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Fuzzy Cognitive Study on Post Pandemic Impact on Occupational Shift in Rural Areas

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Abstract

The pandemic has created a wide range of impacts on the livelihood of the people especially in their occupation and income generation. The horrific pandemic impacts have caused the populace to switch their occupations for the sake of their livelihood sustainability. This research works aims in determining the impacts of the occupational shifts especially in case of rural populace. The decision-making method of Fuzzy Cognitive Maps (FCM) is used in combinations with the statistical data collection methods of survey methodology, participatory approach and multi stage purposive sampling. It is observed that a significant percentage of people have shifted from their occupation and the occupational shifts have impacts on the personal, economic, social and health dimensions of the rural populace. The factors under each dimension and their inter associational impacts are also determined using the method of FCM and FCM Expert software. Based on the findings of the research work, it is very evident that the occupational shifts have created a lot of impacts on the livelihood of the rural populace and also each of the person has experienced the impacts more personally. The societal contribution of the research lies in communicating the results and inferences to the concerned administrators so as to facilitate the affected rural populace in getting back to their primary occupation.

Keywords: Fuzzy cognitive maps, Occupational shift, Pandemic impact.

1 | Introduction

Fuzzy Cognitive Maps (FCM) developed by Kosko [1] is an extension of cognitive maps. FCMs are basically directed graphs with fuzzy weights that are widely applied in making optimal decisions. The four primary functions of FCM are explanatory, prediction, reflective, strategic. In a decision-making environment involving various factors, the FCM modeling considers these factors as the nodes and the relationship between the factors are represented using edges. FCM is explanatory as it builds the cause and impact relationship representations; it is predictive as it forecasts the impacts of new occurrences; it is reflective as it always possess space for making changes and it is strategic as it handles the complex situation with its precise description.

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Inspite of several decision-making methods, FCM is the choice to handle a multifaceted decision-making situation. FCM models are developed using deductive and inductive modelling approaches. Expert based methods under deductive modelling and computational methods under inductive modeling are used to construct FCM models. The development of learning algorithms of FCM has labelled FCM models as supervised learning fuzzy neural systems in the point of view of Artificial Intelligence.

FCM has been extended to accommodate and to increase the magnitude of flexibility and adaptability in solving highly complex problems. Researchers in FCM have contributed to the extensions of FCM. Carvalho and Tome [4] developed Rule based FCM, Salmeron [5] introduced fuzzy grey cognitive maps, Iakovidis and Papageorgiou [6] developed Intuitionistic FCM, Miao et al. [3]. developed Dynamical Cognitive Networks, Aguilar [16] proposed dynamic random FCM, Cai et al. [8]. constructed evolutionary FCM, Wei et al. [9]. built fuzzy time cognitive maps, Song et al. [17] developed fuzzy rules incorporated in FCM, Ruan et al. [10]. developed belief-degree distributed FCM, Chunying et al. [18] developed rough cognitive maps, Acampora et al. [11]. developed Time Automara-based FCM. Kandasamy and Smarandache [7] introduced neutrosophic cognitive maps, Martin and Smarandache [13] developed Plithogenic Cognitive Maps. FCM models are extended to increase the reliability and feasibility of decision making.

FCMs are widely applied in many fields of science and technology. The bountiful applications of FCM in behavioural sciences, medicine, telecommunication, engineering, production systems, information and technology management, education business and management are highly noteworthy. The FCM models are not only used in handling scientific issues or problems in the domain areas of science, but also commonly applied to deal with political, social, economic and strategic issues. FCMs are used to model the social problems and social researchers have applied FCM modelling approaches. Vasantha et al. [12] has dealt the issues of unemployment, socio-economic distress and its impacts on the life of mankind using FCM models. The other FCM models dealing with social aspects are associated with the dimensions of education, climate change and other related facets. In all these FCM models the associational impacts between the factors of the problems are analysed and also the factors are not grouped.

Presently the pandemic situation has accelerated the construction of FCM models to determine the cause and effect of COVID 19 Peter Groumpos [14] has developed FCM model to determine the cause and effect impact of the symptoms of COVID. The FCM model is dealt with symptom-disease aspect. Goswami et al. [15]. have applied FCM approach in determining the impact of COVID on small holder agricultural systems and to develop new strategies. It is inferred from the models that FCM is applied both in scientific and social sense to handle COVID issues and impacts. But in the model developed by Goswami et al. [15], FCM is used only as a tool to find the impact between the factors of the decision-making problem and the sub factors were not discussed. Based on the social utility of COVID FCM models, in this research work the impacts of occupational shift on the rural populace caused by pandemic is modelled using FCM. The researchers have made an extensive study on the impacts of COVID on employment but the literature on their occupational shifts of rural populace are sparse. This has motivated the authors to model the impacts of occupational shifts using FCM deductive modelling approach.

