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Introducing Fuzzy Cognitive Maps as an Artificial Intelligence-Based Framework for Conflict Resolution

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ABSTRACT

Conflict is an intricate part of any systems with cooperating entities with common or differing goals. In computing systems, conflict occurs between different entities because of shared resources, and this can degrade overall system performance. In the same way, human society is plagued with challenges of resource conflicts that are difficult to analyse and resolve. Some works have used methods like graph models of conflict resolutions conflict problems and resolution while some have used optimization techniques. However, these methods often model only resolution options without components that provide for proper analysis of the conflict. Also, the various root causes of the conflict and their interaction are not incorporated in the resolution models. This paper used Fuzzy Cognitive Maps as an AI modelling tool to provide a framework for modelling conflict problems and resolution. It provides a multi-layer system with various components of conflict model, conflict resolution, and ranking of various resolution options to get the optimal solution. Compared to other methods, it is simpler, providing a total picture of the conflict situation which is useful to analysis and provides various means of resolution for the user of the model.

INTRODUCTION

Conflict is an intricate part of any systems with cooperating or competing entities. This is a common occurrence in every human society, biological system and computing components. Resource sharing system amongst several human communities have resulted in various forms of human conflicts that have devastated human society and life (Wang & Ting, 2011). In some instances, the multidimensional nature of the root-causes and the conflict itself produce a nonlinear system that is difficult to comprehend and analyse. Common forms of this among humans are the water resource conflict which among the community of human. The same conflicts are also observed in physical system like air traffic control (Kuchar & Yang, 2000). The resolution of these conflicts entails finding an acceptable ground of compromise or resource sharing formular that is fair to all actors or components of the system. The resolution is however a task that is difficult to achieve due to the intertwine nature of the root-cause, factors, action and reactions of the actors and the prevailing circumstances.

Research effort in the field of conflict studies have develop methods to model interaction among various components for conflict analysis. In particular, conflict resolution from various authors use tools from various discipline to model and study dynamic behaviour of conflict and the causative factors (Colaresi & Mahmood, 2017; Muchlinski & Kocher, 2015; Musumba et al., 2021). Conflict resolution rely on scientific techniques like mathematical programming, econometric models, optimization techniques or artificial intelligence (Aydoğan et al., 2021; Chadefaux, 2017; Ogunnigbo & Ogunwumi, 2021; Yinka-banjo & Ugot, 2019) to find solution to complex conflict problems. Prominent among various conflict resolution model is Graph Model of Conflict Resolution (GMCR).

GMCR has been wildly used to resolve waterer resource conflict, environmental conflict, manufacturing and production conflict and many more (Damázio & Magalhães, 2005; Hipel & Kilgour, 2018; Huang et al., 2023; Komeili & Sheikhmohammady, 2022; Zhao et al., 2022). GMCR has four tuple that include decision-makers' strategies, feasible states, state transition graphs, and preference information (Zhao et al., 2022). These components provide tools for modelling various conflict resolution. Though a great modelling tool, GMCR omits the causes of the conflict which are important in studying the conflicts. This paper proposed a FCM as an AI-based framework for modelling conflict resolution.

Artificial Intelligence (AI) plays a significant role in shaping progress and understanding of complex and multi-dimensional systems like conflict, example are the works of (Aydoğan et al., 2021; Rattenberger et al., 2006). The influence of AI is in the machine learning algorithms that provide the intelligence components to the system. As an aspect of AI, machine learning optimise the performance of a computing systems (Lokanan & Sharma, 2022).

Fuzzy Cognitive Map (FCM) is a graph structure-like machine learning algorithm (MLA) with nodes and edges. The nodes stands for components, factors or concepts of a system being modelled; while the weights (edges) are representation of the relationships among the components of the modelled system (Chen & Chiu, 2021; Edwards *et al.*, 2023). FCM combines the elements of fuzzy logic which is used to quantify the values of the edges/nodes and graph-based components use for inferencing. These attributes place FCM as a tool for developing both expert-based models and models from historical data.

