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Evaluation of a Hybrid Knowledge-Based System Using Fuzzy Approach

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Abstract**—**This paper describes the main features of a knowledge-based system evaluation method. System evaluation is placed in the context of a hybrid legal decision-support system, Advisory Support for Home Settlement in Divorce (ASHSD). Legal knowledge for ASHSD is represented in two forms, as rules and previously decided cases. Besides distinguishing the two different forms of knowledge representation, the paper outlines the actual use of these forms in a computational framework that is designed to generate a plausible solution for a given case, by using rule-based reasoning (RBR) and case-based reasoning (CBR) in an integrated environment. The nature of suitability assessment of a solution has been considered as a multiple criteria decision-making process in ASHAD evaluation. The evaluation was performed by a combination of discussions and questionnaires with different user groups. The answers to questionnaires used in this evaluations method have been measured as a fuzzy linguistic term. The finding suggests that fuzzy linguistic evaluation is practical and meaningful in knowledge-based system development purpose.

Keyword**—**Case-based reasoning, decision-support system, fuzzy linguistic term, rule-based reasoning, system evaluation.

I. Introduction

THE development of decision support systems (DSS) have been proven useful in the diverse area of application for solving problem, for example – medicine, engineering, applied science, law, and management science. To solve a problem, DSS incorporate human reasoning in automated software that helps users apply analytical and scientific methods to decision making. DSS that focus on the legal domain are referred to as legal decision support systems, providing knowledge-based tools to support user legal reasoning process to come up with a solution for a problem. Legal reasoning can be considered as an intellectual process by which legal professionals use legislative instruments (statutes or regulations) and previously tried cases (precedents) to solve legal problems. Legal practitioners mainly use two types of reasoning mechanisms when contesting a lawsuit: reasoning by deduction and reasoning by analogy [3], [24], [25]. Legal reasoning is more than 'deduction', whereby lawyers count on explanation and guidance materials (reports, illustration, interpretation, observation, practice guides, precedent cases, opinions of well-known academics and legal practitioners) to help add some contextual information to legal rules. Hence, legal reasoning can be viewed as an attempt to understand statutes firstly through the use of the rules, deliberating legal precedent cases only when the rules run out, or when the use of rules prove inappropriate in finding clear concepts.

There exists at least three noteworthy approaches in the development of the current legal knowledge-based DSS: *rule-based reasoning* (RBR) [2], [26], [27], [28]; *case-based reasoning* (CBR) [29]-[32]; and *hybrid reasoning* (i.e. a combination of RBR and CBR [33], [14] or an integration of other reasoning methods [34]).

Each of these approaches focuses on enriching some aspects of the traditional legal knowledge-based DSS. In addition, these automated software systems make use of models regularly, where the models are expected to be reasonably accurate reflections of real-world work practice. In the term reasonably accurate, one discovers the need for evaluation. The manner in which these models are obtained and deployed across decision-making entities (i.e. human and machine) can introduce inconsistencies, incompleteness, redundancies, as well as a problem in co-ordination. Consequently, there is a clear need for the evaluation of knowledge-based systems that are intended for serious use.

There are three important approaches have been suggested in the academic literature for evaluating knowledge-based systems [1], [6], [7], [9], [16], [17] that involves the following assessment mechanisms.

A. Technical Assessment

This particular type of assessment is a way to examine the practical characteristics of the performance of a knowledge-based system based on several criteria such as coherence and perfectness. It aims at the system tests for assessing the practical characteristics, examining its constituent parts and checking the knowledge sources used for the system. It goes even in the programming level to eliminate coding mistakes and assess how well the knowledge-based system has been designed, how appropriate its advice, and explanation facilities are used.

B. Empirical Assessment

It includes assessing aspects of the system that examines the performance of the system and its users. In other words, this assessment tries to substantiate whether the decision-makers make suggestively better or quicker decision by using implemented decision-support systems.

