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Modeling uncertain requirements

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Abstract

Anticipating all technical requirements that a product must meet throughout its lifespan has become difficult due to a rise in market, regulatory, and technological uncertainty. As a result, the attribute values of these requirements may be highly uncertain at the start of product development. We propose a mathematical model that captures and quantifies this uncertainty in a clear and comprehensive manner. We evaluate the approach by encoding uncertain requirements for an automotive project. Misconceptions regarding probabilities are alleviated and the requirements are unambiguously defined.

Keywords: requirements management, uncertainty, modelling

1. Introduction

Product development projects of electronic- and software-based products have been challenged by an increase in external uncertainty within the last few years: Environmental crises and political tensions have led to supply chain uncertainties and fast regulatory changes (see e.g., Herrmann et al. (2023)). Meanwhile, technology still advances with a high pace and user needs change frequently (Dajsuren and van den Brand, 2019). As a result, it is challenging to determine the product's major technical requirements with certainty before product development starts. Consequently, in early stages of design, statements regarding technical requirements often take on a form similar to the following:

"We expect that the response time of the system must be about five seconds."

Market dynamics, new user needs, or regulatory constraints might further define such a statement or alter it completely in the future. This is especially challenging for complex and long-living mechatronic products like a car. Certain design decisions – e.g., regarding the physical or electronic architecture – must already be made in early stages of development. Possible changes in the technical requirements must be considered for a long time (10 to 25 years) in advance (Schäuffele and Zurawka, 2016). Yet, knowledge about the possible realizations of such uncertain technical requirements are crucial during development. It is the basis to reason about future proof design choices regarding flexibility, changeability, and robustness for example (Abdelmadjid and Mimoun, 2022; Letier et al., 2014). Failing to do so might limit future adaptions of the product, for example due to insufficient computing hardware or missing sensors for a functionality update. Consequently, it is necessary that the uncertainty in the technical requirements is captured and communicated.

With respect to the above statement, an uncertain technical requirement can be understood as the extension of a "normal", certain requirement. Instead of one specific attribute value, multiple attribute values exist in parallel, all of which are possible. We can state for example that the attribute "response time" of the above referenced requirement is not specifically five. Rather, it is a set of attribute values, containing five and its neighbourhood.

Requirements engineering aims to elicit, analyze, specify, validate, and manage the needs and constraints of a product or system under development. Thereby, the needs and constraints – defined through the requirements – should be correct, clear, complete, consistent, and verifiable (Pohl, 2008; Abdelmadjid and Mimoun, 2022). "Clear" means information is conveyed in a clear and comprehensible manner, which can be difficult when dealing with uncertainty. It must be recorded unambiguously and must still be easy to understand. Currently, requirements are often defined as certain or fixed needs and constraints of the system. Thus, requirements engineering does not provide a way to record such uncertainty in the attribute values. Instead, the uncertain attribute values are discretized via an upstream decision process to fixed values and the requirements are then considered to be necessary or not. However, this approach results in suboptimal decisions regarding flexibility and architecture design, as it strips away the information bases (Letier et al., 2014; Block et al., 2021).

Consequently, the objective of this paper is to introduce a method for recording uncertain attribute values of technical requirements in an unambiguous and understandable manner. Our focus is specifically on irreducible uncertainty in the attribute values. Reducible uncertainty can be managed through the acquisition of additional knowledge or the adaptation of processes. Therefore, it is not necessary to encode reducible uncertainty in the requirements themselves; rather, it should be minimized to the extent that the attribute values can be precisely defined (Chalupnik et al., 2009). Irreducible uncertainty typically arises from external sources such as market dynamics, regulatory changes, or technological advancements. This type of uncertainty falls outside the control of the development organization. Gathering further information to mitigate this uncertainty is often challenging, making it necessary to encode it in the requirements (Luft and Wartzack, 2014). To achieve this, we employ a mathematical modeling approach. We evaluate the effectiveness of our approach by encoding 31 uncertain requirements for an automotive development project. Our methodology not only clarifies misconceptions related to probabilities but also ensures an unambiguous definition of the uncertain requirements.

