Aggregate experts knowledge in Fuzzy Cognitive Maps

Giovanni Mazzuto, Maurizio Bevilacqua
Dipartimento Ingegneria Industriale e Scienze Matematiche
Università Politecnica delle Marche
Ancona, Italy
(g.mazzuto@univpm.it; m.bevilacqua@univpm.it)

Chrysostomos Stylios
Laboratory of Knowledge and Intelligent Computing (KIC), Department of Computer Engineering
Educational Institute of Epirus
Arta, Greece
(stylios@teiep.gr)

Voula C. Georgopoulos
School Health and Welfare Professions
TEI of Western Greece
Patras, Greece
(*voula@teiwest.gr*)

***Abstract*— In the last years, increased attention has been paid to the use of experts' opinions as concerned with the decision-making process and problem solving. Several approaches for aggregating them have been analysed but the literature review has highlighted that the experts' credibility in many cases is neglected. Thus, the present study aims at developing a novel approach for Fuzzy Cognitive Maps modelling, described in the literature as the unique methodology able to aggregate individuals knowledge and beliefs, combining a group decision-making technique, such as the Aggregation of Individual Evaluations one, and a structured credibility evaluation method according to the expertise areas of each expert. In particular, using a numerical example, the comparison between the traditional outcomes and those of the proposed method, highlights how the second one allows to obtain results more concordant with the single experts judgements than the first one, criticized of smoothing the experts opinion excessively.**

Keywords*— *Expert credibility; Fuzzy Cognitive Maps; Group decision-making; Expert opinion aggregation.

I. INTRODUCTION

More and more often, companies, organisations and people make decisions following some form of group decision-making (GDM) process. Indeed, the complementary skills of each group member allow the team to present and examine issues from various angles and see the implications of their decisions from a variety of perspectives [1]. Generally, the group share the same common objective, but since everybody of its members has only a partial knowledge on any considering problem, many conflicts of interests and perspectives may occur. Reaching an overall consensus on the solution is one of the most important steps in the decision-making process [2]. This is the reason why many researchers, in various fields, focus their attention on this problem starting from the experts' judgements credibility evaluation [3], because group members' credibility may need to be weighted [4] and then to be aggregated. Within the social sciences context, many studies have examined various approached on credibility evaluation. Bottoms and Goodman [5] performed a series of experiments how to identify the main relevant factors affecting children's credibility witness about sexual abuse. Greene and Dodge [6] analysed how to evaluate the testimonies' credibility with respect to the juror decision-making process and many others. More recently, Brodsky et al. [7] realised a Witness Credibility Scale, based on four main factors in order to measure the witness' credibility, which is also useful for evaluation of instructors, managers, or even political candidates.

On the other hand, there is a wide discussion about aggregation methods but quite limited research works have been published about the credibility evaluation process. There has been proposed a method to combine experts' opinions on how to evaluate the uncertainty inherent in accident management using a fuzzy probabilistic approach so that to make the opinions comparable [8]. Another approach [9] introduced linear opinion pooling aggregation method (explained in detail at [10]) on how to create a multi-agent expert system for finding matching services in the case of selection process planning.

Another procedure for structuring and combining experts' knowledge aggregation, mainly coming from social sciences, is cognitive mapping [11] and, in particular their extension Fuzzy Cognitive Maps [12].

In most of cases, although the experts' opinion is still considered, the experts' credibility factor is neglected. For example, Yedla and Shrestha [13] avoid the experts' evaluation for the judgement of aggregation implementing different mathematical equations for the analysis of the urban transport sector, using the Analytic Hierarchy Process (AHP). Another approach is proposed by Kubler [14], based on a scenario of data dissemination using intelligent products. In particular, all the provided judgements of all expert opinions are aggregated through a uniform fuzzy set, in which the lower and upper limits are respectively the lower and upper opinions. This means that the resulting fuzzy set expresses equal importance for all the opinions.

