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Aswani Kumar Cherukuri
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Intelligent Systems Design and Applications

18th International Conference on Intelligent Systems Design and Applications (ISDA 2018) held in Vellore, India, December 6-8, 2018, Volume 2

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Preface

Welcome to the Proceedings of the Joint Conferences on 18th International Conference on Intelligent Systems Design and Applications (ISDA) and 10th World Congress on Nature and Biologically Inspired Computing (NaBIC), which is held in VIT University, India, during December 6–8, 2018. ISDA - NaBIC 2018 is jointly organized by the VIT University, India, and Machine Intelligence Research Labs (MIR Labs), USA. ISDA - NaBIC 2018 brings together researchers, engineers, developers, and practitioners from academia and industry working in all interdisciplinary areas of intelligent systems, nature-inspired computing, big data analytics, real-world applications and to exchange and cross-fertilize their ideas. The themes of the contributions and scientific sessions range from theories to applications, reflecting a wide spectrum of the coverage of intelligent systems and computational intelligence areas. ISDA 2018 received submissions from 30 countries, and each paper was reviewed by at least five reviewers in a standard peer-review process. Based on the recommendation by five independent referees, finally 189 papers were accepted for ISDA 2018 (acceptance rate of 48%). NaBIC 2018 received submissions from 11 countries, and each paper was reviewed by at least five reviewers in a standard peer-review process. Based on the recommendation by five independent referees, finally about 23 papers were accepted for NaBIC 2018 (acceptance rate of 37%). Conference proceedings are published by Springer Verlag, Advances in Intelligent Systems and Computing Series.

Many people have collaborated and worked hard to produce the successful ISDA - NaBIC 2018 conference. First, we would like to thank all the authors for submitting their papers to the conference, for their presentations and discussions during the conference. Our thanks go to program committee members and reviewers, who carried out the most difficult work by carefully evaluating the submitted papers. Our special thanks to Raija Halonen, University of Oulu, Finland, Junzo Watada, Universiti Teknologi Petronas, Malaysia, and Nelishia Pillay, University of Pretoria, South Africa, for the exciting plenary talks. We express our

sincere thanks to the session chairs and organizing committee chairs for helping us to formulate a rich technical program.

Enjoy reading the articles!

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Contents

Differential Evolution Trained Fuzzy Cognitive Map: An Application to Modeling Efficiency in Banking

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Abstract. In this work, we developed a Differential Evolution (DE) trained Fuzzy Cognitive Map (FCM) for predicting the bank efficiency. We developed two modes of training namely (i) sequential and (ii) batch modes. We compared the DE trained FCM models with the conventional Hebbian training in both modes. We employed Mean Absolute Percentage Error (MAPE) as an error measure while predicting the efficiency from Return on Assets (ROA), Return on Equity (ROE), Profit Margin (PM), Utilization of Assets (UA), and Expenses Ratio (ER). We employed 5x2-fold cross-validation framework. In the first case i.e. sequential mode of training, the DE trained FCM statistically outperformed the Hebbian trained FCM and in the second case i.e. batch mode of training, DE trained FCM is statistically the same as the Hebbian trained FCM. To break the tie in the batch mode, the training time is compared where DE trained FCM turned to be 19% faster than the Hebbian trained FCM. The proposed model can be applied to solving similar banking and insurance problems.

Keywords: Bank efficiency prediction · Financial ratios · Differential Evolution · Fuzzy Cognitive Map · Hebbian learning

1 Introduction

Kosko in the seminal work [12] introduced Fuzzy Cognitive Maps (FCM) in the year 1986. An FCM is a map of the cognitive process wherein the interconnection of the components i.e. concepts are utilized to evaluate the degree of the effect of the components in the psychological scene or area of the imagination. FCM is mainly

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employed for causal knowledge representation and reasoning process. FCMs come under the family of neuro-fuzzy systems that are employed for decision making and are also utilized for modelling and simulation of complex systems. FCM is also employed for the prediction, forecasting and classification tasks to acquire the causal knowledge.

