ORIGINAL RESEARCH

Design of a hybrid intelligent system for the management of flood disaster risks

Oluwole Charles Akinyokun*[1], Emem Etok Akpan[2], Udoinyang Godwin Inyang[3]

[1] Department of Software Engineering, Federal University of Technology, Akure, Nigeria
[2] Department of Computer Science, Federal Polytechnic, Nassarawa, Nigeria
[3] Department of Computer Science, University of Uyo, Uyo, Nigeria

Received: December 24, 2018 **Accepted:** January 30, 2019 **Online Published:** March 6, 2019
DOI: 10.5430/air.v8n1p14 **URL:** https://doi.org/10.5430/air.v8n1p14

Abstract

The frequency of occurrence and intensity of floods is a huge threat to environment, human existence, critical infrastructure and economy. Flood risk assessments depend on probabilistic approaches and suffer from non-existence of appropriate indices of acceptable risk, dearth of information and pieces of knowledge for explicit view and understanding of the characteristics and severity level of flood hazard. This paper proposes a hybridized intelligent framework comprising fuzzy logic (FL), neural network and genetic algorithm for clustering and visualization of flood data, prediction and classification of flood risks severity level. A multidimensional knowledge model of flood incidence using star, snowflake and facts constellation schemas was proposed for the knowledge warehouse. A six-layered adaptive neuro-fuzzy inference system implementing mamdani's inference mechanism was design to evaluate input features based on fuzzy rules held in the multidimensional data model. The system is aimed at predicticting and classifying flood risk severity levels. The perception of emergency risk management is very important in modern society. Therefore, this work provides a framework for the practical applications of data mining techniques and tools to emergency risk management. The work would assist to identify locations with significant flood risk.

Key Words: Neural networks, Fuzzy logic, Genetic algorithm, Knowledge mining, Clustering, Visualization, Knowledge warehouse, Knowledge marts, Star schema, Snowflake

1. Introduction

The trend of floods worldwide and their accumulative economic impacts is increasing. Flooding is a critical environmental issue and a leading hazard in most developing economies. It disrupts the effective functioning of urban ecosystems, especially in the areas of infrastructure and service delivery, which are vital to a sustainable high standard of living. Flood hazard data are massive, vague and complicated; therefore exhibit high level of ambiguity especially those associated with the input features. The conventional statistical techniques applied to the treatment of flood risks are unable to effectively process huge data repositories largely because of vagueness of input features and cannot perform detail searches in the course of pattern discovery and extraction. More so, the traditional methods of referencing database objects produce degraded results that cannot support meaningful decision making. Hence, the need for the integration of intelligent tools capable of adapting in a noisy and complex environment, as well as handling imprecision data. In addition, efforts to deal with flood disasters are

*Correspondence: Oluwole Charles Akinyokun; Email: admin@akinyokun.com; Address: Department of Software Engineering, Federal University of Technology, Akure, Nigeria.

time consuming, ineffective and expensive because there is no explicit understanding of the characteristics and severity level of flood hazard.[1–4] Flood risk assessment suffers from non-existence of specific metrics of determining acceptable flood risks, dearth of data and presence of stochastic distribution.[1,5]

The complex nature of natural disasters and the vagueness of their determinants make Fuzzy Logic (FL) a necessary tool in the treatment of risks. Four key indexes to effectively classify and predict the degrees of severity of disaster were discovered from mining dataset consisting flood disaster incidence in thirty cities of China in 2008 using fuzzy cluster analysis driven by the equivalent relations of fuzzy systems.[1] The resultant fuzzy matrices are mined by means of transitive closure methodology to obtain cluster graphs indicating the various classes based on risk severity index. The results demonstrate the suitability of fuzzy cluster techniques in partitioning of flood disaster dataset. However, every indicator in the input space performs distinct function in the model, although some weights have significant influence, making the outcomes more fitting with the realities, which this study would address.

In Ref.,[6] an application of Triangular Fuzzy Number (TFN) and Fuzzy Analytic Hierarchy (FAH) methods to flood risk analysis is proposed, with the ranking flood risk factors, perform the overall flood risk assessment and selection of risk response measures, as specific objectives. The methodology spans a review of TFN and FAH, characterization of risk indicators and the development of a structured ranking of risk and response elements. Although, risk factors were ranked based on the relative weights of various factors, the work was limited to high subjectivity since weight indices must be computed manually prior to the application of FAH technique.

In Ref.,[7] the analysis of flood disaster risks with FL methods; Improved Information Diffusion Method (IIDM) and fuzzy sets technique, are presented. That paper reviewed the application of Variable Fuzzy Sets (VFS) and IIDM approaches in the construction of an integrated model. The proposed method aimed at evaluating catastrophic risks by combining several factors and transforming ambiguous ones into crisp values using specific criteria. The application of FL methodologies to flood disaster risk assessment successfully replaced stochastic estimations with realistic and deterministic results capable of supporting efficient decision making for flood disaster risk management. The work was only simulated and lacks intelligence to give sufficient information for flood risk management.

In Ref.,[8] a multi-objective optimization algorithm for drainage system flood risk management is presented. The specific objectives of the research are to improve the computational efficiency of the multi-objective genetic based flood risk model and to test and verify computational efficiency of the proposed methodology. However, the work is only simulated considered urban drainage flood system and failed to handle uncertainty likely to come from the flood incident data used.

In Ref.,[9] a flood hazard risk evaluation and monitoring model based on intelligent learning model and Random Forest (RF) is presented. RF is a machine learning algorithm which features combination method based on statistical principles used for classification and predictive modeling. The specific objectives of that research are to develop systematic procedure for flood risk assessment using RF, demonstrate feasibility and practicality of RF solution to flood risk assessment and implement the proposed solution based on the flood hazard risk allotment of the review area.

