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Some Methodological Issues Related to Preliminary QoS Planning in Enterprise Systems

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Abstract. Developing a new enterprise business service, it is necessary to plan required investments. For this aim, it is necessary at least roughly to plan the quality of service (QoS) of this service, taking into account the viewpoints of different stakeholders as well as constraints of financial and other resources. Due to the fact that the quality itself is a vague and highly subjective concept, different stakeholders have different viewpoints what the quality itself is and which should be QoS of the service in question. A possible approach to modelling QoS in this context is fuzzy modelling. One of the problems in fuzzy modelling is construction of the most appropriate membership functions. The paper surveys state of the art in this area, proposes a problem-independent methodological framework for constructing membership functions and demonstrates how to apply this framework in the context of the QoS planning problem.

Keywords: service-oriented architecture, quality of service, service-oriented enterprise system, enterprise business service, fuzzy sets, membership function, phenomenographic research

1. Introduction

Today, the concept of Service-oriented Architecture (SOA) became dominant in the field of both information systems and software systems engineering. The symbiosis between the Enterprise Architecture and SOA results in the so-called Service-oriented Enterprise Architecture. Systems that implement this architecture are addressed as service-oriented enterprise systems (SoESs) (Lupeikiene et al., 2013). They are composed of enterprise business services, i.e. components implementing some business logic that is embedded in web services. Typically, SoES acts in the intranet/extranet environment. When developing a new business service for SoES, called as enterprise business service (EBS), its QoS should be planned, at least roughly, taking into account the viewpoints of different stakeholders as well as constraints of financial and other resources. Due to the fact that the quality itself is a vague and highly subjective concept (Abramowicz et al., 2008), the most suitable formalisms to be used for this purpose are fuzzy sets theory and the fuzzy logic (Zimmermann, 2010; Klir et al., 1995; Lupeikienė, et al., 2013a). The methodology of logical positivism (Juma'h, 2006) that requires QoS to be decomposed into measurable characteristics and desirable values of each characteristic be precisely defined, is here completely inappropriate. The phenomenography and a fuzzy modelling approach are more suitable for this aim (Sin, 2010; Wang et al., 2006). In order to apply this approach, membership functions should be defined for all QoS characteristics in question. The paper deals with the methodological aspects of this problem. Considerations of methodological aspects are not limited only by our research context. The paper provides an extensive overview of related works and, on the basis of analysis of this material, proposes a methodological framework for constructing MFs which is quite general and applicable in the context of almost any problem, for which MFs should be constructed. The scientific contribution of the paper is twofold: apart from the mentioned problem-independent MFs construction framework, it also demonstrated how this framework can be applied to construct membership functions for QoS characteristics.

The remainder of the paper is structured as follows. Section 2 introduces the technical preliminaries on fuzzy modelling formalisms. Section 3 presents modelling of QoS: the proposed approach. Section 4 presents the related work and analysis of the proposed approaches. Section 5 proposes the problem-independent MF construction framework. Section 6 presents an illustrative example how to apply the proposed methodological framework in the construction of MFs for QoS characteristics. Finally, section 7 concludes the paper.

2. Technical preliminaries

Vague and imprecise concepts, including quality, are formalized using fuzzy sets. The concept of a fuzzy set is an extension of the classical set. It describes a set without a crisp, clearly defined boundary. A fuzzy set contains elements with only a partial degree of membership. Formally it is defined in the following way:

Definition 2.1. Let X be the universe of discourse (UoD) containing elements x. Then a set of ordered pairs $A=\{x, \mu_A(x)|x\epsilon X, \mu_A: X\to[0,1]\}$ is a fuzzy set in X and, $\mu_A(x)$ is the membership function (MF) of x in A.

A linguistic variable is a variable the values of which are words rather than numbers. It represents a concept that is measurable in some way, either objectively or subjectively (e.g., quality). Linguistic variables are characteristics of an object or situation. Formally a linguistic variable is defined in the following way:

Definition 2.2. A linguistic variable is a quintuplet (L,$T(L)$,X,G,M) in which

- L is the name of a linguistic variable;
- $T(L)$ denotes the term set of L, i.e., the set of names of linguistic values of L, with each value being a fuzzy variable denoted generically by A and ranging across the universe of discourse X which is associated with the base variable x;
- X is a universe of the discourse;
- G is an optional syntactic rule (which usually takes the form of a grammar) for generating the names of values of L, if it is necessary; and
- M is a semantic rule for associating its meaning with each linguistic term of L, $M(t)$, where $t\in T(L)$, is a fuzzy subset of A.

