wjert, 2018, Vol. 4, Issue 5, 340-363. *Original Article* ISSN 2454-695X

World Journal of Engineering Research and Technology
WJERT
www.wjert.org SJIF Impact Factor: 5.218

DEVELOPMENT OF A FUZZY LOGIC MODEL FOR PREDICTING THE LIKELIHOOD OF CHOLERA DISEASE

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Article Received on 01/08/2018 **Article Revised on 20/08/2018** **Article Accepted on 10/09/2018**

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ABSTRACT

Water-borne diseases such as cholera often leads to other devastating illnesses. Most existing works developed a number of predictive models for environmental health related diseases with less emphasis on water-borne diseases. Hence, this research developed predictive model for cholera disease using Fuzzy Logic (FL).

Index Terms: Fuzzy Logic, Model, Predicting and Water Borne Diseases.

INTRODUCTION

WATER is an indispensable element to survival of both plants and animals, hardly can any plant or animal survive without water for certain limited period of time. The type of water in a particular environment has either positive or negative impact on the people living in the environment. Its uses in all living things cover a huge variety of everyday functions which are immeasurably important to the continuity of the organism. Water is a regional resource, but water shortage is becoming a global issue due to increasing population, economic growth and climate change. Water-borne diseases are any illness caused by drinking water contaminated by many factors such as human or animal faeces, which contain pathogenic microorganisms (Lenntech, 2014) Water borne diseases spread by contamination of drinking water systems with the urine and faeces of infected animal or people. In Nigeria, contaminations of drinking water with pathogens have also been reported in several towns (Bai et al., 2007). Water-borne outbreaks of enteric diseases have occurred either when public drinking water supplies were not adequately treated after contamination with surface water or when surface waters contaminated with enteric pathogens have been used for recreational purpose (Johnson et al., 2003) Today, only 58% of Nigerians have access to safe water (UNICEF and WHO, 2012). Thus, many households have to resort to drinking water from wells and streams especially in the rural and sub-urban communities. These water sources are largely untreated and might harbor water-borne and vector-borne diseases such as cholera, typhoid fever, diarrhoea, hepatitis and guinea worm (Rahman et al. 2001; Adekunle, 2004; Fenwick, 2006). In developing countries, particularly in Nigeria, the two main water problems man contends with are the quantity and quality of water (Adeniyi, 2004; Olajuyigbe, 2010). In view of its occurrence and distribution pattern, water is not easily available to man in the desirable Amount and quality. These factors have led to the growing rate of water borne diseases like typhoid fever and cholera experienced in this part of the world (Edwards, 1993).

The link between the problem of attaining safe clean water and high incidence of water borne diseases has not been clearly understood (Mudundulu, 2011). This is a serious problem that affects people all over the world, national as well as in local communities, but those living in the third world is especially the most affected. From literature, a number of predictive models have been developed by Chun Xiang et al. (2013), Fakai et al. (2013), Idowu et al. (2012), Koepke et al. (2014) and Ibrahimmal et al. (2013) to deal with different water related problems. However, these models did not take into consideration some factors that causes cholera disease after fetching water from a good source. Hence, this research developed a model for predicting the likeklihood of cholera using fuzzy logic. The most prominent reasons that justify the use of fuzzy logic systems today are (Aramideh et al, 2014):

a. The sophistication of the natural world which leads to an approximate description or a fuzzy system for modeling; and
b. The necessity of providing a pattern to formulate mankind knowledge and applying it to actual systems.

The process of development of the fuzzy inference system needed for the prediction of water related disease may be summarized as follows:

- Fuzzification of inputs and outputs;
- Construction of the inference engine;

- Rule aggregation; and
- Defuzzification of output variables.

The aim of this work is to develop a fuzzy logic model for predicting the likelihood of cholera disease. The specific objectives are to: examine the variables causing cholera in southwestern of Nigeria; formulate a fuzzy logic model for predicting the likelihood of cholera disease; simulate the formulated model in a matlab environment; and validate the formulated model based on the simulation results and the cholera disease historical data. Owing to the menace of cholera disease in Nigeria, this paper develop a predictive model to forecast the likelihood of cholera disease in Nigeria, to address the problems associated with water-borne disease. This will help the environmental health workers to educate people and aids in effective decision-making. This research work was limited to the development of a model that could predict the likelihood of water-borne disease (cholera) in south-western Nigeria. The south western Nigeria was used as a case study for Nigeria. Four local government areas were randomly selected from each state and South western Nigeria comprises of six states.