Various training methods are employed for the dynamic adaptation of the FCM model and to tune the weights. Most of the training methodologies come from the field of study of Artificial Neural Networks (ANN). In [4], the Differential Hebbian Learning (DHL) was employed to train the FCM. A wide range of modifications is proposed to this Hebbian algorithm which is, by nature, deterministic. Another paradigm of training algorithm includes the Swarm Intelligence and Evolutionary Computation (EC)-based approaches which are, by nature, stochastic. The above-mentioned training algorithms are employed to decrease the human intervention in the FCM, and to make the FCMs adaptive and non-black box, unlike ANNs.

Our focus is on the application of Evolutionary algorithms (i.e. Differential Evolution) which are, population-based stochastic search strategies, where a population of variables gets updated iteratively utilizing heuristics until the point where optimum or near optimum is achieved. These methods contrast in how the variables are encoded and the heuristics they utilize when refreshing the variables. Genetic Algorithms [6], Differential Evolution [21, 23, 24], Particle Swarm Optimization [9], Ant Colony Optimization [5], Firefly Algorithm [22], are a portion of the meta-heuristics from this family.

Banking, Financial Services and Insurance (BFSI) sector is the backbone of the economy of any country, and it does have many operational issues as well as financial issues. BFSI sector is moving away from conventional ways towards more automated and robust methods. EC based techniques play a vital role in solving the above-mentioned operational issues because they yield global or near-global optimal results [11]. For instance, how EC techniques are useful in solving various customer relationship management problems is captured very well in a survey paper by Krishna and Ravi [10]. Finding the causal knowledge from the data using the cognitive map for the bank efficiency prediction is an important operational issue.

In this section, a brief introduction of the FCMs, Evolutionary Computation (EC) and the role of ECs in solving the operational issues are provided. Motivation and contributions of the current work are presented in Sects. 2 and 3. Related literature of the present work is reported in Sect. 4. The proposed methodology is described in Sect. 5. Description of the bank efficiency dataset is given in Sect. 6. Experimental design of the proposed method is illustrated in Sect. 7. Results and discussion are presented in Sect. 8. Finally, we conclude with some future directions in Sect. 9.

2 Motivation

The motivation for the work is as follow:

- To the best of our knowledge, bank efficiency is never predicted as a function of the important financial ratios using FCM.
- To find the causal knowledge and the cognitive process behind the bank efficiency and its relationship with Return on Assets (ROA), Return on Equity (ROE), Profit Margin (PM), Utilization of Assets (UA), and Expenses Ratio (ER).

– To investigate the sequential and batch mode of training in FCMs, which may be useful to future researchers.
– To automate the decision-making process in the banking domain with multiple solutions using Differential Evolution (DE) trained Fuzzy Cognitive Map (FCM) (i.e. DE-FCM).

3 Contribution

The contributions of the work are as follows:

– Developed DE trained and Hebbian trained FCM models separately for the bank efficiency prediction.
– Developed FCM training algorithms in two modes i.e. sequential and batch modes.
– Modeled Efficiency of a bank with respect to five financial ratios using DE and Hebbian trained FCM.

4 Related Work

In [20], a seminal work on utilizing ECs for training FCMs i.e. a genetic learning trained FCM is developed. In [19], a data-driven non-linear Hebbian learning (DD-NHL) was proposed for training multiple samples of data. Multiple applications like precision agriculture, geo-spatial dengue outbreak risk prediction of tropical regions, predicting yield in cotton crop production, Radiation Therapy Systems where FCM based prediction is employed is studied in [7, 8, 13, 16]. Two surveys [13, 14] were performed by the author Papageorgiou on FCMs. One of the surveys describes [14] the types of training i.e. Hebbian trained, EC trained and a hybrid of both as well as different applications of FCMs. Another survey describes [15] the different types of cognitive maps and possible applications areas of FCMs. In [1, 2], stability, parameter convergence, existence and uniqueness of solutions is studied and analyzed. In [3], the behaviour of various activation functions i.e. sigmoid, hyperbolic, step function, threshold linear function is studied.

