Fuzzy Cognitive Maps designing through large dataset and experts' knowledge balancing

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***Abstract*— This paper presents an extension of a hybrid method for modelling Fuzzy Cognitive Maps (FCMs), which combines human expert knowledge with existing recorded information and historical data. The proposed approach at first step extracts information from any type of dataset, extracts useful information and transforms it into knowledge in a form suitable to stracture a FCM. The proposed approach is still dependent on experts' knowledge but it support them by providing the information and supportive data inferred from the dataset. Moreover, the approach highlights, through a supportive numerical example, that experts' knowledge and information from the dataset cannot be considered separately, since their combined use compensates possible errors in knowledge. In particular, it can be used to model a complex Decision Support Systems, and it also allows to identify the accuracy of the considered models.**

Keywords—Fuzzy Cognitive Map; Knowledge extraction; Soft computing; Data analysis, modeling FCMs.

I. INTRODUCTION

A known mental model for modeling and structuring the human decision making process is cognitive maps [1], which have been further expanded to Fuzzy Cognitive Maps (FCMs) [2, 3] in order to better model causality among natural factors. FCMs have been extensively used in many research fields and application areas, reaching a great awareness as a soft computing modelling method for complex systems as asserted by [4, 5]. The main reason of their use is due to their ability to infer and suggest decisions by applying a similar to human reasoning method in an uncertain environment [6]. The FCM approach allows the description of any system through concepts, identified as the main factors affecting the investigated problem, and positive or negative weighted relationships among them, which represent their reciprocal influence [7, 8].

FCMs could be considered as a unique methodology able to aggregate knowledge to represent a "scaled-up" version of individuals' knowledge and beliefs, but most of FCMs models have been developed based on human participation [9]. Experts' panels are asked to identify concepts and relationships about a specific problem thus obtaining a collective FCM [10]. Many research fields are investigated using FCMs, from industrial solutions to healthcare and many others. For example, FCMs and experts' knowledge have been used by [11, 12] to define the equipment criticality in a refinery plant and so properly plan the maintenance activity. FCMs have been used for developing a decision making tool for supporting container transport logistics [13]. A prototype for evaluating information technology risks in health care has been formulated by [14]. Furthermore, [15] have used FCMs in the evaluation of the cancer thermography to diminish medical errors.

However, a complex system model can be constructed either by the experts or, in a similar way, learned based on historical data in more structured approaches. Moreover, FCM models learned from data are denser than those created by humans [16]. For example, [17] developed an evolutionary learning approach based on density and system performance indicators allowing to select only the most significant connections between concepts using real-life and historical data. Additionally, [18] developed a general framework to learn large-scale sparse FCMs from observed data automatically, not considering any prior knowledge and so not being bound by the expert's presence.

Learning algorithms are also used to avoid the limitations that the traditional FCM present but, de facto, reducing the human expertise by suggested automated FCM candidates [19]. In particular, several algorithms based on the Hebbian algorithm have been proposed [20, 21] to adapt the expert model expert-knowledge based on the actual system. More recently, FCMs have been used to model the complex structure of public support for insurgency and terrorism combining multiple experts' knowledge and, then, applying a differential

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Hebbian learning algorithm to refine the final map using time-series data [22].

Some other supplementary approaches exist in the literature. For example, [23] combined the graphical representation level, an updating mechanism receiving feedback from a physical system and the storing of acquired knowledge. Reference [24] provided an FCM model improved by a multi-local and balanced local search algorithm combining memetic algorithms for tuning the map with different local search strategies. Moreover, [25] presented a hybrid modelling methodology using genetic algorithms and extending previous work on Competitive FCM for Medical Decision Support Systems. Although the mentioned list is not exhaustive, it is a brief and good review of what has been done using FCMs and how this research field is in continuous development.

