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Uncertainty treatment in expert information systems for maintenance policy assessment

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ABSTRACT

This paper proposes a framework based on the Dempster–Shafer Theory of Evidence (DSTE), Possibility Theory (PT) and Fuzzy Random Variables (FRVs) to represent expert knowledge and propagate uncertainty through models. An example of application is given with reference to a check valve of a turbo-pump lubricating system in a Nuclear Power Plant, which is degrading due to mechanical fatigue and undergoes condition-based maintenance interventions. The component degradation-failure model used to evaluate the performance of the maintenance policy contains parameters subject to epistemic uncertainty.

Introduction

Processing of uncertainty is crucial in industrial applications and consequently in decision making processes [1]. In practice, it is often convenient to distinguish uncertainty due to the inherent variability of the phenomena of interest from that due to lack of precise knowledge [2]. The former type is referred to as aleatory, irreducible, stochastic or random uncertainty and describes the inherent variation associated with the physical system or the environment, the latter is referred to as epistemic, subjective or reducible uncertainty, and relates to the lack of precise knowledge of quantities or processes of the system or the environment. Although probability theory is well suited to handle stochastic uncertainty due to variability, it has been argued that the probabilistic approach may have some limitations in the representation and treatment of epistemic uncertainty in situations of poor knowledge, since it tends to force assumptions which may not be justified by the available information [3]. For example, ignoring whether a value of a parameter is more or less probable than any other value within a given range does not justify assuming a uniform probability distribution, which is the less informative probability distribution according to both the Laplace principle of insufficient reason and the maximum entropy criterion [4].

In this work, we consider alternative approaches to probability theory for the representation of epistemic uncertainty, such as Dempster–Shafer Theory of Evidence (DSTE) and Possibility Theory (PT). These approaches have been considered due to their ability in handling the uncertainty associated to the imprecise knowledge on the values of parameters used by expert information systems and for which reliable data are lacking. In this respect, it is worthy noticing that some research effort has been devoted to capture the relationships between DSTE, PT and probability theory, and a vivid research debate is still ongoing about the capability of probability theory in representing the epistemic uncertainty ([4–7]). For example, in Ref. [8], a new framework is proposed, which extends Bayesian Theory to perform probabilistic inference with uncertain evidence. The extension is based on an idealized view of inference in which observations are used to rule out possible valuations of the variables in a modeling space. On the contrary, in Ref. [9] probability is conceptualized at the 'betting' level where decisions are made, which is different from the 'credal' level, where we find the epistemic uncertainty we are dealing with in this work. A pignistic transformation is required to pass from the credal level to the betting level. In Ref. [9], the authors also provide a comparison between the Bayesian framework and the Transferable Belief Model (TBM), which highlights that they may lead to different results.

The strength of DSTE and PT lies in their capability of representing the epistemic uncertainty in a way less committed than

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$\underset{\sim}{Z} = (Z_1, Z_2, \ldots, Z_O)$ vector of the O output variables
$g(\cdot)$ link between the vector of the input uncertain variables $\underset{\sim}{Y}$ and that of the output variables $\underset{\sim}{Z}$
$\underset{\sim}{Y} = (Y_1, Y_2, \ldots, Y_k)$ input uncertain variables
$F_{Y_j}(y_j; \boldsymbol{\theta}_j)$ CDF of Y_j
$\boldsymbol{\theta}_j = \{\theta_{j,1}, \ldots, \theta_{j,M_j}\}$ Vector of the parameters of the CDF $F_{Y_j}(y_j; \boldsymbol{\theta}_j)$ of variable Y_j
A_i, $i = 1, \ldots, n$ Generic interval provided by the expert for parameter θ
q_i, $i = 1, \ldots, n$ Generic confidence level associated to A_i
$A_i^{j,p}$ i-th interval provided by the expert for the p-th parameter of the j-th input variable Y_j
$q_i^{j,p}$ Confidence level associated to $A_i^{j,p}$
$\theta_{j,p}$ p-th parameter of the j-th random variable
θ Generic uncertain parameter
ϑ Generic value of θ
$N(A)$ Necessity measure associated to the set A
$\Pi(A)$ Possibility measure associated to the set A
$\pi_\theta(\vartheta)$ Possibility function of parameter θ
$\{u_j^\omega\}\omega = 1, 2, \cdots, N_T$ sample a vector for variable Y_j made of N_T uniform random numbers in [0,1[
$[\underline{y}_j^\omega, \overline{y}_j^\omega]_{\alpha_i}$ Random interval of Y_j corresponding to the random number $\{u_j^\omega\}$, using the α_i-cut$[\underline{\boldsymbol{\theta}}_j, \overline{\boldsymbol{\theta}}_j]_{\alpha_i} = \{[\underline{\theta}_{j,1}, \overline{\theta}_{j,1}]_{\alpha_i}, \ldots, [\underline{\theta}_{j,M_j}, \overline{\theta}_{j,M_j}]_{\alpha_i}\}$
$[\underline{\boldsymbol{\theta}}_j, \bar{\boldsymbol{\theta}}_j]_{\alpha_i} = \{[\underline{\theta}_{j,1}, \bar{\theta}_{j,1}]_{\alpha_i}, \ldots, [\underline{\theta}_{j,M_j}, \bar{\theta}_{j,M_j}]_{\alpha_i}\}$ α_i–cut of $\boldsymbol{\theta}_j$
$\underline{g}_{\alpha_i}^{Z_0}(\omega) = \inf_{j, y_j \in [\underline{y}_j^i, \bar{y}_j^i]_{\alpha_i}} g(y_1, \ldots, y_j, \ldots, y_k)$ Smallest value of the Z_0 component of g, within the intervals $[\underline{y}_j^\omega, \bar{y}_j^\omega]_{\alpha_i}$, $j = 1, 2, \cdots, k$
$\bar{g}_{\alpha_i}^{Z_0}(\omega) = \sup_{j, y_j \in [\underline{y}_j^i, \bar{y}_j^i]_{\alpha_i}} g(y_1, \ldots, y_j, \ldots, y_k)$ Largest value of the Z_0 component of g, within the intervals $[\underline{y}_j^\omega, \bar{y}_j^\omega]_{\alpha_i}$, $j = 1, 2, \cdots, k$
$Pl(A)$ Plausibility measure of set A
$Bel(A)$ Belief measure of set A

