FUDMA Journal of Sciences (FJS)
ISSN: 2616-1370
Vol. 2 No. 1, April, 2018, pp 223-230

FUZZY COGNITIVE MAP AND NONLINEAR HEBBIAN LEARNING ALGORITHMS FOR MODELLING AND CONTROLLING INTRA-STATE CONFLICT IN NIGERIA

[1]Jiya, E. A., [2]Bakpo F. S., [3]Fawole, B. E.,

[1 *]Department of Computer Science and IT, Federal University, Dustinma, Katsina State, Nigeria.
[2]Department of Computer Science, University of Nigeria, Nsukka, Enugu State, Nigeria.
[3]Department Agricultural Extension and Rural Sociology, Federal University, Dustinma, Katsina State, Nigeria
*corresponding author: jiyaeli@fudustima.edu.ng

ABSTRACT
Ethnic conflict, communal clashes, terrorism and insurgency are major security challenges in the twenty-first century. These are responsible for the deaths of millions of people around the world. At the moment intra-state conflict in the form of Farmer/herder conflict has claimed several thousands of lives in Nigeria; however, controlling this conflict system has been a great challenge for many years. Combining Fuzzy Cognitive Map (FCM) and Non-liner Hebbian Learning (NHL), this work modelled Farmer/Herder conflict in Nigeria as a nonlinear system and demonstrates the ability of the machine learning algorithms to provide control mechanism for the conflict system. Factors understood to be influential in Farmer/Herder conflict were used to form FCM model that represents the conflict situation, while NHL was used as a control mechanism to find levels of weights between these causative factors that will minimize the conflict and maximize peace. The result of the work showed that keeping certain factors within some threshold and ensuring these factors interact at particular levels will reduce conflict and bring peace.

Keyword: *Fuzzy Cognitive Maps, Nonlinear Hebbian Learning, Conflict Control, Farmer-Herder Conflict, Conflict modelling, Conflict Forecasting.*

INTRODUCTION
Ethnic conflict, communal clashes, terrorism and insurgency are major security challenges in the twenty-first century. These are responsible for the deaths of millions of people around the world. According to Trijono (2004) and Perry (2013), these violent conflicts have occurred more in developing countries of the world, especially Africa. For Nigeria in particular who has several ethnic groups, numerous religious organisations, and diverse culture; conflict has been a continuous occurrence since her emergence as an independent state. These conflicts are of various dimensions - religions, political, ethnic, intra-communal, and inter-community. Of note in this work is the farmer/herdsmen conflict in Nigeria.

Of recent, clashes between the farmers and the Fulani-herdsmen have become a public concern in Nigeria. From the report of UNDP (2009), several factors contribute to this conflict which includes: environmental factors, and character, lifestyle, attitude, behaviour, ideology, etc of Fulani herdsmen and their host communities. Several regimes in Nigeria have struggled with this conflict with no success or permanent solution. The most recent measure is the use of military to stop the escalation any time it turns deadly. But this new measure only provides what is referred to as *"false peace"* in some conflict literatures.

With the end of the cold war, and spurred with increase in the number of conflicts that followed, United Nations initiated the call for development of models for analysing, understanding and preventing conflict. However, the daunting challenge lies in making sense of large volume of data from past conflicts in other to draw up useful knowledge on conflicts and to control and manage present and future ones (Perry,2014) . Conflict models consist of standardized mechanisms for analysing socio-political and armed conflict data in study the conflict and provide a causal interpretation of the results (Rupesingh, 2009). The causal interpretations provide understanding of the reasons for the conflict and ways to resolve or control them. These models which are either quantitative or qualitative make use of longer-term, society-wide, structural variables or event-data which are called indicators. Quantitative models handle conflict as complex interdependencies of nonlinear, interactive and context-dependent factors (Tettey,2003) They quantify conflict variables and use mathematical techniques to study the trends and to derive models of the relationship between certain factors or variables and occurrence of conflict.

common approach to controlling conflict in Nigeria and globally is the use of military force to suppress it and bring it under control, yet the intensification of many conflicts and the difficulties that security agencies have experienced in many nations in tackling domestic conflict situations shows the inadequacy of this approach. thus, need to redress this weakness by mathematical, statistical and computational models which can manipulate societal factors to manage and bring conflict under control. using conflict control and conflict management interchangeably and adopting the above theoretical approaches, conflict control in this research work employ Fuzzy Cognitive Maps to model conflict, using the environmental factors as inputs; while Nonlinear Hebbian Learning (NHL) provide the mechanism for controlling conflict.