This work aims at improving and expanding the modelling approach described in [26] and [27] to combine the information derived by large datasets and the experts' knowledge in an FCM Decision Support Systems. In particular, the proposed integrated approach highlights how the experts' knowledge can model a complex system, but it is not unfailing and, at the same time, the information derived by stored data are not always able to describe the same system perfectly. The results discussed for the case of a numerical example, found in the literature, so that to well explain their complementarity.

This paper is structured as follows. Section II provides a general description of Fuzzy Cognitive Maps. Section III describes the proposed algorithm for developing the FCM. Section IV briefly describes the numerical example to explain the proposed approach. Section V analyses and discusses the results. Finally, Section VI concludes the paper, briefly discussing the proposed approach and suggesting further developments.

II. Fuzzy Cognitive Mapping

Originally, the FCMs foundations have to be identified in the Cognitive Maps developed by Axelrod to represent social scientific knowledge in the form of signed digraphs, which used to present positive or negative causality with fixed values of +1 or -1 or no causality with the absence of the linkage between the concepts.

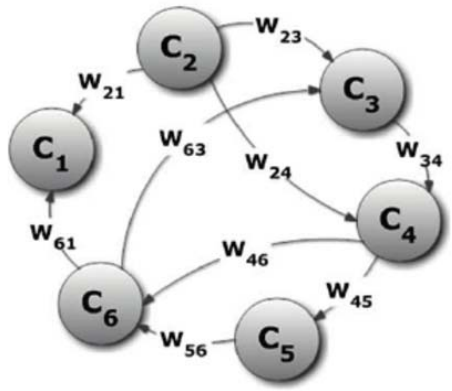

Fig. 1: An example of FCM

Indeed, a cognitive map can be considered a conceptual map, reproducing mental processing, comprised of collected information and several cognitive notions, individually filtered, about experiences and physical phenomena indicating causal relationships [1]. Thus, cognitive maps are visual representations of an individual's "mental model" constructs, comparable to concept maps for representing human reasoning and knowledge or beliefs. However, cognitive maps are very binding for knowledge-based building since the causal connection values were limited to -1,0, or 1. Indeed, according to [2] and [3], in causality it is important to consider varying degrees and in particular, in order to represent human reasoning, vague degrees at that. It occurs partially, sometimes, very little, usually, more or less, and so on. More generally still, the knowledge-based building promise of cognitive maps is combining knowledge sources' cognitive maps, but the fuzziness of the combined knowledge rises to the level of fuzziness of the fuzziest knowledge source. Fuzzy cognitive maps accommodate this knowledge-based building property. Thereof, according to Kosko's definition [2, 3], FCMs are fuzzy-graph structures for representing causal reasoning. Their fuzziness allows hazy degrees of causality between hazy causal concepts. Their fuzzy signed directed graph structure, permitting feedback and circular interactions, allows systematic causal propagation, forward and backwards chaining, and it allows knowledge bases to be improved by connecting different FCMs.

FCMs represent a particular soft computing approach aiming at modelling systems and support decision-making procedures based on a reasoning approach in a human-like way. According to the majority of the soft computing approaches, human knowledge and experience are innate in the model through a human-based designing and creation procedure reflected in the FCM structure itself. Different Fuzzy Cognitive Map applications, alternatives and variations have been proposed where they integrate aspects of fuzzy logic, semantic networks, neural networks, genetic algorithms, expert systems and they are usually complemented with other soft and hard computing approaches.

Hence, a generic problem is considered, and an experts' group is formed for its in-depth analysis to model a collective FCM identifying concepts and relationships about the considered problem. Specifically, the concepts are the FCM key elements that represent the main features of the abstract mental model for whichever complex system [2]. For this reasonone of the major uses of FCM is modelling complex systems. Once identifying concepts, experts have been asked to assign a numerical value w_{ij}, which represents the influence of concept C_i on concept C_j and it ranges in interval [–1, 1] (see Fig. 1). Specifically, $w_{ij}=0$ indicates no causality between concepts; $w_{ij} >0$ indicates causal C_j increases as C_i increases (or Cj decreases as C_i decreases), and $w_{ij}<0$ indicates causal decrease or negative causality: C_j decreases as C_i increases (and or C_j increases as C_i decreases).

