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A STUDY ON A COMBINATION OF FUZZY COGNITIVE MAP MODEL AND CONFLICTING BIFUZZY SET THEORY ON THE IMPACT OF CHENNAI FLOOD

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ABSTRACT

The flood is the alarming rate in India's teeming cities. Heavy rain is one of the reasons for the dangerous flood. Losses are unavoidable when there is more rain. But speed recovery and relief are the precaution for the major losses. In India, Chennai is one of the largest industrial and trading hubs. The city of Chennai met with the calamity in 2015, its consequences are very severe. This paper discusses the reason for the flood, which has a lot of impact on people in the Chennai city by using the fuzzy cognitive map approach. Fuzzy cognitive map is a tool for predicting human knowledge to deal the problems with uncertainty. Also analysis the concept of Bifuzzy Set theory which is the extension of fuzzy set theory by using the Linguistic Geometric Aggregation method (LGA) for multi- attribute decision making process.

Keywords: Aggregation method, Bifuzzy Set theory, Disaster, Flood, Fuzzy Cognitiv Map (FCM), Uncertainty.

I. INTRODUCTION

A disaster is an intense trouble for the society that causes the ecology and materials which are the basic needs of the people. Disaster can be classified as ' natural' and 'man-made' disasters. Floods, Earthquakes, Droughts are considered as natural disasters and bomb blast, pollution, accidents, etc., are considered as man-made disaster [6].

In November – December 2015, Tamil Nadu experienced heavy rains due to the depression and cyclone formation over the southwest region. Andhra Pradesh and some parts of Karnataka are also affected by waterlogging and the flood. Tamil Nadu was one of the most affected areas of high rainfall. In particular, Chennai city was the worst hit in the state which received a maximum of 1200mm rainfall in the month of November. This paper discusses the sensitive and stunning reasons that caused flooding in Chennai city. The cause for the above problem is indeterminant. The tool which is dealing with the unsupervised problems is a Fuzzy Cognitive Map model.

Lofti A.Zadeh (1965) proposed the concept of fuzzy set theory. Later it was developed by Atanassov (1986) by using the concept of membership and non-membership degrees named Intutionistic fuzzy set which are independent from one another. The sum of the two grades not exceeding 1.A new concept of evaluation method is proposed by Abu Osman [4], utilizing both the positive and negative aspects simultaneously namely, Conflicting bifuzzy set (CBFS).

Definition. 1.1

Let X be a Universal set. Let $A \subset R$. Define A: X→ [0, 1] is called membership grade of A. Any set A defined by its membership function $A(x)$ is called the fuzzy set denoted by $\widetilde{A} = \{(x, A(x)) : x \in X\}$[2,3].

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Definition.1.2

An Intuitionistic fuzzy set (IFS) A in E is defined as an object of the following form A={<x,μ_A(x), γ_A(x)>}: x∈E}where the functions: μ_A:E→[0,1] and γ_A: E→[0,1].define the degree of membership and the degree of non-membership of the element x∈E, respectively, and for every x∈E : $0 \le \mu_A + \gamma_A \le 1$ [1,3].

Conflicting Bifuzzy set theory

Consider two CBFS μ: X→ [0,1] and γ: → [0,1] defined on the same set of X developed by the following definition.

Definition 1.3

Let X be a set. A conflicting bifuzzy set *A* of *X* is an object has the following form:

$$A= \{<x,\mu_z(x), \gamma_z(x)>/x \in X; 0< \mu_z(x)+ \gamma_z(x) \le 1.5\}$$

Where the functions μ_z(x):→ [0,1] represent the positive degree of x with respect to Z and x∈ X such that μ_z(x)∈ [0,1],and the functions γ_z: X→[0,1] represent the negative degree of x with respect to Z and x ∈X such that γ_z(x)∈ [0,1] [4].

Table 1: Comparison of set theories (Fuzzy Set, IFS, CBFS) evaluation approaches.