2. Literature review

McManus and Hastings (2005) and Walker et al. (2003) define uncertainty as a lack of knowledge. Knowledge describes interrelated information that enables to act and decide in a particular context (North and Güldenberg, 2008). With respect to the existence of uncertain technical requirements, this means that the information currently available in the development organization is not sufficient or not connected enough to specifically define the requirements and attribute values under consideration. This paper focuses on external uncertainty, which is difficult to estimate, to control and to reduce (see Section 1) (Luft and Wartzack, 2014). In consequence, sufficient knowledge cannot always be gathered. The risk, arising from uncertainty, must be disclosed and mitigated through the product's design (Chalupnik et al., 2009; Letier et al., 2014). However, Block (2023) states that at least partial information about such an uncertain requirement has to be present, when modeling it. Otherwise, the uncertain requirement would be unknown. Consequently, the information, available in the development organization, must be recorded to describe the given external uncertainty further.

Close to 6,000 publications can be identified, when looking at scientific literature containing the keyword "uncertain requirements" (Google Scholar, 2023). Letier et al. (2014) for example propose to apply decision analysis and multi-objective optimization techniques to evaluate uncertain requirements in software development projects. Ebert and Man (2005) analyze over 200 software development projects and identify internal sources of requirement uncertainty, stemming for example from miscommunication, early project starts and other problems in requirements engineering. Yet, this type of uncertainty can be reduced by improving processes or training employees in requirements engineering for example. Thus, it does not fit our definition of uncertain requirements (see Section 1). Consequently, the number of relevant literature reduces drastically, when focusing on publications which aim to describe or record irreducible uncertainty in attribute values of technical requirements. Like Yu et al. (2013), many of the publications present approaches how to deal with uncertain requirements in the development process (see e.g., Kang et al. (2018), Foith-Förster et al. (2016), Gembarski et al. (2021)). Thereby, the description of the uncertain requirements is driven by the chosen approach and not the information which must be encoded. Kang et al. (2018) for example

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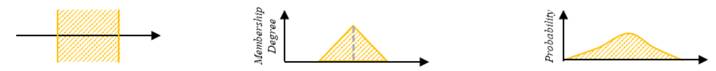
propose an optimization framework based on Real Options Theory. They aim to deal with requirement uncertainties, which stem from external sources (e.g., gas prices) and model them probabilistically. Gembarski et al. (2021) use Bayesian decision networks to minimize design changes in late phases of product development. Whittle et al. (2010) propose a requirements modeling language which addresses uncertainty for self-adaptive, mechatronic systems via fuzzy sets.
Multiple authors show that different kinds of uncertainty exist (see. e.g., Kreye et al. (2011), Luft and Wartzack (2014), Walker et al. (2003)). Han et al. (2020) for example identify three characteristics of uncertainty: Randomness, Roughness, and Fuzziness. Block et al. (2021) and Block (2023) indicate that these three dimensions are sufficient to describe attribute uncertainty in engineering design. A major part of the knowledge about possible future requirements in design is encoded as expert knowledge (Block et al., 2021). It is expressed in natural language. All three characteristics from Han et al. (2020) can be associated with specific linguistic constructs that allow for the mathematical encoding of such expert statements (see Figure 1, (Block, 2023)): Randomness describes whether an uncertain event will occur. It is expressed in terms of probability theory (e.g., *"with a probability of 80 %"*). Roughness expresses whether the information itself is complete. Partially known and imprecise information is thus modeled by Rough Set Theory and expressed for example with statements such as *"between 2 and 5 Kilobytes of data"*. Fuzziness focuses on whether the information is clearly expressed (e.g., *"about five seconds"*). It is modeled by Fuzzy Set Theory. Thereby, all three characteristics coexist in engineering design. As such, all of the previously mentioned approaches fail to describe uncertain attributes in technical requirements properly, because they assume them to be either probabilistic (see e.g., Letier et al. (2014), Gembarski et al. (2021)) or of a fuzzy nature (see e.g., Whittle et al. (2010)).



