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Guideline for the classification and modelling of uncertainty and fuzziness

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Abstract

Methods for managing uncertainty and fuzziness caused by a turbulent and volatile corporate environment play an important role for ensuring long-term competitiveness of producing companies. It is often difficult for practitioners, to choose the optimal approach for modelling existing uncertainties in a meaningful way. This contribution provides a guideline for classification of uncertain information and fuzzy data based on a flowchart and proposes suitable modelling methods for each characterized uncertainty. In addition, a measure for *modelability*, the degree to which an uncertain or fuzzy parameter can be modelled, is proposed. The method is based on a literature review comprising a discussion of the terms *uncertainty* and *fuzziness*.

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1. Introduction

Globalization, shorter product lifecycles and growing need for individualized products lead to higher complexity in manufacturing systems [1]. The major challenge arising from this increasingly complex manufacturing environment is uncertainty [2]. The steadily increasing numbers of scientific papers concerning uncertainty published every year [3] confirm the eminent importance of this topic in research. If uncertainty is neglected in management decisions, this can lead to severe consequences including the risk of business failure. Therefore, companies are forced to apply methods for incorporating uncertainty in their decision making processes in order to stay profitable.

It is often difficult, however, for researchers and practitioners to determine the type of uncertainty they are dealing with as it depends on the context of application. To the best knowledge of the authors a general guideline to classify the uncertainty based on the available information and data doesn't exist so far. [4] explicitly demands for an "investigation that incorporates all types of uncertainty in an integrated manner". To achieve this, a profound analysis of existing classification schemes for uncertainty and fuzziness is essential. The basis for the main part of the contribution is provided in chapter 2 where "uncertainty", "fuzziness" and

related terms are defined and differentiated. The objective of this paper is to achieve three main benefits: (1) A literature review is presented to analyze the different existing classification schemes for uncertainty and fuzziness (chapter 3). (2) A guideline which helps practitioners and researchers identify the type of uncertainty they are coping with and (3) a decision support model are developed to choose a valid and useful form for modelling the context-specific uncertainty based on the available data and information (chapter 4).

Chapter 5 provides a conclusion and further research directions.

2. Fuzziness, uncertainty and related terms: definition and differentiation

The objective of this chapter is to introduce common definitions used in the sequel of this paper. This is especially important as the terms related to fuzziness and uncertainty are used in many different, often arbitrary and inconclusive ways [5]. It is not the goal to profoundly analyze linguistic aspects of the relevant terms (the interested reader is referred to [6]).

The term "fuzziness" is the nominalization of the adjective "fuzzy" which means "not firm or sound in substance, or fringed with loose fibers" according to [7]. As [6] correctly point out, the definition of "fuzzy" which can be found in

common dictionaries, doesn't reflect the meaning of the word in a mathematical sense. In this case, "fuzzy" is used as a supplement for adjectives ("large is fuzzy") or data ("the material flow is fuzzy") if their meaning or value is not precise or crisp. "Fuzzy" also relates to the idea of partial membership and gradual transition from one state to another [8]. In this sense, "fuzzy" is more similar to the meaning of "vague", whereas "vague" includes more non-crisp concepts according to [7], like ambiguity. [9] defines "ambiguity" as being related to situations where several alternatives exist and it is not specified, which one is the best to choose. [10] describe vagueness as an umbrella-term for fuzziness and possibility. [11] elaborates that vagueness describes the "difficulty of making sharp or precise distinctions in the world" and lists the following expressions as being connected with vagueness: fuzziness, haziness, cloudiness, unclearness, indistinctiveness, sharplessness. According to [8] gradualness must be added. He argues that there are many concepts to which a vague notion only applies partly. This "gradualness" is modelled in fuzzy membership functions. Thus, in accordance with [7] we call this gradualness phenomenon inherent in vagueness fuzziness. Therefore, the membership of a concept to a certain fuzzy notion can be "true to a degree" [7].

In this contribution we follow the definition of [11] who uses fuzziness as a synonym for vagueness.

Whereas "vagueness" or "fuzziness" is mostly related to signs of natural language (so-called linguistic variables, [1]), the term "imprecision" is used for measurements, where data is collected and often documented in the form of numbers. This data does not precisely reflect the situation in reality as no measurement can provide unlimited accuracy [7].

