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A Neuro-Fuzzy Model for Conflict Prediction in the Niger Delta Region of Nigeria

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ABSTRACT

This paper proposes a soft computing system driven by Neural Networks, Fuzzy Logic and Principal Component Analysis (PCA) for the prediction of conflict in the Niger Delta (ND) region of Nigeria. Identifying conflicts along the level of severity with which they arise in oil bearing host communities (OBHC) is of primary importance to government and other stakeholders, as the accompanying conflict risks mitigation course administered could be planned based on the level of severity of the conflict situations. The system is implemented using MATLAB and Microsoft Excel running on Microsoft Windows 10 operating system. The data set chosen for classification and experimental simulation is based on a statistical data obtained from a three-year field study of the nine states of the ND region of Nigeria. The average training and testing errors of 0.015514 and 0.053247 were obtained at 50 epochs for the model using a hybrid algorithm. PCA reduced the dimension of the original data set at a Cronbach's alpha of over 0.8 with a 10-fold cross validation, thereby reducing the computational complexity and inference time of the model. The model predicted the conflict risk with an average accuracy of 92.85% and this compared favourably with domain experts conventional conflict prediction approaches. The result obtained gives a promising conclusion that the model is effective in predicting at high level of accuracy, the degree of conflict and presents a veritable decision support for conflict resolution and mediation agencies and stakeholders.

Keywords: ANFIS, Conflict prediction, Fuzzy logic, Fuzzy sets, Neural network, PCA, Soft computing

INTRODUCTION

A conflict is the expression of disagreement over something important to both or all sides in a dispute. The conflict in the ND has been attributed to many factors [1]. Several approaches instituted to resolve the ND conflict includes; adoption of public relations approach through the establishment of the Niger Delta Development Commission (NDDC), a mediation mechanism

setup by the Nigerian government and the multinational oil companies (MNOCs) operating within the OBHCs and mediation strategies through grass root participatory approaches between MNOCs and OBHCs [2, 3, 4, 5]. The prediction of conflicts is seen as a challenging task for many systems and organizations that have attempted to build and develop systems for accurate and effective conflict prediction. Determining the severity in the conflict situation can guide facilitators in their decision making tasks in ameliorating the causes and prevent occurrences of conflicts in the region.

In this paper Section 2 discusses relevant literatures and Section 3 discusses the materials and methods deployed in the study. Section 4 discuss the experimental simulations performed and the intermediate and final result obtained. In Section 5, conclusions are drawn and further work proposed.

LITERATURE REVIEW

Commonly used models in conflicts analysis are logistic regression models as stated by [6] and [7]. Iswaran and Percy in [6] reported that the statistical models have poor positive predictive performances in conflict analysis where outcomes are either true or false. [7] utilized random forest and Naïve Bayes classification to develop an early warning model of conflict using subnational conflict data in Africa and discovered that both methods were able to improve conflict prediction accuracy based only on lagged conflicts. In [8] a text mining tools was used to generate frequencies of references to topics relating to conflicts in newspaper articles and concluded that this variable had a strong predictive power in a conventional linear regression prediction framework. In [9] a variant of logit regression, random forest and neural network was developed to generate predictions of conflict using subnational data from Liberia. The system predicted the conflict situation in Liberia distinguishing between groups of explanatory variables.

Soft computing techniques, such as Fuzzy sets and Fuzzy logic (FL), Artificial Neural Networks (ANN), and Genetic Algorithms (GA) are useful in handling the uncertainty, imprecision and vagueness associated with real world data [10,11]. To complement each other's merits, hybrid techniques are popularly used in several fields. Zadeh in [12] introduced FL as a tool for representing uncertainty by permitting an input to have a value in a range of values between 0 (completely false) to 1 (completely true). It became useful in decision-making problems where representative inputs are not clearly binary. A fuzzy inference system (FIS) is based on the concept of fuzzy set theory, fuzzy IF-THEN rules and fuzzy reasoning [11, 12]. FIS can then be defined as a process of mapping from a given input to an output, based on expert knowledge encoded as a set of explicit linguistic rules, which are easily understood. In [13, 14], knowledge from an expert can be encoded as a set of rules, expertise captured and the human reasoning process provided at a cognitive level. So that one can express knowledge with subjective concepts such as 'low', 'moderate', 'high', 'very high', and so on, which can be mapped into exact quantitative ranges. Bashar et al. in [15] proposed a fuzzy graph model for conflict resolution (GMCR), so that real world conflicts in which decision makers (DM) have uncertain preferences can be modelled and analysed mathematically in order to gain strategic insights. The framework predicted different conflict resolutions based on GMCR developed by Keith et al. in [16]. Leveraging on fuzzy advantage of handling imprecise, incomplete and crisp real-world scenarios, the model was tested in a conflict situation having more than two DMs concerning groundwater contamination in a city. The fuzzy preferences obtained were very close to those

