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# ENHANCEMENT OF FCM FOR FORECASTING AND DECISION SUPPORT SYSTEM

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## Abstract

In spite of the numerous solutions that have recently been offered in this field, the search for better approaches to represent and analyze the complexity of data-driven models continues to grow. Decomposing each element/concept on a higher map level into another FCM that delivers more full and correct representation of complicated time series data is the goal of this study. It shows how to create a layered structure based on FCMs. After that, evolutionary learning techniques are used to optimize the hierarchical structure. In order to infer meaningful connections between map ideas at each nesting level and calculate the weights of these linkages using available time series, a dynamic optimization strategy is used. This method allows for the detection and description of linkages between crucial map themes that are otherwise concealed. A tiered approach to time series forecasting and decision-making for appliance energy consumption is described in the paper.

## 1. Introduction

Over the last few years, the use of FCMs (fuzzy cognitive mappings) has grown in popularity. An FCM may be conceived of as a recurrent neural network that combines essential fuzzy logic elements. The use of an FCM enables the replication of a system or phenomenon utilizing fundamental ideas and causal relationships. FCM models are well-suited for modelling and

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decision-making in complex systems. Modeling an underwater virtual world with dolphins and fish and sharks for sustainable socioeconomic development and pattern identification are just a few of the applications. A decision support system for the photovoltaic solar energy industry has also been implemented.

This project aims to provide a way for generating a layered FCM structure that better reflects the complexity of a situation. In order to arrive at an FCM, the suggested technique deconstructs each concept at a higher map level. $K$-means clustering is used to group data attributes (ideas) based on their similarity in the proposed approach. Next, the Real-Coded Genetic Algorithm and the Structure Optimization Genetic Algorithm are used to identify significant connections between concepts at each nesting level for the purpose of learning FCMs. The study recommends that the layered approach be utilized for time series forecasting and decision-making in appliance energy consumption prediction.

For both long-term planning and short-term savings, the ability to precisely forecast one's energy usage is vital. As energy prices rise, we'll need better technology to analyze, regulate, and recommend ways to reduce and optimize our energy usage. Multiple linear regression, support vector machines with radial kernels, random forests, and gradient boosting machines were used to anticipate building energy usage in Reference. In Reference, on the other hand, radial kernel support vector machines were used. Multiple linear regression and support vector machines with radial kernels are beaten by gradient boosting machines and random forests when it comes to error prediction. ANNs, ARIMA, and multiple linear regression models were all employed by Reference to make their predictions about energy consumption. Using an autoencoder-based deep learning model, the reference describes how to forecast future energy demand in a range of circumstances.

For a deeper knowledge of energy usage patterns and reduction opportunities than can be gained from traditional energy prediction models, additional factors (concepts) must be uncovered and monitored. These are the main points of the article's research contribution:

Deconstructing each concept at a higher map level permits the construction of a more complete FCM. The layering structure described in the study is successful. Consider, for example, the recommended strategy for optimizing the FCM layered structure. It performs admirably and is quite adaptable.

Researchers recommend using the rigorous SOGA method to optimize and establish the proper multilayer FCM design in order to improve prediction performance. The authors employed SOGA algorithms to identify the most significant ideas from among the numerous viable concepts at each nesting level of the layered structure.

The FCM-based layered structure may also be used to predict appliance energy use through simulation, according to the researchers. The nested FCM and the classic FCM were thoroughly analyzed to evaluate how well the novel approach worked. The tests were carried out utilizing a database intended to forecast appliance energy use.

## 2. Fuzzy Cognitive Maps Overview

FCM's knowledge graph is made up of nodes (concepts) and the links that connect them. Variables in a causal system are represented nonlinearly by the ideas described below. Acceptable values are those that fall within the specified range. Negative or positive values can be assigned to the connections between ideas that are referred to as "directed connections". FCMs have been used to study the evolution of photovoltaic solar energy in Brazil, as seen in Figure 1.

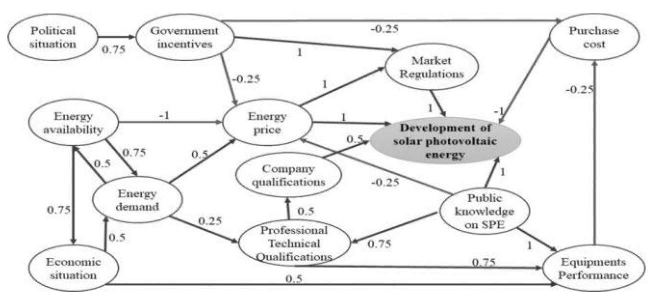


**Figure 1.** A fuzzy cognitive map prepared by a group of professionals for the growth of photovoltaic solar energy in Brazil.

