EXPLORING OWA OPERATORS FOR AGGREGATING FUZZY COGNITIVE MAPS CONSTRUCTED BY EXPERTS/STAKEHOLDERS IN AGRICULTURE

Konstantinos Papageorgiou[1], Elpiniki Papageorgiou[2,3], Asmaa Mourhir[4] and George Stamoulis[1]

[1] University of Thessaly, Department of Computer Science, 35100 Lamia, Greece

[2] University of Thessaly, Faculty of Technology, 41110 Larisa, Greece

[3] Institute for Bio-economy and Agri-technology, Center for Research and Technology Hellas, Greece

[4]Computer Science Department, School of Science and Engineering, Al Akhawayn University in Ifrane, Morocco

konpapageorgiou@uth.gr, elpinikipapageorgiou@uth.gr, a.mourhir@aui.ma

ABSTRACT

Fuzzy cognitive maps are graph-based models mostly constructed in a participatory setting either by experts to given domains or by a large number of stakeholders in various scientific areas of interest. Usually each expert or stakeholder designs individually a FCM based on his/her knowledge or opinion for the specific application domain. For scenario analysis and decision-making purposes, an overall FCM for the specific problem needs to be constructed, aggregating all individual FCMs designed by the experts and/or stakeholders. The average aggregation method for weighted interconnections among concepts is the most common method in FCM modeling, which is quite simple, regardless the inherent uncertainty induced by the different experts' or stakeholders' opinions. The aim of this research work is two-fold: (i) to propose an alternative aggregation method based on learning Ordered Weighted Average (OWA) operators in aggregating FCM weights, assigned by many experts and/or stakeholders, and (ii) to present a new software tool for FCM aggregation, called FCM-OWA, leveraging the different FCM aggregation methods. A precision farming problem, considering apple yield prediction, is used to show the applicability and usefulness of the proposed methodology in modeling. The results after comparing OWA operators with the traditional average aggregation method imply that the proposed approach is really challenging on modeling experts' knowledge in agricultural domain.

Keywords: fuzzy cognitive maps, knowledge aggregation, OWA, participatory approach, decision making.

1. INTRODUCTION

A Fuzzy cognitive map (FCM) is a flexible and innovative technique which combines neural networks and graph theory, for modelling human knowledge in decision-making processes. Introduced by Kosko in 1986, FCMs are simple models that can easily incorporate human knowledge and adapt to a given domain (Stach, 2010), so they have gained considerable research interests and have been extensively applied to many research fields and application areas (Papageorgiou & Salmeron, 2013). Designing a FCM for modelling a given system often includes the aggregation of knowledge from a variety of sources. Typically, aggregated input models are developed by multiple experts from the application domain (Stach, 2010), aiming at improving the reliability of the final model which is less susceptible to potentially erroneous beliefs of a single expert or knowledge discrepancies among participants. There are a couple of techniques for combining multiple FCMs into a single collective model commonly used in a wide range of real-life problems (Mezei & Sarlin, 2016), which are namely the weighted average, and the OWA method introduced by Yager (1988).

In a traditional FCM, considering the weighted average method, the weights are fuzzy values in the interval [0, 1] and the collective FCM model is constructed by averaging values for a given interconnection (Gray et al., 2014). This approach is also particularly useful when the causal relationships are described using linguistic terms. The rules for a given interconnection are aggregated using fuzzy operators, and the overall output is elaborated by using the weighted average of each rule's output (Papageorgiou & Stylios, 2008).

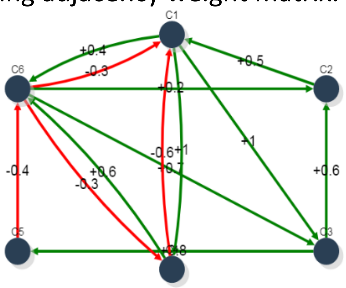
From the reviewed literature, few research papers were found regarding the application of OWA operators in aggregating individual FCMs. Among them, Zhenbang and Lihua (2007) introduced OWA operators, as numeric aggregation operators, into the conventional FCMs. They also discussed the issues related to determining weights for the OWA aggregation under different conditions. The aim of this work is to develop an alternative FCM aggregation method by learning OWA operators' weights. A precision farming problem with apple yield prediction is used to show the applicability and usefulness of the proposed methodology to support decision making.