The application of tree-based approaches (decision trees, bagging, RF, regression trees and boosting) in the quantification of the impact of floods is reported in Ref.[10] The main objective of the work was to perform a detailed and complete exploration of flood fatalities held in Vietnam DANA database. The work provided a significant insight into flood-related fatalities in Vietnam and by extension provided a suitable framework for application in other databases. However, the generated models suffer from over fitting because no sensitivity analysis was carried out on the input parameters.

This paper aims at proposing a hybridized system framework driven by intelligence provided by FL, NN and GA for the collation, cluster analysis and visualization of data and information as well as knowledge for the management of flood disaster risks.

2. Conceptualization of a hybrid intelligent system

The architecture of a Hybridized Intelligent System for Flood Risk Management (HISFRM) is presented in Figure 1. HISFRM is made up of Knowledge Warehouse, Knowledge Mining Engine, Decision Support System Engine and User Interface.

2.1 Knowledge warehouse

Knowledge Warehouse (KW) of the HISFRM is the domain where facts are processed into knowledge, stored and propagated. It is structured as a network of logically connected static and dynamic sub-components, each of which are modelled in a relational form.[11–13] The KW is an integration of knowledge marts which provides intelligent analysis facilities that boosts the knowledge management processes. The design of knowledge marts follows the top-down approach presented in Ref.[14] and is viewed as composite of multidimensional model, NN, FL and GA.

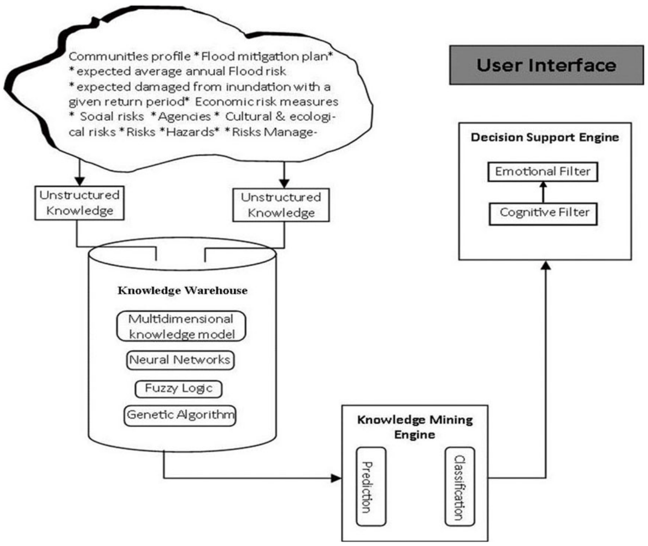

Figure 1. Architecture of a HISFRM

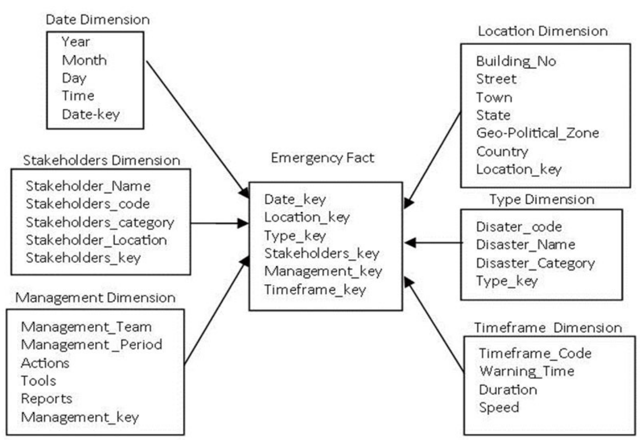

Figure 2. Star Schema for Emergencies Fact Table

2.2 Multidimensional knowledge modelling

The multidimensional knowledge is modelled as a cube of facts and dimensions. Facts constitute the basic elements of interest in a business process and are associated with dimensions and measures. Dimensions are descriptive attributes that specifies the aggregation (levels of summarization) for the analysis of facts.[15] Measures are attributes of facts, (numeric or non-numeric) which denotes their performance relative to the dimensions. Star schema and Snowflake schemas described in Ref.[14] are used in providing the multidimensional models for the knowledge items. The conceptualized star schema of HISFRM knowledge warehouse for flood risk fact table is presented in Figure 2 while Figure 3 gives the conceptual star schema of HISFRM knowledge warehouse for risks, fact and table.

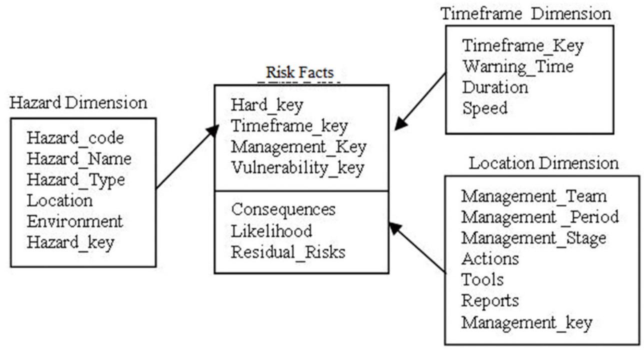

Figure 3. Conceptualized Star Schema of Risks Fact Table

The conceptualized star schema of HISFRM KW for community fact table is presented in Figure 4 where location, type, profile, hazard and stakeholders are the dimensions. The knowledge captured by profile dimension are topography, demography, infrastructure, communication links, emergency logs and risk models. The star schemas are further normalized into snowflake model thereby splitting some of the dimension tables into further dimension tables. Figure 5 shows a snowflake schema of a conceptualized schema for knowledge warehouse. The multidimensional knowledge model acts as the platform for holding the pieces of knowledge, their relationship and patterns.