Characteristics of uncertainty	Roughness	Fuzziness	Randomness
Linguistic constructs	*e.g., "between ... and ..."*	*e.g., "about ..."*	*e.g., "with a probability of ...%"*
Mathematical encoding	Rough Sets	Fuzzy Sets	Probability Theory

Figure 1. Characteristics of uncertainty

As such, randomness, fuzziness, and roughness must be respected, when recording uncertain attribute values in technical requirements. Otherwise, assumptions need to be made to convert fuzzy and rough statements into the probability or fuzzy set domain. The recorded uncertain requirements are then not unambiguous. Abdelmadjid and Mimoun (2022) state that current research does not consider uncertainty in this way. Thus, they propose to include belief degrees modeled via the Dempster-Shafer evidence theory. The Dempster-Shafer evidence theory is a belief model, which can describe roughness and randomness. However, Abdelmadjid and Mimoun (2022) do not specify nor explain the concept of using the Dempster-Shafer evidence theory in their model; nor do they extend it to the fuzzy domain.

3. Approach

Our approach is based on two main steps. Firstly, the given textual statements about the technical requirements are analysed. Uncertain attribute values are identified via the linguistic constructs from Block et al. (2021) and Block (2023). Secondly, the identified uncertainty is then captured in a formalized model. Formalized models - for example mathematical expressions - are unambiguous. Furthermore, they convey uncertainty in a way that is easy to understand for human decision makers if probabilities are used to communicate them (Yen, 2008; Smets and Kennes, 2008). Thus, our approach requires a formalized model to describe technical requirements as well as uncertainty about the requirements' attribute values in a probabilistic manner. In practice, multiple approaches exist to describe technical requirements in a measurable way (e.g., ReqIF). However, a mathematical formulation does not exist yet, which addresses all three characteristics from Han et al. (2020) and can

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deliver them in terms of a probability distribution (see Section 2). Consequently, we develop such a mathematical formulation in the following.

In general, the incomplete knowledge (i.e., uncertainty) is recorded by capturing the fuzzy, rough, and probabilistic information from the textual statements. The information in such a statement is usually two-folded: Firstly, an anchoring attribute value is given, which describes the expected attribute's value or its range. In the exemplary statement in Section 1 the anchoring attribute value would be *"five seconds"* which refers to the attribute "system response time". The second part is the linguistic construct (e. g., *"about"* or *"with a probability of 80%"*), which describes the characteristics and thus the "shape" of the expected attribute value range, surrounding the anchoring value (see Figure 1).

Within our mathematical model, we denote the requirements' attribute, which is uncertain, with the variable a. The set of all possible values for a is denoted by Ω_a and the individual attribute values within Ω_a are described by ω_a. The expected attribute value range of a specific statement (e.g., *"about five seconds"*) is depicted by the set A, which consists of individual attribute values ω_a. Consequently, it is sufficient to find a mathematical formulation which can encode and combine fuzzy, rough, and probabilistic statements about A into one single probability distribution over the possible values ω_a.

For this, we use the Dempster-Shafer evidence theory for fuzzy sets. It represents the combination of all three characteristics of uncertainty and their associated mathematical theories. Furthermore, the Dempster-Shafer evidence theory follows a Bayesian world interpretation: The statements of the different knowledge sources are considered to be individual beliefs rather than expressions of statistical significance (Beck, 2010). This is consistent with the observations in Block et al. (2021): Statements about uncertainty in technical requirements usually stem from expert knowledge.