Review of Related Literature
Tettey (2003) used Multilayer Perceptrons Neural Networks to model militarized interstate disputes. The model was trained in the Bayesian framework with classification output of peace or conflict. Features like democracy, dependency, capacity, alliance, contiguity, distance and major power about states in conflict were used as variables. These variables were quantified

using various scales and were used as inputs to the neural network with the output from the model as either peace or conflict. The model was trained using militarised interstate dispute data which contains 27737 instances; 26845 peace samples and 892 conflict samples. The result of the work showed that the model could predict peace with 73.64% accuracy and conflict with 73.1% accuracy

Dorffner, Rattenberger, Hortnagl, bervcovitch, and trappl (2006) worked on Neural Computation for International Conflict Management. They applied Multilayer Perceptrons (MLPs) as nonlinear classifiers to predict the outcome of conflict management using the dataset of 333 conflicts between the years 1945 to 2000, with 5000 mediation attempts. The output from the model was conflict management outcome which was either 1 (success), or 0 (failure). The model was reported to have 59.4% accuracy.

Perry (2013) used Naive Bayes and Random Forest Algorithm to develop a political conflict prediction model. The model used 14 features considered to be indicators of impending armed conflict, these features were quantified for all the years and used as variables and input. The features include: poverty, GDP of the country, land usage, infant mortality, population density, ethnic composition, etc. The worked made use of Armed Conflict Location and Events Dataset (ACLED) composing of description of armed conflict from 1997 to 2013 in over 50 African countries. The model was trained with 70%, while 30% was used for testing. The result of the work as reported by the author showed that the model has accuracy of 98.9% in predicting occurrence of conflict and peace.

Schrodt (1999), worked on Early Warning of Conflict in Southern Lebanon using Hidden Markov Models to forecast outbreak of armed violence between Israel and Arab forces in southern Lebanon. The work used a dataset from Behavioural Correlates of War (BCOW) data. The events codes taken from the data were used as the symbol set of the HMM, while different phases of crisis from "durable peace" to "war" were used as different state of the model. The model was trained using 6 cases of armed conflict between Israel and Arab forces during the period of 1979 to 1997 and then fitted to the entire period. The result of the work showed that the model identify about 50% of the conflict correctly.

Marwala, Lagazio, and Tettey (2009) developed a model using Bayesian Neural Network for classifying Military Interstate disputes. They used a dataset of Militarized Interstate Dispute (MID) between the years 1946 to1992. The training was done on a balanced dataset while the testing was done on an unbalanced dataset. The seven variables used for the model were: Democracy, Allies, Contingency, Distance, Capability Ratio, Dependency, Major power. To make analysis of the impact of each variable on MID, they used the automatic relevance determination (ARD) method. The analysis showed strong interaction between democracy, countries power, economic dependence and allies. Finally they applied control system theory to conflict resolution field to attain peace. Experiments were performed for both controlling one variable at time and a set of variables simultaneously. The model classified 73% of MID and 74% of non-MID correctly.

Trappl, Hortnagl, Schwank, and Bercovitch (2006), used Decision Tree and Case-Based Reasoning to construct conflict management model from 4570 Conflict Management Attempts (CMAs) data, each of the attempts has 41 attributes. Of the 4570 CMAs, 2045 were successful attempts while 2525 were failed attempts. They constructed a decision-tree with 258 leaves which was pruned to 10 leaves. To predict an outcome of a CMA, they used the attributes of the tree and calculated the probability of success outcome in conflict management attempt. The result of the model showed accuracy of 59.1% prediction.

