A FUZZY DECISION SUPPORT SYSTEM FOR RATING POTENTIAL CUSTOMERS AND BUSINESS PARTNERS

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ABSTRACT: A prototype of a fuzzy expert-knowledge based decision support system is presented. The system facilitates meaningful and objective decision-making, which sometimes can be sensitive or confidential, by automatically rating entities, such as preferred potential customers or business partners, candidates for a position, applicants for a tender, etc. The system applies the fuzzy rule based method as the preferable option. It has been given a modular structure, and was made easy to adapt, without compromising on accuracy. Practitioners in the field of intelligent technologies and soft computing as well as newcomers to the trade can easily employ this solution as a stand-alone classifier or as an extension to other software packages.

KEYWORDS: Fuzzy expert system, fuzzy logic, fuzzy knowledge base, fuzzy inference engine, rules reduction.

1. PROBLEM STATEMENT AND SOLUTION

In the mental process of natural decision-making, a common method used for evaluating the different alternatives at hand is by weighing their characterizing features and then ranking them by use of appropriate quality indices. Management decision-making assignments concerning selected entities, like appointment of candidates to a position, choice of business partners, assessment of potential customers, selection between applicants for a tender and many others, evidently belong to this category. Much uncertainty is usually involved in such decision processes, which when frequently repeated can also become burdensome and time-consuming. Characteristically, members of the management and staff involved in such decision-making have accumulated sufficient knowledge to act as individual or corporate process-experts. When the rectangular array size of objects vs. features is moderate, the abundant data at their disposal can be effectively exploited by cognitive decisions, see [Zimmermann 1997]. When large amount of complex data is involved, this knowledge can be elaborated and augmented by use of conventional as well as intelligent technologies of data-analysis and processing, which nowadays have become accessible even to non-specialists. To this end, statistical tools together with modern technologies like clustering and feature selection methods, neural networks, automatic fuzzy rules generation or other algorithms facilitating data-mining, can be understood and practiced, i.e. [Angstenberger 1998], by adequately educated users.

A system for rating customers and business partners was developed at Indic as a pilot framework for a fuzzy expert knowledge based decision support system (KB-DSS), [Zimmermann 1997]. The fuzzy rule based approach was found as most advantageous in the decision-making environment concerned, able to better express both the experience and intentions of the decision-makers. The system has been successfully demonstrated and proposed as a possible platform for a class of special purpose application project developments. It has been built using the DataEngine® development tool [MIT 1997], and offers considerable benefits, mainly: 1. Many features can be considered simultaneously. 2. Problems of uncertainty are resolved to a large extent by use of fuzzy rule-based logic and a fuzzy inference engine. 3. Human-factor problems like fatigue, decision under stress conditions, or inconsistency of judgement can be practically eliminated. 4. It is easy to construct and to adapt. 5. It has a transparent structure, thus enabling one to track the automatic decision-making process. 6. Almost instantaneous alphanumeric and graphic results are obtained following data file input.

2. SYSTEM BASICS

The prototype fuzzy KB-DSS system described here makes use of the fuzzy rule-based method, see ref. [Zimmermann 1994], [Klir 1995] and [Schneider 1996]. By this methodology, logical rules are defined, regarding entities ("objects") characterized by features, each one defined by data sets expressed by fuzzy membership functions. The system has a modular and easily adaptable structure. The specific application described below is based upon a choice of 24 typical customers and business-partners of a well-established software company marketing products, projects and services. Each one of these was characterized by a series of 13 identical features (or attributes) regarded by the professional sales and marketing staff as being most significant to successful development of mutual business relations. Another convenience of the system is that the input file data can be imported into DataEngine automatically (i.e. from a company follow-up program) or be filled-in manually. For each object, each of its attributes was assigned with an individual index rating, decided upon by the company expert team.

