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

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Received 07 May 2007; revised 13 June 2008; accepted 04 July 2008

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 management1-2 (KM) and artificial intelligence (AI) are interconnected disciplines3-7 to discern information for information management systems. Researchers have raised issues of knowledge that are living and active6,8. Decisions based on real life knowledge bases are subjective judgments in nature12,13. 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).

Methodology

Fuzzy Cognitive Map (FCM)

Cognitive maps14 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. FCM15-19 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 functions20 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 possible18. FCM applications in knowledge organizations belong to business21-22, stock investment23 and finance24 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;
and iii) estimation of connection weights. To estimate connection weights, Differential Hebbian Learning\(^2^{5,26,28,29}\) (DHL) and Genetic methods\(^2^{7}\) 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\(^1^{5,17,18}\) was first to transplant DHL into FCM to operate in self adaptive or unsupervisory mode. Connection weight \(e_{ij}\)'s denote edge values between \(i\)th and \(j\)th concepts for \(i=1,\ldots,N\) and \(j=1,\ldots,N\). 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
values over two immediate time points as $\Delta C_i(t) = C_i(t) - C_i(t-1)$. Edge values are iteratively changed as follows:

\[ e_{ij}(t+1) = e_{ij}(t) + \mu_i [\Delta C_i(t)\Delta C_j(t) - e_{ij}(t)] \]  
(1)

If $\Delta C_i(t) = 0$, $e_{ij}(t+1) = e_{ij}(t)$  
(2)

Where, $\mu_i$ is learning rate and defined\(^{30}\) as

\[ \mu_i = 0.1 \left[ 1 - \frac{t}{1.1N} \right] K \]  
(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 $\mu_i > 0$. 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 $e_{ij}$’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 (IJ); $C_4$, 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.

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<td>16</td>
<td>21</td>
<td>6</td>
<td>11</td>
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<tr>
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<td>30</td>
<td>37</td>
<td>26</td>
<td>16</td>
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<tr>
<td>Royalty earned, Rs lakhs</td>
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<td>1.504</td>
<td>2.60</td>
<td>6.225</td>
<td>13.50</td>
<td>2.000</td>
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<tr>
<td>Ph D’s awarded, No.</td>
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<td>3</td>
<td>4</td>
<td>5</td>
<td>3</td>
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<tr>
<td>NET/GATE entrants, No.</td>
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<td>2</td>
<td>11</td>
<td>5</td>
<td>10</td>
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Table 1 — Time series data on R & D performance indicators based on CGCRI annual reports
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 C2 and C3 promote C4, which have similar effect on causal nodes as C2 and C3 are believed to contribute to C4. The concept C4 enhances C1. With increase in number of C7, domain experts believe that it is possible to keep up C1 and also promote C2 and C4 because of more manpower involvement. Rise in research entrants would consequently lead to doctoral awards. Increase in C1 would promote C2 and C3, 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 C1 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 C2, that have impact factors (IFs). Hence, increased C1 will decrease C2, which will promote C3; as experts believe that C2 and C3 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 = [eij]

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

Changes in data patterns (Table 1) are represented as concept difference ΔCij(t) matrix as

\[
\Delta C_{ij}(t) = \begin{bmatrix}+1 & -1 & +1 & +1 & -1 & +1 & +1 \\+1 & +1 & +1 & +1 & +1 & +1 & +1 \\-1 & -1 & +1 & -1 & +1 & +1 & -1 \\+1 & +1 & -1 & -1 & +1 & -1 & +1 \\
-1 & +1 & +1 & -1 & -1 & -1 & -1 \end{bmatrix}
\]

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

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

Causal connections in Ei 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 C1 is the first component of state vector C and state [1,0,0,0,0,0] implies that ECF has been generated. In Ei, all diagonal elements must be set to zero to avoid self feedback. A stimulus state vector C, [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

\[
C1 \times E1 = [1, 0.124, 1.550, 1.045, 0.040, 0.861, 0.271] \rightarrow C2 = [1, 0.1, 1.0, 0.1, 1.1] \\
C2 \times E1 = [1.17, 0.658, 3.268, 2.851, -0.095, 1.151, 1.17] \rightarrow C3 = [1, 1.1, 1.0, 1.1] \\
C3 \times E1 = [1.232, 0.676, 2.466, 3.419, 0.059, 1.008, 1.232] \rightarrow C4 = [1, 1.1, 1.0, 0.1, 1.1]
\]
Stimulus state vector $C_i$ is repeatedly passed through matrix $E_i$. 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 $C=\vec{c}^2$ is reached. If $C_1$ and $C_2$ continue to increase, $C_3$, $C_4$, 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 ($C_1$, $C_2$, $C_3$, $C_4$, $C_5$ and $C_6$) 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:

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

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

$$E_3 =
\begin{bmatrix}
0.334 & -0.552 & 0.662 & 0.186 & 0.018 & 0.147 & 0.334 \\
0.144 & 0.334 & -0.732 & 0.788 & 0.081 & -0.044 & 0.144 \\
-0.004 & -0.732 & 0.247 & 0.811 & -0.028 & 0.184 & -0.004 \\
0.186 & 0.788 & 0.811 & 0.334 & -0.131 & 0.168 & 0.186 \\
0.684 & 0.081 & -0.028 & -0.131 & 0.247 & 0.036 & 0.018 \\
0.147 & 0.622 & 0.849 & 0.834 & 0.036 & 0.334 & 0.813 \\
0.000 & 0.809 & 0.662 & 0.851 & 0.018 & 0.813 & 0.334
\end{bmatrix}$$

In $E_3$ ($e_{11} = 0.828$, $e_{14} = 0.643$, $e_{43} = 0.613$ 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.

