Communications of the IIMA

Volume 13 | Issue 4 | Article 5

2013

Supporting Complex Business Decisions with a Fuzzy Mobile Assistant

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ABSTRACT

Researchers have recognized the importance of semantic expressiveness in understanding and solving complex problems and have identified a need to incorporate reasoning about uncertainty into decision tools that assist business managers. This study extends current approaches and develops new tools to allow artificial mobile assistants to manage rule-driven consultations by capturing and recommending problem solutions through natural language interfaces. A prototype assistant is described to support fuzzy knowledge representations and fuzzy rule-based consultations. The prototype's application is implemented in a Windows 8 mobile device and applied in a case study of business outsourcing decisions.

Keywords: fuzzy logic, mobile applications, natural language interfaces

INTRODUCTION

Popular mobile assistants such as Google's Now and Apple's Siri provide a natural language interface to respond to user queries to offer suggestions and assist users by triggering context sensitive help. Nevertheless, these artificial assistants are limited in their ability to make recommendations on complex problems that require human expertise. Managing such complex problems requires a knowledge base organized by experts and sound inference processes to assist managers in making nuanced decisions.

Business experts iteratively explore problems and investigate solutions through processes that continually refine what is known and unknown. Fuzzy Computing with Words (CW) suggests complex decisions are best supported in the domain of natural language. In CW, a linguistic fuzzy variable's value is defined by a natural language term that qualitatively constrains its meaning. For example, the statement "Mary is young" constrains the implied linguist variable "age" to the fuzzy-set labeled "young." The range of a linguistic variable, such as "age" is typically limited to an ordinal and graded set of terms that defines its permissible linguistic values (e.g., young, middle-aged, old). Each term is semantically mapped to the interval [0.0, 1.0] and where 0.0 indicates 0% possibility and 1.0 indicates a 100% possibility that the linguistic variable is constrained by the term (Zadeh, 1973, 1975, 1986, 2002). Recommending solutions to complex problems requires CW reasoning schemes that support that ability to

interpret and reason with imprecise and subjective knowledge (Appelt, Milch, Handgraaf, & Weber, 2011; Boegl, Adlassnig, Hayashi, Rothenfluh, & Leitich, 2004; Yazici, George, Buckles, & Petry, 1992).

Fuzzy theory with CW has guided the representation and management of uncertainty and has improved decisions across a wide range of disciplines. These disciplines include medicine, logistics, weather forecasting, strategic decision making, supply chain management, climate change and group decision making (Ben-Arieh & Chen 2006; Budescu, Broomell, & Por, 2009; Carrasco, Muñoz-Leiva, Sánchez-Fernández, & Liébana-Cabanillas, 2012; Florez-Lopez & Ramon-Jeronimo, 2012; Han, Klein, & Arora, 2011; Joslyn & LeClerc, 2012; Lee & Wang, 2011; Mikaelian, 2009; Politi, Han, & Col, 2007; Voigt & Inderfurth, 2012).

Mobile devices offer a new opportunity to improve business decision making with fuzzy CW based tools. This study develops a prototype and investigates a mobile assistant that applies fuzzy knowledge representations and fuzzy rule-based consultations to aid managers in a complex business decision. The fuzzy system is implemented in a Windows 8 mobile device that asks questions and processes responses to provide rule-driven recommendations. This study follows a design science research methodology by defining a fuzzy CW system architecture and implementing and testing a prototype implementation (Hevner, March, Park, & Ram, 2004; March & Smith, 1995).

As of this writing, this is a pioneer study to explore fuzzy linguistic tools in the context of mobile devices. We define a prototype that: 1) helps business managers express their subjective insights to describe a business situation in natural language and 2) provides a scheme and fuzzy inference tools to support assistants in reasoning and recommending natural language approaches to difficult business problems. The use of the prototype is demonstrated in a case study that supports managers in business outsourcing decisions.

METHODOLOGY

For over fifty years, fuzzy set theory has proven a useful an extension of the mathematical concept of a set. A key concept of a fuzzy set is a function that associates a membership inclusion degree with each element of a set. For example, a membership function, based on a person's height, may assign an individual member to the set "tall" to degree 0.8 and to set "average" to degree 0.3. The membership assignments should not be interpreted with classical probability theory since they are not related to quantitative probabilities. Instead, membership sets define a fuzzy possibility distribution with richer semantics and more robust inference processes Fuzzy set theory may be appropriately applied to decision-making tools of a complex business nature.

A Fuzzy Rule-Base Approach for Augmenting Mobile Assistants

Enterprises must function in an environment where information is often imprecise, vague and ambiguous (Yazici et al., 1992). Approaching complex and evolving business situations, managers must reflect on both what is known and what is changing and uncertain. In order to

support decision making in complex and uncertain environments, knowledge base designers have identified the need to explicitly represent and manage three levels of uncertainty. Managing the three levels rely on fuzzy set theory to represent and infer degrees of certainty associated with a resulting recommendation

Levels of Fuzziness. The **first level** of fuzziness concerns the assignment of degrees of confidence to individual decision rules where each rule may contribute to varying level of certainty to an overall recommendation. For example, a rule for determining the need for "Cloud-based Storage" may not completely apply nor completely not apply to a "Tablet PC" reflecting the first level of fuzziness.

The **second level** of fuzziness concerns the certainty of assignment of specific instances that may characterize a business situation; for example, one triggering event may imprecisely match the patterns required by a rule's antecedent clauses and thus only partially trigger a rule's conclusion. A particular instance of a hand-held mobile device that *somewhat* resembles a tablet may be judged to represent a 30% membership to the class, "Tablet PC." Illustrating a concept reflecting the second level of fuzziness.

