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# Adaptive fuzzy cognitive maps vs neutrosophic cognitive maps: decision support tool for knowledge based institutions

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This paper explores feasibility of self-adaptive Fuzzy cognitive maps (FCM) in context of knowledge-based organizations. An illustration of encoding explains how combination of initial subjective knowledge with real life data can help a knowledge organization exploring its strategic decisions. Neutrosophic generalization of FCM offers more practical implications of problem domain.

**Keywords**: Decision support systems, Fuzzy cognitive maps (FCM), Neutrosophic cognitive maps (NCM)

## Introduction

Knowledge management[1-2] (KM) and artificial intelligence (AI) are interconnected disciplines[3-7] to discern information for information management systems. Researchers have raised issues of knowledge that are living and active[8-11]. Decisions based on real life knowledge bases are subjective judgments in nature[12,13]. AI has well-developed cognitive tools that can process qualitative information of knowledge domains (universities, educational bodies, research laboratories, business enterprises and bureaucracy). Artificial Neural Network (ANN) is a simulation of human brain consisting of billions of neurons interconnected by network of synapses. Due to uncertainties involved in relationships, system cannot model human expert's behaviour as the number of rules increases. Decision support system (DSS) tools should be equipped to model dynamically evolving knowledge through feedback mechanisms.

This paper evolves a decision-making system using Fuzzy cognitive maps (FCM) for knowledge-based institutions. The paper showing FCM of a research institution encoded with symbolic input knowledge learns through selective interconnected alternatives and evolves its strategic decisions. Learning is finally generalized using Neutrosophic cognitive maps (NCM).

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## Methodology

### Fuzzy Cognitive Map (FCM)

Cognitive maps[14] are a collection of causal nodes linked by arcs or edges. Nodes drawn as circle (Fig. 1) represent concepts ($C_I$ i=1,…., N), which are variables of problem domain. FCM[15-19] is a fuzzy version of Axelrod's cognitive maps. FCM combines ideas of fuzzy logic and neural network (NN) in a hybrid mode, wherein an organization(s)[11] can be interconnected. In Axelrod's cognitive maps, interconnections are crisp values [+1, -1]. In fuzzy version, connection weights are obtained from either fuzzy membership functions[20] or fuzzified from crisp values. These weights (edge values) are posted along digraph arrows in the map. Causal influence between concepts can be negative, positive or none. Influences are expressed in fuzzy terms as weak, medium, strong, very strong etc. Concepts can assume any of three values: –1 (moderately on); 0 (off); or +1 (on). Inclusion of real values assigned to concepts has recently been made possible[18]. FCM applications in knowledge organizations belong to business[21-22], stock investment[23] and finanace[24] disciplines in supervised mode. Present study describes FCM in unsupervised mode, which has relatively limited applications.

#### *FCM: Theoretical Framework*

Major steps to build FCM are: i) identification of domain concepts; ii) identification of causal connections;