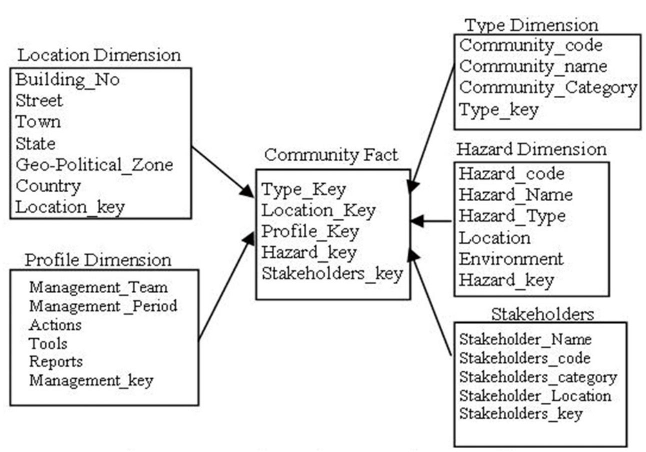

Figure 4. Star Schema for Community Fact Table

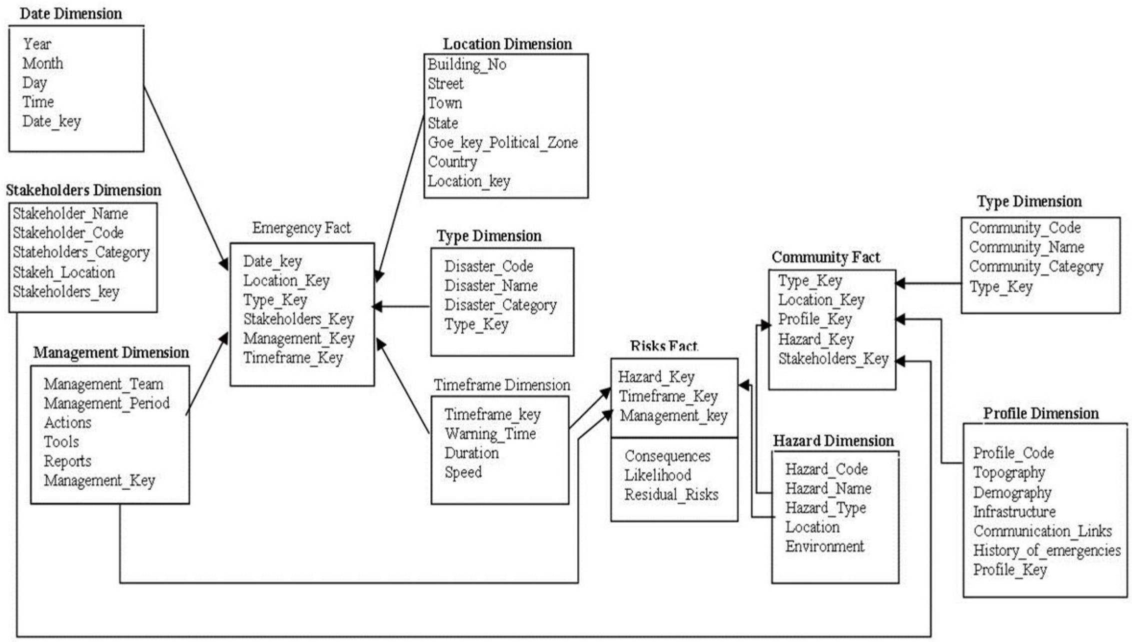

Figure 5. Conceptual Schema for Knowledge Warehouse

3. Neural network model for the management of flood disaster risks

The model of NN for flood risk management follows three steps[16, 17] the selection of variables, NN architecture and transfer function selection. This paper adopts a two layered feed-forward, multi-input units and single output unit architecture as in Ref.[18] The configuration of the NN (see Figure 6) has input layer with flood risk indicators as nodes, flood risk analysis as hidden layer and flood risk level is as the output layer node. Suppose there are m neurons in the input layer and input vectors $x \in R_m, x = (x_1, x_2, \cdots, x_m)$, then an input layer neuron i is a component of the input vector x_i. Let the number of nodes in the hidden layer be represented by $q, y \in R_q, y = (y_1, y_2, \cdots, y_m)$. These neurons are connected to one another in order to perform some tasks. In addition, the connections determine whether it is possible to inhibit or excite one another while the weights of the links specify the influence of the input feature.

A link is connection joining the ith input layer neuron and the jth neuron in the hidden layer, it is denoted by $w_{i,j}$ and value of jth hidden neuron as $\theta_{j,i}$, the outcome of a neuron in the hidden layer is as presented in Ref.:[19]

$$y_j = f(net_{i,j}) = f\left(\sum_{i-1}^{m} \omega_{i,j} x_i - \theta_j\right) \tag{1}$$

where $i = 1, 2, 3, \cdots, m$; $j = 1, 2, 3, \cdots, q$, f is sigmoid function for neuron activation and is given as:

$$f(\mathrm{u}) = [1+\exp(-\mathrm{u})]^{-1} \tag{2}$$

The output layer neuron is given as:

$$z_k = \left(1 + \exp(-\sum_{i=1}^{m} \omega_{i,j} x_i) - \theta_j\right)^{-1} \tag{3}$$

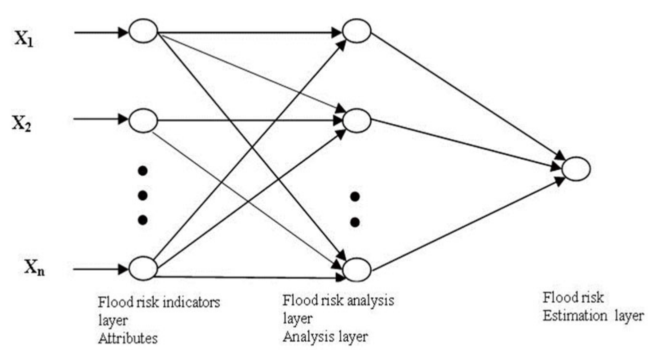

Figure 6. Architecture of HISFRM NN model

The flood risk indicators includes population density (Inhabitants/km^2), location of flood disaster area, day, month and year of incidence, housing density (Houses/km^2), drainage network length (km), population without qualifications (% of total), number of death, drainage density (km/km^2), unemployment rate (%), purchase power (related to the national mean), annual turnover (Naira), average annual rainfall (mm), density of companies (number of companies per km^2), average annual flow (mm), number of dams. GA is employed to evolve optimal connection weights and topology for the NN model to fast track and improve the predicative capability of the system.