The most general term to be defined in this context is "uncertainty". It is often used as an umbrella-term for the concepts defined above [6]. In decision theory, the cases of certainty and uncertainty are differentiated. Uncertainty is the case of incomplete information and can be further broken down into risk and ignorance, whereas risk refers to situations where possible outcomes of an event and their probabilities are known [12]. In case of ignorance, the probabilities are unknown. As a third term "total ignorance" [13] can be attributed to the umbrella-term uncertainty, describing a situation in which neither the probabilities nor the possible future environmental states are known.

In order to define uncertainty and fuzziness, a clear distinction has to be drawn. In accordance with [14] we define uncertainty as being related only to the occurrence of events (future environmental states), whereas fuzziness can be attributed to different reference objects (RO), e.g. models, data, linguistic variables. For the sequel of this paper, *uncertainty* is therefore defined as follows: *A lack of knowledge or information that causes the occurrence of an event or future environmental state not to be known with certainty. Uncertainty can further be differentiated by the degree to which each state is known and can be attributed a probability of occurrence (risk, ignorance, total ignorance).*

In contrast, fuzziness can only be defined together with its object of reference [14]. In this contribution, three concepts are distinguished:

Fuzzy data: A set of data that is inexact, i.e. differs from reality.

Fuzzy parameter: One single value which is inexact, i.e. differs from reality.

Fuzzy linguistic variable: A notion or term (i.e. one or a group of words) of which different persons have varying perceptions regarding its meaning (ambiguity) or that reflects a state which cannot be sharply differentiated from other states ("gradualness phenomenon" / vagueness).

Fuzziness can be attributed to both measurable (quantitative) as well as non-measurable (qualitative) reference objects and arises as a consequence of uncertainty.

In the following elaboration, these definitions are used. However, differing nomenclature by other authors is not altered to keep citations authentic. Wherever we deem it necessary, deviations from the definitions above are indicated.

3. Review of existing classification schemes for fuzziness and uncertainty

In literature, fuzziness and uncertainty are distinguished regarding different characteristics. These can be aggregated into three meta-characteristics, namely *nature*, *level* and *source* of fuzziness and uncertainty (the two terms are mentioned together as depending on the author one or the other is applied).

3.1. Nature of uncertainty/fuzziness

The nature of uncertainty or fuzziness refers to the question: "Is uncertainty reducible with extra effort or at additional cost (e.g. for collecting more data or increasing the quality/resolution of a measurement) or whether the outcome of a situation is random?" The first case (uncertainty is reducible) is referred to as "epistemic uncertainty" [15, 16], "lack of knowledge" [17], "subjective" [18], "reducible", "type B" [19] or "type 2" uncertainty [20]. The second case (uncertainty is not reducible) is designated as "aleatory" [15, 16], "ontological" [21] or "ontic" uncertainty [22], "variability" [17], "stochastic" [18], "irreducible", "type A" [19] or "type 1" uncertainty [20]. In the sequel of this paper the expressions *epistemic* and *aleatory* uncertainty are used, as they appear to be the most commonly applied in literature.

3.2. Levels of uncertainty/fuzziness

The level is the second meta-characteristic of uncertainty targeting the question "To what degree is uncertainty or fuzziness quantifiable?" In the light of available data an experiment is based on, [23] distinguishes six levels, from "scientific laboratory experiment suitable to develop an analytical model" to "weak quasi-rational or intuitive judgment". The conceptual framework for classifying uncertainties developed by [24] is based on these modes of thought, aggregating them into four levels: empirical (monitoring or measurement data available), theoretical (mathematical models, simulation, etc.), virtual (integrated assessment models, output metrics, etc.) and perceptual (scenario definitions, policy impacts, etc.) uncertainty.

In the simplest case only quantitative and qualitative uncertainty is distinguished (e.g. [1, 25]). This differentiation of quantifiable and non-quantifiable uncertainty is also addressed by different authors under the term probability theory, i.e. classical statistics, and possibility theory, i.e. fuzzy

programming and optimization [11, 26, 27]. [21] developed a more detailed framework, addressing four levels of uncertainty: statistical uncertainty (all future environmental states and their probabilities are known), scenario uncertainty (a range of some plausible future states are known, their probabilities are unknown), qualitative uncertainty (not all future states necessarily known, no statistical modelling possible) and ignorance (awareness that there are unknown future environmental states). [13] adds the level total ignorance (no awareness about the unknown) to the levels defined by [21].

[28] elaborate on probability distributions and distinguish hard or objective (can be determined by measurement) from soft or subjective distributions (are chosen by experts based on logical reasoning).

3.3. Sources of uncertainty/fuzziness

The third meta-characteristic “source” of uncertainty and fuzziness answers the question: “Where does uncertainty/fuzziness originate?” As the source mainly depends on the context of application, examples relating to manufacturing are given. A comprehensive review of these sources is not the aim of this section.