Different mathematical definitions of the Dempster-Shafer evidence theory for fuzzy sets exist, due to different interpretations of the knowledge, which is represented by the mathematical expressions (see e.g., Ishizuka (1982), Yager (1982), Yazdi and Kabir (2020), Mahler (1995)). In this paper, we follow the definition of Mahler (1995) because it is consistent with the empirical observations of Block et al. (2021) and Block (2023) for uncertainty in engineering design. Mahler's (1995) approach does not make any assumptions about the distribution of information, which may be present in a fuzzy proposition about A. This leads to a more conservative approach in encoding the incomplete knowledge and gives the approach a wider range of applications in design. No preconditions must be fulfilled.

Based on the Dempster-Shafer evidence theory, we can then state that each knowledge source s describes a probability mass function $m_{a,s} > 0$ with the following characteristics (Equation 1-4, see e.g., Beierle and Kern-Isberner (2019)):

$$m_{a,s}(\emptyset) = 0 \tag{1}$$

$$\sum_{A \subseteq \Omega_a} m_{a,s}(A) = 1 \tag{2}$$

$$bel_{a,s}(A) := \sum_{B \subseteq A} m_{a,s}(B) \tag{3}$$

$$pl_{a,s}(A) := 1 - bel_{a,s}(\bar{A}) \tag{4}$$

A and B are attribute value ranges, whereas A is the range of the specific statement given by knowledge source s. The belief function $bel_{a,s}(A)$ describes the minimum belief that an attribute value out of A will be required in the future. The plausibility function $pl_{a,s}(A)$ represents the maximum belief that can be assigned to A, considering the belief towards the inverse set $\bar{A}$ of A. Thus, $bel_{a,s}$ and $pl_{a,s}$ represent lower and upper probabilities. With this set of definitions, it is already possible to express uncertain requirements like the following:

> *"With a probability of 25 % to 60 %, the response time of the system must be below five seconds."*

The anchoring value in this statement is *"below five seconds"*. As such, the attribute value range A is $A = \{0, 1, 2, 3, 4, 5\}$. The linguistic construct is *"with a probability of 25 % to 60 %"*. It describes bounds for the lower and upper probability, which can be encoded to $bel_{a,s}(A) = 0.25$ and $pl_{a,s}(A) = 0.6$. Thereby, $bel_{a,s}$ and $pl_{a,s}$ are uniquely defined via the same probability mass function $m_{a,s}$ (see

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Equation 3-4). Thus, we can derive $m_{a,s}$ from $bel_{a,s}$ and $pl_{a,s}$ to be as follows (Equation 5-8), assuming that the attribute "response time" can in general take values between zero seconds and ten seconds:

$$\Omega_a = \{0, 1, 2, \dots, 10\} \qquad A = \{0, 1, 2, 3, 4, 5\} \qquad \bar{A} = \Omega_a \backslash A = \{6, 7, 8, 9, 10\} \tag{5}$$

$$m_{a,s}(A) = bel_{a,s}(A) = 0.25 \tag{6}$$

$$m_{a,s}(\bar{A}) = bel_{a,s}(\bar{A}) = 1 - pl_{a,s}(A) = 1 - 0.6 = 0.4 \tag{7}$$

$$m_{a,s}(\Omega_a) = 1 - 0.25 - 0.4 = 0.35 \tag{8}$$

The remaining $1 - \sum_{A \subseteq \Omega_a} m_{a,s}(A)$ probability mass value was assigned to $m_{a,s}(\Omega_a)$, because the source s does not give any further information about the remaining probability mass (see Equation 8). The statement about the uncertain attribute value "response time" is now fully encoded in $m_{a,s}$ and is unambiguous because it is a mathematical description.
However, fuzzy statements (linguistic constructs such as e.g., *"about"*) cannot be expressed yet, because A and B were defined to be crisp sets. Elements ω_a either belonged to the sets A or B or they didn't. As such, we extend the Dempster-Shafer evidence theory in the following by the fuzzy set operations of Mahler (1995). A and B are now fuzzy sets with membership degree functions μ over Ω_a. Attribute values ω_a can now partially belong to the set A or B, e.g., $\mu_A(\omega_a) = 0.5$. The fuzzy set operations of Mahler (1995) are defined as follows (Equation 9-13) (Mahler, 1995; Lucas and Araabi, 1999).