found using complex pairwise comparison approaches. Yu and Yu in [17] extended the work in [15] and proposed a conflict analysis framework using fuzzy GMCR as well. It was tested in resolving a water pollution conflict between an upstream and downstream area of a reservoir in China. The capability of fuzzy logic in handling vagueness, imprecision and incomplete data in real world scenarios was harnessed in resolving the conflict efficiently. Lempp in [18] developed a propositional model for conflict resolution. The model consisted of an input module that allowed data about negotiation situation to be entered, and an output module that generated outputs which are results of all incompatible goal pairs on a graph displaying the compatibility relationship. Sutoyo et al. in [19] proposed a softset approach with the ability to handle conflict situations. The system provided the capability to handle vagueness from conflict data sets and combined rough set and decision rules to achieve lower computational time of 3% when compared to rough set theory alone.

Developments in intelligent social systems research have exploited these expert system methodologies in building programs intended to assist policy-makers in decision-making. Neuro fuzzy systems are SC models that combine the parallel computation and learning capability of ANN with the knowledge and explanation capability of FL to form an intelligent system capable of solving complex non-linear problems [20]. ANN has been widely accepted as a better model for conflict analysis and prediction due to their flexibility, ability to cope with non-linear, interdependent and interactive, and context dependent data often associated with conflict analysis, that statistical models cannot cope with [7]. While ANN has the ability to approximate any continuous function and to learn as they encounter new input-output pairs, some decision problems have inputs that are imprecise, ambiguous or incomplete. A hybrid of ANN and FL provides a solution that integrates the strength of both techniques and eliminates their weaknesses. This allows the NN model to learn from patterns in a given dataset in order to automatically compute the MF parameters that best drives the associated FIS [14]. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) can construct a FIS whose MF parameters will be tuned from the NN model using Backpropagation (BP) algorithm, Least Squares Estimation (LSE) method or a hybrid of both [10,11]. To our knowledge, this study presents the first novel use of ANN and FL hybrid soft computing technique for the prediction conflicts.

METHODOLOGY

In our methodology, we propose a neuro-fuzzy conflict prediction system (NFCPS) driven by ANN, FL and PCA and the architecture is presented in Figure 1. The components that make up the architecture of this system include; Data preprocessing (Normalization and Feature extraction), the ANFIS model, and output mapping.

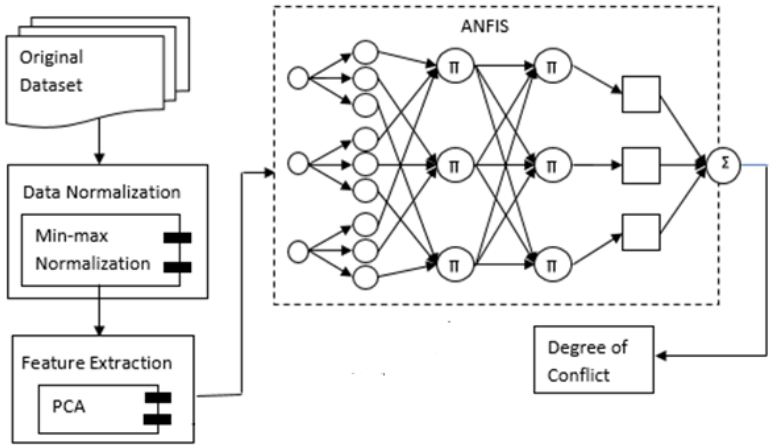


Figure 1: Architecture of the Neuro-fuzzy Conflict prediction system (NFCPS) model.

Data Collection and Normalization

Data for the conflict resolution and prevention system were obtained from the statistical data collected in a three-year field study of the ND region (2014-2017) reported in [1]. The quantitative and qualitative data comprised of the following indicators of conflicts in the ND: Youth unemployment in communities (YUC), Multinational oil companies in community (MNC), Environmental degradation (ENV), Cost of living (CLV), Poverty and poor economic conditions (PPE), Government policy (GOP), Scholarship opportunities (SCH) and Current conflict resolution method (CRM)) as well as a single predictor or class called Degree of Conflict (DOC). A sample of the original data set after preprocessing is presented in Table 1.