3.1 Genetic algorithm model

In Refs.,[20,21] the GA was employed to optimize only the connection weights of NN so that it could learn better. However, in this paper, GA is adopted for choosing the topology and weights of the NN in the analysis and prediction flood risks. GA optimizes HISFRM model training parameters including number of nodes, membership functions, learning and momentum rate, and was implemented in four steps; generation of initial population, selection, crossover and mutation as described in Refs.[22–25] The basic GA implementation stages adopted are as follows steps:

- problem representation.
- initialize population randomly.
- calculate fitness value for each chromosome.
- perform selection.
- perform crossover.
- perform mutation.
- obtain the fitness values associated with every new chromosome.
- add chromosomes associated with high fitness values and delete those with lower fitness values.
- check for convergence, if the solution is not satisfactory repeat steps d to i.

Suppose a back propagation feed forward NN configuration presented in Figure 7, the detailed description of the stages of GA is that the count of nodes in the input layer is represented by i, h is the sum of nodes in the hidden layer while p describes the amount of nodes in the output layer. The weight vector from the input to the hidden layer is $\{w_{1,1}, w_{1,2}, \cdots, w_{m,q}\}$ while the weight vector from the hidden to the output layer is represented by $\{w_{1,1}, w_{1,2}, \cdots, w_{q,v}\}$. Since there is a single node in the output layer, $q = 1$; the weight vector is therefore represented as $\{w_{1,1}, w_{2,1}, \cdots, w_{q,1}\}$. The binary encoding scheme where each gene (connection weight) is represented as a binary string has the advantage of eliminating irrelevant values, but may cause significant loss of information. Real value encoding is most appropriate for NN optimization.[24] Though GA works with binary encoding, the cost function requires real values.[26] These reasons account for the fusion of binary and real-value encoding schemes. The stages involve a 5-bit binary encoding of weights and conversion of the encoded bits into real values using Equation 4. In 5-bit binary string representation, the first bit represents sign bit, (1 for positive and 0 for negative), in the range [01010, 11010].

$$R_1 = \frac{g_i}{10} \sum_{t=2}^{m} \left(b_t \, x \, 2^{m-t} \right) \tag{4}$$

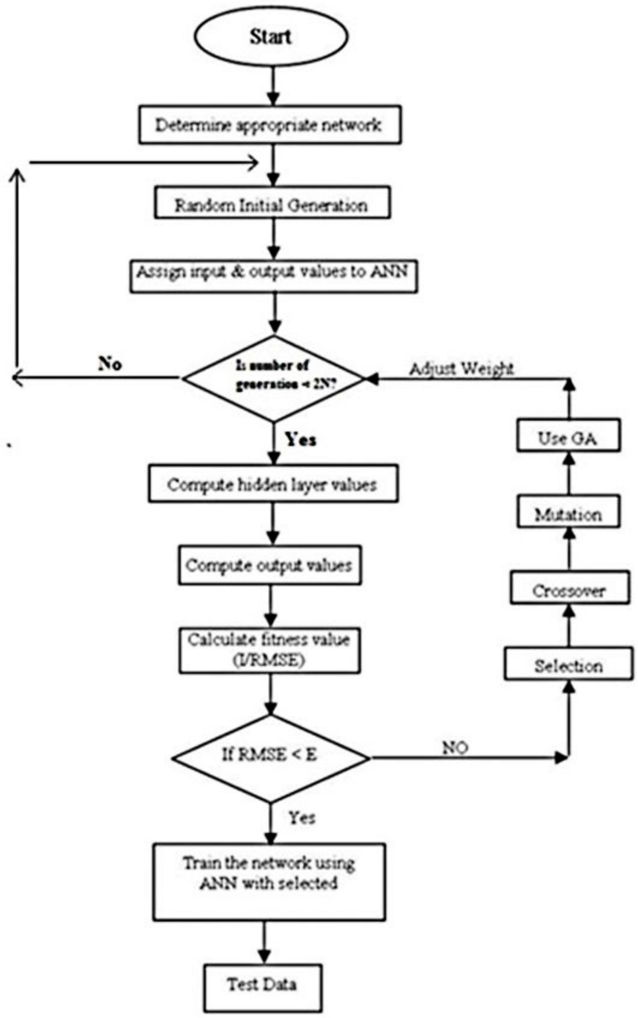

Figure 7. Flowchart for Hybridized NN and GA Algorithm

where m, is the gene length and b_t represents the sign bit, R_i gives the real-value representation of the ith gene, $t = 2, 3, \cdots 5$. g_i is a function (defined in Equation 5) that returns a value corresponding to the sign bit.

$$g_i = \begin{cases} 1 & if \quad b_i = 1 \\ -1 & if \quad b_i = 0 \end{cases} \tag{5}$$

The encoding of the chromosome with real values suitable for NN implementation is of the form $\{R-1, R-2, R-3, \cdots, R_m\}$. The flowchart representing the NN genetic hybrid algorithm is as shown in Figure 7.