Once the total weights matrix W, is designed, 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).

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

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_{ji} is the weight of the interconnection from concept C_j to concept C_i and f is an opportune threshold function, used to force the concept value to be monotonically mapped into a normalised range [28]. For this study, the hyperbolic tangent function has been used with $\lambda=1$ since it is necessary to have numerical into [-1 1]. Other equations can be used in place of equation (1) as suggested by [29]. Moreover, [30] gives a general technique for data fusion and or knowledge combination.

III. THE PROPOSED APPROACH

The proposed approach aims at expanding the modelling approach developed by [26] and [27] and described by equation (2).

$$w_{i,j} = sgn(sw_{i,j})\left(l_1 \cdot iw_i + \sum_{k=1}^{n} l_2 \cdot |sw_{i,j}^k|\right) \quad (2)$$

Where $sw^k_{i,j}$ (**specific weight**) is the relationship strength between the concepts C_i and C_j identified by the *k-th* expert; n is the number of the experts; iw_i (**importance weight**) represents the impact of the concept C_i for the examined problem under consideration and its value is identified by the experts. In particular, they analyse the available dataset to comprehend when and how a specific concept has an impact on a specific output. Every expert describes the degree of influence of one criterion towards a decision, using a linguistic variable, such as "strong influence", "medium influence", "weak influence", etc.

Finally, the constants l_1 and l_2 represent the participation of the **importance weight** $\boldsymbol{iw_i}$ and the **specific weight** $\mathbf{sw^k_{i,j}}$, on the overall weight describing the influence of every factor concept towards the decision concept. - In this approach all developed FCMs from experts are treated equally in the final aggregation without taking into consideration the varying degrees of experts' knowledge. The proposed approach starts from some relevant considerations.

Firstly, as asserted, the identification of the importance weights iw_i is provided by the experts' analysis of the available dataset. The authors do not question the validity of this procedure, but its accuracy in case of a large dataset for which, the analysis could be complex and approximate. For this reason, the new approach provides for the designing of an FCM by the dataset analysis through a modelling technique. In this paper, a regression model has been used [31]. Then, the obtained model has been fuzzified according to [26], to design the system model in the form of FCM (**$\mathbf{FCM_d}$**). Concerning the FCMs derived from the experts' knowledge (**$\mathbf{FCM_e^k}$**), it is possible to refer to one of the approaches described in the literature. In this way, the experts' FCMs and the data one are independent; in doing so, each FCM_e^k is not influenced by the FCM_d (and *vice-versa*). Thus, possible errors in one of them do not affect the others.

Secondly, the constants l_1 and l_2 values are unchanged since they represent the participation of the **importance** and **specific weight** on the overall problem. However, depending on their value, a different aggregation method has been developed, to properly combine the experts' FCMs and the dataset FCM, to define the collective FCM (**$\mathbf{FCM^C}$**).

Given the above, Eq. (3) describes the proposed approach.

$$w_{i,j}^C = \left(l_1 \cdot piw_i + \sum_{k=1}^{n} l_2 \cdot psw_{i,j}^k\right) \quad (3)$$

Where $w^C_{i,j}$ represents the "collective" relationship strength between the concepts C_i and C_j. l_1 and l_2 are the relevance of the **importance** and **specific weight** on the overall problem. Finally, $psw^k_{i,j}$ (**penalised specific weight**) and piw_i (**penalised importance weight**) represent the strength value, for each considered relationship, provided by experts and dataset, respectively, adjusted according to the l_1 and l_2 values. By comparing equation (2) with equation (3), it is evident that the factor $sgn(sw_{i,j})$ has been removed. In fact, in the authors' opinion, considering the new problem formulation, its consideration would imply a greater relevance for the experts' model, generating a conflict with the l_1 and l_2 values. This problem has been avoided thanks to the penalisation procedure developed and proposed here.