Linguistic terms rate the characteristic denoted by one linguistic variable. A linguistic term is a fuzzy set, and a linguistic variable defines its domain.

Definition 2.3. A fuzzification problem is a problem how to construct a set of MFs which transform a phenomenon in question, characterized by a variable, which values are defined in the universe of discourse (UoD) and categorized according to some criterion into a linguistic variable so that the names of the given categories match the names of linguistic values. Fuzzification is a process of generating membership values for a fuzzy variable using MFs.

Example.

The QoS concept, expressed through fuzzy sets, is defined as follows:

A linguistic variable is a characteristic of QoS and is described as a quadruple (*L*,*T(L)*,*X*,*M*) in which

- L is a linguistic variable that achieves the values from the given set of linguistic terms;
- T(L) is a linguistic term set where linguistic terms are words characterizing the linguistic variable degree of intensity of the phenomenon;
- X is a universe of discourse. Each linguistic term has a corresponding subset (domain of the term) of values of the characteristics that define the phenomenon under consideration;
- M is a semantic rule. It is a meaning of the linguistic term expressed by the shape of MF (triangular, trapezoidal, sigmoidal, etc.), i.e. defined by MF which defines the membership of values of quality characteristics to the sets of terms of the linguistic variable *Quality*.

The concept of the linguistic variable *Quality* and fuzzification problem is presented in Figure 1.

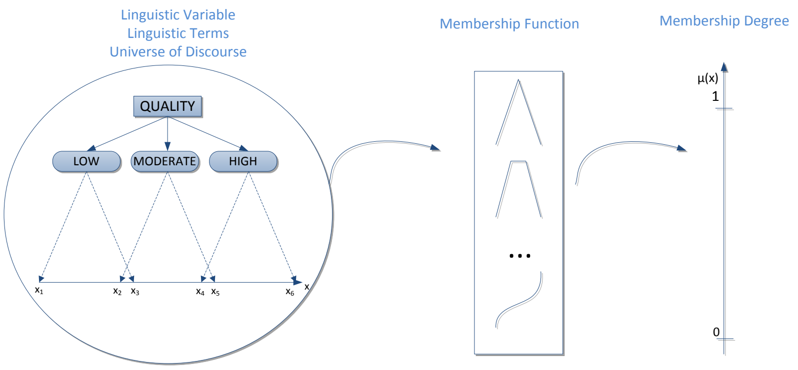

Figure 1. Compositional parts of the concept of linguistic variable *Quality*

3. Modelling of QoS: the Proposed Approach

In the context of our research, the most appropriate conceptual basis for constructing MFs is the phenomenographic approach (Richardson, 1999). A phenomenographic method allows us to point up and specify different understandings (views) of QoS, as well as to compare and sum up these understandings (Leite, 1989). In the literature on information systems and software systems engineering, the phenomenographic approach is used as a methodological basis for view integration (Leite, 1989; Sommerville et al., 1997). In the context of quality modelling, the phenomenographic approach is typically used to specify the quality of experience (QoE) (Alben, 1996), but it is reasonable to use this approach to specify also the QoS. Although QoS understandings differ depending on stakeholders’ attitudes, values, aims, and highly subjective opinions, any understanding may be described in some structured way, using this approach.

In our research (Lupeikiene et al., 2013; Lupeikienė et al., 2013a; Lupeikienė, et al., 2013b) that is done transforming quality categories of the bottom level QoS characteristics into linguistic terms of the linguistic variable *Quality*. For each pair <quality characteristic, linguistic term> its own MF should be defined, which maps the linguistic term-related sub-domain of this characteristic into an appropriate fuzzy set (Zadeh L. A., 1965; Zimmermann, 2010; Lababidi et al., 2006; Zadeh L., 1975). The domains of QoS characteristics may be discrete as well as continuous. The MFs should be defined so that, for the QoS characteristic under consideration the subdomain of its values, related to this same linguistic term, for example, “*moderate quality*”, could be mapped to the same fuzzy set, or, in other words, the interpretation of linguistic terms for any QoS characteristic should not depend on a particular view. It means that MF should unify the understanding of linguistic terms. On the other hand, it does not mean that understanding of QoS is also unified. It remains view-dependent. Thus, the proper MFs construction methods are very important modelling QoS for enterprise business services under development and should be chosen very carefully.

