Integrating multiple fuzzy expert systems under restricting requirements

Integrace mnohonásobných fuzzy expertních systémů za omezujících podmínek

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Abstract: The multiple, different and specific expertises are often needed in making YES-or-NO (YES/NO) decisions for treating a variety of business, economic, and agricultural decision problems. This is due to the nature of such problems in which decisions are influenced by multiple factors, and accordingly multiple corresponding expertises are required. Fuzzy expert systems (FESs) are widely used to model expertise due to its capability to model real world values which are not always exact, but frequently vague, or uncertain. In addition, they are able to incorporate qualitative factors. The problem of integrating multiple fuzzy expert systems involves several independent and autonomous fuzzy expert systems arranged synergistically to suit a varying problem context. Every expert system participates in judging the problem based on a predefined match between problem context and the required specific expertises. In this research, multiple FESs are integrated through combining their crisp numerical outputs, which reflect the degree of bias to the Yes/No subjective answers. The reasons for independency can be related to maintainability, decision responsibility, analyzability, knowledge cohesion and modularity, context flexibility, sensitivity of aggregate knowledge, decision consistency, etc. This article presents simple algorithms to integrate multiple parallel FES under specific requirements: preserving the extreme crisp output values, providing for null or non-participating expertises, and considering decision-related expert systems, which are true requirements of a currently held project. The presented results provides a theoretical framework, which can bring advantage to decision making is many disciplines, as e.g. new product launching decision, food quality tracking, monitoring of suspicious deviation of the business processes from the standard performance, tax and customs declaration issues, control and logistic of food chains/networks, etc.

Key words: Fuzzy expert systems, output combination/aggregation, AHP, Knowledge integration, multiple parallel processing, group decision making.

Abstrakt: Pro řešení celé řady podnikatelských, ekonomických nebo zemědělských rozhodovacích problémů jsou často potřebné mnohanásobné a specialisované expertízy v Ano/Ne rozhodováních. Vyžaduje to povaha těch problémů, ve kterých rozhodování je ovlivňováno mnoha faktory a je tedy potřebná mnohostranná expertíza. Často se používají fuzzy expertní systémy, protože jsou schopny modelovat hodnoty, které nejsou vždy přesné, ale spíše neurčité. Problém integrování mnohanásobných fuzzy expertních systémů znamená synergické propojení několika nezávislých a autonomních expertních systémů tak, aby to odpovídalo proměnlivému kontextu problematiky. Každý z expertních systémů se podílí na posouzení problému na základě předdefinované shody mezi kontextem problému a požadovanými specifickými expertízami. V našem výzkumu jsou fuzzy expertní systémy integrovány kombinováním jejich ostrých numerických výstupů, které vyjadřují stupeň tendence k Ano/Ne subjektivní odpovědi. Důvodem pro nezávislost může být schopnost údržby, analyzovatelnost, odpovědnost za rozhodnutí, modularita, citlivost ke kontextu, atd. Tento článek uvádí jednoduché algoritmy pro integrování paralelních fuzzy expertních systémů při specifických realistických požadavcích, např.: zachovat extrémní ostré výstupní hodnoty nebo umožnit neúčast některých expertů. Uvedené výsledky vytvářejí teoretický rámec, který může být užitečný v mnoha disciplínách, např. při zavádění nových produktů, monitorování kvality (potravin), zjiš-

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ťování podezřelých odchylek podnikových procesů od normálu, u problematiky daňových a celních deklarací, logistiky a řízení obchodních řetězců a sítí, atd.

Klíčová slova: Fuzzy expertní systémy, kombinace/agregace výstupů, integrace znalostí, paralelní zpracování, skupinové rozhodování.

INTRODUCTION

Integrating multiple intelligent or decision support systems is considered particularly useful in obtaining a high quality, more comprehensible, and reliable decision solution. This paper attempts to treat one of the complex problems that have not gained much attention before, in spite of the wide prevalence of the situation in which a group of expertises concurrently evaluate YES/NO decision problems. The problem of integrating multiple FESs involves combining or aggregating the crisp outputs produced by the individual systems to obtain a final, consolidated, YES/NO output decision. The need for multiple expert systems (ESs) can occur frequently when a complex problem in hand has multiple related aspects for which the existence of multiple independent and separated expertise is necessary, and there is no available expertise that covers the whole aspects of the problem. There are still some other reasons behind independence amongst ESs e.g. as follows:

– Cohesion of knowledge units.
– Control and final decision responsibility.
– Avoidance of knowledge interaction or mutual influence.
– Modularity in analyzing and explaining the final decision.
– Sensitivity of aggregate knowledge.
– Existence of context-based reasoning.
– Consistency in handling relationships and reasoning.