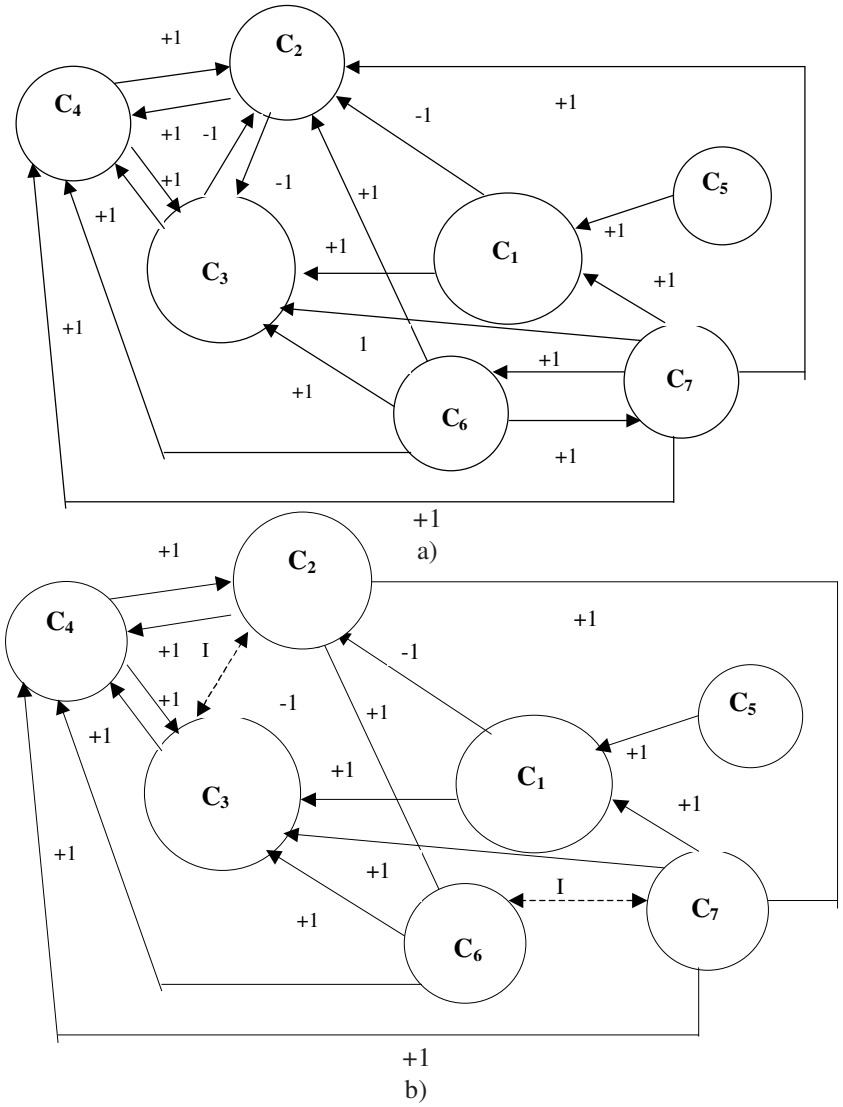


Fig. 1 — R&D domain: a) FCM; b) NCM ($C_1$, ECF; $C_2$, *SCI* journal publication; $C_3$, Indian journal publication; $C_4$, Patent filings; $C_5$, Royalty earned; $C_6$, Ph.D's awarded; $C_7$, *NET/GATE* entrants)

and iii) estimation of connection weights. To estimate connection weights, Differential Hebbian Learning[25,26,28,29] (DHL) and Genetic methods[27] are used.

*(i) DHL Paradigm*

Hebbian Learning involves a sequence of iterative runs, in which network output from previous run is mapped as their back onto the input for next run. For the system to evolve a new scenario, state vector (a set of concepts) is repeatedly passed through a matrix of connection weights, which are used to draw inferences. If E designate connection weights–matrix and C(t) the state vector of concepts at time t, transformation of multiplication is written as C(t+1) = F[C(t), E], where F is non-linear input-output transformation function, C(t+1) is output value of concepts at time t+1. In next iteration, C (t+1) becomes input for output value of concepts at time t+2 and so on. In most practical applications, concepts are assumed to be bivalent as 0 or 1. In present study, an activation value of 0.5 (a midpoint of bivalent concepts) has been considered.

*(ii) DHL— Mathematical Abstractions*

Kosko[15,17,18] was first to transplant DHL into FCM to operate in self adaptive or unsupervisory mode. Connection weight eij's denote edge values between ith and jth concepts for i=1,…,N and j=1,…,N. Edge values are altered over time steps t, t+1, t+2 and so on. Discreet version of DHL accounts for the difference in concept

Table 1 — Time series data on R & D performance indicators based on CGCRI annual reports

| Variables | 1999-00 | 2000-01 | 2001-02 | 2002-03 | 2003-04 | 2004-05 |
|---|---|---|---|---|---|---|
| External cash flow, Rs crores | 4.06 | 5.38 | 10.16 | 3.83 | 5.21 | 4.25 |
| *SCI* journal publication, No. | 41 | 36 | 46 | 43 | 55 | 58 |
| Indian journal publication, No. | 4 | 8 | 16 | 21 | 6 | 11 |
| Patent filings, No. | 24 | 30 | 37 | 26 | 16 | 22 |
| Royalty earned, Rs lakhs | 4.251 | 1.504 | 2.60 | 6.225 | 13.50 | 2.000 |
| Ph D's awarded, No. | 2 | 3 | 4 | 5 | 3 | 1 |
| *NET/GATE* entrants, No. | 0 | 2 | 11 | 5 | 10 | 7 |

values over two immediate time points as $\Delta C_i(t) = C_i(t) - C_i(t\text{-}1)$. Edge values are iteratively changed as follows: if $\Delta C_i(t) \neq 0$,

$$e_{ij}(t+1) = e_{ij}(t) + \mu_t[\Delta C_i(t)\Delta C_j(t) - e_{ij}(t)] \quad ...(1)$$

$$\text{If } \Delta Ci\ (t) = 0, e_{ij}(t+1) = e_{ij}(t) \quad ...(2)$$

Where, $\mu_t$ is learning rate and defined[30] as

$$\mu_t = 0.1\left[1 - \frac{t}{1.1N}\right]K \quad ...(3)$$

where N, number of concepts in the map.

DHL formalism reveals that connection weights diminish exponentially on moving back as t, t-1, t-2, etc. The value of N should be such that $\mu_t > 0$. This arrangement fuzzifies connection weights. Besides this, DHL cannot automate connection weight estimation. Genetic and other algorithms have been proposed to get over these disadvantages[27,28] of DHL. However, these schemes are computationally rigorous and for accuracy purposes more relevant to control systems. Their use in DSS mode reduces qualitative emphasis of FCM[31].

In present study, a simple way to combine human expert's initial assignment of crisp causal links with historical data of the problem domain has been provided to automate generation of initial causal connection weight matrix using adaptive FCM.

