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A new trend in environmental education based on the neurofuzzy modelling of collaborative interactions

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ABSTRACT: In this article, the authors detail the development of an adaptive model, namely the Collaboration/Metacognition-Adaptive Fuzzy Model (C/M-AFM), to support the advancement of online collaborative skills. In particular, C/M-AFM employs a neurofuzzy structure to model the individual collaborative strategy across sessions of peers' collaboration, ie at the micro-level. Using this knowledge, it estimates the value of a feedback indicator concerning the quality of the individual collaborative activity in a forthcoming session of collaboration. This kind of formative support provokes learning on how to collaborate at the macro-level. Experimental data from a case study in environmental education concerning the collaborative composition of an environmental impact assessment allowed the exploration of two different modelling scenarios that provide useful information on the design considerations for the development of the C/M-AFM model.

INTRODUCTION

Decision-making is based upon the analysis and comparison of *appropriate* information according to criteria of effectiveness. When decisions upon environmental issues are concerned, the environmental impact assessment (EIA) process is carried out to provide the relevant information. In particular, an EIA is an instrument that is undertaken for proposed activities in order to ensure that they are environmentally sound and sustainable [1].

An EIA entails a planning process that is used to predict, analyse and interpret the adverse environmental effects of a proposal so as to minimise or prevent them and, in parallel, maximise the benefits of the proposal. On this basis, an EIA provides information for competent decision-makers to decide upon the proposed development. Interdisciplinary teams of people with an appropriate range of scientific, economic and social expertise usually carry out an EIA. Moreover, the participation of the public in stages of the EIA process is also encouraged to lend transparency to its content. Thus, an EIA is produced in a collaborative mode among people who usually have divergent backgrounds of professional skills, eg critical thinking, collaborative and metacognitive skills, etc. Moreover, the spatial dispersion of the people involved (either experts or the public) may place further barriers to the on-time delivery of an EIA. In such cases, new technologies may facilitate online collaboration. In particular, rapidly developing Web technology may challenge the engagement of more people in active participation and facilitate their collaboration.

Environmental education may contribute to students becoming conversant with the above real-life collaborative scenario by providing analogous supported educational experiences at the academic level. In particular, many Web-based collaborative tools have been developed with integrated supporting facilities that could contribute to successful peer-to-peer collaboration. Two primary procedures may be supported during collaboration, ie the learning of the task and learning to collaborate [1]. The provision of support for the enhancement of the latter is the focus of the present work.

Web-based collaboration evolves by means of computer-mediated social interactions that are logged in databases as raw data. A collaboration supporting system needs to employ knowledge extraction processes to map these low-level data to other, more abstract, yet more meaningful, information, eg prediction of future behaviour [2]. Such modelling could aim at realising changes in the individual collaborative strategy as they are observed at previous successive sessions of collaboration and upon them, predicting an indicator of the quality of the peer's collaborative activity in a forthcoming session of collaboration. This approach results in the development of an adaptive module that supports each peer at the metacognitive level, ie towards the management of his/her collaborative performance through self-regulation procedures [3]. Unlike other machine learning (ML) and Artificial Intelligence (AI) algorithms, a neurofuzzy network manages to deal with the uncertainties of complex systems, as well as provides a model with a transparent and interpretable structure [2][4].

In this article a novel, adaptive neurofuzzy model, namely the Collaboration/Metacognition-Adaptive Fuzzy Model (C/M-AFM), is presented. In particular, the presented work is an exploratory study of the modelling procedure of two versions of the C/M-AFM, namely the C/M-AFM_1 and C/M-AFM_2. They are differentiated mainly on the basis of the number of collaborative sessions that are considered during the modelling procedure. A comparison of the models' structures and performances provides interesting information regarding the design strategy for the development of the adaptive feedback module under consideration, establishing a new trend in environmental education that promotes collaborative skills.

