Learning FCMs with multi-local and balanced memetic algorithms for forecasting industrial drying processes

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Abstract

In this paper, we propose a Fuzzy Cognitive Map (FCM) learning approach with a multi-local search in balanced memetic algorithms for forecasting industrial drying processes. The first contribution of this paper is to propose a FCM model by an Evolutionary Algorithm (EA), but the resulted FCM model is improved by a multi-local and balanced local search algorithm. Memetic algorithms can be tuned with different local search strategies (CMA-ES, SW, SSW and Simplex) and the balance of the effort between global and local search. To do this, we applied the proposed approach to the forecasting of moisture loss in industrial drying process. The thermal drying process is a relevant one used in many industrial processes such as food industry, biofuels production, detergents and dyes in powder production, pharmaceutical industry, reprography applications, textile industries, and others. This research also shows that exploration of the search space is more relevant than finding local optima in the FCM models tested.

Keywords: Fuzzy Cognitive Maps, Machine Learning, Industrial drying, Memetic Algorithm

1. Introduction

Fuzzy Cognitive Maps (FCMs) are soft computing tools with the ability to model the dynamics of complex systems by incorporating the casual relationships between the main concepts that model the system.

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In this paper, we propose a FCM learning approach with a multi-local search in balanced memetic algorithms for forecasting industrial drying processes. The main contributions of this study are as follows

- We propose a hybrid approach. The FCM model is constructed by an Evolutionary Algorithm (EA), but the resulted FCM model is improved by a multi-local and balanced local search algorithm.
- We propose optimizing the selection of the FCM's activation function using a pool of functions. After the function is selected, the parameters and slopes are optimized.
- We check the balance of the effort between EA and local search for learning FCMs in memetic algorithms.

To the best of our knowledge, there is no work that considers a multi-local search and different effort balance between global and local search. Consequently, we check the influence of local search strategies and the balanced effort.

Our proposal is tested on the industrial drying process. The moisture loss of a drying process is a complex problem with associated risk and uncertainties because it involves two simultaneous processes, transfer of heat and transfer of mass, with the possible appearance of physical, chemical and even biological transformation processes. These processes can change the characteristics of the product to dry and therefore turn mechanisms of heat and mass transfer. So, experimental testing drying with maintaining the essential external variables (temperature, humidity, rate and direction of airflow, the physical form of the solid, and so on) are necessary for forecasting moisture loss and dryers design. The relevance of this proposal is to achieve an improved dryer, foreseeing the behaviour from different magnitudes of external variables without having to try experimental drying tests again.

The remainder of this paper is organized as follows. First, in Section 2 we provide background knowledge on Fuzzy Cognitive Map technique with a focus on its structure, reasoning and learning. Section 3 details the methodological proposal. The experimental evaluation of the proposed approach is described in Section 4. Section 5 concludes the paper.

2. Fuzzy Cognitive Maps

A Fuzzy Cognitive Map (FCM) combines artificial neural networks and fuzzy logic, and it is useful to model a kind of dynamical systems call complex adaptive systems (Salmeron, 2009a). In addition, it is able to process the associated uncertainty. FCM was proposed by Kosko (1986, 1992) and it has become a technique for knowledge representation (Salmeron, 2012; Miao et al., 2001). They constitute a way to represent real-world dynamic systems, in a form that corresponds closely to the way human beings perceive it (Salmeron, 2009b).

FCMs are digraph with variables or concepts (as nodes in the model) that represent the components of the system (or problem) to model, and directed edges, which model the causal relationships between the nodes. The edges are weighted ones with fuzzy values in the range $[0.0, 1.0]$ for unipolar FCM models, or $[-1.0, +1.0]$ for bipolar ones, that show the influence between the variables (Salmeron, 2016). The adjacency matrix A collects the influence (with w_{ij} weights) between each pair of nodes, where i is the presynaptic node and j the postsynaptic one.