Further we shall mention some important aspects of ESs

Configurations of the multiple expert systems

There are two main possible configurations that can connect together several ESs, i.e. series and parallel configurations (Beeri, Spiegler 1996).

(a) Multiple series expert systems

ESs are arranged in such a way that the problem input is presented to the first ES which passes its output answer to its successor, and so on as in Figure 1.

(b) Multiple parallel expert systems

ESs are arranged in such a way that the same problem is presented to every ES concurrently in order to reach at one consolidated output decision. Here

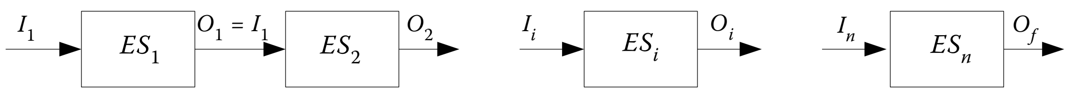

Figure 1. Multiple series expert systems

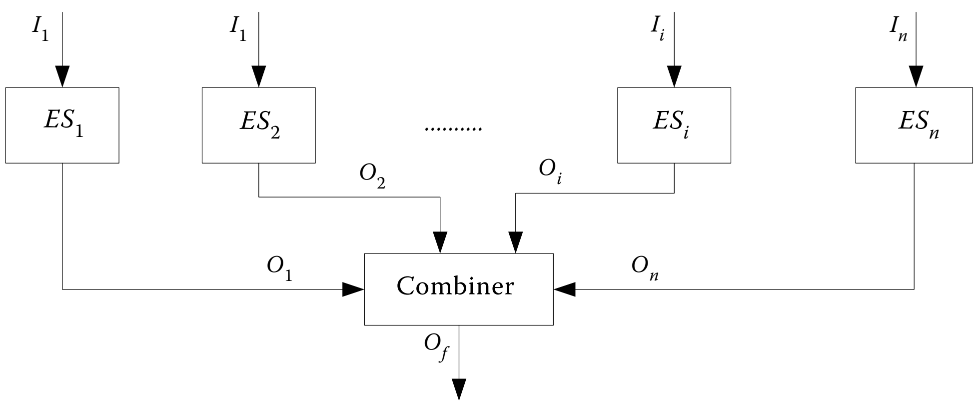

Figure 2. Multiple parallel expert systems

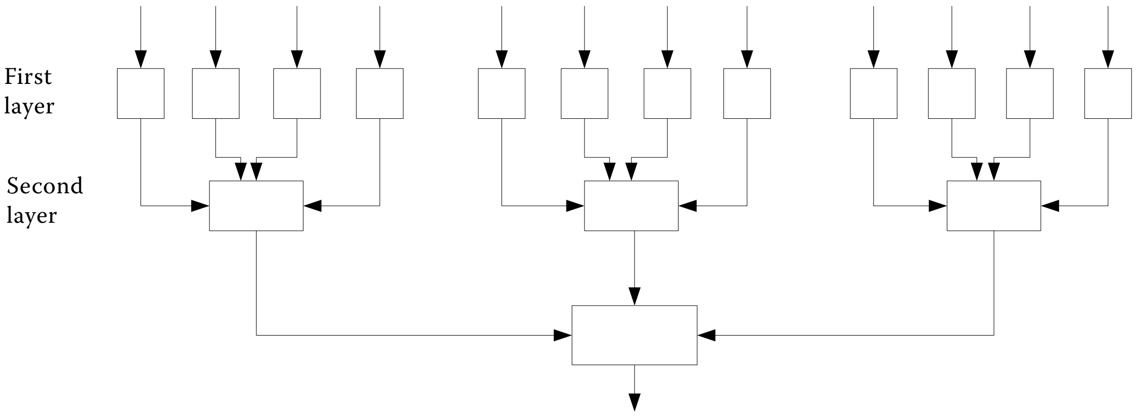

Figure 3. Layered groups of expert systems

the problem is how to combine the crisp outputs of multiple parallel expert systems to obtain such a representative consolidated output. Solving this problem specifically for fuzzy expert systems will be our concern in this research.

