

# A PYTHAGOREAN FCM ANALYSIS ON THE IMPACTS OF ADVERSE CHILDHOOD EXPERIENCES IN LEARNING OF SCHOOL CHILDREN

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## *Abstract*

*Learning is a dynamic activity and it involves the active presence of both mind and body. The factors that affect the process of learning, especially of school children, are mostly the factors that relate to their mind or psyche. The minds of the children are shaped or affected mostly by the factors in their family as the children's world is very much confined to the family. The family background and the experiences of children in the family or neighbourhood plays a vital role in setting their mind towards learning. In this paper, we analyse several factors which are the adverse childhood experiences that affect the learning process of school children and determine the most important of them. For this purpose, fuzzy cognitive maps (FCM) is modified with Pythagorean fuzzy numbers as edge weights. A new simulation process is proposed and executed. The fixed points obtained through this process indicates the dominant factors that affect learning of school children.*

**Keywords:** *Fuzzy cognitive maps, Pythagorean FCM, Pythagorean numbers, Modified FCM, Pythagorean membership functions.*

## **1. Introduction**

In 1986, Kosko introduced the idea of Fuzzy cognitive maps (FCMs) [21]. FCMs are conceptualized as fuzzy graphs that represent the casual link between concept nodes. The edges of these graphs represent the degree of membership that can be systematically created when certain threshold function such as sigmoid, bivalent, trivalent, saturation, hyperbolic functions, etc. are used. FCMs are more applicable especially in soft knowledge domain for example political science, military science, history, international relations, organization theory. FCMs are a promising human knowledge-based modelling approach that can deal with complexity and uncertainty and learn how to respond to the unknown or evolving environment.

Recently, Apostolopoulos et al. developed an MCDM method using FCM and neutral network system for the prediction of the coronary artery disease [4] and also they introduced non - invasive modelling methodology for the diagnosis of coronary artery disease [5]. Azarand Dolatabad [1] proposed new migration method from FCM to Bayesian belief networks (BBN) which deal inadequate data problems to enhance Bayesian network. A new approach for automatic design of Fuzzy Cognitive Maps (FCM) is proposed by Dikopoulou et al. [14], using ordinal data based on the efficient abilities of mixed graphic models. Vergini et al. developed a new conception of FCM with various approaches and different learning algorithms have been used in this work [31]. Devadoss and Ajay [9] analysed the causes of farmers suicides in India using FCM model. Amirkhani et al. present a new method based on

fuzzy cognitive map (FCM) and possibilistic fuzzy c-means (PFCM) clustering algorithm for categorizing celiac disease (CD) [3].

A novel approach called Takagi–Sugeno Fuzzy cognitive maps ANN as traceability chain algorithm was proposed by Chen [6]. Kaiqi et al. introduced an improved fuzzy C-means clustering (IFCM) algorithm for color image segmentation and it is used to solve the problem of heavy calculating burden [20]. While Lavin, E. A., & Giabbanelli [23] used a factorial design of experiments and implemented to analyse and simplify the uncertainty in FCM, Osoba and Kosko introduced the way of combining directed acyclic graphs (DAGs) which tends to produce an FCM [26]. Salmeron et al. propose a new approach to learning FCMs as a predictive model for time series forecasting [29]. FCM was also utilized to construct the systematic mapping relationship between ship navigational risk factors and safety level and this approach enhanced the fuzzy inference system and evidential reasoning to develop the proposed FCM model by Wang et al. [32]. Another important application that the novel FCM approach found was the development of a dynamic rule-based FCM variant to explore precision farming scenarios [24].

The other novel applications of FCMs include the work done by Ladeira et al. to develop an FCM to identify and analyze the determinants of digital entrepreneurship [22]. FCM is also used to prove the usefulness of FCM theory in a health problem by Groumpos [16] and in yet another seminal work Froelich et al. proposed a new approach to granular modelling of time series [15]. While many different approaches to FCM are proposed, a new intuitionistic fuzzy method for constructing FCMs was introduced by Despi [8] which served as the motivation for this work. Hajek and Froelich developed a novel multi-criteria group decision-making method that integrates TOPSIS with IVIFCMs (interval-valued intuitionistic fuzzy cognitive maps) [17]. Interval-valued fuzzy cognitive maps for supporting business decisions is presented by Hajek and Prochazka [18]. A comparison between FCM learning approaches and algorithms is conducted by Salmeron et al. [28]. In the field of software engineering domain FCM method has been used in Harmati et al. [30] mathematically discussed the dynamics of fuzzy cognitive maps with hyperbolic tangent threshold function [19]. From the available literature one can observe that FCM method is widely used in many fields [10-13]. In this paper, FCM Expert (Software Tool for Scenario Analysis and Pattern Classification Based on Fuzzy Cognitive Maps) is utilized [25].

## 2. Preliminaries

This section discusses some of the basic concept of fuzzy sets and neutrosophic idea. The scale values of linguistic variables are framed.

### Definition 2.1 (Fuzzy sets)

A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership function which assigns to each object a grade of membership ranging between zero and one.

### Definition 2.2 (Linguistic Variables)

Linguistic variable is a term from a natural language which is derived using fuzzy logic.

**Definition 2.3 ( Fuzzy Membership )**

A membership function for a fuzzy set  $A$  on the universe of discourse  $X$  is defined as  $\mu_A(x): X \rightarrow [0,1]$ , where each element of  $X$  is mapped to a value between 0 and 1. This value is called membership value or degree of membership.

**Definition 2.4 Pythagorean fuzzy sets**

Let  $X$  be a universal non empty set. A Pythagorean fuzzy set  $A$  in  $X$  is given by

$$A = \{ \langle x, \mu_A(x), \vartheta(x) \rangle \mid x \in X \}$$

Where  $\mu_A(x) : X \rightarrow [0,1]$  depicts the degree of membership and  $\vartheta(x) : X \rightarrow [0,1]$  depicts the degree of no membership of the element  $x \in X$  to the  $A$ , respectively, with the condition that  $0 \leq \mu_A(x) + \vartheta(x) \leq 1$ . The degree of indeterminacy  $\pi(x) = \sqrt{1 - (\mu_A(x) + \vartheta(x))}$ .

**Definition 2.5:** A Pythagorean FCM (PyFCM) can be assumed as a directed graph with nodes which represent characteristics and the weights of the causality as edges.

**Definition 2.6:** When the edges of the FCM are Pythagorean numbers, they are called as Pythagorean edges.

**Definition 2.7:** Let  $N_1, N_2, \dots, N_n$  be the nodes or vertices of a Pythagorean FCM. An instantaneous vector  $A = (a_1, a_2, \dots, a_n)$ , where  $a_i \in [0,1]$  represents the level of the presence of a node.

$a_i = 0$  if  $a_i$  is off and

$a_i = 1$  if  $a_i$  is on, where  $i = 1, 2, \dots, n$ .

**Definition 2.8:** Let  $N_1, N_2, \dots, N_n$  be the vertices of a PyFCM. The edges of the PyFCM are denoted by  $\overrightarrow{N_1 N_2}, \overrightarrow{N_2 N_3}, \dots, \overrightarrow{N_i N_j} (i \neq j)$ . Then, the edges form a directed cycle. A PyFCM is said to be cyclic if it possesses a directed cycle.

**Definition 2.9:** A PyFCM which possesses a cycle is called an FCM with feedback.

**Definition 2.10:** A PyFCM with feedback makes the information represented by the edge weights flow through a cycle and when such a cycle settled at an instantaneous vector, then the PyFCM is called a dynamical system.

**Definition 2.11:** If the equilibrium state of a dynamical system is a unique state vector, then it is called a fixed point.

**3. Pythagorean FCM Model:**

Three types of key parameters should be considered when constructing an PyFCM, namely concept nodes (say  $A_1, A_2, \dots, A_i$ ), directed edges (arcs), and signed weights ( $E_{ij}$ ). Concept nodes represent key features and parameters of complex modelled structures whose values vary significantly. For representing the causality between adjacent nodes, directed edges (arcs) are used. The initial point of the arc is always the triggering concept, and the influence concept is imposed at the end of the edges. Fuzzy positive and negative numbers (from  $[-1, +1]$ ) are signed weights, showing how strongly concept  $N_i$  induces concept  $N_j$ . A value of  $+1$

indicates complete positive, a value of  $-1$  indicates complete negative, and a null value indicates no causal effect.