Fuzzy Cognitive Map

To model farmer-herder conflict, Fuzzy Cognitive Maps (FCMs) was used. FCMs are machine learning algorithm for modelling complex system; it's a symbolic representation of complex system which consist of nodes and weighted arc that graphically illustrates a signed weighted graph. The nodes of the map represent factors or characteristics of the system being modelled while the weighted arcs represent the causal relationship among concepts (Kosko, 1986). This graphic display shows clearly which concepts influences the other concepts and what this degree of influence is (Groumpos, 2010). The human experience and knowledge of the system is used to develop FCM. FCM illustrates the system by a graph showing the cause and effect along concepts, and it is a simple way to describe the system's behaviour in a symbolic manner, exploiting the accumulated knowledge of the complex system.

Basically, a typical FCM has a number of nodes-concepts c_i $(i = 1 \,..\, n)$ and interconnections or weights w_{ij} $(i = 1 \ldots n$, $j = 1 \ldots m)$ between concept c_i and concept c_j. The structure represents a dynamic complex system of concepts with a cause and effect relationship between concepts. A simple illustrative picture of a Fuzzy Cognitive Map is depicted in figure 1 ; it is consisted of five nodes-concepts and several weights.

Each concept is characterized by a number C_i that represents its value or state in a particular time. Every concept of the system must be in a particular state at any instance of time. According to Groumpos (2010),.the state that a concept can be is confined within the chosen closed interval [0, 1]. Causal weight w_{ij} between concepts c_i and c_j allows degrees of causality and not the usual binary logic, so the weights of the interconnections can range in the interval [-1,1], [-2, 2] or as may be set by the user (Kosko, 1986). The associated weights take the form

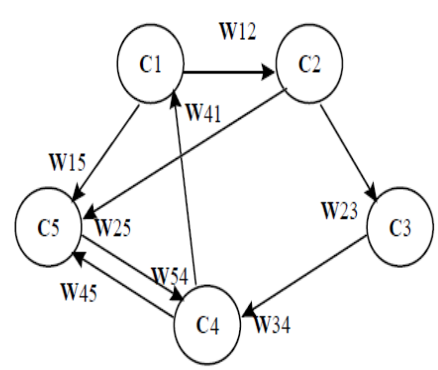

Figure 1. A Simple Fuzzy Cognitive Map (Stylios and Groumpos, (1999)

w_{ij}>0, or w_{ij}<0, or w_{ij}= 0.

- w_{ij}>0 indicates direct (positive) causality between concepts $c_i$and c_j That is, the increase or decrease in the value of $c_i$leads to the increase or decrease in the value of c_j.
- w_{ij}<0 indicates inverse (negative) causality between concepts $c_i$andc_j. That is, the increase in the value of $c_i$leads to the decrease in the value of c_j and the decrease in the value c_i of leads to increase in the value of c_j
- w_{ij}= 0 indicates no relationship between c_i and c_j.

In FCM, model implications are revealed by using an iterative vector-matrix multiplication procedure to assess the effects of these perturbations on the state of a model. A model implication converges to a global stability or equilibrium, or get trap in a limit cycle (Aguilar, 2004). The simplicity of the FCM model consists in its mathematical representation and operation. A FCM which consists of $n$concepts is represented mathematically by n state vector A, which gathers the values of the n concepts, and an n x $n$weighted matrix W. Each element $E_{ij}$of the matrix indicates the value of the weight between concepts $c_i$andc_j. The activation level $Ai$for each concept $c_i$is calculated by the following rule.

$$C_i^{new} = f\left(\sum_{j=1}^{n} C_j^{new} w_{ji}\right) + C_i^{old} \quad (2)$$

Two kinds of threshold functions which keep the value of weighted sum within certain bounded region are used in the Fuzzy Cognitive Map framework. The unipolar sigmoid function, where $\lambda > 0$, determines the steepness of the continuous function f:

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \quad (3)$$

When nature of concepts can be negative, their values belong to the interval [-1, 1], the following threshold function is used:

$$f(x) = tanh(x) \quad (4)$$

Since the introduction of FCMs by Kosko (1986), several extensions have been made; among such are: random Fuzzy Cognitive Maps, Dynamic Random Fuzzy Cognitive Maps, Rule-based Fuzzy Cognitive Maps (Tome, 1999), Probabilistic fuzzy Cognitive Maps (Song, Shen,, Miao, Liu,, & Miao, 2006), and several others. A very detailed compilation of fuzzy cognitive map extension and their application in various fields can be found in Glykas (2010) and Papageorgiou (2013).