There are two possible structures for the parallel configuration: single layer (Figure 2) and multi-layer structure (Figure 3).

(c) Combination
Hybrid: Parallel of series ESs or series of parallel ESs.

Fuzzy Expert System (FES)

The system consists of four components: a fuzzification subsystem, a knowledge-base, an inference mechanism, and a defuzzification subsystem which converts the implied fuzzy sets into *crisp values* expressing the YES/NO decisive degree (Figure 4). The special concern around fuzzy expert systems is attributed to their wide applicability and use due to their capability to treat vagueness, and subjectivity. Especially important is the possibility to convert subjective non-sharp factors into the corresponding easily manageable and comprehensible numerical scale. More description of the fuzzy set theory and FES can be found in (Zadeh 1965; Kilagiz et al. 2005).

The Analytical Hierarchy Process (AHP)
(Dweiri, Meier 1996; Saaty 1980)

AHP is a basic approach to decision making. In this process, the decision maker carries out simple pair-wise comparative judgments, which are then used to develop overall priorities for ranking alternatives, factors or criteria. The AHP allows for inconsistency in the judgments and provides a mean to improve consistency. The decision makers assign an importance intensity value from the fundamental scale shown in Table 1, which represents the true preference of each reason with respect to another reason. The importance intensity of factor (also criterion, or alternative) i over j is denoted by a_{ij}, and the reciprocal importance intensity of factor j over i is denoted by $a_{ji} = 1/a_{ij}$, and $a_{ji} = 1$, if i = j. It is clear that a_{ij} is greater than 1 if factor i is more important than factor j, and is less than 1 if factor i is less important than factor j.

The AHP procedure, suggested by Saaty in 1980, is as follows Dweiri, Meier (1996):

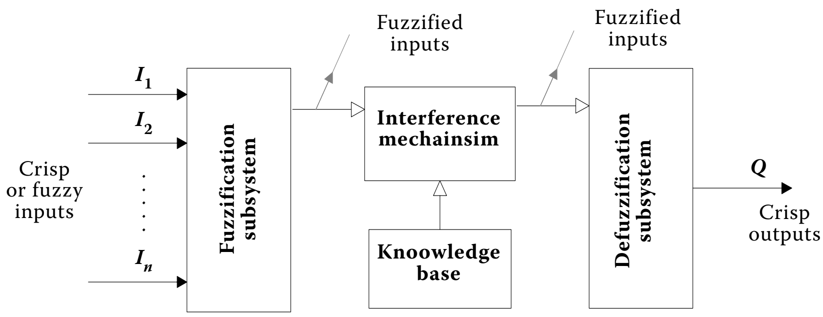

Figure 4. The structure of fuzzy expert system

Table 1. The fundamental scale of AHP importance intensity value.

Importance intensity a_{ij}	Definition
1	Equal importance of *i* and *j*
2	Between equal and weak importance of *i* over *j*
3	Weak importance of *i* over *j*
4	Between weak and strong importance of *i* over *j*
5	Strong importance of *i* over *j*
6	Between strong and demonstrated importance of *i* over *j*
7	Demonstrated importance of *i* over *j*
8	Between demonstrated and absolute importance of *i* over *j*
9	Absolute importance of *i* over *j*

(1) Develop the importance intensity matrix **A**:

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}$$

Where:
n = the number of factors or alternatives to be compared.

(2) Finding vector (**P**) of priorities of factors, P_i:
- (a) Multiplying the n elements in each row in the intensity importance matrix by each other. The result is the vector ($\mathbf{X}_i$).
- (b) Taking the nth root of the vector ($\mathbf{X}_i$) for each row. The result is the vector ($\mathbf{Y}_i$).
- (c) Normalizing by dividing each number in the vector ($\mathbf{Y}_i$) by the sum of all the numbers, ΣY_i. The result is a vector (**P**).