Fuzzy values	Types Of Set theory		
	Fuzzy Set	IFS	CBFS
$\mu_z(x) = 0.8$ $\gamma_z(x) = 0.2$	√	√	√
$\mu_z(x) = 0.8$ $\gamma_z(x) = 0.1$	×	√	√
$\mu_z(x) = 0.8$ $\gamma_z(x) = 03$	×	×	√

Note: '√' means belongs to the set, '×'means does not belong to the set.

II. LINGUISTIC VARIABLES

In this paper, the linguistic terms were used to calculate the initial derivation through this concept. Suppose that K= { K_α / α= 0.2,0.4,0.6,0.8,1} is a finite set where K_α represents a possible values for a linguistic variable. A set of five terms could be given as follows [7].

K ={ $K_{0.2}$ = Extremely negative, $K_{0.4}$ = Slightly negative, $K_{0.6}$ = Fair,$K_{0.8}$= slightly positive, K_1 = extremely positive}

III. AGGREGATION METHOD FOR BIFUZZY SET

The modified Linguistic Geometric averaging (LGA) operator is used for combining positive and negative aspects [7]. This Aggregation method is used to assist group decision makers in the decision making process. In order to get the equilibrium preference degree $(E_P)_i^p$ of the ith alternative over all the other alternatives is defined as follows [7].

$$(E_P)_i^p = \mathrm{LGA}\ \{(k_{1j}^{(1)+} \otimes k_{1j}^{(1)*})^{\frac{1}{2}} \otimes \ldots.. \otimes (k_{1n}^{(1)+} \otimes k_{1n}^{(1)*})^{\frac{1}{2}}\}^{1/(n-1)} \quad (j = 1, 2 ,3,...n)$$

Where $(k_{1j}^{(1)+} \otimes k_{1j}^{(1)*})$ means (positive labels', non- negative labels')

By using the definition of LGA operator the combined single matrix is found from the expert's opinion.

IV. PROBLEM DESCRIPTION

Chennai city has been bound by the Bay of Bengal with an average of 6mm from the sea level. In every year, the month of October - December the city experiences the highest rainfall due to the depressions and cyclones and it was frequently affected by flooding due to heavy rain. In the years 1996,1998,2005,2008,2010 and 2015 caused major consequences. Even though there is good rain in Chennai every year, the water shortage is a big problem. The reason is, more than half of the wetlands have been occupied for other uses. In and around the Chennai city, there has been almost 600 water bodies are located. Due to the various governmental issues, it was

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reduced to 30.Almost one -third of the water bodies and lakes are either declined or disappeared. The protection Law came into the act, but it was not implemented yet. Unfortunately, around 500 people lost their lives and relatives in 2015, because of the improper planning and expansion of Chennai city [8].

V. EMPIRICAL STUDY

In this section, a case study on the impact of Chennai flood faced by the people in the Chennai city was adopted by the proposed method (Bifuzzy set theory and Linguistic geometric aggregator in FCM).

Eight possible factors were considered, Improper design and maintenance of drainage system (C_1), Failure to ensure timely desilting of water bodies (C_2), Illegal construction of housing, commercials and industrials by destroying water bodies (C_3), Climate change related flood (C_4), Disrespect of natural resources (C_5), Dumped solid wastages into the fresh water bodies (C_6), Improper planning and maintenance of rainwater harvesting (C_7), Total disconnection between hydrology and urban planning(C_8).

Three experts were involved and gave their opinion based on their experience and knowledge. Experts compare these eight factors and using the fuzzy values in the set L = {0, 0.1,....,1}. The conflicting preference relation S^n (n= 1, 2, 3...) denoted by $(k_{1j}^{(1)+} \otimes k_{1j}^{(1)-})$ are shown in the tables (2, 4, 6) respectively. Meanwhile the equilibrium preference relations denoted by $(k_{1j}^{(1)+} \otimes k_{1j}^{(1)*})$ are shown in the tables (3, 5, 7) respectively.