978-1-5090-6020-7/18/$31.00 ©2018 IEEE

From the literature review, even though the mentioned list is not exhaustive, it is quite clear that there is a great interest for the experts' opinion aggregation while highlighting little attention to the experts' credibility. However, in most approaches where credibility values have been used, a unique weight value is considered, which is subsequently modifiable. Conversely, using a unique credibility value for each expert, this is the main weakness of the method. In fact, in the case that a single expert has been judged "extremely" ("scarcely") credible, his/her judgements will be "extremely" ("scarcely") credible also for those research areas in which he/she does not have enough knowledge (has a great knowledge). Thus, this approach does not take into consideration that usually experts have various knowledge expertise in specific subdomains, unable to cover the whole problem domain [15]. Moreover, there would be applied adaptation algorithms such as the consensus scheme [16] or the procedures for constructing an optimised consensus [17] to obtain suitable outcomes. Indeed, this research work aims at developing an alternative aggregation model for the FCM modelling since, according to [18], FCMs have been proposed as a unique methodology able to aggregate several knowledge to represent a "scaled-up" version of individuals' knowledge and beliefs. Thus, it starts from the Aggregation of Individual Evaluations method [17], where a Group Decision Making (GDM) is used, a structured approach for the experts' credibility evaluation according to their expertise area has presented.

This the paper is structured as following: Section II describes the theoretical background about the FCMs, the Aggregation of Individual Evaluations method and the proposed approach. Section III briefly explains a numerical example in order to comprehend the system outcomes, collected and discussed in Section IV. Finally, Section V summarises the study conclusions with suggestions for further expansions and explanations.

II. Materials and Methods

A. The FCM basic notions

Cognitive maps where introduced and thought to represent concept maps reflecting mental processing, comprised of collected information and several cognitive abstractions, individually filtered, about physical phenomena and experiences [11]. Cognitive maps are visual representations of an individual's "mental model", which are constructions analogous to concept maps for representing human reasoning, knowledge or beliefs. If a generic problem is considered, and an experts' panel is formed for its in-depth analysis, since different individuals may face the same problem from various perspectives, depending on their own area of expertise and their cultural/geographical background, then a suitable model could be a collective FCM identifying concepts and relationships about the considered problem. In particular, concepts are the FCM key elements and thety stand for the main characteristics of the abstract mental model for whichever complex system. Once concepts are identified, experts are asked to assign a linguistic weight value, which is transformed into a numerical w_{ij} weight (the weight describing the relation from concept *i-th* towards *j-th* concept) that form the overall *W* matrix, which gathers all the weights representing the influence among all concept C_i of the Fuzzy Cognitive Map. The weight values ranges in the interval $[-1, 1]$. Specifically, $w_{ij}=0$ indicates no causality between the two concepts; $w_{ij} > 0$ indicates causal C_j increases as C_i increases (or C_j decreases as C_i decreases), and $wij<0$ indicates causal decrease or negative causality: C_j decreases as C_i increases (and or C_j increases as C_i decreases).

B. The collective FCM modelling

There are quire many studies with respect to the dynamical representation of FCMs, but with concern to the experts' opinions aggregation for gathering the collective weights matrix, the provided fuzzy experts' estimations are aggregated using the SUM method [19] and, then, an overall linguistic weight is evaluated using the centre of gravity (COG) defuzzification method [20]. Some examples are [21], [22], [23] where a unique credibility value is assigned to each expert and a threshold function is used in the aggregation of the suggested weights.

On the other hand, [24] and [25] introduced a corrective factor for an experts' credibility weight when his/her judgement is too much discordant with the others. This however, does not take into consideration the fact that in a complex multidisciplinary problem most experts have deep knowledge of parts of the problem and not the entire problem. In order to neglect the impact of expert credibility on the FCM modelling, [26] considers different groups, homogenous in knowledge so as to not consider any credibility value in the mathematical formulation.

C. The FCM behaviour analysis

Once the total weights matrix, *W,* has been determined, it is possible to analyse the system behaviour through simulations. Thus, if A_i defines the instantaneous value of concept C_i, its evolution over time can be evaluated computing the influence of the interconnected concepts C_j on the specific concept C_i according to (1):

$$A_i^{k+1} = f\left(A_i^k + \sum_{j=1}^{n} A_j^k w_{ji}\right) \quad (1)$$

where A_i^{k+1} is the value of concept C_i at simulation step $k+1$, A_j^k is the value of concept C_j at simulation step k, w_{ii} is the weight of the interconnection from concept C_j to concept C_i and f is an appropriate threshold function, used to force the concept value to be monotonically mapped into a normalised range [27]. Other equations can be used in place of (1) as suggested by [28] and [29].

