Reducing Uncertainty by Imprecise Judgements on Probability Distributions: Application to System Reliability*

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Abstract

In this paper the judgement consisting in choosing a function that is believed to dominate the true probability distribution of a continuous random variable is explored. This kind of judgement can significantly increase precision in constructed imprecise previsions of interest, which of great importance for applications. New formulae for computing system reliability are derived on the basis of the technique developed.

Keywords

imprecise probabilities, probability density function, reliability

1 Introduction

Natural extension, a tool to extend statistical knowledge to other domains and to make a set of available statistical partial evidence coherent, can appear and be used in different forms. In [1] four equivalent forms of the natural extension were reported. They are all nothing other than properly stated optimisation problems for obtaining lower and upper coherent bounds of probability characteristics of interest. The primal form suggests seeking coherent bounds defined by a set of feasible probability distributions, and this set, in turn, is formed by the available evidence expressed as constraints in the optimisation task. If no evidence is available (the state of complete ignorance), then the solution is sought over the set of all possible probability distributions, which brings us to the vacuous probability of the event of interest A, i.e., $P(A) \in [0,1]$. The crux of such optimisation problems

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is that their solutions are defined on the family of degenerate probability distributions[1], which are included on equal footing in the set of all possible probability distributions. As proven in [1], solving these optimisation problems, on the set of all possible probability distributions, gives the same solution as that obtained on only the set of degenerate distributions. This issue is closely related to the central theorems and methods of Chebychev systems as described in [2]. All this would simply be mathematical subtlety, that is, far from practitioners' interest, if this did not give us a clue for deriving more precise previsions of interest for continuous random variables. For these variables it is often not realistic to assume that the probability masses are concentrated in a few points as opposed to being continuously distributed over the set of possible outcomes. The existence of solutions on degenerate distributions often results in high imprecision, negating the pragmatic value of the assessments of interest. For example, in reliability applications the time to failure of a system/component can not admit (except for very special cases) the concentration of probability masses in a very few points of the positive real line. Not being able to utilise such evidence leads to the fact that imprecision in the reliability of a system grows rapidly as the number of components in the system increases, making the results rather practically useless [3].

This feature of the natural extension was found disturbing and precluded wider implementation of imprecise statistical reasoning into reliability analysis. An attempt to mitigate the influence of degenerate probability distributions on the solutions was undertaken in [4]. No significant effect was attained through the introduction of judgements on the skewness and unimodality of the distributions as, in this case, the peaks of degenerate distributions simply become repositioned and probability masses become redistributed among the peaks. The nature of the distributions defining the solutions stays the same.

In this paper we explore a more drastic and, as it will be demonstrated, effective way to exclude the family of degenerate distributions from the set of probability distributions, which, as was expected, results in more precise previsions of interest. This is attained through judgements on a value (or a function, in general) that dominates the probability density function $\rho(x)$ of a continuous random variable X. That is, we introduce judgements of the form $\rho(x) \leq \Psi(x)$, where $\Psi(x)$ is a real-valued positive function satisfying the inequalities $1 \leq \int_{R_+} \Psi(x)dx < \infty$, and demonstrate a way of their utilisation. In particular, $\Psi(x)$ can be set as $\Psi(x) = K \cdot I_{[a,b]}(x)$ where $a, b \in R_+$ and $a \leq b$, $I_{[a,b]}(x)$ is the indicator function such that $I_{[a,b]}(x) = 1$ if $x \in [a,b]$, and $I_{[a,b]}(x) = 0$ otherwise, and $K \geq (b-a)^{-1}$ is a constant.

Similar ideas of utilising bounds on density functions were explored in [5]. The tool of their utilisation was dynamic programming which gives us numerical

[1] The probability distribution of a continuous random variable is referred to as degenerate if the probability masses are concentrated in a finite number of points belonging to the continuous set of possible states

solutions of the stated problems, while we suggest an approach to solving the problems analytically.