The **third level** concerns imprecision in the assignment fuzzy values to describe the properties associated with a fact, where an attributes are assigned values consisting of fuzzy linguistic terms such as "tall" or "warm" A "Tablet PC" may be described by a combination of linguistic variables that are assigned fuzzy values reflecting the third level of fuzziness. For example, the "Tablet PCs" definition may include the attribute "touch-screen usability" that is assigned the fuzzy linguistic value "easy to use" (de Caluwe, Van Gyseghem, & Cross, 1997; Ma, 2006; Ma & Yan, 2010).

Algorithms for linguistic representation. Popular algorithms for linguistic representation rely on a Triangular Fuzzy Number (TFN) to represent a linguistic variable's fuzzy membership function. A TFN is a generalization of an interval of confidence and are a standard way to define membership

A collection of TFNs are placed along an ordinal scale to reflect the ordered structure of a linguistic term set representing the possibility distribution of a linguistic variable. The first step in applying computational models for computing with words (CW) is to translate decision makers' judgment into locations along that ordinal scale and then determine the intersecting set of TFNs. The identified TFNs are then manipulated by linguistic aggregation operator to combine judgments through fuzzy computational weighting schemes. The result of aggregation operations are then retranslated into a linguistic terms to guide interpretation by decision makers (Yager, 2004).

The retranslation step is an approximation process that requires mapping an aggregations' result into a set of linguistic terms. It was shown by Herrera and Martinez (2000) that a 2-tuple linguistic computational model avoids loss of information and produces superior retranslation results. The 2-tuple representation extended previous approaches by introducing a new symbolic translation parameter. The symbolic translation parameter is a numerical value in the range [-0.5, .0.5] that augments the meaning of a linguistic term**.** Figure 1 presents an example of the 2-tuple

representation for an academic grading scale where each letter grade is represent by a TFN arranged along an ordinal scale. Figure 1 illustrates the result of a retranslation for a student with an average weighted grade point of 3.25 that is interpreted as the 2-tuple representation (B, 0.25).

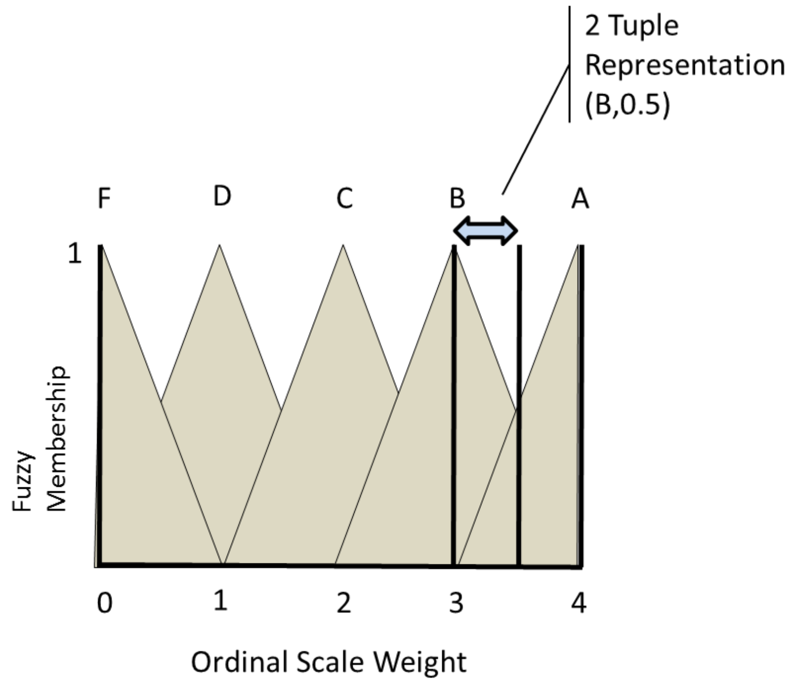

Figure 1: TFN Academic Scale.

By specifying the additional information required to form a 2-tuple representations, decision makers can increase the sensitivity associated with their perceptions. Information preserving aggregation operators then combine translated 2-tuple pairs to into an aggregated measure that can be retranslated to understandable linguistic labels. The 2-tuple representational scheme has been used extensively in modeling decision processes and improving understandability of fuzzy decision (Herrera & Martínez, 2000; Martınez & Herrera 2012; S. –Y. Wang, 2008).

A recognized limitation of fuzzy 2-tuple representations is the need to assume a symmetrical distribution with equal distance among terms along the ordinal scale representing a term set. An new extension to the 2-tuple representation relaxes these assumption by first defining a pair (l_i, l_{i+1}) of two successive ordinal terms and adding a symbolic proportions (α, β) to define a proportional pair ($\alpha\ l_i$, βl_{i+1}) where α+β=1. In the case of symmetric distributions and equidistant labels, the symbolic proportional extension reduces to a 2 tuple representation. Decision makers define the symbolic proportional pair by comparing adjacent terms. For example, a vehicle's capacity could be expressed as 25% "small" and 75% "medium." Figure 2 shows the symbolic proportional pair representation for the 3.25 grade point average (J. –H. Wang & Hao, 2006).