In the area of FCMs modelling, a novel expansion was the introduction of evaluation parameters such as the Indirect Effect (**IE**) and Total Effect (**TE**) [11, 22, 23], allowing precise analysis of the map, just as cognitive maps. The indirect effect is defined -by (2):

$$IE_k(C_i, C_j) = \min\{e(C_p, C_{p+1}\} \quad (2)$$

The calculation is based on reports of lower intensity. $I_k (C_i, C_j)$ indicates the path (or paths) between concepts C_i and C_j. In

particular *p* and *p+1* are indices of all the concepts that form the path amongst the nodes C_j and C_i. The total effect (given by the relation of higher intensity) is instead given by (3):

$$TE(C_i, C_j) = \max\{|I_k(C_i, C_j)|\} \quad (3)$$

The Total Effect (TE) is calculated considering the Indirect Effect (IE) absolute value and, then, the relative sign. In particular, a positive TE means that each indirect effect is also positive; a negative total effect implies that each indirect effect is also negative. In other cases, it is possible to identify indeterminate effects of some concepts if, in presence of several paths, some of them has positive indirect effects and others negative [12]. This means that the identified concepts have to be analysed in-depth since, according their concatenations, they can have different influence on the system.

Reference [30] gives a well explanation about the meaning of the Indirect and Total effects using the "weak ring in the chain" metaphor. Indeed, each possible path between two concepts can be identified as a chain. Each chain has a relative hardiness value equal to the hardiness of its weakest ring that is the IE for this specific path. Hence, the IE expresses the effect of each concept on a specific top-event through all the possible concatenations impacts. At this time, if it is necessary to choose what kind of chain it is suitable to use, the most relevant impact for a concept on the top-event, the chain with highest hardiness value will be used and it means that, according to the value of hardiness derived by equation (2); and equation (3) allows to define the most resistant chain. In so doing, the chain hardiness identifies the relevance of the first concept in the concatenations on the top event through the TE value.

D. The Aggregation of Individual Evaluations method

According to [17], each expert provides their own linguistic estimates for each alternative, taking into consideration different criteria. Afterwards, all of the singular estimates are grouped into a collective one per criterion and, using different methods for multi-attribute analysis, so that it is possible to identify the final alternatives ranking. Specifically, the collective fuzzy estimates $F_p^C(X_k)$ for each criterion is given in equation (4).

$$F_p^C(X_k) = \sum_{y=1}^{v} \omega_y F_p^y(X_k) \quad (4)$$

Where *p* is *p*-th considered criterion, *y* is the *y*-th considered expert and X_k represent the k-th alternative to be analysed. Moreover, ω_y is the credibility value related to the *y*-th expert with the condition that the sum of all the experts' weights is equal to one.

Having at hand a collective evaluation matrix of alternatives, it is possible to construct fuzzy preference relations per criterion and, they can be analysed using several discrete models of multi attribute decision-making such as those proposed by [31] and [32].

E. The proposed approach

The proposed approach revises and expands (4) so as to model an FCM as expressed in equation (5):

$$FCM_{i,j}^C(X_{i,j}) = \sum_{y=1}^{v} \omega_y FCM_{i,j}^y(X_{i,j}) \quad (5)$$

where *X(i,j)* is the relation between concepts C_i and C_j, $FCM^y_{i,j}(X_{i,j})$ is the fuzzy estimate of the relation strength between concepts C_i and C_j considering the *y*-th expert and where the ω_y correspond to the credibility value related to the *y*-th expert.

However, considering ω_y as a unique constant value means that an expert can cover the whole problem domain with the same credibility, neglecting that an individual could have vague information about alternatives and, consequently, cannot estimate his/her preference in the same way all the time [15]. Hence, if a single expert has been judged "extremely" ("scarcely") credible, his/her judgements will be "extremely" ("scarcely") credible also for those areas of which he/she does not have knowledge (has a great knowledge).