Table 2: Conflicting Linguistic Preference relation (E_1)

Factors	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
A_1	-	$(K_{0.6},K_{0.2})$	$(K_{0.4}, K_{0.9})$	$(K_{0.5}, K_{0.9})$	$(K_{0.2}, K_{0.25})$	$(K_{0.65},K_{0.8})$	$(K_{0.6}, K_{0.45})$	$(K_{0.3}, K_{0.7})$
A_2	$(K_{0.6}, K_{0.5})$	-	$(K_{0.2}, K_{0.75})$	$(K_{0.35}, K_{0.5})$	$(K_{0.42}, K_{0.65})$	$(K_{0.67},K_{0.42})$	$(K_{0.8}, K_{0.5})$	$(K_{0.4}, K_{0.6})$
A_3	$(K_{0.8}, K_{0.32})$	$(K_{0.4}, K_{0.76})$	-	$(K_{0.5}, K_{0.42})$	$(K_{0.3}, K_{0.8})$	$(K_{0.6}, K_{0.75})$	$(K_{0.72}, K_{0.52})$	$(K_{0.46}, K_{0.89})$
A_4	$(K_{0.1}, K_{0.5})$	$(K_{0.15}, K_{0.6})$	$(K_{0.23},K_{0.45})$	-	$(K_{0.5}, K_{0.65})$	$(K_{0.45}, K_{0.5})$	$(K_{0.2}, K_{0.6})$	$(K_{0.25}, K_{,0.4})$
A_5	$(K_{0.4}\ K_{0.7})$	$(K_{0.3}, K_{0.6})$	$(K_{0.5}, K_{0.8})$	$K_{0.7}, K_{0.9})$	-	$(K_{0.2}, K_{0.6})$	$(K_{0.3}, K_{0.7})$	$(K_{0.32}, K_{0.65})$
A_6	$(K_{0.5}, K_{0.8})$	$(K_{0.45},K_{0.7})$	$(K_{0.6}, K_{0.5})$	$(K_{0.2}, K_{0.65})$	$(K_{0.25}, K_{0.55})$	-	$(K_{0.35}, K_{0.6})$	$(K_{0.5}, K_{0.6})$
A_7	$(K_{0.45}, K_{0.7})$	$(K_{0.5}, K_{0.8})$	$(K_{0.6}, K_{0.9})$	$(K_{0.2}, K_{0.5})$	$(K_{0.5}, K_{0.6})$	$(K_{0.3}, K_{0.7})$	-	$(K_{0.6}, K_{0.9})$
A_8	$(K_{0.2}, K_{0.8})$	$(K_{0.4}, K_{0.75})$	$(K_{0.5}, K_{0.65})$	$(K_{0.3}, K_{0.45})$	$(K_{0.25}, K_{0.67})$	$(K_{0.5}, K_{0.75})$	$(K_{0.45},K_{0.65})$	-

Table 3: Equilibrium Linguistic preference relation (E_1)

Factors	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
A_1	-	$(K_{0.6}, K_{0.8})$	$(K_{0.4}, K_{0.1})$	$(K_{0.5}, K_{0.1})$	$(K_{0.2},K_{0.75})$	$(K_{0.65}, K_{0.2})$	$(K_{0.6},K_{0.55})$	$(K_{0.3},K_{0.3})$
A_2	$(K_{0.6}, K_{0.5})$	-	$(K_{0.2},K_{0.25})$	$(K_{0.35}, K_{0.5})$	$(K_{0.42, 0.35})$	$(K_{0.67},K_{0.58})$	$(K_{0.8}, K_{0.5})$	$(K_{0.4},K_{0.4})$
A_3	$(K_{0.8},K_{0.6})$	$(K_{0.4}, K_{0.24})$	-	$(K_{0.5}, K_{0.58})$	$(K_{0.3, 0.2})$	$(K_{0.6},K_{0.25})$	$(K_{0.72},K_{048})$	$(K_{0.46},K_{0.11})$
A_4	$(K_{0.1}, K_{0.5})$	$(K_{0.15}, K_{0.4})$	$(K_{0.23}, K_{0.55})$	-	$(K_{0.5, 0.35})$	$(K_{0.45},K_{0.5})$	$(K_{0.2}, K_{0.4})$	$(K_{0.25},K_{0.6})$
A_5	$(K_{0.4}\ K_{0.3})$	$(K_{0.3}, K_{0.4})$	$(K_{0.5}, K_{0.2})$	$(K_{0.7}, K_{0.1})$	-	$(K_{0.2}, K_{0.4})$	$(K_{0.3}, K_{0.3})$	$(K_{0.32},K_{0.35})$
A_6	$(K_{0.5}, K_{0.2})$	$(K_{0.45}, K_{0.3})$	$(K_{0.6}, K_{0.5})$	$(K_{0.2},K_{0.35})$	$(K_{0.25},K_{0.45})$	-	$(K_{0.35},K_{0.4})$	$(K_{0.5}, K_{0.4})$
A_7	$(K_{0.45},K_{0.3})$	$(K_{0.5}, K_{0.2})$	$(K_{0.6}, K_{0.1})$	$(K_{0.2} ,K_{0.5})$	$(K_{0.5}, K_{0.4})$	$(K_{0.3}, K_{0.3})$	-	$(K_{0.6}, K_{0.1})$
A_8	$(K_{0.2}, K_{0.2})$	$(K_{0.4}, K_{0.25})$	$(K_{0.5}, K_{0.35})$	$(K_{0.3},K_{0.55})$	$(K_{0.25},K_{0.33})$	$(K_{0.5},K_{0.73})$	$(K_{0.45},K_{0.35})$	-