Nonlinear Hebbian Learning (NHL) Algorithm

In modelling complex system with FCMs, the objective sometimes is to control the system to converge to a desired state; but this is not always the case with complex or natural systems as they tend to converge to undesired state. In the case of models developed using FCMs, learning algorithms are used to train them so the system learns to converge to a steady state (Papageorgiou, Parsopoulos, Groumpos, and Vrahatis, 2004).
Learning involves updating the strengths of causal links so that FCM converge in a desired region. This is achieved by modifying or fine-tuning its initial causal link or edge strengths through training algorithms until in reach a steady state. A steady state of the FCM is characterized by concept values that satisfy the objective function. After this stage, the FCM can simulate the system accurately. Among the proposed learning procedure is nonlinear Hebbian learning.

The NHL is a machine learning algorithm based on the nonlinear Hebbian-type learning rule that was introduced for Artificial Neural Networks. it uses Oja learning rule which was developed train neural networks but later adapted to FCMs. The algorithm adjusts the weights based on initial experts' knowledge, i.e. initial sketch of the map, and additional information on the modelled system expressed by restrictions imposed on some concepts, to derive the connection matrix.
The main goal of learning in FCMs is to determine the values of the weights of the FCM that produce a Desired Output Concepts (DOCs) of the system (Papageorgiou, Stylios, and Groumpos, 2003). The desired behaviour of the system is characterized by values of the DOCs that lie within pre-specified bounds, determined by the experts. These bounds are in general problem dependent.
For n number of nodes in a FCM, Let$c_{i,}(i = 1,2, \dots .m)$ be the DOCs of the FCM, while the remaining concepts are considered input or interior concepts. The interest is in restricting the values of these DOCs in strict bounds, $c_i^{min} \leq c_i \leq c_i^{max}$ which are crucial for the proper operation of the modelled system. Thus, the main goal is to detect a weight matrix $W = [w_{ij}], i, j = 1, \dots, N$, that leads the FCM to a steady state, and at which the DOCs lie in their corresponding bounds, while the weights retain their physical meaning. The latter is attained by imposing constraints on the potential values assumed by weights. To do this, an objective function$F$, is define or declared. The application of NHL for the model system is to minimization objective function *F*. the global minimisers of the objective function *F* are weight matrices that lead the FCM to a desired steady state, When a weight configuration that globally minimizes *F* is reached, the algorithm stops.

Computational Modelling of Farmer-herder using FCM

There is a dearth of data on many of the variables in farmer-header conflict (Evans, 2011) which makes a purely quantitative research almost impossible; this case is even more challenging in Nigeria due to poor record keeping system. However, FCM permits the use of experts' knowledge Therefore our model comprises of both quantifiable and qualitative variables. To model the farmer-herder conflict, environmental variables (or primary factors) and what was termed *the reactive variables* (secondary factors) of the conflict were combined together to form a fuzzy cognitive map. Working with several experts, both who have studied the conflict, those living in the heart of the conflict, and information from various sources, we came up with 8 variables and conflict itself to model farmer-herder conflict in Nigeria. Though various experts had their own view on the key factors, yet agreed on the following as fundamental variables.

1. Desert Encroachment,
2. Population Growth,
3. Livestock Migration of Herdsmen (within Nigeria) - towards middle belt
4. Water Availability
5. Vegetation cover,
6. Trans-border Migration (Neighbouring countries) – into Nigeria for pasture
7. Deforestation and Fuel-Wood Consumption,
8. Competition,
9. Conflict.