This paper is structured as follows. Section 2 describes the theoretical background about the OWA operators along with the proposed algorithm for learning OWA operator weights for aggregation purposes. Section 3 presents the FCM aggregation tool. The results of the examined apple yield case study are presented and discussed in Section 4. Section 5 summarizes the study's findings and conclusions.

2. Methodology

2.1 Fuzzy Cognitive Maps Overview

FCMs, introduced by Kosko (1986), allow representing knowledge in the form of a directed graph whose nodes denote the main factors of the analyzed problem, and links represent the causal relationships between concepts. Each of FCM's link is associated with a weight value w_{ij} which varies from -1 to 1, that describes the strength of the corresponding relation between two concepts C_i and C_j. There are three different types of possible causalities between every pair of concepts C_i and C_j: (i) $W_{ij} > 0$, which designates a positive causality, (ii) $W_{ij} < 0$, which designates a negative causality, and (iii) $W_{ij} = 0$, which designates no causality. Figure 1 shows an example of a Fuzzy Cognitive Map with its corresponding adjacency weight matrix.



$$W = \begin{bmatrix} 0 & 0 & 1 & 1 & 0 & 0.4 \\ 0.5 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.6 & 0 & 0 & 0.8 & 0 \\ -0.6 & 0 & 0 & 0 & 0 & 0.6 \\ 0 & 0 & 0 & 0 & 0 & -0.4 \\ -0.3 & 0.2 & 0.7 & -0.3 & 0 & 0 \end{bmatrix}$$

Figure 1. Fuzzy cognitive map (left) and the correspondent weight adjacency matrix (right), showing the positive and negative causal influences.

Typically, a FCM of n concepts could be represented mathematically by a $n \times n$ weight matrix (W). By feeding the fuzzy cognitive map with an initial stimulus state vector X(t) (state vector at time (t)), it can model the evolution of a scenario over time by evolving forward and letting concepts interact with one another. Each subsequent value of the concept state $X^{(t+1)}$ can be computed as previous state $X^{(t)}$ and weight matrix multiplication, according to Eq. (1).

$$X_i^{(\kappa+1)} = f\left(\sum_{j=1, j\neq i}^{n} w_{ji} \times X_j^{\kappa}\right) \tag{1}$$

In the average aggregation method, all the numerical weighted interconnections suggested by various experts, are summed and then divided by the number of experts, thus producing an average numerical weight. An example of this average method is presented in (Stach, 2010).

2.2 Main aspects of ordered weighted averaging (OWA) operators

An OWA operator of dimension n is a mapping: $f: R^n \rightarrow R$, that has an associated weighting vector W, $W = [w_1 \ w_2 \ \dots \ w_n]^T$, such that $\sum_i w_i = 1$; $w_i \in [0,1]$ and $f(a_1, \dots, a_n) = \sum_{j=1}^{n} w_j \ b_j$, where b_j is the j[th] largest element of the collection of the aggregated objects $a_1, a_2 \dots, a_n$. The function value $f(a_1, \dots, a_n)$ determines the aggregated value of arguments $a_1, a_2 \dots, a_n$ (Filev & Yager, 1994).

A fundamental aspect of the OWA operator is the re-ordering step, in particular, an argument a_i is not associated with a particular weight w_i but rather a weight w_i is associated with a particular ordered position i of the arguments.