In order to overcome this weakness, in the proposed approach, the set of FCM concepts have been categorised by expertise area so that each expert's credibility is evaluated with respect to them. This means that ω_y will not be a unique constant value but an array (6), ω_y^{ea}:

$$\bar{\omega}_y^{ea} = \left[\omega_y^{ea,1} \quad \omega_y^{ea,2} \quad \dots \quad \omega_y^{ea,n}\right] \quad (6)$$

Where n is the number of district defined expertise areas and $\omega_y^{ea,i}$ is the credibility value for the *y*-th expert with respect to the *i*-th area, obtained by the aggregation and, subsequently, the defuzzification of the experts' estimate for each member. In order to identify an expert's credibility value, according to [33], a participatory approach has been used as no group accepts evaluation by an external agency for a lack of confidence. Since, an external agency doesn't have enough knowledge about the single expert expertise and the group dynamics, after an introductory meeting, experts have been asked for a cross evaluation of the other ones.

However, the ω_y^{ea} array has to be again revised since for each relationship, concepts C_i and C_j can or cannot belong to the same expertise area. Thus, considering the (5), if the concepts C_i and C_j belong to same expertise area, the weight that has to be taken into account; will be that expressed by the expert credibility value referred to the concerned area. Otherwise, if C_i and C_j belong to different expertise area the relative value of expert's credibility can be calculated as the min, max or mean value between those weights related to the areas for each concept in the relationship. For example, the mean value can be used when equal importance is conferred on each expert. Moreover, [34] gives a general technique for data fusion and or knowledge combination.

Finally, the credibility value for each expert is an (*n x n)* symmetric matrix, described in equation (7):

$$\overline{\overline{\omega_y^{ea}}}(ea_i, ea_j) = \begin{bmatrix} \bar{\omega}_y^{ea,1} & \cdots & \text{mean}(\bar{\omega}_y^{ea,1}, \bar{\omega}_y^{ea,n}) \\ \vdots & \ddots & \vdots \\ \text{mean}(\bar{\omega}_y^{ea,1}, \bar{\omega}_y^{ea,n}) & \cdots & \bar{\omega}_y^{ea,n} \end{bmatrix} \quad (7)$$

Thus, equation (5) could be modified in equation (8):

$$FCM_{i,j}^{C}(C_i, C_j) = \sum_{y=1}^{v} \overline{\overline{\omega_y^{ea}}}(ea_i, ea_j) \cdot FCM_{i,j}^{y}(C_i, C_j) \quad C_i \in ea_i \text{ and } C_j \in ea_j \quad (8)$$

In conclusion, the proposed approach on constructing FCMs using a method based on introducing experts' credibility so that to provide better modelling is well expressed by equations (6), (7) and (8). In the following sections, an explanatory paradigm will better illustrate the proposed construction approach.

III. An Example on Developing FCM for the Healthcare Sector

Here a case study coming from the healthcare sector, is examined. The study was performed at a small Italian hospital that offers services of cardiology, general surgery, vascular surgery, general medicine, neurology, oncology etc. and the experts' panel is composed of three different professionals: a physician, a nurse and a pharmacy operator. The main objective of this example is modelling and analysis of the clinical risk in drug administration. Reducing the clinical risk refers to the possibility of designing and managing organizations that can both reduce the likelihood of errors (prevention) or to recover and mitigate the effects of errors that could still occur (protection).

The panel of experts collaborated under the consultation of a FCM engineer, for a period of about two weeks in order to outline and define the main concepts, which could describe and influence the drug administration, and then to design and develop the corresponding FCM based on these concepts. In particular, the first two meetings were dedicated in introducing the approach and promoting mutual acquaintance since they were chosen from different hospital wards. After these group meetings, every expert was asked to provide a personal evaluation on the expertise of the other ones experts using only the last five terms of the determined Likert scale.

In the following meetings, every expert was able to provide his own FCM on the specific case, using a fuzzy Likert scale with 9 terms, according to [35]. Then, the overall collective FCM was developed and refined for the considered problem.