Figure 2 is the graphical representation of the conflict model using fuzzy cognitive maps.
These variables are either quantitatively or qualitatively measured. For the variables whose data are available and quantitatively measured, they were transformed them into fuzzy values using the mathematical function that provides membership value for the variable
Population Growth: represents the population of Nigeria over several censuses that were conducted. It exerts influence over other some other variable like deforestation and fuel-wood usage, and competition for resources as seen in farmer-herders conflict presently. The figure 3. below represents the population of Nigeria from several censuses conducted till 2006

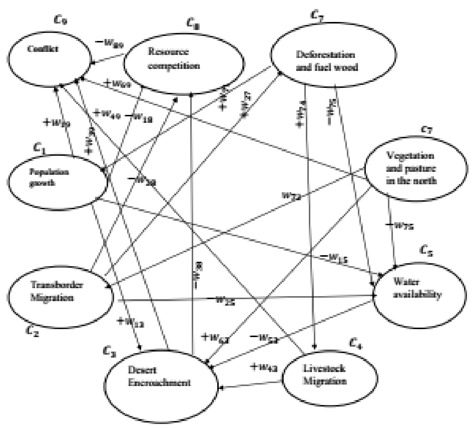

Figure 2: FCMs Farmer- Herder conflict

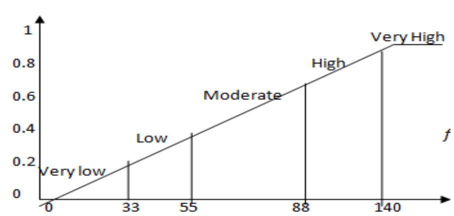

Figure 3 Population in millions

The $f(x)$represents the function that normalise the population value into fuzzy value in the interval 0 and 1, in Equ 5. x represents the population value in its ordinary form, while the output of $f(x)$ is found using Equation 5

$$f(x) = \begin{cases} 0; & x < 1 \\ \frac{x}{140}, & 1 \leq x \leq 140 \\ 1; & x \geq 140 \end{cases} \quad \text{..................} (5)$$

The *Desert encroachment (D):* This variable is the percentage of Nigeria landmass encroached by Sahara desert. The entire land mass represent 100%, this is further normalised to a bounded region of 0 and 1 in Equ 6 . Very high desertification is equals to 1 while no (0%) desertification is equals 0. For the sake of easy normalisation and coding, the following function $f(d)$ in equation 3.2 below was used; with d as the percentage of the encroached landmass. The output of $f(d)$ is a fuzzy value.

$$f(d) = \begin{cases} 0; & x < 1\% \\ \frac{d}{100}; & 1 \leq x < 94\% \\ 1; & x \geq 95\% \end{cases} \quad \text{............} (6)$$

After values of *Desertification* and *Population Growth* were fuzzified, the values are map to Table 1 during interpretation of the result.
The other factors may not be directly measureable; however, For the sake of modelling and analysis, numerical values were used to represent the magnitudes of these variables; this is consistent with the practice in FCMs. Fuzzy logic permits representation of human linguistic estimations (like low, moderate, high, etc.) with numbers. The variables: *Migration of Herdsmen, Availability of Water, Vegetation Cover, Trans-border Migration, Deforestation and Fuel-Wood Consumption, Competition,* and *Conflict* were measured in human language as High, moderate, Low and assigned specific value intervals in the region of [0, 1]. *The* factors are fuzzified in the region 0 and 1 using the Table 1. Since our interest is to model the conflict situation, if a particular factor is *very low,* it has possible value between 0.0 to 0.1 i.e, it can take value like 0.05.

Table 1: Linguistic variable of conflict factors

Factors	
Linguistic Terms	**Fuzzy Value**
Very Low	>0.0 - 0.1
Low	> 0.1 - 0.3
Moderate	> 0.3 – 0.6
High	>0.6 – 0.8
Very High	>0.8 – 1.0

The various factors used to model the conflict have natural connections and influences each other in a complex manner to produce the conflict situation, this influences are referred to as weights in the work. In general, a particular factor can have either positive or negative weight on another factor it influences. Though the levels of these weights vary and depend on human categorisation; 5 levels were chosen on both negative and positive sides to allow close representation of the real situation. The weight between any two factors in the map takes its values in the region [-1, 1], this is summarised in Table 2.