In applying FCM to solve any problem, the initial model can be constructed from experts' qualitative knowledge or through inductive method which extracts information from historical data. After the model development, simulation of a FCM model can converge to any state (Salmeron & Papageorgiou, 2014) of equilibrium point, a limited cycle or a chaotic attractor (Nápoles *et al.*, 2017). This possibility necessitates the use of learning algorithm for training FCM model. The training/learning algorithms are also variants of MLs which are formulated to find connection matrix that will bring a FCM model to a stable state.

MATERIALS AND METHODS

The proposed system framework uses FCM and FCM learning algorithm as the basic AI tools for framing conflict resolution.

Fuzzy Cognitive Maps

Fuzzy Cognitive Maps is graph structure with multiple edges representing relationships among the components of the map while the nodes are domain concepts (Salmeron, & Palos-Sanchez, 2017). They are employ to model complex systems (Bakhtavar *et al.*, 2021). FCM models complex systems through the representation of these systems as graphs composed of nodes and arcs (Edwards & Kok, 2021). The nodes within this graph symbolize the various factors or attributes of the system under consideration, whereas the weighted arcs signify the causal associations between these elements (Papageorgiou & Oikonomou, 2012). Example of a typical FCM can be seen in figure 1. One important element of FCM is the fuzzy natures of the node values instead of ordinary numerical values. Each of the values belong to a fuzzy class as may be determine by the user.

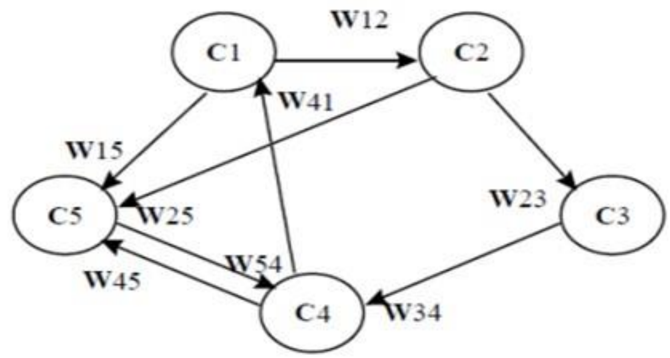

Figure 1: Simple FCM (Source: Papageorgiou *et al*, 2003)

In modelling with FCM, experts determine the nodes of FCM and the kind of relationships that exists between them. The relationships could be a positive or negative relationship which may be measured using linguistic language like low relationship and high relationship (Shen *et al.*, 2019). Subject to different versions of the FCM, the nodes of the map update their values using equation 1. In this equation, the general assumption is based on the idea that nodes do not have self-looping edges (though research on FCM has advanced to areas where some system allows self-looping of nodes, application of FCM to such systems require modification of the equations as can be seen in some studies (Szwed, 2021; Kyriakarakos *et al*., 2017)

$$A_i^t = f\left(A_i^{t-1} + \sum\nolimits_{j\neq i, j=1}^{n} A_j^{t-1} w_{ji}\right) \quad (1)$$

In the equation 1, the A_i^t stands for value of the node A_i at time t while w_{ji} stands for the values of the edge from A_j to A_i. Both nodes and edges have their values in the range of closed interval [0, 1] or [-1, 1]. (Brandl *et al.*, 2023; Papageorgiou, 2012; Poczęta *et al*., 2015). The relationship between the nodes of the FCM could be in any of the 3 forms: w_{ji}>0, w_{ji}<0, or w_{ji}= 0.

FCM Optimising or learning techniques

Modelling any system using FCM for any domain can be wonderful achievement, however, the problem after model development is the reality of FCM models convergence to undesired state (Vergini & Groumpos, 2016). The convergence to unexpected-state output of FCM warranted formulation of other learning algorithms to train the map to produce a desired output. The process of training FCM models involves continual of adjudgment weight values until the system converges or solution is found(Vergini & Groumpos, 2016). Though several methods and algorithm exist for fine-tuning FCM, they can be grouped into Hebbian, population-based or combination of Hebbian and population-based (Shen *et al*., 2019).