At this point, as mentioned above, the penalisation procedure depends on the l_1 and l_2 values. In particular, three different cases can be performed, and they are described by the following.

Case 1 **($l_1 > l_2$)** – it represents the case in which FCM_d is more accurate than FCM_e^k. Thus, each $sw^k_{i,j}$ is penalised according to its distance from the relative $iw_{i,j}$, according to equation (4).

$$psw_{i,j}^k = \begin{cases} sw_{i,j}^k / iw_{i,j} & sw_{i,j}^k / iw_{i,j} \leq 1 \\ 1 - mod(sw_{i,j}^k / iw_{i,j}) & sw_{i,j}^k / iw_{i,j} > 1 \end{cases} \qquad piw_{i,j} = 1 \quad (4)$$

Case 2 **($l_1 < l_2$)** – it represents the case in which FCM_e^k is more accurate than FCM_d. Thus, each $sw^k_{i,j}$ and $iw_{i,j}$ is penalised according to their distance from the centre of gravity ($cg_{i,j}$) of the experts' evaluations, according to equation (5).

$$cg_{i,j} = mean([sw_{i,j}^k]) \qquad k = 1,2,\dots,n$$
$$psw_{i,j}^k = \begin{cases} sw_{i,j}^k / cg_{i,j} & sw_{i,j}^k / cg_{i,j} \leq 1 \\ 1 - mod(sw_{i,j}^k / cg_{i,j}) & sw_{i,j}^k / cg_{i,j} > 1 \end{cases}$$
$$piw_{i,j} = \begin{cases} iw_{i,j} / cg_{i,j} & sw_{i,j}^k / cg_{i,j} \leq 1 \\ 1 - mod(iw_{i,j} / cg_{i,j}) & sw_{i,j}^k / cg_{i,j} > 1 \end{cases} \quad (5)$$

Case 3 **($l_1 = l_2$)** – it represents the case in which the FCM_e^k and the FCM_d have similar accuracy.

Thus, each $sw^k_{i,j}$ and $iw_{i,j}$ is penalised according to their distance from the overall centre of gravity ($cg_{i,j}$), according to equation (6).

$$cg_{i,j} = mean([sw_{i,j}^k \quad iw_{i,j}]) \qquad k = 1,2,\dots,n$$
$$psw_{i,j}^k = \begin{cases} sw_{i,j}^k / cg_{i,j} & sw_{i,j}^k / cg_{i,j} \le 1 \\ 1 - mod(sw_{i,j}^k / cg_{i,j}) & sw_{i,j}^k / cg_{i,j} > 1 \end{cases} \qquad (6)$$
$$piw_{i,j} = \begin{cases} iw_{i,j} / cg_{i,j} & sw_{i,j}^k / cg_{i,j} \le 1 \\ 1 - mod(iw_{i,j} / cg_{i,j}) & sw_{i,j}^k / cg_{i,j} > 1 \end{cases}$$

If the accuracy of each model is unknown or the study also aims to identify them, it is possible to properly tune the value of l_1 and l_2 using the dataset and an iterative approach and an objective function.

The values of the concepts in this implementation follow Eq (1) with the weight matrix calculated as described above.

IV. THE NUMERICAL EXAMPLE

To demonstrate the proposed algorithm efficacy, it has been adopted a large dataset provided by [32]. This dataset was developed with the aim of designing a statistical machine-learning framework to assess the effect of several variables on the heating and cooling load calculation of residential buildings, shown in Table I, better understanding of the data is provided at [33] and [34].