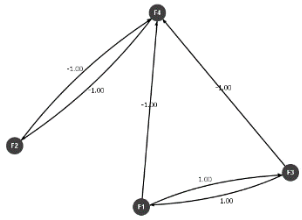
The paper is segmented into the following sections, Section 2 presents the fundamentals of FCM, Section 3 consists of FCM model, Section 4 discusses the results and the last sections concludes the work.

2 | Fundamentals of FCM

FCM is a directed graph comprising of nodes and edges representing the factors and their associations respectively. FCM are the extensions of cognitive maps in which the weights of the relationship assume fuzzy values rather than crisp values. In a simple FCM, the weights assumes values from the set {-1,0,1}. The value -1 signifies the negative associational impact between the factors, the value signifies the positive associational impact between the factors and the value 0 represent the null associations. But in reality the values -1, 0, and 1 alone cannot be used as benchmark to represent the relational impacts as these values are used only at times of pure existence of associational or relational impacts, but where as in real life situation, the chances of complete relational impacts are very less as the dominance of somewhat existence of relational impacts exist. In almost every time the existence of associational impact may differ in magnitude. At some instances it may be high, very high, moderate, less, very less. To handle such instances, the weighted FCM that assumes the relational weight in the interval range [-1,1] shall be used.

Let us consider a real life example of a decision making environment characterized by the factors contributing to weight management. The prime factors that are taken into account are F1 balanced diet, F2 physical exercises and F3 high hydration levels, F4 reduction of cholesterol levels. Let us try to determine the inter associational impacts between these four factors intuitively. The graphical representation of FCM is the respective connection matric of the above directed graph as shown below.

	F1	F2	F3	F4
F1	0	0	1	-1
F2	0	0	0	-1
F3	1	0	0	-1
F4	0	-1	0	0

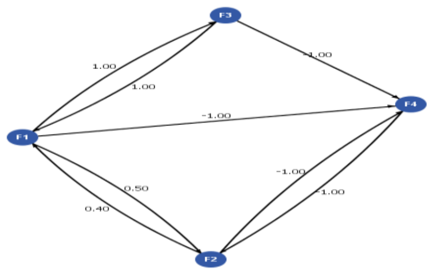


If balanced diet is maintained then the cholesterol levels will be reduced, so F1 has negative relational impacts on F4. Similarly F2 and F3 have also negative associational impacts on F4. Also F1 has positive associational impact on F3, as a good balance diet will certainly enhance high hydration levels. At a quick glance, the associational impacts between the factors F1 and F3 on F2 seems to be nil, but on profound analysis, there lies associational impacts as taking balanced diet and maintaining high hydration levels, the stamina is sustained at times of physical exercises. So in this case the direct relational impact is not represented but the indirect association is represented using fuzzy values.

It is inferred from the connection matrix that the representations using crisp weights -1,0 and 1 have focussed only on few inter associational impacts. Some of the factors and their inter associational impacts are not taken into account.

The representations using fuzzy weights have facilitated to accommodate more number of factors and their inter associations, but not all.

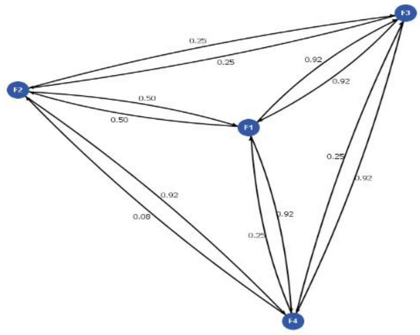
	F1	F2	F3	F4
F1	0	0.5	1	-1
F2	0.4	0	0	-1
F3	1	0	0	-1
F4	0	-1	0	0



The same representations shall be made using linguistic variable. In this case all the factors have been taken into account and the linguistic variables shall be quantified using fuzzy numbers.

To determine the associational impact between the factors of decision-making, let us assume the factor F1 in on position, The vector obtained is called as instantaneous vector which will be of the form (1 0 0 0). This shows that the first factor is in ON position and other factors are in OFF position. The most generalized form of representing an instantaneous vector is (a1, a2, ... an) whereaitakes the value either 0 or 1 indicating the ON and OFF position respectively. On passing the initial vector to either of the connection matrices of crisp, fuzzy and linguistic a new vector is obtained which on after applying the threshold values,the new updated vector is obtained. By repeating in the same fashion, the fixed point is attained which is the limit cycle of the dynamical fuzzy system.

	F1	F2	F3	F4
F1	0	M	VH	VH
F2	M	0	L	VH
F3	VH	L	0	VH
F4	L	VL	L	0



3 | Methodology

In this section, the pandemic impacts on the occupational shifts are determined by applying suitable statistical methods of data collection such as survey, participatory research and multi-stage purposive sampling. Also the method of FCM is applied to determine the inter associational effects between the pandemic impacts. The place chosen for study is Usillampatti block in Madurai district in Tamil Nadu state of Indian nation. Usilampatti is a Panchayat Union consisting of 57 villages and a population of around one lakh people. The literacy rate is 63.17%. The total percentage of agricultural farmers is 11.21% and the labour percentage is 24.68%.