RESULTS AND DISCUSSION

The Framework and its Components

The proposed conflict resolution framework conceptual diagram can be seen in figure 2. The system is composed of 2 subsystems: the FCM-based conflict subsystem and the conflict resolution subsystem.

FCM-based Conflict Modelling Sub-system

This phase requires proper understanding of the conflict, the actors, causes and events that are at the core of the conflict. It may require interactions with experts and actors within the conflict domain. The core aim is to elicit necessary information for modelling the conflict.

Under this subsystem, all the actors in the conflict are identified, the actions/reactions of the actor that may impact the conflict are identified, the root-causes of the conflict are identified, and the options of resolution are identified. The relationship/influence among these factors identified are also sought. This information is used to form FCM model of conflict.

In the transformation to a FCM conflict model, various membership functions are design for each of the factor or a class boundaries can be design for ease of implementation. Being a fuzzy system model, proper information is needed on the linguistic values of the causes and other factors of the conflict. The information will ensure proper transformation of the problem into an FCM-based conflict model.

In the FCM conflict model, let A_i, for i= 1, *2, . m* represents the set of factors and concepts of the conflict domain. They are the vertices of the FCM conflict model. The relationships among the factors are used as the weighted edge w_{ji} = degree ($A_{j,}$ A_i) of the FCM conflict model. The edge measures the degree to which A_i may cause, impact, or influence A_j and how much negatively or positively this impact is. w_{ij} is measure in the interval of [-1,1].

Conflict Resolution Subsystem

This phase contains the generation of feasible solution and finding the values of such feasible solution. This phase contains the following steps:

Generation of feasible conflict resolution solution set.

The resolution component utilizes the information from the conflict model formation to generate the feasible set of resolution. While there are several options of resolution, not all options are feasible or utilised the same time. Also, some of the options are mutually exclusive, meaning that the choice of certain options automatically excludes the other option. The major output of this phase is a combination of various options that are feasible to resolve the conflict.

Let S_k for {k= 1, 2 , . . m} represents the set of feasible resolutions to the conflict which are describe as the combinations of some of the vertices of the nodes of FCM conflict system, where k is the number of the feasible resolution. Assuming a conflict with 3 Actors (A), and the conflict model with 14 nodes (C_i*; i, =1, 2 , . . 14),* including ‘*conflict*’ as a concept.