The simulation process of a PyFCM is done by the following steps:

**Step 1.** Identifying the problem and select important concepts as nodes.

**Step 2.** Form the adjacency matrix with edge weights represented by their corresponding fuzzy linguistic variables.

**Step 3.** Replace the edge weights with Pythagorean fuzzy numbers.

**Step 4.** Calculate the Pythagorean fuzzy score values of edges using the formula  $S(A) = \mu_A(x) - \nu_A(x)$ .

**Step 5.** Set the initial activation state  $A_0$  which represent ON and OFF states or triggering nodes.

**Step 6.** Select the threshold function and its iteration level of the system.

**Step 7.** Use a vector - multiplication procedure repeatedly until the hidden pattern is determined.

**Step 8.** Analyse the main concept nodes from the fixed points.

#### 4. Application of the proposed PyFCM model

Learning is a dynamic process. It involves the active presence of both, body and mind. The minds of children are so fragile. They are so flexible that they get easily affected positively and negatively. Hence children with positive mind tend to show more learning capability compared to their counterparts with less or no positive psyche. The atmosphere in the family and their experiences in the family shape the minds of children. The childhood experiences in the family atmosphere are long lasting and studies show that they leave a strong impact on the learning pattern of children. Children who face adverse experiences tend to show difficulty in learning in the school. Several studies have been conducted to analyse the impact of these adverse childhood experiences on later life. Crandall et al. [7] have analysed the influence of such experiences during adolescence on health while Almuneef et al. [2] carried out a pilot study on the impact of such experiences on risky health behaviours later in their life among adults in Saudi Arabia. Studies also show that adverse experiences affect obesity in later life and who have had such experiences have the tendency to smoking [27]. In this section we analyse the factors that contribute to adverse childhood experiences and use PyFCM to check which of these are the major factors.

The following factors are identified as the most dominant adverse experiences in childhood. They are taken as the nodes of PyFCM for the problem under the scanner and their interrelationships are analysed through the proposed algorithm.

$A_1$  . *The experiences of Emotional abuse at childhood in the family or the neighbourhood*

$A_2$  . *Children who are physically abused face difficulty in concentration and challenge in learning*

A<sub>3</sub> .Sexual abuse faced by children leaves a lasting scar on their psyche and an impact on their learning capability

A<sub>4</sub> .Children who face emotional neglect in childhood are unable to connect with others in the school and hence have an unequal learning environment

A<sub>5</sub> . Parental addiction to alcohol is the most common phenomena that results in several adverse experiences for the child and may introduce the child early to addiction

A<sub>6</sub> . Children with the experiences of Physical neglect due to genuine or ingenuine reasons in the family develop negative feelings

A<sub>7</sub> .Another common factor is the domestic violence faced by the mother of the child. The mother is beaten up or treated violently and this serves as an adverse experience for the child.

A<sub>8</sub> .Household substance abuse

A<sub>9</sub> .Household mental illness

A<sub>10</sub> .Extra marital relationship or polygamy of the parents creates a turmoil in the family atmosphere in which the child is very much rooted

A<sub>11</sub> . Children living with separated or divorced parents miss the much needed care and affection and develop conflict consciousness which detrimental to learning

A<sub>12</sub> . If a member of a family, especially one of the parents, is incarcerated, the children face severe discrimination from the society and grow in criminalised social background

The following table explains transformation of linguistic variables to their corresponding Pythagorean fuzzy numbers

Table .1 Linguistic variables

| Variables              | Pythagorean Numbers |     | Score |
|------------------------|---------------------|-----|-------|
| Very Weak (VW)         | 0.1                 | 0.9 | -0.8  |
| Weak ( W)              | 0.3                 | 0.7 | -0.4  |
| Slightly Moderate (SM) | 0.4                 | 0.6 | -0.2  |
| Moderate (M)           | 0.5                 | 0.5 | 0     |
| Strong (S)             | 0.7                 | 0.3 | 0.4   |
| Verry Strong (VS)      | 0.9                 | 0.1 | 0.8   |

The important nodes have been analysed and their causal relationship or connection is done by the experts

Table. 2 Causal relationship or connection of each nodes

| E   | A1 | A2 | A3 | A4 | A5 | A6 | A7 | A8 | A9 | A10 | A11 | A12 |
|-----|----|----|----|----|----|----|----|----|----|-----|-----|-----|
| A1  | 0  | W  | VW | VS | W  | M  | VW | S  | VS | VW  | W   | W   |
| A2  | VS | 0  | VS | VS | VW | VS | SM | VS | S  | W   | M   | SM  |
| A3  | VS | VS | 0  | S  | SM | S  | W  | M  | VW | VW  | W   | M   |
| A4  | SM | W  | VW | 0  | W  | S  | VS | W  | S  | VW  | VW  | VW  |
| A5  | M  | S  | W  | S  | 0  | S  | SM | VS | VS | VS  | VS  | W   |
| A6  | VW | VS | SM | S  | VW | 0  | M  | W  | W  | VW  | VW  | VW  |
| A7  | S  | VS | VW | S  | SM | S  | 0  | VS | SM | VW  | W   | VW  |
| A8  | M  | S  | SM | S  | VW | SM | VS | 0  | M  | VW  | VW  | VW  |
| A9  | VS | S  | VW | M  | S  | S  | SM | S  | 0  | S   | S   | VW  |
| A10 | VS | M  | VW | VS | VS | S  | SM | VW | VS | 0   | VS  | W   |
| A11 | M  | S  | SM | S  | M  | VS | W  | VW | W  | VS  | 0   | VW  |
| A12 | M  | SM | W  | S  | M  | S  | SM | M  | VS | M   | W   | 0   |

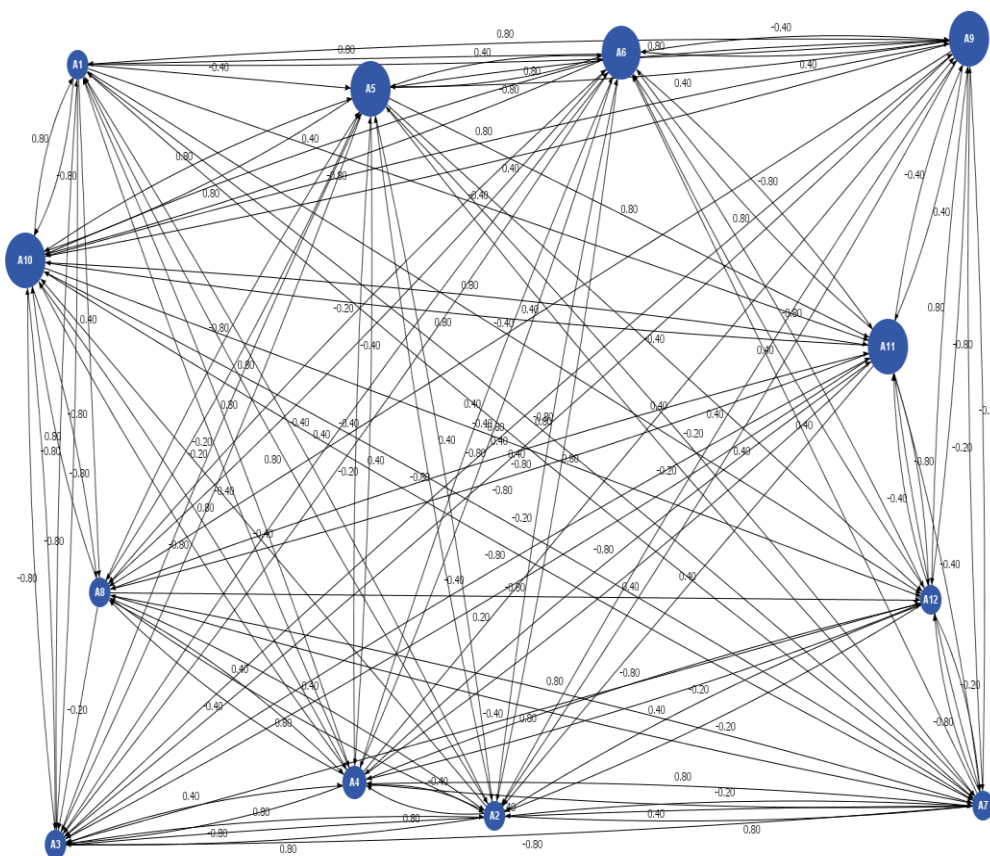
After replacing the fuzzy linguistic variables by Pythagorean fuzzy score values, table.3 is arrived