4. Related work and analysis of the proposed approaches

There exist a lot of various approaches for constructing MFs (Bilgiç et al., 2000; Chameau et al., 1987; Lee, 2006). A decision which approach should be used to construct MF in a particular case depends on many circumstances. The most fundamental one among them is the chosen semantic of a fuzzy set, which, in turn, heavily depends on the problem in question. Three main semantics of MF are modelling of similarity (imprecision), preference (vagueness), and uncertainty (Dubois et al., 2000). We interpret fuzziness as vagueness or, in other words, use fuzzy sets to model vague human concepts. Despite the chosen understanding of fuzziness, all MF construction approaches technically can be divided into *manual* and *automatic* ones (Figure 2).

The main characteristics of *manual approaches* are: 1) usage of the empirical data, typically collected applying some phenomenography-based methodology; 2) a relatively small amount of collected data; 3) monotonous, time-consuming, and less efficient than an automatic MF construction process; 4) possible subjective bias caused by the improper selection of interviewees; 5) possible problem-related bias caused by inappropriate knowledge acquisition techniques (Aamodt, 1993).

The main characteristics of automatic approaches are: 1) nonattendance of experts, 2) supplied large data sets that are used to extract knowledge about the shape and parameters under consideration; 3) non-transparency (any justification of the result) 4) adjusting MF through learning, optimization or using other techniques. The supplied data sets are often graphically represented in a normalized relative frequency function and histograms (Fisher, 1955). They contain the samples of MF values for some elements of the fuzzy set under construction. Automatic approaches are adaptive in the sense that they generate initial MF from the supplied data set and further adaptively change this MF, when additional data sets are provided. It means that these approaches can also be used in the cases where MF should be changed dynamically in real-time systems.

The *manual MF construction approaches* can be further subdivided into:

- *Intuition-based MF construction approaches.* In these approaches, the shape and parameters of MF are defined processing phenomenographic descriptions, prepared by experts in the field (interviewees) on the basis of their subjective perceiving of the quality. Usually, their understanding of the quality depends not only on their personal attitudes, but also on their individual knowledge, innate intelligence, experience, and, possibly, on the relevant literature. The final decision on the shape and parameters of MF under consideration is made by its developer (interviewer) on the basis of experts' opinions as well as on the basis of his subjective judgement.
- *MF construction through experiments*. These approaches rely on psycholinguistic experiments, by which the MF developer investigates what the given linguistic terms "mean" to the experts who represent the different understandings of the quality. The experiments can be carried out using different assumptions on the nature of fuzziness (e.g. interpersonal disagreement or individual subjective uncertainty) and applying different techniques (e.g. rating, exemplification, interval estimation, etc.).

The *automatic MF construction approaches* can be further subdivided as follows (Lee, 2006):

- *Statistical approaches.* There exists a great number of various statistical approaches (e.g. histogram-based methods (Medasani et al., 1998), frequency-driven (Pedrycz et al., 2002), etc.) that combine various statistical techniques in different ways. One among those was proposed in (Wijayasekara et al., 2014). It is a simple method that maintains MF understandability. MF is constructed by applying statistical techniques to calculate MF centers, spread, overlap, slope, etc. The method helps to provide initial intervals that define linguistic variables, and to identify the optimal parameters for MFs. A general shortcoming of statistical approaches is a questionable reliability of statistical data because such data can be biased by spot noises.
- *Fuzzy cluster*. Clusters can be seen as subsets of a supplied data set. Consequently, they can be classified as crisp (hard) or fuzzy (soft) clusters (Babuška, 2000). In fuzzy clustering, data elements can belong to more than one cluster. So, each data element can be associated with a set of membership levels. For details of the fuzzy clustering-based MF construction procedure see in (Bowie, 2004; Rokach et al., 2005).
- *Neuro-fuzzy approaches.* There exist several neuro-fuzzy techniques, used for the MF construction (Bilgiç et al., 1997). All these techniques are based on the integration of artificial neural networks and fuzzy sets theory. The main idea is to use some neuro-fuzzy learning algorithm (Shi et al., 2000) for adjusting the parameters of MF, extracted from the supplied data sets. *Inter alia,* this approach allows us to construct dynamical MF that is dependent on the available values of variables at a given time moment t (Cerrada et al., 2005).
- *Genetic algorithms.* In the MF construction process, genetic algorithms are used to cluster the values of quantitative attributes into fuzzy sets with respect to the given fitness evaluation criteria. Many different algorithms (e.g. (Kaya et al., 2006; Arslan et al., 2001; Jacob, 2005)) were proposed for this aim. They differ in fitness functions, chromosome encoding, selection procedures, and other details.