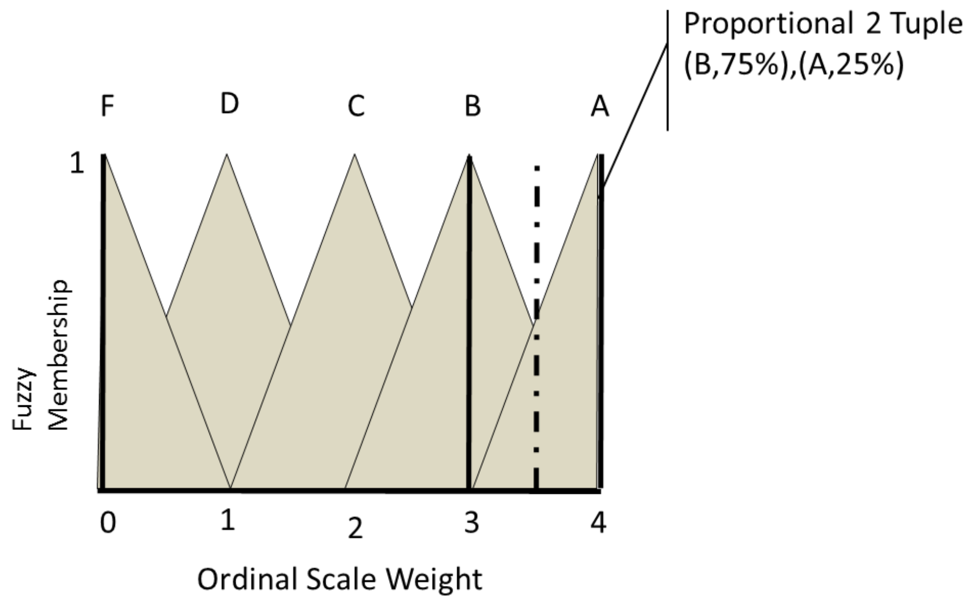

Figure 2: Symbolic Pair Representation Academic Scale.

Defining Reasoning Processes for a Fuzzy Mobile Assistant

The literature reveals difficult business problems are characterized by unavoidable elements of uncertainty. The following presents architectural designs and explores a rule-driven fuzzy mobile assistant. The mobile assistant system, which employs fuzzy theory with the goal of 1) providing a rule-based framework that leverages 2-tuple symbolic proportional linguistic representation to identify and manage three levels of uncertainty associated with recommending solutions and 2) defining a fuzzy inference structure to support natural language and rule driven consultations to assist decision makers in exploring and understanding a problem domain.

The next section discusses techniques for defining and supporting fuzzy rule-base inferences for the system. Subsequent sections define the system's architecture for knowledge based processing of fuzzy rules. A prototype system is then developed and its application is described in a case study.

Applying Rule-based Linguistic Representations and Inference Procedures. Fuzzy expert systems define IF-THEN rules where a rule's antecedents and conclusions are composed of linguistic variables. For example, a fuzzy linguistic rule may declare a policy that:

IF Project Funding is Adequate Rule #1
AND Project Time is Reasonable
THEN
Project Risk is Low

Applying this rule to a particular case requires a managerial judgment to determine if the "Project Funding" and "Project Time" corresponds with the linguistic terms "*Adequate*" and

"*Reasonable,*" respectively. As an example of the second-level of fuzziness, business domain experts assign values by considering an instance of an actual project and judge its level of "Project Funding" as between "*Mostly* Inadequate and *Slightly* Adequate," This assignment represent a 2-tuple symbolic proportions representing the pair (l_i, l_{i+1}) consisting of two of the successive ordinal terms. Similarly, "Project Time" may be judged between "*Somewhat* Un-Reasonable and *Possibly* Reasonable" where the hedges "*Mostly,*" "*Slightly,*" "*Somewhat*" and "*Possibly*" are analogous to symbolic proportions (α, β).

Assigning confidence values. Within a knowledge base's set of rules, confidence values may be assigned to individual rules relating to the first level of fuzziness. For example, Rule #1 may be assigned a confidence of 0.9 indicating that any inferred conclusions concerning "Project Risk" cannot be considered absolute but instead the strength of its conclusion is valid only to a confidence level of 90%.

Within a rule, the first level of fuzziness represents fuzzy measure of a rule's confidence and the second level of fuzziness capture fuzzy truth-values assigned by domain experts during a consultation about a specific business situation. If the combination of antecedent judgments and rule confidence reaches a triggering threshold, the rule is said to fire which assigns linguistic values to a rule's conclusion. For Rule #1, this results in assigning attribute "Project Risk" the fuzzy value "Low" representing a new fuzzy level-three description.

Logical relations. The strength rule's conclusion also depends on logical relations connecting a rule's antecedents. The fuzzy *Minimum* operator is commonly used for conjunctive (AND) connections and drives the truth-value of the conclusion to the minimum of the truth-values among its antecedents. The fuzzy *Maximum* operator is commonly used for disjunctive (OR) connection the strength of a rule's inference is related to its highest truth-value among antecedents.

Additional aggregation operators include the probabilistic operator that assumes independence among antecedents where the conjunctive combination of antecedent memberships P <u>AND</u> Q=P * Q. The disjunctive form for independence is P <u>OR</u> Q=P+Q–P*Q. The bounded sum operator another alternative that assume negative correlation between operators and applies the formulas: P AND Q=Max(0,P+Q-1) and P <u>OR</u> Q=Min(1, P+Q). Selecting among these operators requires, in addition to truth-value of the antecedents, a judgment of the correlation between two statements. The correlation parameter is used to select a fuzzy aggregation operator and yields a truth-value for assigning a truth-value to a rule's conclusion (Siler & Buckley, 2005). A rule fires it conclusion defines a new fuzzy linguistic measure.

Multiple rules may apply and fire. During a consultation several rules may fire where each may assigns a different fuzzy term to the same fuzzy variable. For example, consider another rule that in addition to rule (1) above states:

IF Project Scope is Justified Rule #2
AND Project Team is Qualified
THEN
Project Risk is Low

Given "Project Risk" is assessed on an ordered ordinal scale containing the terms "Absent," Low," and "Medium," assume a consultation triggers Rule #1's firing and fuzzy operators process antecedents to produce the inferred conclusion's represent by the 2-tuple proportional truth values of ((Risk is Low, 75%), (Risk is Medium, 25%)). Now assume, during the same consultation, Rule #2 also fires to yield an inferred conclusion that assigns the truth-values ((Risk is Absent, 75%), (Risk is Low, 25%)). Combined this set of inferred conclusions forms a fuzzy distribution constraining the value of the linguistic variable "Project Risk."