Table 2: Linguistic variable of weights/relationship among the conflict factors

Weights/Influence of the factors	
Linguistic Terms	**Fuzzy Value**
Negatively Very Low	>-0.0 - -0.1
Negatively Low	> -0.1 - - 0.3
Negatively Moderate	>- 0.3 – - 0.6
Negatively High	>- 0.6 – - 0.8
Negatively Very High	>-0.8 – -1.0
No relationship/Influence	0.0
Positively Very Low	>0.0 - 0.1
Positively Low	> 0.1 - 0.3
Positively Moderate	> 0.3 – 0.6
Positively High	>0.6 – 0.8
Positively Very High	>0.8 – 1.0

RESULTS

The model relied strongly on the knowledge of experts, so the causal weight was established based on the trend of the conflict in Nigeria and states of the factors of the system over time. The causal weights were developed through a long process of refinement of the weight and running of the model until the weights, output values were certified to reflect the actual conflict situation. The weight matrix in Table 3 represents the final expert values for weights or degree of influence among the several factors of the model. For the model to output the value of conflict; it iteratively carryout numerical inference using the formulae in Equ 2 and Equ 3 until it converges to a stable state. Also, numerical value 3 was used for the value of the constant $\boldsymbol{\lambda}$ in the Equ 3, the value was chosen after trials with different parameters, this is consistent with the standard practice or use of FCMs.

Table 3: connection weight of the conflict model conflict scenario

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	0.000	0.000	0.000	0.000	0.000	-0.010	0.400	0.100	0.100
C_2	0.010	0.000	0.000	0.200	0.000	0.000	0.000	0.000	0.000
C_3	0.000	0.000	0.000	0.000	-0.400	-0.500	0.000	0.000	0.000
C_4	0.000	0.000	0.000	0.000	0.000	0.250	0.000	0.100	0.000
C_5	0.000	0.000	0.000	-0.400	0.000	0.100	0.000	-0.300	-0.600
C_6	0.000	0.000	-0.800	-0.600	0.300	0.000	0.000	-0.700	-0.800
C_7	0.000	0.000	0.000	0.000	-0.300	-0.400	0.000	0.000	0.000
C_8	0.000	0.000	0.010	0.000	0.000	0.000	0.000	0.000	0.650
C_9	-0.100	-0.200	0.000	-0.200	0.000	0.000	0.000	0.000	0.000

Table 4: Input values for the conflict control scenario

Concepts	**Input Value**
Desert Encroachment,	0.2
Population Growth,	0.5
Livestock Migration of Herdsmen	0.21
Water Availability	0.89
Vegetation cover,	0.87
Trans-border Migration	0.1
Deforestation and Fuel-Wood Consumption,	0.1
Competition,	0.1
Conflict.	0.01

Control of the conflict using Nonlinear Hebbian Learning

In an attempt to simulate conflict control, it was desired that the value of vegetation ($\boldsymbol{C_7}$) in the FCM conflict model should be between 0.65 and 0.85. it is believed that if vegetation can be improved that high level, there will be less conflict; therefore, this desired range is the constraints impose on vegetation. The work of NHL is to find the level of the weights that will produce vegetation value between 0.65 and 0.85. The various values inputted for the factors or concepts of the model can be found in Table 4 while the initial weights are in Table 5. The object was to minimise the cost function $F = \sqrt{\sum_J \|C_7(k) - T_7\|^2}$, where T_7 is the average or mean value of vegetation (C_7) with the constraint $0.65 \leq C_7 \leq 0.85$ imposed on it. The output in table 6 is the solution of the problem. Some of the result could be explained as competition for access to vegetation ($\boldsymbol{C_8}$) must not allow to increase deforestation ($\boldsymbol{C_7}$) beyond *very low* level of 0.002, seasonal migration of herder ($\boldsymbol{C_3}$) for pasture must never be allow to influence deforestation ($\boldsymbol{C_7}$) beyond *very low* level of 0.001, etc. All these connection weight matrix stipulate the necessary conditions for having vegetation with high level of 0.8063 and *very low* (0.0544) conflict.