- *Others.* The most important automatic approaches for constructing MF include other methods, such as inductive reasoning (Kim et al., 1993), deformable prototypes (Olivas, 2000), gradient methods (Khan et al., 2010), etc.

Intuition-based approaches can be subdivided further into direct and indirect ones. In either direct or indirect approaches, single or multiple experts' opinions can be taken into account (Klir et al., 2002; Chaturvedi, 2008). The main characteristics of direct approaches are: 1) assumption that vagueness arises from an individual subjective uncertainty; 2) MF is constructed using some aggregation technique of (possible, weighted) experts' evaluations (i.e. degree of membership), assigned to the given crisp values, mapped to a fuzzy set under construction (instead of aggregation, some interpolation technique can be used); 3) used to fuzzify the concepts with measurable properties (e.g. execution time or throughput); 4) MF reflects subjective experts' evaluations directly (i.e. explicitly); 5) experts are required to give overly precise answers; 6) it is simple and easy to implement. The main characteristics of indirect approaches are: 1) MF is constructed on the basis of expert evaluations of certain relations (e.g. pair-wise comparisons) among the elements within the crisp set under consideration; 2) MF reflects subjective experts' evaluations indirectly (i.e. implicitly); 3) less sensitive to various biases of subjective judgment.

MF construction approaches through the experiment (Bilgiç et al., 2000; Chameau et al., 1987; Derbel et al., 2008) can be further subdivided into:

- *Polling.* It assumes that the fuzziness arises from interpersonal disagreements. The different experts answer the question: "Do you agree that object/subject *a* is a linguistic term *F*?" The answers of yes/no type are polled and the average is taken to construct MF.
- *Direct rating*. It assumes that the fuzziness arises from individual subjective vagueness. The same question "How *F* is *a*?" is given to the same expert over and over again, and the answers are compared to that MF, predefined by the experimenter. The construction of MF is based on the frequency of a particular response.
- *Reverse rating. It a*ssumes that fuzziness arises from individual subjective vagueness. The expert, who defines MF, is asked, to indicate how much strongly a given crisp value under evaluation corresponds to the given linguistic term. This approach can be used for periodical verification of the results obtained by the direct rating method.
- *MF exemplication (also called continuous direct evaluation).* Experts are asked the question "To what degree does a given crisp value belong to the linguistic term *F*?" and to express the compatibility of each term with each combination of items by answering yes/no and assigning the number from 0 to *n* to indicate their degree of confidence in the answer. A great variability of answers is likely. The approach is oriented to the trained experts.
- *Pairwise comparison.* Experts are asked to select an object that explains the fuzzy variable best from among a pair of objects. The question is: "Which is more *F* (by how much)?" MF is constructed combining the results.
- *Interval estimation*. Experts are asked to give an interval of crisp values that describes the linguistic term *F*. The method is appropriate to situations where a strong linear order can be defined on the measurements of the fuzzy concept.

The summary of the approaches, described in related works, is presented in Figure 2. This figure shows those that of the surveyed approaches which are relevant to our research. Several among them are at least partly based on the methodology of phenomenography. In Figure 2, the names of such approaches are placed in grey boxes. The names of approaches, used in our research, are placed in boxes outlined by thick blue lines.