The NN in this hybridized model is a backward propagation network (BPN) with 4-3-1 configuration of nodes. The four input layer nodes are the flood hazard attributes: the hidden nodes represent the likelihood of flood risk analysis. The NN configuration of (4–3-1) produces a total of fifteen (15) connection links, each with weights (w_i). The initial population of chromosomes are generated randomly encoded in a fixed order, from left to right, from top to bottom and placed in a list – Chromosome = $\{w_1, w_2, w_3, \cdots, w_{15}\}$. A population size (P) is set to 2N (where N is the total number of nodes in the network) and given as in Equation 6. The quality of each individual chromosome to the environment is measured by evaluating the fitness function (f_i) defined in Equations 6 and 7.

$$E_i = T_i - Y_i \tag{6}$$

$$f_i = \frac{1}{1 + E_i^2} \tag{7}$$

where the ith error value is represented by E_i, (high error implies low fitness), T_i represents the ith expected output, Y_i represents the ith observed output and f_i represents the fitness value of the ith chromosome. Reproduction is implemented by a selection operator. Selection is strategic for enhancing population or 'survival of the finest' operator. It adds structures with higher fitness values and drops structures with insignificant fitness values. The fitness proportionate selection technique is adopted. The fitness function is devised using algorithm in Refs.[27,28] Normalization of the Fitness values are derived from each individual chromosomes using Equation 8:

$$T_i = \frac{f_i}{\frac{1}{n}\sum_{i=1}^{n} f_i} \tag{8}$$

where T_i represents normalized fitness of the chosen chromosome while n is the sum of nodes in the NN, $i = 1, 2, \cdots n$ and f_i is the likelihood of the ith chromosome chosen for crossover and mutation operations.

(1) Arrange the population of chromosomes in descending order of its fitness values.
(2) Calculate and agglomerate the normalized fitness values ($\sum Pf_i$).
(3) Randomly choose and fix a number R between 0 and 1.
(4) Select the first individual whose normalized fitness value is greater than or equals to R (Pf_2> R).

The selection parameters are presented in Table 1. The crossover operation follows the selection operator; the pair of chromosomes with the best fitness subjected to crossover operation to produce new offsprings at the rate of 0.5.

Table 1. Selection Parameters for Flood Risk Analysis

	Chromosomes	Pf_i	Accumulated fitness (pf)
1	{$gene_1$, $gene_2$, $gene_3$ $gene_4$, $gene_5$}	Pf_1	Pf_i
2	{$gene_1$, $gene_2$, $gene_3$ $gene_4$, $gene_5$}	Pf_2	$Pf_1 + Pf_2$
3	{$gene_1$, $gene_2$, $gene_3$ $gene_4$, $gene_5$}	Pf_3	$Pf_1 + Pf_2 + Pf_3$
…	…	…	…
P	{$gene_1$, $gene_2$, $gene_3$ $gene_4$, $gene_5$}	Pf	$Pf_1 + Pf_2 + ... + Pf_p$

The mutation operator is performed by selecting k non-input units and accumulation of a random variable that lies between -1.0 and +1.0 to the weights on the edge for each incoming edge to those k units and ends after completing 2N epochs, with the selected individuals having better fitness values to represent the optimal weight vector of the NN.

3.2 Fuzzy logic model

The architecture of the FL sub-system for flood risk assessment and monitoring, as shown in Figure 8, consists of fuzzification, fuzzy inference engine and defuzzification as major modules. The decision variables and their implementation in each of these modules are given as follows:

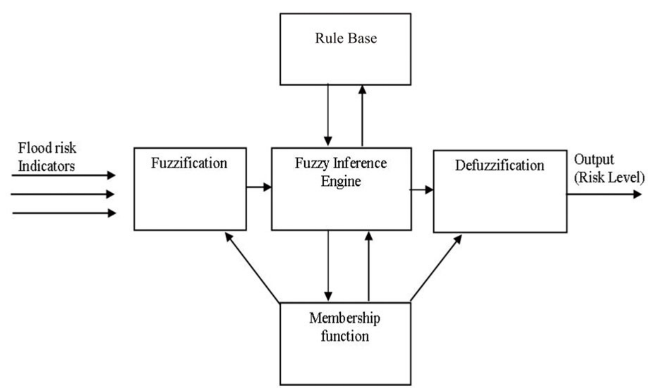

Figure 8. Block Diagram of Fuzzy Logic Model

3.2.1 *Fuzzification*

The initial stage of every fuzzy system is the conversion of the elements of the inputs space from the natural crisp universe to fuzzy universe. Measures of flood hazard and flood risks require likelihood (probability) of flood occurrence based on indicators, average volume of flood, magnitude of flood, impact of flood and risks. The fuzzy sets of each of these measures are expressed as functions while the elements of the set are mapped to Membership Function (MF). Some of the commonly used MFs are gaussian, triangular, trapezoidal, s-function and 1-function.[27] The works of Refs.[28,29] influenced the adoption of the Tiangular Membership Function (TMF) defined Equation 9.

$$\mu_{(x)} = \begin{cases} 1, & if\ x = b \\ \dfrac{x-a}{b-a} & if\ a \le x < b \\ \dfrac{c-x}{c-b} & if\ b \le x < c \\ 0, & if\ c \le x \end{cases} \tag{9}$$

where, a and c are the limits of TMF, b is area of the triangular shape represented by the value of $\mu(x)$ equals to 1 defined as $b = 1/2(a + c)$. The fuzzy variables are expressed with elements of the set "very low", "low", "medium", "high" and "very high". The linguistic expressions for the input values and their membership functions are assessed as1-point and 2-point scores as defined in Equation 10 and 11 respectively.

$$Var(x) = \begin{cases} "Very\ Low" & if\ Var(x) < 0.1 \\ "Low" & if\ 0.1 \le Var\ (x) < 0.4 \\ "Medium" & if\ 0.4 \le Var\ (x) < 0.6 \\ "High" & if\ 0.6 \le Var\ (x) < 0.8 \\ "Very\ High" & if\ 0.8 \le Var\ (x) \le 1.0 \end{cases} \tag{10}$$

$$Var(x) = \begin{cases} "Very\ Low" & if\ Var(x) \le 0.2 \\ "Low" & if\ 0.2 \le Var\ (x) \le 0.6 \\ "Medium" & if\ 0.6 \le Var\ (x) \le 1.0 \\ "High" & if\ 1.0 \le Var\ (x) \le 1.5 \\ "Very\ High" & if\ 1.5 \le Var\ (x) \le 2 \end{cases} \tag{11}$$