THE PROPOSED C/M-AFMs

The proposed C/M-AFMs are presented through the description of their operational components, ie input-output vectors, neurofuzzy structure, training and testing procedures.

The construction of the input-output vectors of the C/M-AFMs is achieved by means of a Web-based collaboration tool, namely *Lin2k* [3]. The latter facilitates Web-based asynchronous written collaboration between two peers and, at the same time, provides support for improving their professional skills at the task and collaboration levels.

A meta-model of the structural components of *Lin2k*, is depicted in Figure 1, where the pedagogic domain defines the character of all the other components, the educational aim, the target group and the learning theories employed. On the other hand, at the task domain, the case study methodology is utilised that enhances the environmental education by providing opportunities for the examination of open-ended, real-life problems. Furthermore, it serves as a means for the improvement of critical thinking skills and the implementation of a holistic approach to the problems under consideration, ie from environmental, economic and social perspectives. Writing skills are also promoted through the composition of a technical report, based on the case study, in successive collaborative sessions, namely steps (*s*).

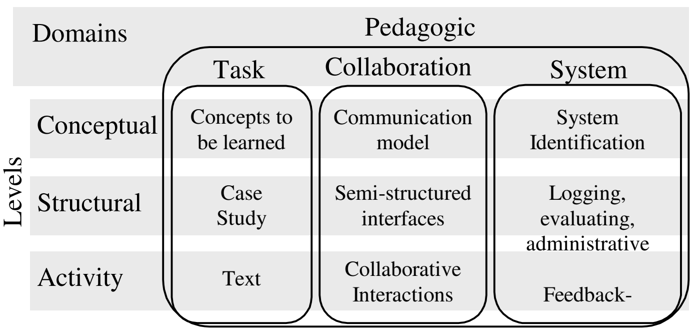

Figure 1: The meta-model for the realisation of *Lin2k* [3].

At the collaborators' side, the communication model is realised by semi-structured interfaces, ie interfaces that possess prepared areas that allow specific collaborative and metacognitive interactions to take place. More specifically, the collaborative interactions refer to the submission of specific types of text, ie *proposal, contra-proposal, clarification, agreement, comment, low and high level questions* [3]. These cover either the task or the coordination of the collaboration. On the other hand, the metacognitive interactions refer to the *ticks* that each peer performs on a Web-form at the end of each step. In particular, by the completion of this form, the peer denotes his/her intention to improve specific aspects of his/her collaborative performance at the next step of the collaboration. All the collaborative and metacognitive interactions are logged by the system as raw data. During the collaboration, intermediate collaborative and metacognitive *variables* are quantified by the system by means of weighting the raw data to provide appropriate feedback.

The *Lin2k* employs a Fuzzy Inference System (FIS), namely Collaboration/Metacognition-FIS (C/M-FIS), which manifests the evaluation system of a domain expert, ie the teacher (Figure 2a) [5]. The C/M-FIS combines the acquired values of the intermediate variables to infer two values at the end of each step, ie $C_n^s(p)$ and $M_n^s(p)$, where n = A, B denotes the student, $p = 1,\ldots,N$ signifies the pair, and $s = 1,\ldots L$ denotes the step of the case study. In particular, the $C_n^s(p)$ values for n = A, B are complementary percentages up to 100% that reflect the quality of each peer's collaborative activity, as compared to the total pair activity. On the other hand, the $M_n^s(p)$ value ranges from 0% (no improvement is required) to 100% (total improvement is required), and reflects the evaluation of each peer's intention of improvement at the next step of the collaboration (s + 1). Both $C_n^s(p)$ and $M_n^s(p)$, values are depicted to each peer at the end of each step (Figure 2a). This feedback targets the convergence of peers' collaborative activity to equilibrium through self-adjustment procedures. The experimental verification of the efficacy of the C/M-FIS performance can be found elsewhere [3][5].