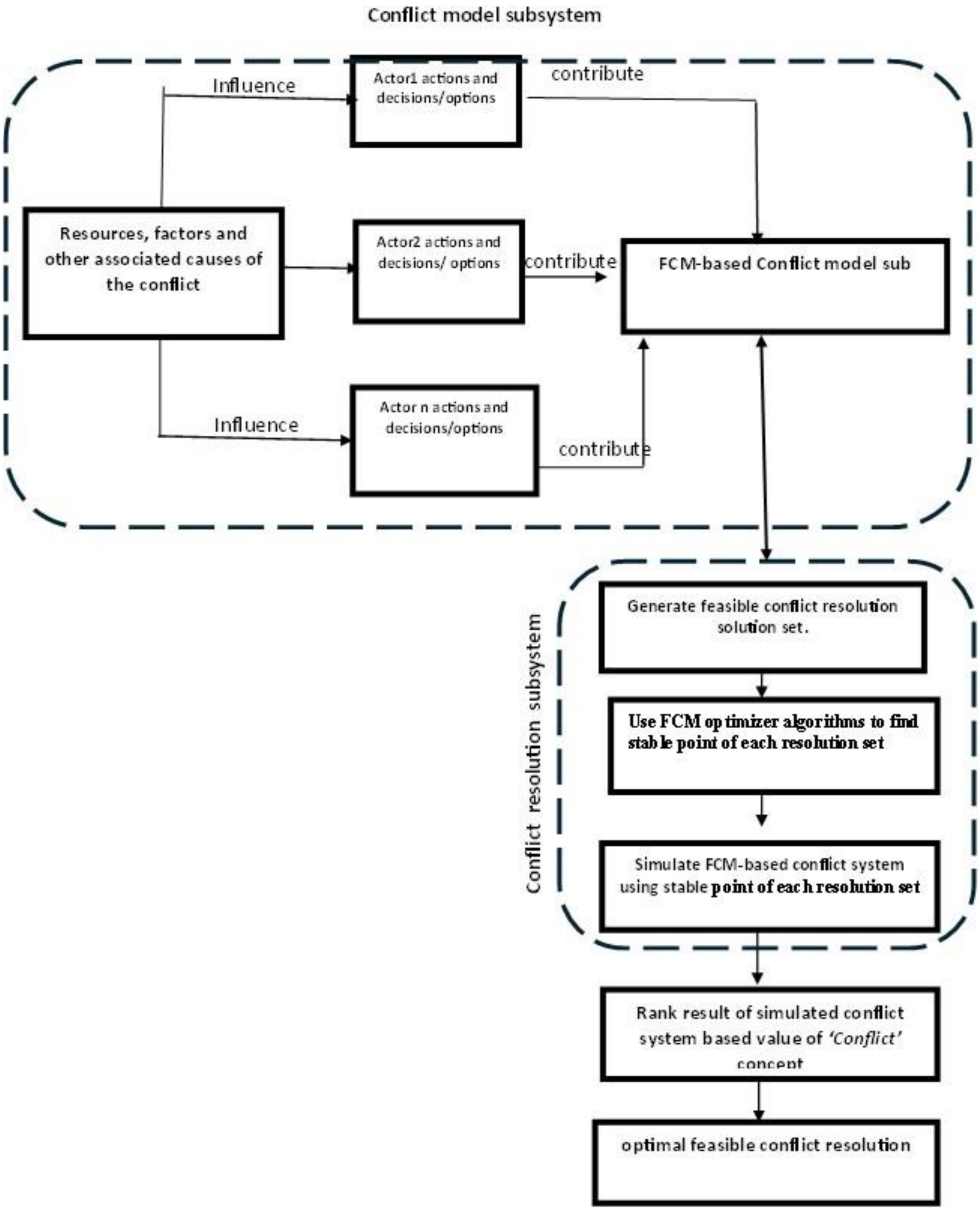

Fig 2: AI-based Conflict resolution framework based on FCM

Some of the nodes represents the options for the actors and can be expressed as follows:

Actor 1

a. Moderated interference of C_2
b. Improve resource in C_5
c. Jointly decrease effect of C_4, C_9

Actor 2

a. Utilise the resources in C_{10}
b. Use (C_6) as alternative C_6

Actor 3

a. Supply some percentage of C_7
b. Improve mediation effort C_{11}

From the above synthetic options of resolution, the feasible resolution set can be generated in the form of the table 1. In the table, 'Y' means that the option is included in the resolution set while 'N' means the option is excluded.'?' represent the value of the 'conflict' node/concept node after running that resolution set.

Table 1: feasible resolution set

Actor/options		S_1	S_2	S_3	S_4	S_5	S_6	S_7	...	S_{n-1}	S_n
Actor 1									...		
1. Moderated interference of	C_2	Y	Y	Y	Y	N	Y	N		Y	Y
2. Improve resource	C_5	N	Y	Y	N	N	N	Y	...	N	N
3. Jointly decrease effect of (C_4, C_9)	C_4, C_9	N	N	Y	N	N	Y	N	...	N	N
Actor 2									...		
4. Utilise the resources in	C_{10}	Y	Y	Y	Y	N	Y	N		Y	Y
5. Use (C6) as alternative	C_6	N	Y	Y	Y	N	Y	N	...	N	Y
Actor 3									...		
6. Supply some percentage of	C_7	Y	Y	Y	N	N	N	Y		Y	Y
7. Improve mediation effort	$C_{11,}$	N	N	N	N	Y	N	N	...	N	N
Conflict	C_{14}	**?**	**?**	**?**	**?**	**?**	**?**	**?**	**?**	**?**	**?**

FCM optimizer algorithms for stable point of feasible resolution sets

The feasible resolution sets in table 1 combine some nodes (options from each actor) of FCM-based conflict model to form a resolution set. Except the class/state of the nodes are stated in the options of the solution, else, being a fuzzy system, each of the node could be in different state/class like low, moderate, high, etc. This means that for $\boldsymbol{S_1}$ resolution components of C_2, C_{10}, and C_7, each of the node could be tested from low, moderate, high, etc. to further solve this problem of increase in states, further analysis of class combination could be done for each resolution set.