In [17], Data Envelopment Analysis and Fuzzy Multi-Attribute Decision Making hybrid was developed for ranking banks based on efficiency. In [18], a review of sequential learning is performed where the terminology of “catastrophic forgetting” for sequential learning is described.

5 Proposed Methodology

The continuous FCM is utilized, with modified Kosko activation function and sigmoid threshold function as described in Sect. 5.1. The objective is to minimize the MAPE and the convergence criterion is either reaching a pre-specified number of iterations or MAPE value falling below 0.1%. The procedure for training the DE-FCM, where both sequential and batch modes of training are presented in Sect. 5.3. The Hebbian learning with Oja's weight update rule [19], where both sequential and batch modes of training is performed, is described in Sect. 5.4.

5.1 Activation Function

Concepts of the model are denoted by C_i where i = 1…N where N is the total number of concepts. Each concept has an activation value $A_i \in [0, 1]$, i = 1…N and signed fuzzy weights W_{ij}, which takes the values in the range [−1, 1], of the edge between C_i and C_j where j = 1…N.

The value of each concept A_i at any occurrence 'k' is calculated by the sum of the previous value A_i in a precedent occurrence 'k − 1' with the product of the value of A_i of the concept node C_i in the precedent occurrence 'k − 1' and the value of concept effect link weight W_{ij}. The mathematical formula is given below.

$$A_i^k = Sigmoid(A_i^{k-1} + \sum_{\substack{j \neq i \\ J=1}}^{N} A_j^{k-1} * W_{ji}^{k-1})$$

$$Sigmoid(x) = \frac{1}{1 + e^{-\lambda x}}, \text{ where } \lambda = 1.$$

5.2 MAPE Measure

The Mean Absolute Percentage Error (MAPE), is a measure of prediction accuracy in statistics. It usually expresses accuracy as a percentage, and is defined by the formula:

$$MAPE = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{Actual_t - Predicted_t}{Actual_t} \right|$$

5.3 RMSE Measure

The Root Mean Squared Error (RMSE), is a measure of prediction in statistics. It is defined by the formula:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (Actual_t - Predicted_t)^2}$$

5.4 DE-FCM

DE trained FCM in 2 modes: (i) sequential & (ii) batch mode as described in Algorithm 1.

```
procedure SEQ-DE-FCM
no_itr ← fixed_value
ncv_train ← nrow(concept_vec_train)
    while i ≤ ncv_train do
        cv_train ← concept_vec_train[i]
        itr ← 1
        while itr ≤ no_itr do
            Step-1: Generate weights
            of FCM using DE heuristic
            Step-2: Apply Modified
            Kosko with Sigmoid on
            the cv_train for the
            weights generated by DE
            Step-3: Compute
            MAPE_new on actual and
            predicted productivity
            concept values of cv_train
            Step-4: If MAPE of new
            weight vector less than the
            MAPE value of current
            weight vector in the DE
            population then replace
            the current weight vector
            and MAPE value in DE
            with the new weight vector
            and new MAPE value
        end while
    end while
    ncv_test ← nrow(concept_vec_test)
    no_pop ← nrow(DE_Population)
    while pop ≤ no_pop do
        while j ≤ ncv_test do
         cv_test ← concept_vec_test[j]
            Apply Modified
            Kosko with Sigmoid on
            the cv_test for the
            weight vector in the DE
            population i.e. DE[pop]
        end while
        For all the samples in
        in concept_vec_test compute
        MAPE on actual and
        predicted productivity
        concept values
    end while
    Pick the weight vector with
    less MAPE value on cv_test
    from the DE_Population
end procedure
```