Among 57 villages nearly 30 villages were chosen for the study based on the percentage of working population and also on the feasibility of data collection. The data was collected from a minimum of 15 people from each village and the total respondents were 465. The method of structured interview was used to collect the data on occupational shifts at times of pandemic impact and also semi-structured interview method along with discussion method were used for convenience to collect data from the target groups on their adaptability and adoptability of new occupations.

From the data collected, it is inferred that the occupational shift at times of pandemic period has caused impacts on the dimensions of personal, social, economic and health of rural populace and it is represented in *Table 1*.

Table 1. The dimensions of personal, social, economic and health of rural populace.

Dimension	Sub-Factors
Personal	C_1 Self-satisfaction
	C_2 Acceptance of occupational change by the family members
	C_3 Adaptability to the new working environment
	C_4 Mutual support from the peer employees
	C_5 Creating flexible workplace
Social	C_6 Change in the social status
	C_7 Recognition gain in the society
	C_8 Disruption to self-identity
	C_9 Declination of self-respect and dignity
Economic	C_{10} Difficulty in accommodating the financial needs
	C_{11} Increase in Financial constraints
Health	C_{12} Physical stresses
	C_{13} Mental ailments
	C_{14} Emotional ill health

The initial linguistic connection matrix, based on the deductive approach of expert based method is shown in *Table 2*.

Table 2. The initial linguistic connection matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}
C_1	0	VH	H	VL	VL	L	H	VL	VL	VL	VL	VL	VL	L
C_2	VH	0	H	VL	M	VL	H	L	VL	VL	VL	L	VL	VL
C_M	VH	VH	0	VL	VL	VL	H	VL	VL	VL	VL	VL	VL	VL
C_4	VH	VH	H	0	VL	L	H	VL	VL	VL	VL	VL	VL	VL
C_5	VH	VH	H	VL	0	L	H	VL	L	VL	L	VL	L	L
C_6	VH	VH	H	VL	VL	0	H	VL	VL	VL	VL	VL	VL	VL
C_7	VH	VH	H	L	L	M	0	L	L	VL	L	L	L	L
C_8	VH	VH	H	VL	VL	VL	H	0	VL	VL	VL	VL	VL	VL
C_9	VH	VH	H	M	L	VL	H	VL	0	VL	VL	VL	VL	VL
C_{10}	VH	VH	H	VL	VL	VL	L	VL	VL	0	VL	VL	VL	VL
C_{11}	VH	VH	H	VL	M	VL	H	VL	VL	VL	0	VL	VL	VL
C_{12}	VH	VH	H	VL	VL	VL	H	VL	VL	VL	VL	0	VL	VL
C_{13}	VH	VH	H	VL	VL	VL	L	VL	VL	VL	VL	VL	0	VL
C_{14}	VH	VH	H	VL	VL	VL	H	VL	VL	VL	VL	VL	VL	0

The linguistic terms are quantified using triangular fuzzy numbers of the form $A = (a_1,a_2,a_3)$ where $a_1 \le a_2 \le a_3$ and the triangular fuzzy number is defuzzified using average method of $(a_1+a_2+a_3)/3$ (*Table 3*).

Table 3. The quantified triangular fuzzy numbers.

Linguistic Variable	Very Low (VL)	Low (L)	Medium (M)	High (H)	Very High (VH)
Triangular Fuzzy number Quantification	(0, 0, 0.25)	(0, 0.25, 0.50)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1)	(0.75, 1,1)
Defuzzified Value	0.08	0.25	0.5	0.75	0.92

