Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X
IMPACT FACTOR: 6.017

IJCSMC, Vol. 6, Issue. 5, May 2017, pg.453 – 458

Vintage Prediction in Arachis Hypogaea using Fuzzy Cognitive Map and Multi Objective Firefly Approach

[1]**K.P.MALARKODI**- Research and Development Center, Bharathiar University, Coimbatore
[2]**Dr. K.Arthi**- Assistant Professor, Department of Computer Science, Government Arts College, Coimbatore
Mail-Id: kpmalarkodi85@gmail.com

Abstract: ***This work explores the yield exhibiting and prediction procedure in groundnut using the dynamic influence graph of Fuzzy Cognitive Maps (FCMs). In this work, a statistics determined non-linear FCM learning attitude was chosen to classify yield in Groundnut, where very few decision making techniques were inspected. Through the anticipated technique, FCMs were measured and recognized to epitomize experts' information for vintage estimate and crop supervision. The advanced FCM prototypical entails of nodes connected by focused boundaries, where the nodes characterize the main soil aspects moving produce, soil temperature, air temperature, humidity, organic matter (OM), soil surface temperature, and the directed edges show the cause-effect (weighted) relationships between the soil properties and yield. The main persistence of this learning was to categories groundnut yield using an resourceful FCM and firefly algorithm, and to compare it with the straight FCM tool and other hybrid algorithms. All algorithms have been executed in the similar data set of 56 cases restrained in 2005 in an groundnut orchard located in Coimbatore. The examination displayed the advantage of the FCM and multi objective approach in vintage forecast.***

Keywords: Fuzzy Cognitive Maps, and multi objective approach, firefly algorithm, hybrid algorithms

I. INTRODUCTION

Soil changeability within a farm happens in maximum soils and sections. This changeability interrelates with climate, inputs and the changeability of hereditary measurable to yield crop and variability. The problem is that historical data cannot continuously predict yield changeability and final yield. It seems that yield changeability is withdrawing out after 3 years. Yield expectation in Groundnut, and other crops in general, is very significant, because it could be used to advance crop management. The main of the current study was to build the FCM modal for yield classifying in ground nut based on experts ' observation and to use powerful learning techniques to train this modal with information and then exploit yield considerations . The NHL modal was used for the yield classification and its implementation capabilities
were related with FCM tool without studying and commonly used and well-known machine learning Procedure .it was shown that the NHL method for FCMs gives improved production precisions then those found with the use of conventional FCMs and machine learning methods.

II. MECHANISM AND APPLICATIONS

The samples were air-dried, passed through a 2 mm. All data were inserted on a 30 m grid, which resembles to a dependable field unit, in order to create the maps.

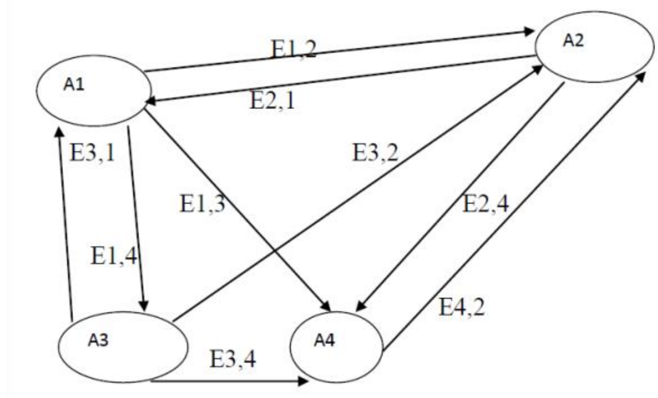

Fig. 1 shows a generic representation of the FCM model.

For the drives of this paper, we describe FCM as an directive pair A, E, where A is the set of labels and E is the connection matrix. Every label A_i e A is mapped to its initiation value A_i e [0, 1], where 0 means no initiation, and 1 means full initiation. The labels from A can be taken as verbal terms that fact to fuzzy sets. In such case, the initiation value A_i is read as the value of fuzzy membership function that procedures the degree in which an experiential value goes to the fuzzy set keen by the linked term. The other, basic explaining of A can be such that the labels A_i represent the real valued variables, the fields of these variables are expected as regulated into the [0, 2] interval.