First, each attribute was defined as a "linguistic variable". Next, within the range of each linguistic variable, the experts defined the appropriate fuzzy sets by their term names (i.e. company importance: low, medium, high; software feasibility: low, medium, high; etc.) for each such variable and assigned their membership functions. The sets were built in a fashion that at most two membership values belonging to two intersecting sets represent one linguistic variable value (Figure 1). Formulation of a complete rule base, considering combinations of all the participating sets in our example, would theoretically lead to N_c = 1,889,568 possible rules. N_c can be calculated by the product of the number of fuzzy sets, n_j, which characterize each one of the m linguistic variables:

$$N_c = \prod_{j=1}^{m} n_j$$

In order to enhance design modularity and simplicity of the rule-base, the attributes could be partitioned into four weakly inter-correlated groups consisting respectively of 4, 4, 3 and 2 attributes. A considerably smaller number of rules could thus be achieved, resulting from the limited number of attributes in each group. The maximal number of rules in the four groups could be now reduced to the total sum of 81, 108, 27 and 8 respectively. The numbers represent the complete rule base within each group. For each group of attributes one concluding "linguistic symbol" and its terms were defined by ranks (i.e. client-index: dormant, …, close, ready; project-index: low, …, very good; and so on). Now, for each of the four groups of attributes, a separate set of fuzzy rules could be defined, in the form: "If **go-ahead** is very good and **software-feasibility** is high and **interfacing-compatibility** is very good and **client cooperation** is good, then **project-index** is very good with a certainty factor of 0.9".

Generation of over two hundred rules, even when "objective" criteria were applied, would not avoid accumulation of considerable systematic errors, beyond of being a meticulous task. Therefore an alternate and direct approach was employed as described below. Rules were formulated, based on the existing universe of discourse in each group, by expressing the best judgement, combining both previous experience and vision of the task by the expert staff. The rules generated at the first stage refer just to the higher and lower values of the linguistic symbols while omitting the "medium" ones. The resulting membership values of each linguistic symbol were obtained in the range (0,1), after running the data and rules in the inference process, see Figure 2. At this stage, the resulting membership values of all "medium" linguistic symbol terms (the dark column) were zero. However, observation of the results indicates that missing membership output values of the "medium" linguistic symbols can be estimated from the data processed in the way described below. The number of rules generated in the respective groups was 10, 22, 8 and 4. During the first stage of inference, operators of aggregation (minimum), implication (algebraic product) and accumulation (maximum) [MIT 1997] were chosen, expressing a rather conservative attitude.

Next, advantage was taken of the fact that the DataEngine inference engine can execute multiple inference of rule sets in a cascade. Accordingly, a second set of fuzzy rules was built whose role was to single out the membership values of linguistic symbols scored in the "medium" range. This was achieved after summing-up (for each customer or partner being rated) the membership values of each linguistic symbol term listed in the output file columns of the respective group as resulting from the inference process of the first set of fuzzy rules. Evidently, all the "medium" linguistic symbol terms with full membership rating (1.0) are identified as those having scored in the summation zero values, and those with zero membership rating as those which scored values of 1.0 or more. The "medium" linguistic symbol terms of fractional membership rating are expected to share membership with resulting linguistic symbol terms having either higher or lower ranks adjacent to them (Figure 2). Now, fractional membership rating of those "medium" linguistic symbol terms can be determined with sufficient accuracy by inference of simple fuzzy rules processed right after the first set. Slight inaccuracy in calculating the "medium" linguistic symbol terms having fractional membership ratings was considered acceptable. It was reasoned that an alternative of applying full fuzzy rule sets, stated by experts, for the four groups within a single-stage, to cover all the values of the linguistic symbols (the "medium" values included) would lead to an even higher total uncertainty. Clearly, such default solution would also demand a much larger rule base, increase system complexity and run time.

3. RATING AND RESULTS

In the third part of the system, all the membership ratings scored for the different linguistic symbol terms are factorized and summed up according to a relative hierarchy of values set by the experts. Finally, the factored scorings of all the linguistic symbol terms are totaled:

$$\sum S_t = \sum_{i-1}^{k} \sum_{j=1}^{l} C_i m_{ij}$$

ÓS$_t$ is the individual customer's total rating index scored, C_i is a scoring coefficient of the i-th rating grade (k=6), m_{ij} is the membership assigned to the i-th rating grade belonging to the j-th linguistic symbol term (*l*=15) in any of the four groups. In this partition many of the m_{ij} have zero values. The results are visualized in Figure 3. The highest possible total rating index score is 48.0. Processing is performed in a single run on a common office PC within a few seconds. The results and the method were approved by the expert-staff concerned, and had been also favorably accepted in a course of different presentations.