Table. 3 Fuzzy decision matrix

| E   | A1   | A2   | A3   | A4  | A5   | A6   | A7   | A8   | A9   | A10  | A11  | A12  |
|-----|------|------|------|-----|------|------|------|------|------|------|------|------|
| A1  | 0    | -0.4 | -0.8 | 0.8 | -0.4 | 0    | -0.8 | 0.4  | 0.8  | -0.8 | -0.4 | -0.4 |
| A2  | 0.8  | 0    | 0.8  | 0.8 | -0.8 | 0.8  | -0.2 | 0.8  | 0.4  | -0.4 | 0    | -0.2 |
| A3  | 0.8  | 0.8  | 0    | 0.4 | -0.2 | 0.4  | -0.4 | 0    | -0.8 | -0.8 | -0.4 | 0    |
| A4  | -0.2 | -0.4 | -0.8 | 0   | -0.4 | 0.4  | 0.8  | -0.4 | 0.4  | -0.8 | -0.8 | -0.8 |
| A5  | 0    | 0.4  | -0.4 | 0.4 | 0    | 0.4  | -0.2 | 0.8  | 0.8  | 0.8  | 0.8  | -0.4 |
| A6  | -0.8 | 0.8  | -0.2 | 0.4 | -0.8 | 0    | 0    | -0.4 | -0.4 | -0.8 | -0.8 | -0.8 |
| A7  | 0.4  | 0.8  | -0.8 | 0.4 | -0.2 | 0.4  | 0    | 0.8  | -0.2 | -0.8 | -0.4 | -0.8 |
| A8  | 0    | 0.4  | -0.2 | 0.4 | -0.8 | -0.2 | 0.8  | 0    | 0    | -0.8 | -0.8 | -0.8 |
| A9  | 0.8  | 0.4  | -0.8 | 0   | 0.4  | 0.4  | -0.2 | 0.4  | 0    | 0.4  | 0.4  | -0.8 |
| A10 | 0.8  | 0    | -0.8 | 0.8 | 0.8  | 0.4  | -0.2 | -0.8 | 0.8  | 0    | 0.8  | -0.4 |
| A11 | 0    | 0.4  | 0.2  | 0.4 | 0    | 0.8  | -0.4 | -0.8 | -0.4 | 0.8  | 0    | -0.8 |
| A12 | 0    | -0.2 | -0.4 | 0.4 | 0    | 0.4  | -0.2 | 0    | 0.8  | 0    | -0.4 | 0    |

Causal connection between each node is shown as below in figure:

Figure. 1 Causal link of the nodes



When implementing the **Step 5**, the initial activation state is taken as  $A_0$  which represents ON and OFF states or triggering nodes.

When C1 is ON state, then

$$A_0 = [1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0];$$

$$A_0 * E = [0\ -0.40\ -0.80\ 0.80\ -0.40\ 0\ -0.80\ 0.40\ 0.80\ -0.80\ -0.40\ -0.40]$$

$$A_1 = [0\ 0\ 0\ 1\ 0\ 0\ 0\ 1\ 1\ 0\ 0\ 0];$$

$$A_1 * E = [0.60\ 0.40\ -1.80\ 0.40\ -0.80\ 0.60\ 1.40\ 0\ 0.40\ -1.20\ -1.20\ -2.40]$$

$$A_2 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 0\ 1\ 0\ 0\ 0];$$

$$A_2 * E = [1.00\ 1.20\ -2.60\ 2.40\ -2.20\ 2.00\ -0.40\ 1.60\ 1.00\ -3.20\ -2.00\ -3.80]$$

$$A_3 = [1\ 1\ 0\ 1\ 0\ 1\ 0\ 1\ 1\ 0\ 0\ 0];$$

$$A_3 * E = [0.60\ 0.80\ -2.00\ 2.40\ -2.80\ 1.40\ 0.40\ 0.80\ 1.20\ -3.20\ -2.40\ -3.80]$$

$$A_4 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

$$A_4 * E = [1.00\ 1.60\ -2.80\ 2.80\ -3.00\ 1.80\ 0.40\ 1.60\ 1.00\ -4.00\ -2.80\ -4.60]$$

$$A_5 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

The fixed points are  $[1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0]$ :  $[1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0]$ ;

When C2 is ON state, then

$$A_0 = [0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0];$$

$$A_0 * E = [0.8\ 0\ 0.8\ 0.80\ -0.80\ 0.80\ -0.20\ 0.80\ 0.40\ -0.40\ 0\ -0.20]$$

$$A_1 = [1\ 0\ 1\ 1\ 0\ 1\ 0\ 1\ 1\ 0\ 0\ 0];$$

$$A_1 * E = [0.60\ 1.60\ -2.80\ 2.00\ -2.20\ 1.00\ 0.20\ 0\ 0\ -3.60\ -2.80\ -3.60]$$

$$A_2 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 0];$$

$$A_2 * E = [0.20\ 0.80\ -1.80\ 2.40\ -2.60\ 1.60\ -0.20\ 1.20\ 1.00\ -3.60\ -2.40\ -3.00]$$

$$A_3 = [1\ 1\ 0\ 1\ 0\ 1\ 0\ 1\ 1\ 0\ 0\ 0];$$

$$A_3 * E = [0.60\ 0.80\ -2.00\ 2.40\ -2.80\ 1.40\ 0.40\ 0.80\ 1.20\ -3.20\ -2.40\ -3.80]$$

$$A_4 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 1\ 0];$$

$$A_4 * E = [1.00\ 1.60\ -2.80\ 2.80\ -3.00\ 1.80\ 0.40\ 1.60\ 1.00\ -4.00\ -2.80\ -4.60]$$

$$A_5 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

The fixed points are  $[0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0]$ :  $[1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0]$

When C3 is on state, then

$$A0 = [001000000000];$$

$$A0 * E = [0.80 \ 0.80 \ 0 \ 0.40 \ -0.20 \ 0.40 \ -0.40 \ 0 \ -0.80 \ -0.80 \ -0.40 \ 0]$$

$$A1 = [110101000000];$$

$$A1 * E = [-0.20 \ 0 \ -1.00 \ 2.00 \ -2.40 \ 1.20 \ -0.20 \ 0.40 \ 1.20 \ -2.80 \ -2.00 \ -2.20]$$

$$A2 = [000101011000];$$

$$A2 * E = [-0.20 \ 1.20 \ -2.00 \ 0.80 \ -1.60 \ 0.60 \ 1.40 \ -0.40 \ 0 \ -2.00 \ -2.00 \ -3.20]$$

$$A3 = [010101100000];$$

$$A3 * E = [0.20 \ 1.20 \ -1.00 \ 1.60 \ -2.20 \ 1.60 \ 0.60 \ 0.80 \ 0.20 \ -2.80 \ -2.00 \ -2.60]$$

$$A4 = [110101111000];$$

$$A4 * E = [1.00 \ 1.60 \ -2.80 \ 2.80 \ -3.00 \ 1.80 \ 0.40 \ 1.60 \ 1.00 \ -4.00 \ -2.80 \ -4.60]$$

$$A5 = [110101111000];$$

The fixed points are  $[001000000000] : [110101111000]$

When C4 is on state, then

$$A0 = [000100000000];$$

$$A0 * E = [-0.20 \ -0.40 \ -0.80 \ 0 \ -0.40 \ 0.40 \ 0.80 \ -0.40 \ 0.40 \ -0.80 \ -0.80 \ -0.80]$$

$$A1 = [000001101000];$$

$$A1 * E = [0.40 \ 2.00 \ -1.80 \ 0.80 \ -0.60 \ 0.80 \ -0.20 \ 0.80 \ -0.60 \ -1.20 \ -0.80 \ -2.40]$$

$$A2 = [110101010000];$$

$$A2 * E = [-0.20 \ 0.40 \ -1.20 \ 2.40 \ -3.20 \ 1.00 \ 0.60 \ 0.40 \ 1.20 \ -3.60 \ -2.80 \ -3.00]$$

$$A3 = [010101111000];$$

$$A3 * E = [1.00 \ 2.00 \ -2.00 \ 2.00 \ -2.60 \ 1.80 \ 1.20 \ 1.20 \ 0.20 \ -3.20 \ -2.40 \ -4.20]$$

$$A4 = [110101111000];$$

$$A4 * E = [1.00 \ 1.60 \ -2.80 \ 2.80 \ -3.00 \ 1.80 \ 0.40 \ 1.60 \ 1.00 \ -4.00 \ -2.80 \ -4.60]$$

$$A5 = [110101111000];$$

The fixed points are  $[000100000000] : [110101111000]$

When C5 is on state, then

$$A0 = [000010000000];$$



$$\begin{aligned}
A0 * E &= [ 0 \quad 0.40 \quad -0.40 \quad 0.40 \quad 0 \quad 0.40 \quad -0.20 \quad 0.80 \quad 0.80 \quad 0.80 \quad 0.80 \quad -0.40 ] \\
A1 &= [ 0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 ]; \\
A1 * E &= [ 1.40 \quad 1.60 \quad -1.80 \quad 2.80 \quad -1.60 \quad 2.60 \quad 0.60 \quad -1.20 \quad 0.80 \quad -1.60 \quad -1.20 \quad -4.60 ] \\
A2 &= [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 ]; \\
A2 * E &= [ 1.00 \quad 1.20 \quad -2.60 \quad 2.40 \quad -2.20 \quad 2.00 \quad -0.40 \quad 1.60 \quad 1.00 \quad -3.20 \quad -2.00 \quad -3.80 ] \\
A3 &= [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ]; \\
A3 * E &= [ 0.60 \quad 0.80 \quad -2.00 \quad 2.40 \quad -2.80 \quad 1.40 \quad 0.40 \quad 0.80 \quad 1.20 \quad -3.20 \quad -2.40 \quad -3.80 ] \\
A4 &= [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ]; \\
A4 * E &= [ 1.00 \quad 1.60 \quad -2.80 \quad 2.80 \quad -3.00 \quad 1.80 \quad 0.40 \quad 1.60 \quad 1.00 \quad -4.00 \quad -2.80 \quad -4.60 ] \\
A5 &= [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ]; \\
\text{The fixed points are } & [ 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 ] : [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ]
\end{aligned}$$