It can be easily shown that the OWA operators are aggregation operators, satisfying the commutativity, monotonicity and idempotency properties and that they are bounded by the Max and Min operators (Yager, 1993), for OWA operators

$$\operatorname*{Min}_i a_i \leq f(a_1, \dots, a_n) \leq \operatorname*{Max}_i a_i$$

Since this class of operators runs between the Max (or) and the Min (and), Yager (1988) introduced a measure to characterize the type of aggregation being performed for a specific value of the weighting vector. This measure called the $orness \ measure$ of the aggregation is defined as shown by (2).

$$Orness(W) = \frac{1}{n-1} \sum_{i=1}^{n} (n-1) w_i. \tag{2}$$

As suggested by Yager (1988), this measure which lies in the unit interval, characterizes the degree to which the aggregation is like an or (Max) operation. It can be shown that

$$orness([1\,0 \dots 0]^T) = 1, \quad orness([0\,0 \dots 1]^T) = 0, \quad orness\left(\left[\frac{1}{n}\,\frac{1}{n} \cdots \frac{1}{n}\right]^T\right) = 0.5.$$

Therefore the Max, Min and arithmetic mean operators can be regarded as OWA operators with a degree of orness, respectively, 1, 0 and 0.5. A second measure introduced by Yager (1988) was the dispersion or entropy associated with a weighting vector:

$$Disp(W) = \sum_{i=1}^{n} w_i \ \ln w_i. \tag{3}$$

This was suggested for use in calculating how much of the information in the arguments is used during an aggregation based on W.

2.3 Calculating OWA weights from experts/stakeholders' opinions

Based on the previously suggested method by Yager (1988) for obtaining the weights associated with the OWA aggregation when observed data on the arguments have been provided, this research study presents an algorithm which can be used for aggregating weights assigned by experts/stakeholders' opinion in designing FCMs. The proposed algorithm learns the weights associated with a particular use of the OWA operator from a group of experts and stakeholders for the specific scientific domain. The steps below, describe the procedure to obtain the learning OWA weights (Fig.2).

We consider Expert opinions as argument values ($a_{k1}, a_{k2} \dots, a_{kn}$), and sample as each edge-weight (n) of data.

Step 1: Generate slightly different parameters ρ for each argument which represents the optimism of the decision maker, 0≤ρ≤1.

Step 2: Calculate the aggregated values for each sample using the Hurwics method according to which, the aggregated value d obtained from a tuple of n arguments, $a_1, a_2 \dots, a_n$, is defined as a weighted average of the Max and Min values of that tuple.

$$\rho \text{Max } a_i + (1-\rho)\text{Min} a_i = d$$

Step 3: Reorder the objects ($a_{k1}, a_{k2} \dots, a_{kn}$).

Step 4: Calculate the current estimate of the aggregated values dk

$$\hat{d}_k = b_{k1}w_1 + b_{k2}w_2 + \cdots + b_{kn}w_n$$

with initial values of the OWA weights $w_1 = 1/n$.

Step 5: Calculate the total $\hat{d}_k$, d_k, b_{ki} for each i. The parameters λ_i determine the weights of OWA and are updated with the propagation of the error $\hat{d}_k - d_k$ between the current estimated aggregated value and the actual aggregated value (Filev & Yager, 1994).

Step 6: Calculate the current estimates of the λ_i

$$\lambda_i(l+1) = \lambda_i(l) - \beta w_i(l)\left(b_{ki} - \hat{d}_k\right)\left(\hat{d}_k - d_k\right)$$

with initial values $\lambda_i(0) = 0$, i = (1, n), and a learning rate of β = 0.35.

Step 7: Use λ_i, $i = (1, n)$, to provide a current estimate of the weights

$$w_i = \frac{e^{\lambda_i(l)}}{\sum_{j=1}^{n} e^{\lambda_i(l)}},\ i = (1, n)$$

Step 8: Update w_i and $\hat{d}_k$ at each iteration until the estimates for all the λ_i converge to, that is Δ = $|\lambda(l+1) - \lambda(l)|$ are small.

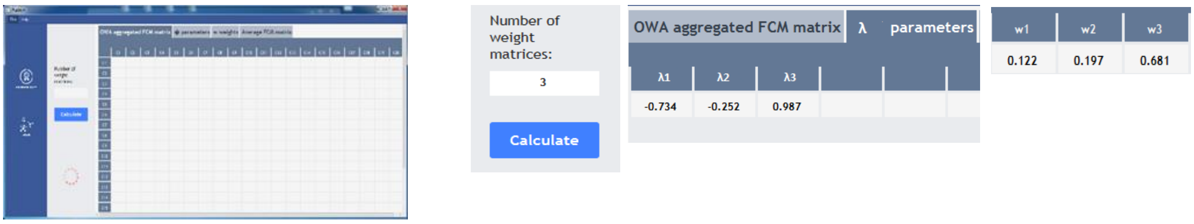
Figure 2. The algorithm for learning the OWA weights

In what follows, an explanatory paradigm from precision farming devoted to apple yield prediction will better illustrate the proposed FCM construction approach by experts (see section 3).