Adogi (2013) noted that the vegetation in some states in northern Nigeria has reduced lower than 10%, therefore we are experiencing the present level of conflict in the country. The implication of this result is that if the government can work to fight desertification and restore greenness to the north, there will be natural backward migration with very low competition and conflict in the middle belt. The weights give expected level of influence between the factors must be maintained in other have low level of conflict.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	0.000	0.012	0.003	0.002	0.014	0.003	0.408	0.102	0.101
C_2	0.022	0.000	0.002	0.202	0.012	0.011	0.012	0.002	0.001
C_3	0.003	0.002	0.000	0.001	-0.391	-0.491	0.003	0.000	0.000
C_4	0.002	0.002	0.001	0.000	0.002	0.249	0.002	0.100	0.000
C_5	0.014	0.012	0.003	-0.397	0.000	0.112	0.013	-0.298	-0.599
C_6	0.013	0.011	-0.797	-0.597	0.309	0.000	0.012	-0.698	-0.799
C_7	0.013	0.012	0.013	0.002	-0.282	-0.383	0.000	0.002	0.001
C_8	0.002	0.002	0.010	0.000	0.002	0.002	0.002	0.000	0.650
C_9	-0.098	-0.197	0.000	-0.200	0.001	0.001	0.001	0.000	0.000

Table 5: the initial connection weight of the conflict model

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	0.000	0.000	0.000	0.000	0.000	-0.010	0.400	0.100	0.100
C_2	0.010	0.000	0.000	0.200	0.000	0.000	0.000	0.000	0.000
C_3	0.000	0.000	0.000	0.000	-0.400	-0.500	0.000	0.000	0.000
C_4	0.000	0.000	0.000	0.000	0.000	0.250	0.000	0.100	0.000
C_5	0.000	0.000	0.000	-0.400	0.000	0.100	0.000	-0.300	-0.600
C_6	0.000	0.000	-0.800	-0.600	0.300	0.000	0.000	-0.700	-0.800
C_7	0.000	0.000	0.000	0.000	-0.300	-0.400	0.000	0.000	0.000
C_8	0.000	0.000	0.010	0.000	0.000	0.000	0.000	0.000	0.650
C_9	-0.100	-0.200	0.000	-0.200	0.000	0.000	0.000	0.000	0.000

CONCLUSION

Government should focus on spending to control the environmental factors which are the primary causes of the conflict rather than spending on deescalating conflict through military means. The peace achieve through the use of force will only result in a temporary level of peace with conflict reoccurring over time, it is actually short-time solution to a long-time problem. Environmental factors are natural regulatory forces that affect the occupation of the herders; therefore those factors should be properly controlled to achieve a lasting peace with a very minimal level of conflict. Military approaches are short-time methods while Economic development assistance or increased political participation is examples of structural prevention. This work suggests a structural approach to the control of Farmer/herder conflict in Nigeria.

From the entire work, Farmer/herder conflcit is a conflict centres on access to depleting natural resources – vegetation and water, and is cause by several factors within the environment. From the causative analysis, the most significant factors in the conflict cases are the fast encroaching desert in the north and the resultant lowering vegetation/pasture level with low water. If desert is properly control in the north and the greenness returns to the places that are overrun by desert and sand dune, there will be a natural backward migration of herdsmen back to the north with a less conflict in the zone.

While several models reviewed in this work could test for level of accuracy due to the availability of raw data which was used to train and developed those models, this model uses the knowledge of the expert on the conflict and the trend of the conflict over the period of time, therefore, such test could not be carried out. However, the model reflects the conflict domain very well due rigorous effort to continually fine-tune it, and can therefore be used in controlling the conflict.

REFERENCE

Adogi, M (2013). Fulani-farmers conflicts in Nasarawa State: The ecology, population and politics. *Abuja: Murry Greens Consult*

Aguilar, J. (2004). Dynamic Random Fuzzy Cognitive Maps. *Computación y Sistemas* . 7(4), 260-270.

Dorffner G., Rattenberger, J., Hörtnagl, E., Bercovitch, J., & Trappl R. (2006) Neural Computation for International Conflict Management in *Programming for peace: computer-aided methods for international conflict resolution and prevention* (Vol. 2) Trappl, R. ed. Springer Science & Business Media. Dordrecht,: Netherlands. Springer, 185-225.