When C6 is on state, then

$$\begin{aligned}
A0 &= [ 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 ]; \\
A0 * E &= [ -0.80 \quad 0.80 \quad -0.20 \quad 0.40 \quad -0.80 \quad 0 \quad 0 \quad -0.40 \quad -0.40 \quad -0.80 \quad -0.80 \quad -0.80 ] \\
A1 &= [ 0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 ]; \\
A1 * E &= [ 0.60 \quad -0.40 \quad 0 \quad 0.80 \quad -1.20 \quad 1.20 \quad 0.60 \quad 0.40 \quad 0.80 \quad -1.20 \quad -0.80 \quad -1.00 ] \\
A2 &= [ 1 \quad 0 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ]; \\
A2 * E &= [ 0.20 \quad 1.60 \quad -3.60 \quad 2.00 \quad -2.20 \quad 1.00 \quad 0.60 \quad 0.80 \quad 0.60 \quad -3.60 \quad -2.80 \quad -4.40 ] \\
A3 &= [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ]; \\
A3 * E &= [ 1.00 \quad 1.60 \quad -2.80 \quad 2.80 \quad -3.00 \quad 1.80 \quad 0.40 \quad 1.60 \quad 1.00 \quad -4.00 \quad -2.80 \quad -4.60 ] \\
A4 &= [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ]; \\
\text{The fixed points are } & [ 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 ] : [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ]
\end{aligned}$$

When C7 is on state, then

$$\begin{aligned}
A0 &= [ 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 ]; \\
A0 * E &= [ 0.40 \quad 0.80 \quad -0.80 \quad 0.40 \quad -0.20 \quad 0.40 \quad 0 \quad 0.80 \quad -0.20 \quad -0.80 \quad -0.40 \quad -0.80 ] \\
A1 &= [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 ]; \\
A1 * E &= [ -0.20 \quad 0.40 \quad -1.20 \quad 2.40 \quad -3.20 \quad 1.00 \quad 0.60 \quad 0.40 \quad 1.20 \quad -3.60 \quad -2.80 \quad -3.00 ] \\
A2 &= [ 0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ];
\end{aligned}$$

$$A2 * E = [ 1.00 \quad 2.00 \quad -2.00 \quad 2.00 \quad -2.60 \quad 1.80 \quad 1.20 \quad 1.20 \quad 0.20 \quad -3.20 \quad -2.40 \quad -4.20 ]$$

$$A3 = [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ];$$

$$A3 * E = [ 1.00 \quad 1.60 \quad -2.80 \quad 2.80 \quad -3.00 \quad 1.80 \quad 0.40 \quad 1.60 \quad 1.00 \quad -4.00 \quad -2.80 \quad -4.60 ]$$

$$A4 = [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ];$$

The fixed points are  $[ 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 ] : [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ]$

When C8 is ON state, then

$$A0 = [ 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 ];$$

$$A0 * E = [ 0 \quad 0.40 \quad -0.20 \quad 0.40 \quad -0.80 \quad -0.20 \quad 0.80 \quad 0 \quad 0 \quad -0.80 \quad -0.80 \quad -0.80 ]$$

$$A1 = [ 0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 ];$$

$$A1 * E = [ 1.00 \quad 0.40 \quad -0.80 \quad 1.20 \quad -1.40 \quad 1.60 \quad 0.60 \quad 1.20 \quad 0.60 \quad -2.00 \quad -1.20 \quad -1.80 ]$$

$$A2 = [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ];$$

$$A2 * E = [ 1.00 \quad 1.60 \quad -2.80 \quad 2.80 \quad -3.00 \quad 1.80 \quad 0.40 \quad 1.60 \quad 1.00 \quad -4.00 \quad -2.80 \quad -4.60 ]$$

$$A3 = [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ];$$

The fixed points are  $[ 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 ] : [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ]$

When C9 is ON state, then

$$A0 = [ 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 ];$$

$$A0 * E = [ 0.80 \quad 0.40 \quad -0.80 \quad 0 \quad 0.40 \quad 0.40 \quad -0.20 \quad 0.40 \quad 0 \quad 0.40 \quad 0.40 \quad -0.80 ]$$

$$A1 = [ 1 \quad 1 \quad 0 \quad 0 \quad 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 0 ];$$

$$A1 * E = [ 0.80 \quad 1.60 \quad -1.40 \quad 4.00 \quad -2.00 \quad 2.20 \quad -1.00 \quad -0.00 \quad 2.00 \quad -1.20 \quad -0.40 \quad -3.80 ]$$

$$A2 = [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 ];$$

$$A2 * E = [ 0.60 \quad 0.40 \quad -1.80 \quad 2.00 \quad -2.00 \quad 1.60 \quad -0.40 \quad 0.80 \quad 1.20 \quad -2.40 \quad -1.60 \quad -3.00 ]$$

$$A3 = [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ];$$

$$A3 * E = [ 0.60 \quad 0.80 \quad -2.00 \quad 2.40 \quad -2.80 \quad 1.40 \quad 0.40 \quad 0.80 \quad 1.20 \quad -3.20 \quad -2.40 \quad -3.80 ]$$

$$A4 = [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ];$$

$$A4 * E = [ 1.00 \quad 1.60 \quad -2.80 \quad 2.80 \quad -3.00 \quad 1.80 \quad 0.40 \quad 1.60 \quad 1.00 \quad -4.00 \quad -2.80 \quad -4.60 ]$$

$$A5 = [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ];$$

The fixed points are  $[ 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 ] : [ 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 ]$

When C10 is ON state, then

$$A0 = [0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0];$$

$$A0 * E = [0.80\ 0\ -0.80\ 0.80\ 0.80\ 0.40\ -0.20\ -0.80\ 0.80\ 0\ 0.80\ -0.40]$$

$$A1 = [1\ 0\ 0\ 1\ 1\ 1\ 0\ 0\ 1\ 0\ 1\ 0];$$

$$A1 * E = [-0.20\ 1.20\ -2.80\ 2.00\ -1.20\ 2.00\ -0.80\ 0\ 1.20\ -0.40\ -0.80\ -4.00]$$

$$A2 = [0\ 1\ 0\ 1\ 0\ 1\ 0\ 0\ 1\ 0\ 0\ 0];$$

$$A2 * E = [0.60\ 0.80\ -1.00\ 1.20\ -1.60\ 1.60\ 0.40\ 0.40\ 0.40\ -1.60\ -1.20\ -2.60]$$

$$A3 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

$$A3 * E = [1.00\ 1.60\ -2.80\ 2.80\ -3.00\ 1.80\ 0.40\ 1.60\ 1.00\ -4.00\ -2.80\ -4.60]$$

$$A4 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

The fixed points are  $[0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0] : [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0]$

When C11 is ON state, then

$$A0 = [0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0];$$

$$A0 * E = [0\ 0.40\ 0.20\ 0.40\ 0\ 0.80\ -0.40\ -0.80\ -0.40\ 0.80\ 0\ -0.80]$$

$$A1 = [0\ 1\ 1\ 1\ 0\ 1\ 0\ 0\ 0\ 1\ 0\ 0];$$

$$A1 * E = [1.40\ 1.20\ -1.00\ 2.40\ -1.40\ 2.00\ 0\ -0.80\ 0.40\ -2.80\ -1.20\ -2.20]$$

$$A2 = [1\ 1\ 0\ 1\ 0\ 1\ 0\ 0\ 1\ 0\ 0\ 0];$$

$$A2 * E = [0.60\ 0.40\ -1.80\ 2.00\ -2.00\ 1.60\ -0.40\ 0.80\ 1.20\ -2.40\ -1.60\ -3.00]$$

$$A3 = [1\ 1\ 0\ 1\ 0\ 1\ 0\ 1\ 1\ 0\ 0\ 0];$$

$$A3 * E = [0.60\ 0.80\ -2.00\ 2.40\ -2.80\ 1.40\ 0.40\ 0.80\ 1.20\ -3.20\ -2.40\ -3.80]$$

$$A4 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

$$A4 * E = [1.00\ 1.60\ -2.80\ 2.80\ -3.00\ 1.80\ 0.40\ 1.60\ 1.00\ -4.00\ -2.80\ -4.60]$$

$$A5 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

The fixed points are  $[0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0] : [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0]$

When C12 is ON state, then

$$A0 = [0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1];$$

$$A0 * E = [0\ -0.20\ -0.40\ 0.40\ 0\ 0.40\ -0.20\ 0\ 0.80\ 0\ -0.40\ 0]$$

$$A1 = [0\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 1\ 0\ 0\ 0];$$

$$A1 * E = [-0.20 \quad 0.80 \quad -1.80 \quad 0.40 \quad -0.80 \quad 0.80 \quad 0.60 \quad -0.40 \quad 0 \quad -1.20 \quad -1.20 \quad -2.40]$$

$$A2 = [0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0];$$

$$A2 * E = [0.20 \quad 1.20 \quad -1.00 \quad 1.60 \quad -2.20 \quad 1.60 \quad 0.60 \quad 0.80 \quad 0.20 \quad -2.80 \quad -2.00 \quad -2.60]$$

$$A3 = [1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0];$$

$$A3 * E = [1.00 \quad 1.60 \quad -2.80 \quad 2.80 \quad -3.00 \quad 1.80 \quad 0.40 \quad 1.60 \quad 1.00 \quad -4.00 \quad -2.80 \quad -4.60]$$

$$A4 = [1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0];$$

The fixed points are  $[0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 1] : [1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0]$