FCMs may be used to represent decision support systems and time series prediction because of the causal nature of the interactions between the concepts. The model's dynamic behavior causes ideas to alter over time. Using a prominent nonlinear dynamics model, this paper's concepts are estimated.

$$X_i(t+1) = F\left(X_i(t) + \sum_{\substack{j=1 \\ j=i}}^{n} X_j(t) \cdot w_{j,i}\right) \tag{1}$$

When using the FCM, the value of the i-th concept is $X_i(t) = i,\ j = 1, 2, \ldots, n$ is the total number of concepts, $wj, i$ is the weight that determines the linkage strength between the j-th concept and that of i-th concept with values in the interval and $F(x)$ is a sigmoidal transformation function that normalizes concept values to the range. Choice (output) concepts are ideas that should not be studied further since they can be categorized in this way.

Expert knowledge or machine learning approaches may both be used to create FCMs. Learners in FCM are interested in discovering the weights that already exist between concepts. FCM learning algorithms, such as the Real-Coded Genetic Method (RCGA), represent the weights of connections (linkages) as floating-point vectors. After that, an FCM model is built for each individual, and their fitness is assessed using the fitness function:

$$fitness_p(eror\eta) = \frac{1}{aeror\eta_{i+1}} \tag{2}$$

The population size is $p$, the generation number is $l$, and an is a parameter. The following is how Error $l$ signifies a mistake in learning:

$$eror\eta = \frac{1}{T}\sum_{t=1}^{T}(Z(t) - X(t))^2 \tag{3}$$

$Z(t)$ is the real normalized decision (output) concept normalized value at the t-th iteration of $X(t)$ $t$ is equal to one, two, three, four, five, six, seven, eight, nine,

The Design of a Structure's Optimization an improvement on the Randomized Constrained Genetic Algorithm (RCGA) is called the SOGA extension. SOGA's learning method helps to optimize an FCM's structure by identifying significant ideas and their relationships. Individuals in SOGA are represented as a floating-point vector with a binary vector of length $n$ holding information on the concepts integrated into the proposed FCM model. We employ a novel learning error to evaluate a possible FCM. A high number of ideas and their non-zero connections make the FCM more challenging and costly. In order to compute the learning error, use the following formula:

$$eror\eta_{i} = eror\eta + b_1 \frac{n_r}{n^2} eror\eta + b_2 \frac{n_c}{n} eror\eta \tag{5}$$

The number of existing conceptual links, the number of concepts in the analyzed fuzzy cognitive map, the number of concepts in error $l$, and the total number of conceivable ideas are all given by error 1.

The Proposed Approach for Constructing Nested Structure Based on Fuzzy Cognitive Maps.

This section outlines the suggested technique for creating a layered FCM structure in which each notion at a higher level may be dissected into another FCM model, resulting in a more thorough representation of complicated data.

## 3. Data Clustering

1. K-means clustering is used to group data characteristics (concepts) based on the closeness of their values. The following are the steps involved:

2. Determine the number of clusters $K$ through trial and error.

3. Newly created clusters should be used to store output ideas.

4. Utilizing the available information, establish K1 cluster centres (excluding the output concept).

5. Calculate the Euclidean distance between cluster centers and concept values:

$$d(A, C) = \sqrt{\sum_{t=1}^{\tau} (x_A(t) - x_c(t))^2} \tag{5}$$

6. Where $t$ is a positive integer ranging from 1 to for each iteration, $xA(t)$

represents the value of concept $A$ and $xC(t)$ represents the value of cluster centre $C$. Together, these three variables represent the number of records in each iteration. The concept of output is absent from this step.

7. Concepts should be assigned to the cluster centre closest to where they are located.

8. Each time a new value is entered into a cluster centre, it is updated.

9. Steps 4-6 should be repeated until convergence occurs.

In addition, the predicted values for the output concept should be calculated using the FCM models from the second layer of the layered structure (at the second level). Second-level FCM models were used to predict output values using a simple average technique. The average accuracy can be improved by increasing the number of merged single models, however each model is equally weighted in this technique.

This appliance's predicted energy consumption is used to demonstrate a method for creating a tiered structure based on FCMs. 'Appliances' was selected as the FCM's output idea. The normalized data was divided into learning and testing records (totaling 15,000). (4735 total in number). Table 1 shows some of the results of the clustering data for the appliance energy dataset.