(3) Determining the consistency of judgments:
- (a) Finding the vector **F** by multiplying matrix **A** by vector **P**.
- (b) Dividing every F_i by P_i to determine Z_i.
- (c) Summing Z_i, and dividing by n to obtain the maximum eigen value = λ_{max}, which is the average.
- (d) Computing the "consistency index", ${}^iC = (\lambda_{max} - n)/(n - 1)$.
- (e) Finding the "random index", ${}^iR$ from the Table 2, for the corresponding number of compared factors, n.
- (f) Computing the consistency ratio ${}^rC = {}^iC/{}^iR$. Any value of ${}^rC \leq 0.1$ is considered an acceptable ratio of consistency.

See Saaty (2001) for more details.

We shall utilize AHP in our proposed approach to weigh the importance of every fuzzy expert system in the matched set.

Literature review

Related to the issue of knowledge and expertise aggregation are some articles that were conducted in the following scientific fields: pattern recognition (Mak et al. 1996; Trout et al. 1997; Kittler et al. 1998, Constantindis et al. 2001), agents integration and blackboards architectures (Venkatasubramanian, Chen 1986; Engel et al. 1990; Ritchie 1990, Huang 2003), group decision making (GDM) and group decision support systems (GDSS) (Ölcer, Odabai 2005; Turban, 1990), information processing (Major, Ragsdale 2000).

It should be noted that group decision techniques (Jessup, Valacich 1993), from simple majority rule to more elaborate techniques, are available for combining knowledge and can be applied to our case of combining multiple parallel FESs, but they are unsuitable in case of existence of restricting requirements, the case which we address here in this research.

In this research, we shall proceed beyond the formerly presented results. We present algorithms to illustrate how to combine the outputs of multiple parallel FESs in different possible cases of problem structure. We argue that the simple weighted average formula commonly used to combine the multiple expertises is not always adequate in the presence of some requirements like the need to preserve the extremes. We provide practical suggestions for how a group of requirements, which are truly imposed requirements of a current project, could be satisfied.

Table 2. The random index ${}^iR$ versus the number of factors assessed

N	1	2	3	4	5	6	7	8	9	10	11	12
${}^iR$	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.58

THE PROPOSED APPROACH

In this section, we present several algorithms to combine and aggregate the outputs of multiple parallel FESs into a finally consolidated one. For each developed algorithm, we show how to satisfy a group of requirements, which are true requirements associated with the currently held project. These requirements are:

(1) Preserving the extreme values of the FESs outputs.
(2) Allowing for null expert systems, who are not willing or do not have sufficient knowledge to participate in the judgment process.
(3) Providing for related expert systems decisions.

First we structure the problem and divide it into two main case problems:

– Integrating multiple parallel fuzzy expert systems each of which holds or shares the same domain knowledge ("knowledge-equal" FESs); and
– Integrating multiple parallel fuzzy expert systems each of which holds a different or unique domain knowledge ("knowledge-unique" FESs).

Based on the current judgment problem, an adequate, relevant, and predefined group of FESs is selected. The problem is then either to *combine* the outputs of multiple expert systems acquiring or specializing in the same knowledge domain or to *aggregate* the outputs of multiple ones specializing in different, relevant domains of knowledge.

The basic difference between the two main problems is that, in the second case, different expertises corresponding to different aspects or views are necessary to be aggregated in order to comprehensibly tackle and solve the problem. In both main cases, we shall consider two sub-cases: the case of different relative importances, and the case of equal relative importances. Moreover, in every sub-case, the possibility of existing restrictions are treated (non-restricted and restricted problem sub-cases). Figure 5 shows the taxonomy of the structured integration problems. The proposed algorithms are described below for the two main case problems.

Integrating multiple parallel fuzzy expert systems each of which holds the same domain knowledge (referred as "knowledge-equal")

Here, several FESs share the same knowledge and participate in judging the YES/NO decision problem. They share the same knowledge, but incorporate different knowledge bases and, maybe, different relationships and variables, or may acquire different skills or processing tools. Accordingly, here we say combining the output values, more accurately than