TABLE I. TABLE I: AN IDENTIFIED CONCEPT FOR THE NUMERICAL EXAMPLE

ID	Concept Name	ID	Concept Name
C1	Relative compactness	C6	Orientation
C2	Surface area	C7	Glazing area
C3	Wall area	C8	Glazing area distribution
C4	Roof area	C9	Heating load
C5	Overall height	C10	Cooling load

Once the concepts have been identified and explained to the experts', they have been asked to provide their personal relationships weighted matrix to identify the connections strength among all concepts, using a fuzzy Likert scale with 9 terms, according to [26]. In particular, they identified some doubts about the relationships referred to concepts C7 and C8 with the others.

At the same time, through the application of a regression method [30], the relationships among the concepts have been identified to obtain the relationships weighted matrix taking into consideration the available dataset. Taking into consideration only the two output value, the obtained model can be considered valid since the mean values of the dataset outputs are equal to 22.30 (Heating) and 24.58 (Cooling) respectively, and for the regressed model they are equal to 22.22 (Heating) and 24.49 (Cooling). Specifically, the t-student test accepts the null hypothesis with a p-value of 0.81 for the Heating variable and 0.78 for the Cooling one, considering a significance level α equal to 0.05. At this point, the relationships matrix, so obtained, has been fuzzified according to [26].

V. RESULTS AND DISCUSSION

To evaluate the efficacy of the proposed method, first of all, the FCM obtained from the dataset (FCM_d) and those from the experts' knowledge (FCM^e_k) have been compared. By the comparison, it has been possible to analyze that the experts have identified about 15 relationships more than FCM_d and it could mean a smaller ability to explain the problem by the experts' knowledge. In particular, these connections are evident concerning uncertain concepts described above.

Since the main objective of this study is the development of an application able to esteem the Heating and Cooling Load of a residential building, the available dataset has been used for simulating the collective FCM so to compare its outputs with the actual one. In particular, as shown in Table II, the whole dataset has been standardized.

TABLE II: EXCERPT OF THE AVAILABLE DATASET

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
0,86	588	294	147	7	4	0	0	19,340	23,49
0,86	588	294	147	7	5	0	0	18,31	27,87
0,82	612,5	318,5	147	7	2	0	0	17,05	23,77
0,82	612,5	318,5	147	7	3	0	0	17,41	21,46
0,82	612,5	318,5	147	7	4	0	0	16,95	21,16
0,82	612,5	318,5	147	7	5	0	0	15,98	24,93

For the simulations set, 11 combinations have been designed taking into consideration the value of l_1 and l_2, ranging in [0 1] such that $l_1+l_2=1$, with a step equal to 0.1 and, then, other 11 combinations with a step equal to 0.02.