In the above case, if C_2 is to be moderated to low level, C_{10} to high level and C_7 to a very high level. upper and lower class boundaries of the classes are used to find the stable point of each node (components of resolution set). The problem can be expressed as in the form of constraints as follow:

1. $C_{2_{moderate}}^{lower-class\ boundary} \leq C_2 \leq C_{2_{moderate}}^{upper-class\ boundary}$

2. $C_{10_{high}}^{lower-class\ boundary} \leq C_{10} \leq C_{10_{high}}^{upper-class\ boundary}$

3. $C_{7_{very-high}}^{lower-class\ boundary} \leq C_7 \leq C_{7_{very-high}}^{upper-class\ boundary}$

All the resolution sets ($S_1, S_2, \dots \dots \dots . S_{n-1}, S_n$) are to be transformed into the above format. The problem of finding the stable point for each resolution set is solved by using any FCM learning algorithms to find the stable point for each node. In finding the solution, the system used the initial FCM-based conflict and imposed the constraints stated above on the nodes in the problem. the output of the resolution set represent point where the conflict is stable for all parties and possible resolution point.

Simulation of FCM-based Conflict system with Resolution Sets

The stable points for each node in the resolution state that was found from FCM learning is used to simulate the FCM-based conflict system to find the impact that solution will have on the entire conflict. The values of the '*conflict'* (as a node of the map) is the key focus of this stage. In this simulation for each resolution set, the values of the nodes of the resolution set are kept constant while other nodes are allowed to change state, this continues until the FCM-based conflict system attains a stable state of convergence. After the FCM-based conflict system attains a stable state, the value of the '*conflict'* is recorded for ranking of each resolution set impact on the conflict.

Ranking of Feasible Resolution Set

R^r=r {r, 1, 2 , . . m} represents the rank of all the feasible resolution set where r is the rank. Based on the value of the *'conflict'* from all feasible resolution set, the set is ranked from lowest to the highest, the resolution set with the highest rank qualify as the optimal resolution. The rank can be seen in table 2.

Table 2: feasible resolution set ranking

$\boldsymbol{R^r}$	$\boldsymbol{R^1}$	$\boldsymbol{R^2}$	$\boldsymbol{R^3}$	$\boldsymbol{R^4}$	$\boldsymbol{R^5}$	$\boldsymbol{R^6}$	$\boldsymbol{R^7}$	**…**	$\boldsymbol{R^{n-1}}$	$\boldsymbol{R^n}$
State ($\boldsymbol{S_k}$)	?	?	?	?	?	?	?	…	?	?
Conflict Value	?	?	?	?	?	?	?	…	?	?

Optimal Feasible Conflict Resolution

The optimal resolution set is that set of resolution that produces the lowest level of conflict. the various nodes of the conflict under this resolution are expected to be analysed further to ascertain how the set impact the factors of the conflict.

The multiple natures of the resolution sets suggest that the optimal resolution may sometimes be chosen based on factors like long-time and short-time solution. this comes natural from the fact that some of the set combine options that are not feasible within short period of time.

CONCLUSION

The methodology presented in this paper used FCM as an AI technique for modelling conflict resolution problem. The frameworks provide simple method to represent all the key element of conflict resolution which include, actor, causes of conflict, the options of resolution each actor and stability analysis of the resolution.

Being a fuzzy based methodology, the framework provides more tools to analysis various resolution set and to provide more solution point than could have been done with other methods. It also reduces the complex mathematical work of other optimization techniques like mathematical programming. The key strength of the framework is the incorporation of the conflict system together with the options of resolution, this provides analysis of each resolution solution on the entire conflict.

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