The modified connection matrix is

Table 4. The modified connection matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}
C_1	0	0.92	0.75	0.08	0.08	0.25	0.75	0.08	0.08	0.08	0.08	0.08	0.08	0.25
C_2	0.92	0	0.75	0.08	0.5	0.08	0.75	0.25	0.08	0.08	0.08	0.25	0.08	0.08
C_3	0.92	0.92	0	0.08	0.08	0.08	0.75	0.08	0.08	0.08	0.08	0.08	0.08	0.08
C_4	0.92	0.92	0.75	0	0.08	0.25	0.75	0.08	0.08	0.08	0.08	0.08	0.08	0.08
C_5	0.92	0.92	0.75	0.08	0	0.25	0.75	0.08	0.25	0.08	0.25	0.08	0.25	0.25
C_6	0.92	0.92	0.75	0.08	0.08	0	0.75	0.08	0.08	0.08	0.08	0.08	0.08	0.08
C_7	0.92	0.92	0.75	0.25	0.25	0.5	0	0.25	0.25	0.08	0.25	0.25	0.25	0.25
C_8	0.92	0.92	0.75	0.08	0.08	0.08	0.75	0	0.08	0.08	0.08	0.08	0.08	0.08
C_9	0.92	0.92	0.75	0.5	0.25	0.08	0.75	0.08	0	0.08	0.08	0.08	0.08	0.08
C_{10}	0.92	0.92	0.75	0.08	0.08	0.08	0.25	0.08	0.08	0	0.08	0.08	0.08	0.08
C_{11}	0.92	0.92	0.75	0.08	0.5	0.08	0.75	0.08	0.08	0.08	0	0.08	0.08	0.08
C_{12}	0.92	0.92	0.75	0.08	0.08	0.08	0.75	0.08	0.08	0.08	0.08	0	0.08	0.08
C_{13}	0.92	0.92	0.75	0.08	0.08	0.08	0.25	0.08	0.08	0.08	0.08	0.08	0	0.08
C_{14}	0.92	0.92	0.75	0.08	0.08	0.08	0.75	0.08	0.08	0.08	0.08	0.08	0.08	0

This is the connection matrix relating the associational impacts between the sub-factors of all the factors. The graphical representation of the associations is presented in *Fig. 1*.

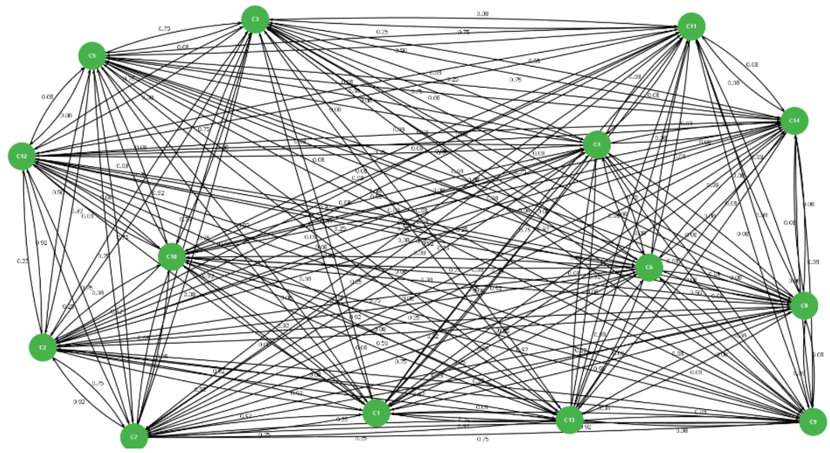


Fig. 1. Graphical representation of overall factors of FCM.

By using FCM expert software, the inference process is obtained and it is represented in *Fig. 2*

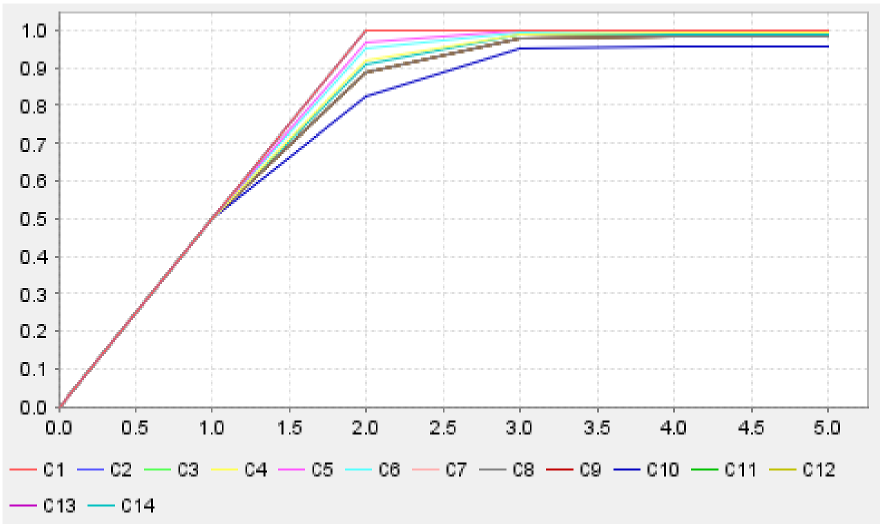


Fig. 2. Overall FCM inference process.

The interrelational impacts between the core factors are analyzed. The graphical representation of the interrelational impacts between Personal (P) and Social (S) factors and the respective inference process are presented in *Fig. 3* and *Fig. 4*, respectively.