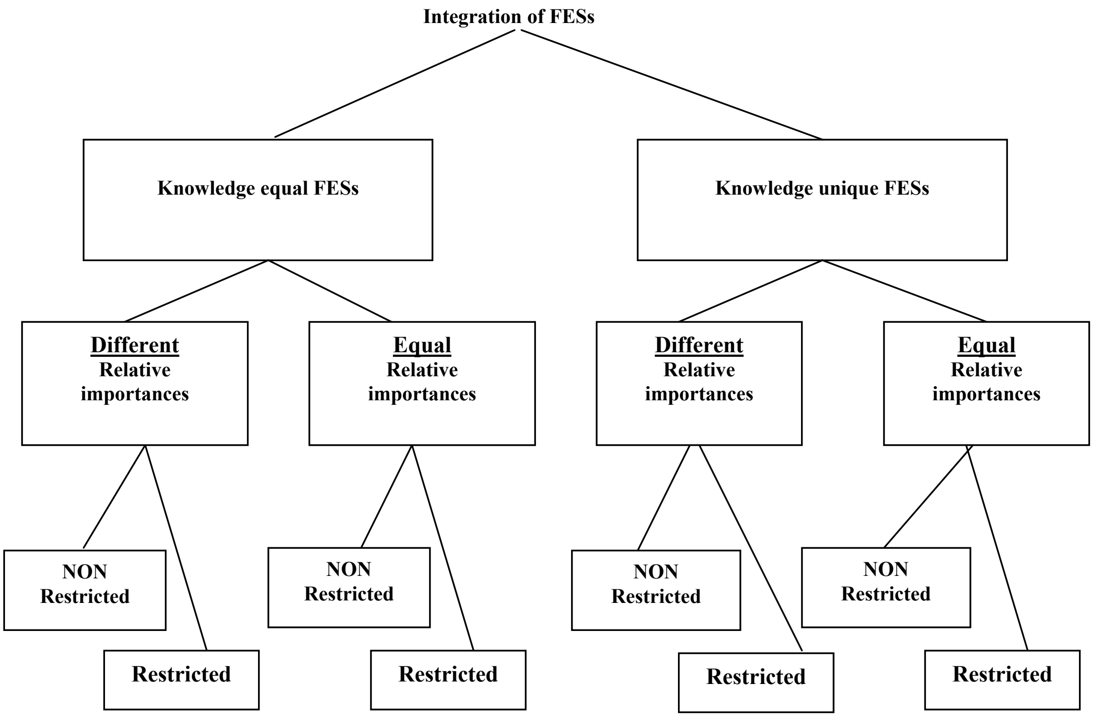

Figure 5. The structure of the integration problem

aggregating. For consistency requirements, the outputs of all fuzzy expert systems should be in between 0 to 10 or in any other similar, corresponding chosen scale. For the moment we chose the scale 0 to 10 as a representative, but it can still be changed. The value 0 represents the exact NO answer, and the value 10 represents the exact YES answer; any other value represents the bias toward either answer. There are two sub-cases: either every FES has a different relative importance or all the FESs is assumed to have the equal relative importances in making the decision. The algorithms to combine the outputs of FESs in both sub-cases are described below.

Combining knowledge-equal fuzzy expert systems with different relative importances

Let us denote:

O_i = the crisp output of the i^{th} FES.

W_i = the weight or priority of the i^{th} FES.

N = the total number of FESs within the predefined matched set.

O_f = the finally consolidated output for all FESs.

In our proposed algorithms, we will first consider the non-restricted case, in which no restricting requirements are imposed, and then the restricted case, in which a group of requirements mentioned previously, are imposed and should be satisfied.

Non-restricted case

Stage 1: Apply AHP to rank the matched FESs to obtain their priorities:
$W_1, W_2, \dots W_i, \dots, W_n$.

Stage 2: Calculate the weighted average to represent the finally consolidated output:

$$O_f = \frac{\sum_{i=1}^{N} W_i \times O_i}{\sum_{i=1}^{N} W_i} \qquad (1)$$

Then, the final output decision is YES if this final output value happens to be above the middle (5) and it is NO if the final output value happens to be below the middle. If the final value was exactly at the middle, it means no bias, then the decision solution cannot be attributed to YES or NO.

Restricted case

Preserving extremes

Generally, the extreme output values, which are far from the middle value, may represent a special importance. The weighted average formula does a smoothing effect on all output values, which in most cases causes the ignorance and loss of such extremes and consequently can lead in some cases to incorrect judgment, or at least information loss. So, it should be more seriously taken into consideration. We adjust the above procedure in order to satisfy this requirement. It is as follows:

Stage 1: Apply AHP to rank the matched FESs to obtain their priorities:
$W_1, W_2, \dots W_i, \dots, W_n$.
(This step is same as in the non-restricted case.)