Construction of this fuzzy KB-DSS was made easy through use of the graphical macro language cards of DataEngine. These cards offer a possibility of choice from a menu of resourceful and effective function blocks arranged in specialty groups (Mathematics, Statistics, Signal Processing, etc.), which makes the manipulation of rows and columns as described above a straightforward proposition. The card system also facilitates addition of user-defined functions to the application. Transparency of the knowledge base design enables use of interim as well as extended custom-built classifiers.

4. CONCLUSIONS AND FUTURE PERSPECTIVES

1. A modular fuzzy rule based KB-DSS for rating potential customers and business partners was constructed. Simplicity of design, applicability to a wide class of applications and adaptability were main objectives of the system.
2. The system can be applied as a stand-alone classifier or, by using the DataEngine ADL run time module, to extend other software packages. This module is available as a dynamic link library (DLL) for MS Windows, as a C++ class library for various compilers, and it can also generate C source code.
3. The system developed can also be utilized and modified by newcomers to the field of intelligent technologies and soft computing using the DataEngine shell. Practitioners in the trade can use the method used here as a basis for more specific or elaborate solutions.

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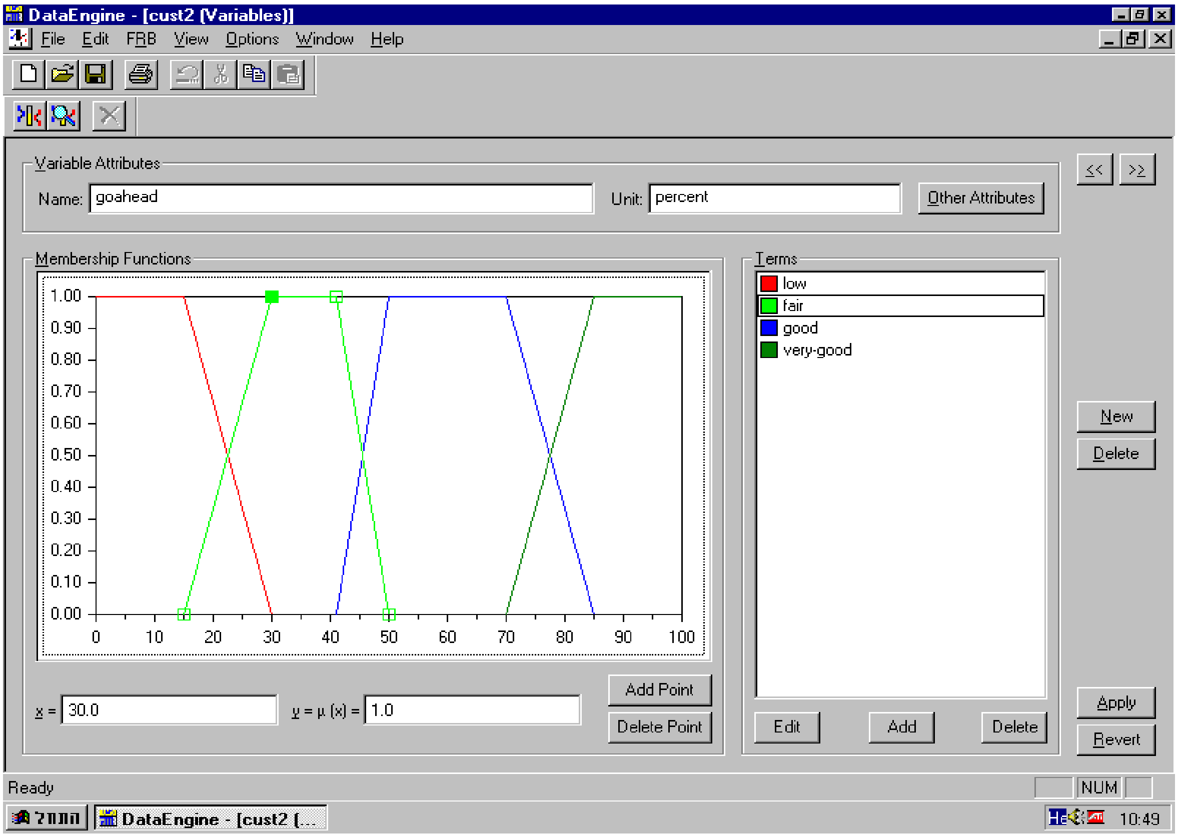
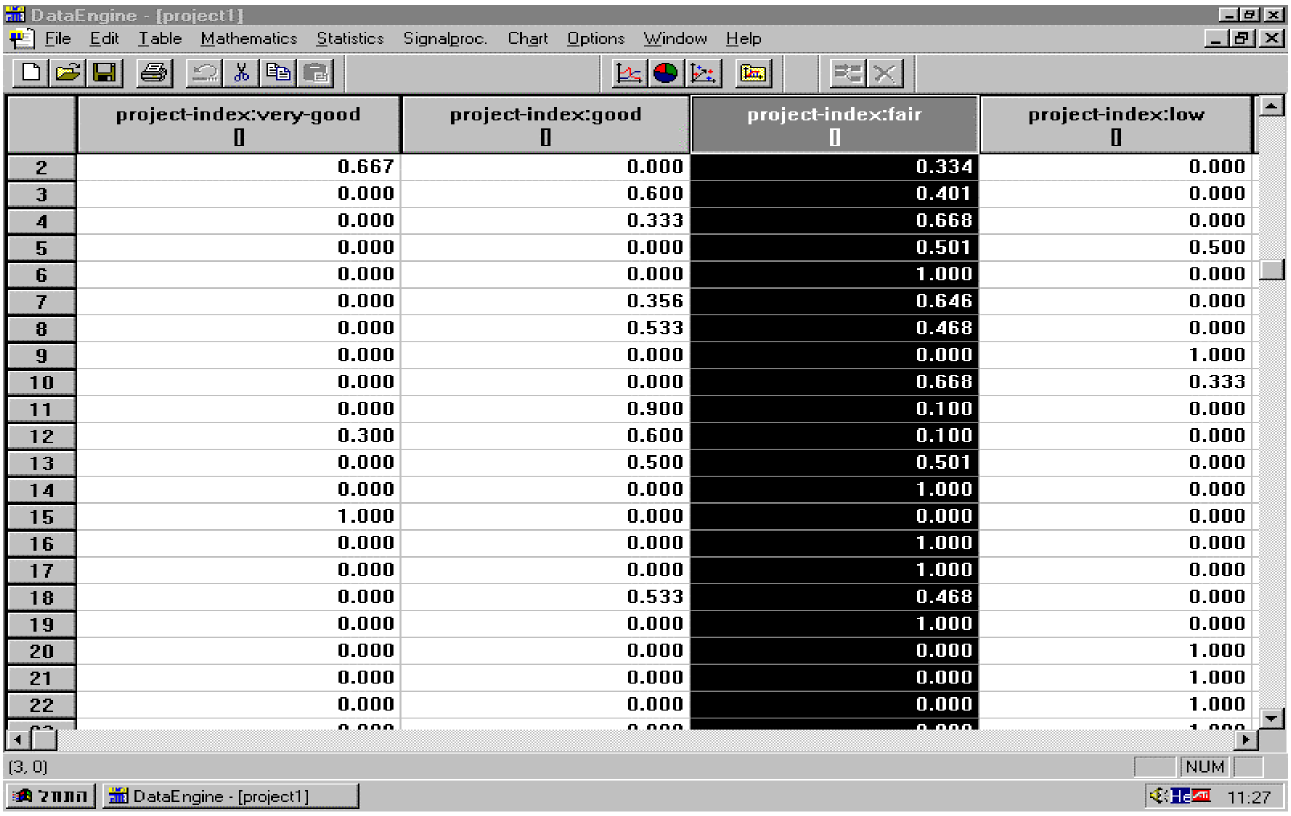