B. *Non-linear Hebbian learning algorithm*

The steps of the NHL algorithm for FCM training task to forecast the class of groundnut yield are described as follows:

C. Algorithm FCM-NHL ()

Input: Conception values in vector A and weight matrix E Process

Step 1: Initialize the input values of four concepts A_i, the weights E_{ji} for each interconnection given by the experts, control learning rate parameter g_k = 0.001, weight decay parameter c = 0.98 and the three target values related with all the three categories, $T_{imin} \leq T_i \leq T_{i_{max}}$, where i = 1-3. For this work, one decision output concept (DOC) is allowed to exhibit the output category, which can be categorized in the classes [i.e. low yield (T1), medium yield (T2) and high yield (T3)] and therefore produce the output of these system

Step 2: For every iteration step k go to next step
Step 3: Update the weights related to Eq. (2).

$$E_{jk}^{(K)} = y.e_j^{(K-1)} + \pi A_1^{(K-1)} - \mathrm{sgn}(e_{ji}^{(K-1)})\, e^{(K-1)}\, A_1^{(K-1)}$$

Step 4: Assign A(k + 1) using the formulation presented in Eq. (1). Calculate values $A_j^{(K+1)}$ using Eq. (3) for the candidate weight set $e_j^{(K)}$, until a fixed state is reached

Step 5: Evaluate stopping conditions, using $A_{24}^{(K+1)}$ and $A_{24}^{(K)}$ from Step 4, and candidate E(k)

Step 6: When one of the two termination circumstances are met, go to step 2

Step 7: finally Return the produced E(k). Check the value $A_{24}^{(K)}$ for the DOC_i and classify it in one of the three related classes

Stopping conditions: Either the circumstances 1 or 2 has to be satisfied to terminate the iterative process

Condition 1: Calculate F1 = $\sqrt{\sum^{m}_{i=1}(DOC_i\text{-}T_j)^2}$ Where m is the number of DOCs and T_i describes the target value which can be calculated as $T_i = (T_{i_{min}} + T_{i_{max}})/2$ where i = 1-3 The final state that is regularly expert in all circumstances is the fixed-point state and in this fixed-state we check if the intended value of DOC_i (for Concept A24) meets one of the three limits (T-targets) and thus we finally categorize this design in one of the three classes. If the made class is the same with the initial one, then this design is classified correctly.

D. Progress of FCM model for yield variability forecast in Groundnut

Conferring to the FCM progress process, the number and kind of notions were determined by a group of specialists. Three experts were used: from the Agriculture University the experts' answers were mutual to- gather to control the main factors of the model, which represented techniques as well as the interconnected, among techniques. Every interconnection was defined by the experts with the help of if-then rules that infer a fuzzy linguistic variable from a determined set T{influence}, which associates the relationship between the two notions and determines the grade of causality between the two notions. The familiarity of experts can be easily encoded to a number of if-then rules, which is future used for the determination of adjacency weight matrix. The experts support in designing the FCM model following the step by step approach described in what follows.

Step 1: Determination of concepts and fuzzy membership functions for each one concept. The problem of yield prediction in Groundnut was described using a number of factors that mainly affect the production. At first, the experts stated that there are mainly eight factors - variables that determine the yield (Table 1). Each one of the variables represents soil properties and has only the non-zero weights are updated three or five fuzzy values. Then, using a questionnaire which was created for this process that was completed by the team of experts, the fuzzy linguistic weights among these concepts (which Step 4: Assign A(k + 1) using the formulation presented in Eq. 2.2.4.2. Step II: Fuzzy rules and linguistic terms that describe the influences among concepts. The quantitative values of concepts measured in the orchard under study were categorized into qualitative values, using the Fuzzy toolbox.

Table 1: variables deterring the yield

	WIND (A1)	**HUMIDITY(A2)**	**AIR TEMP (A3)**	**S.S TEMP E (A4)**
WIND (A1)	0	0.2	0.36	0.7
HUMIDITY (A2)	1	0.06	0.51	0.8
AIR TEMP (A3)	0.58	0.86	0	1
S.S TEMP (A4)	0.83	0.89	0.53	0

Step 2: Fuzzy rules and linguistic terms that defines the influences among concepts. The FCM model for describing spatial variation in groundnut yield is constructed by experts using their knowledge to describe the associations between concepts. The three experts assigned associations for the FCM model, and determined the relationships among all the nine factors.