(a) Sequential mode DE-FCM algorithm

```
procedure BATCH-DE-FCM
no_itr ← fixed_value
ncv_train ← nrow(concept_vec_train)
    itr ← 1
    while itr ≤ no_itr do
        Step-1: Generate weights
        of FCM using DE heuristic
        while i ≤ ncv_train do
        cv_train ← concept_vec_train[i]
            Step-2: Apply Modified
            Kosko with Sigmoid on
            the cv_train for the
            weights generated by DE
        end while
        Step-3: For all the samples in
        in concept_vec_train compute
        MAPE_new on actual and
        predicted productivity
        concept values
        Step-4: If MAPE of new
        weight vector less than the
        MAPE value of current
        weight vector in the DE
        population then replace
        the current weight vector
        and MAPE value in DE
        with the new weight vector
        and new MAPE value
    end while
    ncv_test ← nrow(concept_vec_test)
    no_pop ← nrow(DE_Population)
    while pop ≤ no_pop do
        while j ≤ ncv_test do
         cv_test ← concept_vec_test[j]
            Apply Modified
            Kosko with Sigmoid on
            the cv_test for the
            weight vector in the DE
            population i.e. DE[pop]
        end while
        For all the samples in
        in concept_vec_test compute
        MAPE on actual and
        predicted productivity
        concept values
    end while
    Pick the weight vector with
    less MAPE value on cv_test
    from the DE_Population
end procedure
```

(b) Batch mode DE-FCM algorithm

Alg. 1: Two modes of Training

5.5 Hebbian Trained FCM

Oja's learning rule [19] is a modification of the standard Hebb's Rule that, through multiplicative normalization, which solves all stability problems.

$$w_{ij}^{n+1} = w_{ij}^{n} + \eta * A_j^{new} * \left(A_j^{old} - w_{ij}^{n} * A_j^{new}\right)$$

The above mentioned Oja's weight update rule is employed for training the FCM in both sequential and batch modes. This weight update rule is a nonlinear weight update rule, employed to capture the non-linearity in data-driven approaches.

5.6 Sequential and Batch Modes of Training

In the sequential mode of training, the FCM is trained with a single concept vector one after another. One main disadvantage of the sequential mode of training is the lack of memory of the previous trained values of the model. It has an advantage of fast training. But, repeated training with individual concept vectors also makes it slow. In the batch mode of training, the FCM is trained with all the concept vectors in one go. This mode of training is good for small datasets. But, takes a lot of training time when training data is large. Both modes are described in Algorithm 1-a and 1-b.

6 Description of the Dataset

The data of the five financial ratios along with the corresponding efficiency levels as computed by the DEA-FMADM model are taken from [17]. There are 5 input and one output concept in the dataset of 27 different banks. The five ratios viz., Return on Assets (ROA), Return on Equity (ROE), Profit Margin (PM), Utilization of Assets (UA), and Expenses Ratio (ER) are presented in Table 1. The output concept is efficiency. Out of the 15 possible concept linkages among the 6 concepts, only 13 were considered logically plausible by the domain expert.

Table 1. Concept description

S. no.	Input ratio name	Definition
1	Return on Assets (ROA)	Assets/Net profit
2	Return on Equity (ROE)	Net profit/Owned funds
3	Profit Margin (PM)	Net profit/Interest income + Non-interest income
4	Utilization of Assets (UA)	Interest income + Non-interest income/Assets
5	Expenses Ratio (ER)	Operating Expenses/Spread
Output: Efficiency		

7 Experimental Setup

Training and testing are performed on an Intel (R) Core (TM) i7-6700 processor with 32 GB RAM in fastR. The data is divided into 60:40 percent training and testing respectively randomly for 5 times i.e. the data is divided into 16 concept vectors (samples) of training and 11 concept vectors (samples) of testing. On each of the five training and test sets, two models i.e. DE-FCM and Hebbian trained FCM are built in each of the two modes of training i.e. sequential and batch modes of training. In DE-FCM the best weight matrix out of the population of 25 on the test data is picked. The above experimentation for DE-FCM in both modes of training is repeated for 30 runs, as DE is stochastic by nature and the best MAPE values out of 30 runs are considered. Hebbian-FCM is deterministic by nature and so the above procedure considered for DE-FCM is not followed for Hebbian trained FCM.