Evans, A. (2011). Resource Scarcity, Climate Change And The Risk Of Violent Conflict: World Development Report Background Paper. Center On International Cooperation, New York University.

Glykas, M. (Ed.). (2010). *Fuzzy Cognitive Maps: Advances in theory, methodologies, tools and applications* (Vol. 247). Springer Science & Business Media.

Groumpos, P. P. (2010) Fuzzy Cognitive Maps: Basic Theories and Their Application to Complex Systems", In *Fuzzy Cognitive Maps Advances in Theory, Methodologies, Tools and Applications*, M. Glykas, ed. Berlin Heidelberg, Springer-Verlag, 1-22

Kosko, B., (1986). Fuzzy Cognitive Maps. *Int. Journal of Man-Machine Studies*, 24, 65-75.

Marwala, T., Lagazio, M., & Tettey, T. (2009). An integrated human–computer system for controlling interstate disputes. *International Journal of Computers and Applications*, *31*(4), 239-246.

Papageorgiou, E. (2013). Review study on fuzzy cognitive maps and their applications during the last decade. *Business Process Management*, 281-298.

Papageorgiou, E. I., Parsopoulos, K. E., Groumpos, P. P., & Vrahatis, M. N. (2004). Fuzzy cognitive maps learning through swarm intelligence. In *International Conference on Artificial Intelligence and Soft Computing* (pp. 344-349). Springer, Berlin, Heidelberg.

Papageorgiou, E., Stylios, C., & Groumpos, P. (2003). Fuzzy cognitive map learning based on nonlinear Hebbian rule. In *Australasian Joint Conference on Artificial Intelligence* 256-268. Springer, Berlin, Heidelberg.

Perry, C. (2013) *Machine Learning and Conflict Prediction: A Use Case*, available at http://www.stabilityjournal.org/article/view/sta.cr/153 [Accessed on 7th march, 2014].

Rupesingh, K. (2009). *FCE Citizen-based Early Warning and Early Response System: A New Tool for Civil Society to Prevent Violent Conflict,* Colombo, Sri Lanka: Foundation for Co-Existence, pp 12.

Schrodt, P. A. (1999). Early warning of conflict in southern Lebanon using Hidden Markov Models. *The Understanding and Management of Global Violence*, 131-162.

Song, H. J., Shen, Z. Q., Miao, C. Y., Liu, Z. Q., & Miao, Y. (2006). Probabilistic fuzzy cognitive map. *Fuzzy Systems, 2006 IEEE International Conference on fuzzy systems* (pp. 1221-1228). IEEE.

Stylios, C. D., Groumpos, P. P. (1999) Mathematical Formulation of Fuzzy Cognitive Maps", Proceedings of the 7th Mediterranean Conference on Control and Automation (MED99) Haifa, Israel, 2251-226.

Tettey, T. (2003) A Computational Intelligence Approach to Modeling Interstate Conflict: Forecasting and Causal Interpretations. Master of Science thesis, University of the Witwatersrand Johannesburg, , pp. 1+ Available at http://wiredspace.wits.ac.za/bitstream/handle/10539/5863/Thesis-0200136J.pdf?sequence=1 [accessed March 3, 2014.]

Tome, J. P. C. J. A. (1999). Rule based fuzzy cognitive maps: fuzzy causal relations. *Computational Intelligence for Modelling, Control & Automation: Evolutionary Computation & Fuzzy Logic for Intelligent Control, Knowledge Acquisition & Information Retrieval*, *2*, 276.

Trappl, R., Hörtnagl, E., Rattenberger, J., Schwank, N., & Bercovitch, J. (2006). Machine Learning Methods for Better Understanding, Resolving, and Preventing International Conflicts. In *Programming for Peace* (pp. 251-318). Springer, Dordrecht

Trijono, L. (2004). Structural-cultural Dimensions of Ethnic Conflict: Toward a Better Understanding and Appropriate Solution In Managing Ethnic Conflict. *The Making of Ethnic and Religious Conflicts in Southeast Asia: Cases and Resolution. Yogyakarta: CSPS Books*.

UNDP (2009), *From Conflict to Peace building: The role of Natural Resources and the Environment*. Nairobi: UNEP, pp. 5.