$$\mu_{A \cup B} \coloneqq \max(\mu_A, \mu_B) \tag{9}$$

$$\mu_{A \cap B} \coloneqq \min(\mu_A, \mu_B) \tag{10}$$

$$\mu_{\bar{A}}(\omega_a) \coloneqq 1 - \mu_A(\omega_a) \tag{11}$$

$$(A \subseteq B) \Leftrightarrow (\mu_A(\omega_a) \leq \mu_B(\omega_a), \forall \omega_a \in \Omega_a) \tag{12}$$

$$(A = B) \Leftrightarrow (\mu_A(\omega_a) = \mu_B(\omega_a), \forall \omega_a \in \Omega_a) \tag{13}$$

With this formulation all propositions about uncertain attribute values can be encoded into a mathematical representation. Minimum and maximum probability values are to be understood as $bel_{a,s}(A)$ and $pl_{a,s}(A)$ assignments, whereas A represents the fuzzy range of the uncertain attribute. For example, the sentence (see Equation 14-16):

> *"With a probability of 25 % to 60 %, the response time of the system must be about five seconds."*

is encoded to:

$$bel_{a,s}(A_{\sim 5}) = 0.25 \tag{14}$$

and

$$pl_{a,s}(A_{\sim 5}) = 0.6 \tag{15}$$

with the definition of the attribute value range $A_{\sim 5}$ as follows:

$$\mu_{A_{\sim 5}}(3) = 0.5, \mu_{A_{\sim 5}}(4) = 1, \mu_{A_{\sim 5}}(5) = 1, \mu_{A_{\sim 5}}(6) = 1, \mu_{A_{\sim 5}}(7) = 0.5. \tag{16}$$

All $bel_{a,s}(A)$ and $pl_{a,s}(A)$ which are provided through statements of one and the same information source s define the probability mass function $m_{a,s}$ of this information source. The mathematical formulation is also capable to encode fuzzy probability values, e.g., *"with a probability of about 40 %"*. Further insights into the math and how to encode fuzzy probabilities can be found in Beer (2009).
After all $m_{a,s}$ have been determined for the information sources s, they need to be joined to one common probability mass function m_a. For example, let's assume that the two statements for the equations 5 to 8 and 14 to 16 stem from different information sources s. As such, their mass probability functions must now be joined. The resulting overall mass probability function m_a then incorporates the joint knowledge of all information sources about a. m_a is derived from the individual probability mass functions $m_{a,s}$ via a so-called rule of combination. There are several different rules of combination for the Dempster-Shafer evidence theory. They address distinct properties of the knowledge encoded in the mass

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probability functions $m_{a,s}$. For uncertainty related knowledge in the development domain, we suggest to use the $\wedge Q$-rule of combination from Cattaneo (2011).
The $\wedge Q$-rule of combination differs from other combination rules, in that the information sources can depend and build upon each other. It is idempotent. According to Block et al. (2021), propositions of different stakeholders may be based on the same information from within the development organization. They might even be communicated from one person to another. Consequently, idempotency, as provided by the $\wedge Q$-rule of combination, is necessary. The $\wedge Q$-rule is defined as follows (Equation 17-19).

$$q_a(A) := min_{\forall s}\{\, q_{a,s}(A)\} \qquad \forall A \subseteq \Omega_a \tag{17}$$

with

$$q_{a,s}(A) := \textstyle\sum_{\forall B \subseteq \Omega_a \mid A \subseteq B} m_{a,s}(B) \qquad \forall A \subseteq \Omega_a \tag{18}$$

$$m_{a,s}(A) \;= max\{0, q_{a,s}(A) - \textstyle\sum_{\forall B \subseteq \Omega_a \mid B \subset A} m_{a,s}(B)\} \qquad \forall A \subseteq \Omega_a \; in\ decreasing\ order \tag{19}$$