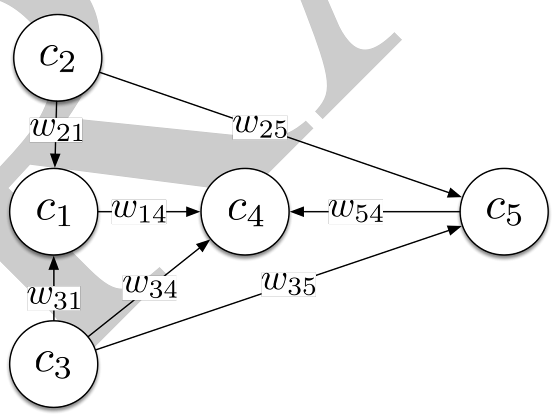

Figure 1: FCM model

The weight of the node i in the time lapse t is represented by the value $c_i(k)$. In this sense, the state of all the FCM nodes in time lapse k is modelled by the state vector $c(k) = [c_i(k), \ldots, c_n(k)]$. The state c_i of the concept i in the time lapse $k+1$ is computed by the sum of the products of the values c_j of the cause nodes j in the former time lapse k and the value of the edges from the node j to the i (w_{ji}). If the nodes have memory, the previous value of c_i in a previous time lapse k will add to the former result (Salmeron and Papageorgiou, 2012).

The updating rule of the FCMs' nodes can take one the following forms, if the node has memory (Eq. 1b) of its former state or not (Eq. 1a):

$$c_i(k+1) = f\left(\sum_{j=1}^{n} c_j(k) \cdot w_{ji}\right) \tag{1a}$$

$$c_i(k+1) = f\left(c_i(k) + \sum_{j=1}^{n} c_j(k) \cdot w_{ji}\right) \tag{1b}$$

where $f(\cdot)$ is the transformation (activation) function (Tsadiras et al., 2003). The transformation function reduces the unbounded weighted sum to a certain range, which hinders quantitative analysis, but allows for qualitative comparisons between concepts (Salmeron and Gutierrez, 2012; Stylios and Groumpos, 2004). The most common FCM's transformation functions are the unipolar sigmoid and hyperbolic tangent (Bueno and Salmeron, 2008). A concept is activated by making its state in the vector different to 0 or $c_i \in \{(0, +1.0]\} \vee \{[-1.0, 0.0), (0.0, +1.0]\}$. Unipolar sigmoid function gives values of concepts in the range $[0.0, 1.0]$ and is computed as follows

$$f(c_i) = \frac{1}{1 + e^{-\lambda \cdot w_{ji} \cdot c_j}} \tag{2}$$

The expression of the hyperbolic tangent is as follows

$$f(c_i) = \frac{e^{2 \cdot \lambda \cdot w_{ji} \cdot c_j} - 1}{e^{2 \cdot \lambda \cdot w_{ji} \cdot c_j} + 1} \tag{3}$$

where $\lambda > 0$ is a real positive number for controlling the slope of the function (Stylios and Groumpos, 2004; Tsadiras et al., 2003). Moreover, hyperbolic tangent gives values in the range $[-1.0, +1.0]$.

The dynamic of the whole FCM model with an input vector $c(0)$ follows a time trace within a n-dimensional space Φ^n, which can gradually converge into an equilibrium point, a limited cycle or a chaotic attractor within a fuzzy hypercube (Salmeron

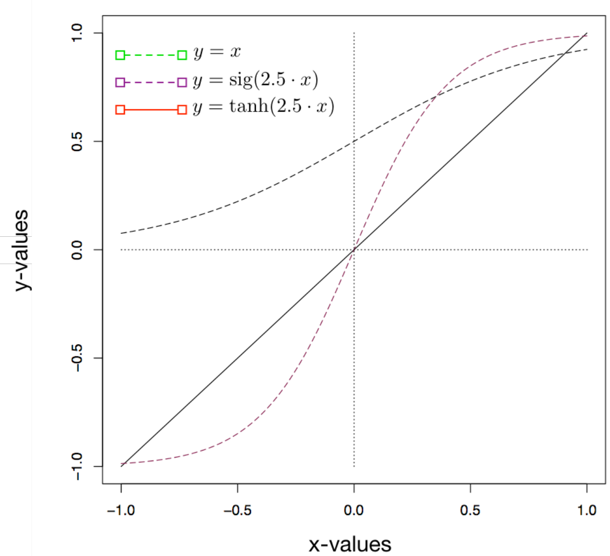

Figure 2: Main transformation functions (linear, unipolar sigmoid and hyperbolic tangent)

and Lopez, 2012). To which attractor the system will converge depends on the value of the input vector $c(0)$ and the causalities.

FCM learning is usually based on the automatic learning of the adjacency matrix ($\mathbf{A}$) from the available historical raw data (Papageorgiou and Froelich, 2012; Salmeron and Froelich, 2016). The learning approaches could be divided into three categories; hebbian-based, evolutionary-based and hybrid.