8 Results and Discussion

The 5x2 fold cross validation (5x2 FCV) is performed on the dataset and the results are reported in Tables 2 and 3. In the sequential and batch modes, we assessed the statistical significance of the performance of Hebbian-FCM versus DE-FCM. Thus, we performed t-test on the average best (out of 30 runs of the DE-FCM) MAPE value over 5 folds versus average MAPE of the Hebbian-FCM value at 1% level of significance.

Table 2. Sequential trained FCM

5x2 FCV	Hebbian-FCM (MAPE)	DE-FCM (MAPE)	Hebbian-FCM (RMSE)	DE-FCM (RMSE)
1	30.9878	5.2727	0.23562	0.04811
2	29.2433	3.9027	0.22489	0.03765
3	16.1033	14.8488	0.14209	0.12802
4	20.51599	12.8809	0.15409	0.11803
5	33.12868	4.1504	0.24733	0.04473
Mean	25.995814	*8.2111*	0.200804	0.075308
Variance	53.558542	*27.387970*	*0.002396*	*0.001924*
t-Value	*4.420107317*		*4.269079683*	
p-value	*0.002226*		*0.002727*	

It turned out that the DE-FCM is statistically significant compared to Hebbian trained FCM with a p-value of 0.002. But, in a batch mode of training, DE trained FCM turned out to be statistically the same as Hebbian trained FCM with a p-value of 0.663. Similar results were noticed in the case of RMSE too.

It is worth noticing that the proposed method employs MAPE as the objective function, while RMSE is just computed on the convergence of the algorithm. Thus, MAPE and not the RMSE drives the entire learning process.

Table 3. Batch trained FCM

5x2 FCV	Hebbian-FCM (MAPE)	DE-FCM (MAPE)	Hebbian-FCM (RMSE)	DE-FCM (RMSE)
1	6.446347	5.525913	0.05554	0.05229
2	5.18635	5.231981	0.04297	0.05401
3	15.3066	15.213922	0.13614	0.12734
4	18.95404	15.201556	0.14485	0.12717
5	7.921394	4.337817	0.06182	0.04286
Mean	10.7629562	*9.1022378*	0.088264	0.080734
Variance	36.386283	*31.255764*	0.002328	0.001821
t-Value	*0.4515155*		*0.2613553*	
p-value	*0.66361*		*0.80042*	

To break the tie in batch mode, the training time is compared where DE trained FCM is 19% (i.e. 0.2x) faster than Hebbian trained FCM. Though batch mode DE-FCM may not seem faster (0.2x) in the current setup of multi-threaded and high-end processor setup. But, DE-FCM will show its significance in the low end and single threaded configurations.