Fig. 2 shows the experimental results for the first 11

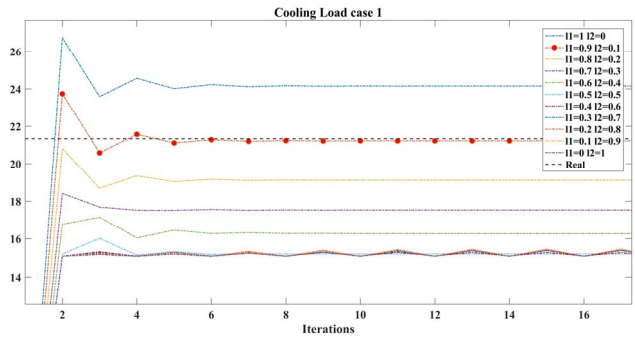

Fig. 2: the experimental results

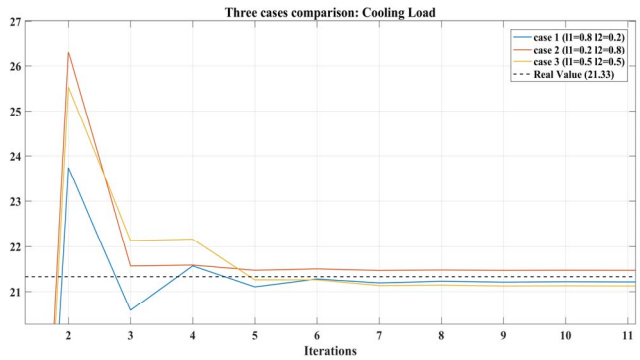

Fig. 3. Three cases comparison for the Cooling Load

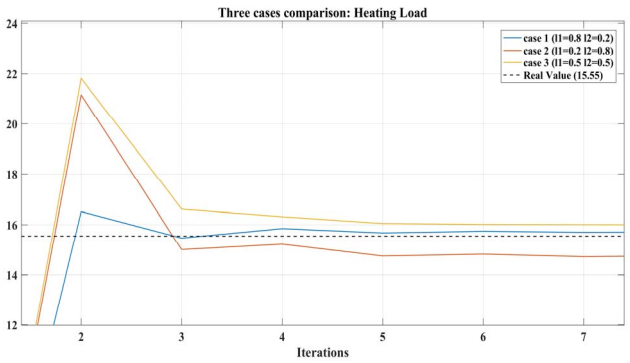

Fig. 4. Three cases comparison for the Heating Load

combinations. By analyzing Fig. 2, the higher the l_1 value, the higher is the proposed method precision, and this result is nothing but the validation of the fact that the FCM_d is more accurate than the FCM_e^k.

However, this observation could induce readers to prefer only the FCM_d that means $l_1=1$ and $l_2=0$ but, from Fig. 2, it is evident that this situation recedes the system outputs from the actual value. It is also true the opposite ($l_1=1$ and $l_2=0$). Hence, it suggests that the knowledge of data and experts' opinion are inseparable. On the other hand, it does not mean that l_1 has to be always greater that l_2. In fact, their value depends on the accuracy of both the FCMs so that it is possible to tune these two parameters properly using the dataset and minimising a specific objective function. This consideration is well explained in Fig. 3 and Fig. 4. They show three different cases: (i) the FCM_d is more accurate than FCM_e^k; (ii) the FCM_e^k is more accurate than FCM_d, and (iii) FCM_d, and the FCM_e^k has the same accuracy. These three scenarios have been developed introducing errors in the FCM_d and correcting the FCM_e^k according to the connection identified by the data analysis.

In the first case, the simulations identify the best values for l_1 and l_2 such that $l_1=0.8$ and $l_2=0.2$, so it is confirmed the initial hypothesis about the accuracy of the regress model rather than the experts' maps. The case (ii) is the opposite, $l_1=0.2$ and $l_2=0.8$ so, also, in this case, the initial hypothesis has been demonstrated. Finally, the case (iii) find the right solution in $l_1=0.5$ and $l_2=0.5$. In fact, in this specific scenario, all the FCMs used have been designed by that obtained by the regression model and introducing some discrepancies. Thus, also considering the third case, the initial hypothesis is supported.

VI. Conclusion

This paper presents an extension of a method for modelling Fuzzy Cognitive Maps (FCMs), combining human expert knowledge with existing recorded information and historical data.

In particular, it aims at extracting information from a large dataset and transforming it into knowledge in the form of an FCM. It also highlights, through a supportive numerical example, that experts' knowledge and information from dataset cannot be considered separately since their combined use compensates possible errors in knowledge. Hence, it suggests the fundamental idea that the knowledge of data and experts' opinion are inseparable.

Moreover, by the system outcomes analysis, it has been possible to assert that the proposed algorithm does not provide only an accurate predictor for the considered problem but, at the same time, a useful method for evaluating the accuracy of the information involved into the problem-solving process.

The proposed algorithm extends the classical fuzzy based approaches for developing FCMs with historical data and information leading to a more advanced approach, suitable for developing FCMs for decision support systems, balancing the information relevance provided by the experts and a large dataset.

Future research will focus on examining the validity of the algorithm in various real world problems, such as industrial problems, develop the overall FCM and compare its performance with other analogous approaches to give more significance to the proposed algorithm outcomes..

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