I. Related Works

Idowu (2012) Worked on development of a web based geo-spatial environmental health tracking system for Southwestern Nigeria studied and assessed the problem of environmental health, developed a spatial environmental health data and predictive models to forecast the likelihood of environmental health related diseases. This was with a view to prototyping the models for environmental health tracking. Data were collected from purposively twenty four local government areas within Southwestern Nigeria comprising of four local government areas from each of the six states. Observation and personal interview (both structured and unstructured) were also used to identify and assess environmental health problems within Southwestern Nigeria. The design of a spatial environmental health data model was done using the unified modelling language (U`ML). The model to predict the likelihood of environmental related diseases based on environmental health problems was formulated using the MATLAB Fuzzy Logic Toolbox. The prototype was developed using MySQL and PhP codes. Data collected from the local government areas was used to validate the performance of the model. The result showed that, when general sanitation, water, toilet facility and refuse disposal facility had probability of 0.000, the probability that environmental related diseases could occur was 0.870. If general sanitation, water, toilet facility and refuse disposal facility had probability of 0.500, then the probability that environmental related diseases could occur was 0.581. Also, if general sanitation, water, toilet facility and refuse disposal facility had probability of 1.00, then the probability that environmental related diseases could occur was 0.130. In addition, the performance assessment of the environmental health tracking system was done on three occasions and the average value for the three occasions was recorded. The system was accessed for 4 different xv mobile broadband networks at the radius of 100m away from their base stations. It was observed that on the average for the 4 mobile broadband networks, the response time were 2.60, 2.60, 3.00 and 3.00 seconds respectively. On the average, the response time to access the system in any mobile broadband network in Nigeria is 2.80 seconds. In conclusion, the environmental health tracking system allows real time tracking of environmental health problem with the ability to forecast the possibility of environmental health related diseases within the study area.

III MATERIALS AND METHODS

A. Research design

In this paper, a fuzzy logic-based prediction model is proposed with the aim of predicting the likelihood of water-borne disease in South western Nigeria. In order to achieve this, the research design presented in Figure 1 was used. The study started with the identification of the problem of predicting water related disease likelihood given a number of symptoms/factors considered as input variables (3 in all). A review of related literature was performed to identify understand water related disease and its symptoms in addition to related works done in the past. Following this, knowledge was elicited from an expert (medical practitioner) located at the primary health Centre Osogbo, osun state Federal Medical Center Owo, Ondo State in understanding and verifying the information concerning water related disease symptoms. The elicited knowledge was used to build the inference engine of the proposed system. This is part of the model formulation technique which also includes the fuzzification of the input and output variables. the model formulation is made complete by the identification of the aggregation method chosen for the inference engine alongside the defuzzification method required for producing the output variable which is the likelihood of water related disease –cholera-(No and Yes).

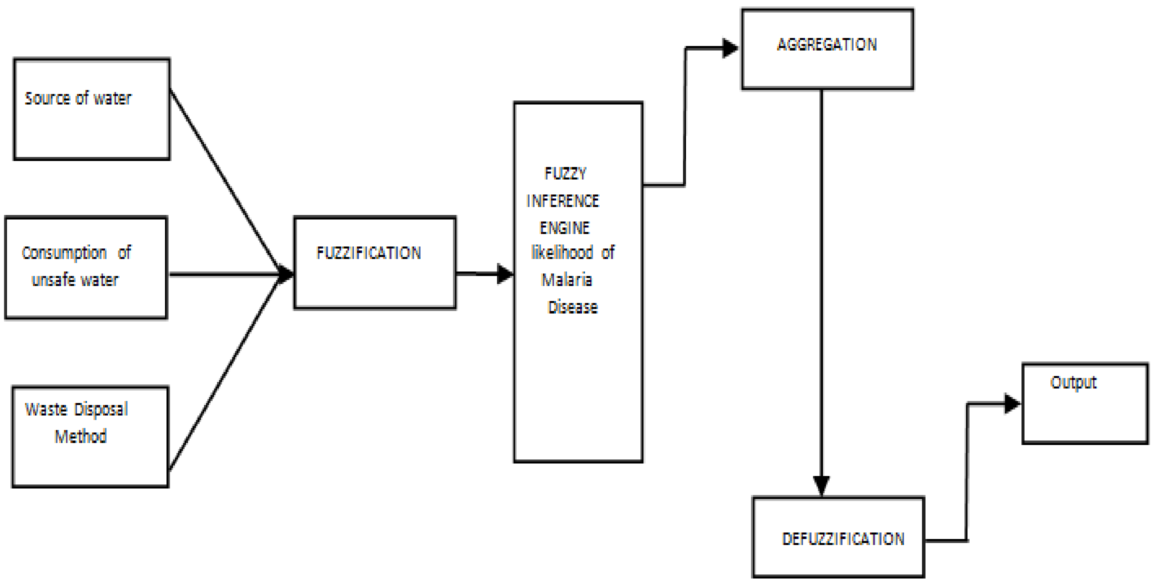

Figure 1: Schematic diagram of the model.

B. Data identification and collection

A number of symptoms/factors are known to be connected to cholera disease, among all these factors only three were identified as being the most important and relevant symptoms: the level of fetal water borne disease. This information was collected via structured interview with the medical practitioner who identified the factors and emphasized 3 main factors which are most easily used in identifying the likelihood of cholera disease based on his experience in medical practice. The water borne disease likelihood is defined as either: 0%, between 50% and 100%, and greater than 50%; the cholera was classified as either No, probable and high while the degree of likelihood of cholera is classified as either less than 50% and greater than or equal to 50%.