Breaking down a multidimensional case, $\boldsymbol{X}=(X_1,\ldots,X_n)$, provides a theoretical basis for system reliability computations, which is a subject of the second part of the paper.

2 Relevant basics of the approach

Comprehensive coverage of the foundation of the theory of imprecise previsions can be found in the books [6] and [7]. In this section we briefly describe only those concepts that are necessary to understand the approach developed.

Consider a system consisting of n components. Let $f_{ij}(x_i)$ be $j-$th function of the i-th component lifetime x_i, $i=1,\ldots,n$, and $j=1,\ldots,m_i$. Suppose that reliability characteristics of the components are not known precisely and represented as a set of lower and upper previsions $\underline{a}_{ij}=\underline{M}(f_{ij}(x_i)),\overline{a}_{ij}=\overline{M}(f_{ij}(x_i)),i=1,\ldots,n$, and $j=1,\ldots,m_i$, which means that there exist m_i interval-valued judgements for the i-th component formally represented as expected values. The functions $f_{ij}(x_i)$ can be regarded as gambles, where a gamble is a real-valued function on a possibility space whose value is uncertain [6]. If, for instance, $f_{ij}(x_i)=x$, then the lower prevision $\underline{a}_{ij}$ is the lower bound of the mean time to failure of the i-th component; or if $f_{ij}(x_i)=I_{[t,\infty)}(x_i)$, where $I_{[t,\infty)}(x_i)$=1 if $x_i\in[t,\infty)$ and $I_{[t,\infty)}(x_i)$=0 otherwise, then the lower prevision $\underline{a}_{ij}$ is the lower bound of the probability of a failure occurrence within $[t,\infty)$.

Denote $\boldsymbol{X}=(X_1,\ldots,X_n)$ a random vector and $x=(x_1,\ldots,x_n)$ is the vector of numerical values for $X_1,...,X_n$. Then, there exists a function $g(\boldsymbol{X})$ of the component lifetimes that characterises the system's reliability. The function $g(\boldsymbol{X})$ is also a gamble.

In order to compute the coherent lower and upper previsions $\underline{M}(g)$ and $\overline{M}(g)$ of interest characterising the system reliability, a proper optimisation problem (also referred to as the natural extension in its primal form) can be posed

$$\underline{M}(g)\langle\overline{M}(gt)\rangle=\inf_{\Re^n}\left\langle\sup_{\Re^n}\right\rangle\int\limits_{R_+^n}g(x)\rho(x)dx \tag{1}$$

subject to

$$\left.\begin{array}{l}0\le\rho(x),\ \int\limits_{R_+^n}\rho(x)dx=1,\\ \underline{a}_{ij}\le\int\limits_{R_+^n}f_{ij}(x_i)\rho(x)dx\le\overline{a}_{ij},i=1,...,n,j=1,...,m_i.\end{array}\right\} \tag{2}$$

Here the minimum and maximum are taken over the set $\Re^n$ of all possible n-dimensional density functions $\{\rho(\boldsymbol{x})\}$ satisfying conditions (2). That is, each constraint in (2) is associated with a subset of $\Re^n$ and the intersection of those subsets,

if not empty, defines the solutions of the above optimisation problems. If the initial interval-valued data, forming the constraints, are not consistent, then some of the subsets of $\Re^n$ associated with the constraints are disjoint and the solution does not exist. The requirement of the existence of a non-empty set of probability distributions associated with the set of constraints is the only consistency principle imposed on the initial interval-valued data. This requirement is equivalent to the principle of avoiding sure loss [6] and is easily subject to technical checks.

If the components of a system are independent, then $\rho(\boldsymbol{x}) = \rho_1(x_1),\ldots,\rho_n(x_n)$.