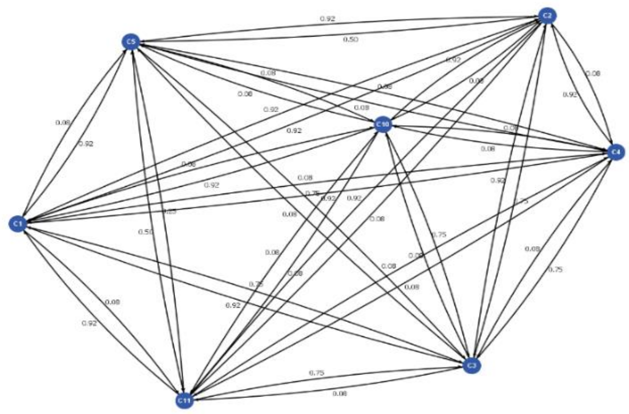


Fig. 3. Graphical representation of P&S factors of FCM.

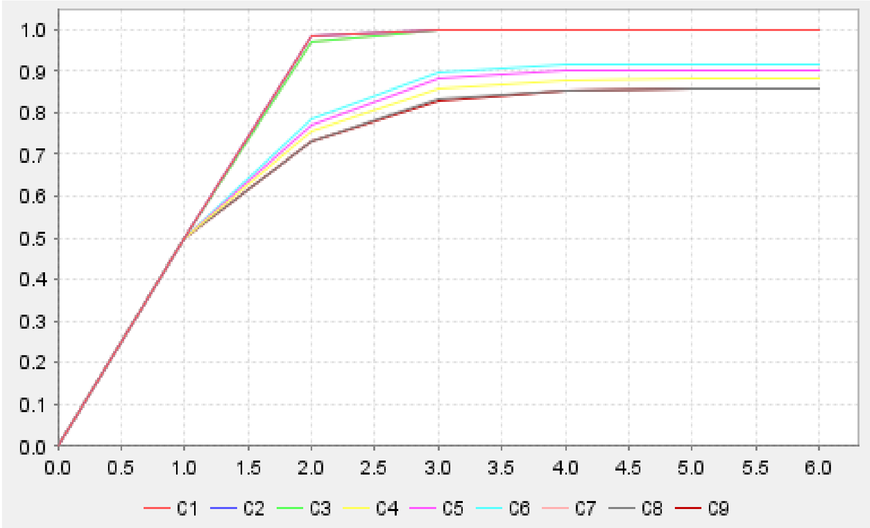


Fig. 4. FCM of P&S inference process.

The graphical representation of the interrelational impacts between Personal (P) and Economic (E) factors and the respective inference process are presented in *Fig. 5* and *Fig. 6*, respectively.

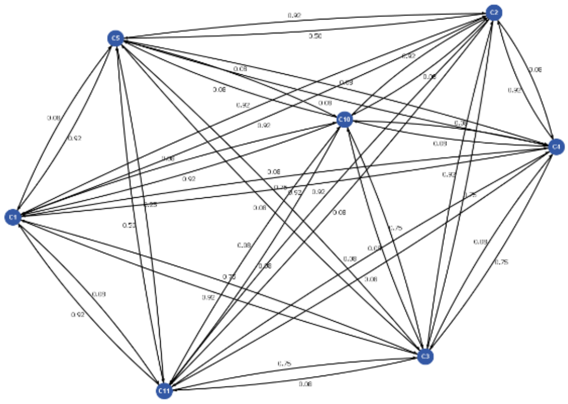


Fig. 5. Graphical representation of P&E factors of FCM.

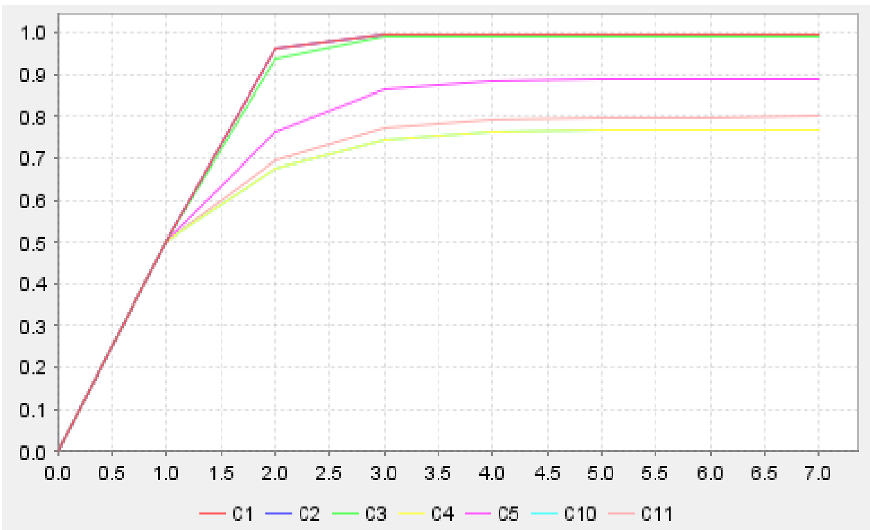


Fig. 6. FCM of P&E inference process.