In addition to the identification of the data variables, an understanding of the pattern of distribution was important in identifying the best membership function that could be used in plotting the labels of each variables. The number of rules required by the fuzzy logic inference system was calculated by multiplying the labels of each variable with each other; therefore were 3*3*3 = 27 different rules Indicated in Table 1. This information was necessary in the development of the fuzzy logic inference system.

C. Fuzzy logic model formulation

In order to develop the fuzzy logic system required for the prediction of the likelihood of cholera disease, a number of activities are needed to be accomplished. The Fuzzy Logic

System available in the Fuzzy Logic Toolbox of the Matrix Laboratory 8.1(R20013a) software has three parts:

A. A set of Inputs represented by their respective membership functions;

B. An Inference Engine which contains the IF-THEN rules (domain knowledge); and

C. An Output represented by its membership functions.

The membership functions was used to map the values of each input and output variables into a [0,1] interval with the use of triangular membership functions (was appropriate); this process is referred to as a Fuzzification process. After Fuzzification; the fuzzified inputs must be mapped to the fuzzified output via the use of operators (AND, OR and NOT) to develop IF-THEN rules that describe the relationship between every input (water borne likelihood factors) and output (likelihood of the disease) variable indicated in Figure 1. The different rules are used to generate different results which are then aggregated to just one fuzzified output. This fuzzified output will then be defuzzified using the centroid method which selects the centre of the polygon to determine the label of the output variable as high, probable or No.

D. Defining membership functions

Before the process of Fuzzification, it is very important to properly describe the crisp values that were used in mapping the values of the membership function which was needed by the fuzzy logic system. For the discrete variables with nominal values or Boolean (yes/no) – the values: 0, 1, 2…... n-1 was assigned to each value for n labels; this is the case for cholera as NO=0, propable=0.2-0.4 and Yes=1. For the continuous variables which are measured; a value of the percentage expressed as a proportion of 0, 0.5and 1 was used, i.e. 0%, 50% and 100% respectively into the appropriate membership functions.

E. Fuzzification of the variables

For this paper, the triangular and trapezoidal membership functions were used to map the degree of membership of the labels of each variable used both input and output variable. Following is a description of each variable and the type of membership function used for the labels alongside the ordered pair that was used in mapping the degree of membership for each variable's label.

a. The cholera outbreak prediction model

Source of Water = (No

Consumption of unsafe water

Waste Disposal Method

For the development of the Likelihood of Cholera diseases Outbreak model; the input variables are:

a. Source of Water;

b. Consumption of unsafe water; and

c. Waste disposal method.

Likelihood of Cholera Disease: No (0), Probably (0.5) and High (1.0) indicated

Likelihood of cholera Disease = (No [-0.25 0 0.25], Probably [0.25 0.5 0.75], Yes [0.75 1 1.25]).

Following are the classification of the degree of membership of each output variable:

Likelihood of Cholera Disease: No (0), Probably (0.5) and High (1.0) indicated in Table 1. a For the likelihood of cholera disease, they are:

i. If (Source of Water = Good) and (Consumption of Unsafe water = No) and (waste disposal method = Good) then (Likelihood of cholera disease = No); and

ii If (source of water = Poor) and (consumption of unsafe water = Yes) and (waste disposal = Poor) then (Likelihood of cholera disease = Yes).

Table 1: Rule Base for cholera disease prediction model.

Rule#	Source of Water	Consumption of unsafe water	Waste disposal method	Likelihood of Cholera Disease
1	Good	Never	Good	No
2	Good	Never	Fair	No
3	Good	Never	Poor	No
4	Good	Sometimes	Good	No
5	Good	Sometimes	Fair	No
6	Good	Sometimes	Poor	Probably
7	Good	Yes	Good	Probably
8	Good	Yes	Fair	Probably
9	Good	Yes	Poor	Probably
10	Fair	Never	Good	Probably
11	Fair	Never	Fair	Probably
12	Fair	Never	Poor	High
13	Fair	Sometimes	Good	No
14	Fair	Sometimes	Fair	No
15	Fair	Sometimes	Poor	Probably
16	Fair	Yes	Good	Probably
17	Fair	Yes	Fair	Probably
18	Fair	Yes	Poor	High

19	Poor	Never	Good	No
20	Poor	Never	Fair	Probably
21	Poor	Never	Poor	High
22	Poor	Sometimes	Good	Probably
23	Poor	Sometimes	Fair	High
24	Poor	Sometimes	Poor	Probably
25	Poor	Yes	Good	Probably
26	Poor	Yes	Fair	High
27	Poor	Yes	Poor	High

F. Simulation of the Formulated Fuzzy Logic Model

The simulation and analysis of FIS model was done in the MATLAB environment using historical water-borne disease data. After the development of the Fuzzy Inference System for the prediction of the likelihood of water-borne disease in south-western part of Nigeria, the developed model was simulated for their functionality and effectiveness. In the simulation of the model, information from 27 patients who were diagnosed by doctors in a hospital in south-western Nigeria was taken; twenty seven (27) was taken for cholera disease. The variable that was used by the doctors in diagnosing the disease was used as inputs for the model developed using the fuzzy logic inference engine.