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Table 4: Conflicting Linguistic Preference relation (E_2)

Factors	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
A1	-	$(K_{0.6},K_{0.3})$	$(K_{0.4}, K_{0.8})$	$(K_{0.1}, K_0)$	$(K_{0.3},K_{0.2})$	$(K_{0.1}, K_1)$	$(K_{0.7},K_{0.4})$	$(K_{0.8},K_{0.2})$
A2	$(K_{0.5}, K_{0.2})$	-	$(K_{0.2},K_{0.8})$	$(K_{0.6},K_{0.5})$	$(K_{0.7, 0.3})$	$(K_{0.6},K_{0.2})$	$(K_1, K_{0.8})$	$(K_{0.8},K_{0.1})$
A3	$(K_{0.9},K_{0.1})$	$(K_{0.7}, K_{0.2})$	-	(K_0, K_0)	$(K_{0.2, 0.8})$	$(K_{0.5},K_{0.2})$	$(K_{0.8},K_{0.5})$	$(K_{0.6},K_{0.2})$
A4	(K_0, K_0)	$(K_{0.8}, K_{0.6})$	(K_0, K_0)	-	$(K_{0.8, 0.7})$	(K_0,K_0)	$(K_{0.5}, K_{0.2})$	$(K_{0.1},K_0)$
A5	$(K_{0.1}, K_{0.1})$	$(K_{0.6}, K_{0.2})$	$(K_{0.2}, K_{0.8})$	$(K_{0.5}, K_{0.5})$	-	$(K_{0.1}, K_{0.2})$	(K_0, K_0)	$(K_{0.2},K_{0.1})$
A6	$(K_{0.8}, K_{0.7})$	$(K_{0.6}, K_{0.2})$	$(K_{0.6}, K_{0.8})$	(K_0,K_0)	$(K_{0.1},K_{0.2})$	-	$(K_{0.6},K_{0.2})$	$(K_{0.1}, K_0)$
A7	(K_0,K_0)	$(K_{0.8}, K_{0.7})$	$(K_{0.5}, K_{0.5})$	$(K_{0.5} ,K_{0.2})$	$(K_{0.2}, K_{0.1})$	(K_0, K_0)	-	(K_0, K_0)
A8	$(K_{0.8}, K_{0.7})$	$(K_{0.2}, K_{0.8})$	$(K_{0.8}, K_{0.7})$	$(K_0,K_{0.1})$	(K_0,K_0)	$(K_{0.2},K_{0.1})$	$(K_{0.5},K_{0.2})$	-

Table 5:Equilibrium Linguistic preference relation (E_2)