## Development of Proposed FCM

Adaptive FCM[32] is used with a novelty that instead of direct assignment of bivalent data to concepts, time changes in past data of the concept designated policy variables in decision domain are incorporated as concept differentials $\Delta C_i(t)$ over time t. If there is a rise in the value of data, $\Delta C_i(t) = +1$, and if there is fall, $\Delta C_i(t) = -1$. In case of neither rise nor fall, $\Delta C_i(t) = 0$. In this way, a set of past quantitative data gets transformed into trivalent data of concept differentials over successive time intervals, which can be plugged into DHL's iterative scheme for connection weight estimations. However, values of causal connections at t=0 are crisp and depend on experts' judgment. Under DHL iterative scheme, edge value eij's at t=1 will require previous knowledge of $e_{ij}$'s at t=0, in Eqs (1) - (3) respectively. This set of values at t=0 is provided by a matrix of crisp values of causal relations based on tacit knowledge of domain expert about concepts and their causal relations. Table 1 presents time changes in concepts over a period of 5 years.

### Knowledge Domain

FCM (Fig. 1a) is designated by concepts representing variables of R&D performance indicators data of CGCRI, Kolkata. Different concepts are: $C_1$, external cash flow (ECF); $C_2$, Science Citation Indexed (SCI) journal publications; $C_3$, Indian journal publications (IJP); $C_4$, patents filing; $C_5$, royalty earned; $C_6$, Ph D's awarded; and $C_7$, NET/GATE qualifiers joined. Values of +1 and –1 along arrows (Fig. 1a) are crisp edge values. Concepts $C_i$'s i=1,..,N refer to research inputs and outputs, which are variables of problem domain. While $C_2$, - $C_6$ are soft output indicators, $C_1$ and $C_7$ are research inputs. Indian journals refer to journals under non-SCI category. ECF is fund generated from research sponsored by the state and corporate world and *NET*/*GATE* refer to India's highly rated National Eligibility Test (NET)

in science and Graduate Aptitude Test in Engineering (GATE) streams to promote scholarships in science and technology.

FCM (Fig. 1a) explains by symbols (+1 and –1) that $C_2$ and $C_3$ promote $C_4$, which have similar effect on causal nodes as $C_2$ and $C_3$ are believed to contribute to $C_4$. The concept $C_5$ enhances $C_1$. With increase in number of $C_7$, domain experts believe that it is possible to keep up $C_1$ and also promote $C_2$ and $C_4$ because of more manpower involvement. Rise in research entrants would consequently lead to doctoral awards. Increase in $C_6$ would promote $C_2$ and $C_4$ and further attract fresh *NET/ GATE* qualifiers into the domain as doctoral success of predecessors would embolden confidence of fresher to choose the Institute as workplace for research.

There is dark side also. High level of $C_1$ implies high volume of exploratory work. Sponsors will stipulate project duration and this would leave very little quality time for project staff to produce at short notice $C_2$ that have impact factors (IFs). Hence, increased $C_1$ will decrease $C_2$, which will promote $C_3$; as experts believe that $C_2$ and $C_3$ are inversely related. Thus, bright young research entrants who are generally attracted to research in basic science may get discouraged and choose other places to pursue research of their choice. Decrease in inflow of bright research workers would lead to decline in soft outputs. With all these perceptions of domain experts, FCM will examine if it is possible to maintain a high level of soft intellectual outputs simultaneously with a heavy inflow of revenue

**Fuzzy Edge Value Computation**

Crisp connection weight matrix imposed on problem domain is given by E, which reflects features of knowledge domain. Crisp values (-1 and +1) are initial values of connection weights assigned by experts of problem domain. Matrix is represented as $E = [e_{ij}]$

$$E = \begin{bmatrix} 0 & -1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 & 1 & 0 \end{bmatrix}$$

Changes in data patterns (Table 1) are represented as concept difference $\Delta C_i$ (t) matrix as

$$\Delta C_i\,(t) = \begin{bmatrix} +1 & -1 & +1 & +1 & -1 & +1 & +1 \\ +1 & +1 & +1 & +1 & +1 & +1 & +1 \\ -1 & -1 & +1 & -1 & +1 & +1 & -1 \\ +1 & +1 & -1 & -1 & +1 & -1 & +1 \\ -1 & +1 & +1 & +1 & -1 & -1 & -1 \end{bmatrix}$$

With initial values of connection weights and concept difference matrix, Eqs (1) to (2) of DHL are applied to fuzzify edge value $[e_{ij}]$ matrix over 5 years time period represented as

$E_1 =$

$$\begin{bmatrix} 0.271 & -0.667 & 0.725 & 0.108 & 0.020 & 0.066 & 0.271 \\ 0.062 & 0.271 & -0.802 & 0.768 & 0.089 & -0.143 & 0.062 \\ -0.004 & -0.802 & +0.271 & 0.888 & -0.031 & 0.201 & 0.004 \\ 0.108 & 0.768 & 0.888 & 0.271 & -0.143 & 0.089 & 0.108 \\ 0.749 & 0.089 & -0.031 & -0.143 & 0.271 & 0.039 & 0.020 \\ 0.066 & 0.586 & 0.930 & 0.818 & 0.039 & 0.271 & 0.795 \\ 1.000 & 0.791 & 0.725 & 0.837 & 0.020 & 0.795 & 0.271 \end{bmatrix}$$

Causal connections in $E_1$ now become initial values for subsequent simulation. One can thus avoid use of fuzzy membership functions to define causal links between concepts.