They were asked to define the degree of influence from one concept to other using if-then rules among factor technique and yield from the term set T{influence}. In the case of fuzzy rules for the specific problem of yield description in Groundnut, some examples, as derived from experts, are given: IF a small change occurs in the value of concept A_1 (Shallow EA), THEN a small change in the value of concept D_4 (yield) is caused. This means that: the influence from concepts A_1 to A_4 is low. IF a high change occurs in the value of concept A_3 , THEN a high change in the value of concept A_4 (yield) is caused. This means that: the influence from concepts A_6 to A_9 is high. IF a medium change occurs in the value of notion A_4 (Clay), Then a negative middle change in the value of notion A_4 (yield) is caused. This means that: the inspiration from concepts A_3 to A_6 is negatively medium.

Step 3: Purpose of numerical weights. The inferred fuzzy linguistic weights (strengths of influences) are combined using the SUM method. Then, using the defuzzification method of centroid, the linguistic weights y with membership functions l(y) are altered into a numerical weight e_{ji} which lies in the range [0, 1]:

$$E_{ij} = \frac{\int_y Y.\mu(y)dy}{\int_y \mu(y)dy}$$

The weights are collected into a weight matrix ($E = (E_{ji})$) 9 X 9, where 9 is the number of concepts. The formed FCM model for modelling and predicting yield in Groundnut which includes the initial calculated values of weights is shown in. All the four concepts are considered as factor concepts by the experts as they are listed in Table 1 to design the FCM model and each concept denotes three, or five fuzzy values. In this problem, the concept A9 has been considered from the experts as Judgment the Output Concept (DOC) and could be categorized as low yield (‘‘low’’), medium yield (‘‘med’’) and high yield (‘‘high’’). The data which were measured are stored in a two-dimensional matrix denotes the spatial distribution of all the factors in the field .each cell of the matrix parallels to an area of 30mwhich is the altitudinal resolution of the yield of data modal.

III. Results

The weights are grouped into a weight matrix ($E = (E_{ji})$) 6 Â 6,wherever 6 is the number of approaches ,the produced FCM modal for modeling and assuming the yield in the groundnut which includes the internal calculated values of weight s as shown in fig 4..thus,FCM is an abstract conceptual modal which is based on the three experts who decided around the input and output decision approaches as well as for the casual relational ship among them all the eight approaches are considered as factor approaches by the experts as given in the table 1 to design the FCM modal and every approach signifies three ,or five fuzzy principles .

In this problem ,the approach C6 has been taken from the experts as decision output concept(DOC)and can be categorized as low yield (“low”),maximum yield (“med”)and high yield. The data which was measured where stored in a two –dimensional matrix that denotes the spatial distributions of all factors in the yield .every cell of the matrix that denotes an area 30 Â 30 m which is the spatial resolution of the yield data modal. A Simulation results of two cases examined by FCM-NHL and FCM tool the proposed methodology based on FCM and NHL learning FCM tools for influential category of yield. In the first case, a "med" yield pixel 30 Â 30 from the production area was selected, with the following real measured values for each factor;

ED=32.989msm^{-1}(D_1) Ca = 125 mg kg^{-1} (D_2), K = 151 mg kg^{-1}(D3),

OM = 1.69% (D4), P = 5.5 mg kg$^{–1}$ (D4),Zn = 0.98 mg kg_1 (D3), Clay = 15.1% (D4) and Sand = 63.1% (D4).