The fixed points obtained from various initial state vectors are listed in the table below

|     | ON State                  | Fixed Points              |
|-----|---------------------------|---------------------------|
| A1  | [1 0 0 0 0 0 0 0 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A2  | [0 1 0 0 0 0 0 0 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A3  | [0 0 1 0 0 0 0 0 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A4  | [0 0 0 1 0 0 0 0 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A5  | [0 0 0 0 1 0 0 0 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A6  | [0 0 0 0 0 1 0 0 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A7  | [0 0 0 0 0 0 1 0 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A8  | [0 0 0 0 0 0 0 1 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A9  | [0 0 0 0 0 0 0 0 1 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A10 | [0 0 0 0 0 0 0 0 0 1 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A11 | [0 0 0 0 0 0 0 0 0 0 1 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A12 | [0 0 0 0 0 0 0 0 0 0 0 1] | [1 1 0 1 0 1 1 1 1 0 0 0] |

The fixed points obtained through FCM analysis enables us to identify the important nodes of the problem. It can be observed from the table that the same fixed point is obtained for all initial state vectors while only one of the factors is in ON position. The nodes A1, A2, A4, A6, A7, A8 and A9 are the nodes central to the problem under analysis. Hence children who have had adverse experiences of emotional and physical abuse, emotional and physical neglect, domestic violence, household substance abuse and mental illness in childhood face severe challenges in learning in school.

In an another effort to identify the important factors, two nodes of initial state vectors are kept in ON state and their impact is analysed.

When two alternatives A1 & A2 are ON state, then

$$A0 = [1 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]$$

$$A0 * E = [0.80 \quad -0.40 \quad 0 \quad 1.60 \quad -1.20 \quad 0.80 \quad -1.00 \quad 1.20 \quad 1.20 \quad -1.20 \quad -0.40 \quad -0.60]$$

$$A1 = [1 \quad 0 \quad 0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 0 \quad 0 \quad 0];$$

$$A1 * E = [-0.20 \quad 0.80 \quad -2.80 \quad 1.60 \quad -2.00 \quad 0.60 \quad 0.60 \quad 0 \quad 0.80 \quad -2.80 \quad -2.40 \quad -3.60]$$

$$A2 = [0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0];$$

$$A2 * E = [1.00 \quad 1.60 \quad -1.80 \quad 1.60 \quad -1.80 \quad 2.00 \quad 0.40 \quad 1.20 \quad 0.20 \quad -2.40 \quad -1.60 \quad -3.40]$$

$$A3 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

$$A3 * E = [1.00\ 1.60\ -2.80\ 2.80\ -3.00\ 1.80\ 0.40\ 1.60\ 1.00\ -4.00\ -2.80\ -4.60]$$

$$A4 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

$$A4 * E = [1.00\ 1.60\ -2.80\ 2.80\ -3.00\ 1.80\ 0.40\ 1.60\ 1.00\ -4.00\ -2.80\ -4.60]$$

$$A5 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

The fixed points are  $[1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0] : [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0]$

When two alternatives A1 & A4 are ON state, then

$$A0 = [1\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0]$$

$$A0 * E = [-0.20\ -0.80\ -1.60\ 0.80\ -0.80\ 0.40\ 0\ 0\ 1.20\ -1.60\ -1.20\ -1.20]$$

$$A1 = [0\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 1\ 0\ 0\ 0];$$

$$A1 * E = [-0.20\ 0.80\ -1.80\ 0.40\ -0.80\ 0.80\ 0.60\ -0.40\ 0\ -1.20\ -1.20\ -2.40]$$

$$A2 = [0\ 1\ 0\ 1\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 0];$$

$$A2 * E = [0.20\ 1.20\ -1.00\ 1.60\ -2.20\ 1.60\ 0.60\ 0.80\ 0.20\ -2.80\ -2.00\ -2.60]$$

$$A3 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

$$A3 * E = [1.00\ 1.60\ -2.80\ 2.80\ -3.00\ 1.80\ 0.40\ 1.60\ 1.00\ -4.00\ -2.80\ -4.60]$$

$$A4 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

The fixed points are  $[1\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0] : [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0]$

When two alternatives A1 & A6 are ON state, then

$$A0 = [1\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0]$$

$$A0 * E = [-0.80\ 0.40\ -1.00\ 1.20\ -1.20\ 0\ -0.80\ 0\ 0.40\ -1.60\ -1.20\ -1.20]$$

$$A1 = [0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0];$$

$$A1 * E = [1.40\ 0\ -0.80\ 0.80\ -0.80\ 1.60\ 0.40\ 0.80\ 0.80\ -0.80\ -0.40\ -1.80]$$

$$A2 = [1\ 0\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

$$A2 * E = [0.20\ 1.60\ -3.60\ 2.00\ -2.20\ 1.00\ 0.60\ 0.80\ 0.60\ -3.60\ -2.80\ -4.40]$$

$$A3 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

$$A3 * E = [1.00\ 1.60\ -2.80\ 2.80\ -3.00\ 1.80\ 0.40\ 1.60\ 1.00\ -4.00\ -2.80\ -4.60]$$

$$A4 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

The fixed points are  $[1\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0] : [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0]$

When two alternatives A1 & A7 are ON state, then

$$A0 = [ 1 0 0 0 0 0 1 0 0 0 0 0 ]$$

$$A0 * E = [ 0.40 \quad 0.40 \quad -1.60 \quad 1.20 \quad -0.60 \quad 0.40 \quad -0.80 \quad 1.200 \quad 0.60 \quad -1.60 \quad -0.80 \quad -1.20 ]$$

$$A1 = [ 1 1 0 1 0 1 0 1 1 0 0 0 ];$$

$$A1 * E = [ 0.60 \quad 0.80 \quad -2.00 \quad 2.40 \quad -2.80 \quad 1.40 \quad 0.40 \quad 0.80 \quad 1.20 \quad -3.20 \quad -2.40 \quad -3.80 ]$$

$$A2 = [ 1 1 0 1 0 1 1 1 1 0 0 0 ];$$

$$A2 * E = [ 1.00 \quad 1.60 \quad -2.80 \quad 2.80 \quad -3.00 \quad 1.80 \quad 0.40 \quad 1.60 \quad 1.00 \quad -4.00 \quad -2.80 \quad -4.60 ]$$

$$A3 = [ 1 1 0 1 0 1 1 1 1 0 0 0 ];$$

The fixed points are [ 1 0 0 0 0 0 1 0 0 0 0 0 ] : [ 1 1 0 1 0 1 1 1 1 0 0 0 ]

When two alternatives A1 & A8 are ON state, then

$$A0 = [ 1 0 0 0 0 0 0 1 0 0 0 0 ]$$

$$A0 * E = [ 0 \quad 0 \quad -1.00 \quad 1.20 \quad -1.20 \quad -0.20 \quad 0 \quad 0.40 \quad 0.80 \quad -1.60 \quad -1.20 \quad -1.20 ]$$

$$A1 = [ 0 0 0 1 0 0 0 1 1 0 0 0 ];$$

$$A1 * E = [ 0.60 \quad 0.40 \quad -1.80 \quad 0.40 \quad -0.80 \quad 0.60 \quad 1.40 \quad 0 \quad 0.40 \quad -1.20 \quad -1.20 \quad -2.40 ]$$

$$A2 = [ 1 1 0 1 0 1 1 0 1 0 0 0 ];$$

$$A2 * E = [ 1.00 \quad 1.20 \quad -2.60 \quad 2.40 \quad -2.20 \quad 2.00 \quad -0.40 \quad 1.60 \quad 1.00 \quad -3.20 \quad -2.00 \quad -3.80 ]$$

$$A3 = [ 1 1 0 1 0 1 0 1 1 0 0 0 ];$$

$$A3 * E = [ 0.60 \quad 0.80 \quad -2.00 \quad 2.40 \quad -2.80 \quad 1.40 \quad 0.40 \quad 0.80 \quad 1.20 \quad -3.20 \quad -2.40 \quad -3.80 ]$$

$$A4 = [ 1 1 0 1 0 1 1 1 1 0 0 0 ];$$

$$A4 * E = [ 1.00 \quad 1.60 \quad -2.80 \quad 2.80 \quad -3.00 \quad 1.80 \quad 0.40 \quad 1.60 \quad 1.00 \quad -4.00 \quad -2.80 \quad -4.60 ]$$

$$A5 = [ 1 1 0 1 0 1 1 1 1 0 0 0 ];$$

The fixed points are [ 1 0 0 0 0 0 0 1 0 0 0 0 ] : [ 1 1 0 1 0 1 1 1 1 0 0 0 ]