**Architecture of Proposed FCM**

***(i) New FCM Creation***

FCM state vector at any time-year is a picture of events in the scenario being created. FCM (Fig 1a) reveals that $C_1$ is the first component of state vector C and state [1,0,0,0,0,0,0] implies that ECF has been generated. In $E_1$, all diagonal elements must be set to zero to avoid self feedback. A stimulus state vector $C_1$ [1,0,0,0,0,0,1] that represents ECF generation and *NET/ GATE* qualifiers, and gives rise to future scenario or sequence of vectors is defined as

C1 x E1 = [1, 0.124, 1.550, 1.045, 0.040, 0.861, 0.271] → C2= [1,0,1,1,0,1,1]

C2 x E1=[1.17, 0.658,3.268, 2.851, - 0.095, 1.151, 1.17] → C3=[1,1,1,1,0, 1, 1]

C3 x E1=[1.232, 0.676, 2.466, 3.419, 0.059,1.008, 1.232] → C4=[1,1,1,1, 0,1,1]

Stimulus state vector $C_1$ is repeatedly passed through matrix $E_1$. If elements in product matrix exceed activation value of 0.5, corresponding concepts in stimulus state vector are put on as 1; otherwise, elements remain off at zero level. In three passes, a limit vector as $C_3$=$C_4$ is reached. If $C_1$ and $C_7$ continue to increase, $C_2$, $C_3$, $C_4$ and $C_6$ will also continue to increase. The notion that increase in ECF will lead to decrease in soft R&D output is not true. Also, the belief that an inverse relation exists between *SCI* and Indian journal publications is not tenable Hence, organizational priority[33] on ECF generation can continue without any soft output being risked. If training called encoding of network is done, subsequent FCMs can reach the same limit.

***(ii) Encoding (Simultaneous)***

FCM is fed with knowledge of a sequence of policy events so that current scenario of FCM is able to generate a new scenario. Events ($C_1$, $C_2$, $C_4$, $C_6$ and $C_7$) can occur simultaneously and can be accentuated by new contracts of exploratory work and backlog effect of previous R&D work done would result in these parallel events. It is assumed that these events occur from values of concepts at previous time t-1, which are at zero level as follows:

C(t-1): 0 0 0 0 0 0 0; C(t): 1 1 0 1 0 1 1

Above encoding in DHL will generate a new edge value matrix represented as

$E_2$ =

$$\begin{bmatrix} 0.334 & -0.552 & 0..662 & 0.186 & 0.018 & 0.147 & 0.334 \\ 0.144 & 0.334 & -0.732 & 0.788 & 0.081 & -0.044 & 0.144 \\ -0.004 & -0.732 & 0.247 & 0.811 & -0.028 & 0.184 & -0.004 \\ 0.186 & 0.788 & 0.811 & 0.334 & -0.131 & 0.168 & 0.186 \\ 0.684 & 0.081 & -0.028 & -0.131 & 0.247 & 0.036 & 0.018 \\ 0.147 & 0.622 & 0.849 & 0.834 & 0.036 & 0..334 & 0.813 \\ 1.000 & 0.809 & 0.662 & 0.851 & 0.018 & 0..813 & 0.334 \end{bmatrix}$$

In $E_2$ ($e_{72}$ = 0.809, $e_{74}$ = 0.851 and $e_{67}$= $e_{76}$ =0.813), weights have increased compared to their earlier values in $E_1$. Increase in $C_1$ and $C_7$ enhances the belief that there will be increase in number of $C_2$, $C_4$ and $C_6$.

***(iii) Encoding (Sequential 1)***

In this case, events do not occur in parallel but follow a time sequence, in which one is dependent on the other. As before, events are assumed to start from knowledge that the values of concepts at initial time t-1 are at zero level. Stimulus state vector is as follows:

C(t-1): 0 0 0 0 0 0 0
C(t): 1 0 0 0 0 0 1
C(t+1): 1 0 0 1 0 0 1
C(t+2): 1 0 1 1 0 0 1
C(t+3): 1 1 1 1 0 0 1

At time t, concepts $C_1$ and $C_7$ are put on. Consequently, concept $C_4$ gets on at time t+1 followed by $C_3$ at t+2 and finally $C_2$ at t +3 are put on. Connection between $C_2$ and $C_3$ is negative as $e_{32}$ = -0.732 in $E_2$. Above encoding in DHL will generate a new connection matrix $E_3$ as