The graphical representation of the interrelational impacts between Personal (P) and Health (H) factors and the respective inference process are presented in *Fig. 7* and *Fig. 8*, respectively.

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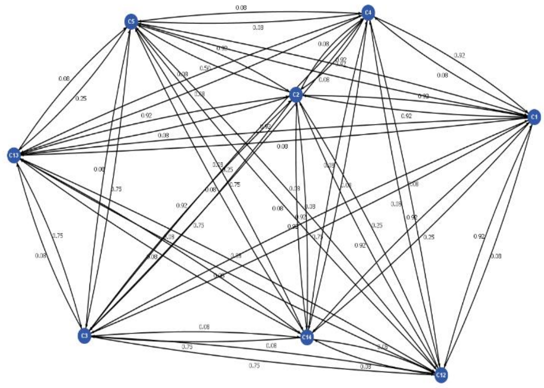

Fig. 7. Graphical representation of P&H factors of FCM.

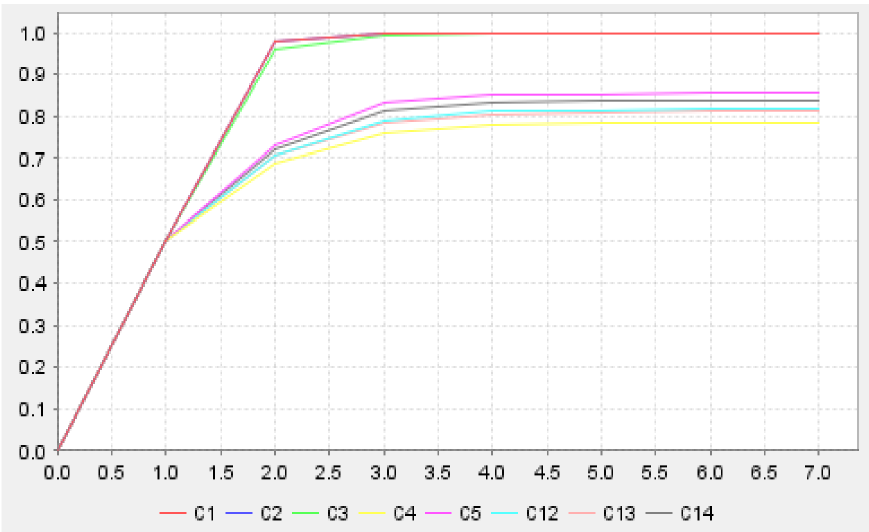

Fig. 8. FCM of P&H inference process.

The graphical representation of the interrelational impacts between Social (S) and Economic (E) factors and the respective inference process are presented in *Fig. 9* and *Fig. 10*, respectively.

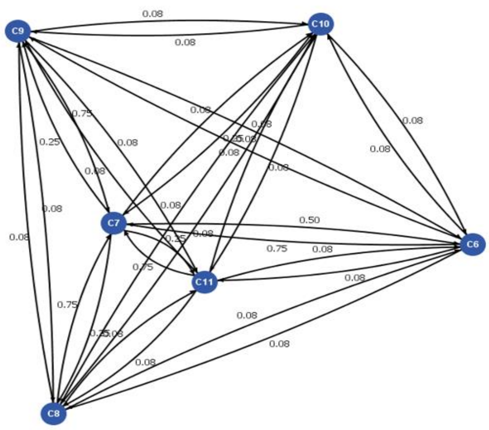

Fig. 9. Graphical representation of S&E factors of FCM.

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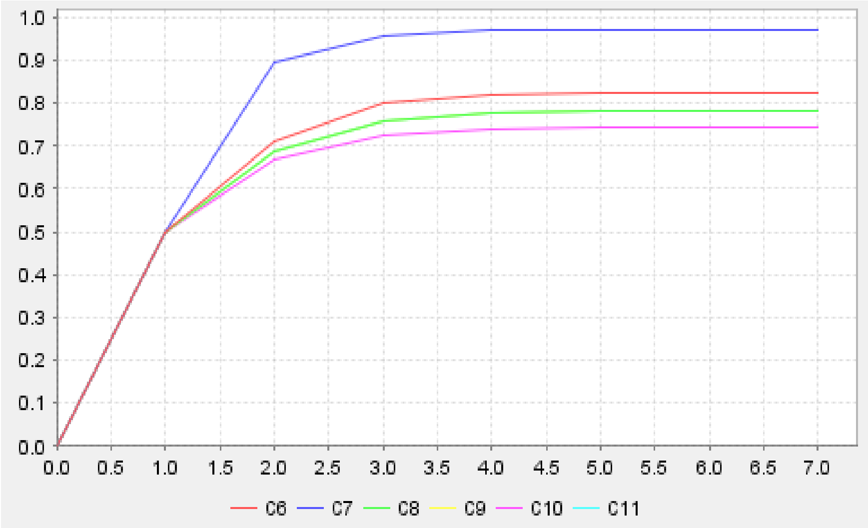

Fig. 10. FCM of S&E inference process.