The aim of the proposed C/M-AFM is, by means of the collaborative performance reflected in the $C_n^s(p)$ and $M_n^s(p)$ values (input data), to estimate the peer's collaborative activity of the next step $\widetilde{C}_n^{s+1}(p)$ (output data), prior to the concrete collaborative experience. The desired C/M-AFM output is fixed to the estimated $\widetilde{C}_n^{s+1}(p)$ value, whereas two different input set-ups are adopted, resulting in two realisations of the C/M-AFM, ie the C/M-AFM_1 and C/M-AFM_2, as depicted in Figures 2b and 2c, respectively.

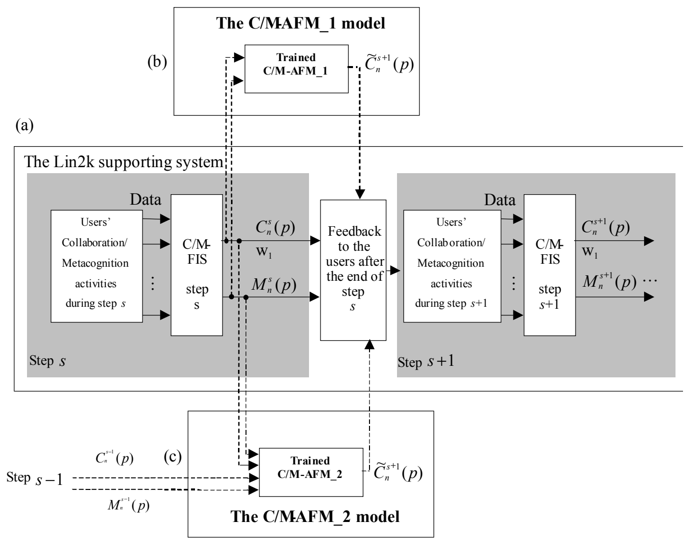

Figure 2: The integrated *Lin2k* model, with (a) the *Lin2k* supporting system [3]; (b): the C/M-AFM_1; and (c): C/M-AFM_2 embedded during the *s* step of collaboration

In particular, the C/M-AFM_1 is a model that estimates the $\widetilde{C}_n^{s+1}(p)$ value when presented with the $C_n^s(p)$ and $M_n^s(p)$ values, whereas the C/M-AFM_2 considers the collaborative and metacognitive activities of both the steps *s* – 1 and *s*. Thus, the input data for this model are the $C_n^{s-1}(p)$, $M_n^{s-1}(p)$, $C_n^s(p)$ and $M_n^s(p)$ values, as depicted in Figure 1(c). In order to allow C/M-AFM_2 to perform an estimation of the $\widetilde{C}_n^{s+1}(p)$ value from the second step (ie $s + 1 = 2$) as well, the $C_n^0(p) = M_n^0(p) = 0$ values were used as initial conditions.

Both the C/M-AFMs have a fuzzy neural network (FNN) structure that permits knowledge extraction from empirical data. In particular, their structure is a layered neural network, materialised by means of interconnected nodes [4]. Weights that are assigned to the node connections represent the parameters of a set of i = 1:k IF/THEN fuzzy rules, namely rule-base. The IF/THEN implication operator defines two parts in each fuzzy rule; the antecedent and the consequent, where adjacent parameters are realised.

Two primary identification procedures take place in the realisation of the C/M-AFMs structures. The first refers to the identification of the structural parameters, ie the number of rules [6]. The second procedure refers to the premise and consequent parameters identification through a *training procedure*. It is performed on the basis of about 75% of the available input-output data that form the training set. The values of the above parameters are identified by means of the back-propagation algorithm [4]. This minimises, with a predefined accuracy, the training Root Mean-Squared Error (RMSE) between the estimation $\widetilde{C}_n^{s+1}(p)$ of $C_n^{s+1}(p)$ for each C/M-AFM realisation [4]. The parameters' identification is achieved in repetitive cycles for the RMSE minimisation, namely epochs. Having all the parameters calculated, a model of the input-output relation is identified. When new data (lying within the parameters' range of values) are presented as an input to the trained model, the latter is then able to generalise and output the $\widetilde{C}_{n,i}^{s+1}(p)$ value.