Applying defuzzification operator. In order to provide a combined interpretation of the inference from these two rules a defuzzification operator is used to determine the centroid of the resulting possibility distribution (Sugeno & Kang, 1988). Figure 3 shows the centroid that indicates the "Project Risk" is inferred to be "Low" at the 2 tuple proportional membership level of ((Risk is Absent, 0%, Risk is Low, 100%)

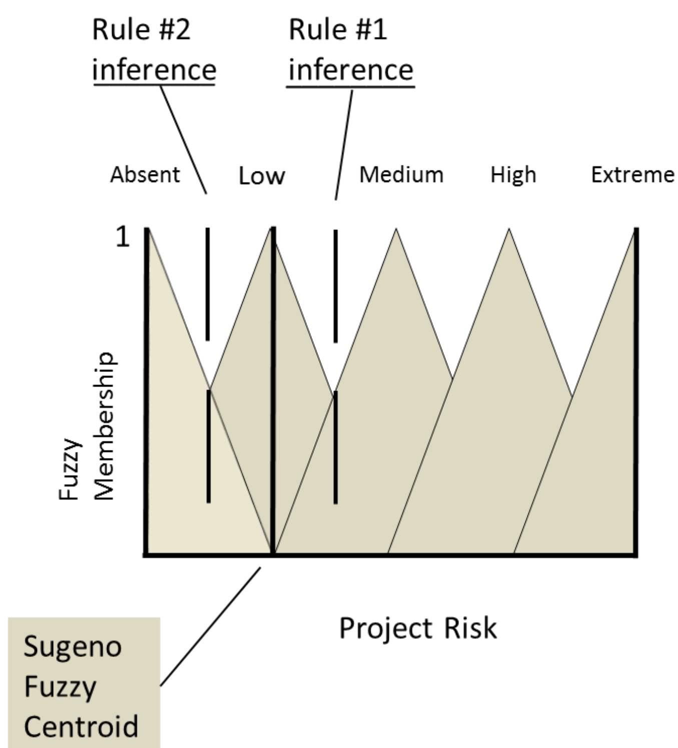

Figure 3: Applying Sugeno and Kano (1988) Defuzzification Operator for Combining Rule Inferences.

In the above example, the symbolic proportions (percentages) in the above 2-tuple proportional representation may also be represented by linguistic term acting as hedges to improve understandability. Table 1 shows the resulting interpretation by applying linguistic hedges to the rule conclusions.

	2–Tuple Proportional Pair Representations	Linguistic Hedged Representation
Rule #1 Conclusion	((Risk is Low, 75%), (Risk is Medium, 25%))	Risk *is probably not* Low but Risk is *Somewhat* Medium
Rule #2 Conclusion	((Risk is Absent 75%), (Risk is Low, 25%))	Risk *is Mostly* Absent but Risk *is a Little* Low
Conclusion from Sugeno Centroid	((Risk is Absent, 0%, Risk is Low, 100%)	Risk *is Surely not* Absent but Risk *is Definably* Low

Table 1: Interpretation of Symbolic Proportions as Linguistic Hedges.

System Architecture

The above defines fuzzy inference processes for managing uncertainty in rule based consultations. Figure 4 presents a system that implements these reasoning processes. Business domain experts first define possible linguistic variables, linguistic term sets and related hedges, which are then used to form fuzzy rule structures. The resulting fuzzy knowledge base is exported into the consultation subsystem, which guides interviews by soliciting managers' opinions. The consultation system then makes recommendations and maintains records to support later dialogues among managers. The following describes the functionality of each subsystem.

The system's components represent fuzzy uncertainty at level one, two and three. Level-one fuzziness is supported by facilities that allow experts to annotate rules by specifying fuzzy memberships representing degrees of certainty associated with each rule. Level-two fuzziness is supported by fuzzy rule-based consultations where business managers describe attributes and apply the rules to business situations through the knowledge consultation component. Level-three fuzziness is provided by facilities that allow experts to characterize uncertainty associated with the predicates defining fuzzy linguistic variables, associated term set and hedges.