[21] refer to sources as “locations of uncertainty” and distinguish context uncertainty, expert judgment, four types of model uncertainty, data and output uncertainty. [20] further elaborates on model uncertainties: Uncertainty in model quantities include input data and parameters, uncertainty about the model form refers to uncertain equations and model structure and uncertainty about model completeness comprises levels of confidence and model validity.

[29] and [30] state sources of uncertainty related to manufacturing and distinguish system or internal (arises within the manufacturing process, e.g. maintenance and queueing times, rework, defects, etc.) from environmental or external uncertainty (originates from external conditions which are not influenced by the company itself, e.g. demand, product mix, supplier reliability, etc.). There is a plethora of literature building on these types of uncertainties and proposing different mechanisms to compensate them adequately, namely flexibility, transformability, adaptability, etc. (see i.a. [30, 31, 32, 33]). [34] differentiates these manufacturing-related sources into input (supply), production system (process times, quality, capacity) and output (demand, market share, orders) uncertainty.

[35] lists three groups of sources of fuzziness in the context of data modelling. The first group primarily addresses the complexity of real systems, the limits of human perception about future environmental conditions and the difficulty of precisely formulating utility functions or requirements. The second group according to [35] refers to fuzziness due to the use of natural language in terms of expressing thoughts (big, small, etc.) and relations (e.g. “much smaller than”). In addition, fuzziness due to erroneous or ill-suited measuring methods, high volatility and differences depending on location and environment are considered. The third group of sources is fuzziness due to abstraction (isolating and structuring relevant system characteristics on an aggregated level to reduce complexity) and transformation (transforming real processes into e.g. a simulation model) in modelling.

3.4. Existing approaches for mapping uncertainty and deficits

This chapter shortly introduces three relevant existing approaches for mapping uncertainty with the aim of providing support for context-specific uncertainty classification and modelling. [36] developed the uncertainty mode and effect analysis, short UMEA (derived from failure mode and effect analysis), in order to analyze uncertainty within the product life cycle with a focus on development. The UMEA-method includes five steps of which the second “identification of uncertainty and its causes” is of relevance for this paper. [36] first distinguishes between quantitative and qualitative uncertainty and proposes different methods for their identification (e.g. process analysis, estimation, statistics, etc.). The method includes an analysis of cross-links between different uncertainties via matrices. The user is not provided a detailed guideline for case-specific classification and modelling, relevant steps are listed but not explained further.

A second, more sophisticated approach is developed by [37] based on the work of [21]. The proposed uncertainty matrix includes sources (context, expert judgment, model, data and output uncertainty) in one dimension and levels (statistical, scenario uncertainty and ignorance) as well as the nature (epistemic and aleatory) in the other dimension. Additionally, the matrix provides a column to estimate the “qualification of the knowledge base” (strengths and weaknesses of the assessment of uncertainty) and “value-ladenness of choices” (biases occurring in the assessment). The aim of this matrix, according to [37, p.81] is to provide an “overview of where one expects the most important uncertainties [...], how they can be further characterized and [...] where a more elaborate uncertainty assessment is required”. However, the application of this matrix might be hampered as the user has to be aware of the meaning of the terms connected to uncertainty in the matrix, especially correctly determining the level and nature of case-specific uncertainties poses a challenge to practitioners.

The third approach for classifying uncertainties is provided by [1] who distinguishes decisions under certainty, uncertainty (further subdivision into risk and ambiguity) and risk as deviation from set targets and proposes modelling methods for each situation. For instance, according to [1] a situation where risk occurs, i.e. future environmental conditions and their probabilities are known, this can be modelled via probability distributions. In this contribution, the idea of attributing a range of modelling options to each class of uncertainty or fuzziness is further developed. The objective of this paper is to provide a comprehensive guideline for the classification and modelling of uncertainties and fuzziness for persons without profound knowledge about terminology and modelling in this field. In addition to existing approaches, a metric for comparing how well different ROs’ fuzziness or uncertainty can be modelled, is introduced.

4. Guideline for classification and modelling of fuzziness and uncertainty

The guideline developed at *iwb* follows the logic of a simple flowchart and is displayed in fig. 1. It consists of junctions that contain questions to be answered by the user with ‘yes’ or ‘no’. Depending on the specific case of uncertainty or fuzziness, the user is lead through the guideline

and finally a modelling technique is proposed for each individual case. The result not only contains a suggestion for a certain probability distribution or membership function, but also aggregates the different modelling techniques and attributes the relevant theoretical domain to the results. Three domains are differentiated: Fuzzy set theory, Intervals and Probability theory (grey boxes in fig. 1).