Factors	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
A_1	-	$(K_{0.6},K_{0.7})$	$(K_{0.4}, K_{0.2})$	$(K_{0.1}, K_0)$	$(K_{0.3},K_{0.8})$	$(K_{0.1}, K_0)$	$(K_{0.7},K_{0.6})$	$(K_{0.8},K_{0.8})$
A_2	$(K_{0.5}, K_{0.8})$	-	$(K_{0.2},K_{0.2})$	$(K_{0.6},K_{0.5})$	$(K_{0.7, 0.7})$	$(K_{0.6},K_{0.8})$	$(K_1, K_{0.2})$	$(K_{0.8},K_{0.9})$
A_3	$(K_{0.9}, K_{0.9})$	$(K_{0.7}, K_{0.8})$	-	(K_0, K_0)	$(K_{0.2, 0.2})$	$(K_{0.5},K_{0.8})$	$(K_{0.8},K_{0.5})$	$(K_{0.6},K_{0.8})$
A_4	(K_0, K_0)	$(K_{0.8}, K_{0.4})$	(K_0, K_0)	-	$(K_{0.8, 0.3})$	(K_0,K_0)	$(K_{0.5},K_{0.8})$	$(K_{0.1},K_0)$
A_5	$(K_{0.1}, K_{0.9})$	$(K_{0.6}, K_{0.8})$	$(K_{0.2}, K_{0.2})$	$(K_{0.5}, K_{0.5})$	-	$(K_{0.1}, K_{0.8})$	(K_0, K_0)	$(K_{0.2},K_{0.9})$
A_6	$(K_{0.8}, K_{0.3})$	$(K_{0.6}, K_{0.8})$	$(K_{0.6}, K_{0.2})$	(K_0,K_0)	$(K_{0.1},K_{0.8})$	-	$(K_{0.6},K_{0.8})$	$(K_{0.1}, K_0)$
A_7	(K_0,K_0)	$(K_{0.8}, K_{0.3})$	$(K_{0.5}, K_{0.5})$	$(K_{0.5} ,K_{0.8})$	$(K_{0.2},K_{0.9})$	(K_0, K_0)	-	(K_0, K_0)
A8	$(K_{0.8}, K_{0.3})$	$(K_{0.2}, K_{0.2})$	$(K_{0.8}, K_{0.3})$	$(K_0,K_{0.9})$	(K_0,K_0)	$(K_{0.2},K_{0.9})$	$(K_{0.5},K_{0.8})$	-

Table 6: Conflicting Linguistic Preference relation (E3)

Factors	A1	A2	A3	A4	A5		A7	A8
A1	-	$(K_{0.2},K_{0.8})$	$(K_{0.3}, K_{0.9})$	$(K_{0.4}, K_{0.6})$	$(K_{0.2},K_{0.9})$	$(K_{0.1}, K_{0.8})$	$(K_{0.2},K_{0.8})$	$(K_{0.5}K_{0.5})$
A2	$(K_{0.2},K_{0.8})$	-	$(K_{0.4}, K_{0.7})$	$(K_{0.3},K_{0.6})$	$(K_{0.4}, K_{0.8})$	$(K_{0.1},K_{0.9})$	$(K_{0.2}, K_{0.8})$	$(K_{0.5}K_{0.7})$
A3	$(K_{0.3},K_{0.8})$	$(K_{0.4}, K_{0.8})$	-	$(K_{0.5}, K_{0.5})$	$(K_{0.4, 0.5})$	$(K_{0.2},K_{0.8})$	$(K_{0.3},K_{0.7})$	$(K_{0.2},K_{0.6})$
A4	$(K_{0.1}, K_{0.3})$	$(K_{0.2}, K_{0.5})$	$(K_{0.4}, K_{0.6})$	-	$(K_{0.2},K_{0.8})$	$(K_{0.5},K_{0.6})$	$(K_{0.2}, K_{0.5})$	$(K_{0.5},K_{0.8})$
A5	$(K_{0.2}, K_{0.3})$	$(K_{0.5}, K_{0.6})$	$(K_{0.4}, K_{0.6})$	$(K_{0.2},K_{0.8})$	-	$(K_{0.6}, K_{0.5})$	$(K_{0.2}, K_{0.5})$	$(K_{0.1},K_{0.6})$
A6	$(K_{0.2},K_{0.8})$	$(K_{0.3}, K_{0.2}$9	$(K_{0.4}, K_{0.8})$	$(K_{0.2},K_{0.5})$	$(K_{0.3},K_{0.2})$	-	$(K_{0.6},K_{0.7})$	$(K_{0.3}, K_{0.8})$
A7	$(K_{0.2},K_{0.8})$	$(K_{0.3}, K_{0.9})$	$(K_{0.2},K_{0.8})$	$(K_{0.4},K_{0.5})$	$(K_{0.3}, K_{0.5})$	$(K_{0.2}, K_{0.8})$	-	$(K_{0.3}, K_{0.7})$
A8	$(K_{0.4}, K_{0.6})$	$(K_{0.2}, K_{0.7})$	$(K_{0.2},K_{0.8})$	$(K_{0.2},K_{0.4})$	$(K_{0.3},K_{0.5})$	$(K_{0.2},K_{0.8})$	$(K_{0.4},K_{0.7})$	-