Hebbian-based FCM learning objective is to improve the FCM's adjacency matrix built from the experts' heuristic knowledge that lead the FCM to converge into a desired area for the modelled system.

Furthermore, evolutionary FCM learning approaches evolve adjacency matrices from historical raw data that best fit the steady states represented by the historical data or the sequence of input state vectors ($c(0)$). The main reward of this approach is that humans' engagement is not required. The main goal is to find the optimal adjacency matrix for modelling complex systems (Salmeron and Froelich, 2016).

Table 1: Learning algorithms in FCMs

Learning categories	Learning technique	Source
Hebbian	Differential Hebbian Learning (DHL)	(Dickerson and Kosko, 1994; Kosko, 1996)
	Active Hebbian Learning (AHL)	(Zhai et al., 2009)
	Nonlinear Hebbian Learning (NHL)	(Papageorgiou and Groumpos, 2005a; Papageorgiou and Salmeron, 2012; Salmeron and Papageorgiou, 2014)
	Petri Nets	(Konar and Chakraborty, 2005)
Evolutionary	Evolution Strategies	(Koulouriotis et al., 2001)
	Tabu search	(Alizadeh et al., 2007)
	Genetic Algorithm	(Froelich and Salmeron, 2014; Mateou et al., 2005; Salmeron and Froelich, 2016)
	Real-coded Genetic Algorithm	(Stach et al., 2005, 2007; Salmeron and Froelich, 2016)
	Particle Swarm Optimization	(Papageorgiou et al., 2005; Salmeron and Froelich, 2016)
	Ant Colony	(Chen et al., 2012)
	Artificial Bee Colony	(Yesil et al., 2013; Salmeron and Froelich, 2016)
	Simulated annealing	(Alizadeh and Ghazanfari, 2009; Salmeron and Froelich, 2016)
	Differential Evolution	(Salmeron and Froelich, 2016)
	Inmune Systems algorithm	(Lin, 2009)
	Game-Based Learning	(Luo et al., 2010)
	Big Bang - Big Crunch Learning	(Yesil and Urbas, 2010)
	Extended Great Deluge Algorithm	(Baykasoglu et al., 2011)
	Memetic algorithms	(Petalas et al., 2005)
Hybrid	NHL-DE	(Papageorgiou and Groumpos, 2005b)
	NHL-RCGA	(YanChun and Wei, 2008)

Lastly, FCMs models can be built with hybrid machine learning methods. The learning goal is to modify the adjacency matrices from the proposed experts' ones and evolve them from the historical data at a two-stage learning procedure.

Note that hebbian and hybrid ones need to be applied to data including the whole sequence, because they head to reproduce the whole FCM dynamics and not just the steady state.

Table 1 includes a summary of the studies about the machine learning proposal for building FCMs divided into the categories mentioned above. The Table 1 exhibits that the evolutionary proposals are the most popular ones.

3. Proposed methodology

This paper proposes an algorithm mixing Real Coded Genetic Algorithms with local search. Genetic Algorithms hybridized with local search techniques are often called memetic algorithms (Molina et al., 2011). The proposed memetic algorithm for learning FCMs is shown in Algorithm 1.

Algorithm 1: Proposed FCM learning approach

```
Data: Domain's raw data, Population size, Max iterations, Local search
      strategy, Balanced effort
Result: Automatic built FCM
Design fitness function;
Choose initial FCM population (random);
Evaluate each FCM's fitness;
while Termination is false do
    Select best-ranking FCM to reproduce;
    Mate pairs at random;
    Prune FCM population;
    Crossover operator;
    Mutation operator;
    while Local Search is applied do
        for Each candidate solution do
            Apply selected local search strategy
            if New solution improves the RCGA solution then
                Update the candidate solution
            end
        end
    end
    Evaluate each FCM's fitness;
end
Select best-fitness FCM
```

Fitness function must be designed. The fitness function must quantitatively measure how fit a given candidate solution is. In our proposal, the fitness function measures the Root Mean Square Error (RMSE) (Eq. 4) between the predicted moisture loss ($\hat{c}_{4j}$) and the observed (real) moisture loss (c_{4j}).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{j=1}^{n}(\hat{c}_{4j} - c_{4j})^2}{n}} \tag{4}$$

where c_{4j} is the moisture loss of the j^{th} row of the training dataset.