Applying the $\wedge Q$-rule of combination to the two propositions from equations 5 to 8 and 14 to 16 yields to the following result (Equation 20-24):

$$m_a(A) = 0.17 \qquad \mu_A(7) = 0.5, \;\; \mu_A(6) = 1 \tag{20}$$

$$m_a(B) = 0.17 \qquad \mu_B(3) = 0.5, \;\; \mu_B(4) = \mu_B(5) = 1 \tag{21}$$

$$m_a(C) = 0.17 \qquad \mu_C(3) = 0.5, \;\; \mu_C(0) = \mu_C(1) = \mu_C(2) = 1 \tag{22}$$

$$m_a(D) = 0.26 \qquad \mu_D(7) = 0.5, \;\; \mu_D(8) = \mu_D(9) = \mu_D(10) = 1 \tag{23}$$

$$m_a(\Omega_a) = 0.23 \tag{24}$$

However, this result is not easy to understand for human decision makers (Yen, 2008; Smets and Kennes, 2008). Thus, we transform the mass function m_a into a probability distribution P_a over a's realizations $\omega_a \in \Omega_a$. We use Smets and Kennes' (2008) transferable belief model for this. It calculates the probabilities in such a way that uncertain attribute values with no information in the probability mass function m_a are assigned probabilities via a uniform distribution. Realizations with more information in m_a are assigned more precise probabilities. Thus, it solves for the highest entropy of P_a without making any further assumptions about the information in the textual statements. The corresponding calculation is given in Equation 25 (Dubois, 2006).

$$P_a(\omega_a) = \textstyle\sum_{\forall A \subseteq \Omega_a \mid \mu_A(\omega_a)>0} \sum_{j=0,\dots,n} \frac{\alpha_j - \alpha_{(j+1)}}{|A_{>\alpha_{j+1}}|} \cdot m_a(A) \tag{25}$$

$P_a(\omega_a)$ is the probability for the realization ω_a and $1 = \alpha_0 > \alpha_1 > \cdots > \alpha_n > \alpha_{n+1} = 0$ are the alpha cuts of the fuzzy set $A \subseteq \Omega_a$. P_a is also unambiguous because m_a is unambiguous. Additionally, it is easy to understand because P_a is a simple probability distribution over a. The probability distribution P_a for the two propositions from the equations 5 to 8 and 14 to 16 is represented in Equation 26-29:

$$P_a(0) = P_a(1) = P_a(2) = P_a(3) = 0.07 \tag{26}$$

$$P_a(4) = P_a(5) = 0.09 \tag{27}$$

$$P_a(6) = 0.14 \tag{28}$$

$$P_a(7) = P_a(8) = P_a(9) = P_a(10) = 0.10 \tag{29}$$

According to the statements, the attribute values "4" to "10" all have a probability of around 10 %, except for the attribute value "6" with a slightly higher probability. Consequently, using a value of four for the attribute "system response time" yields that 72 % the expected attribute values will be covered.
Finally, the proposed mathematical approach also works for more complex statements: Multiple attributes a_0 and a_1 can be considered via multidimensional realization spaces $A \subseteq \Omega_{a_0} \times \Omega_{a_1}$. Statements about only one attribute a_0 can be enhanced via a vacuous extension to $\Omega_{a_0} \times \Omega_{a_1}$. Dependencies $m(a_0 \mid a_1)$ between attributes a_0 and a_1 can be modeled by the conditional embedding of m_{a_0} in m_{a_1}. For further explanation how to express such dependencies, see Shenoy (2020) and our implementation (see Section 4).