$E_3$ =

$$\begin{bmatrix} 0.324 & -0.394 & 0..500 & 0.141 & 0.014 & 0.111 & 0.324 \\ 0.109 & 0.300 & -0.553 & 0.595 & 0.061 & -0.033 & 0.109 \\ -0.003 & -0.553 & 0.245 & 0.613 & -0.021 & 0.139 & -0.003 \\ 0.141 & 0.595 & 0.613 & 0.319 & -0.099 & 0.127 & 0.141 \\ 0.517 & 0.061 & -0.021 & -0.099 & 0.187 & 0.027 & 0.014 \\ 0.111 & 0.470 & 0.642 & 0.630 & 0.027 & 0.252 & 0.614 \\ 0.828 & 0.611 & 0.500 & 0.643 & 0.014 & 0..614 & 0.324 \end{bmatrix}$$

In $E_3$ ($e_{71}$ = 0.828, $e_{74}$ = 0.643, $e_{43}$ = 0.613 and $e_{32}$ = -0.553), magnitude of weights has fallen compared to their earlier values in $E_1$. Magnitude of link value ($e_{32}$ = -0.553) in $E_3$ has reduced from $e_{32}$ = -0.732 in $E_2$ with time. This means that strength about the belief of inverse relation between $C_2$ and $C_3$ is weakened. Thus it cannot be explicitly concluded that with increase in number of papers in Indian journals, number of papers in *SCI* journals will decrease over time. DHL points that allotment of tacit knowledge, $e_{23}$ = $e_{32}$ = -1 in E is improper. Publications, no matter in Indian or *SCI* journals, are result of human intellect and therefore the reason to think of an inverse relation between two systems is not a proper judgment. Causal link $e_{23}$ = $e_{32}$ should have been taken positive in initial matrix E. Thus self-adaptive FCM is able to question the judgment of domain experts, which exemplifies its intelligent computational ability.

***(iv) Encoding (Sequential 2)***

Events in this case follow a sequence of interdependent concepts. It is again assumed that these events do occur from knowledge that initial values of concepts are at zero level.

C(t-1): 0 0 0 0 0 0 0
C(t): 1 0 0 0 0 0 1
C(t+1): 1 0 0 1 0 0 1
C(t+2): 1 0 1 1 0 0 1
C(t+3): 1 0 1 1 0 1 1
C(t+4): 1 0 1 1 0 1 1

Here, sequence of events is $C_1$ and $C_7$ at t followed by $C_4$ at t+1, $C_3$ at t+2, $C_6$ at t+3 followed by recruitment of fresh batch of $C_7$ at t+4 occur sequentially. Above encoding in DHL rule will generate a new matrix $E_4$ of causal connections as

$E_4$ =

$$\begin{bmatrix} 0.306 & -0.287 & 0..365 & 0.103 & 0.010 & 0.081 & 0.306 \\ 0.079 & 0.219 & -0.403 & 0.434 & 0.044 & -0.024 & 0..079 \\ -0.002 & -0.403 & 0.235 & 0.447 & -0.015 & 0.101 & -0.002 \\ 0.103 & 0.434 & 0.447 & 0.296 & -0..072 & 0.093 & 0.103 \\ 0.377 & 0.044 & -0.015 & -0.072 & 0.136 & 0.020 & 0.010 \\ 0.081 & 0.343 & 0.468 & 0.459 & 0.020 & 0.230 & 0.448 \\ 0.673 & 0.446 & 0.365 & 0.469 & 0.010 & 0..448 & 0.306 \end{bmatrix}$$

In $E_4$ ($e_{71} = 0.673$, $e_{72} = 0.446$, $e_{74} = 0.469$ and $e_{67} = e_{76} = 0.448$), magnitude of weights has further fallen compared to their earlier values in $E_3$. Thus, with increase in fund and manpower, the belief that publication in Indian journals will increase followed by increase in Ph D is weakened. Hence, result produced by $E_2$ only leads to a reasonable position as concerned weights increase and strengthen belief that if level of ECF and *NET/GATE* entrants increase, number of publications in *SCI* journals would also increase along with number of Ph D awards.

As before, all diagonal elements in $E_4$ are set at zero to avoid feedback. A stimulus state vector C1=[1,0,0,0,0,0,1] represents $C_1$ and $C_7$ in symbolic terms of unity and as resultant stimulus state vector is repeatedly passed through $E_4$, the sequence of state vectors obtained is

C1x E4 = [0.673, 0.159, 0.730,0.572,0.020,0.529,0.612]
→ C2= [1,0,1,1,0,1,1]

C2x E4 = [0.754, 0.53, 1.645, 1.465, 0.03, 0.650,0.855]
→ C3= [1,0,1,1,0,1,1]

C3x E4 = [0.934, 0.533, 1.242, 1.912, 0.03,0.699,0.934]
→ C4= [1,0,1,1,0,1,1]

State vectors $C_4$=$C_2$ implies that new scenario after 3 sets of encoding has repeated limit vector attained by FCM before encoding. This means that new scenario of FCM has learned to repeat the limit obtained by old scenario of FCM. This has helped in current decision-making. The decision is that given a fleet of bright research scholars and ECF on hand, it is possible to produce soft performance outputs in terms of publications in ´:*SCI* and Indian journals, Patent filings, Ph D awards and entry of fresh *NET/GATE* qualifiers. Tacit notion of inverse relationship between publications indexed in *SCI* and Indian journals cannot be proved explicit. On contrary, limit vector C**4** suggests that both these concepts can be concurrent. Mandate of *NET/GATE* qualifiers for the organization to be right place to pursue their research career is brought to focus. These points also reveal that it is not exploratory research but the right choice of exploratory problems, which makes the difference in quality of research performance.