In some cases the duals of optimisation problems (1)-(2) can be stated, which makes it technically easy to solve them [1]. The duals of (1)-(2) are

$$\underline{M}(g) = \sup_{c_0,c_{ij},d_{ij}} \left(c_0 + \sum_{i=1}^{n} \sum_{j=1}^{m_i} (c_{ij}\underline{a}_{ij} - d_{ij}\overline{a}_{ij}) \right), \tag{3}$$

subject to $c_0 \in R,\ c_{ij}, d_{ij} \in R_+$ and for any $x_i \geq 0$, $i = 1,2,...,n, \quad j = 1,2,...,m_i$,

$$c_0 + \sum_{i=1}^{n} \sum_{j=1}^{m_i} (c_{ij} - d_{ij}) I_{[t,\infty)}(x_i) \leq g(x). \tag{4}$$

And

$$\overline{M}(g) = \inf_{c_0,c_{ij},d_{ij}} \left(c_0 + \sum_{i=1}^{n} \sum_{j=1}^{m_i} (c_{ij}\overline{a}_{ij} - d_{ij}\underline{a}_{ij}) \right), \tag{5}$$

subject to $c_0 \in R, c_{ij}, d_{ij} \in R_+$ and for any $x_i \geq 0$, $i = 1,2,...,n$, $j = 1,2,...,m_i$,

$$c_0 + \sum_{i=1}^{n} \sum_{j=1}^{m_i} (c_{ij} - d_{ij}) I_{[t,\infty)}(x_i) \geq g(x). \tag{6}$$

The validity of the transition from a primal form similar to (1)-(2) to the dual form is explained in [1], [8].

Problems (3)-(4) and (5)-(6) are linear optimisation problems and and have technically straightforward solutions.

In some cases dual problems do not exist. This takes place if a primal optimisation problem is not linear. For example, the judgement of independence among system components, which is equivalent to the introduction of $\rho(\boldsymbol{x}) = \rho_1(x_1),\ldots,\rho_n(x_n)$, makes the problem non-linear, and, as a consequence, it leads to the non-existence of the dual optimisation problem.

3 Extending knowledge: one-dimensional case

Let us consider first a one-dimensional case of extending partial statistical information to probability characteristics of interest. That is, we will be focusing in this section on the construction of new imprecise characteristics provided some

other imprecise statistical characteristics are known on the same possibility set, and, more important, we will demonstrate how "soft" judgements on the probability density function of a random variable can be modelled and utilised in the framework of the theory of imprecise probabilities.

Assume that there are m interval-valued judgements on probability characteristics on a specific possibility set, i.e. $M(f_i(X)) \in [\underline{a}_i, \overline{a}_i]$, and there is an additional judgement of $\rho(x) \leq \Psi(x)$, $1 \leq \int_{R_+} \Psi(x)dx < \infty$. The objective is to extend this evidence to the prevision of interest $M(g(X))$ that cannot be found precisely, as the initial data are partial.

Write the primal form of natural extension

$$\underline{M}(g)\left\langle \overline{M}(g)\right\rangle = \inf_{\Re}\left\langle \sup_{\Re}\right\rangle \int_{R_+} g(x)\rho(x)dx \tag{7}$$

subject to

$$\left.\begin{array}{l} 0 \leq \rho(x) \leq \Psi(x), \int_{R_+} \Psi(x)dx = H < \infty, \int_{R_+} \rho(x)dx = 1 \text{ and} \\ \underline{a}_i \leq \int_{R_+} f_i(x)\rho(x)dx \leq \overline{a}_i, i = 1,2,...,m. \end{array}\right\} \tag{8}$$

The dual of the above optimisation problem cannot be straightforwardly written. First, introduce a new variable $z(x)$ instead of $\rho(x)$

$$z(x) = \frac{\Psi(x) - \rho(x)}{H-1},$$

and denote $\Gamma = \int_{R_+} g(x)\Psi(x)dx$; $\Phi_i = \int_{R_+} f_i(x)\Psi(x)dx$, $i = 1,2,...,m$.