(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:

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

At time $t$, concepts $C_1$ and $C_2$ are put on. Consequently, concept $C_1$ gets on at time $t+1$ followed by $C_2$ at $t+2$ and finally $C_3$ 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

$$E_3 =
\begin{bmatrix}
0.324 & -0.394 & 0.500 & 0.141 & 0.014 & 0.111 & 0.324 \\
0.109 & 0.300 & -0.553 & 0.595 & 0.061 & -0.033 & 0.109 \\
-0.003 & -0.553 & 0.245 & 0.613 & -0.021 & 0.139 & -0.003 \\
0.141 & 0.595 & 0.613 & 0.319 & -0.099 & 0.127 & 0.141 \\
0.517 & 0.061 & -0.021 & -0.099 & 0.187 & 0.027 & 0.014 \\
0.111 & 0.470 & 0.642 & 0.630 & 0.027 & 0.012 & 0.014 \\
0.082 & 0.611 & 0.500 & 0.643 & 0.014 & 0.614 & 0.324
\end{bmatrix}$$

In $E_3$ ($e_{11} = 0.828$, $e_{14} = 0.643$, $e_{43} = 0.613$ 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.
Here, sequence of events is C1 and C7 at t followed by C4 at t+1, C1 at t+2, C6 at t+3 followed by recruitment of fresh batch of C7 at t+4 occur sequentially. Above encoding in DHL rule will generate a new matrix E4 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 E4 (\(e_{i1} = 0.673, e_{i2} = 0.446, e_{i3} = 0.469\) and \(e_{i6} = e_{i6} = 0.448\)), magnitude of weights has further fallen compared to their earlier values in E4. 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 E2 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 E4 are set at zero to avoid feedback. A stimulus state vector C1=[1,0,0,0,0,1] represents C1 and C7 in symbolic terms of unity and as resultant stimulus state vector is repeatedly passed through E4, the sequence of state vectors obtained is

\[
C1 \times E4 = [0.673, 0.159, 0.730, 0.572, 0.020, 0.529, 0.612] \\
\rightarrow C2 = [1.0, 1.0, 1.0, 1.1] \\
C2 \times E4 = [0.754, 0.53, 1.645, 1.465, 0.03, 0.650, 0.855] \\
\rightarrow C3 = [1.0, 1.1, 0.1, 1.1] \\
C3 \times E4 = [0.934, 0.533, 1.242, 1.912, 0.03, 0.699, 0.934] \\
\rightarrow C4 = [1.0, 0.1, 1.0, 1.1]
\]

State vectors \(C_2=C_4\) 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 \(C4\) 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 Smarandache\(^4\) 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)\(^5\). An NCM (Fig. 1b) is a neutrosophic directed graph with indeterminate casualties between concepts as edges. Let \(C_1, C_2, \ldots, C_n\) denote n concepts, where it is assumed that each concept is a neutrosophic vector. So a concept \(C_i\) will be represented by \(x_i\) where \(x_i\)'s are zero or one or I; \(x_i = 1\) means that \(C_i\) is in on state, \(x_i = 0\) means, it is in off state, and \(x_i = I\) 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 \(C_j\), \(e_{ij} = 0\); if \(C_i\) causes increase (or decreases) as \(C_j\) increase (or decrease), \(e_{ij} = 1\); if \(C_i\) causes increase (or decreases) as \(C_j\) decrease (or increase), \(e_{ij} = -1\), and if effect of \(C_i\) on \(C_j\) is indeterminate, \(e_{ij} = I\). With \(C_i, C_j, \ldots, C_n\) as concepts of NCM, that have feedback, let N(E) be associated neutrosophic adjacency matrix. Hidden pattern is to be found when \(C_i\) is switched on. An input is given as vector \(A_i = (1, 0, 0, \ldots, 0)\), the data is passed through matrix
N(E), which is done by multiplying $A_i$ by matrix. Let $A_i \times N(E) = (a_{i1}, a_{i2}, \ldots, a_{in})$ with threshold operation by replacing $a_{ij}$ by 1 if $a_{ij} > k$ and $a_{ij}$ by 0 if $a_{ij} < k$ (k – a suitable positive integer) and $a_{ij}$ by 1 if $a_{ij}$ 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 $A_i \times N(E) = A_{i+1}$, then $A_i \times N(E)$ 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 batches 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

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

Since FCM has proved that increased $C_1$ would lead to increase in $C_4$, connection weight between these concepts in matrix $N(E)$ is treated as $e_{2i} = e_{12} = +1$. 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 $C_4$. The effect of $A_1$ on neutrosophic system $N(E)$ is given by

$$A_1 \times N(E) = [0, 2, 2, 1, 0, 0, 0] \rightarrow A_2$$
$$= [1, 1, 1, 1, 0, 0, 0]$$

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

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 $C_1$ in $A_1$ 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 $C_j$ and $C_1$ is examined on neutrosophic system. Effect of $A_1$ on neutrosophic system $N(E)$ is given by

$$A_1 \times N(E) = [0, 1, 1+1, 1, 0, 0, 0] \rightarrow A_2$$
$$= [1, 1, 1, 1, 0, 0, 0]$$

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

State vector $A_1$ indicates that strategy of increased $C_1$ coupled with $C_2$ will put the concepts $C_j$, $C_4$ 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

$$A_1 \times N(E) = [0, 1, 1, 0, 0, 0, 0] \rightarrow A_2$$
$$= [1, 1, 1, 0, 0, 0, 0]$$

$$A_2 \times N(E) = [0, 1+1, 1+1, 2, 0, 0, 0] \rightarrow A_3$$
$$= [1, 1, 1, 0, 0, 0, 0]$$

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.

Acknowledgements

Author thanks Director, CGCRI for permission to publish the paper and Dr D K Bhattacharyya, Head, PMD, CGCRI, for constant encouragement.

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