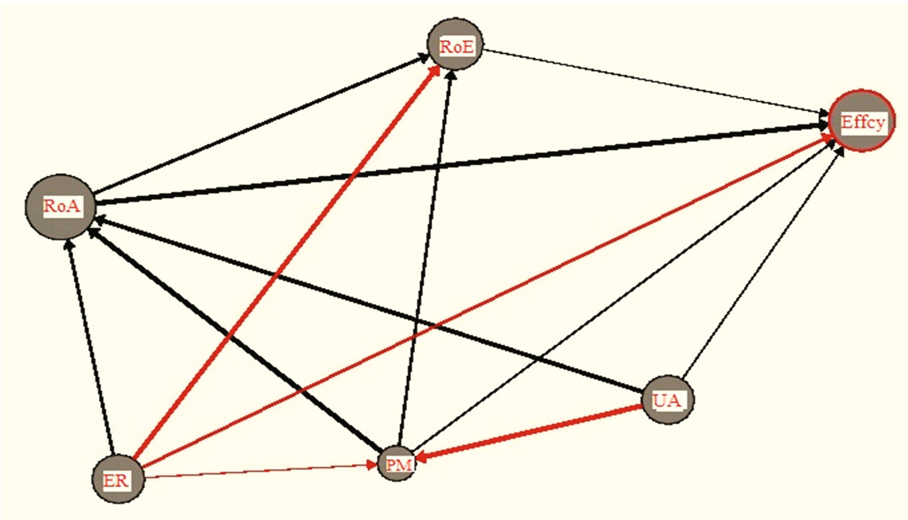

Fig. 1. FCM of the banks' efficiency data

In order to obtain the cognitive knowledge from the given data, both Hebbian trained and DE trained FCM were built on the whole dataset of five financial ratios and the corresponding efficiency level of 27 banks in both sequential and batch modes of training for visual and cognitive understanding. This is because the given data set is too small in size, thereby building FCM under 5x2 FCV is fraught with inaccuracies. However, when FCM is used for prediction purpose, 5x2 FCV is considered in order to have an authentic method of testing.

In order to generate the FCM graph (see Fig. 1), owing to the small size of the dataset, we trained the FCM with Hebbian and DE in both sequential and batch modes on the entire data without resorting to 5x2 cross validation. In Fig. 1, a positive correlation is represented with a positive weight (i.e. black edge) and negative correlation is represented with a negative weight (i.e. red edge), though weights are not mentioned in the Fig. 1. It turned out that graph of the DE trained FCM with sequential training (depicted in Fig. 1) conformed to the domain expert's knowledge with the least number of violations (i.e. two) of both the positive and negative correlations between the nodes of the FCM. According to domain expert only ER should have a negative correlation with other concepts including Efficiency, especially when expenses do not lead to profits. But, the weights obtained by the DE-FCM in sequential mode of training has three negative correlations for the ER. Except for ER all the remaining nine edges should have positive correlations, but DE-FCM in sequential mode obtained eight positive correlations. It is noteworthy that these the violations are not very serious because we considered only 5 input concepts and it would have matched with the domain expert's knowledge, has we considered an exhaustive list of ratios. Another interesting aspect of Fig. 1 is that the thickness of the edges between two nodes in the FCM is proportional to the level of correlation between of the two concepts in question and the black lines indicate a positive correlation, while red lines indicate negative correlation. It should be noted that the present work can be used for both descriptive and predictive analytics purposes. Firstly, the FCM can be used as an analytical tool to predict the efficiency of a bank based on five financial ratios taken from 27 banks' data corresponding to the year 2004. Secondly, the FCM obtained by DE in the sequential mode of training and presented in Fig. 1 can also be used for causal visualization of the influence of five financial ratios on the efficiency of a bank.

9 Conclusion and Future Directions

In the current work, we proposed DE trained and Hebbian trained FCM training algorithms separately for predicting bank efficiency. In both cases, FCM was trained in two modes i.e. sequential and batch modes. Minimizing the Mean Absolute Percentage Error (MAPE) error measure (i.e. on the efficiency concept values) is chosen as the convergence criteria. To automate and to help the decision-maker with multiple solutions of the population of EC-based techniques, we employed Differential Evolution (DE) for training the Fuzzy Cognitive Map (FCM).

One limitation of the study from the domain perspective, is that a few number of financial ratios are considered to model efficiency. In future, we plan to extend this study by including more financial ratios that directly or indirectly influence efficiency. It will hopefully, present better picture of the ground realities.

In the future, better convergence criteria may be developed and studied with the success of this approach. Better training algorithms may be proposed by hybridizing both the training algorithms implemented in the current work. Even better modes of