It is clear that $\int_{R_+} z(x)dx = 1$. Then, optimisation problem (7)-(8) can be rewritten

$$\begin{array}{l} \underline{M}(g)\left\langle \overline{M}(g)\right\rangle = \inf_{\Re}\left\langle \sup_{\Re}\right\rangle \int_{R_+} g(x)\rho(x)dx = \\ = \Gamma - (H-1)\sup_{Z}\left\langle \inf_{Z}\right\rangle \left\{ \int_{R_+} g(x)z(x)dx \right\} \end{array} \tag{9}$$

subject to

$$\left.\begin{array}{c} 0 \leq z(x), \int_{R_+} z(x)dx = 1, \frac{\Phi_i - \overline{a_i}}{H-1} \leq \int_{R_+} f_i(x)z(x)dx \leq \frac{\Phi_i - \underline{a_i}}{H-1}, \\ i = 1,...,m. \end{array}\right\} \tag{10}$$

And finally, the challenge is to solve the following problems

$$\underline{s}(g)\left\langle \overline{s}(g)\right\rangle = \inf_{Z}\left\langle \sup_{Z}\right\rangle \int_{R_+} g(x)z(x)dx, \tag{11}$$

subject to (10).

Before we go on to the duals, one consistency condition must be fulfilled. It is of avoiding sure loss [6] and is transparent from the stand of common sense and can be written as $\inf(f(x)) \le \underline{M}(f(x)) \le \overline{M}(f(x)) \le \sup(f(x))$. Applied to objective functions (9), it appears as

$$\inf(g) \le \Gamma - (H-1)\sup_{Z}\left\{\int_{R_+} g(x)z(x)dx\right\} \le$$

$$\Gamma - (H-1)\inf_{Z}\left\{\int_{R_+} g(x)z(x)dx\right\} \le \sup(g)$$

Optimisation problems (11) subject to (10) have their duals

$$\underline{s}(g) = \sup_{c_0,c_i,d_i}\left\{c_0 + \sum_{i=1}^{m}\left[c_i\left(\frac{\Phi_i - \overline{a}_i}{H-1}\right) - d_i\left(\frac{\Phi_i - \underline{a}_i}{H-1}\right)\right]\right\} \tag{12}$$

subject to $c_0 \in R,\ c_i, d_i \in R_+$ and for any $x \ge 0$ $c_0 + \sum_{i=1}^{m}(c_i - d_i)f_i(x) \le g(x)$. And

$$\overline{s}(g) = \inf_{c_0,c_i,d_i}\left\{c_0 + \sum_{i=1}^{m}\left[c_i\left(\frac{\Phi_i - \underline{a}_i}{H-1}\right) - d_i\left(\frac{\Phi_i - \overline{a}_i}{H-1}\right)\right]\right\} \tag{13}$$

subject to $c_0 \in R,\ c_i, d_i \in R_+$ and for any $x \ge 0$ $c_0 + \sum_{i=1}^{m}(c_i - d_i)f_i(x) \ge g(x)$.

Thus, having derived the dual optimisation problems (12) and (13), we have got a tool for utilising "soft" judgements concerning probability density functions and extending them to other probability characteristics of interest defined on a one-dimensional possibility set.

Example 1. The information concerning a continuous random variable X is that of $\rho(x) \le \Psi(x) = K \cdot I_{[0,T]}(x) < \infty$, where T, K are fixed positive numbers. What are the bounds for the expectation $M(X)$?

The above approach brings us to the following results

$$\underline{M}(X) = \frac{KT^2}{2} - (KT-1)T = T\left(1 - \frac{KT}{2}\right) \text{ and } \overline{M}(X) = \frac{KT^2}{2}.$$

Example 2. Assume now that besides the information stated in example 1 we know precisely the probability $P\{\underline{a} \le X \le \overline{a}\} = p$, where $0 \le \underline{a} < \overline{a} \le T$. How would the given information change the bounds for the expectation $M(X)$?