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4. Application in an automotive development project

The modeling approach was applied to a set of 31 uncertain requirements within an automotive development project. The aim of the project was to design a car, which can evolve its external sensor architecture and include additional sensors to fulfill new autonomous driving functions. However, the requirements of those new autonomous driving functions towards the sensors were partially unknown. Thus, technical requirements towards the electronic control units, their interfaces and bus bandwidth were also uncertain.

In a first step, the incomplete knowledge about possible future autonomous driving functions and their requirements towards the sensors were collected from the involved engineers. This happened in natural language in text on a virtual whiteboard during a brainstorming session. Exemplary definitions of the knowledge given were:

> *"The sensor's interface might be of type ethernet, CAN or analogue in about 60 % of the cases."*
>
> *"With a probability between 10 % to 20 % we might need about 5 additional sensors or even more."*

About 120 uncertain statements addressing 31 requirements were identified by the ten involved engineers. The knowledge was encoded into the mathematical description as proposed by our approach (see Section 3). We implemented the workflow into a software to make handling of the statements and calculations easier. As a result, only the set of all possible values Ω_a, the attribute value range A and the upper and lower probabilities $pl_{a,s}(A)$ and $bel_{a,s}(A)$ needed to be extracted from each statement. The remaining steps to solve for equations 1 to 25 and derive the probability mass function m_a as well as the probability distribution P_a are covered by our implementation. The source code of the software can be found here: https://gitlab.cc-asp.fraunhofer.de/lblock/uncertainty/ . Overall, we were able to encode all uncertain statements without making further assumptions. Thus, the mathematical approach seems sufficiently expressive to define articulated uncertainty about attribute values in technical requirements.

The probability distribution P_a, as the major result of the workflow, was then checked, regarding its unambiguity and comprehensiveness. Unambiguity was proven by comparing P_a against the subjective expectations of the ten involved engineers. In a Delphi-Workshop, they synchronized their expectations regarding the probabilities of the different alternatives ω_a for a. Subsequently, the consolidated probabilities were compared against the given probability function P_a from our approach.

Thereby, the probabilities for two types of electronic interfaces were unexpectedly high. Due to the mathematical formulation of the uncertainty, it was possible to analyze the reasons for the probabilities and backtrace the issue. It was found that no statements were made regarding those two types of electronic interfaces. As such, the remaining probability mass was accumulated to them, when deriving $m_{a,s}$ from $bel_{a,s}$ and $pl_{a,s}$ (see Equation 8). Subsequently, further statements regarding the expectations towards the necessity of those interfaces were added. Figure 2 displays the final probabilities derived from all the statements given by the engineers.

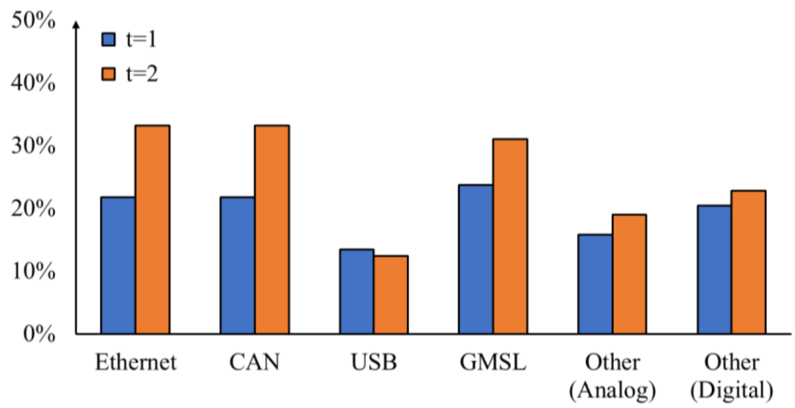

Figure 2. Probabilities regarding the interface type of one of the electronic control units