The real value of yield was 31.714 Mg haÀ1 at this pixel. These numerical values of measured soil parameters are distorted to Concepts Di/Dj 3 based fuzzy sets, normalized and then, using defuzzification, the initial activated values of concepts are produced. The value of EC corresponds to the fuzzy set "high" which is altered to normalized numerical initial value A_1 = 0.66. The measured value of Da corresponds to the fuzzy set "very low" and transferred to numerical value A_2 = 0.1. The same happens with all other concepts. K has a "med" value which is transferred to A_4 = 0.34, OM has a "medium" value which is moved to A_6 = 0.43, P has a "low" value which is changed to A_3 = 0.16, Zn has a "very low' value which is applied as A_5 = 0.12, Clay has a "med" value which is changed to A_7 = 0.32 and sand has a "med" value which is transferred to A_8 = 0.59. The initial value of yield production is equal to 0.345 and it denotes a "med" yield category. The primary fuzzy qualitative values which corresponds to "med" yield construction are represented at the following vector of concept values: A^{first} ¼ ½0:66 0:1 0:34 0:43 0:16 0:12 0:32 0:59 0:345 This vector denotes the numerical values of measured soil parameters of the physical process, after revolution, normalization to (0, 1) and correspondence to numerical values. Then, using, the FCM inference method as described in Section 2.2.3, the equilibrium AREA is reached after 10 iteration steps and the obtained values of concepts are depicted at the following vector: Initial scheme of DDNHL-based FCM, the case of ”med” yield was classified appropriately as “med” yield in the next case ,a high yield pixel from the production area is a selection of the subsequent real measured values for every factor ; ; ED = 8.034 mS mÀ1 (D_1), Da = 276 mg kgÀ1 (D_2), K = 354.8 mg kgÀ1 (D_3), OM = 1.8% (D_4), P = 1.98 mg kgÀ1 (D_5), Zn = 1.15 mg kgÀ1 (D_6), Clay = 17.3% (D_7) and Sand = 64% (C_8) and yield = 59.46 Mg haÀ1which were considered as “high” yield. The following numerical values of measured soil parameters are converted to corresponding fuzzy sets then defuzzified and A^{second} of numerical values are produced. Values of internal fuzzy qualities concepts, which gives “high” yield production, the following vector of concept values are represented: A^{second} ¼ ½0:16 0:25 0:77 0:45 0:057 0:144 0:37 0:708 0:657Š A FCM ¼ ½0:1525 0:1000 0:3400 0:4300 0:1600 0:1200 0:3200 0:5900 0:1243Š Then, using Eqs. (1) and (2), the FCM tool simulates, the equilibrium region is reached after 10 iteration steps and the calculated values of concepts are depicted in the following vector:.

The output of this FCM approach shows that this case is classified as "low" yield, and does not concur with the initial category/ state. For the same input vector, using the FCM-NHL algorithm, the resulting output vector is produced. First A CM^{second} ¼ ½0:2479 0:2500 0:7700 0:4500 0:0570 0:1440 The calculated value of DOC (yield) is 0.1843 which assigns a "low" yield value for this specific case. This case was not classified For the same input vector, using the FCM-NHL algorithm, the resulted output vector is produced, which is: From the calculated DOC value (0.4996), which prescribes the output "yield" of the FCM-NHL approach, it is assigned that the yield is considered as "med" and it is the same with its initial category.

Table 2: classification with high performance

	Low	Med	High
Low	12	4	5
Med	2	19	2
High	2	15	17
Correctly classified	48/56		
Accuracy	85.71%		

The produced weight matrix is illustrated in Table 3. The algorithm performance keeps the preliminary zero values of weights due to non-consideration of influences. It is concluded, from the obtained weight matrix after FCM- NHL algorithm, that almost all the weights have changed their values. Some of them show smaller and others higher changes from their initial ones. in General, all the weights were altered to lower values. Examples of some weights (E_{ij}), where we observe minor changes, without any significant difference to the strength of impudence among methodologies, are the E_3 [where a small modification to the initial weight value arose after training, the value 0.25 (Table 2) was altered to 0.2059 (Table 3)], E_{29}, (where also a small alteration to the initial weight value occurred after training, the value 0.6 was modified to 0.4744), E_{31}, E_{41}, E_{39}, E_{49}, E_{59}, E_{71}, E_{81}, E_{79} and E_{89}. We observe that accuracy two causal influences-weights have changed their values at an important level. These influences (weights) are: E_{21}, which describes that, an initial high impudence among D_2 and D_1 (weight = 0.8) has changed to a medium impudence between these techniques (E_{21} = 0.62), and causal impudence E_{69}, which means that, an initial medium impudence among D_4 and D_4 (weight = 0.45) has changed to a low impudence between these concepts (E_{69} = 0.34). It is observed that only in second technique of DDNHL-based FCM, the case of ‘‘med’’ yield was classified correctly as ‘‘med’’ yield. The early value of yield production is considered equal to 0.75.