Furthermore, a *testing procedure* is employed to verify the quality of the above generalisation ability of the model [4]. To this end, about 25% of the available data, forming the testing set, are properly selected on the basis of emulating the real conditions and differing from the training set [4]. The value of the testing RMSE is utilised as an indicator of the quality of the performance of the model.

IMPLEMENTATION ISSUES

Experimental uses of *Lin2k* provided the dataset for the development of the C/M-AFM models [3]. More specifically, 16 civil engineering students from the 10th semester at Aristotle University of Thessaloniki, Thessaloniki, Greece, were randomly selected and paired (ie N = 8). The peers were asked to collaborate through the *Lin2k* and to prepare an EIA concerning the construction of a wastewater treatment plant in a suburban area, given the visual and text information provided [3]. Collaboration was split into six successive steps (ie L = 6), and the collaborative and metacognitive parameters, $C_n^s(p)$ and $M_n^s(p)$, were estimated by the *Lin2k* system and used as input data for the C/M-AFMs. However, the size of the dataset was regarded as poor, considering the complexity of the model and the number of the parameters involved. In order to increase the generalisation ability of the model, the dataset was interpolated by up to 64 pairs. From the overall 64 pairs, the data from the 14 pairs were selected as the testing set, whereas the remaining 50 pairs were used as the training set. The training and testing procedures were performed by means of the *Adaptive Fuzzy Modeler* (AFM) 2.0 software from STMicroelectronics [6].

RESULTS AND DISCUSSION

Different scenarios in the training set-up were examined during the training procedure of the C/M-AFMs in order to select the optimal one. Variations in these scenarios, covering the initial conditions defined through appropriate selections in the AFM interfaces, included the number of inputs and outputs, the number of the membership functions (MFs*)* per input variable, the type of MFs, the selection of operators, and the criterion for the completion of the training procedure, that is either the number of epochs or a desired value of the RMSE. In all scenarios under consideration, the completion of the training procedure criterion was set as RMSE < 0.05 or number of epochs <300 and negligible variations in the estimated RMSE value.

From the above procedure in the best-trained C/M-AFM_1, five Gaussian-type MFs per input were used and the minimum inference method was adopted [6]. The training procedure resulted in 25 rules and an almost constant value of RMSE = 0.03053 for the number of epochs less than 300. Similarly, the best C/M-AFM_2 was trained with the two input-one output dataset, five Gaussian-type MFs per input and the minimum inference method. The training procedure resulted in 625 rules and a value of RMSE = 0.01745 for 290 epochs.

Apart from the results of the training procedure, results from the testing procedure, by means of the testing dataset, are presented for both the best-trained C/M-AFM_1 and C/M-AFM realisations in Figure 3. In particular, Figure 3a depicts the mean values of the experimental $C_n^s(p)$ from all peers across the steps (s = 2,3,…,6), which serve as target values for the C/M-AFMs. The grey area shows the estimated standard deviation (*std*). In Figure 3b, the mean values of the estimated $\widetilde{C}_n^s(p)$ from all peers across the steps (s = 2,3,…,6) derived with the C/M-AFM_1 realisation are shown, while the same ones, when the C/M-AFM_2 was used, are shown in Figure 3c; again, the grey area in Figures 3b and 3c denote the estimated *std.* When comparing Figure 3a with Figures 3b and 3c, a similar morphology between the experimental and the estimated data can be seen, justifying the efficient performance of the C/M-AFMs in both realisations. The mean RMSE ± *std* across the steps (s = 2,3,…,6) was found to be equal to 0.0443±0.028 and 0.0436±0.031 for the C/M-AFM_1 and C/M-AFM_2, respectively.