The graphical representation of the interrelational impacts between Social (S) and Health (H) factors and the respective inference process are presented in *Fig. 11* and *Fig. 12*, respectively

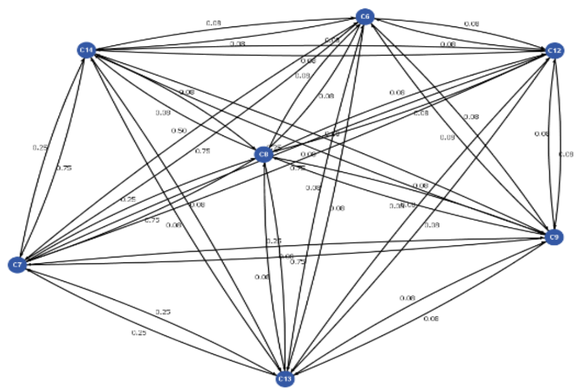

Fig. 11. Graphical representation of S&H factors of FCM.

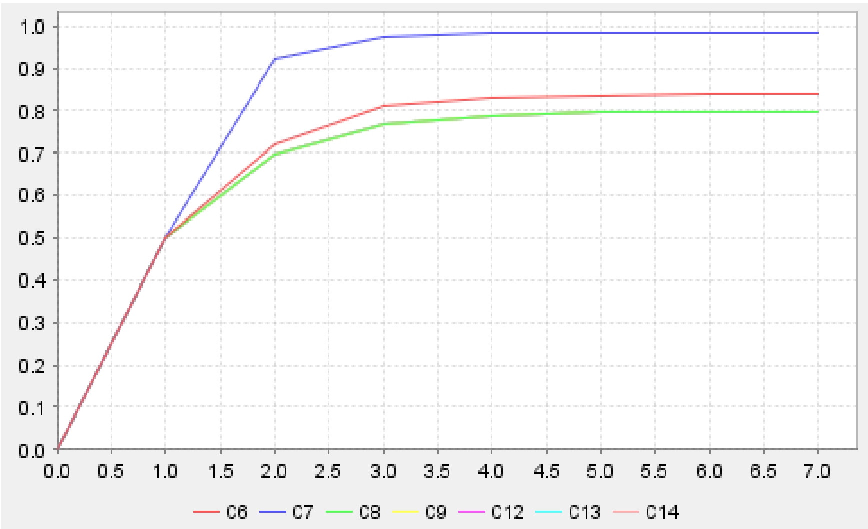

Fig. 12. FCM of S&E inference process.

The graphical representation of the interrelational impacts between Economic (E) and Health (H) factors and the respective inference process are presented in *Fig. 13* and *Fig. 14*, respectively.

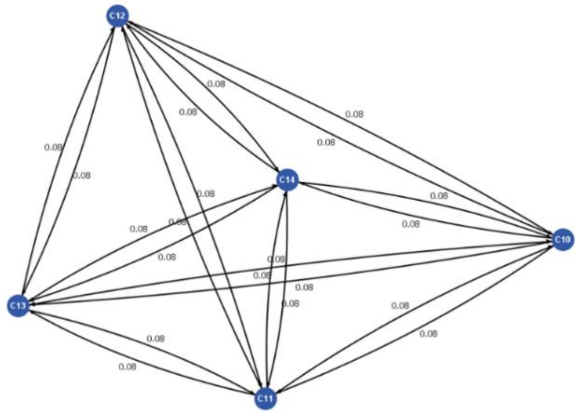

Fig. 13. Graphical representation of E & H factors of FCM.

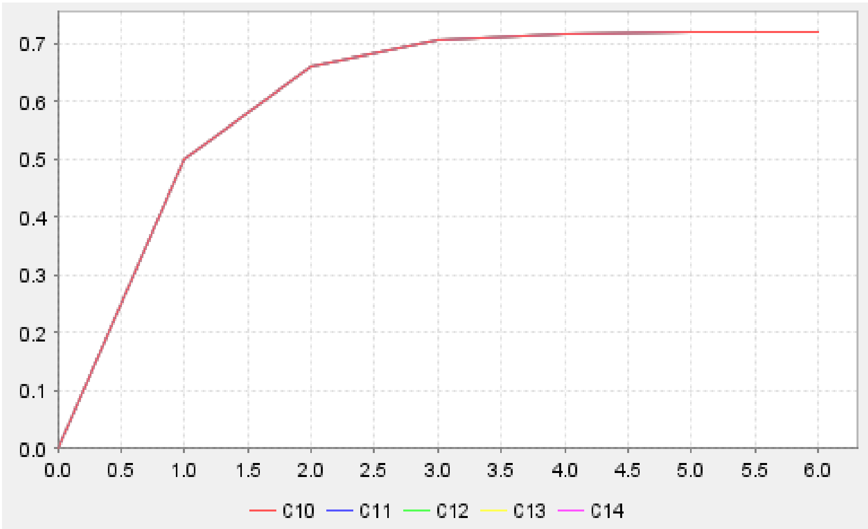

Fig. 14. FCM of E & H inference process.