**Neutrosophic Cognitive Maps (NCM)**

A Neutrosophic treatment of the problem is carried out to generalize results. The notion of neutrosophic logic created by Florentin Samarandache[34] is an extension of fuzzy logic, in which indeterminacy is included. Indeterminacy will be introduced into causal relationships between some of concepts of FCM. This is a generalization of FCM and the structure is called Neutrosophic Cognitive Maps (NCM)[35]. An NCM (Fig. 1b) is a neutrosophic directed graph with indeterminate casualties between concepts as edges. Let $C_1$, $C_2$, …., $C_n$ denote n concepts, where it is assumed that each concept is a neutrosophic vector. So a concept $C_i$ will be represented by $x_k$ where $x_k$'s are zero or one or I; $x_k = 1$ means that $C_k$ is in on state, $x_k = 0$ means, it is in off state, and $x_k$ = I means, the concept state is an indeterminate at that time or in that situation.

Like FCM, directed edge $e_{ij}$ from $C_i$ to $C_j$ denotes causality of concept called connections. Every edge in NCM is weighted with a number in the set {-1, 0, 1, I}. If $C_i$ does not have any effect on $C_i$, $e_{ij} = 0$; if $C_i$ causes increase (or decreases) as $C_j$ increase (or decrease), $e_{ij} = 1$; if $C_i$ causes increase (or decreases) as Cj, decrease (or increase), $e_{ij} = -1$, and if effect of $C_i$ on $C_j$ is indeterminate, $e_{ij}$ = I. With $C_1$, $C_2$, …., $C_n$ as concepts of NCM, that have feedback, let N(E) be associated neutrosophic adjacency matrix. Hidden pattern is to be found when $C_1$ is switched on. An input is given as vector $A_1$ = (1, 0, 0,…, 0), the data is passed through matrix

N(E), which is done by multiplying $A_1$ by matrix. Let $A_1$ x N (E) = ($a_1$, $a_2$,…, $a_n$) with threshold operation by replacing $a_i$ by 1 if $a_i > k$ and $a_i$ by 0 if $a_i < k$ (k – a suitable positive integer) and $a_i$ by I if $a_i$ is not an integer. It is then updated. Concept $C_1$ is included in updated vector by making first coordinate as 1 in resulting vector. Suppose $A_1$ x N (E) =$A_2$, then $A_2$ x N(E) is considered and same procedure is repeated. This is continued till a limit cycle or a fixed point is arrived.

**Working of NCM**

It is assumed that the connection between concepts $C_2$ and $C_3$ and that between $C_6$ and $C_7$ are indeterminate. NCM is utilized to examine effect of indeterminate nature of relationships on problem domain. The conclusion that doctoral successes of NET/GATE students will attract more bathes of NET/GATE fresher is not within management control. Such a conclusion may prove its falsity; hence this relation is also treated as indeterminate. Neutrosophic adjacency matrix is written as

$$N(E) = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & I & 1 & 0 & 0 & 0 \\ 0 & I & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & I \\ 1 & 1 & 1 & 1 & 0 & I & 0 \end{bmatrix}$$

Since FCM has proved that increased $C_1$ would lead to increase in $C_2$, connection weight between these concepts in matrix N(E) is treated as $e_{12} = e_{21} = +1$. Now, an instantaneous stimulus vector is defined as $A_1$ = [1,0,0,0,0,0,1], which indicates that increased $C_1$ would attract $C_7$. The effect of $A_1$ on neutrosophic system N(E) is given by

$A_1$x N(E) = [ 1, 2, 2, 1, 0,.I, 0] $\rightarrow A_2$
= [ 1, 1, 1, 1, 0, I, 1]
$A_2$ x N(E) = [ 1, 2I+3, 2I+3, I+3, 0, I, $I^2$ ] $\rightarrow A_3$
= [ 1, 1, 1, 1, 0, I, 1] = $A_2$

Here $I^2$ =I and neutrosophic system has converged to a fixed point in just three passes. Vector $A_2$ suggests that if $C_1$ and $C_7$ concepts are kept on the concepts $C_2$, $C_3$, $C_4$ will be on state while concept $C_5$ will be off state. However, advent of $C_7$ fresher does not give indication that they would lead to their doctoral success, as $C_6$ concept in $A_3$ is indeterminate. Hence, influx of bright researchers does not ensure that number of Ph D awardees will increase. Again an instantaneous vector is defined as $A_1$ = [1,0,0,0,0, 1,0]. Effect of increased $C_1$ and $C_6$ would be examined especially on fresh $C_7$. Effect of $A_1$ on neutrosophic system N(E) is given by