**Table 1.** Results of clustering.

| Cluster | Attributes (Concepts) |
|---|---|
| First Cluster | T1 T2 T3 T4 T5 T7 T8 T9 |
| Second Cluster | RH1 RH2 RH3 RH4 RH5 RH6 |
| Third Cluster | Pressure |
| Forth Cluster | Lights T6 Tout |
| Fifth Cluster (output) | Appliances |

The FCM models were built using RCGA and SOGA, two different types of evolutionary learning algorithms. In order to reduce the number of incorrect predictions, the learning parameters were tuned by trial and error. The learning procedure was repeated ten times for each parameter combination. Calculated using the standard deviation, averages for the evolution criteria were generated. Random mutation had a mutation probability of 0.01 and ranking selection was used for parent selection in the simulations. The children of one generation replace the parents totally. In order to employ the elite strategy, only the best person was maintained. There was a limit of 100 generations in each case study, regardless of population size.

Table 2 summarizes the nested FCM's first and second tier prediction errors (MAE, MSE, and RMSE). A thorough comparison of the nested FCM and the normal FCM was carried out in order to evaluate the recommended approach's performance. A second round of analysis focused on the models with the lowest MSE values in order to derive predictions for second-level appliance energy use (second level). Using the top FCM models, we can see in Table 3 how accurate the model's predictions are (in terms of MAE, MSE, and RMSE).

**Table 2.** Comparison results among the nested fuzzy cognitive map and standard fuzzy cognitive map.

| Model | Algorithm | MAE | MSE | RMSE |
|---|---|---|---|---|
| Start level | SOGA | 0.0423 ± 0.0140 | 0.0058 ± 0.0017 | 0.0754 ± 0.0099 |
| | RCGA | 0.0370 ± 0.0015 | 0.0052 ± 0.0006 | 0.0720 ± 0.0039 |
| First Cluster | SOGA | 0.0454 ± 0.0099 | 0.0067 ± 0.0019 | 0.0814 ± 0.0104 |
| Second Cluster | RCGA | 0.0424 ± 0.0038 | 0.0060 ± 0.0006 | 0.0772 ± 0.0038 |
| | SOGA | 0.0453 ± 0.0077 | 0.0064 ± 0.0009 | 0.0801 ± 0.0054 |
| Third Cluster | RCGA | 0.0409 ± 0.0051 | 0.0060 ± 0.0007 | 0.0774 ± 0.0045 |
| | SOGA | 0.0423 ± 0.0140 | 0.0058 ± 0.0017 | 0.0754 ± 0.0099 |
| Fourth Cluster | RCGA | 0.0370 ± 0.0015 | 0.0052 ± 0.0006 | 0.0720 ± 0.0039 |
| | SOGA | 0.0414 ± 0.0036 | 0.0061 ± 0.0008 | 0.0778 ± 0.0050 |
| Standard FCM | RCGA | 0.0373 ± 0.0022 | 0.0054 ± 0.0005 | 0.0731 ± 0.0036 |

**Table 3.** Best results for the nested fuzzy cognitive map and standard fuzzy cognitive map.

| Model | Algorithm | MAE | MSE | RMSE |
|---|---|---|---|---|
| Start level | SOGA | 0.0348 | 0.0045 | 0.0671 |
| | RCGA | 0.0348 | 0.0045 | 0.0667 |
| First Cluster | SOGA | 0.0369 | 0.0048 | 0.0692 |
| | RCGA | 0.0398 | 0.0053 | 0.0731 |
| Second Cluster | SOGA | 0.0401 | 0.0053 | 0.0730 |
| | RCGA | 0.0344 | 0.0052 | 0.0722 |
| Third Cluster | SOGA | 0.0348 | 0.0045 | 0.0671 |
| | RCGA | 0.0348 | 0.0045 | 0.0667 |
| Fourth Cluster | SOGA | 0.0351 | 0.0048 | 0.0690 |
| | RCGA | 0.0342 | 0.0044 | 0.0666 |
| End Level | SOGA | 0.0354 | 0.0047 | 0.0682 |
| | RCGA | 0.0334 | 0.0045 | 0.0673 |
| Standard FCM | SOGA | 0.0389 | 0.0055 | 0.0740 |
| | RCGA | 0.0397 | 0.0054 | 0.0736 |

If you're looking for an indicator of the best performance and the lowest predicted mistakes, go no further.

Figure 3 depicts a layered structure that was created by combining the RCGA and SOGA techniques. Using a genetic algorithm optimization technique, a layered fuzzy cognitive map may be created, with each node representing a different FCM model and the associated ideas. Predictions of appliance energy consumption may be studied in a variety of methods, from the most basic (or widest) to the most comprehensive (or particular) (with the use of the detailed FCM models constructed for each cluster). In addition, SOGA software was used to determine the most critical ideas in each cluster, which improved the layered structure even further.