G. Validation of the developed Fuzzy Logic Model

The simulation result for the model and historical data were used to validate the performance of the model to judge the performance of the result of the model developed. This was done with the use of a confusion matrix. The confusion matrix gave the results of the actual result along the horizontal/row while the predicted results are on the vertical/columns. Correct classifications were plotted along the diagonal from the North-west position for the no cases predicted as no, followed by probably predicted as probably and high predicted as high on the south-east corner (also called true positives and negatives). The incorrect classifications were plotted in the remaining cells of the confusion matrix (also called false positives).

The developed model was validated for the functionality and effectiveness. In the validation of developed model; information from 27 patients who were diagnosed by doctors in a hospital in south-western Nigeria was taken; twenty seven (27) was taken for cholera disease. The variable that was used by the doctors in diagnosing the disease was used as inputs for the model developed. The data collected for the cholera disease likelihood contained 6, 16 and 5 cases for No, Probably and high respectively. The validation of the developed model was carried out using t-test. Two hypotheses were identified for the test. The data analysis is carried out using Table 2.

Let the null hypothesis be and the alternative hpothesis be

H_0: There is no significant difference between the simulated and real data

H_1: There is significant difference between simulated and real data.

$$\overline{X}_1 = \frac{\sum X_1}{n_1} \quad (3.1)$$

$$\overline{X}_2 = \frac{\sum X_2}{n_2} = \frac{45}{9} = 5 \quad (3.2)$$

$$S_1^2 = \frac{\sum X_1^2}{n_2} - \overline{X}_1^2 = \frac{261}{9} - 5^2 \quad (3.3)$$

$$S_1^2 = 29 - 25 = 4 \quad (3.4)$$

$$S_2^2 = \frac{\sum X_2^2}{n_2} - \overline{X}_2^2 = \frac{253}{9} - 5^2 = 3.1111 \quad (3.5)$$

Let t_{cal} represent t-calculated.

$$\therefore t_{cal} = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1+n_2-2}\left(\frac{1}{n_1}+\frac{1}{n_2}\right)}} \quad (3.6)$$

$$= \frac{5-5}{\sqrt{\frac{(9-1)\times 4 + (9-1)\times 3.1111}{9+9-2}\left(\frac{1}{9}+\frac{1}{9}\right)}} \quad (3.7)$$

$$t_{cal} = \frac{0}{\sqrt{\frac{8\times 4 + 8\times 3.1111}{16}\left(\frac{2}{9}\right)}} \quad (3.8)$$

$$t_{cal} = 0$$

t_{table}-at the level of significan t 0.05 is given by 1.75.

Since t_{cal} is less than $t_{cal} (<) t_{table}$, then, the null hypothesis H_0 is accepted while the alternative hypothesis H_1 is rejected. Therefore, it can be concluded that there is no significant difference between the simulated and real data.

Table 2: Data Analysis Table.

Actual likelihood (X_1)	Predicted likelihood (X_2)	X_2^1	X_2^2
4	5	16	25
9	7	81	49
2	3	4	9
5	4	25	16
7	8	49	64
3	3	9	9
4	3	16	9
6	6	36	36
5	6	25	36
$\sum X_2 = 45$			$\sum X_2^2 = 253$

I. Fuzzy logic model formulation results

The formulation results for membership functions that were developed for the model are as follows:

Cholera disease likelihood prediction model

Each membership function for cholera disease model is described as follows: Source of Water = (Good [-0.25 0 0.25], Fair [0.25 0.5 0.75], Poor [0.75 1 1.25])

$$\text{Source Of Water} \quad (Good; -0.25\ 0\ 0.25) = \begin{Bmatrix} 0, & x > -0.25 \\ \frac{x+0.25}{0.25}, & -0.25 < x \leq 0 \\ \frac{0.25-x}{0.25}, & 0 < x \leq 0.25 \\ 0, & 0.25 > x > 0.25 \end{Bmatrix}$$

$$\text{Source Of Water} \quad (Fair; 0.25\ 0.5\ 0.75) = \begin{Bmatrix} 0, & x \leq 0.25 \\ \frac{x-0.25}{0.25}, & 0.25 < x \leq 0.5 \\ \frac{0.75-x}{0.25}, & 0.5 < x \leq 0.75 \\ 0, & 0.75 < x > 0.75 \end{Bmatrix}$$

$$\text{Source Of Water} \quad (Poor; 0.75\ 1\ 1.25) = \begin{Bmatrix} 0, & x \leq 0.75 \\ \frac{x-0.75}{0.25}, & 0.75 < x \leq 1 \\ \frac{1.25-x}{0.25}, & 1 < x \leq 1.25 \\ 0, & 1.25 < x > 1.25 \end{Bmatrix}$$