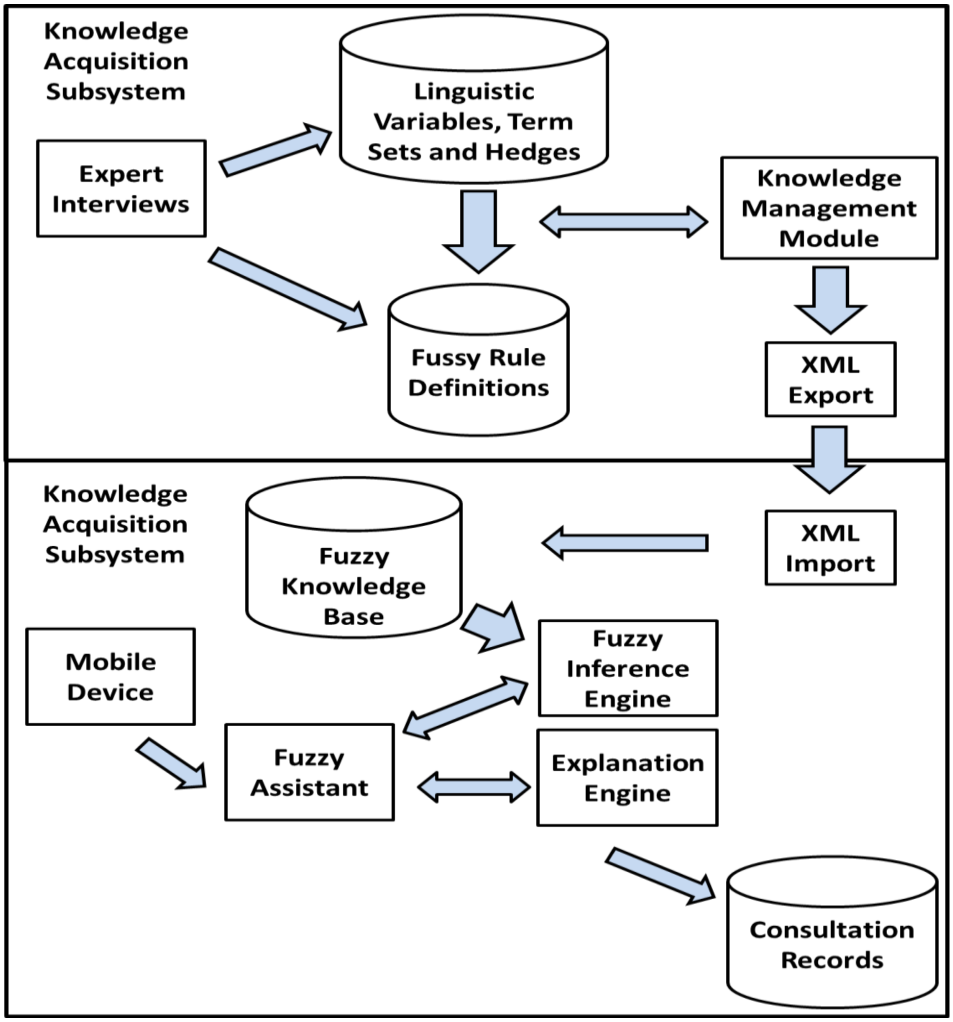

Figure 4: Knowledge Representation and Consultation Architecture.

Knowledge Acquisition Subsystem. The knowledge acquisition subsystem defines components to allow business experts to define rules and associated linguistic hedges. For example, a rule may be expressed with fuzzy linguistic variables that state: An Agent is "*adequately*" qualified, given that he has both "*sufficient*" training and an "*acceptable*" level of experience. In this example, the fuzzy predicates associated with qualifications, training and experience are referred to as fuzzy hedges. The knowledge acquisition system formats these entities as a XML representation of the natural language lexicon, which is then imported into the knowledge consultation module.

Knowledge Consultation Subsystem. Figure 4 also shows the components of the knowledge consultation subsystem system. The system provides functionality to deliver a consultation over a mobile device interface to provide guidance for recommending a course of action. During a consultation rule-driven dialogs guide managers as they answer queries by providing hedged values associated with linguistic variables. Based on management judgments, the system assigns fuzzy membership levels to the variables and if their memberships exceed a threshold, the system's inference engines fires the associated rule, which adds that rules conclusion to the systems working knowledge.

A linguistic variable's fuzzy values are computed from a rule's certainly combined with fuzzy a rule's aggregations algorithms described earlier. During backward chaining, multiple rules may fire and infer different fuzzy values for a same linguistic variable. Defuzzication operations then calculate the variables linguistic fuzzy centroid and translate the resulting value into a natural language recommendation. The system's explanation engine provides rule traces that explain resulting inferences chains. In some cases, the system cannot provide a recommendation and in this case, the knowledge subsystem alerts managers and maintains records collected responses to support later analysis. The following presents a case describing knowledge-based consultations and illustrates its application on Windows 8 mobile device.

CASE DESCRIPTION

AW Enterprises (a fictitious name) wishes to develop a set of policies that will guide management decisions for contracting with outside consultants. Managers must develop realistic guidelines that will identify outsourcing opportunities that balance costs and risks. The following presents a case to illustrate the application of the fuzzy rule-base prototype to help judge the acceptability of outsourcing contracts.

The prototype's knowledge acquisition subsystem was used to develop fuzzy rules to capture expert insight into desired patterns of interaction among a company's divisions and individual consultants participating in outsourcing arrangements.

Subsequently management discussions recognized a range of intangible and uncertain factors that may be involved in recommending outsourcing arrangements. It was difficult to express their recommendations concisely and initial discussions revealed layers of semantic ambiguity and uncertainty related to the meaning and relationships of a division's readiness to manage outsourcing and a contractor ability to complete contracted work.

It was decided that a "Service-Assessment" rule depends on the fuzzy attributes concerning 1) a Division's experience in contracting services, 2) the strength of the commitment by senior management to support outsourcing and 3) the ease of measuring the outcome of the provided service. It was also decided that a "Contract Assessment" rule depends on 1) the contractor's motivational level and 2) the contractor's flexibility to adapt to changing work demands. Experts felt that while both were important in determining outsourcing potential, contractor qualities was a slightly more important variable than service-assessment qualities.

The next step considered the fuzzy attributes of rules where manager defined the possible linguistic values representing linguistic term and related hedges. Figure 5 presents the resulting linguistic variables, terms, and hedges.