Table 1: Sample of the original Data set

S/N	YUC	MNC	ENV	CLV	PPE	GOP	SCH	CRM	DOC
1	2.846	0.2000	0.038	0.032	0.019	0.500	0..439	0.419	11.429
2	2.250	0.2000	0.148	0.062	0.051	0.500	3.176	0.510	9.375
3	0.317	0.2000	0.244	0.139	0.068	0.500	0.193	0.668	6.673
:	:	:	:	:	:	:	:	:	:
185	0.683	0.700	0.568	0.617	0.608	0.500	0.065	0.618	11.681

A 10-fold cross validation was performed to partition the training and test data sets in the ratio 7:3. The data set is normalized into a scaled range of [-1,+1] and presented in Table 2. Data reliability is measured by computing a Cronbach's alpha (α) on the whole data set using 95% confidence interval (CI).

Table 2: Normalized Data set

S/N	YUC	MNC	ENV	CLV	PPE	GOP	SCH	CRM	DOC
1	-0.3450	-1.0000	-0.9894	-0.9759	-0.9908	0.9716	-0.8945	-0.2385	-0.6458
2	-0.4881	-1.0000	-0.9559	-0.9502	-0.9736	0.9716	-0.1227	-0.0428	-0.7361
3	-0.9520	-1.0000	-0.9267	-0.8840	-0.9644	0.9716	-0.9639	0.2971	-0.8550
:	:	:	:	:	:	:	:	:	:
185	-0.8642	1.0000	-0.8282	-0.4734	-0.6734	-0.8357	-1.0000	0.1680	-0.6347

Feature Extraction Using PCA (Principal Component Analysis)

The desired output of any computing model (linear or non linear) heavily depends on the information content of its inputs. Initially eight (8) indicators were considered in this study to be the major causes of upsurge of conflict in the Niger Delta region. From our study, the need to prune the features is as a result of the large auto-generated fuzzy rules which is of magnitude m^n, where m is the number of MFs in each input and n is the number of inputs. PCA is used to extract the hidden features from the multidimensional data [21]. It reduces the dimension by pruning unwanted attributes. The principal component (PC) of the new data set after computing the PCA are YUC, MNC and CRM.

The Neuro-Fuzzy Model

A Sugeno type fuzzy logic model is employed as an initial input to the ANFIS. Gaussian membership function (GMF) is considered for mapping the inputs and the output. GMF is chosen due to its limited amount of adjustable parameters. Two points (c, σ) are chosen to define one MF of the linguistic variable. The GMF is defined in Equation 1.

$$f(x) = e^{\frac{-1}{2}\left(\frac{x-c}{\sigma}\right)^2} \quad (1)$$

Where, c is the center of the GMF, σ is the variance (or width) of the MF, e is the exponential function, and x is the input vector. The inputs and the output are assigned class labels of 'low ('L')', 'moderate ('M')' and 'High ('H')' using numeric ranges. The MF distributions for the inputs are presented in Equations 2 – 10.

a. Membership function for PC1 (YUC)

$$\mu_{low}(x) = e^{\frac{-1}{2}\left(\frac{x-(-2.026)}{0.992}\right)^2} \quad (2)$$

$$\mu_{moderte}(x) = e^{\frac{-1}{2}\left(\frac{x-2.08}{0.9157}\right)^2} \quad (3)$$

$$\mu_{high}(x) = e^{\frac{-1}{2}\left(\frac{x-6.185}{1.24}\right)^2} \quad (4)$$

b. Membership function for PC2 (MNC)

$$\mu_{low}(x) = e^{\frac{-1}{2}\left(\frac{x-(-1.81)}{1.575}\right)^2} \quad (5)$$

$$\mu_{moderate}(x) = e^{\frac{-1}{2}\left(\frac{x-3.57}{1.562}\right)^2} \quad (6)$$

$$\mu_{high}(x) = e^{\frac{-1}{2}\left(\frac{x-8.854}{1.63}\right)^2} \quad (7)$$

c. Membership function for PC3 (CRM)

$$\mu_{low}(x) = e^{\frac{-1}{2}\left(\frac{x-(-0.663)}{1.712}\right)^2} \quad (8)$$

$$\mu_{moderate}(x) = e^{\frac{-1}{2}\left(\frac{x-4.8}{1.899}\right)^2} \quad (9)$$

$$\mu_{high}(x) = e^{\frac{-1}{2}\left(\frac{x-11.21}{2.08}\right)^2} \quad (10)$$

MATLAB R2015a is used to plot the GMF distributions (GMFD) and they are presented in Figures 3 to 5.