Then, according to the fuzzy set theory, all of the provided evaluations have been aggregated in order to identify the ω_y^{ea} array and the relative matrix.

The evaluation phase was organised in two main steps. In the first one, each member provided a unique mark for him/herself and the others, as shown in Table I. In the second one, once the expertise areas were identified, the experts provided the marks according to them, as shown in Table II.

TABLE I. THE EXPERTS' SINGULAR EVALUATION (THE MEAN VALUES HAVE BEEN OBTAINED BY NORMALISING THE DEFUZZIFIED MEMBERSHIP FUNCTIONS)

	Expert 1	**Expert 2**	**Expert 3**
Expert 1	8	8	7
Expert 2	9	7	7
Expert 3	8	8	7
Mean value	0.42	0.32	0.26

In particular, three expertise areas were identified: "**Knowledge**" (ea^1), "**Procedures**" (ea^2) and "**Storage**" (ea^3).

TABLE II. THE EXPERTS' EVALUATION ACCORDING TO THE EXPERTISE AREAS

	Expert 1	**Expert 2**	**Expert 3**
Expert 1	[8, 8, 6]	[7, 9, 7]	[5, 7, 9]
Expert 2	[9, 8, 5]	[7, 7, 7]	[5, 5, 9]
Expert 3	[9, 8, 5]	[7, 9, 7]	[5, 5, 9]

Then, the main concepts of the FCM (see Table III) and the relationships among them have been identified and the collective FCMs have been designed.

TABLE III. THE LIST OF CONCEPTS (THE * IDENTIFIES THE FCM TOP-EVENT)

ID	**Concept Name**	**ID**	**Concept Name**
C1	Prescription Errors	C6	Knowledge Pathology
C2	Preparation Errors	C7	Drug Knowledge
C3	Administration Errors	C8	Bad procedures
C4	Mismanagement Drug	C9	Lack of Procedures
C5	Knowledge Therapy	C10*	Clinical Risk

IV. Results and Discussion

Specifically, two FCMs have been realised, according to the value reported in Tables I - III in order to compare the outcomes. Table IV shows an extract about the differences between the relationships obtained through the traditional approach (W_T) and those obtained with the proposed one (W_N); in particular, only the non-zero relations have been reported.

TABLE IV. THE RELATIONSHIPS WEIGHTS USING TRADITIONAL APPROACH (W_T) AND THE PROPOSED ONE (W_N)

Ci	**Cj**	W_T	W_N	**ΔW**	**ΔW%**
C1	**C2**	0,14	0,28	0,14	100%
C1	**C3**	0,21	0,35	0,14	67%
C1	**C8**	0,18	0,38	0,2	111%
C1	**C10**	0,21	0,41	0,2	95%
C2	**C3**	0,13	0,24	0,11	85%
C2	**C8**	0,17	0,29	0,12	71%
C2	**C10**	0,21	0,35	0,14	67%
C3	**C8**	0,13	0,26	0,13	100%
C3	**C10**	0,13	0,24	0,11	85%

The first evident outcome is about the relationships strength calculated with the proposed approach. Indeed, each relation has a value greater than the traditional weight. Specifically, the absolute difference between them is on average equal to 0.14 and, if the traditional approach is considered the comparison touchstone, it means that the strength obtained with equation (8) is greater than the traditional one by about 88%. The discrepancy concerning the relationships strength is more

evident analysing Fig. 1. The experts proposed some initial concepts values, which formed array A_0 that then simulated. We use the same initial concept values for the two FCMs, the one obtained with the traditional approach and, the other FCM designed with the proposed approach. Fig. 1 highlights a high criticality value for the considered top-event (C_{12}, Clinical Risk), on average 0.94, for as concern the personal experts' evaluations. On the contrary, the indicator value derived by the traditional collective FCM has a smaller value (0.33). Taking into consideration the simulation result derived by the FCM of the proposed approach, the convergent final situation is almost comparable (0.76) to the single evaluations.

Another observation can be derived also by analysing the TEs for the single expert FCMs and the traditional and proposed ones, which are presented at Table V. Indeed, considering that $Expert_1$, $Expert_2$ and $Expert_3$ belong to the $area_1$, $area_2$ and $area_3$ respectively, it is possible as is highlighted in Table V an under-estimation about their own expertise area. Indeed, the TE value with respect to their expertise area has always the minimum values (in bold).