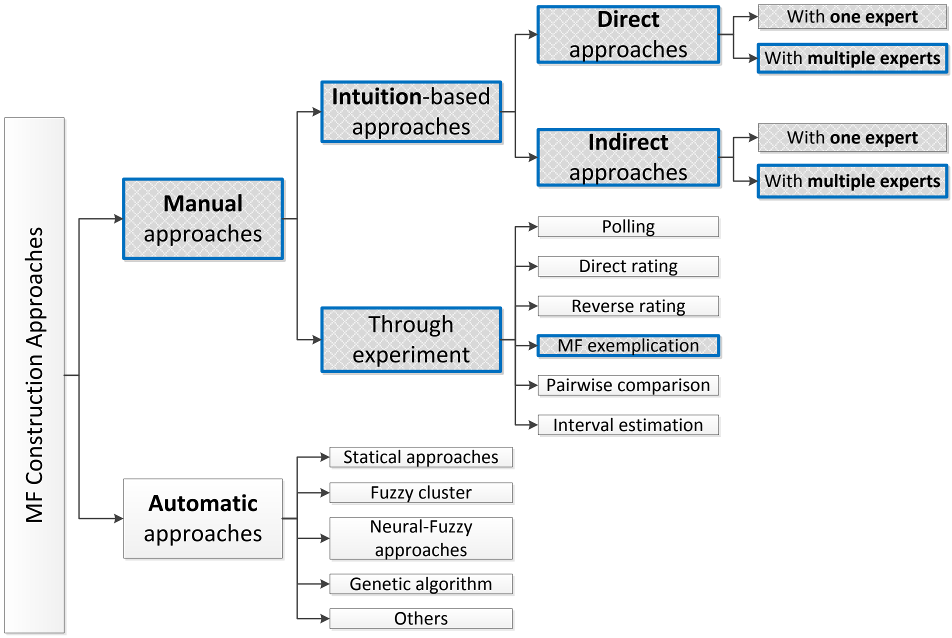

Figure 2. MF construction approaches

Thus, there exist a lot of MF construction approaches. Which one should be chosen depends on the problem in question. Therefore it is desirable to develop a problem-independent methodological MF construction framework that would be applicable to any particular problem.

5. The problem-independent MF Construction Framework

The proposed problem-independent methodological MF construction framework is based on the ideas, described in (Anonymous, 2010; Ragin, 2000). It is presented in Figure 3. The framework provides 10 steps, starting from the analysis of the problem in question and finishing by the definition of the MF that is most suitable for this problem. By a problem we mean the construction of MFs taking into account the allowed degree of subjectivity, sources of input data, data collection methods, etc. (see Figure 2). The framework provides a number of backtrackings to the previous steps when it is necessary that the obtained results should be refined. In Figure 3, the backtrackings are shown by dotted lines. Step 10 is required only in cases, where MFs are constructed using automatic approaches. The main scheme of the proposed approach is as follows. First of all, we should decide which property of the object under consideration should be modelled, and which MF construction approach should be chosen. Further, UoD of this property should be categorized, the linguistic variable (including linguistic terms) should be defined, and MF should be constructed, verified, and validated. If an automatic MF construction approach was applied, MF may be improved using the appropriate learning algorithms.

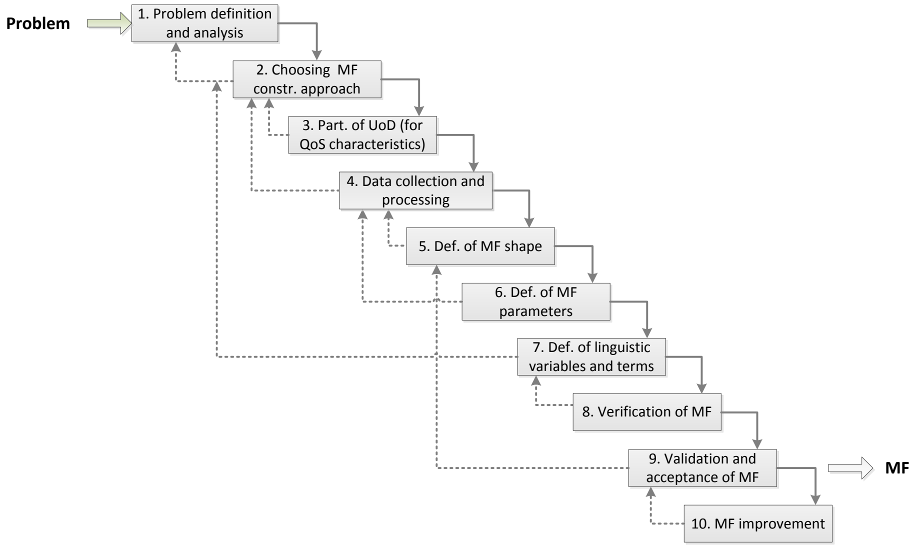

Figure 3. MF construction process

A more detailed description of the steps, shown in Figure 3, is presented below:

1. The fuzzy modelling problem under consideration should be defined and analysed. It means that it should be decided which properties of the object (or objects) in question should be modelled and UoD should be defined for each of these properties: discrete and finite or continuous and infinite. Further, specification MF requirements should be developed. The specification should define: a) allowed degree of subjectivity of MF; b) allowed problem-related bias; c) the kind of data used to extract knowledge about the shape and parameters of MFs; d) necessity to justify these results; e) automatic MF construction approach (if applicable); f) how – directly or indirectly –subjective experts' evaluations should be reflected (if applicable); and g) kind of questionnaires. Some problem-specific requirements may be added.
2. On the basis of requirements specification, a MF construction approach (a branch in Figure 2) should be chosen for each property.
3. UoDs of each property should be partitioned into categories according to the chosen criteria (e.g. categories of the quality or temperature).
4. The data required for extracting knowledge about shape and parameters of MFs should be collected and processed.
5. On the basis of the obtained results, the shape of MF (e.g. triangular, trapezoidal, L-shaped, Gamma-shaped, Sigmoidal, etc.) is determined.
6. The parameters of MF are defined. The number and meaning of the parameters depend on the shape of a function. For example, triangular MF is defined by 3 parameters that define the three corners of the underlying triangular, and

Gaussian MF is defined by 2 parameters that define the centre and width of this function graphic.

7. A linguistic variable (including linguistic terms) should be defined for each property under consideration.
8. Verification of MF is performed. The MF verification is checking whether MF complies with its requirements specification.
9. Validation of MF is a process of making sure that the MF really captures the intended meaning of the linguistic terms in the best way.
10. Improvement of MF is usually performed by learning. The improvement is going in a cycle until, finally, MF is accepted. Artificial neural networks, genetic algorithms, and other machine learning methods can be used for this aim.

On the example of the performance characteristic, the next section demonstrates the application of the proposed methodological framework to construct QoS membership functions. The extended example is presented in (Miliauskaite, 2014).

6. Construction of membership functions for QoS: An example

Let us present an illustrative example how to apply the proposed methodological framework in construction of MFs for QoS characteristics. The steps of applying the MF construction framework, using the performance characteristic, are explained as follows:

1. *Problem definition and analysis.*

Context description: In a Service-oriented Enterprise System, a new EBS, namely, an Invoice Submission service, should be developed. The quality of this service should be preliminary planned or, in other words, the property "quality" of the object "Invoice Submission service" should be modelled. We refer to this property as QoS. Syntactically, QoS can be considered as a composition of its characteristics. Each QoS characteristic has a hierarchical structure and can be represented as a tree of its lower levels sub-characteristics. Semantically, QoS can be understood in a number of different ways called viewpoints (Lupeikienė, 2013a). Besides, for each viewpoint QoS can be defined from 8 different perspectives: presentation, transportation, infrastructure, web service, application, data, domain, and socio-economic (Lupeikienė, 2013a). So, final QoS is defined as a result of aggregation of perspectives and balancing of viewpoints. It is supposed that an expert (or a group of experts), taking into account the specifics of EBS in question, should decide on the common categorization of UoD to the bottom level QoS sub-characteristics and on the shape and parameters of MF, which should also be common for all these sub-characteristics. After this, representants of each perspective (they may have different viewpoints on what the quality means) should propose its quality for each bottom-level sub-characteristic plan in terms of common categorization. Finally, the problem is fuzzified and preliminary QoS is calculated using the methods described in (Lupeikienė, 2013a).

Problem statement: For simplicity, we consider only one bottom-level sub-characteristic, namely, *Execution time* of the characteristic *Performance* (Figure 4), i.e. the values of execution time range in the interval $(0,+\infty)$. In Figure 4, this characteristic is placed in a box, outlined by a thick blue line. Its UoD is continuous and infinite. Besides, in this example, we deal only with perspectives and, for the sake of simplicity, ignore different viewpoints on the nature of quality.

MF requirements specification:

a) *The allowed degree of subjectivity*: Subjectivity of MF should be minimised.
b) *The allowed problem-related bias*: The problem-related bias should be minimized. Expert evaluations should take into account the specificity of EBS under consideration. It means that the expert group should include at least one expert familiar with this specificity.
c) *Data requirements*: Empirical data should be used to extract knowledge about the shape and parameters of MFs. Data should be collected applying the phenomenography-based methodology. Relevant sources of literature should also be used.
d) *Justification of results*: The shape and parameters of MF should be justified using MF construction through experiment techniques.
e) *Automatic MF construction approach*: Not applicable.
f) *Reflection of experts' evaluations*: MF should reflect expert evaluations directly.
g) *Kind of questionnaires*: MF exemplication.
h) *Problem-specific requirements*: Static MF should be constructed. The shape of MF should also be applicable (with different parameters) to the fuzzification of sub-characteristics *Transaction time*, *Throughput*, and *Queue delay*.