After, the population of candidate solutions are randomly generated (2000 adjacency matrices). Then, the fitness of each candidate solution is computed. Then the algorithm starts the iterations of the RCGA until one the termination criteria stops it. We use a couple of stopping criteria. The first one is the maximum number of iterations (5000) and the other one is RMSE $< \epsilon$, where $\epsilon = 0.0001$ is the tolerance. Note that the moisture loss is just one value and there is no need for including more nodes of the model in the stopping criteria. Now, the iteration cycle of the RCGA starts with the selection of the best-ranked FCM to reproduce, mating pairs at random, pruning population, applying crossover and mutation operators.

The next step in our proposal is the local search. The local search can be embedded within the RCGA process principally in a couple of ways. The first one is the application of the local search to every candidate solution. The second way is the application of the local search during the solution generation. We select the first one.

The selection of the local search strategy and its harmonization with the RCGA is critical for the performance of memetic approaches (de Oca et al., 2012). We consider four local search strategies (Molina et al., 2011):

- The Covariance Matrix Adaptation Evolution Strategy (CMA-ES). It is a powerful local search strategy. As a drawback, when the problem has a huge number of parameters to optimize it does not scale well.

- A Solis Wets solver (SW). The SW solver is a randomized hill climber. It is pretty simple and therewith fast.

- Subgrouping Solis Wets (SSW). The SSW strategy is the modified version of SW and it is designed for data with high dimensionality. This local search method explores, at each step of the algorithm, only a random subset of the variables.

- Simplex. It is the well-known simplex algorithm.

In the last step of the local search, if the local search strategy improves the candidate solution by the global search algorithm, it will be updated. At the end, the proposed algorithm settles in the global optimum.

4. Experiments

4.1. Moisture loss

Dehydration prevents the proliferation of microorganisms. The action of the sun and the wind manages an effective method of food conservation (meats, fish, fruit, vegetables and cereals). On the other hand, the use of dry wood as fuel allowed the control of the fire, which is considered one of the fundamental pillars of the technological development. Nowadays, the drying processes are widely applied: food industry, biofuels production, detergents and dyes in powder production, pharmaceutical industry, reprography applications, textile industries and others.

Thermal drying is one of the most ancient and more widely used in many industrial processes (Mujumdar, 2007; Pedreno-Molina et al., 2005). Thermal drying is the result of two simultaneous actions: one is the heat transfer, where heat is provided to the product to evaporate the liquid, and the other is mass transfer, in which the liquid or vapour is moved through the product. The fluid movement, by which the vapour leaves the product surface, depends on the structure, characteristics and moisture content of the material. The migration of the vapour from the solid is a function of the environment pressure and temperature, the external solid surface, the value of Reynolds number and drying agent relative humidity.

A proper design of drying equipment requires the knowledge of the drying behaviour of the product. This behaviour can be analyzed experimentally at the laboratory, by obtaining the drying curves as starting point. In the case of convective thermal drying, to determine the Moisture Ratio (MR), the mass of a sample placed in the airflow must be measured as function of drying time.

When the temperature, moisture content and velocity of air are constant, drying takes place under constant drying conditions. Subsequently, and using these experimental results, the mathematical modelling of the process can be accomplished. The drying curves represent the changes in the moisture ratio with time during the drying process under the established conditions. The dimension less moisture ratio is computed as follows (Midilli, 2001)

$$\mathrm{MR} = \frac{\mathrm{Mt} - \mathrm{Me}}{\mathrm{M0} - \mathrm{Me}} \tag{5}$$

where M0, Mt and Me indicate moisture content (water / dry solid) in grams at time 0, time t and equilibrium, respectively. Moisture content was determined using the equation:

$$\mathrm{M} = \frac{(\mathrm{W0} - \mathrm{W}) - \mathrm{Wd}}{\mathrm{Wd}} \tag{6}$$

where W0 is initial weight of sample in grams, W is the amount of evaporated water and Wd is dry matter content of sample. Since the value of equilibrium moisture content is usually low, it is frequently simplified as (Mt / M0), provided this simplification does change the value of MR.

The process modelling provides a set of equations which properly describe the process, under given conditions. The thin-layer models can be distinguished in three categories, called the theoretical, the semi-theoretical and the empirical ones (Sharaf-Eldeen and Hamdy, 1979).