The result is

$$\underline{M}(X) = T\left(1 - \tfrac{KT}{2}\right) + (T - \overline{a})\left[K(\overline{a} - \underline{a}) - p\right],$$
$$\overline{M}(X) = \tfrac{KT^2}{2} - \underline{a}\left[K(\overline{a} - \underline{a}) - p\right].$$

4 Computation of system reliability

Extending knowledge on multidimensional possibility sets, taking into account imprecise judgements on probability density functions, is undertaken in a similar way to the one-dimensional case described above. The multidimensional case is broken down in detail in [9]. In this section we represent the results concerning system reliability computations that follow from this case.

As it has been found earlier (see elsewhere [3], [10], [11]), the reliability of a system, P_{Series}, the components of which are connected in series given the lower and upper bounds of the components' reliabilities and the state of complete ignorance concerning their dependence, is calculated according to the formulae

$$\underline{P}_{Series} = \underline{M}\left(I_{[t,\infty)}(\min_i x_i)\right) = \max\left(0; \sum_{i=1}^{n} \underline{p}_i - (n-1)\right),$$

and

$$\overline{P}_{Series} = \overline{M}\left(I_{[t,\infty)}(\min_i x_i)\right) = \min_i \overline{p}_i,$$

where $\underline{P}_{Series} \le P_{Series} \le \overline{P}_{Series}$, and $\underline{p}_i$ and $\overline{p}_i, i = 1,...,n$ are the lower and upper reliabilities of the components.

By applying the above described approach, the formulas for the calculation of the reliability of series systems become updated in the light of the evidence concerning the probability density function of time to failure

$$\underline{P}_{Series} = \Gamma - (H-1)\min_i\left(\frac{\Phi_i - \underline{a}_i}{H-1}\right) = \Gamma - \min_i(\Phi_i - \underline{a}_i),$$

$$\overline{P}_{Series} = \Gamma - (H-1)\max\left(0; \sum_{i=1}^{n}\left(\frac{\Phi_i - \overline{a}_i}{H-1}\right) - (n-1)\right) =$$
$$= \Gamma - \max\left(0; \sum_{i=1}^{n}(\Phi_i - \overline{a}_i) - (H-1)\cdot(n-1)\right).$$

The reliability of a system, $P_{Parallel}$, the components of which are connected in parallel given the lower and upper bounds of the components' reliabilities and the state of ignorance concerning their independence, is calculated according to the formulas (see elsewhere [3], [10], [11])

$$\underline{P}_{Parallel} = \underline{M}\left(I_{[t,\infty)}(\max_i x_i)\right) = \max_i \underline{p}_i,$$
$$\overline{P}_{Parallel} = \overline{M}\left(I_{[t,\infty)}(\max_i x_i)\right) = \min\left(1; \sum_{i=1}^{n} \overline{p}_i\right)$$

Their update in the light of the new evidence appears as follows

$$\underline{P}_{Parallel} = \Gamma - (H-1)\min\left(1; \sum_{i=1}^{n}\left(\frac{\Phi_i - \underline{a}_i}{H-1}\right)\right) =$$
$$= \Gamma - \min\left((H-1); \sum_{i=1}^{n}(\Phi_i - \underline{a}_i)\right),$$

and

$$\overline{P}_{Parallel} = \Gamma - (H-1)\max_i\left(\frac{\Phi_i - \overline{a}_i}{H-1}\right) = \Gamma - \max_i(\Phi_i - \overline{a}_i).$$

For a system of an arbitrary structure the reliability bounds satisfy the inequalities [3], [10], [11]:

$$\underline{P}_{ArbStruct} \geq \max_{1\leq j\leq r}\max(0, L_j),$$

where r is a number of system minimal paths $\pi_1, \pi_2, ..., \pi_r$, $L_j = \sum_{i\in\pi_j}\underline{p}_i - (\mu_j - 1)$, and μ_j is the number of components belonging to path π_j, and

$$\overline{P}_{ArbStruct} \leq \min_{1\leq j\leq s}\min\left(\sum_{i\in \mathrm{K}_j}\overline{p}_i; 1\right),$$

where s is a number of system minimal cut sets denoted by $\mathrm{K}_1, \mathrm{K}_2, ..., \mathrm{K}_s$.