When two alternatives A1 & A9 are ON state, then

$$A0 = [ 1 0 0 0 0 0 0 0 1 0 0 0 ]$$

$$A0 * E = [ 0.80 \quad 0 \quad -1.60 \quad 0.80 \quad 0 \quad 0.40 \quad -1.00 \quad 0.80 \quad 0.80 \quad -0.40 \quad 0 \quad -1.20 ]$$

$$A1 = [ 1 0 0 1 0 1 0 1 1 0 0 0 ];$$

$$A1 * E = [ -0.20 \quad 0.80 \quad -2.80 \quad 1.60 \quad -2.00 \quad 0.60 \quad 0.60 \quad 0 \quad 0.80 \quad -2.80 \quad -2.40 \quad -3.60 ]$$

$$A2 = [ 0 1 0 1 0 1 1 0 1 0 0 0 ];$$

$$A2 * E = [ 1.00 \quad 1.60 \quad -1.80 \quad 1.60 \quad -1.80 \quad 2.00 \quad 0.40 \quad 1.20 \quad 0.20 \quad -2.40 \quad -1.60 \quad -3.40 ]$$

$$A3 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

$$A3 * E = [1.00\ 1.60\ -2.80\ 2.80\ -3.00\ 1.80\ 0.40\ 1.60\ 1.00\ -4.00\ -2.80\ -4.60]$$

$$A4 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

$$\text{The fixed points are } [1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0] : [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0]$$

The combined fixed points are

|        | ON State                  | Fixed Points              |
|--------|---------------------------|---------------------------|
| A1, A2 | [1 1 0 0 0 0 0 0 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A1, A4 | [1 0 0 1 0 0 0 0 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A1, A6 | [1 0 0 0 0 1 0 0 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A1, A7 | [1 0 0 0 0 0 1 0 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A1, A8 | [1 0 0 0 0 0 0 1 0 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |
| A1, A9 | [1 0 0 0 0 0 0 0 1 0 0 0] | [1 1 0 1 0 1 1 1 1 0 0 0] |

When all the important alternatives are ON state i.e A1, A2, A4, A6, A7, A8, A9.

$$\text{Then } A0 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0]$$

$$A0 * E = [1.00\ 1.60\ -2.80\ 2.80\ -3.00\ 1.80\ 0.40\ 1.60\ 1.00\ -4.00\ -2.80\ -4.60]$$

$$A1 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

$$A1 * E = [1.00\ 1.60\ -2.80\ 2.80\ -3.00\ 1.80\ 0.40\ 1.60\ 1.00\ -4.00\ -2.80\ -4.60]$$

$$A2 = [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0];$$

$$\text{The fixed points are } [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0] : [1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0]$$

This analysis keeping any two nodes at a time in ON stage also suggests that the same nodes A1, A2, A4, A6, A7, A8 and A9 are the nodes central to the problem.

#### 4.1 The simulation process of PyFCM with different types of threshold functions

**Step 1.** Draw the connection graph and build a connection matrix E with the causal relationship

**Step 2.** Set value for the constant c in function, say c=6.

**Step 3.** Set the initial activation state A0 . Using the above example, let us assume that we are going to find out the impacts of adverse childhood experiences in learning of school children. Thus, we can start with  $A0 = [0.8\ 0.3\ 0.6\ 0.4\ 0.6\ 0.3\ 0.2\ 0.1\ 0.2\ 0.2\ 0.5\ 0.3]$  which represents the order of nodes and the percentage of their presence.

**Step 4.** Use a vector - multiplication procedure repeatedly until the hidden pattern is determined.

**Threshold function 1.** For the chosen problem, the logistic signal function (sigmoid function) has been set as the threshold function

The function  $f$  is a threshold function which can clip the outcome to a certain range, normally set to be the interval  $[0,1]$ , such as the logistic signal functions:

$$f(x) = \frac{1}{1 + e^{-cx}}$$

The number of iteration when epsilon is 0.001 are shown as follows:

A0 = [ 0.8 , 0.3, 0.6, 0.4, 0.6, 0.3, 0.2, 0.1, 0.2, 0.2, 0.5, 0.3 ]

A1 → [ 0.9918, 0.9955, 0.0001, 1.0, 0.0031, 0.9999, 0.0025, 0.9334, 0.9969, 0.0015, 0.0166, 0.0 ]

A2 → [ 0.9728, 0.9911, 0.0, 1.0, 0.0, 0.9998, 0.8892, 0.9909, 0.9992, 0.0, 0.0, 0.0 ]

A3 → [ 0.9966, 0.9999, 0.0, 1.0, 0.0, 1.0, 0.924, 0.9999, 0.9975, 0.0, 0.0, 0.0 ]

A4 → [ 0.997, 0.9999, 0.0, 1.0, 0.0, 1.0, 0.9182, 0.9999, 0.9977, 0.0, 0.0, 0.0 ]

A5 → [ 0.997, 0.9999, 0.0, 1.0, 0.0, 1.0, 0.9181, 0.9999, 0.9977, 0.0, 0.0, 0.0 ]

The figure for the above iterations is shown as below

Figure. 2 Sigmoid threshold function



**Threshold function 2.** Similarly for the same problem, the Bivalent function with iteration values up to 0.001

$$\text{Bivalent function } f(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases}$$

The iterations are listed as follows:



A0 = [ 0.8 , 0.3, 0.6, 0.4, 0.6, 0.3, 0.2, 0.1, 0.2, 0.2, 0.5, 0.3 ]

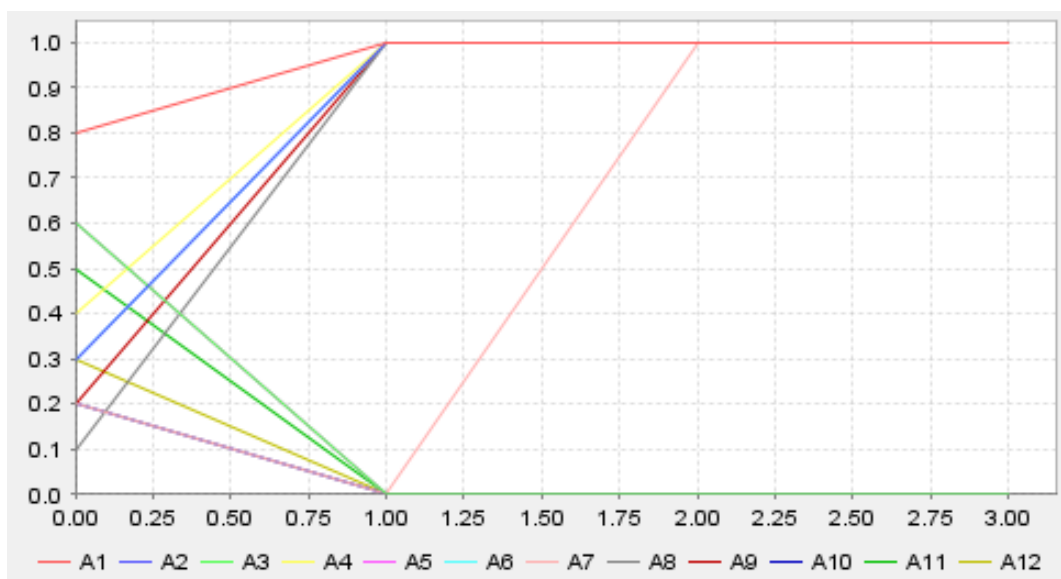
A1 → [ 1.0, 1.0, 0.0, 1.0, 0.0, 1.0, 0.0, 1.0, 1.0, 0.0, 0.0, 0.0 ]

A2 → [ 1.0, 1.0, 0.0, 1.0, 0.0, 1.0, 1.0, 1.0, 1.0, 0.0, 0.0, 0.0 ]

A3 → [ 1.0, 1.0, 0.0, 1.0, 0.0, 1.0, 1.0, 1.0, 1.0, 0.0, 0.0, 0.0 ]

When threshold function is bivalent function then the figure is

Figure. 3 Bivalent threshold function



**Threshold function 3.** Using trivalent function,

$$\text{Trivalent function } f(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases}$$

The iterations are listed as follows:

A0 = [ 0.8 , 0.3, 0.6, 0.4, 0.6, 0.3, 0.2, 0.1, 0.2, 0.2, 0.5, 0.3 ]

A1 → [ 1.0, 1.0, -1.0, 1.0, -1.0, 1.0, -1.0, 1.0, 1.0, -1.0, -1.0, -1.0 ]

A2 → [ -1.0, -1.0, 1.0, -1.0, -1.0, -1.0, 1.0, 1.0, 1.0, -1.0, -1.0, -1.0 ]

.

.