3.2.2 *Fuzzification of flood risks attributes*

Suppose H is a set of flood risk hazard indicators (universe of discourse), and the members of the set are denoted by x, then the set h in H is denoted by:

$$h = \{(x,\ 2\mu_h(x))\ Ix \in H,\ \mu_h(x) \in [0,1]\} \tag{12}$$

where $\mu_h(x)$ represents a set of MF of x in h and μ_h denotes the degree of membership of x in h that ranges between 0 and 1. The flood likelihood is in the range [0,1]. The linguistic terms "very low" is in the range [0,0.1,0.2], "low" in the range [0.2,0.3,0.4] while "medium" is in the range of [0.4,0.5,0.6]. "high" is in the range [0.6,0.7,0.8] and "very high" is in [0.8,0.9,1.0].

3.3 ANFIS Engine

The ANFIS engine is designed with the main objective of extracting and evaluating rules from the the knowledge base component and generating fuzzy outcomes. The model of the ANFIS for flood risk assessment and monitoring is shown in Figure 9. The model features are the likelihood of flood indicators in the input layer and gives the conditional probability (influence) of an attribute to the severity of flood derived from the NN learning by the GA components follows:

$$P_i = \frac{\sum_{j=1}^{h} \omega_{i,j}}{h} \tag{13}$$

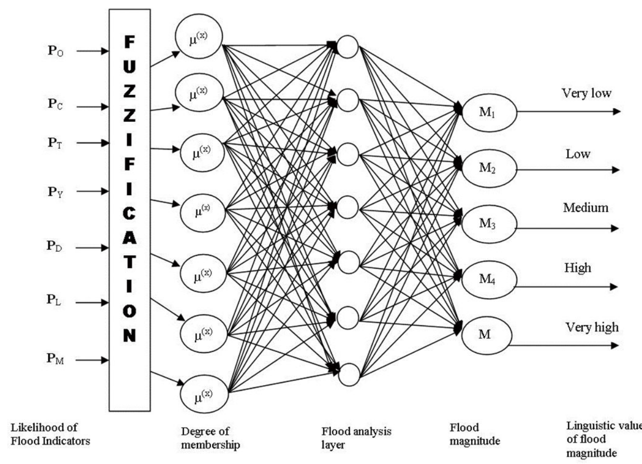

Figure 9. Neuro-Fuzzy Architecture for Flood Risk Management

where, h denotes the sum of the neurons in the hidden layer and P_i is the likelihood of the ith attribute. The ANFIS performs fuzzy inference in the stages detailed in Figure 10.

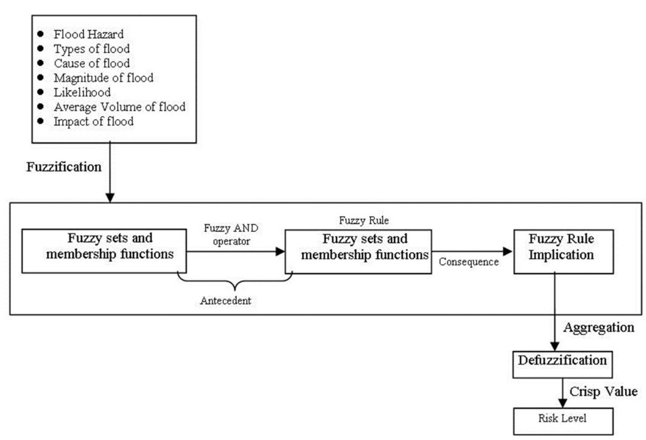

Figure 10. Model of Fuzzy Inference Procedure

As presented in Figure 10, the process of obtaining the fuzzy output consists of the following steps:

(1) Fuzzifying of linguistics variables.

(2) Determining fuzzy implication (firing strength) of each rule.
(3) Aggregating (OR operator) the fuzzy outputs of each rules to obtain the final output.
(4) Defuzzification of the overall system output.

The antecedent and implication method is adopted in this work which is driven by Mamdani's inference mechanism.[30–32] The values are picked within the defined ranges for flood hazard and the degree of membership (ji) from their respective graphs of MF is derived. The values of the flood hazard indicators and the degree of membership is presented in Table 2.

Table 2. Membership Function of Flood Indicators

Likelihood of Flood Indicators	Fuzzy set	Value(y)	μ(y)
Type of flood	Low	0.3	0.66
Location of flood	High	0.7	0.5
Day of flood	High	0.5	0.65
Month of flood	Low	0.2	0.5
Cause of flood	High	0.8	1.0
Year of flood	High	0.5	0.17

From the rule definition, the AND logic operator is applied, thereafter the Mamdani MIN operator is used to evaluate the firing level α of the rule. The implication process is performed on the rule consequent through a single value obtained from the antecedent to produce the fuzzy implication value. For example, $\alpha = 0.17$ is passed to the implication step. The weight value (w) of each rule is set to 1. The resultant antecedent value is multiplied by the weight factor to give a degree of support or firing strength for the rule $F_i = \alpha_i w_i$. If $w_i = 1t$, then

$$F_i = \alpha_i \tag{14}$$

During aggregation, fuzzy output sets of each rule derived from the implication process are agglomerated through the fuzzy MAX operator (OR operator) to produce a fuzzy set as presented in Equation 15

$$\mu_{A \cap B}(x) = \max\left[(\mu A(x),\ \mu B(x)\right] / x \varepsilon H \tag{15}$$

Assume there are N rules for flood hazard assessment and the fuzzy implication of each rule is denoted by F_i. Then F_i is the fuzzy implication (firing strength) of the ith rule, where $i = 1, 2, \cdots, N$. Then, the aggregation operator generates the final single fuzzy value.

$$F = \max(F_1, F_2, F_3, \ldots, F_N) \tag{16}$$

This will return the largest value while the output fuzzy sets has to be defuzzified to produce crisp value in the real world domain. Centroid method which produces crisp value generated by centre of area under the curve[33] is chosen as the defuzzification operator since it is the most commonly used operator. This is presented in Equation 17:

$$Z = \frac{\sum_{i=1}^{n} \alpha_i y_i}{\sum_{i=1}^{n} \alpha_i} \tag{17}$$

where Z is the expected crisp value in and now can be applied for real life decision making. α_i represents the fuzzy implication which the degree of activation of the rule to determine the ith rule. The optimal parameters of each flood hazard attribute for each level of flood risk magnitude represents the conditional probabilities of each indicator, the combined probabilities are derived from the adaptive neuro-fuzzy inference system (ANFIS).