On the contrary, while the traditional approach considerably decreases the TE, the proposed approach seems to behave such as a mediator function between the expert and the traditional TEs.

TABLE V: TOTAL EFFECTS COMPARISON

Totale Effects							
ID	***C_{area}***	***Ex 1***	***Ex 2***	***Ex 3***	***Mean Ex***	***Trad.***	***Prop.***
C1	1	**0,32**	0,46	0,46	0,41	0,21	0,41
C2	2	0,46	**0,32**	0,46	0,41	0,21	0,35
C3	2	0,46	**0,23**	0,46	0,39	0,13	0,26
C4	3	0,24	0,46	**0,12**	0,28	0,13	0,24
C5	1	**-0,36**	-0,64	-0,64	-0,54	-0,26	-0,46
C6	1	**-0,12**	-0,46	-0,24	-0,28	-0,13	-0,19
C7	1	**-0,32**	-0,46	-0,46	-0,41	-0,21	-0,41
C8	2	0,64	**0,36**	0,64	0,54	0,26	0,46
C9	2	0,46	**0,32**	0,72	0,50	0,21	0,35

The proposed approach reflects the single judgement of each expert from a collective point of view, taking into consideration different values with respect the specific expert relationship with the considered problem.

On the other hand, the behaviour of the traditional collective FCM flattened the judgements determining a result discordant if compared to the experts' considerations. Thus, according to the experts' opinion, the proposed approach for modelling a collective FCM is more suitable than the traditional one.

Moreover, Table V could allow to assert that, the described situation could be equal to consider an FCM composed of the mean values of each expert. On the other hand, Fig. 1 shows that considering the FCM with the experts' judgements mean values, the system outcomes result to have a convergence value lower than the proposed methodology one.

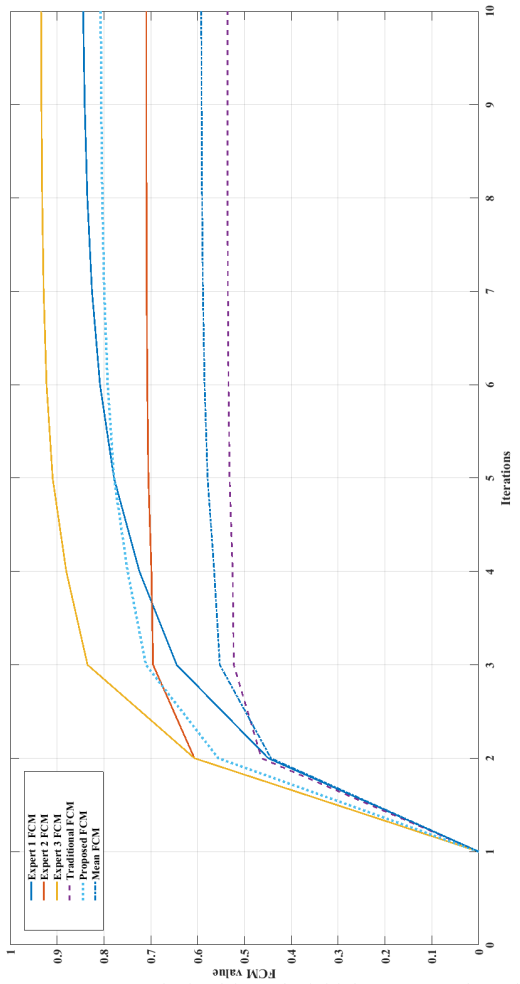

Fig. 1. The system outputs obtained from the initial array A_0 and considering the personal experts' FCMs, traditional FCM and the porposed one.

V. CONCLUSION

This work proposed a new approach developing FCMs, based on experts' credibility evaluation. In particular, conversely to the traditional approach, the expert credibility is not represented by a unique value but by a matrix composed of different values related to the expertise of each one of them about all the thematic areas involved for the concepts identification. In fact, each concept has been classified in specific expertise areas, according to the experts' experience and skills. Thus, the experts' credibility is evaluated according to these areas.