that offered by probability theory. PT has been embraced to tackle a number of interesting issues pertaining to different fields such as graph theory [10], database querying [11], diagnostics [12], data analysis [13] and classification [14], agricultural sciences [15], probabilistic risk assessment (e.g., [16,17]), etc. to cite a few. Analogously, applications of DSTE can be found in diverse domains such as signal and image processing [18], business decision making [19], pattern recognition [20], clustering [21], etc.

In spite of the liveliness of the research in the field, it seems fair to say that the non-probabilistic treatment of uncertainty within soft computing methods has not yet been exhaustively investigated. After all, given the relative immaturity and small size of research community working on non-probabilistic approaches, it is hardly fair to expect that these are elaborated from soft methods to the same extent of that of probability theory [22]. In this respect, two main considerations can be done on the basis of the authors' best knowledge:

- There is no work in the literature which performs a comprehensive comparison of the main techniques to represent and propagate epistemic uncertainty together with aleatory uncertainty, from a practical, engineering point of view. For example, an interesting comparison of PT, DSTE and probability theory is provided in Ref. [23], where a simple case study is introduced as a workbench to highlight the differences among those approaches; however, also in that case the comparison is not complete, as neither (type 1 or 2) fuzzy theory nor Bayesian probability theory are considered. In conclusion, the issue of comparing the different frameworks is still open and future research effort will be spent by the authors in this direction. On the other side, while doing this, it is important to bear in mind that, quoting Smets [9]:

  > "Uncertainty is a polymorphous phenomenon. There is a different mathematical model for each of its varieties. No single model fits all cases. The real problem when quantifying uncertainty is to recognize its nature and to select the appropriate model. The Bayesian model is only one of them. The Transferable Belief Model is also only one of them. Each has its own field of applicability. Neither is always better than the other"

  For example, in Ref. [24] a different technique has been proposed to cope with the maintenance assessment issue in the case in which a team of experts is available to provide the ill-defined parameters, whereas the method proposed in this work assumes that there is just one expert providing them.
- PT has never been applied in the context of maintenance modeling, which is the core of this paper.

Maintenance is a key factor for safety, production, asset management and competitiveness. Establishing an optimal maintenance policy requires the availability of logic, mathematical and computational models for:

(i) The evaluation of performance indicators characterizing a generic maintenance policy. Possible performance indicators are the production profit, the system mean availability, the maintenance costs, etc.
(ii) The identification of the optimal maintenance intervention policy from the point of view of the identified performance indicators, while fulfilling constraints such as those regarding safety and regulatory requirements. In practice, this multi-objective optimization problem has to be faced in a situation in which some constraints and/or the objective functions are affected by uncertainty. To effectively tackle this problem, a number of approaches have been already propounded in the literature considering different framework for uncertainty representation: probability distributions in Refs. [25–27], fuzzy sets in Ref. [28] and [29], and plausibility and belief functions in Refs. [30,31].

The present work aims at contributing to the above step (i) by developing a methodology for maintenance performance assessment that properly processes the involved uncertainties. More specifically, we consider a situation in which:

- a stochastic model of the life of the component of interest, in terms of degradation process, failure behavior and maintenance interventions is known without any uncertainty. This is, for example, the case for the degradation process 'fatigue' which has been successfully modeled by means of gamma processes [32], Weibull distributions [33], Paris–Erdogan law [34], etc.
- The model of the component's behavior depends on a number of ill-defined parameters. With reference to the example of fatigue degradation, the gamma process, Weibull distribution and Paris–Erdogan law depend on parameters whose values are usually not precisely known. Moreover, knowledge of other model parameters such as those describing the maintenance effectiveness (e.g., the improvement of the component degradation), duration and cost may also be imprecise. This framework