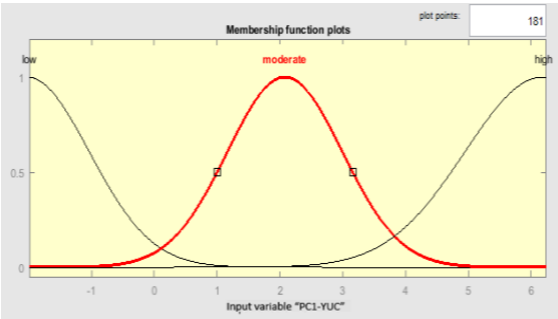


Figure 3: GMF plot for PC1 (YUC)

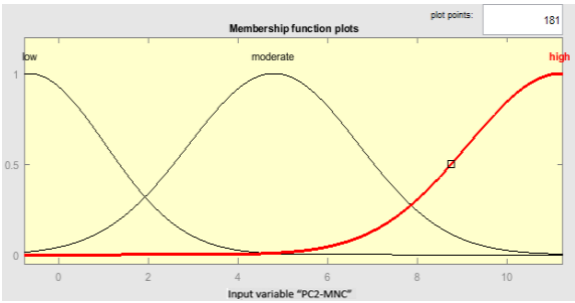


Figure 4: GMF plot for PC2 (MNC)

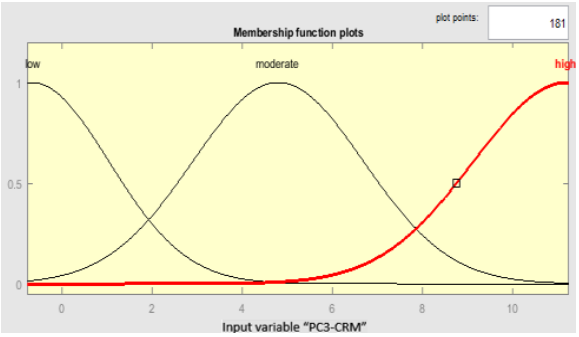


Figure 5: GMF plot for PC3 (CRM)

The NFCRP model utilize a hybrid learning algorithm to identify the parameters of the FIS and applies a combination of LSE method and the BP gradient descent algorithm for training the GMF parameters in order to match the given training data set. The ANFIS component is composed of a five layer feed forward multilayer NN (FFM-NN). The input layer maps input (I) to the first hidden layer (HL-1), by performing a fuzzification task that calculates the membership values using GMFD. The second layer or product layer (HL-2) is where the AND operation is performed. The third layer or normalization layer (HL-3) allows for the respective firing strength to be computed following the fired or activated fuzzy rules. The fourth layer or consequent layer (HL-4) represents the consequent part of the fuzzy rule. The fifth layer or summation layer (HL-5), is the output (O) layer that performs an OR operations on the fired fuzzy rules. The predicted output (P) is then compared with the target output (O) for each input and their mean square error (MSE) is computed. Subsequently, the network weights are updated and the training is said to be completed when the minimum MSE value is obtained. The layered computation are explained as follows:

Input Layer: The node in this layer holds the input fed into the system. In the context of this system, the inputs are; YUC, MNC, and CRM.

HL- 1 (MF Layer): In this layer, each node I is a parameterized GMF (i.e. Low, Moderate, and High). The output of this layer is computed as;

$O_{1,i} = \mu_{YUC_i}(a) \quad for\ i = 1, \dots, 3$

$O_{1,i} = \mu_{MNC_{i-3}}(b) \quad for\ i = 4, \dots, 6$

$O_{1,i} = \mu_{CRM_{i-6}}(c) \quad for\ i = 7, \dots, 9$

$O_{1,i}$ is the output of layer 1 with index i, $\mu_{YUC_i}(a)$ is the degree of membership of a in the MF. YUC_i is the index of the MF i belonging to a variable YUC, and a, b, c are the inputs.

HL-2 (Product Layer): The nodes of this layer calculate the firing strength of a rule using Equation 11:

$$O_{2,i} = w_i = \mu_{YUC_i}(a) * \mu_{MNC_i}(b) * \mu_{CRM_i}(c) \quad for\ i = 1, \dots, 3 \qquad (11)$$

The auto-generated rules are of magnitude m^n where m is the number of MFs in each input and n is the number of inputs. The number of rules generated for the system is $3^3 = 27$ rules.

HL-3 (Normalization Layer): The nodes of this layer normalize the firing strength of a rule by calculating the ratio of the *i*th rule's firing strength to the sum of all rule's firing strength using Equation 12:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2 + w_3}, \quad i = 1, \dots, 3 \qquad (12)$$

w_1 is the firing strength of first rule, w_2 is the firing strength of second rule, w_3 is the firing strength of third rule, w_i is the i^{th} rule firing strength, $\bar{w}_i$ is the normalized firing strength of *i*th rule.