$A_1$x N(E) = [ 0, 2, 2, 1, 0,.0, I] $\rightarrow A_2$
= [ 1, 1, 1, 1, 0, 1, I]
$A_2$ x N(E) = [ I, 2I+3, 2I+3, I+3, 0, $I^2$ , I] $\rightarrow A_3$
= [ 1, 1, 1, 1, 0, 1, I] = $A_1$

Neutrosophic system has converged to fixed point in just two passes and vector $A_1$ suggests that result is same as before. However, doctoral success of NET/GATE qualifiers does not give indication that fresh batch of NET/GATE qualifiers would be motivated by success of their predecessors. Concept $C_7$ in $A_3$ remain indeterminate. Hence, NCM has proved that increased Ph.D output does not ensure inflow of bright youngsters to the organization. Again an instantaneous vector is defined as $A_1$ = [1,1,0,0,0,0,0]. Effect of concepts $C_1$ and $C_2$ is examined on neutrosophic system. Effect of $A_1$ on neutrosophic system N(E) is given by

$A_1$x N(E) = [ 0, 1, I+1, 1, 0,.0, 0] $\rightarrow A_2$
= [ 1, 1, 1, 1, 0, 0, 0]
$A_2$ x N(E) = [I, I+2, I+2, 2, 0, 0 , 0] $\rightarrow A_3$
= [ 1, 1, 1, 1, 0, 0, 0] =$A_1$

State vector $A_1$ indicates that strategy of increased $C_1$ coupled with $C_2$ will put the concepts $C_3$, $C_4$ on state while $C_5$ will put off. However, this strategy will not produce Ph D output and attract NET/GATE qualifiers. If an input vector is defined as $A_1$ = [1,0,0,0,0,0,0], effect of concept $C_1$ on neutrosophic system will produce same result. Effect of $A_1$ on neutrosophic system N(E) is given by

$A_1$x N(E) = [ 0, 1, 1, 0, 0,.0, 0] $\rightarrow A_2$
= [ 1, 1, 1, 0, 0, 0, 0]
$A_2$ x N(E) = [ 0, I+1, I+1, 2, 0, 0 , 0] $\rightarrow A_3$
= [ 1, 1, 1, 1, 0, 0, 0]
$A_3$ x N(E) = [0, I+2, I+2, 2, 0,0,0] $\rightarrow A_4$
= [ 1, 1, 1, 1, 0, 0, 0] = $A_3$

While FCM suggested that it is not exploratory or applied research rather the choice of problems, which would lead to high number of Ph D's that would further motivate NET/GATE qualifiers to join Institute as right place for research, NCM has proved that it is not the

choice of problem but the choice of profession that could make the difference. A fresh batch of bright researchers may join research but may not complete their research as proven by indeterminate components of resulting state vectors. They may opt for other professions ushered in by globalization. It is true that young people are motivated by glamour of managerial positions in corporate jobs because of large pay packets. The results offered by NCM appear more practical and pervasive. Injection of indeterminacy into few relationships between concepts of problem domain is able to create difference in the results and their implications.

## Conclusions

Self-adaptive FCM can be used as a decision support tool for conducting qualitative studies of knowledge based organizations in situations where knowledge domain is tacit or unstructured. The paper serves to reproduce fixed point limit of an R&D institution after neuro-fuzzy formulation of organization has been simultaneously and sequentially encoded with knowledge in a decision support mode. Soft intellectual output can be sustained even with high level of revenue generation. Organization can reproduce its desired state under changed context, as connection weights between concepts of FCM are trained and adapted to knowledge inputs of empirical data and experts' belief. However, FCM cannot handle real life indeterminacy. NCM can serve such purpose. NCM reveals that it is possible to sustain soft intellectual outputs with high ECF generation. However, question on choice of research organizations by NET/GATE qualifiers remains indeterminate. Even if these research entrants join organization, ultimately rise in number of successful Ph D's would still remain indeterminate. Thus, it is not the choice of research problem but the choice of research profession that is a critical factor. Results by NCM are therefore more practical. Such a result could be achieved because two pairs of causal relations in NCM were contemplated indeterminate.

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## References

1 Wiig K, Knowledge Management Foundations: Thinking about Thinking – How People and Organizations Create, Represent and Use Knowledge (Schema Press, Texas) 1993, 471.

2 Courtney J F, Decision making and knowledge management in inquiring organizations: toward a new decision-making paradigm for DSS, *Decision Support Syst*, **31** (2001) 17-38.

3 Haeley P, Exploring synergies between knowledge management and case based reasoning, in *American Association for Artificial Intelligence Workshop* (American Association for Artificial Intelligence, California) 18-19 July 1999.

4 Noh J B, Lee K C, Kim J K, Lee J K & Kim S H, A case based reasoning approach to cognitive map-driven tacit knowledge management, *J Expert System Applications*, **19** (2000) 249-259.

5 Smith R G & Farquhar A, The road ahead for knowledge management: An AI perspective, *Winter*, **21** (2000) 17-40.

6 Liebowitz J, *Building Organizational Intelligence: A Knowledge Management Primer* (CRC Press, ca Raton, Florida) 2000, 160.