C. Subjective Assessment

This assessment technique uses its end-user critiquing in regards to the usefulness of the knowledge-based system. It includes the examination of the properties of the system that is

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whether it represents an important problem, how systematic and methodological its problem-solving technique is, and whether the system satisfies the requirements of its end-users. It consists of subjective criterion such as ease of use and user satisfaction based on usability, flexibility and correctness of the implemented system.

Different research highlighted in academic literature by using these assessment approaches. For example, the human expert panel-based approach is often used for knowledge-based evaluation purpose. This method has been used in different real-world knowledge-based system, such as divorce settlement [22], new product management [18], therapy planning [10] and optimization of complex engineering system [12]. The outputs of the knowledge-based system, in some predefined case studies, are compared against the recommendations of one or more real-world experts to assess the performance of the system.

Several studies examined the performance of a knowledge-based system by assessing the quality of the decision taken by the decision-makers after using the automated system [3], [19]. As [1] notes, technical evaluation methods concentrate on internal appropriateness and represent verification methods. This type of assessment techniques aims to correct the logical inconsistencies and amend mistakes in the systems. Empirical evaluation methods, on the other hand, focus on validation issues such as, how well a system performs its tasks and whether it has enhanced the performance of the decision-makers.

As a matter of fact, questionnaires-based assessment technique is also popular and it has been used in a variety of application such as marketing [13], printed wiring board assembly [4], strategic decision making [8] and assessment of user interfaces [11]. Questionnaires are usually used to measure perceived usefulness and perceived ease of use. Adelman [1] discusses in details regarding the factors to be considered when evaluating a decision-support system.

The evaluation of decision quality in an automated DSS is an important and complex task. In particular, the decision quality is dependent on the belief of the perceive evaluation of the end-users. Different persons or end-users can have different views and attitude towards quality of the decision based on automated DSS software. Attitude can be viewed as an overall evaluation of a decision perceived by end-users based on their likes, dislikes and domain knowledge of the DSS. Thus, evaluation of decision quality depends on end user's preference structures and attitudes, and it is very difficult to put a numeric number on a decision quality. Linguistic expressions, for example, very good, good, fair, are regarded as the natural form of the preference or judgement. This characteristic attracts the use of fuzzy set theory to get the decision-makers' preference in measuring the decision quality. It also helps to capture the ambiguity of concepts that are associated with human being's subjective judgement. Nowadays, the fuzzy set theory has been applied to the field of applied science, like the decision-making business world [35] and computer science [36]. However, it is rarely used in the area of legal DSS's judgement quality assessment purpose. This study includes fuzzy multi-criteria decision making (MCDM) [5] approach to strengthen the comprehensiveness and reasonableness of the decision-making process. Based on these premises, the aim of this paper is to assess the quality of a hybrid DSS from end-users perceptions using a fuzzy decision evaluation approach. In particular, the objectives are to collect user preferences using multi-criteria questionnaires; convert the user fuzzy judgement into a non-fuzzy number by using a defuzzification process; and rank the decision criteria based on their performance in the user evaluation process.

The rest of the paper is organized into four more sections. Section II describes the main structure of ASHSD, which consists of a rule-based module, a case-based reasoning part, and suitability of reasoning methods. Section III briefly describes the fuzzy set theory and in particular overview of the triangular fuzzy number. The fuzzy-set-based assessment of ASHSD is described in Section IV. Finally, Section V puts forward some concluding remarks.

II. Structure of ASHSD

The main structure of ASHSD consists of a rule-based reasoning module, case-based reasoning module, and a suitability of reasoning method module. The computational framework of ASHSD is shown in Fig. 1.

A. Rule-Based Reasoning Module

The rule base consists of three categories of rules. The first category makes explicit use of legal sources (i.e. statutes, case reports, etc.), and determines whether or not a court has the power to act on. In other words, one way of looking at this issue is to say that the court has a range of options open to it. The first category of rules determines which options are applicable. The second category explains how the courts are likely to act within the range of options available, as determined by the first category of rules. These two types of rule-based advice are known as *preliminary rule-based advice* and *specific rule-based advice* respectively.