HL-4 (Consequent Layer): Each node of this layer corresponds to the consequent part of the fuzzy rule as shown in Equation 13 and 14 respectively;

$$f_i = p_i a + q_i b + r_i c + t_i \qquad (13)$$

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i a + q_i b + r_i c + t_i), \quad i = 1, \dots 3 \qquad (14)$$

$\bar{w}_i$ is the normalized firing strength of the i^{th} rule, $\{p_i a + q_i b + r_i c + t_i\}$ is the first order polynomial of the i^{th} rule's consequent portion. The parameters, $\{p_i + q_i + r_i + t_i\}$ are obtained during the training process of the ANFIS model.

HL-5 (Summation Layer): This node is responsible for the summation of outputs of all the rules from the previous layer as shown in Equation 15;

$$O_{5,i} = \sum_{i=1}^{3} \bar{w}_i f_i = \frac{\sum_{i=1}^{3} w_i f_i}{w_1 + w_2 + w_3} \qquad (15)$$

Equation 15 performs the defuzzification function using the center of area (COA) method, to obtain the output *O*.

RESULTS AND DISCUSSIONS

This section discusses the results of the experiments.

Data Processing

A Cronbach's α of 0.86 was obtained and this is greater than 0.80 (threshold for the data set). Hence, the data used were stable and reliable for PCA. The PCA derived a covariance matrix, eigenvectors and eigenvalues. These are shown in Table 3-5. The conflict attributes of higher eigenvalues were selected as the PC of interest in the study.

Table 3: PCA covariance matrix

YUC	MNC	ENV	CLV	PPE	GOP	SCH	CRM
1.00367	-0.07213	-0.01702	0.57147	0.10853	0.27644	-0.03213	-0.04732
-0.07213	1.00367	-0.06047	0.27765	0.91344	0.12533	-0.00367	-0.05923
-0.01702	-0.0604	1.00367	-0.09796	0.00050	0.04456	1.00047	1.00760
0.57147	0.27765	-0.09796	1.00367	0.40029	0.45507	-0.24565	-0.09800
0.10853	0.91344	0.00050	0.40029	1.00367	0.17730	0.89344	0.00049
0.27644	0.12533	0.04456	0.45507	0.17730	1.00367	0.12333	0.04506

Table 4: PCA eigenvectors

YUC	MNC	ENV	CLV	PPE	GOP	SCH	CRM
-0.30045	0.56861	0.11914	-0.53953	0.52843	-0.04314	0.52846	-0.04311
1.00000	-0.51651	0.69486	-0.11498	0.00501	0.00211	0.00501	0.00212
0.05030	0.00506	0.05198	0.10484	0.19774	0.97193	0.197734	0.97193
-0.50488	35220	0.03566	0.77499	0.11037	-0.08366	0.110368	-0.08366
-0.54462	-0.40124	-0.70626	-0.15229	0.13055	0.05791	0.130548	0.05791
-0.34430	0.35334	-0.01432	-0.24677	-0.80772	0.20768	-0.80771	0.20768

Table 5: Eigen analysis

Attributes	Eigenvalue
YUC	2.363451
MNC	2.118218
ENV	0.900136
CLV	0.327815
PPE	0.720278
GOP	0.022284
SCH	0.051982
CRM	1.512436

From Table 5, YUC (Youth unemployment in communities), MNC (Multinational oil companies in community) and CRM (Current conflict resolution method) had Eigenvalues greater than 1.0 and hence are considered as the PCs. This reduces the dimension of the input space to three. This reduction forces the matrix of the original data set to 185 x 3, and the corresponding Cronbach's alpha (α) recomputed to 0.83, which is well over 0.80. This implies that YUC is

component 1, MNC is component 2, and CRM is component 3 as shown in the Scree plot in Figure 6. The reduced data set is used for the training.

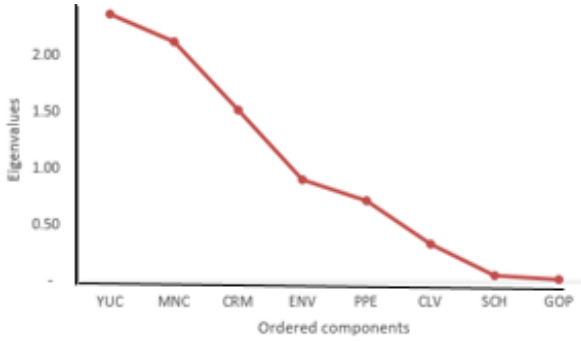


Figure 6: Scree plot of eigenvalues

NFCPS Model

The three attributes extracted by PCA and the degree of conflict are grouped as "low" (L), "moderate" (M) and "high" (H) and are represented into an asymmetric GMFD as shown in Figure 3 to 5. The NFCPS model accepts three inputs, each with two possible mappings at a time, meaning 2^3 or 8 rules might fire from the pool of 27 rules.