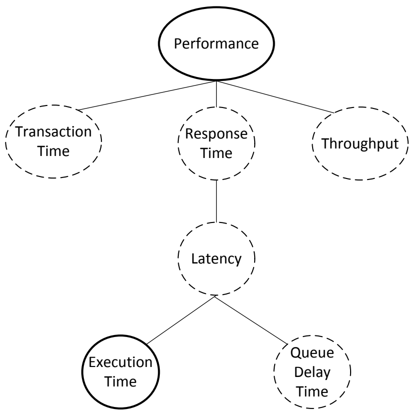

Figure 4. Decomposition of the performance characteristic

2. *Choosing MF construction approaches.*
   On the basis of MF requirements specification, described above, the direct MF construction approach with multiple experts was chosen. The selection of MF construction approaches for *Execution Time* is shown in Figure 5.

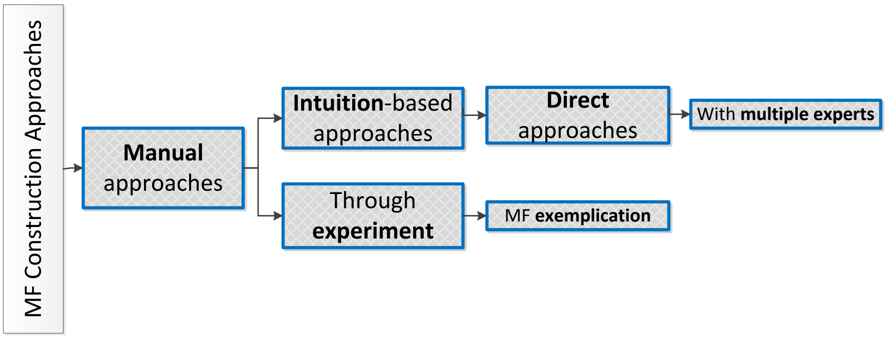

Figure 5. Selected MF construction approaches

3. *Partitioning of UoD*. UoD of *Execution time* is partitioned into 3 categories of quality: Low, Moderate, and High (see Figure 6).

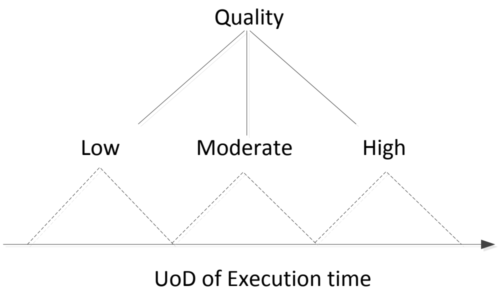

Figure 6. Partitioning of the Quality

4. *Data collection and processing*. In order to minimize the subjectivity of MF, an intuition-based expert judgement approach was combined with a perspective-based approach. In order to minimize the degree of subjectivity and problem-related bias, a group of 9 experts – 8 representing different perspectives plus 1 knowledgeable on the invoice processing issues – was formed. The experts expressed their opinion on partition intervals of linguistic terms *High*, *Moderate*, and *Low* in UoD of *Execution time*, and the shape of MF. The experts took into account the MFs shape of other sub-characteristics of the performance characteristic. The collected data are presented in Table 1.

Table 1. Partition intervals of *Execution time*

Exp.	Perspectives	Execution time (*min*)		
		High/Shape	Moderate/Shape	Low/Shape
E1	Presentation	(0.08,0.32)/L-shaped	(0.22,1.61)/triang.	(1.60,2.40)/Γ-shaped
E2	Transportation	(0.01,0.31)/L-shaped	(0.15,1.57)/triang.	(1.45,2.10)/Γ-shaped
E3	Infrastructure	(0.07,0.31)/L-shaped	(0.38,1.58)/triang.	(1.37,1.90)/Γ-shaped
E4	Web Service	(0.08,0.28)/L-shaped	(0.22,1.38)/triang.	(1.28,1.80)/Γ-shaped
E5	Application	(0.05,0.28)/L-shaped	(0.13,1.41)/triang.	(1.23,1.85)/Γ-shaped
E6	Data	(0.001,0.26)/L-shaped	(0.12,1.27)/triang.	(1.15,1.80)/Γ-shaped
E7	Domain	(0.01,0.24)/L-shaped	(0.25,1.22)/triang.	(1.23,1.90)/Γ-shaped
E8	Socio-economic	(0.05,0.29)/L-shaped	(0.13,1.47)/triang.	(1.37,2.15)/Γ-shaped
E9	EBS	(0.05,0.30)/L-shaped	(0.20,1.50)/triang.	(1.40,2.0)/Γ-shaped