In ASHSD some part of matrimonial-home-related legal decision-making is transformed into an IF <*condition(s)*> THEN <*conclusion*> rule format. The preconditions of second category rules are divided into essential, significant, and non-essential categories. Fig. 2 shows one such rule.

The specific rule-based advice of ASHSD can produce two types of output: complete advice and justification, partial advice and justification, or a message that no rule-based advice is likely to be appropriate.

Complete Rule-Based Advice: In case of specific rule-based advice option selection, it can produce comprehensive advice for the user provided that at least one of the rules for the rule base has triggered. This means that if the given facts of a new case satisfy the conditions of one of the rules, one can draw possible conclusions by applying that particular rule.

In the comprehensive advice, ASHSD presents preconditions, complete advice based on these preconditions and justification to its user. Then the user is free to decide if a suggested conclusion is acceptable or if some external consideration requires it to be set aside.

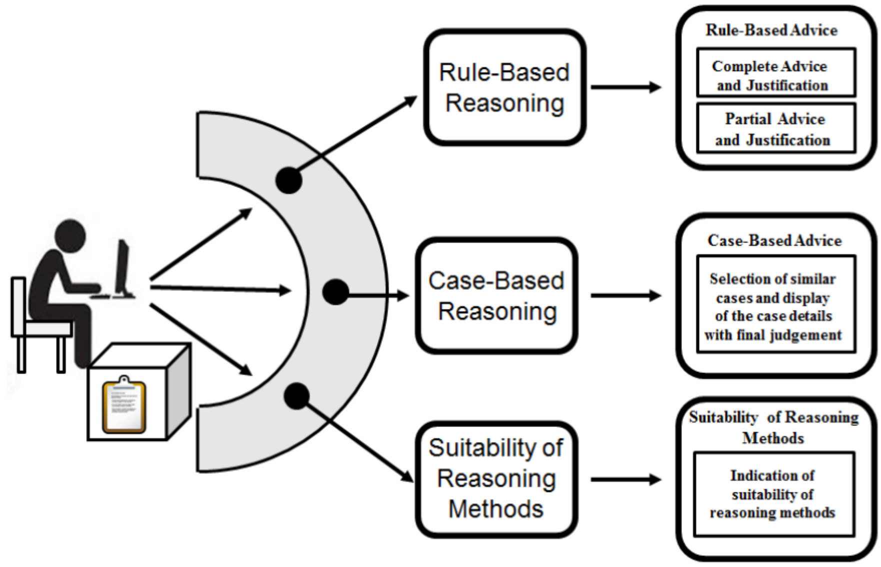

Fig. 1 A simple framework of ASHSD

Partial Rule-Based Advice: When no rule of the second category is triggered by the facts of the new case, ASHSD can generate some partial advice for that case using its rule base. This partial advice consists of the conclusion what would have followed if all the preconditions of the relevant rule(s) had been true, plus information focusing on the failed preconditions (i.e. reason why a conclusion cannot be accepted without reservation).

The first step in generating a piece of partial advice is to identify the second category of rules that are nearly triggered as a consequence of the facts of the new case. A scoring mechanism is used to find out which rules are closed to triggering. The score:

$$Score_{Ri} = \frac{Score_u}{Score_l} \quad (1)$$

where $Score_u = w_1 N_e + w_2 N_s + w_3 N_{ne}$ and $Score_l$ is the total number of preconditions of the rule in (1). N_e, N_s, N_{ne} are the number of essential, significant and non-essential preconditions that are true for the current case. The weighting factors w_1, w_2, w_3 are for the essential, significant and non-essential categories of preconditions.

No Appropriate Rule-Based Advice: It has been found by experiment that there is a consistent threshold in our score, below which any information that ASHSD may give in unhelpful. The system, therefore, offers no advice unless at least one rule of the second category has a score above the threshold.

B. Case-Based Reasoning Module

The case base of ASHSD consists of two parts: a case library, which serves as a repository for cases, and a set of access procedures. The case library of ASHSD is comprised of manually coded previously decided cases. The access procedures are based on a special indexing facility. When the case-based side of ASHSD is invoked, the cases that have the highest similarity rating with respect to a current problem are retrieved and presented according to how closely they match the problem. The relevant similarity is judged by a comparison of main surface features of the cases. To determine the measure of similarity, ASHSD uses the ideas and general approach of fuzzy proximity relation [14]. If a measure of similarity taken over the cases in the case base is always below a threshold, which has been checked by extensive trials, ASHSD makes no recommendations.