Training

The ANFIS model learns by identifying adaptable parameters of the MF (σ, c) for the spread and center of the GMF as well as $\{p_i + q_i + r_i + t_i\}$. A two pass learning process is used based on a hybrid of gradient descent (GD) and least square estimation (LSE). The consequent parameters are updated by the LSE in the forward pass and the premise parameters are trained using GD algorithm in backward pass. The ANFIS model is trained offline using 130 of the PCA reduced data set obtained from a 10-fold cross validation. The average training error of 0.016129 at 50 epochs in the FFMNN using BP algorithm, while an average of 0.015514 was obtained for the ANFIS model at 50 epochs using a hybrid of GD and LSE learning algorithm.

Testing

The validity of the ANFIS model was tested using 30% of the PCA reduced data set. The average testing errors of 0.053247 is obtained at 50 epochs. For the first training case, YUC and CRM is considered. The rule as stated by the domain expert is as: IF YUC is "Low" AND CRM is "High" THEN DOC is "Low". The firing strength of this rule is 0.36 as shown in Table 7.

Table 7: Fuzzification of the first test case

Input (I)	μ(L)	μ(M)	μ(H)	AND
YUC(0.6)	0.64	0.36	-	0.36
MNC(0.7)	-	1.0	-	-
CRM(0.8)	-	0.36	0.64	0.36

The respective firing strengths are computed and firing strengths values ≥ 0.5 are considered "strong" supported by the 10-fold cross validation tests result. These are subsequently used for computing the output of the ANFIS while the other outliers are discarded.

Optimal FIS Evaluation

The ANFIS module successfully learned from the data and produced an optimal FIS. The FIS is composed of the linguistic variables, MFs, and an auto-generated rule base. The components of the FIS and the FIS variables are shown in Figures 7 to 10. A MATLAB implementation of the system generated 27 rules and a snapshot of it is shown in Figure 11.