Now by applying the approach developed and using the substitutions $\overline{p}_i = \frac{\Phi_i - \underline{a}_i}{H-1}$, $\underline{p}_i = \frac{\Phi_i - \overline{a}_i}{H-1}$, we obtain

$$\underline{P}_{ArbStruct} \geq \Gamma - \min_{1\leq j\leq s}\min\left(\sum_{i\in \mathrm{K}_j}(\Phi_i - \underline{a}_i); (H-1)\right),$$
$$\overline{P}_{ArbStruct} \leq \Gamma - \max_{1\leq j\leq r}\max(0, L_j^*),$$

where $L_j^* = \sum_{i\in\pi_j}(\Phi_i - \overline{a}_i) - (H-1)\cdot(\mu_j - 1)$.

Example 3. A system consists of two components (n=2) connected in series, and the reliability of the first component is $p_1 \in [\underline{a}_1, \overline{a}_1]$ and the second is $p_2 \in [\underline{a}_2, \overline{a}_2]$. One more judgement is of the form $\rho(x_1, x_2) \leq \Psi(x_1, x_2) = K \cdot I_{\{[0,T];[0,T]\}}(x_1, x_2)$, where K and$T$ are constants and $I_{\{[0,T];[0,T]\}}(x_1, x_2)$ is a two-dimensional indicator function. What is system reliability?

The reliabilities of the components for an arbitrary time $t$are to be written in the form (2)

$$\underline{a}_1 \leq \int_0^T I_{[t,T]}(x_1)\int_0^T \rho(x_1, x_2)dx_1dx_2 \leq \overline{a}_1,$$
$$\underline{a}_2 \leq \int_0^T I_{[t,T]}(x_2)\int_0^T \rho(x_1, x_2)dx_1dx_2 \leq \overline{a}_2.$$

Note that in this case $H = KT^2$, $\Gamma = K(T-t)^2$, hence

$$\underline{P}_{Series} = \Gamma - \min_i(\Phi_i - \underline{a}_i) = \Gamma - \int_t^T \int_0^T \Psi(x_1, x_2) dx_1 dx_2 + \max_i(\underline{a}_i) =$$
$$= \max_i(\underline{a}_i) - Kt(T-t);$$
$$\overline{P}_{Series} = \Gamma - \max\left(0; \sum_{i=1}^{n} (\Phi_i - \overline{a}_i) - (H-1)\cdot(n-1)\right) =$$
$$= \min\left(K(T-t)^2; (Kt^2 + \sum_{i=1}^{2} \overline{a}_i - 1)\right).$$

5 Concluding remarks

Judgements concerning the function $\Psi(x)$, which is believed to dominate the true probability distribution of a continuous variable, are practically elicitable and may be unambiguously understood by those inexperienced in probabilistic reasoning. So, a sample probability density function is defined by the totality of the values $\rho_i = {}^{n_i}/_{(N\Delta x)}$, $i = 1, 2, ...$, where n_i is the number of observed realisations of a continuous random variable X falling in the $i-$th bin with a width of Δx, and N is the size of the sample. For example, in reliability analysis the continuous random variable is time to failure or time between failures, and usually reliability characteristics are counted for a time period of 1 year. That is, the width of the bins is equal to 1 year for any i except for the last bin which is an open interval $[x_k, \infty)$. As a matter of fact, any reliability calculation and failure reporting systems are scaled to one-year assessments so that the experts in the field are used to think of reliability characteristics as values scaled to a year. A question of "what would be the maximum percentage of failures per year for a specified component over its lifetime?" or alike would be quite easy to answer for an expert or to assess based on even scarce failure evidence.

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