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A97 → [ -1.0, 1.0, 1.0, 1.0, -1.0, 1.0, -1.0, 1.0, 1.0, 1.0, 1.0, -1.0 ]

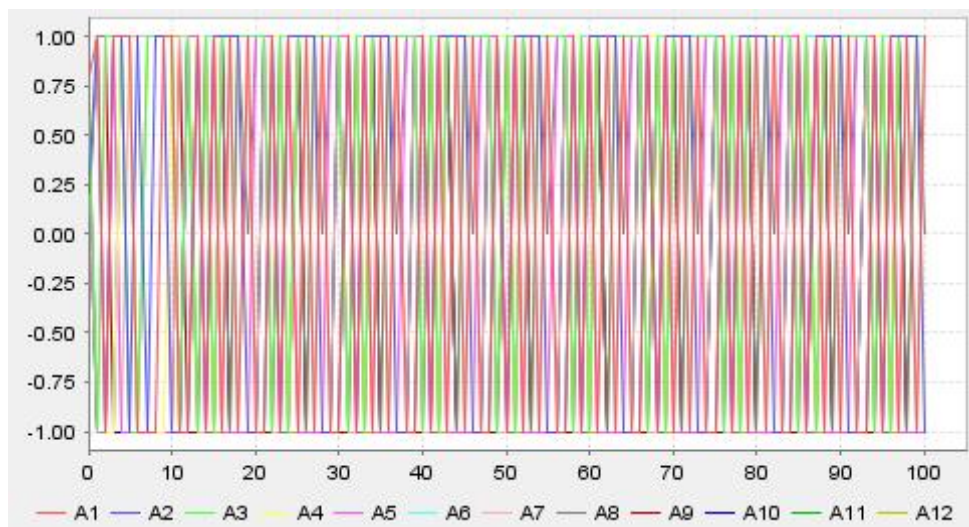
A98 → [ 1.0, 1.0, 1.0, 1.0, -1.0, 1.0, 1.0, -1.0, -1.0, -1.0, -1.0, -1.0 ]

A99 → [ -1.0, 1.0, 1.0, 1.0, -1.0, -1.0, -1.0, 1.0, -1.0, -1.0, -1.0, 1.0 ]

A100 → [ 1.0, -1.0, 1.0, -1.0, -1.0, -1.0, 1.0, 0.0, -1.0, -1.0, -1.0, 1.0 ]

Diagram for trivalent function as shown in fig.4

Figure.4 Trivalent function



**Threshold function 4.** When the threshold is saturation function, then the iterations are listed as follows:

A0 = [ 0.8 , 0.3, 0.6, 0.4, 0.6, 0.3, 0.2, 0.1, 0.2, 0.2, 0.5, 0.3 ]

A1 → [ 0.8, 0.9, 0.0, 1.0, 0.0, 1.0, 0.0, 0.44, 0.96, 0.0, 0.0, 0.0 ]

A2 → [ 0.488, 0.64, 0.0, 1.0, 0.0, 1.0, 0.14, 0.624, 1.0, 0.0, 0.0, 0.0 ]

A3 → [ 0.368, 0.9664, 0.0, 1.0, 0.0, 1.0, 0.5808, 0.4192, 0.6184, 0.0, 0.0, 0.0 ]

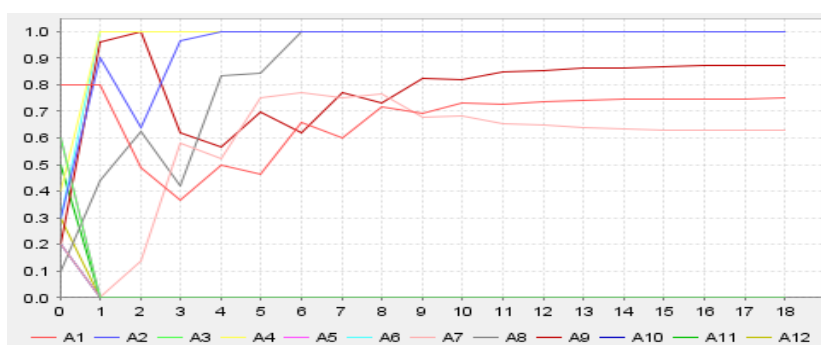
.

A17 → [ 0.7481, 1.0, 0.0, 1.0, 0.0, 1.0, 0.628, 1.0, 0.872, 0.0, 0.0, 0.0 ]

A18 → [ 0.7488, 1.0, 0.0, 1.0, 0.0, 1.0, 0.6271, 1.0, 0.8729, 0.0, 0.0, 0.0 ]

The diagram representation of the above iteration values

Figure. 5 Saturation function



**Threshold function 5.** Hyperbolic function:

Hyperbolic function  $(x) = \tanh(\lambda \times x)$  . Here  $\lambda = 6$

When the threshold function is Hyperbolic function then, the iterations are listed as follows:

A0 = [ 0.8 , 0.3, 0.6, 0.4, 0.6, 0.3, 0.2, 0.1, 0.2, 0.2, 0.5, 0.3 ]

A1 → [ 0.9999, 1.0, -1.0, 1.0, -1.0, 1.0, -1.0, 0.9899, 1.0, -1.0, -0.9994, -1.0 ]

A2 → [ -1.0, -1.0, 0.8377, -0.9844, -1.0, -1.0, 1.0, 0.9999, 0.833, -1.0, -1.0, -1.0 ]

A3 → [ 1.0, 1.0, 0.9997, -1.0, 0.9998, -1.0, 1.0, 1.0, -1.0, -0.9998, -0.9862, 1.0 ]

.

.

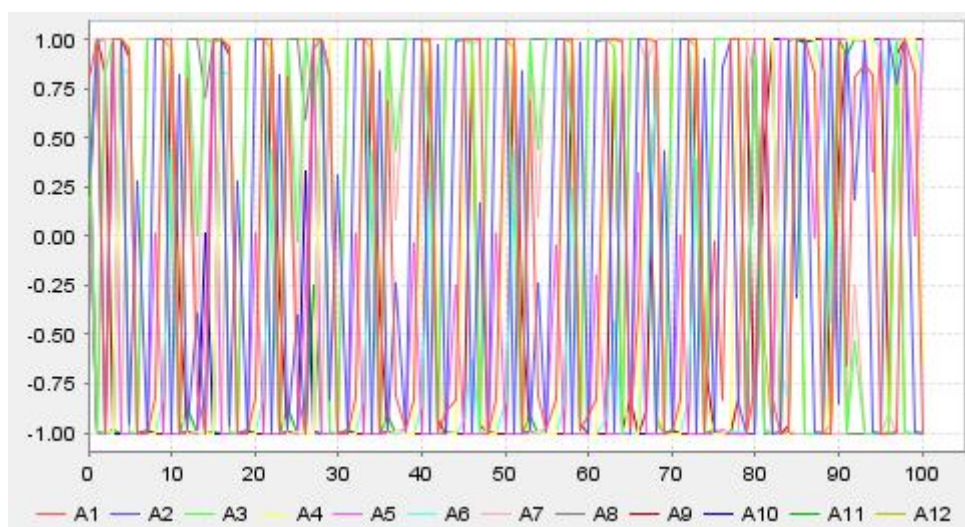
A40 → [ 1.0, 1.0, 1.0, 0.6144, -1.0, -0.8584, 0.9994, 1.0, -1.0, -1.0, -1.0, 1.0 ]

A41 → [ 1.0, -0.9997, 0.449, 1.0, -1.0, 0.2665, 0.9995, 1.0, 0.9814, -1.0, -1.0, 0.9828 ]

A42 → [ -0.9928, 0.9761, -1.0, -0.6193, -1.0, -0.9999, 1.0, 1.0, -0.9323, -1.0, -1.0, -1.0 ]

Diagram representation of the above iteration values is

Figure. 6 Hyperbolic function



## 5. Comparative analysis

When the activation state is  $A_0 = [ 0.8 \ 0.3 \ 0.6 \ 0.4 \ 0.6 \ 0.3 \ 0.2 \ 0.1 \ 0.2 \ 0.2 \ 0.5 \ 0.3 ]$

**Threshold function 1.** Sigmoid Function, then the fixed points are

[ 0.997, 0.9999, 0.0, 1.0, 0.0, 1.0, 0.9181, 0.9999, 0.9977, 0.0, 0.0, 0.0 ]

**Threshold function 2.** Bivalent Function, then the fixed points are

[ 1.0, 1.0, 0.0, 1.0, 0.0, 1.0, 1.0, 1.0, 1.0, 0.0, 0.0, 0.0 ]

**Threshold function 3.** Trivalent Function, then the fixed points are

[ 1.0, -1.0, 1.0, -1.0, -1.0, -1.0, 1.0, 0.0, -1.0, -1.0, -1.0, 1.0 ]

**Threshold function 4.** Saturation Function, then the fixed points are

[ 0.7488, 1.0, 0.0, 1.0, 0.0, 1.0, 0.6271, 1.0, 0.8729, 0.0, 0.0, 0.0 ]

**Threshold function 5.** Hyperbolic Function, then the fixed points are

[ -0.9928, 0.9761, -1.0, -0.6193, -1.0, -0.9999, 1.0, 1.0, -0.9323, -1.0, -1.0, -1.0 ]

## 6. Conclusion

Fuzzy cognitive maps work on the opinion of field experts. It is the experts who define the causal or implicative relationship between the nodes. From real life experiences, we are certain that when the real world problems are analysed, one expresses his views in linguistic terms. Pythagorean fuzzy numbers are effective in expressing the linguistic terms. Hence FCMs powered by Pythagorean fuzzy numbers are used in this analysis. The fixed points obtained through the calculation using PyFCM algorithm helps us to identify the important nodes of the problem. In this case which is under study, this analysis draws our attention to the worst adverse childhood experiences that hinder the process of learning of school children.