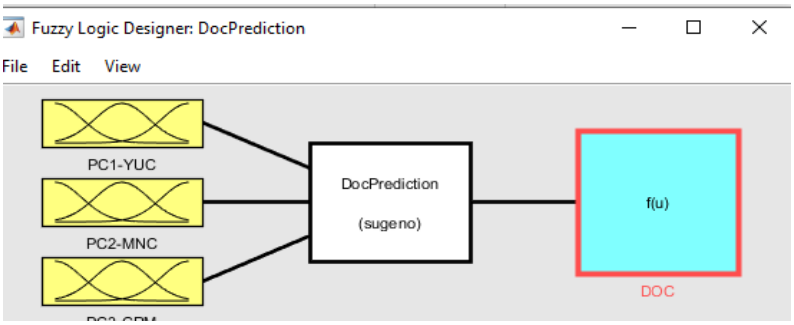


Figure 7: Optimal FIS structure

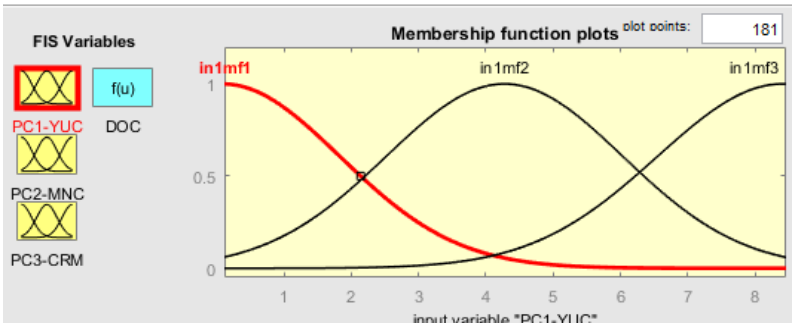


Figure 8: PC1-YUC MF

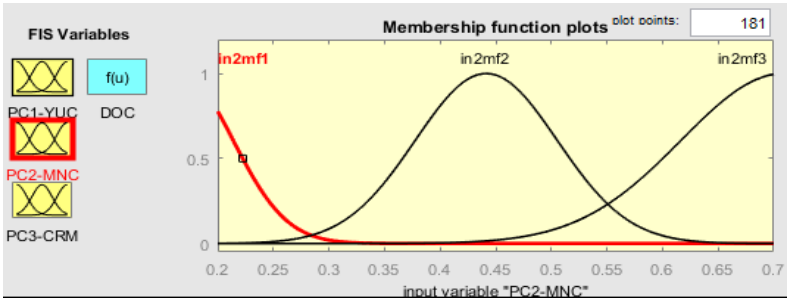


Figure 9: PC2-MNC MF

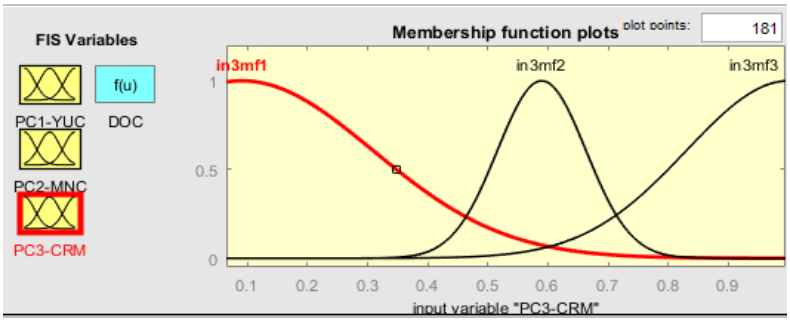


Figure 10: PC3-CRM MF

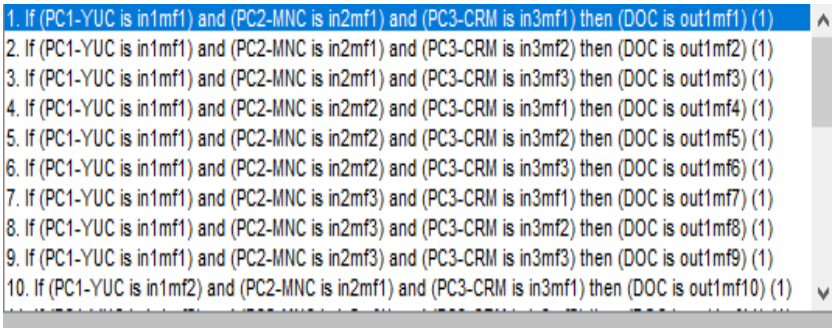


Figure 11: A snapshot of the fuzzy rule base for degree of conflict evaluation

In Figure 12 a Sugeno driven DOC prediction FIS is shown. For instance, if YUC is moderate (YUC=0.569), MNC is low (MNC=0.45) and CRM is moderate (CRM=0.53) then the degree of conflict (DOC) output of 2.27 is produced and the rule number 11 is fired as follows:
Rule 11: If (YUC is Moderate) and (MNC is Low) and (CRM is Moderate) Then (DOC is Low)

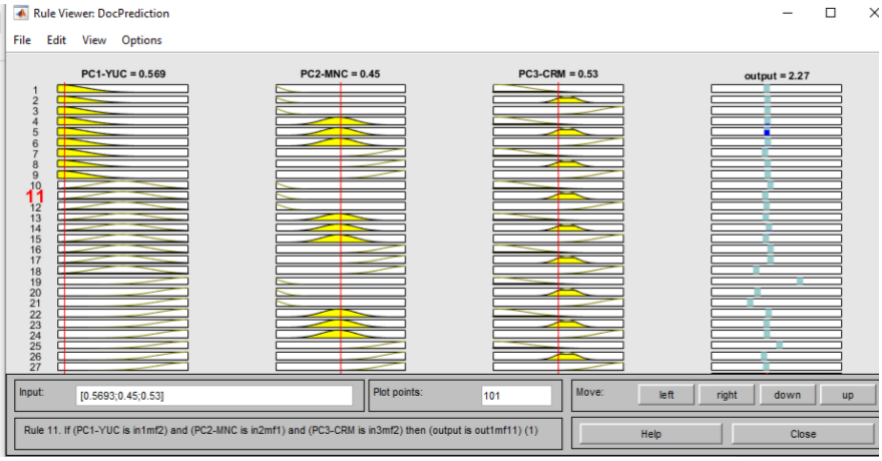


Figure 12: The rule viewer

This result as shown in Figure 12 predicts the output, DOC as 'Low'. The rule viewer allows for a complete interpretation of the entire FIS at once. In Figure 13, a non-linear 3D surface view of the system with input parameters PC1-YUC and PC2-MNC presents a surface view result of the degree of conflict (DOC).