IF
NON-ESSENTIAL:
(applicant is the wife)
(respondent is the husband)
(respondent is the official tenant)

SIGNIFICANT:
(divorce has been granted)
(applicant financially insolvent)
(respondent financially solvent)
(applicant has no alternative accommodation to live)

ESSENTIAL:
(privately rented property)
(property type is small)
(there is a dependent child)
(dependent child is living with the applicant)
(there is no written tenancy agreement)

THEN

The advice is to transfer the tenancy to wife.

Fig. 2 A specific tenancy transfer rule

C. Suitability of Reasoning Method

When no preference is indicated, the system applies each method separately then presented results based on an automated relative rating of the qualities of the RBR and CBR advice.

ASHSD includes a text-based user interface. It collects facts for a new case in a question-answering session with its user.

The user can select either reasoning method (i.e. RBR or CBR), or indicate no preference. In the process of consultation with ASHSD, the user can examine both rule-based and case-based information of formulating a suitable solution for the new case in hand.

A fuzzy multi-criteria evaluation method has been used to measure the performance of the ASHSD by using a questionnaire-based survey.

III. Fuzzy Set Preliminary

This section describes the basic concepts of fuzzy, subjective knowledge. In particular, it provides an overview of fuzzy set theory, triangular fuzzy number, and its arithmetic operations.

A. Fuzzy Subjective Knowledge

Fuzziness occurs when the boundary of a piece of information is not well defined. For example, concepts such as short, long, middling, good, bad, high or low are fuzzy. There is no precise single quantitative value that defines the term low. For some people, flats in central London are good, and for others, flats in the mid-town of New York are good. In fact, the concept 'good' has no clear boundary. The penthouse flat in London may definitely be better than a flat in New York City. However, a flat in central London has only some possibility of being good and usually depends on the context in which it is being considered. Unlike classical set theory where one deals with objects whose membership in a set can be described clearly, in *fuzzy set* theory membership of an element to a set can be partial, i.e., an element belongs to a set with a certain grade (possibility) of membership. More formally a *fuzzy set* A in a universe of discourse U is characterized by a *membership function:*

$$\mu_A(x) : \times \rightarrow [0, 1]$$

which associates with each element *x* of X a number (*x* in the interval [0, 1]) which represents the grade of membership of *x* (e.g. a flat priced at *x* pounds) in the fuzzy set A. Rather than an exact boundary, there is a gradual transition from *good* flats to *not-good* flats.

The theory of fuzzy sets, first outlined by [20], [21] was developed to model the concept of fuzzy information. Bellman presented some applications of fuzzy theories to the various decision-making processes in a fuzzy environment [5]. Fuzziness can be represented in different ways. One of the most useful representations is by its *membership function*.

Definition 1: In a simple way, fuzzy membership function can be defined as:

$$\mu_A(u) = 1 - \mu_A(u)$$

$$f_A(x) = \begin{cases} 1 & if \;\; x \in A \\ 0 & if \;\; x \notin A \end{cases}$$

$$\mu_A(x) = Degree \; (x \in A)$$

The membership function of a fuzzy number can classify in different ways, such as a *triangular fuzzy number* (TFNs), *trapezoidal fuzzy number*, and so on.

Definition 2: A triangular fuzzy number denoted by A = (a, b, c), has the membership function as:

$$\mu_A(x) = \begin{cases} \dfrac{x-a}{b-a} & if \;\; a \le x < b \\ \dfrac{x-c}{b-c} & if \;\; b \le x \le c \\ 0 & otherwise \end{cases}$$

This triangular fuzzy number A can be defined by a triplet (a, b, c) as shown in Fig. 3.