Consumption of unsafe water = (Never [-0.25 0 0.25], Sometimes [0.25 0.5 0.75], Yes[0.75 1 1.25])

$$\text{Consumption Of Unsafe Water } (Never; -0.25\ 0\ 0.25) = \begin{Bmatrix} 0, & x \le -0.25 \\ \frac{x+0.25}{0.25}, & -0.25 < x \le 0 \\ \frac{0.25-x}{0.25}, & 0 < x \le 0.25 \\ 0, & 0.25 < x > 0.25 \end{Bmatrix}$$

$$\text{Consumption Of Unsafe Water } (Sometimes; 0.25\ 0.5\ 0.75) = \begin{Bmatrix} 0, & x \le 0.25 \\ \frac{x-0.25}{0.25}, & 0.25 < x \le 0.5 \\ \frac{0.75-x}{0.25}, & 0.5 < x \le 0.75 \\ 0, & 0.75 < x > 0.75 \end{Bmatrix}$$

$$\text{Consumption Of Unsafe Water } (Yes; 0.75\ 1\ 1.25) = \begin{Bmatrix} 0, & x \le 0.75 \\ \frac{x-0.75}{0.25}, & 0.75 < x \le 1 \\ \frac{1.25-x}{0.25}, & 1 < x \le 1.25 \\ 0, & 1.25 < x > 1.25 \end{Bmatrix}$$

Waste Disposal Method = (Good [-0.25 0 0.25], Fair [0.25 0.5 0.75], Poor [0.75 1 1.25])

$$\text{Waste Disposal Method } (Good; -0.25\ 0\ 0.25) = \begin{Bmatrix} 0, & x \le -0.25 \\ \frac{x+0.25}{0.25}, & -0.25 < x \le 0 \\ \frac{0.25-x}{0.25}, & 0 < x \le 0.25 \\ 0, & 0.25 < x > 0.25 \end{Bmatrix}$$

$$\text{Waste Disposal Method } (Fair; 0.25\ 0.5\ 0.75) = \begin{Bmatrix} 0, & x \le 0.25 \\ \frac{x-0.25}{0.25}, & 0.25 < x \le 0.5 \\ \frac{0.75-x}{0.25}, & 0.5 < x \le 0.75 \\ 0, & 0.75 < x > 0.75 \end{Bmatrix}$$

Likelihood of Cholera Disease = (No [-0.25 0 0.25], Probably [0.25 0.5 0.75], Yes[0.75 1 1.25]).

$$\text{Likelihood Of Cholera Disease } (No; -0.25\ 0\ 0.25) = \begin{Bmatrix} 0, & x \le -0.25 \\ \frac{x+0.25}{0.25}, & -0.25 < x \le 0 \\ \frac{0.25-x}{0.25}, & 0 < x \le 0.25 \\ 0, & 0.25 < x > 0.25 \end{Bmatrix}$$

$$\text{Likelihood Of Cholera Disease} \quad (Probably; 0.25\ 0.5\ 0.75) = \begin{cases} 0, & x \leq 0.25 \\ \dfrac{x - 0.25}{0.25}, & 0.25 < x \leq 0.5 \\ \dfrac{0.75 - x}{0.25}, & 0.5 < x \leq 0.75 \\ 0, & 0.75 < x > 0.75 \end{cases}$$

Table 3: Results of testing Cholera Prediction model on patients.

S. N.	Source of Water	Consum-ption of unsafe water	Waste disposal method	Likelihood of Cholera Disease	
				Actual	Predicted
1	Good	Poor	Good	No	No
2	Good	Poor	Fair	No	No
3	Good	Poor	Poor	No	No
4	Good	Fair	Good	No	Probably
5	Good	Fair	Fair	Probably	Probably
6	Good	Fair	Poor	Probably	Probably
7	Good	Good	Good	No	No
8	Good	Good	Fair	Probably	Probably
9	Good	Good	Poor	Probably	Probably
10	Fair	Poor	Good	No	No
11	Fair	Poor	Fair	Probably	Probably
12	Fair	Poor	Poor	No	No
13	Fair	Fair	Good	Probably	Yes
14	Fair	Fair	Fair	Probably	Yes
15	Fair	Fair	Poor	Probably	Probably
16	Fair	Good	Good	Yes	Yes
17	Fair	Good	Fair	Probably	Probably
18	Fair	Good	Poor	Probably	Probably
19	Poor	Poor	Good	Yes	Yes
20	Poor	Poor	Fair	Probably	Probably
21	Poor	Poor	Poor	Probably	Probably
22	Poor	Fair	Good	Probably	Probably
23	Poor	Fair	Fair	Probably	Probably
24	Poor	Fair	Poor	Probably	Probably
25	Poor	Good	Good	Yes	Yes
26	Poor	Good	Fair	Probably	Probably
27	Poor	Good	Poor	Yes	Probably

$$\text{Likelihood Of Cholera Disease} \quad (Yes; 0.75\ 1\ 1.25) = \begin{cases} 0, & x \leq 0.75 \\ \dfrac{x - 0.75}{0.25}, & 0.75 < x \leq 1 \\ \dfrac{1.25 - x}{0.25}, & 1 < x \leq 1.25 \\ 0, & 1.25 < x > 1.25 \end{cases}$$