To illustrate the procedure how the guideline is applied, an example is employed in the following (dotted lines in fig. 1): The user wants to model the fuzziness of a machine's mean time to repair (MTTR). As MTTR as reference object (RO) is clearly defined and has a generally known meaning, question 1 can be answered positively. MTTR is quantifiable, i.e. question 2 is positive. MTTR is not a discrete event or FEC (future environmental condition) and not a time series (questions 5 and 11 are negative). In our example, a MTTR monitoring system has just recently been installed in the company. However, there is not yet sufficient data available to derive a distribution directly or to produce a sample (questions 12 and 17 negative). The operator of the machine can describe the behavior of MTTR on this machine from his experience, so that a probability distribution can be estimated (question 24 positive). This leads to question 28, the distribution can be characterized as continuous. Questions 35 and 36 have to be negated in this case. The operator states that mostly, MTTR varies within a certain corridor with rare exceptions exceeding the average time, i.e. the outliers (question 38) are mostly positive. Thus, a lognormal distribution can be assumed in this exemplary case. The steps for deriving subjective probability distributions are adapted from and in accordance with [38].

The outlined procedure yields a subjective continuous probability distributions for which parameters have to be estimated. In another case, if empirical data is available (question 12 positive) and exact (question 15 positive), a distribution can be derived by comparison of typical paths and parameters are generally calculated with the method of least squares or the maximum likelihood method (continuous distribution). Special cases, like lifetime or reliability indications, which are typically modelled with exponential or Weibull distributions [39] are considered in separate questions (30, 35). The domain, in which the parameters of the distributions can be calculated, is referred to as 'objective probability distributions' in fig. 1. The steps for deriving objective distributions are adapted from and in accordance with [39].

If neither objective nor subjective probability distributions can be derived due to lack of data (question 12) or because the RO is not quantifiable (question 2), intervals or fuzzy set theory can be applied respectively. If e.g. a sample exists (question 17), methods from inductive statistics can be used to deduce information about the data distribution in the basic population. If the RO is a linguistic variable and terms like weak, medium and strong are attributable to the outcomes of the RO, fuzzy membership functions can be applied to assign numeric intervals to each term. The membership functions can take different shapes, e.g. trapezoid, triangular, uniform, etc. The selection of a suitable form of membership function goes beyond the scope of this paper and is discussed in [7] and [5]

amongst others. For classifying the fuzziness or uncertainty of the RO, the positive answers given during the procedure are registered. In the given example these are question 1, 2, 24 and 28. This combination contains all the necessary information for classification: The user deals with a fuzzy quantifiable reference object, for which empirical data lacks but a subjective continuous probability distribution function can be provided by experts.

Questions 1, 2, 4, 6, 7, 8, 10, 12, 13, 15, 17, 19 and 20 to 25 are directly related to the *modelability*, meaning how well fuzziness or uncertainty can be modelled. These questions are called *modelability-related* questions in the following. The ratio between modelability-related questions answered positively and those answered negatively is used as a measure for modelability M of fuzziness and uncertainty (formula (1)): Every negative answer implies a drawback for modelability, e.g. if question 12 is answered negatively, i.e. there is no empirical data available, it is harder to model the underlying fuzziness as if data could be used to calculate a probability distribution. This metric allows a comparison of different ROs' fuzziness and uncertainty regarding their modelability.

In contrast to the level of uncertainty, which is different according to the individual context of application, the metric for determining modelability proposed in this contribution is generally valid.

$$M = \frac{\sum_1^i answers_{pos_i}}{\sum_1^i answers_{neg_i} + \sum_1^i answers_{pos_i}} \quad (1)$$