In the first part of the study where one or two of the twelve nodes are kept in ON state, the same fixed point is obtained but after different number of iterations. It is noted that the factors A1, A2, A4, A6, A7, A8 and A9 namely, emotional and physical abuse, emotional and physical neglect, domestic violence, household substance abuse and mental illness are to be identified as important factors that affect the process of learning. In the second part of the analysis using different threshold functions, it can be observed that the nodes A1, A2, A4, A6, A7 and A8 are the ones that are repeated in different fixed points. Hence it gets reiterated that the factors that are central to the problem are the same nodes and hence calls for our immediate attention to address these factors. This is very important to Indian scenario as most of the factors identified as the worst factors that affect learning are the factors that are observed as very common among Indian families.

## References:

- [ 1]Azar, A., & Dolatabad, K. M. (2019). A method for modelling operational risk with fuzzy cognitive maps and Bayesian belief networks. *Expert systems with applications*, 115, 607-617.
- [ 2]Almuneef, M., Qayad, M., Aleissa, M., & Albuhairan, F. (2014). Adverse childhood experiences, chronic diseases, and risky health behaviors in Saudi Arabian adults: a pilot study. *Child abuse & neglect*, 38(11), 1787-1793.
- [ 3]Amirkhani, A., Mosavi, M. R., Mohammadi, K., & Papageorgiou, E. I. (2018). A novel hybrid method based on fuzzy cognitive maps and fuzzy clustering algorithms for grading celiac disease. *Neural Computing and Applications*, 30(5), 1573-1588.
- [ 4]Apostolopoulos, I. D., Groumpos, P. P., & Apostolopoulos, D. I. (2017, September). A Medical Decision Support System for the Prediction of the Coronary Artery Disease Using Fuzzy Cognitive Maps. In *Conference on Creativity in Intelligent Technologies and Data Science* (pp. 269-283). Springer, Cham.
- [ 5]Apostolopoulos, I. D., & Groumpos, P. P. (2020). Non-invasive modelling methodology for the diagnosis of coronary artery disease using fuzzy cognitive maps. *Computer Methods in Biomechanics and Biomedical Engineering*, 23(12), 879-887
- [ 6]Chen, R. Y. (2018). A traceability chain algorithm for artificial neural networks using T-S fuzzy cognitive maps in blockchain. *Future Generation Computer Systems*, 80, 198-210.
- [ 7]Crandall, A., Broadbent, E., Stanfill, M., Magnusson, B. M., Novilla, M. L. B., Hanson, C. L., & Barnes, M. D. (2020). The influence of adverse and advantageous childhood experiences during adolescence on young adult health. *Child Abuse & Neglect*, 108, 104644.
- [ 8]Despi, I., Song, G., & Chakrabarty, K. (2011, July). A new intuitionistic fuzzy cognitive maps building method. In *2011 Eighth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)* (Vol. 1, pp. 574-578). IEEE.
- [ 9]Devadoss, A. V., and Ajay, D. (2013). A Fuzzy Analysis on the Causes of Farmers Suicides in India, *International Journal of Computing Algorithm*, 2(2), p.142-145. DOI: 10.20894/IJCOA.101.002.002.017.
- [ 10]Devadoss, A. V., and Ajay, D. (2013). A Study on Community Vitality Using Combined Overlap Block Fuzzy Cognitive Maps, *International Journal of Business Intelligents (IJBI)*, Vol 02, October 2013, Pages: 280-285.
- [ 11]Devadoss, A. V., and Ajay, D. (2013). Farmers' Suicides in India: A Neuro-Fuzzy Analysis, *International Journal of Computing Algorithm*, 3(1), 71-74.
- [ 12] Devadoss, A. V., Sudha, K., and Ajay, D. (2014). The application of Delphi Adapted (weighted) Bidirectional Associative Memories (DABAM) in the analysis of Women empowerment through capabilities, *International Journal of Fuzzy Mathematics and Systems (IJFMS)*, 4(1), p.69-76.
- [ 13]Devadoss, A. V., Ajay, D., Sudha, K. (2014). Delphi Adapted Fuzzy Associative Memories (DAFAM) as a Multiple Expert System and its application to study the Impacts of Climate change on Environment, *International Journal of Communication and Networking System*, 3(1), p.253-257.
- [ 14]Dikopoulou, Z., Papageorgiou, E., Mago, V., & Vanhoof, K. (2017, July). A new approach using mixed graphical model for automatic design of fuzzy cognitive maps from ordinal data. In *2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)* (pp. 1-6). IEEE.
- [ 15]Froelich, W., & Pedrycz, W. (2017). Fuzzy cognitive maps in the modeling of granular time series. *Knowledge-Based Systems*, 115, 110-122.

- [ 16]Groumpos, P. P. (2010). Fuzzy cognitive maps: Basic theories and their application to complex systems. In *Fuzzy cognitive maps* (pp. 1-22). Springer, Berlin, Heidelberg.
- [ 17]Hajek, P., & Froelich, W. (2019). Integrating TOPSIS with interval-valued intuitionistic fuzzy cognitive maps for effective group decision making. *Information Sciences*, 485, 394-412.
- [ 18]Hajek, P., & Prochazka, O. (2016, July). Interval-valued fuzzy cognitive maps for supporting business decisions. In *2016 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)* (pp. 531-536). IEEE.
- [ 19]Harmati, I. Á., & Kóczy, L. T. (2019, June). Notes on the dynamics of hyperbolic tangent fuzzy cognitive maps. In *2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)* (pp. 1-6). IEEE.
- [ 20]Kaiqi, Z., Zhiping, W., & Ming, H. (2008, June). An improved FCM algorithm for color image segmentation. In *2008 3rd International Conference on Innovative Computing Information and Control* (pp. 200-200). IEEE.
- [ 21]Kosko, B. (1986). Fuzzy cognitive maps. *International journal of man-machine studies*, 24(1), 65-75.
- [ 22]Ladeira, M. J., Ferreira, F. A., Ferreira, J. J., Fang, W., Falcão, P. F., & Rosa, Á. A. (2019). Exploring the determinants of digital entrepreneurship using fuzzy cognitive maps. *International Entrepreneurship and Management Journal*, 15(4), 1077-1101.
- [ 23]Lavin, E. A., & Giabbanelli, P. J. (2017, December). Analyzing and simplifying model uncertainty in fuzzy cognitive maps. In *2017 Winter Simulation Conference (WSC)* (pp. 1868-1879). IEEE.
- [ 24]Mourhir, A., Papageorgiou, E. I., Kokkinos, K., & Rachidi, T. (2017). Exploring precision farming scenarios using fuzzy cognitive maps. *Sustainability*, 9(7), 1241.
- [ 25]Nápoles, G., Espinosa, M. L., Grau, I., & Vanhoof, K. (2018). FCM expert: Software tool for scenario analysis and pattern classification based on fuzzy cognitive maps. *International Journal on Artificial Intelligence Tools*, 27(07), 1860010.
- [ 26]Osoba, O., & Kosko, B. (2019). Beyond DAGs: modeling causal feedback with fuzzy cognitive maps. *arXiv preprint arXiv:1906.11247*.
- [ 27]Rehkopf, D.H., Headen, I., Hubbard, A., Deardorff, J., Kesavan, Y., Cohen, A.K., Patil, D., Ritchie, L.D. and Abrams, B. (2016). Adverse childhood experiences and later life adult obesity and smoking in the United States. *Annals of epidemiology*, 26(7), 488-492.
- [ 28]Salmeron, J. L., Mansouri, T., Moghadam, M. R. S., & Mardani, A. (2019). Learning fuzzy cognitive maps with modified asexual reproduction optimisation algorithm. *Knowledge-Based Systems*, 163, 723-735.
- [ 29]Salmeron, J. L., & Froelich, W. (2016). Dynamic optimization of fuzzy cognitive maps for time series forecasting. *Knowledge-Based Systems*, 105, 29-37.
- [ 30]Stach, W., & Kurgan, L. (2004). Modeling software development project using fuzzy cognitive maps. In *Proc. 4th ASERC Workshop on Quantitative and Soft Software Engineering (QSSE'04)* (pp. 55-60).
- [ 31]Vergini, E. S., & Groumpos, P. P. (2016). A new conception on the fuzzy cognitive maps method. *IFAC-PapersOnLine*, 49(29), 300-304.
- [ 32]Wang, L., Liu, Q., Dong, S., & Soares, C. G. (2019). Effectiveness assessment of ship navigation safety countermeasures using fuzzy cognitive maps. *Safety science*, 117, 352-364.