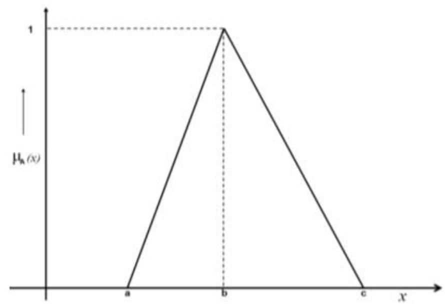

Fig. 3 Membership function of triangular fuzzy number

Definition 3: The following are the four operations that can be performed on triangular fuzzy numbers:

Let $A = (a_1, b_1, c_1)$ and $B = (a_2, b_2, c_2)$ then

Addition:

$$A + B = (a_1 + a_2, b_1 + b_2, c_1 + c_2)$$

Subtraction:

$$A - B = (a_1 - c_2, b_1 - b_2, c_1 - a_2)$$

Multiplication:

$$A \times B = (\min(a_1a_2, a_1c_2, c_1a_2, c_1c_2), b_1b_2, \max(a_1a_2, a_1c_2, c_1a_2, c_1c_2))$$

Division:

$$\frac{A}{B} = \left(\min\left(\frac{a_1}{a_2}, \frac{a_1}{c_2}, \frac{c_1}{a_2}, \frac{c_1}{c_2}\right), \frac{b_1}{b_2}, \max\left(\frac{a_1}{a_2}, \frac{a_1}{c_2}, \frac{c_1}{a_2}, \frac{c_1}{c_2}\right)\right)$$

Modelling using fuzzy sets has proven to an effective way for formulating decision problems where the information available is subjective and imprecise [15], [23]. The subjectivity and imprecision involved in the survey process to reflect the assessments made by the users are better embodied as fuzzy sets. Linguistic terms, satisfaction degree and importance degrees are often vague. For example, linguistic terms, such as *satisfied*, *fair*, *dissatisfied*, are usually regarded as natural representations of users' preferences or judgements to represent evaluations of a knowledge-based decision support system.

Linguistic terms deal with lingual expressions as their values [21], [37]. The possible values for these terms could be satisfied, fair, and dissatisfied. The evaluators are asked to provide their judgments, and each linguistic term can be indicated by a triangular fuzzy number (TFN) within the scale range of 0–10.

An example of the membership function of five levels of linguistic terms is shown in Table I. For instance; the linguistic term ‘good’ can be represented as (2.5, 5.0, 7.5). In this paper, linguistic variables expressed by TFN are adopted for evaluators’ subjective measures to determine the degrees of importance among evaluation criteria.

TABLE I
LEVELS OF LINGUISTIC TERMS

Linguistic scales	TFNs
Extremely good	(7.5, 10, 10)
Very good	(5.0, 7.5, 10)
Good	(2.5, 5.0, 7.5)
Fair	(0, 2.5, 5.0)
Poor	(0, 0, 2.5)

IV. FUZZY APPROACHES FOR ASHSD EVALUATION

In this research three user groups were used for ASHSD’s performance evaluation purpose. The quality of performance of the system perceived by its users has been represented and measured by different criteria.

TABLE II
EVALUATION CRITERIA

No	Evaluation Criteria
1	Comprehensive rule-based advice (C01)
2	Partial rule-based advice (C02)
3	Rule-based advice is not appropriate (C03)
4	Case-based advice is available (C04)
5	Case-based advice is not appropriate (C05)
6	Neither RBR nor CBR is suitable (C06)
7	RBR only is suitable (C07)
8	CBR only is suitable (C08)
9	Both RBR and CBR are suitable (C09)
10	Integration of RBR and CBR (C10)
11	Suitability of the threshold score in RBR (C11)
12	Appropriateness of the threshold score in CBR(C12)
13	Text-based user interface (C13)
14	System help facilities (C14)

A questionnaire-based survey was used to collect the end-users preferences. This questionnaire comprises 14 performance criteria given in Table II.

In the survey process, one set of linguistic terms (*extremely good*, v*ery good*, *good*, *fair*, *poor*) is used for assessing the performance of each criterion respectively.