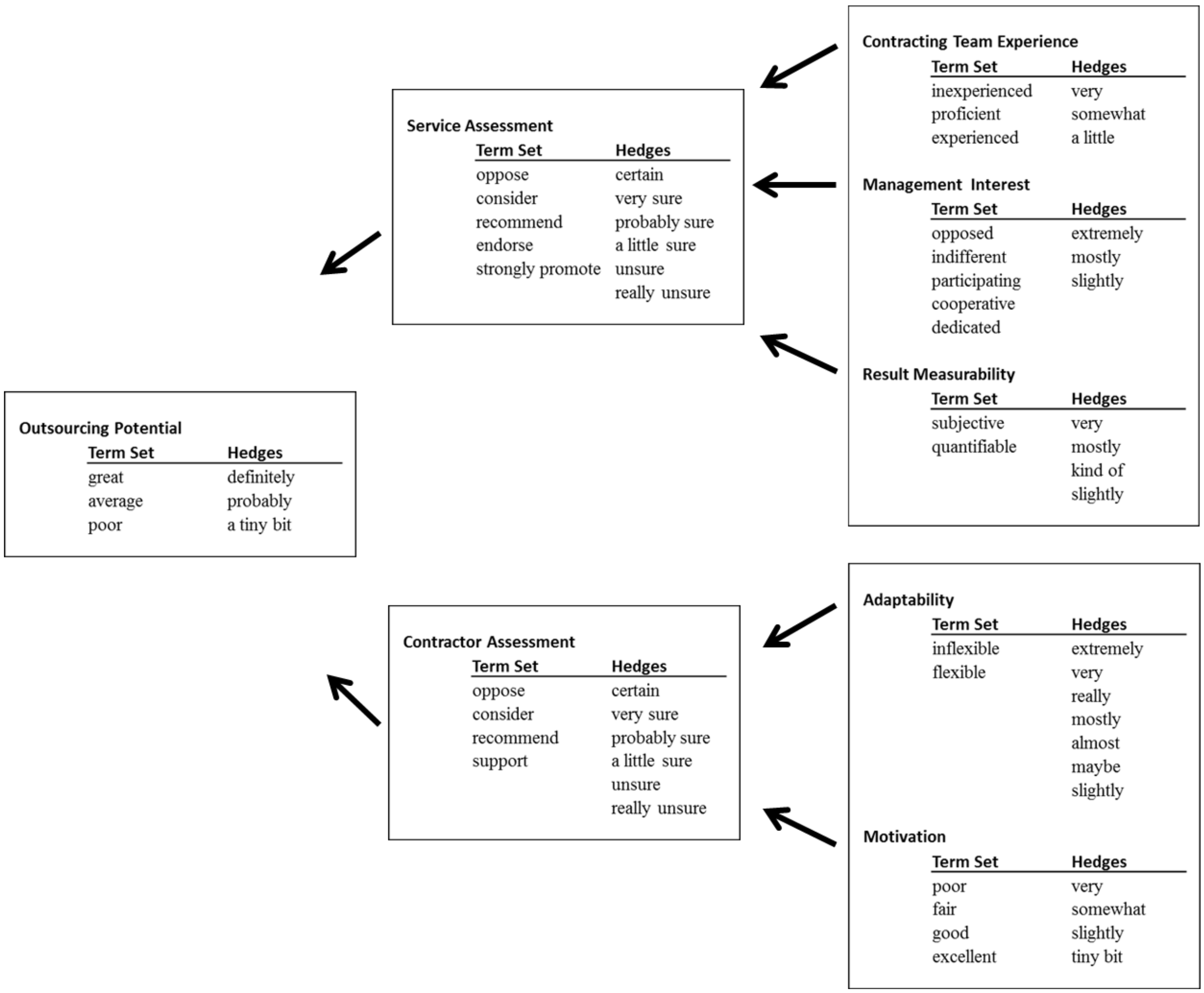

Figure 5: Linguistic Variables, Term Sets and Hedges.

Figure 6 illustrates the mapping of terms and hedge into triangular membership functions for the fuzzy variable "Management Interest." Experts then applied the fuzzy term sets to define nine If-Then rules for determining the acceptability of a contractor and the appropriateness of a service. Additional rules related the perceived level of contractor acceptability and service appropriateness to recommend levels of outsourcing potential.