with $0 \leq M \leq 1$

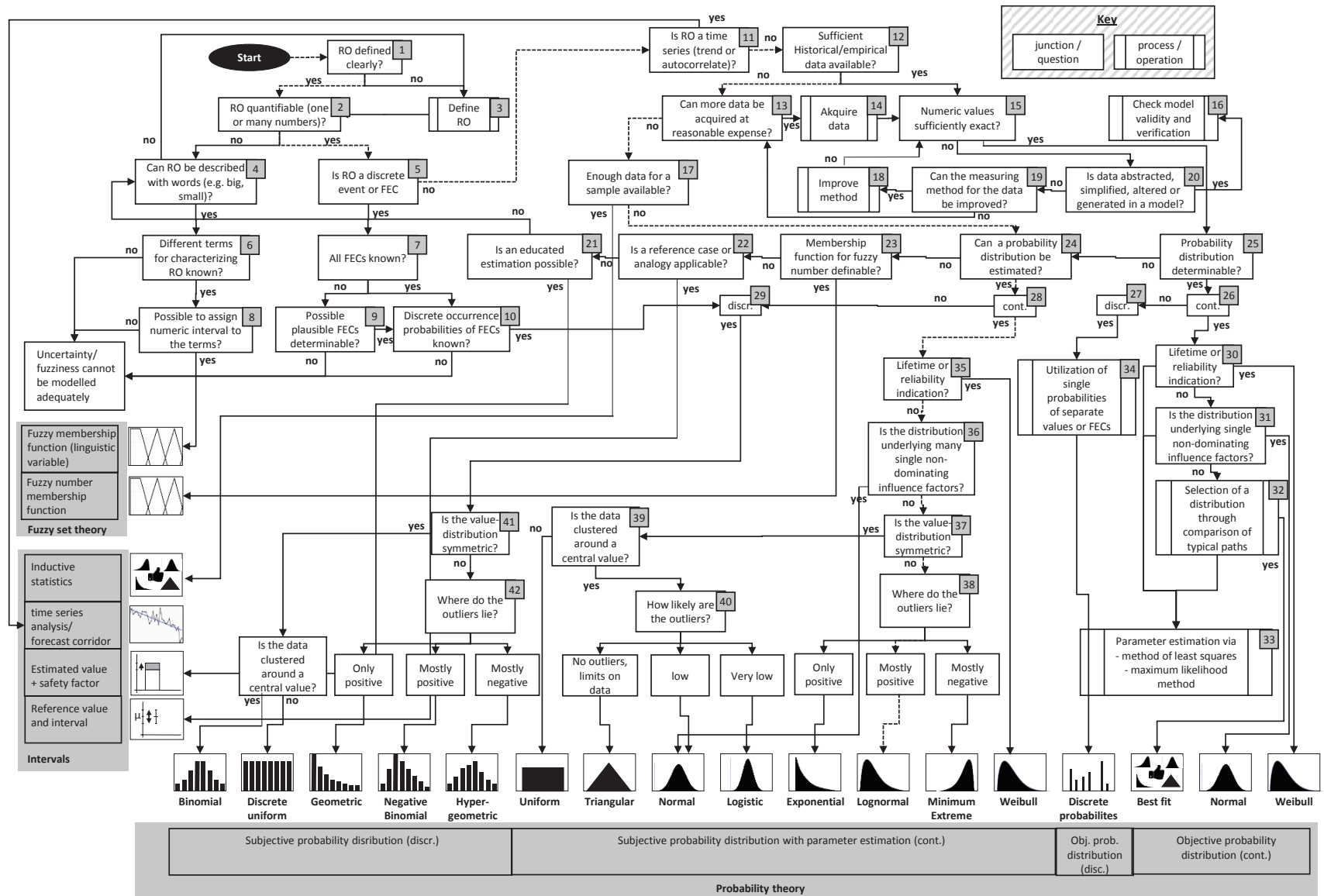
An exemplary calculation of the modelability of two different ROs' fuzziness is illustrated in the following: In the above applied example regarding MTTR, modelability-related questions 1, 2 and 24 are answered positively, whereas questions 12, 13 and 17 are answered negatively, yielding a modelability of 0.5. If empirical data would have been available and question 15 and 25 could also be answered positively, modelability $M=1$ would be the result. Thus, $M=0$ indicates that the uncertainty or fuzziness cannot be modelled at all, whereas $M=1$ indicates very good modelability.

5. Conclusion and research directions

In this contribution, a literature review has been conducted with the aim of defining fuzziness and uncertainty and drawing a differentiation from related terms.

In addition, relevant classification schemes for fuzziness and uncertainty are presented. On this basis, a guideline consisting of simple questions is developed to enable practitioners and researchers to easily identify a possible way of modelling context-specific uncertainty and fuzziness based on the available data. Furthermore, a metric for comparing how well fuzziness or uncertainty of different ROs can be modelled (modelability) is introduced.

Fig. 1 Guideline for the classification and modelling of uncertainty and fuzziness.



The developed guideline needs to be applied in different situations in manufacturing industry to identify potential for improvement and to develop single aspects further. Whereas detailed steps for choosing probability distributions are given, methods for modelling time series and a decision support for selecting a specific form of fuzzy set should be integrated into the method in more detail in future research.

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