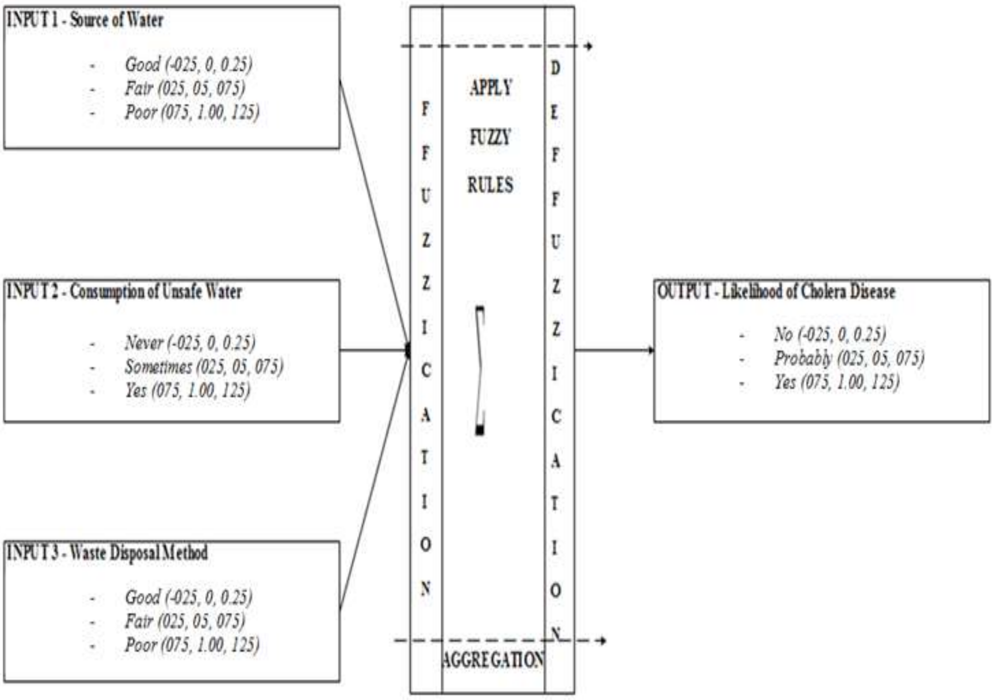

Figure 2: Schematic diagram of model for Cholera Disease Likelihood Prediction.

A. Simulation Result of the formulated Fuzzy Logic Model

The simulation result of the model recorded using the data collected from twenty seven (27) patients as shown in Tables3 is depicted in Figures 2 and discussed as follows; The model provided a view also called the surface view which shows the relationship between each variable with respect to the likelihood of water-related diseases which in the case of this research is Cholera.

The result of cholera FIS model reflected in Figure3 showing the relationship between two variables with respect to the likelihood of cholera that is, the relationship between consumption of unsafe water and the source of water which indicates the following observations: the

likelihood of cholera disease is No and Probably (0 – 0.5) if the consumption of unsafe water is Never and Sometimes (0.0 – 0.6) and the source of water is also good (0 – 0.2) also, the likelihood of cholera disease is Probably and High (0.5 – 1.0) if the consumption of unsafe water is Yes (0.6 – 1.0) and the source of water is fair and high (0.2 – 1.0). Figure 4 surface diagram shows the relationship between waste disposal method and consumption of unsafe water which indicates the following observations: the likelihood of cholera disease is No and Probably (0 – 0.5) if the waste disposal method is Good and fair (0 – 0.7) and the consumption of unsafe water is Never and Sometimes (0 – 0.7) also, the likelihood of cholera disease is Probably and High (0.5 – 1.0) if the waste disposal method is Poor (0.7 – 1.0) and the consumption of unsafe water is Yes (0.7 – 1.0)