The comparison with the traditional outcomes has highlighted how the new calculation of the collective FCM allows obtaining results concordant with the single experts' judgements conversely to the traditional collective FCM that is criticized of smoothing the experts' opinion excessively.

According to [36], which provided a theoretical background to collect and interpret the FCMs outcomes when individual FCMs are aggregated, the aggregation techniques has to be further investigated. However, further development is going to be investigated on how the over/under estimations affecting the

experts' credibility calculations on the final collective FCM realisation and how they could be avoided or reduced. Moreover, the proposed approach has to be refined in order to avoid the negative effects of the group working due to possible conflicts among the panel of experts.

ACKNOWLEDGMENT

This work was performed when G. Mazzuto was a visiting researcher at Laboratory of Knowledge and Intelligent Computing, Dept. of Computer Engineering, Technological Educational Institute of Epirus, Arta – Greece.

This work is co-funded by project: "Enhancing research activities of Laboratory of Knowledge and Intelligent Computing" by Research Committee of TEI of Epirus.

REFERENCES

[1] Pedrycz, W., P. Ekel, and R. Parreiras, Fuzzy multicriteria decision-making: models, methods and applications. 2011: John Wiley & Sons.

[2] Lu, J. and D. Ruan, Multi-objective group decision making: methods, software and applications with fuzzy set techniques. Vol. 6. 2007: Imperial College Press.

[3] Rosqvist, T. and R. Tuominen, *Expert Judgment Models in Quantitative Risk Assessment.* International Atomic Energy Agency, Vienna, Austria, last accessed Feb, 1999. **12**: p. 2015.

[4] Peniwati, K., *Criteria for evaluating group decision-making methods.* Mathematical and Computer Modelling, 2007. **46**(7): p. 935-947.

[5] Bottoms, B.L. and G.S. Goodman, *Perceptions of children's credibility in sexual assault cases.* Journal of Applied Social Psychology, 1994. **24**(8): p. 702-732.

[6] Greene, E. and M. Dodge, *The influence of prior record evidence on juror decision making.* Law and Human Behavior, 1995. **19**(1): p. 67.

[7] Brodsky, S.L., M.P. Griffin, and R.J. Cramer, *The witness credibility scale: An outcome measure for expert witness research.* Behavioral sciences & the law, 2010. **28**(6): p. 892-907.

[8] Yu, D. and W.S. Park, Combination and evaluation of expert opinions characterized in terms of fuzzy probabilities. Annals of Nuclear Energy, 2000. **27**(8): p. 713-726.

[9] Fähndrich, J., Masuch, N., Borchert, L., and Albayrak, S., Learning Mechanisms on OWL-S Service Descriptions for Automated Action Selection. IoA'17@ AAMAS, 2017: p. 56.

[10] Genest, C., *Pooling operators with the marginalization property.* Canadian Journal of Statistics, 1984. **12**(2): p. 153-163.

[11] Axelrod, R., Structure of decision: The cognitive maps of political elites. 2015: Princeton university press.

[12] Kosko, B., *Fuzzy cognitive maps.* International journal of man-machine studies, 1986. **24**(1): p. 65-75.

[13] Yedla, S. and R.M. Shrestha, Multi-criteria approach for the selection of alternative options for environmentally sustainable transport system in Delhi. Transportation Research Part A: Policy and Practice, 2003. **37**(8): p. 717-729.

[14] Kubler, S., Derigent, W., Voisin, A., Främling, K., and Thomas, A., Methods of aggregation of expert opinions in the framework of intelligent products. IFAC Proceedings Volumes, 2013. **46**(7): p. 163-168.

[15] Herrera, F., E. Herrera-Viedma, and J.L. Verdegay, *A sequential selection process in group decision making with a linguistic assessment approach.* Information Sciences, 1995. **85**(4): p. 223-239.

[16] Ben-Arieh, D. and Z. Chen, *Linguistic-labels aggregation and consensus measure for autocratic decision making using group recommendations.* IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 2006. **36**(3): p. 558-568.