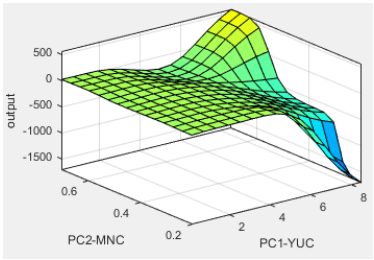


Figure 13: Non-linear 3D surface plot for the ANFIS model for DOC evaluation using PC1-YUC and PC2-NC.

In Figure 14 the same effect is observed from the plot of PC2-MNC, PC3-CRM with DOC. However, the plot shows DOC to remain minimal as PC3-CRM is progressing and PC2-MNC remains unchanged.

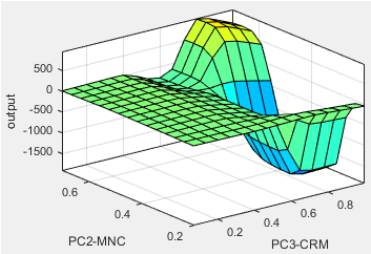


Figure 14: Non-linear 3D surface plot for the ANFIS model for DOC prediction evaluation using PC2-MNC and PC3-CRM

Evaluating the 3D plot for PC1-YUC, PC3-CRM with DOC in Figure 15 shows the DOC value reducing as PC3-CRM increases.

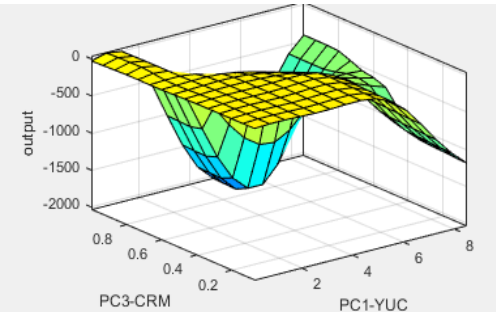


Figure 15: Non-linear 3D surface plot for ANFIS model DOC evaluation using PC1-YUC and PC3-CRM.

When the input variable PC3-CRM is plotted against DOC as shown in Figure 16, it is observed that the DOC decreases as the value of PC3-CRM increases. The plots reveal that for high youth unrest occasioned by unemployment a practicable conflict resolution method will reduce the rate of conflict in the affected region in spite of the operationalization of multinational oil companies in the region [22, 3, 5]. This supports the experts' opinion that a good conflict resolution approach can reduce conflicts in the Niger Delta [1, 2, 4].

Model Performance Evaluation

The performance of the model is tested using 55 cases with the optimized rule set. The Mean Square Error (MSE) is calculated to be 0.053247. The average sensitivity (*Sy*), specificity (*Sp*), precision (*Pc*) and average accuracy (*Ac*) were computed as in Equations 16 – 19. In these equations, *pt* and *nt* denote the positive and negative observations, *tpt* and *fpt* are true and false positive observations, while *tnt* and *fnt* are true and false negative observations and N is the total number of observations.

$$Sy = \frac{tpt}{pt}\text{x}100 \quad (16)$$

$$Sp = \frac{tnt}{nt}\text{x}100 \quad (17)$$

$$Pc = [\frac{tpt}{tpt+fpt}]\text{x}100 \quad (18)$$

$$Ac = \left[\frac{tpt+tnt}{N}\right] \text{x}100 \quad (19)$$

Table 8 presents the results of the performance analysis with an average accuracy of 92.85%.

Table 8: Performance analysis

Metric	L	M	H
tpt	16	17	18
fpt	0	0	0
tnt	0	0	0
fn	1	1	2
N	17	18	20
Sy (%)	94.11	94.44	90.00
Sp (%)	0	0	0
Pc (%)	100	100	100
Ac (%)	92.85%		

CONCLUSION

This paper introduces a neuro-fuzzy model consisting of a Sugeno driven ANFIS technique for predicting the degree of conflict using data from the Niger Delta region of Nigeria. A PCA-ANFIS system is used for the classification which has the advantages of dimension reduction, Neural Network and Fuzzy logic. With a sample of 185 real world conflict cases, the model has been trained and tested. An experimental study of the system predicted the conflict risk with an average accuracy of 92.85% and a precision of 100%. This method was compared to the other current methods, which the results indicated that the integrated PCA-neural-fuzzy (PCA–ANFIS) provides the least error on the testing dataset. The model offers a promising platform for predicting conflict and can be further improved upon with additional features and hidden layers using data of economic growth or resource availability and deep neural network (DNN) learning algorithms. This will lead to further improved performances and form part of our future research, which is to implement a full-fledged web based expert system in Prolog with its standardization.

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