2.4 FCM-OWA Tool Description

The proposed algorithm based on learning OWA operator weights for aggregating FCM models was implemented with the FCM-OWA, a new software tool developed in java programming language. An overview snapshot of the user interface, where the main menu with the "import" and "export" buttons and the "OWA aggregation" function are present, can be seen in Fig. 3a.

The user needs first to define the number of input weight matrices as shown in Fig. 3b, and next to insert an excel file with the weight matrices, one in each sheet, defined by each expert. Once the user clicks on "Calculate", the OWA aggregated FCM matrix appears in the first tab, while in the following 3 tabs, the lamda parameters, the w weights and the average FCM matrix are displayed (Fig.3). Additionally, users are given the option to export the OWA aggregated FCM matrix in an excel file.



(a) The FCM-OWA tool (b)Number of matrices (c) lamda parameters tab (d) w weights tab

Figure 3. Screenshots of (a) The FCM-OWA tool for aggregation (b)The number of weight matrices option, (c) "lamda parameters" tab and (d) "w weights" tab

3. Results

As a case study we selected a precision farming problem of apple yield prediction previously published in Papageorgiou et al. (2013). Specifically, a number of experts designed 17 individual FCM models that were collected and aggregated to provide support to policy making. The FCM models which were designed and developed to represent experts' knowledge for yield prediction and crop management, consist of 9 concepts and 13 weighted connections among them. The developed FCM model comprises nodes linked by directed edges, where the nodes represent the main soil factors affecting yield (such as soil texture (clay (C7) and sand content (C8)), soil electrical conductivity (EC)- (C1), calcium (Ca)-

(C2), potassium (K)- (C3), organic matter (OM)- (C4), phosphorus (P)- (C5), and zinc (Zn)- (C6) contents), and the directed edges show the cause-effect (weighted) relationships between the soil properties and yield. In this work, we consider only 3 out of 17 expert models to demonstrate the implementation of our proposed aggregation methodology. The expert opinions are considered as argument values $a_{k1}, a_{k2} \dots, a_{kn}$ and the weight between two concepts is shown in Table 1.

The aggregated values were calculated using various values for parameter ρ within ρ (0.01≤ ρ≤0.2). For example, ρ=0.153; 0.131; 0.181; 0.075; 0.055. These values have been randomly selected by the algorithm. Using min and max values of ρ, the aggregated value of weight was calculated as follows.

$$0.153(0.58) + (1 - 0.153)(0.43) = 0.45$$

We initialized $\lambda_i(0) = 0$, i = (1, n), β = 0.35 και $w_1 = w_2 = w_3$=0.33. The estimated values of λ_i after 108 iterations were: $\lambda_1 = 0.63$, $\lambda_2 = -0.19$, $\lambda_3 = 0.82$

The following OWA weights were calculated considering the above λ_i:

$$w_1 = 0.146, \qquad w_2 = 0.227, \qquad w_3 = 0.626$$

Applying the OWA tool, all the weight matrices of 3 experts of precision farming were uploaded and their OWA weights were calculated (see Table 1). Furthermore, the same tool calculates the average values of weights (benchmark method Wb) through the Kosko's aggregation method. We followed the same process for parameter ρ for the following ranges: 0.3<ρ<0.5 and 0.5<ρ<0.7.