Table 7:Equilibrium Linguistic preference relation (E_3)

Factors	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
A1	-	$(K_{0.2},K_{0.2})$	$(K_{0.3}, K_{0.1})$	$(K_{0.4}, K_{0.4})$	$(K_{0.2},K_{0.1})$	$(K_{0.1}, K_{0.2})$	$(K_{0.2},K_{0.2})$	$(K_{0.5}K_{0.5})$
A2	$(K_{0.2},K_{0.2})$	-	$(K_{0.4}, K_{0.3})$	$(K_{0.3},K_{0.4})$	$(K_{0.4}, K_{0.2})$	$(K_{0.1},K_{0.1})$	$(K_{0.2}, K_{0.2})$	$(K_{0.5}K_{0.3})$
A3	$(K_{0.3},K_{0.2})$	$(K_{0.4}, K_{0.2})$	-	$(K_{0.5}, K_{0.5})$	$(K_{0.4, 0.5})$	$(K_{0.2},K_{0.2})$	$(K_{0.3},K_{0.3})$	$(K_{0.2},K_{0.4})$
A4	$(K_{0.1}, K_{0.7})$	$(K_{0.2}, K_{0.5})$	$(K_{0.4}, K_{0.4})$	-	$(K_{0.2},K_{0.2})$	$(K_{0.5},K_{0.4})$	$(K_{0.2}, K_{0.5})$	$(K_{0.5},K_{0.2})$
A5	$(K_{0.2}, K_{0.7})$	$(K_{0.5}, K_{0.4})$	$(K_{0.4}, K_{0.4})$	$(K_{0.2},K_{0.2})$	-	$(K_{0.6}, K_{0.5})$	$(K_{0.2}, K_{0.5})$	$(K_{0.1},K_{0.4})$

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A6	**($K_{0.2},K_{0.2}$)**	**($K_{0.3},K_{0.1}$)**	**($K_{0.4},K_{0.2}$)**	**($K_{0.2},K_{0.5}$)**	**($K_{0.3},K_{0.4}$)**	-	**($K_{0.6},K_{0.3}$)**	**($K_{0.3},K_{0.2}$)**
A7	**($K_{0.2},K_{0.2}$)**	**($K_{0.3},K_{0.1}$)**	**($K_{0.2},K_{0.2}$)**	**($K_{0.4},K_{0.5}$)**	**($K_{0.3},K_{0.5}$)**	**($K_{0.2},K_{0.2}$)**	-	**($K_{0.3},K_{0.3}$)**
A8	**($K_{0.4},K_{0.4}$)**	**($K_{0.2},K_{0.3}$)**	**($K_{0.2},K_{0.2}$)**	**($K_{0.2},K_{0.6}$)**	**($K_{0.3},K_{0.5}$)**	**($K_{0.2},K_{0.2}$)**	**($K_{0.4},K_{0.3}$)**	-