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Additionally, the engineers expected different probabilities than given in P_a, regarding the required bus bandwidth for one of the software components (Figure 3). However, it was found that the expectations of the engineers were wrong. Dependencies between different attributes were described by the engineers in their textual statements. Yet, they underestimated their effects by a magnitude of more than two when formulating their expected probabilities in the Delphi-Workshop. Thus, misconceptions regarding the probabilities were also alleviated through the mathematical approach. As a result, the approach was able to record uncertain attribute values in technical requirements unambiguously. The engineers stated unanimously that they found the results from the mathematical approach to be more consistent than their own accumulated probabilities. The mathematical formulation considered different statements and their interdependencies in a neutral and logically correct way. Furthermore, calculating the combined probabilities was much faster than the Delphi-Workshop.

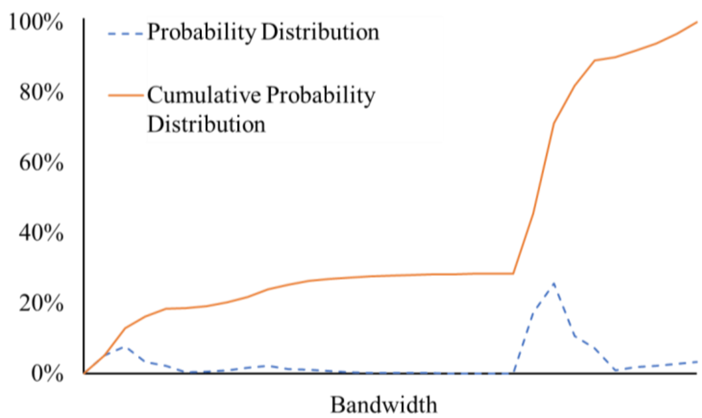

Figure 3. Probabilities for the required bandwidth of one of the software components

5. Discussion and outlook

In this paper, we introduced a new method for recording uncertain attribute values in technical requirements in an unambiguous and comprehensive manner. We chose a formalized (mathematical) model for the uncertainty. This also supports the requirements engineering process: It enables automatic consistency checks, enhances quality of the requirements, and allows for software supported analysis to validate and verify the requirements. This also became clear in the approach's evaluation. 31 uncertain requirements were encoded for an automotive development project. Misconceptions regarding probabilities were alleviated and the requirements were unambiguously defined.

Thereby, one of the major advantages of our approach is that it considers randomness, fuzziness, and roughness simultaneously. Therefore, no assumptions had to be made, to encode the natural language statements into mathematical expressions. Furthermore, objective information sources like market studies and technology forecasts can also be encoded alongside human expectations. Various statements, regarding complementary evidence, contradictions, and different probabilities, are combined into one common probability distribution, depicting all available knowledge.

However, the current state of the approach still possesses some limitations: The identification of the linguistic constructs, extraction of the anchoring values and their encoding into the given mathematical model must still be conducted manually. This partially hinders industrial application because it necessitates experts to extract the required input values from the textual statements. Nonetheless, the experts are guided by the list of linguistic constructs from Block et al. (2021) and Block (2023). Furthermore, our software implementation provides computational support for the calculations (see Section 4). Yet, with the emergence of powerful natural language processing in artificial intelligence applications (e.g., ChatGPT), it might be possible to extend the approach further. The textual information can be encoded automatically into the mathematical description we provide. To accomplish this, the existing list of linguistic constructs from Block et al. (2021) and Block (2023) needs to be expanded. It is not complete yet and lacks detailed explanations on how these constructs map to the mathematical formulation. Furthermore, the language models must be thoroughly examined and trained to effectively operate with the mathematical approach.

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Overall, we present a new approach to describe and record uncertain attribute values in technical requirements. However, it is still undefined how an adapted requirements engineering process must look like and how the uncertain requirements are best handled in the following stages of engineering design. Nevertheless, our research has demonstrated that the proposed mathematical formulation effectively captures uncertainty in an unambiguous and comprehensive manner. As such, it lays the foundation for further research on how to handle this type of uncertainty within the engineering process.

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