Each user assesses the performance rating of each system criteria by using one of the linguistic terms defined in the corresponding term set. The end-users responses to these criteria are considered in the data analysis process. In this process, fuzzy triangular numbers are converted into corresponding crisp real numbers. The expected value (EV) based technique [9] is used for this purpose, and its definition is as:

$$EV(T) = \frac{(a+2b+c)}{4} \tag{2}$$

Synthesis of the user responses is shown in Table III.

TABLE III
DATA ANALYSIS

Criteria	Importance	Group One (G1)		Group Two (G2)		Group Three (G3)	
		Fuzzy	Real	Fuzzy	Real	Fuzzy	Real
C01	0.081	(6.31, 8.81, 9.52)	8.36	(5.94, 8.44, 9.37)	8.04	(6.45, 8.95, 9.47)	8.45
C02	0.085	(6.19, 8.69, 9.52)	8.27	(7.19, 9.69, 10.0)	9.14	(6.45, 8.95, 9.73)	8.52
C03	0.073	(4.54, 5.90, 8.45)	6.72	(3.91, 6.09, 7.81)	5.98	(4.47, 6.71, 8.29)	6.55
C04	0.066	(6.43, 8.93, 9.40)	8.42	(4.06, 6.41, 7.97)	6.21	(6.32, 8.82, 9.34)	8.32
C05	0.069	(5.71, 8.21, 9.17)	7.82	(4.38, 6.72, 8.44)	6.56	(5.92, 8.42, 9.21)	7.99
C06	0.065	(3.93, 6.31, 8.10)	6.16	(4.06, 6.25, 7.97)	6.13	(4.08, 6.45, 8.16)	6.28
C07	0.058	(3.95, 5.12, 7.02)	5.31	(3.91, 6.25, 8.13)	6.14	(3.29, 5.25, 7.24)	5.26
C08	0.059	(4.05, 6.07, 7.62)	5.95	(4.22, 6.72, 8.59)	6.56	(3.82, 5.79, 7.37)	5.69
C09	0.063	(6.31, 8.81, 9.52)	8.36	(5.47, 7.97, 9.06)	7.62	(5.79, 8.16, 9.08)	7.30
C10	0.084	(7.50, 10.0, 10.0)	9.37	(7.03, 9.37, 9.37)	8.79	(7.50, 10.0, 10.0)	9.37
C11	0.076	(3.69, 6.07, 7.74)	5.89	(3.91, 6.09, 7.97)	5.02	(4.08, 6.45, 8.03)	6.25
C12	0.064	(5.24, 7.74, 9.17)	7.72	(4.06, 6.09, 7.66)	5.97	(5.26, 7.76, 9.08)	7.46
C13	0.073	(6.90, 9.40, 9.88)	8.89	(6.87, 9.38, 9.84)	8.87	(7.24, 9.74, 10.0)	9.18
C14	0.084	(7.26, 9.76, 10.0)	9.19	(6.72, 9.22, 9.84)	8.75	(7.24, 9.74, 10.0)	9.18

The expected values are calculated for the user groups based on the user responses, and the values for three user groups are shown in Table IV.

TABLE IV
SYNTHESIS OF RESULT

Group Number	Expected Value
G1	7.6885
G2	7.3095
G3	7.5103

The difference between the expected values for the three user-groups is extremely small, and their order is G1 > G3 > G2. The results also indicate the evaluators were satisfied with the system's most of the system evaluation criteria.

V. CONCLUSIONS

In this paper, an evaluation mechanism of a hybrid knowledge-based system has been described, using a fuzzy linguistic approach based on fourteen performance criteria. Fuzzy numbers and membership function have been used as an adequate mechanism to overcome the uncertainty of concepts that are associated with human beings' subjective judgements. Decision quality of a knowledge-based system has been ranked based on this evaluation exercise. The identification of end-users' perceptions of ASHSD's judgement quality provides a way to improve the performance of the described system.

The basic structure of ASHSD is not particular to this domain or even to the law in general. It is, in effect, the main result of this research, and it is worth considering for adoption in other hybrid knowledge-based system projects.

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