These results show a similar performance of the two C/M-AFMs; however, the C/M-AFM_2 slightly outperformed the C/M-AFM_1 in terms of achieving smaller RMSE values. Nevertheless, due to the FNN structure of the models, the exponential dependence of the number of the rules on the number of inputs should be taken into consideration. This is clear from the significant differences observed in the number of generated rules in the cases of the best-trained C/M-AFM_1 (25) and C/M-AFM_2 (625), where two and four inputs were used, respectively. However, the larger rule-base of the best-trained C/M-AFM_2 manages to model better than the one of the best-trained C/M-AFM_1, with the unknown relation between the input-output dataset achieving the lowest RMSE value with a fast convergence. Some differences were noted in the way that the estimated MFs are distributed in the universes of discourse of the input variables. In particular, the MFs of the C/M-AFM_1 were more overlapped when compared with those of the C/M-AFM_2. This is due to the greater estimated *std* values of the MFs of the C/M-AFM_1 compared with those of the C/M-AFM_2, possibly due to the increased resolution achieved with the employment of more input variables (hence, more fuzzy-rules) into the C/M-AFM_2 realisation.

The generalisation ability of the C/M-AFM, as it is expressed through the testing results of the C/M-AFM_1 and C/M-AFM_2 (see Figure 3), is quite high, since the tendencies observed in the real data are clearly captured by the

C/M-AFMs. The time of the testing procedure for both of the C/M-AFM realisations was almost the same: less than one second in a PC Pentium IV 2.8 GHz. This time delay could be characterised as negligible and allows the integration of the adaptive module under consideration to a synchronous and asynchronous modes of communication.

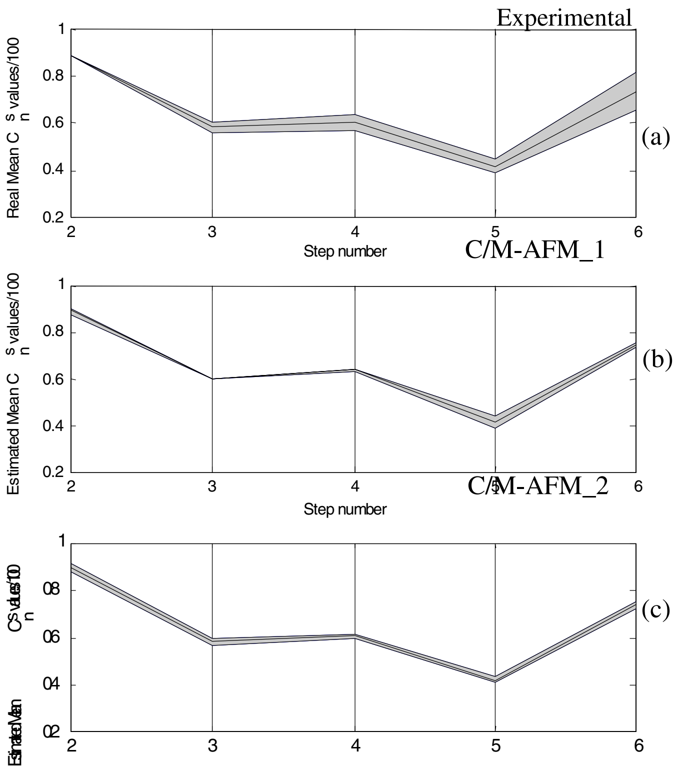

Figure 3a: Experimental and estimated by (b) the best-trained C/M-AFM_1 and (c) the best-trained C/M-AFM_2 of the mean C_n^s values per s step, for the testing input vector. In all cases, the grey area denotes the estimated standard deviation.

Overall, the C/M-AFM_1 and C/M-AFM_2 materialise the best-trained models of the two different design approaches that were tested, as far as the number of the steps considered for the estimation of the $\widetilde{C}_n^{s+1}(p)$ value. Although the C/M-AFM_2 model performed better than the C/M-AFM_1, it also had a more complex structure. Consequently, according to the implementation priorities, the more appropriate realisation could be adopted as a trade-off between the desired error minimisation and afforded complexity.

