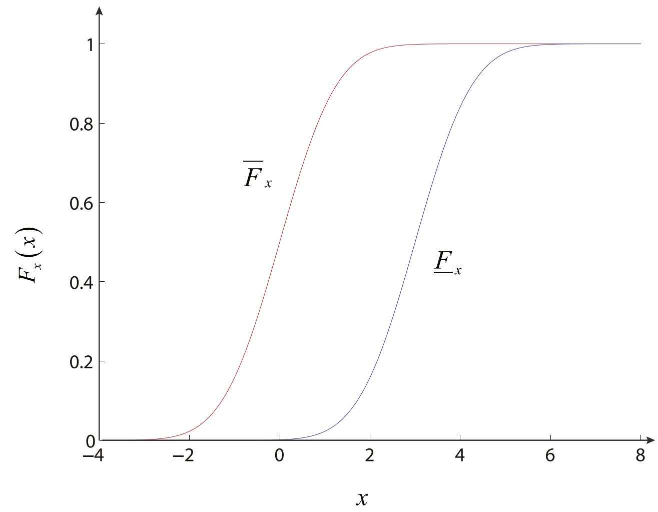

Fig. 1. An illustration of P-box for N([0,3],1).

The remainder of this paper is organized as follows. Section 2 presents how to quantify the epistemic uncertainty on a MDCFP model using P-box. The DRSQP method is developed in Section 3 for efficient construction of the P-box. In Section 4, a two-stage optimization framework is developed for the optimal reduction of epistemic uncertainty. A real case study on a sliding spool is conducted in Section 5 to demonstrate the developed methods. Finally, the paper is concluded in Section 6 with a discussion on possible future research directions.

2. Representing epistemic uncertainty using P-boxes

In this section, we briefly review the concept of P-box in subsection 2.1, and then, apply it in subsection 2.2 to describe epistemic uncertainty on MDCFP models.

2.1. Preliminaries on P-boxes

A P-box comprises of an upper and a lower cumulative density function (CDF), denoted by $\left[\underline{F}_x, \bar{F}_x\right]$. The actual CDF of a random variable x, denoted by $F_x(x)$, is bounded in the area:

$$\underline{F}_x \le F_x(x) \le \overline{F}_x \tag{1}$$

Hence, the distance between the upper and lower CDFs represents the amount of epistemic uncertainty.

A simple illustration of a P-box is given in Fig. 1. Suppose x is a random variable following a normal distribution with the variance $\sigma^2 = 1$. However, due to the limited time and resource, the precise value of the mean value cannot be estimated accurately. The only information we have is that, the mean value lies in the interval of $[0, 3]$. The epistemic uncertainty in x can, then, be described by a P-box in Fig. 1. It is easy to show that the actual CDF lies in the bounded area constructed by $\underline{F}_x$ and $\overline{F}_x$.

2.2. Describing epistemic uncertainties in MDCFP by P-boxes

For most MCDFP, reliability is modeled as an explicit function of t[3]:

$$R(t) = f_{MDCFP}(t; \mathbf{x}), \tag{2}$$

where $\mathbf{x} = [x_1, x_2, \cdots, x_n]^T$ is a vector of parameters in the reliability model. Due to epistemic uncertainty, the precise values of $\mathbf{x}$ is not

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