Fig.1: Membership functions of a linguistic variable belonging to the project group



	project-index:very-good	project-index:good	project-index:fair	project-index:low
2	0.667	0.000	0.334	0.000
3	0.000	0.600	0.401	0.000
4	0.000	0.333	0.668	0.000
5	0.000	0.000	0.501	0.500
6	0.000	0.000	1.000	0.000
7	0.000	0.356	0.646	0.000
8	0.000	0.533	0.468	0.000
9	0.000	0.000	0.000	1.000
10	0.000	0.000	0.668	0.333
11	0.000	0.900	0.100	0.000
12	0.300	0.600	0.100	0.000
13	0.000	0.500	0.501	0.000
14	0.000	0.000	1.000	0.000
15	1.000	0.000	0.000	0.000
16	0.000	0.000	1.000	0.000
17	0.000	0.000	1.000	0.000
18	0.000	0.533	0.468	0.000
19	0.000	0.000	1.000	0.000
20	0.000	0.000	0.000	1.000
21	0.000	0.000	0.000	1.000
22	0.000	0.000	0.000	1.000

Fig. 2: Resulting membership values of the linguistic symbol terms in the project group

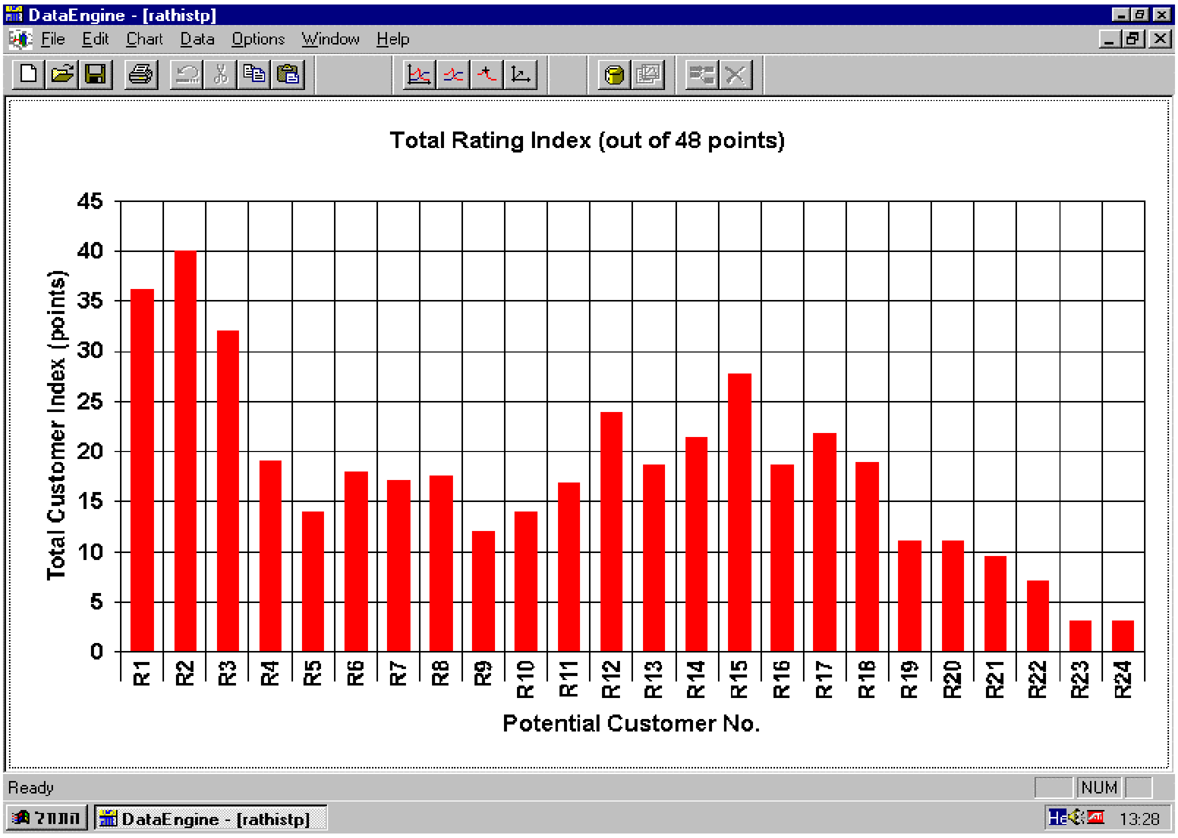


Fig. 3: Total rating index of potential customers