7 Metaxiotis K, Ergazakis K, Samouilidis E & Psarras J, Decision support through knowledge management: the role of the artificial intelligence, *Inform Manage & Compu Security*, **11** (2003) 216-221.

8 Walsh J P & Ungson G R, Organizational memory, *Acad Manage Rev*, **16** (1991) 57-91

9 Bannon L J & Kuutti K, Shifting perspectives on organizational memory: from storage to active remembering, in *Proc. 29th Hawaii Int Conf Syst Sci* (Institute of Electrical and Electronics Engineers, Wailea, HI, USA) 1996, 156-167.

10 Guerrero L A & Pino Jose A, Understanding organizational memory, *Interact Compu*, **8** (1996) 299-310.

11 Huber G P, A theory of the effects of advanced information technologies on organizational design, intelligence and decision making, *Acad Manage J*, **15** (1990) 47-71.

12 Nonaka I, A dynamic theory of organizational knowledge creation, *Org Sci*, **5** (1994) 14-37

13 Bhatt G D & Zaveri J, The enabling role of decision support systems in organization learning, *Decision Support Syst*, **32** (1997) 297-309.

14 Axelrod R, *Structure of Decision: The Cognitive Maps of Political Elites* (Princton University Press, New Jersey) 1976, 404.

15 Kosko B, Differential Hebbian learning, in *Proc AIP Conf 151(*American Institute of Physics, New York) 1986, 265-270.

16 Kosko B, Fuzzy cognitive maps, *Int J Man-Machine Stud*, **24** (1986) 65-75.

17 Kosko B, Hidden patterns in combined and adaptive knowledge networks, *Int J Approx Reason*, **2** (1988) 377-393.

18 Kosko B, *Neural Networks and Fuzzy Systems* (Prentice Hall, New Jersey) 1992, 480-p.

19 Kosko B, *Fuzzy Engineering* (Prentice Hall, New Jersey) 1997, 549p.

20 Klir G J & Folger T A, *Fuzzy Sets, Uncertainty And Information* (Prentice Hall, New Delhi) 1991, 65-106.

21 Kang I, Lee S & Choi J, Using fuzzy cognitive map for the relationship management in airline service, *Expert Syst Applications*, **24** (2004) 545-555.

22 Xirogiannis G & Glykas M, Fuzzy cognitive maps in business analysis and performance-driven change, *IEEE Trans Eng Manage*, **51** (2004) 334-351.

23 Lee K C & Kim H S, A fuzzy cognitive map based bidirectional inference mechanism: an application to stock investment

analysis, *J Intelligent Syst Accounting*, *Finance & Manage*, **6** (1997) 41-57.

24 Xirogiannis G, Glykas M & Staikouras C, Fuzzy cognitive maps as a back end to knowledge-based systems in geographically dispersed financial organizations, *Knowledge Process Manage*, **11** (2004) 137-154.

25 Papageorgiou E, Stylios C D & Groumpos P P, Fuzzy cognitive map learning based on nonlinear Hebbian rule, in 16th *Australian Conf on Artificial Intelligence*( Perth, Australia) 3-5 December 2003.

26 Papageorgiou E, Stylios C D & Groumpos P P, Active Hebbian learning algorithm to train fuzzy cognitive maps, *Int J Approx Reason*, **37** (2004) 219-249.

27 Stach W, Kurgan L, Pedrycz W & Reformat M, Genetic learning of fuzzy cognitive maps, *Fuzzy Sets Syst*, **153** (2005) 371-401.

28 Papageorgiou E L, Stylios C & Groumpos P P, Unsupervised learning techniques for fine-tuning fuzzy cognitive map causal links, *Int J Human-Compu Stud*, **64** (2006) 727-743.

29 Hebb D O, *The Organization of Behavior*, **12th edn** (Wiley, New York) 1949, 378.

30 Dickerson J & Kosko B, Virtual worlds as fuzzy cognitive maps, *Presence*, **3** (1994) 173-189.

31 Khan M S & Quaddus M, Group decision support using fuzzy cognitive maps for casual reasoning, *Group Decision Negotiation*, **13** (2004) 463-480.

32 Khan M S, Chong A & Gredeon T, A methodology for developing adaptive fuzzy cognitive maps for decision support, *J Adv Compu Intelligence & Intelligent Informatics*, **4** (2000) 403-407.

33 Banerjee G, Roadmapping in R&D: A neuro-fuzzy thinking, in *Proc Int Conf Innovation and Technology Management* (Indian Association for Productivity, Quality and Reliability & Central Glass & Ceramic Research Institute, Kolkata) 2006, 281-291.

34 Samarandche F, Definitions derived from neutrosophics, in *Proc First Int Conf Neutrosophy, Neutrosophic Logic, Neutrosophic Set, Neutrosophic Probability and Statistics* (University of New Mexico, Gallup) 1-3 December 2001.

35 Vasanthakandaswamy, W B & Samarandche F, *Fuzzy Cognitive Maps and Neutrosophic Cognitive Maps* (Xiquan, Phoenix) 2003, 123-190.