FCM learning clusters in Figure 3a and 3b were selected using the SOGA method because they contain a greater number of variables than clusters 3 and 4 in Figure 3b. The redesigned FCM structure in Figure 3b has less weighted links between clusters, making it easier to forecast. In the aforementioned example experiment, the SOGA algorithm automatically selects the most critical prediction ideas (see Figure 3b).

In each cluster of nested FCM, there are many crucial concepts: RH9-humidity (in percent) in the parent's bedroom (Cluster 2), RHout-humidity (in percent) outdoors, Press (Cluster 3) and Lights (Cluster 3) and T6-temperature outside the building (Cluster 4). It has a major influence on how appliances predict their behavior.

The nested FCM performed better than the regular FCM in forecasting appliance energy use (see Figure 4).

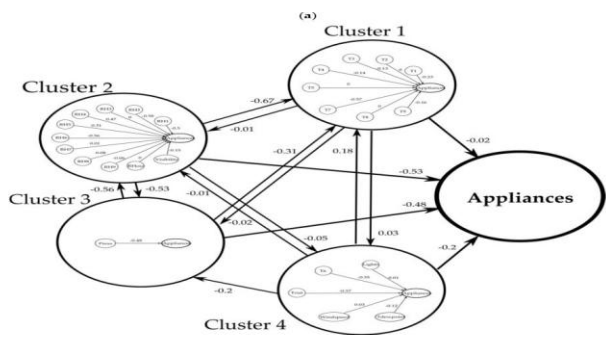


**Figure 3.** Forecasting results for the best model obtained with the use of the SOGA algorithm.

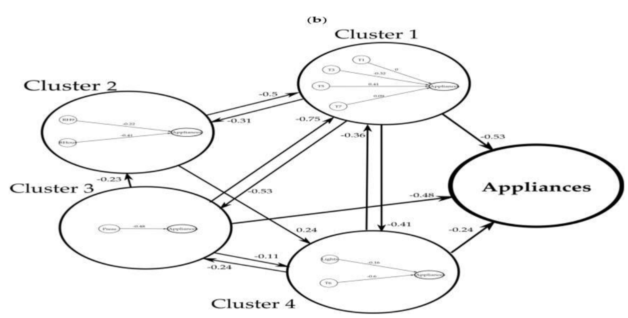


**Figure 3.** Forecasting results for the best model obtained with the use of the SOGA algorithm.

## 4. Discussion of Results and Conclusions

Accordingly, this study investigated a variety of layered FCM topologies, taking into account the parameters outlined in Section 3. Layered FCM structures with the highest prediction accuracy were discovered using a mix in order to better understand the data and determine the effectiveness of the forecasting technique based on layered FCMs, a comparison was made with a standard FCM. The standard FCM has been utilized for analogous energy concerns that have been identified in the literature. All of the findings are summarized in the preceding section's tables and figures. There were 26 ideas linked to appliance energy usage that could be grouped into five groups using the suggested technique, as shown in Table 1. Nested structures with two layers (the first and second level) resulted in reduced errors than traditional approaches with a single FCM, according to Tables 2 and 3. Large datasets may be hampered by the suggested strategy's need to create many FCM models, making it time expensive. Time series prediction can only be used at the highest level of nested structure.

These are the conclusions of this study's primary investigation:

The layered FCM technique suggested in this case study may be used to do an outstanding clustering analysis. Finally, after several trials, the layered structure under consideration was discovered to have an ideal design. A nested FCM model's best fit is determined by weighing the most important interactions between concepts at each level of nesting.

Evidence suggests that the suggested layered architecture is superior to the well-known FCM model when it comes to energy prediction difficulties.

Tables 2 and 3 show that the suggested layered model is a versatile tool for combining concepts and reducing model complexity because of its superior performance in appliance energy prediction (see Figure 1).

A novel strategy for generating multilayered structures based on fuzzy cognitive maps, which we have developed and proposed, has resulted from our investigation. According to the proposed method, forecasting and making judgments about diverse outcomes appear to be possible across a wide variety of scientific areas. It enables for the depiction of a comprehensible hierarchical structure in which each concept at the first level may be broken down into another fuzzy cognitive map. The mentioned approach may be used to a wide range of time series in future study. Adding numerous forecasting models (e.g. artificial neural networks) at the most detailed level of the layered structure will help improve prediction accuracy.

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