Thus, from section III, the algorithm was employed to obtain the combined matrix of the experts opinion. Employ the Linguistic Geometric Aggregation operator (LGA)) to aggregate the non- negative equilibrium linguistic preference degree. For example, the $(E_P)_i^p$ can be calculated as follows: $(E_P)_i^p$ = LGA

$$\{(K_{0.6}\otimes K_{0.8})^{1/2}\otimes(K_{0.4}\otimes K_{0.1})^{1/2}\otimes(K_{0.6}\otimes K_{0.1})^{1/2}\otimes(K_{0.2}\otimes K_{0.8})^{1/2}\otimes(K_{0.65}\otimes K_{0.2})^{1/2}$$
$$\otimes(K_{0.6}\otimes K_{0.6})^{1/2}\otimes(K_{0.3}\otimes K_{0.3})^{\frac{1}{2}}\}^{1/(8-1)}$$

$= (K_{0.4})^{1/14}\otimes(K_{0.04})^{1/14}\otimes(K_{0.05})^{1/14}\otimes(K_{0.16})^{1/14}\otimes(K_{0.13})^{1/14}\otimes(K_{0.36})^{1/14}\otimes(K_{0.09})^{1/14}$
$= K_{0.95}\otimes K_{0.79}\otimes K_{0.81}\otimes K_{0.88}\otimes K_{0.86}\otimes K_{0.93}\otimes K_{0.84}$
$= 0.3$

Similarly, the other ELP degrees $(E_P)_i^p$ (P= 1,2,3; i= 1,2,.....,8) are obtained in matrix M as shown in the Table 6.

Table 6: The aggregate of E_P for all the three experts.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
E_1	0.36	0.45	0.39	0.33	0.38	0.38	0.32	0.33
E_2	0.64	0.46	0.64	0.80	0.41	0.52	0.68	0.53
E_3	0.31	0.25	0.30	0.32	0.33	0.27	0.25	0.29

Implementation of FCM approach

The algorithm is used to obtain the fixed point vector [5].

- Initial vector A_i is defined that corresponds to the identified factors.
- As per the expert results, From the matrix identify the highest value for individual factor.
- The maximum value is considered as an initial vector for the calculation.
- To find the severity, calculated values of decision concept are found by using the criterion in the equation.

$$R(x) = \begin{cases} 0, & x \leq 0.5 \\ \frac{x-0.5}{0.5} \times 100\%, & x>0. \end{cases}$$

Solution

First scenario

From the matrix, consider the highest value for each factor and find the influencing percentage using the above equation.The calculated value of the decision concept (A_1) is 0.64 which following the formula corresponds to the 28% of influencing capacity that means the factor, Improper design and maintenance of drainage system has less influencing capacity according to the related fuzzy sets.

Second scenario

In this step, climate change related flood has been considered with the degree 0.80, which following the above formula corresponds to the 60% of influencing capacity that means the fourth factor has the high influencing capacity according to the related fuzzy sets.

If the calculation continues with different scenarios, the various random values have been considered. First and fourth factor has 28% and 60% influencing capacity. Similarly, the seventh factor has 36% and the rest of the components are also having the influencing percentage in the same manner. Among all the relevant factors, climate change related flood is the most impactful factor for the Chennai flood. The results of the study achieve its goal to point out the factors one by one with the degree of influence.

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VI. CONCLUSION

In this paper, the concept of Bifuzzy set theory and fuzzy cognitive map has been combined to get more clarity of results in decision making problems. The computation intelligent technique used in the study focuses on fuzzy cognitive map model for the estimation of social problems and decision making process. From my point of view, the damage of the Chennai flood is not a natural disaster its a man made disaster. Because the rain poured at the time of rainy reason. It is not an unexpected rainfall. An increased number of multinational companies, housing, commercials in the place of agricultural land and pool is one of the major consequences of Chennai flood. To overcome these problems in the upcoming year, the government has come forward to take serious actions towards Chennai by introducing the concept of new Madras. It is one of the precaution for large impact of flood in teaming cities.Because, population in the Chennai city was high. Surely this study helps the researchers from various fields, Environmentalists and government officials for better clarity of the societal problems.

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