CONCLUDING REMARKS AND FUTURE WORK

Two realisations of an adaptive fuzzy modeller have been tested and their performance compared in terms of error minimisation, speed of convergence and degree of complexity. The results from the training and testing procedures show that both realisations can serve as efficient tools in providing an accurate prediction of collaborative data during a session of collaboration divided into successive steps. In this way, the C/M-AFM could be integrated within a collaborative computer-mediated environment in order to provide more enhanced feedback to peers during the development of their collaboration. The C/M-AFM elaborates on important key actions that challenge a microgenetic approach to the collaboration [7]. This is as follows:

- It regards an individual as a unit of analysis and observes changes in his/her collaborative behaviour over a period of time, ie the duration of the case study in which the change occurs.
- It takes into account the elevated density of the observations within the transition period [7]. That is, observations take place over time intervals, ie weeks for the steps of the case study, shorter than the period in which the change is expected to take place, ie months for the completion of the case study. Its neurofuzzy methodology targets the identification of the processes that give rise to the change. It contributes to the occurrence and acceleration of this change through its generalisation capability. Presenting to the individual, at successive intervals of the micro-level (end of each step of the case study), the estimated value of the forthcoming collaborative activity, $\widetilde{C}_n^{s+1}(p)$, it highly increases the possibilities to effect the desired change. Consequently, the C/M-AFM contributes to a formative improvement of peer collaborative behaviour, which is at the core of the provided support.
- It materialises an *external counsellor*, who gives feedback in order to challenge readjustments in peer collaboration interactions. The importance of this approach is profound, as it grounds a novel, automated, adaptive user support during Internet-based collaboration, which formatively refines the quality of the collaboration and encourages the users to further improve.

Future work includes extensive application of the proposed C/M-AFM in more groups towards its further refinement, especially in terms of achieving smaller RMSE values without significantly increasing model complexity. Further, the application of the model to large-scale experiments could extend its generalisation efficiency and facilitate its integration within the context of intelligent mediator agent design.

REFERENCES

1. Europa, http://europa.eu.int/comm/environment/eia/home.htm
2. Fayyad, U.M., Piatetsky-Sapiro, G. and Smyth, P., *From Data Mining to Knowledge Discovery: an Overview*. In: Fayyad, U.M., Piatetsky-Sapiro, G., Smyth, P. and Uthurusamy, R. (Eds), Advances in Knowledge Discovery and Data Mining. Menlo Park: AAAI Press/MIT Press (1996).
3. Hadjileontiadou, S., Sakonidis, H. and Balafoutas, G., *Lin2k*: a novel Web-based collaborative tool-application to engineering education. *ASEE J. of Engng. Educ*., 4, 313-324 (2003).
4. Horikawa, S., Furuhashi, T. and Uchikawa, Y., On fuzzy modeling using fuzzy neural networks with the back-propagation algorithm. *IEEE Trans. on Neural Networks*, 3, **5**, 643-662 (1992).
5. Hadjileontiadou, S.J., Nikolaidou, G.N., Hadjileontiadis, L.J. and Balafoutas, G.N., A fuzzy logic evaluating system to support Web-based collaboration using collaborative and metacognitive data. *Proc. 3rd Inter. Conf. on Advanced Learning Technologies (ICALT 2003)*, Athens, Greece, 96-100 (2003).
6. Adaptive Fuzzy Modeler (AFM 2.0), STMicroelectronics (1998), http://www.stmcu.com/modules.php?name=mcu&file=mdtdocs
7. Lavelli, M., Pantoja, A.P.F., Hsu, H., Messinger, D. and Fogel, A., *Using Microgenetic Designs to Study Change Processes.* In: Teti, D. (Ed.), Handbook of Research Methods in Developmental Psychology http://www.sv.ntnu.no/psy/studiet/forelesninger/ host 2002/ psy300/ Lavelli.pdf