3.4 Neuro-Genetic-Fuzzy hybrid platform

The algorithm for the design of hybrid platforms described in Ref.[34] are reviewed and adapted in the KW design through the fusion of NN and GA. In Figure 11, the NN is the hub of the system as well as the front-end subsystem. The GA subsystem provides a desirable set of parameters for optimizing the link weights and node arrangement in the NN through training while imprecision, and ambiguity of pieces of knowledge and membership function evaluation were handled by the FL sub-component. The NN unit offers generalization, adaptation, fault-tolerance and parallelism capabilities to the system. Therefore, the hybrid platform components complement each other by utilizing the strengths of constituent units while compensating for their weaknesses and adopt production rules for knowledge representation.

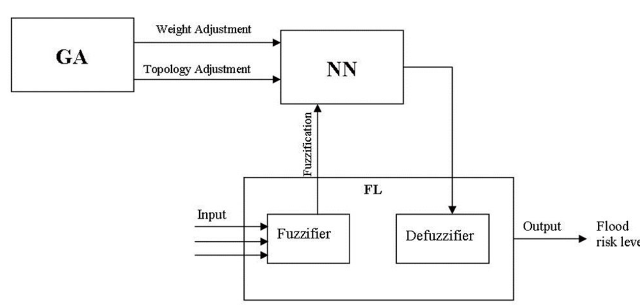

Figure 11. Block Diagram of Neuro-Genetic-Fuzzy Hybrid

Figure 12 shows the interaction of the different components as well as the procedure for the design of the KW. The design of the hybrid platform begins with the multidimensional knowledge model design, which acts as the platform for holding the pieces of knowledge, their relationship and patterns. The community profiling is performed to identify the inputs to the system which are fuzzified to make them suitable for processing by the neural network models. The GA component begins by creating an initial population of weights for the neural network models. The fuzzified inputs variables were initially encoded as 5-bit binary weights and thereafter converted into real values using Equation 4 and fed into the NN models. The adjustments of NN weights was performed by using GA operators evaluated from the GA function using Equation 8 until 2N epochs are completed and the desired NN parameters are identified and subjected for processing by ANFIS.