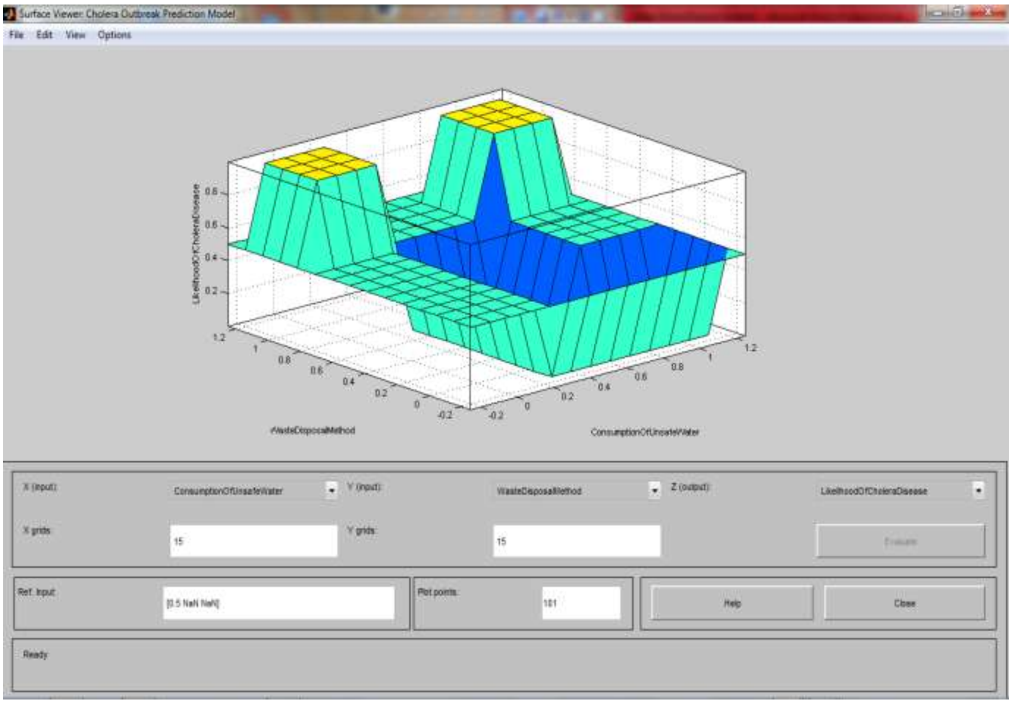

Figure 3: Surface diagram of relationship between consumption of unsafe water and source of water.

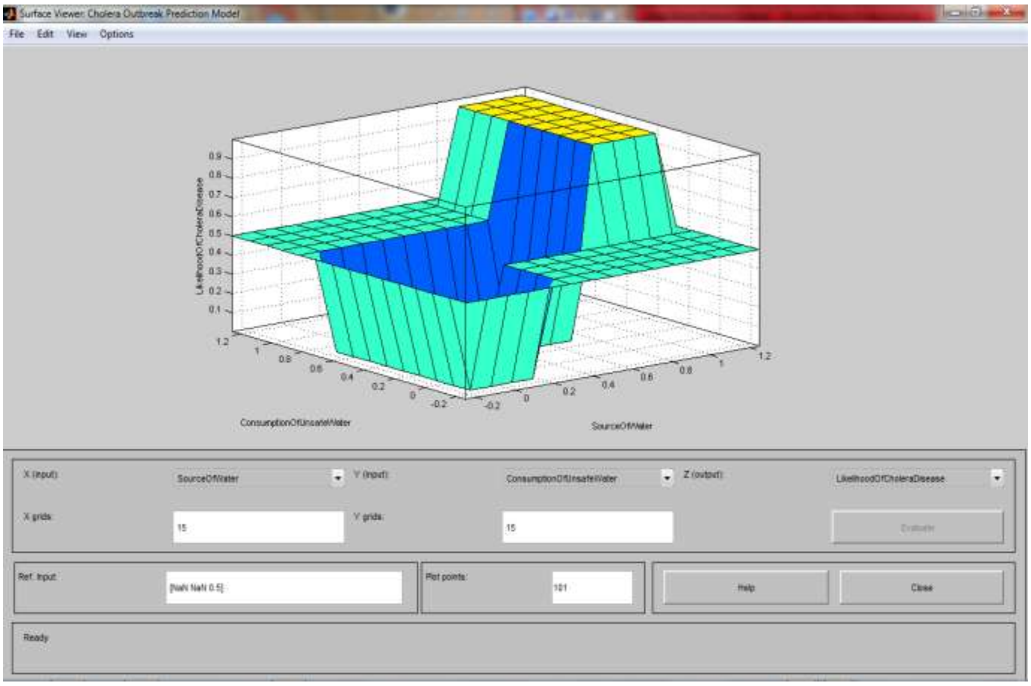

Figure 4: Surface diagram showing the relationship between waste disposal method and consumption of unsafe water.

B. Validation Result of Water-borne Disease Prediction Models

The validation results of developed model for the cholera disease likelihood prediction model is shown in Figure 5 and depicted in Table 4 and, out of the total 27 cases there were 23 correct classifications and 4 incorrect classifications which showed the following distributions. Out of the 7 No cases, 6 was correct while 1 was probably. Out of the 16 probably cases, there was 14 correct classifications and 2 misclassification as yes. Out of the 4 High cases there was 1 misclassification and 3 correct classification.

The validation results of developed model for the cholera disease likelihood prediction model is shown in Figure 5 and depicted in Table 3 and, out of the total 27 cases there were 23 correct classifications and 4 incorrect classifications which showed the following distributions. Out of the 7 No cases, 6 was correct while 1 was probably. Out of the 16 probably cases, there was 14 correct classifications and 2 misclassification as yes. Out of the 4 High cases there was 1 misclassification and 3 correct classification. The number of correct classifications shows that the cholera disease prediction model has an accuracy of 85.19% as shown Table 5.

Figure 5: Confusion matrix for the result of the cholera disease prediction

$$\begin{array}{c} \begin{array}{ccc} \text{No} & \text{Probably} & \text{Yes} \end{array} \\ \left(\begin{array}{ccc} 6 & 1 & 0 \\ 0 & 14 & 2 \\ 0 & 1 & 3 \end{array}\right) \end{array} \begin{array}{l} \\ \text{No} \\ \text{Probably} \\ \text{Yes} \end{array}$$

Table 4: Results of the test of prediction models showing the actual and predicted results.