After the discussions, the experts agreed on the following ranges of QoS intervals: *Low* = (1.4,2.0), *Moderate*= (0.2,1.5), and *High* = (0,0.3).

5. *Definition of the MF shape.* On the basis of step 4, the Gama-shaped MF for *Low* linguistic term, triangular shape of MF for *Moderate* linguistic term, L-shaped MF for *High* linguistic term, and have been chosen.
6. *Definition of MF parameters.* The MF parameters are as follows: *Low* = (1.3,1.99) (Gama-shaped, defined by two parameters); *Moderate*= (0.2,0.83,1.45) (triangular MF, defined by 3 parameters recording to the three corners of the underlying triangular), and *High* = (0.03,0.29) (L-shaped MF, defined by two parameters).
7. *Definition of linguistic variables and terms.* The linguistic variable *Quality* is defined as follows:

$$Quality = \left\langle \begin{array}{c} Execution\ Time, \{Low, Moderate, High\}, (0, +\infty), \quad M(Low) = \begin{cases} 0 & if \quad x \le 1.3 \\ \frac{x - 1.3}{0.69} & if \quad 1.3 < x \le 1.99 \\ 1 & if \quad x > 1.99 \end{cases}, \\ M(Moderate) = \begin{cases} 0 & if \quad x \le 0.2 \\ \frac{x - 0.2}{0.63} & if \quad 0.2 < x \le 0.83 \\ \frac{1.45 - x}{0.62} & if \quad 0.83 < x < 1.45 \\ 0 & if \quad x \ge 1.45 \end{cases}, \quad M(High) = \begin{cases} 1 & if \quad x = 0 \\ 1 - \frac{1}{0.29}x & if \quad 0 < x \le 0.3 \\ 0 & if \quad x > 0.29 \end{cases} \end{array} \right\rangle$$

8. *Verification of MF.* MF was checked whether it complies with its requirements specification described in step 1 (see Table 2).

Table 2. Verification matrix

Req. No.	MF requirements	Degree of verification	Verification method
a	Degree of subjectivity	Partly (result of best efforts)	Expert evaluation
b	Problem-related bias	Partly (result of best efforts)	Expert evaluation
c	Data requirements	+	Inspection
d	Justification of results	+	Inspection
f	Reflection of experts' evaluations	+	Inspection
g	Kind of questionnaires	+	Inspection
h	Problem-specific requirements	+	Inspection

9. *Validation and acceptance of MF.* On the basis of MF exemplication experiment, the shapes of MF for linguistic terms *High*, *Moderate*, and *Low* were slightly modified. The final MF parameters of *Execution Time* are as follows: *Low* = (1.4,2.0); *Moderate*= (0.2,0.7,1.5), and *High* = (0,0.3).

7. Conclusions

The analysis of related works has demonstrated that the literature on MF construction issues is quite rich and that a lot of different approaches, methodologies, methods, and techniques have been proposed for this aim. However, up to date, these propositions are still almost not systematized and exhaustive taxonomy is also absent. It seems that the problem-independent methodology is absent as well.

So, in this paper we summarized the MF construction approaches taking into account the chosen understanding of fuzziness as vagueness. Moreover, we have proposed a problem-independent ten step methodology that could be applicable to any particular problem for constructing MF based on the ideas of various authors, published in the related works.

Due to the fact that *Quality* itself is a vague and highly subjective concept, the formalization is performed using fuzzy sets. The case study approach was used to validate the proposed methodology in the context of the QoS planning problem. The presented case study analysis has demonstrated the applicability of the proposed methodology in the context of preliminary planning of QoS for enterprise business services. On the other hand, the case study has shown that the construction of MFs is far from being a simple task and the degree of subjectivity and problem bias fully depends on the experts' selection procedures.

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