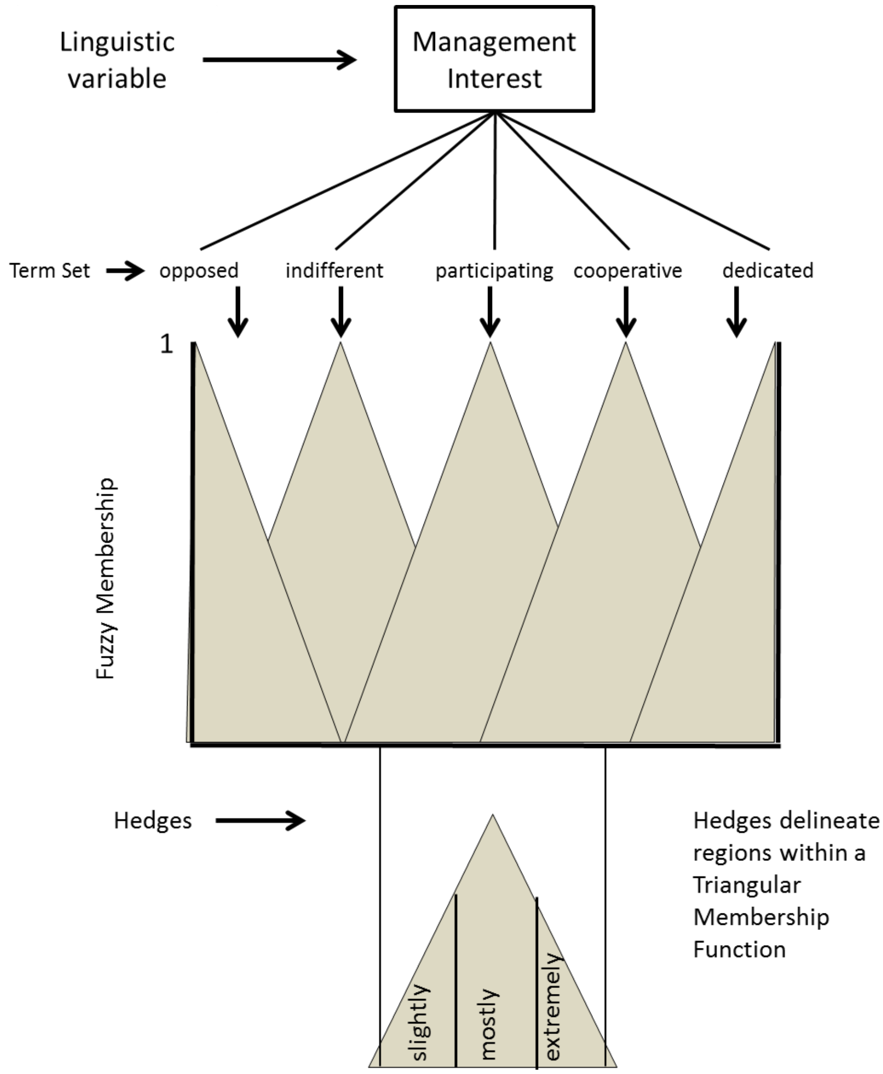

Figure 6: Term Sets and Hedges for Assessing Management Interest with Fuzzy Membership Functions.

The XML representations of three fuzzy linguistic rules for determining contractor acceptability are illustrated in Figure 7. The rules resulted from management team discussions that quickly agreed on required ranges of motivation and flexibility for the edge cases: “Undesirable Contractor Characteristics” and “Desirable Contractor Characteristics.” However, defining rules for determining the intermediate case of “Acceptable Contractor Characteristics” proved difficult where certainty factors (CF) expressed the degrees certainty associated with the rule’s inclusion in the knowledge base.

```
<Rule Name="Undesirable contractor characteristics" Reference=" meeting minutes
8/14">
 <Premises Correlation="1">
 <Premise>AND Motivation == poor CF 100</Premise>
 <Premise>AND Adaptability == inflexible CF 100</Premise>
 </Premises>
 <Conclusions>
 <Conclusion>AND Contractor Assessment == oppose CF 100</Conclusion>
 </Conclusions>
 </Rule>
 <Rule Name="Desirable contractor characteristics" Reference=" meeting minutes 8/14">
 <Premises Correlation="1">
 <Premise>AND Adaptability == flexible CF 100</Premise>
 <Premise>AND Motivation == excellent CF 100</Premise>
 </Premises>
 <Conclusions>
 <Conclusion>AND Contractor Assessment == support CF 100</Conclusion>
 </Conclusions>
 </Rule>
 <Rule Name="Acceptable contractor characteristics" Reference=" meeting minutes
8/14">
 <Premises Correlation="1">
 <Premise>AND Adaptability == flexible CF 90</Premise>
 <Premise>AND Motivation == good CF 70</Premise>
 <Premise>OR Motivation == fair CF 90</Premise>
 </Premises>
 <Conclusions>
 <Conclusion>AND Contractor Assessment == recommend CF 70</Conclusion>
 <Conclusion>ELSE Contractor Assessment == oppose CF 70</Conclusion>
 </Conclusions> </Rule>
```

Figure 7: XML representations of Fuzzy Rules for Determining Contractor Acceptability.

Managers then conducted knowledge based consultations for classifying actual divisions and contractors. A consultation proceeds with the system presenting queries to managers where managers indicate their responses by choosing among hedged term sets. Once managers indicated the terms and associated hedges that describe their judgments, the system updated its working knowledge, performed backward chaining to fire additional rules and present additional queries. At the conclusion of a consultation, the system presents a hedged natural language conclusion.

Figure 8 shows example screen shots from a consultation where the final hedged recommendation suggested, "*We're just a tiny bit leaning toward considering this an average but not a great opportunity for outsourcing*." The explanation engine also allowed managers to

review the inference chain, which led to the system's recommendation. Consultations were repeated to test sensitivity of the conclusion to different hedged responses where each consultation fuzzy inputs and conclusion were stored for later analysis to support rule modifications.