Stage 2: Divides the expert systems' output values O_i into three distinct groups:

The first group, G_1:
contains all output values that are above the middle (> 5)
(biased to YES), O_i^+.

The second group, G_2:
contains all output values that are below the middle (< 5)
(biased to NO), O_i^-.

The third group, G_3:
contains all output values that are exactly at the middle (= 5),
O_i^m.

Stage 3: Sum the weights associated with the outputs for all FESs within each group to obtain the group sum of weights, SW_i: $SW_1 = \sum W_i^+$, $SW_2 = \sum W_i^-$, $SW_3 = \sum W_i^m$. Then, find the group G_{max} which has the largest weight and select its extreme output value among its output values O_k to be the final output. Formally stated as the following two equations:

$$G_{max} = \arg \max_j \{SW_j\} \qquad (2)$$

$$O_f = \underset{k}{\text{extreme}}\{O_k\} \qquad \forall\ O_k \in G_{max} \qquad (3)$$

Then, again the final output decision is YES if this final output value happens to be above the middle (5) and it is NO if the final output value happens to be below the middle.

If all sums of weights are equal, here only use the weighted average criteria to obtain the finally consolidated, combined output. Here the algorithm logically adheres to the group, which has the maximum importance (maximum sum of priorities); it accepts its direction opinion, and then it catches the extreme of such group of experts. Also, if the most important group happens to be that group which contains the middle values, then according to such most important group the decision solution cannot be attributed to YES or NO.

Allowing for null experts

In some situations, some FES have some reasons for not to participate, for instance due to insufficient knowledge or incomplete information, or any others. We would like to assess or include the effect of such null or idle FES in the final decision. We can satisfy this requirement by considering the output of such FES as exactly at the middle, equal 5, which means not YES and not NO. Here we have allowed for null case and allowed it to influence the solution.

Providing for related expert systems decisions

In certain circumstances, we find that some expert systems' opinions are related. In other words, the domain knowledge of an expert system is related to the domain knowledge of another one in making the decision, or it may be more useful or necessary to investigate some expert systems' decisions in a preceding stage before combing them with other reminders in the total group. Special considerations should be put to this circumstance. Our suggestion is to reflect logically the effect of the mutually related expert systems and to combine their outputs separately (Figure 6). It logically follows that if two or more expert systems' decisions are related, so in case of their agreement, this should reinforce their direction opinion; and if their outputs do not agree, then their direction opinions are weakened. How to express that in form of numerical values? We suggest simple, logical, mathematical formulas to accomplish that. In case of agreement of two or more experts' opinions, there are two possible cases; the first case in which the combined output values are all above the middle value of the chosen output scale, 5 (i.e., toward the Yes decision direction). In this case, we need a formula which slightly gives a larger resultant values than the combined output values, and that means positively reinforcing or strengthening the agreeing opinions. In the second case of opinions agreement, the combined output values are below the middle value. In this case, we need a formula that reinforce the opinions but in the other direction opinion (i.e., toward the No decision direction); that is the formula which gives a resultant value that is less the combined ones in order to further strengthen their direction. On the other hand, in case of disagreement, that is the experts' opinions are split toward disparate direction opinions, what is needed here is to decay or weaken both direction opinions due to the effect of opinions conflict, to obtain a compromising resultant value. Three simple mathematical formulas are used to approximate our intention and to mathematically express the above ideas of introducing the effect of mutual relatedness.

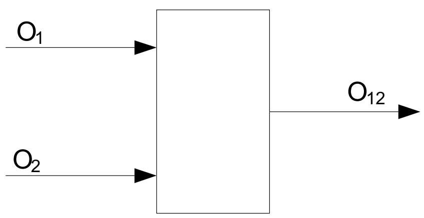

Figure 6. Combining related expertise's

Simply, for two related expert systems FES_1 and FES_2 producing outputs O_1 and O_2 respectively, there are two possible circumstances:

In case of agreement: there are two sub-cases:

Positive reinforcement: the two output values are above the middle. In this case, we suggest to use the Root Mean Square formula, which slightly magnifies the values of two positive numbers, giving a resultant or combined reinforced output, as in equation 4.1:

$$O_{12} = \sqrt{(O_1)^2 + (O_2)^2} \tag{4.1}$$

Negative reinforcement: in contrast with the previous case, it happens if the two output values are both below the middle. In this case, we suggest to use the Square Root formula, which approximates this intention, and slightly decreases the values of two positive numbers obtaining a value that is always slightly less than both numbers, giving a resultant or combined reinforced output, as in equation 4.2:

$$O_{12} = \frac{\sqrt{O_1 + O_2}}{2} \tag{4.2}$$

In both circumstances, the associated combined weight is the sum of their importances:

$$W_{12} = W_1 + W_2 \tag{5}$$

In case of disagreement: it is only one circumstance, in which the two related opinions are disparate. In order to combine the two outputs, we use the Arithmetic Mean formula, which slightly attenuates both positive numbers giving a resultant compromised output as in the following equation:

$$O_{12} = \frac{O_1 + O_2}{2} \tag{6}$$

The resultant weight is computed again the same as in equation 5. The same formulas apply for more than two related FESs.

Combining knowledge-equal fuzzy expert systems with equal relative importances

This is a special case of the previous one. All FESs have the equal importance to the decision making problem. Here we don't have any guiding weights to express the relative importances of different expert systems. All FESs are assumed to have equal absolute weights. Here is no additional information to distinguish the various FESs' outputs.

Non-restricted case

The general procedure to use is the arithmetic average:

$$O_f = \frac{\sum_{i=1}^{N} O_i}{N} \tag{7}$$

Restricted cases

Preserving extremes

Here, the same algorithm in case of different expert systems' weights is utilized, except that all weights are now equal: $W_1 = W_2 = ... = W_i = ... = W_n = 1/n$.

Allowing for null experts

It is same like in case of different weights; the output of null expert systems is set at the middle, 5.

Providing for related expert systems' decisions

The same equations 4.1 through 6 apply.

<u>Integrating multiple parallel fuzzy expert systems each of which holds a unique domain knowledge</u> (referred as "knowledge-unique")

Complex problems usually require a diversity of knowledge and expertises in order to cope with their difficulty and to grasp and comprehend all of their subtle details. Here, every fuzzy expert system represents a unique distinctive knowledge and expertise of specialization areas, and the solution of the complex problem (i.e., the decision YES/NO) is reached by investigating and considering multiple aspects or viewpoints each of which is related to one such specialization area. In order to completely and effectively address the problem, different expertises pertaining to different fields or domains must be exploited. Accordingly, the problem of integrating multiple parallel FESs should be referred to as aggregation more accurately than combination, since here we aggregate or accumulate multi-aspect, different expertises and knowledge participating and contributing to obtaining finally consolidated output decision. Similarly as before, there are two sub-cases. The first case is when the multiple FESs have different relative importances to the decision problem. In the second case, all FESs have the equal relative importances. Below we investigate both sub-cases and provide for the aforementioned requirements satisfaction.

Aggregating knowledge-unique fuzzy expert systems of different relative importances

In this case, we have multiple different expertises having different relative importances. The decision problem itself requires such multiple different views to be fully and comprehensibly tackled. Every expertise or expert system added something or some part to the finally desired decision solution. It logically follows that aggregating the knowledge of such different expertises is equivalent or analogous to summing or accumulating (not averaging) the crisp numerical outputs representing the opinion of every FES. Our proposed algorithm below expresses how to mathematically and formally convey this notion.

Non-restricted case

Stage 1: Apply AHP to rank the matched FESs to obtain the weights or priorities of each: W_1, W_2, ..., W_i, ..., W_n.

Stage 2: Establish a numerical scale from 0 to an arbitrary maximum chosen value, Max, to represent the decisive degree between YES and NO decisions. The value 0 corresponds to NO, and the value Max corresponds to YES. The middle value of such total scale is denoted Mid.

Stage 3: Apportion the total numerical scale established in the previous stage into smaller numerical scales allocated to every FES in proportion to its computed priority, as follows:

$$S_i = W_i \times Max \tag{8}$$

S_i = the maximum value of the output scale of the i^{th} FES.

Then, the crisp output of each i^{th} FES is evaluated within the allocated numerical scale, from 0 to S_i.

Stage 4: Given the crisp output of each FES, accumulate expertises by summing all crisp outputs to given the finally aggregated output of all FESs (equation 9):

$$O_f = \sum_{i=1}^{N} O_i \tag{9}$$

Then, if this finally aggregated output value happens to be above Mid, the middle of the total scale, then the answer is YES; if it was below the Mid, then the decision is NO. If the final value was exactly at the middle, it means no bias, and then the decision solution cannot be attributed to YES or NO.