Table 1. Aggregated (benchmark) weights from 3 experts' opinions and weights produced by learning OWA operators (Wowa)

	Experts' opinions			**Aggregated value**	**Weights produced by learning OWA operators (Wowa)**			**ΔW-Deviation Wb-Wowa**		
Weight	Exp. 1	Exp. 2	Exp. 3	Wb Average	Weight-1 0.01<ρ<0.2	Weight-2 0.3<ρ<0.5	Weight-3 0.5<ρ<0.7	ΔW1	ΔW2	ΔW3
C1-C9	0.43	0.50	0.58	0.45	0.47	0.53	0.58	0.02	0.08	0.13
C2-C1	0.57	0.60	0.68	0.58	0.33	0.40	0.45	0.07	-0.18	0.13
C2-C9	0.57	0.60	0.68	0.58	0.59	0.64	0.68	0.01	0.06	0.10
C3-C1	−0.30	-0.35	-0.25	-0.32	-0.32	-0.28	-0.25	0.00	0.04	0.07

Table 1 gathers the calculated values for OWA aggregated weights for some exemplary interrelationships among FCM concepts, as well as the deviations between the benchmark weight Wb (average method) and the Wowa, weight produced by learning OWA operators. Also, considering the ρ values, it is presented that there are significant deviations for higher values of ρ (ie. for weights C2-C1 and C6-C9) in the overall FCM model. For most of the weighted interconnections above, the deviations are relatively small.

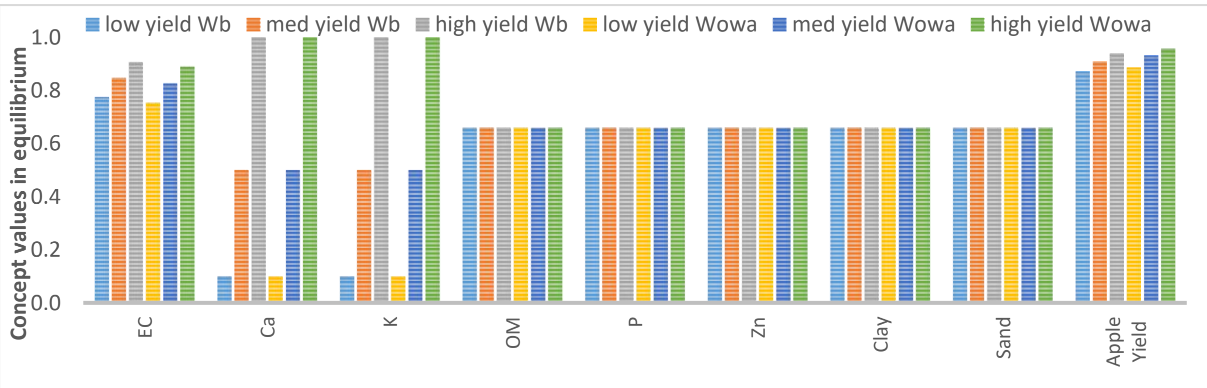


Figure 4. Preliminary results of three scenarios of low, medium and high yield

Preliminary simulations with the aggregated FCM produced by OWA have been accomplished and some illustrative results are given in Fig. 4. Three scenarios of low, medium and high yield were examined. In all cases, the two key concepts affecting apple yield, Ca and K, are modified to generate perturbation in the yield. For example, in the case of high yield, Ca and K have a significant contribution on decision making. The simulation results show deviations between Wb and Wowa for the three examined scenarios of low, medium and high apple yield in the equilibrium. Similar trends are observed overall for both FCMs.

4. Discussion & Conclusions

In this work, an OWA-based FCM aggregation method by learning OWA operator weights from data was introduced and applied to a precision farming case study for apple yield prediction. The first evident outcome that makes this research study important regards the relationships' strengths calculated with the proposed approach. It came up that each weighted relation has a value similar to the benchmark weight when ρ takes small values. Specifically, the absolute difference between them is equal to 0.06 on average, which means that the weight obtained by OWA is slightly greater than the benchmark one. In this preliminary work, it is proved that there is a consistency between the values of the weights came from the OWA method and the benchmark weight, justifying the usefulness of the presented methodology as well as the easiness of use of the new software tool proposed in this study. As future work, we will focus on a more thorough investigation of this aggregation method by performing extended scenario analysis on both OWA aggregating FCMs and benchmark aggregation method, and further comparing the results in the basis of policy making in agriculture.

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