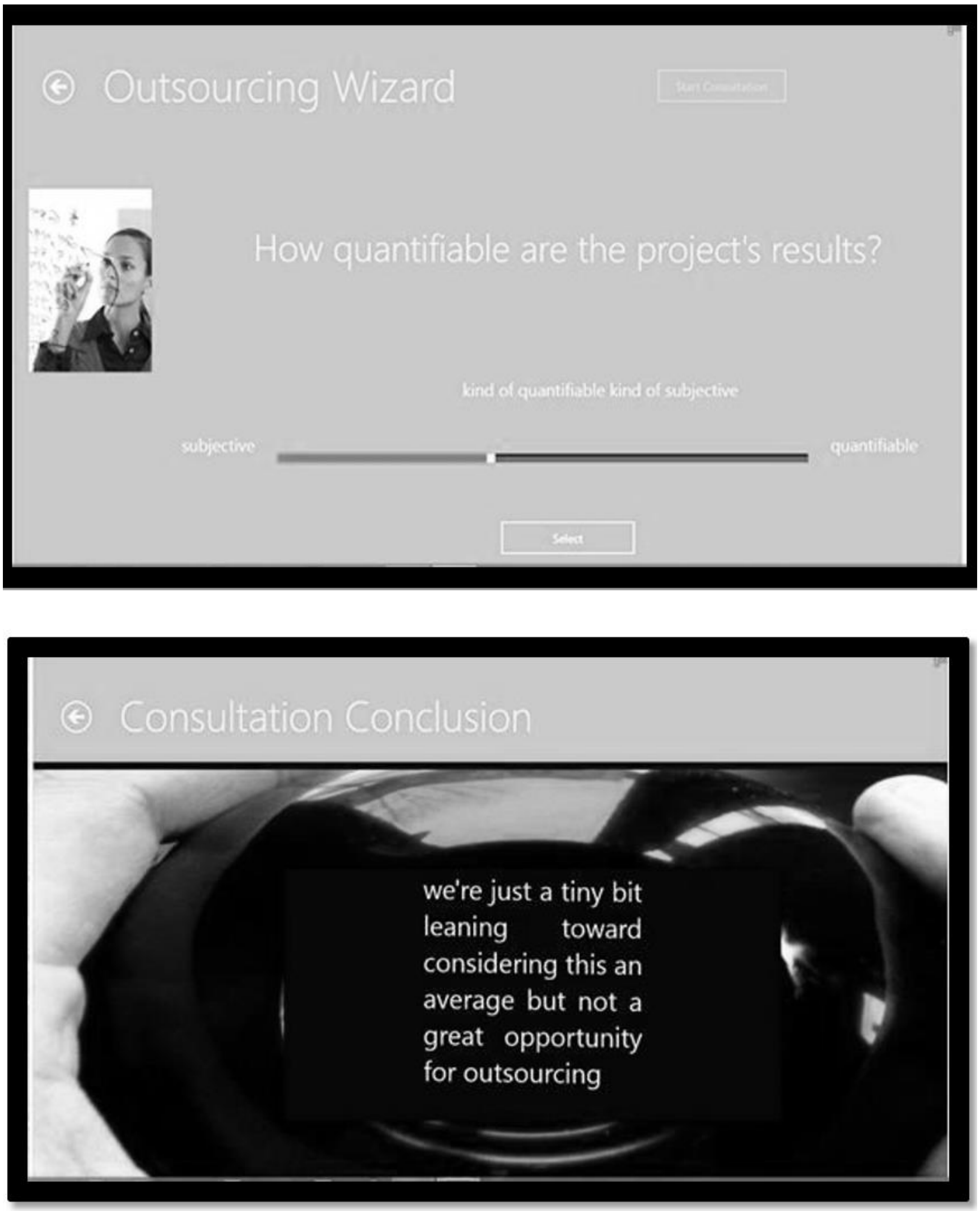

Figure 8: Example Window 8 Mobile Queries and Resulting Conclusions

The history of consultations conducted by two managers evaluating a particular division and contractors is shown in Figure 9. These consultations produced conflicting recommendations where one manager's answers triggered the conclusion that Outsourcing Potential was "probably great and probably not average" and the other's answers triggered the conclusion that Outsourcing Potential was "definitely average and a tiny bit poor." The stored consultation histories facilitate later reviews to help managers collaboratively identify and resolve differences.

Consultation Assessments for Division #2/Contractor #6

Manager #1 Assessment

Service Result Measurability: {slightly observable (18%), mostly quantified (81%)}
Division Management Interest: {slightly cooperative (44%), slightly dedicated (56%)}
Contracting Team Experience: {slightly proficient (16%), somewhat experienced (84%)}

Fuzzy Rule Inference for Service Assessment:

- A little sure about strongly promoting the division

Contractor Adaptability: {slightly inflexible (10%), very flexible (90%)}
Contractor Motivation: {tiny bit good (36%), slightly excellent (63%)}

Fuzzy Rule Inference for Contractor Assessment:

- Probably sure about supporting this Contractor

Fuzzy Consultation Conclusion:

- Overall Outsourcing Potential -> probably Great, probably not Average

Manager #2 Assessment

Service Result Measurability: { slightly qualified (41%), kind of observable (58%)}
Division Management Interest: { slightly participating (12%), mostly cooperative (88%)}
Contracting Team Experience: { slightly proficient (14%), somewhat experienced (86%)}

Fuzzy Rule Inference for Service Assessment:

- Very sure about recommending the division

Contractor Adaptability: {maybe inflexible (25%), really flexible (75%)}
Contractor Motivation: {somewhat good (84%), slightly excellent (15%)}

Fuzzy Rule Inference for Contractor Assessment:

- Unsure we should consider this Contractor

Fuzzy Consultation Conclusion:

- Overall Outsourcing Potential -> definitely Average, a tiny bit Poor

Figure 9: Comparison between Manager Assessments.

The case illustrates three level of fuzziness identified in the data modeling literature. At level-three, the experts' provided sets of linguistic terms and hedges to support a more expressive set of semantic interpretations of attribute describing an outsourcing situation. At level-one, aggregations of linguistic variables are formed into premises and conclusions yielding sets of fuzzy rules, where each rule is assigned a level of certainty representing its contribution to the overall fidelity of a recommendation. At level-two business managers applied rules to classify particular contractors and divisions to yield a linguistic recommendation for an outsourcing decision.

CONCLUSION

Complex problems require a rich set of linguistic representations and understandable sets of rules to reasons about business decisions. Natural language interfaces and fuzzy representations help managers as they create and assess complex problems in a systematic manner.

There are many examples of complex and ambiguous business situations such as the difficult problem of determining employee reimbursements, uncertainty associated with media ownership rights, imprecision involving conditions for the fulfillment of service contracts, fuzziness in the classification of product categories, and the ambiguity of customer sale commitments. Currently there is no organizing framework to represent and manage uncertainty in business decision in a manner that takes advantage of natural language processing on mobile devices. This study's fuzzy modeling approach offers the first attempt to support a framework that manages the three level of fuzziness in complex business decisions.

Fuzzy representations have proven an understandable and effective way to manage uncertainty across a range of disciplines. The prototype's fuzzy extensions and knowledge based consultations offers a new way to capture, represent and classify vague, ambiguous and imprecise business situations. Future research is needed to test the prototypes efficacy and define and test a methodology for its application within business enterprises. In particular, research is needed that applies the system's fuzzy techniques and assesses its ability to support managers as they progress from their initial uncertain, imprecise and rough categorizations toward and enhanced and useful business solutions.

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