Here, we should add expertises not to average them, because the problem essentially has multiple aspects, each aspect participates in giving a contribution about the form of decision. This algorithm accumulates the expertises, which is logically based on the addition of various domain expertises. The decision is YES if there is a bias arising from all domain expertises to YES, and similarly it is NO if there is a bias arising from all domain to NO.

Restricted cases

Preserving extremes

This algorithm does not impose any smoothing effect, like arithmetic average or weighted average formulas it only adds outputs, so here the extreme values are already preserved.

Allowing for null experts

The output of null FES expert systems is set at the middle of its allocated, corresponding scale.

Providing for related expert opinions

The multiple FESs essentially represent unique domain expertises. The mutual relatedness or interactions among them are in most cases non-existing, but if it happens that some domains are mutually related, their output numerical values are still aggregated. It means that the effect of their mutual relatedness is still naturally included. An attempt to emphasize such effect in case of different sizes of allocated scales for each domain expertises can lead to inconsistencies and complications. But it can be investigated in future researches. For simplicity, here we assumed that the different, unique expertises do not have any mutual decision relatedness; they only contribute in judging the same decision problem with no mutual influence or interaction.

Aggregating knowledge-unique fuzzy expert systems of equal relative importances

Non-restricted case

In this case, the algorithm used in case of aggregating multiple FESs having different weights is adjusted. We begin the algorithm directly from stage 2, without computing priorities, and execute the algorithm with the exception that equation 8 is adjusted as follows:

$$S_i = \frac{\text{Max}}{N} \qquad i = 1, 2, \ldots, N \qquad (10)$$

Where:
N = the total number of FESs within the predefined matched set.

Restricted case

The first two requirements are to be satisfied in the same way as in the first case of existing different relative importance's, and the last requirement; that is providing for related decision of expertises again becomes irrelevant under the assumption that the multiple matched set of unique-knowledge FESs have no mutual relatedness in making the decision, and have no mutual influence or interactions as well.

THE ECONOMIC ASPECTS AND IMPACT OF THE PROPOSED RESEARCH

Complex decision making problems confronted in industrial, business and agriculture domains usually require multiple and diverse sources of knowledge and expertises to cope with non-structured, stochastic, vague, subjective features inherent with majority of these problem. Consequently, efficient and effective integration of adequate intelligent systems, like in our case, fuzzy expert systems could be one way to obtain high quality, reliable and practical decision solution. The direct economical impacts and results of high quality reliable decision solutions are usually a reduction in expenses, or elimination of loss in labor, energy, material, equipments, and other scarce economical resources depending on the nature of decision making problem in hand. The YES/NO decision problems are usually confronted in the economical environment, and the results that follow it in most cases are economically crucial that can lead either to realization of profit and gains, or to causing economic loss. Consequently, reliable integrative schemes are often needed in order to avoid loss or attain profit. Our proposed algorithm helps practically to integrate multiple intelligent systems in order to acquire an economically successful integrated decision making system.

CONCLUSION

This research has addressed one of the complex problems that have not received an adequate attention before; that is the numerical integration of multiple, fuzzy expert systems, or generally multiple expertises or knowledge sources. In most cases, the weighted average criteria or simply arithmetic average formulas have been utilized to combine numerical values of multiple ESs or knowledge sources with associated limitations: most of the previous research does not rely on rigorous method to estimate absolute weights, like AHP, and ignore inherent varying requirements like preserving extreme values, and providing for non-participating experts. The most widely used weighted average formula causes smoothing effect and information loss; but generally it can be applied when there is no imposed requirement of preserving extremes. It is noticeable that our developed approach is integrative with the use of the widely utilized *fuzzy* expert systems, since it is rather difficult to combine a group of non fuzzy-based ESs producing subjective binary answer, YES/NO, without converting this subjective judgment into a corresponding numerical scale, which is facilitated with FESs. It is obvious how the conversion of subjective answer YES/NO into a numerical scale (e.g. from 0 to 10) provides the area to handle different requirements and to express non-sharp subjective measures, since the answer YES/NO is always neither sharp YES nor sharp NO. Finally, the proposed approach is simple, practical and computationally not expensive.

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