4 | Discussion

Fig. 1 represents the graphical representation between all the sub-factors of the core factors and in *Fig. 1* the values taken by the concepts over a time of iterations and the convergence of the concept values are also represented. In the inference process, the Kosko [2] activation rule is used with sigmoid function and the concepts are assumed as the decision concept. It is also inferred that a steady state is arrived after a minimum number of iterations. In *Figs. 3, 5* and *7* the inter associational impacts between the sub factors of personal with social, economic and health are represented respectively and the respective *Figs. 4, 6* and *8* present the inference processes of FCM obtaining the steady state values over a period of time. Also *Figs. 9* and *11* present the graphical inter associational impacts between the sub factors of social with emotional and health sub factors. The respective FCM inference processes in *Figs. 10* and *12* presents the values of the concepts over a period of time. The inter associational impacts between economic and health were presented in *Fig. 13* and the respective inference process.

The sub-factors of the core-factors are assumed to be the concepts of FCM and in the above cases the concepts are not assigned to be decision concepts. In the later cases, on assuming one of the concepts in each of the sub-factors as decision concepts, it is inferred that the personal and social sub-factors have greater inter associational impacts between other factors and values in the below table substantiate the same. The factor C1, C2, C3 under personal core factor, C7 under social core factor, C11 under economic core factor and C14 under health core factor assumes higher values in comparison with other sub-factors of the core-factors.

Table 5. The personal and social sub-factors.

Step	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
2	0.9985	0.9985	0.9954	0.7883	0.8334	0.8153	0.9924	0.7667	0.7667	0.735	0.7667	0.7667	0.7667	0.7816
3	1.0	1.0	0.9999	0.8964	0.9399	0.9279	0.9998	0.8793	0.8763	0.8345	0.8763	0.8793	0.8763	0.8948
4	1.0	1.0	1.0	0.9163	0.9527	0.9419	0.9999	0.8984	0.8972	0.8579	0.8972	0.8984	0.8972	0.9132
5	1.0	1.0	1.0	0.9195	0.9544	0.9437	0.9999	0.9013	0.9005	0.8623	0.9005	0.9013	0.9005	0.9159
6	1.0	1.0	1.0	0.92	0.9547	0.944	0.9999	0.9018	0.901	0.8631	0.901	0.9018	0.901	0.9163
7	1.0	1.0	1.0	0.9201	0.9547	0.944	0.9999	0.9019	0.9011	0.8632	0.9011	0.9019	0.9011	0.9163
8	1.0	1.0	1.0	0.9201	0.9547	0.944	0.9999	0.9019	0.9011	0.8633	0.9011	0.9019	0.9011	0.9163
9	1.0	1.0	1.0	0.9201	0.9547	0.944	0.9999	0.9019	0.9011	0.8633	0.9011	0.9019	0.9011	0.9163
10	1.0	1.0	1.0	0.9201	0.9547	0.944	0.9999	0.9019	0.9011	0.8633	0.9011	0.9019	0.9011	0.9163

4.1.1 | Other Findings

It is also found that around 62% of people wishes to practice their earlier occupation as they are not personally convinced by the occupational change also the social impacts hurdle them a lot in sticking on to their new occupations. The remaining percentage of the working rural population who have shifted their occupation adopted and adapted to new working environment by convincing themselves over the reasons of sustaining their family.

4.1.2 | Proposed Suggestions

I. The working rural populace who aspires to practice their earlier occupations due to personal dissatisfaction shall be supported both financially and emotionally, as their personal disassociations with the occupational shift have caused emotional chaos.

II. Counselling and rehabilitation programmes for promoting their emotional quotient shall be exclusively organized for the rural populace and the non-governmental workers together along with the volunteers shall be made involve in such remedial activities.

III. The rural populace who have adopted and adapted to the new working environment shall be set as models and be made to interact and motivate the peer workers so as to gain an exposure to the strategies of adaptation. The hosting of such interactive sessions moderated by experts will certainly facility the learning of new skill sets of getting accustomed to changes.

5 | Conclusion

The research work on the occupational shift on rural populace caused by pandemic shifts has been investigated on the grounds of the dimensions of personal, social, economic and health aspects of the rural populace. This study has deeply examined the inter associational impacts between the factors. This work shall be extended by making a comparative analysis on the impacts of occupational shifts between urban and rural populace of Madurai regions. The same impact study using FCM shall be applied to other social issues and other decision-making problems in the field of education, business, medicine and so many other fileds.

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