[17] Ekel, P., et al., *Fuzzy set based models and methods of multicriteria group decision making.* Nonlinear Analysis: Theory, Methods & Applications, 2009. **71**(12): p. e409-e419.

[18] Özesmi, U. and S.L. Özesmi, Ecological models based on people's knowledge: a multi-step fuzzy cognitive mapping approach. Ecological modelling, 2004. **176**(1): p. 43-64.

[19] Fang, J., *Sums of L-fuzzy topological spaces.* Fuzzy sets and systems, 2006. **157**(6): p. 739-754.

[20] Lin, C.-T. and C.G. Lee, *Neural fuzzy systems.* PTR Prentice Hall, 1996.

[21] Stylios, C.D., P.P. Groumpos, and V.C. Georgopoulos, *Fuzzy Cognitive Maps Modelling Supervisory Large Scale Control Systems.* IFAC Proceedings Volumes, 1998. **31**(20): p. 93-98.

[22] Bevilacqua, M., F.E. Ciarapica, and G. Mazzuto, *A Fuzzy Cognitive Maps Tool for Developing a RBI&M Model.* Quality and Reliability Engineering International, 2016. **32**(2): p. 373-390.

[23] Bevilacqua, M., F.E. Ciarapica, and G. Mazzuto, *Analysis of injury events with fuzzy cognitive maps.* Journal of Loss Prevention in the Process Industries, 2012. **25**(4): p. 677-685.

[24] Stylios, C.D. and P.P. Groumpos, *Modeling complex systems using fuzzy cognitive maps.* IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 2004. **34**(1): p. 155-162.

[25] Stylios, C.D. and P.P. Groumpos, *Fuzzy cognitive maps in modeling supervisory control systems.* Journal of Intelligent & Fuzzy Systems, 2000. **8**(1): p. 83-98.

[26] Ziv, G., et al., The potential impact of Brexit on the energy, water and food nexus in the UK: A fuzzy cognitive mapping approach. Applied Energy, 2017.

[27] Bueno, S. and J.L. Salmeron, *Benchmarking main activation functions in fuzzy cognitive maps.* Expert Systems with Applications, 2009. **36**(3): p. 5221-5229.

[28] Stylios, C.D., and Groumpos, P.P. (1999, June). *Mathematical formulation of fuzzy cognitive maps*. In Proceedings of the 7th Mediterranean Conference on Control and Automation (pp. 2251-2261).

[29] Osoba, O. A., and Kosko, B. Fuzzy cognitive maps of public support for insurgency and terrorism. The Journal of Defense Modeling and Simulation, 2017. **14**(1), 17-32.

[30] Bevilacqua, M., Ciarapica, F.E., Mazzuto, G., and Paciarotti, C, *Application of fuzzy cognitive maps to drug administration risk management.* IFAC Proceedings Volumes, 2013. **46**(7): p. 438-443.

[31] Orlovsky, S., *Decision-making with a fuzzy preference relation.* Fuzzy sets and systems, 1978. **1**(3): p. 155-167.

[32] Yager, R.R. Multicriteria decision making using fuzzy quantifiers. in Computational Intelligence for Financial Engineering, 1995., Proceedings of the IEEE/IAFE 1995. 1995. IEEE.

[33] Ramanathan, R. and L. Ganesh, Group preference aggregation methods employed in AHP: An evaluation and an intrinsic process for deriving members' weightages. European Journal of Operational Research, 1994. **79**(2): p. 249-265.

[34] Kosko, B. *Additive Fuzzy Systems: From Generalized Mixtures to Rule Continua*.Available online at http://sipi.usc.edu/~kosko/Fuzzy-Mixtures-to-appear-IJIS-11June2017.pdf, Last access 07/01/2018.

[35] Stylios, C. and V.C. Georgopoulos. Develop Fuzzy Cognitive Maps based on recorded data and information. in Fuzzy Systems (FUZZ-IEEE), 2015 IEEE International Conference on. 2015. IEEE.

[36] Gray, S.A., E. Zanre, and S. Gray, Fuzzy cognitive maps as representations of mental models and group beliefs, in Fuzzy cognitive maps for applied sciences and engineering. 2014, Springer. p. 29-48.