The initial fuzzy qualitative values of the concepts, which correspond to ‘‘high’’ yield production, are represented at the following vector of concept values: A second ¼ ½0:16 0:25 0:77 0:45 0:057 0:144 0:37 0:708 0:657_Then, using Eqs. (1) and (2), the FCM tool simulates, the equilibrium region is reached after 10 iteration steps and the measured values of concepts are depicted in the following vector: A FCM second ¼ ½0:2479 0:2500 0:7700 0:4500 0:0570 0:1440 0:3700 0:7080 0:1843_: The obtained value of DOC (yield) is 0.1843 which were assigned as ‘‘low’’ yield value for this particular case. This case was not categorised correctly using the FCM tool. For the same input vector, using the FCM–NHL algorithm, the resulted output vector is produced, which is: A NHL FCM second ¼ ½1:00 1:00 0:659 1:00 0:659 1:00 0:659 1:00 0:659_:In the case of FCM-NHL algorithm, the yield is classified as "high" and it concurs with the real value. Thus, for this case, the NHL-based FCM learning methodology gave exact results.

The back propagation algorithm for a multi-layer perceptron to categorize the yield data to three output nodes ("low" = 0, "med" = 1 and "high" = 2) was used. The multilayer perceptron used in our case study has nine in- put nodes, a single hidden layer and three output nodes based on the 10-fold cross-validation procedure, the dataset of the 56 entries were randomly divided into 10 subsets. Then, each subset was used to test the performance of the classifiers trained on the union of the remaining nine subsets.

IV. CONCLUSION

The approach used in this work focuses on the soft computing technique of Fuzzy Cognitive Maps enhanced by the NHL training method for the estimation of yield category in Groundnut with respect to precision agriculture aspects. The presented solution has been raised by some of the requirements imposed by the targeted application: the causal association of soil parameters on yield prediction in Groundnut that seem to be crucial for the right yield classification. The main objective of this work was to present a method based on FCM learning technique to develop a computational intelligent tool for categorizing groundnut yield. The results have shown that the FCM learning approach predicts properly the phenomenon, gives a front-end decision about the class of groundnut yield, and provides similar results to those obtained from horticulturist experts.

References

[1] Bueno, S. and Salmeron, J.L. (2009). Benchmarking main activation functions in

[2] Sharif, A.M., Irani, Z., 2006. Exploring Fuzzy Cognitive Mapping for IS evaluation. European Journal of Operational Research 173, 1175-1187.

[3] Savin, Y., Stathakis, D., Negre, T., Isaev, V.A., 2007. Prediction of crop yields with the use of neural networks. Russian Agricultural Sciences 33, 361-363.

[4] Shearer, S.A., Thomasson, J.A., Mueller, T.G., Fulton, J.P., Higgins, S.F., Samson, S., 1999. Yield Prediction using a Neural Network Classifier Trained using Soil Landscape Features and Soil Fertility Data, ASAE, Paper No. 993042, St. Joseph, MI, USA.

[5] Shumann, A.W., Miller, W.M., Zaman, Q.U., Hostler, K.H., Buchanon, S., Cugati, S., 2006. Variable rate granular fertilization of citrus groves: spreader performance with single-tree prescription zones. Applied Engineering in Agriculture 22 (1), 19-24.

[6] Stach, W., Kurgan, L.A., Pedrycz, W., Reformat, M., 2005. Genetic learning of Fuzzy Cognitive Maps. Fuzzy Sets and Systems 153 (3), 371-401.

[7] Stach, W., Kurgan, L., Pedrycz, W., 2008. Data driven nonlinear Hebbian learning method for Fuzzy Cognitive Maps. In: Proc. IEEE World Congress on Computational Intelligence, Hong Kong, pp. 1975-1981.