The major difference between these categories is that the semi-theoretical and empirical models consider only the external resistance to moisture transfer between product and air; these types of models are valid in the specific ranges of temperature, air velocity and humidity for which they are developed. While the theoretical models suggest that the moisture transfer is controlled mainly by internal resistance mechanisms. The semi-theoretical and empirical models are the most widely used. The basic reason for such choice lies in the fact that those models need no geometric, mass diffusivity nor conductivity assumptions.

There are a wide variety of bibliographical resources devoted to the mathematical modeling using techniques based on non-linear regression, which define characteristically drying parameters of diverse products in which the falling rate period is the most important. The semi-theoretical drying models are derived by simplifying general series solution of Fick's law of diffusion. The empirical models are derived from statistical relations and they directly correlate moisture content with drying time.

Our proposal has been specifically applied to by-products of tomato industry: sludge and peels-seeds. Sludge is obtained after the latter operation, decanting from the wastewater treatment plant, while tomato peels and seeds (organic vegetable solid residues) are presented as by-products of processing of fresh tomato. These materials show a typical moisture content $60-70\%$ by weight (wet basis). Both the products characteristics and the description of the equipment used, as well as the experimental procedure have been described in Ruiz-Celma et al. (2012, 2013).

A convective dryer was used as experimental equipment. Basically it consists of a fan, a resistance battery and a heating control system, air-duct, trays and measurements instruments. The dryer was located inside a laboratory room so that it could work under the appropriate operating conditions: surrounding temperature between 15°C and 25°C, and 60% maximum relative humidity.

The samples were uniformly arranged on the tray as a thin layer and sample thickness (10 mm) was kept constant for each experiment. Moisture loss was recorder at 5 minutes intervals during the drying process in order to determine the experimental drying curves. The experiments ended when the content of moisture in the samples was reduced to approximately 10% by weight (wet basis). All drying experiments were performed in triplicate, and the arithmetic means of the results obtained in each case were used in the experimental drying curves.

4.2. Proposed model

The FCM model is shown at Fig 3. The nodes c_1, c_2 and c_3 represent the velocity, temperature and time. The node c_4 models the potential moisture loss. The goal of the experiments is to find the best combination of local search strategy and balance between global and local search. The proposed algorithm evolves the adjacency matrix in Eq. 7.

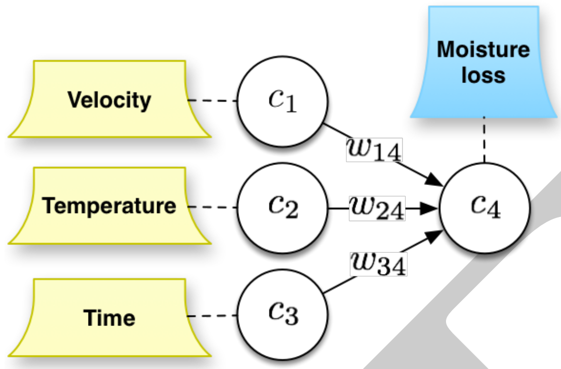

Figure 3: FCM model

$$A = \begin{pmatrix} 0.0 & 0.0 & 0.0 & w_{14} \\ 0.0 & 0.0 & 0.0 & w_{24} \\ 0.0 & 0.0 & 0.0 & w_{34} \\ 0.0 & 0.0 & 0.0 & 0.0 \end{pmatrix} \tag{7}$$

Moreover, the proposed algorithm also evolves the transformation function between the most common ones (linear, unipolar sigmoid and hyperbolic tangent) as represented in Fig. 2. Furthermore, the slope of each activation function is evolved as well. As result the genotype (chromosome) to evolve is as detailed in Fig. 4.

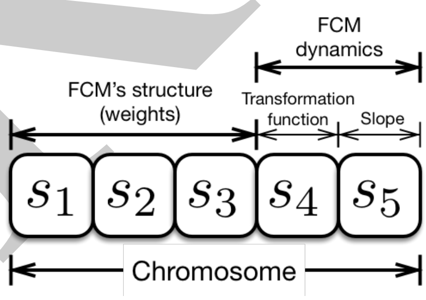

Figure 4: Chromosome and genes

The chromosome has five componentes $\mathbf{S} = \{s_i\}_{i=1}^{5}$. It includes three genes representing the FCM's structure and two ones modeling the FCM dynamics. The genes

s_1 to s_3 represent the weights in the candidates adjacency matrices. The gene s_4 represents the transformation function and the gene s_5 its slope.