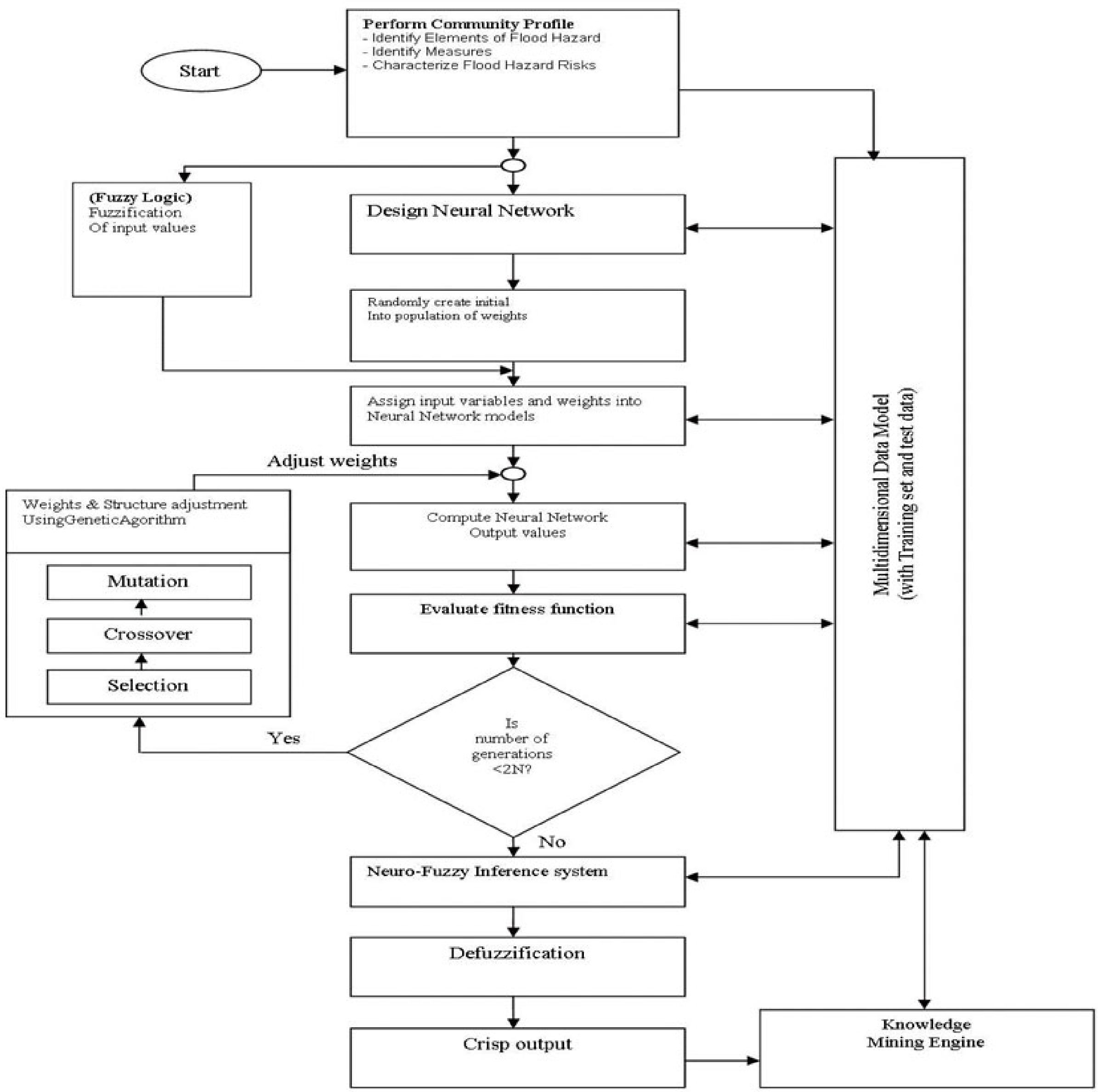

Figure 12. Procedure for neuro-fuzzy-genetic hybrid platform

A set of linguistic terms *"very low","low", "medium", "high","very high" was produced by the execution of the* fuzzifier and was passed to the ANFIS sub system. ANFIS engine evaluates the input variables based on the rules in the fuzzy rule held in the multidimensional data model, derives a set of outcomes from the rules by transforming them into a crisp values (S) by the defuzzification sub-system. The structure of the ANFIS as presented in Figure 13, consists of two categories of nodes; fixed and adaptive, arranged in six layers to implement the mamdani inference mechanism.

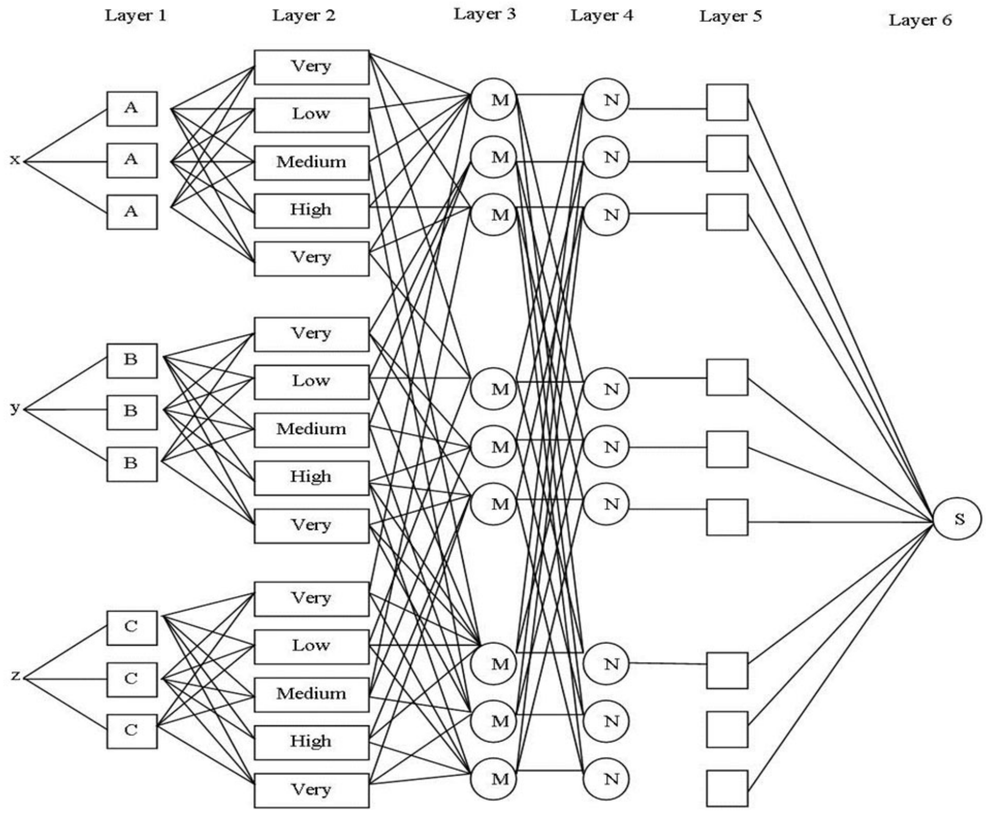

Figure 13. Architecture of Neuro-Fuzzy Inference System

3.5 Decision Support Framework (DSF)

The DSF comprises of cognitive and emotional support engines to assist the disaster mangers to form preferences in making judgements and effective decisions. The emotional component is based on the subjective feelings of the emergency management team or personnel and gets its data from the cognitive support engine. The cognitive support engine analyses the alternative output reports of the inference engine on the basis of the objective filling of the flood risk management team. For example, the occurrence of extreme risk from flood may call for immediate action which may include clean-up of the debris. The cognitive support engine uses the emergency risks information to objectively provide the line of actions to be followed by the emergency response team. Other classification of risks includes high risk (when a low impact results from a risk with high chances of occurrence), moderate risk (flood risks with low rate of occurrence but severe impact on the ecosystem), low and negligible emergency risks. The action plan for each class of risk is contained in the KW. For example, an instance of high rate of fatalities or missing persons creates emotional reasoning modes like fatigue, disappointment, stress, joy, sadness, anger, love and hate.

4. Conclusions

A neuro-genetic-fuzzy hybrid framework and an illustration of its potentials, strengths, and capabilities in the management of flood risks is proposed. The framework would assist to identify locations with significant flood risk severity. The perception of emergency risk management is very important in modern society; therefore this work provides a framework for the practical application of data mining techniques and tools to emergency risk management. The implementation technique of the system for hybrid intelligent system for flood risk management and evaluation of its performance shall be reported in our next paper. In addition, cluster analysis is necessary for the visualization of the relationships and patterns exhibited by flood hazards features.

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29

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