For our experiments we used the 'malschains' function from the 'Rmalschains' package (Molina et al., 2011) of R language that implements an algorithm family for continuous optimization called memetic algorithms with local search chains. The experiments have been run with different local search strategies CMA-ES, SW, SSW and Simplex.

A higher effort means more evaluations for the evolutionary algorithm. In this sense, if effort$= 0.5$, then the memetic algorithm runs the same number of evaluations for evolutionary algorithm and local search. In addition, we have done experiments with different balance between evolutionary algorithms and local search. This balance is represented by a parameter between 0 and 1 which gives the ratio between the number of evaluations used for the local search and for the evolutionary algorithm, respectively.

4.3. Experiment 1: Sludge

The samples of fresh sludge were obtained from the wastewater treatment plant of a local tomato industry located in the province of Badajoz (in the Southwest area of Spain). They showed an initial moisture content 63% by weight (wet basis). This value was calculated as indicated by the Norm UNE 32001 (32001:1981, 1981).

Drying experiments were conducted at 30°C, 40°C and 50°C drying air temperatures and at 0.9 m/s and 1.3 m/s air velocities and according to the methodology indicated.

The results of the experiment 1 are detailed in the Table 2. The best results are achieved with effort 0.8. It means that the evolutionary algorithm was evaluated 4000 iterations and the local search 1000 iterations more. With this effort, all the local search strategies achieve the best result. It means that the local search strategy is not relevant for learning the FCM model in sludge experiment.

4.4. Experiment 2: Peels-Seeds

The origin of the peels and seeds is the same tomato industry. They showed an initial moisture content of 66% by weight (wet basis).

Table 2: Experiments' results

Effort	Local Search Strategy	Sludge	Peels-Seeds
0.8	CMAES	**0.172824**	0.129835
0.8	Solis Wet	**0.172824**	0.128125
0.8	SSW	**0.172824**	**0.123348**
0.8	Simplex	**0.172824**	0.129832
0.5	CMAES	0.174856	0.129835
0.5	Solis Wet	0.174897	0.126321
0.5	SSW	0.173943	0.129321
0.5	Simplex	0.174882	0.129840
0.2	CMAES	0.174855	0.129835
0.2	Solis Wet	0.174956	0.127602
0.2	SSW	0.177324	0.132205
0.2	Simplex	0.174881	0.129840
0.0	CMAES	0.174855	0.129835
0.0	Solis Wet	0.177324	0.127602
0.0	SSW	0.177324	0.126858
0.0	Simplex	0.174881	0.129840

In this case, drying experiments were conducted respectively at 25°C, 35°C and 45°C drying air temperatures and at 1.0 m/s and 1.3 m/s air velocities and according to the methodology indicated.

The results of the experiments 1 and 2 are detailed in the Table 2. The best results are achieved with effort 0.8. It means that the evolutionary algorithm evaluated 4000 iterations and the local search 1000 iterations more. With this effort, the local search strategy achieving the best result is SSW.

Moreover, the results of the experiments 1 and 2 proof that exploration of the search space is more important than finding local optima in sludge and peels-seeds FCM models because better results are achieved with higher effort.

5. Conclusions

In this paper, we proposed a multi-local and balanced memetic algorithms to learning FCM. This proposal has several improvements in relation to the conventional memetic algorithms for FCM learning.

Firstly, the authors compare several local search strategies and the balance between the local and global search in memetic algorithms. Moreover, several local search strategies and the balance between local and global search are checked. According to this, the results of our experiments proof that exploration of the search space is more important than finding local optima in sludge and peels-seeds FCM models, because better results are achieved with higher effort. If the data has multiple local optima it would be necessary to apply more effort to local search.

Secondly, the algorithm evolves the FCM structure and the FCM reasoning. In addition to the optimization of the adjacency matrix, we proposed to optimize the activation function and its slope. In this way, the transformation of each FCM node is optimized together with the transformation function and its slope.

Moreover, the authors applied the proposal to the thermal industry drying process. As far as we know, this is a novel application of FCM learning.

For future studies, several drawbacks of the FCM method should be overcome. During the FCM building stage, the number of degrees of freedom is high. It could lead to potential inaccurate models. In this sense, improved FCM building methods could be proposed.

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