Data Sets	Cholera Disease Likelihood		
	No	Probably	Yes
Predicted Likelihood	6	16	5
Actual Likelihood	7	16	4

CONCLUSION

The Study developed predictive model for cholera disease. The model identified the risk factors of cholera from public health officers in south-western Nigeria. Data was collected from 27 patients for cholera based on the identified risk factors. The study used triangular membership functions with three (3) values to fuzzify the input variables of the identified water-borne diseases.Rules were formulated by the environmental health officers for the construction of the inference engine of the fuzzy inference system of the prediction model for cholera disease.

Simulation of the developed fuzzy logic model was carried out using the MATLAB software for the choleral disease in this study. Three fuzzy logic models were formulated for cholera. The study identified

Table 5: Performance evaluation results of the validation of the cholera, Diarrhoea and Dysentery diseases likelihood prediction models.

Performance Metrics	Cholera Disease Likelihood		
Accuracy (%)	85.19		
Likelihood	No	Probably	Yes
TP rate (recall) or Sensitivity	0.857	0.857	0.750
FP rate (false alarm)	0.000	0.182	0.087
Precision	1.000	0.875	0.600
Specificity	1.000	0.818	0.913

Source of water, consumption of unsafe water and waste disposal methods as factors of cholera. The study validated the fuzzy logic model for the cholera disease based on the data collected. The study concluded that based on the validation of the model, it was observed that the fuzzy logic model had performance of at least 70% with the model for cholera having 85% accuracy The study concluded that the fuzzy logic model would provide an effective means for the detection and management of cholera disease thereby improving decision-making process.

REFERENCES

1. Abraham, B. & Nath, S. "Hybrid Intelligent Systems Design", A Review of aDecade Research, Journal of the School of Computing and Information Technology, Monash, Australia, 2003; 1: 1-37.
2. Adebayo Peter Idowu A Spatial Data Model for Environmental Health Surveillance System in Nigeria. Journal of Research in Science, Technology, Engineering and Management, 2015; 1(1): 7-15.
3. Adekunle, L.V.; Sridhar, M.K.C.; Ajayi, A.A.; Oluwande, P.A. & Olawuyi, J.F. An assessment of the health and socio economic implications of sachet water in Ibadan: A public health challenge. Afr. J. Biomed. Res., 2004; 7: 5-8.
4. Adeniyi, I.F. The concept of water quality. Ife Environmentalist, Official Bulletin of Nigerian Society for Environmental Management (NISEM) O.A.U., 2004; 1(1): 2.
5. Akinyokun, O.C., & Adeniji, O.A. "Experimental Study of Intelligent Computer Aided Medical Diagnosis and Therapy", Association for the Advancement of Modeling and Simulation Techniques in Enterprises (AMSE); Journal of Modeling, Simulation and Control; France, 1991; 27(3): 1-20.
6. Akinyokun, O.C. & Shogbon, J.A "A Framework for Neuro-Fuzzy Expert System for Capital Investment Appraisal", Journal of the Institute of Chartered Accountants of Nigeria, Published by the ICAN, 2006; 56-65.
7. Alayon, S., Robersyon, R., Warfield, S. K., and Ruiz-Alzoa J. A Fuzzy System Forhelping Medical Diagnosis Malformations of Cortical Development. Journalof Biomedical Information, 2007; 40: 221-235.
8. Aleix, M.M. and Manli, Z. "Where Are Linear Feature Extraction Methods Applicable IEEER Transaction on Pattern Analysis and Machine Intelligence, 2005; 27: 12: 1934-1944.
9. Ambler, W. The object primer: Agile model driven development with UML 2.0. 1st ed. Canada: Wiley Publishing, 2003; 23-77.
10. Anderson, J.A. "Cognitive and Psychological Computation with Neural Models", IEEE Trans Sys Man Cyb SCM, 1983; 13: 799-815.
11. Anderson LJ, MS Brumbaugh, RB Jackson. Water and tree-understory interactions: a natural experiment with oak wilt in a savanna ecosystem. Ecology, 2001; 82: 33-49.
12. Arikpo, A., Etor, R., & Usang, E. Development imperatives for the twenty-first century In Nigeria. Convergence, 2007; 40(1/2): 55-66. Retrieved from http://www.uk.sagepub.com /journals/Journal201774.

13. Aramideh, J., Jelodar, H. Application of Fuzzy logic for presentation of an expert system to diagnose anemia. Indian Journal of Science and Technology, 2014; 7(7): 933-938. July 2014. ISSN: 0974-6846.
14. Bagis "Fuzzy rule base design using tabular search algorithm for nonlinear System modelling", *ISA Transactions*, 2008; *47:* 32–44.
15. Balanica, V., Dumitrache, I., Caramihai, M., Rae, W., and Herbst C. Evaluation of Breast Cancer Risk using Fuzzy Logic. *UPB, Science Bulletin Series C.*, 2011; *73(1):*53-64.
16. Bai T.; Shui L.; Sun L. and Wang J. Application of GIS in response to public health emergency. *Strait Journal of Preventive Medicine*, 2007; 13(2): 75-76.
17. Berger, M., Rita Shiau, R. and Weintraub, J.M. Evidence based policy and practice: review of syndromic surveillance: implications for waterborne disease detection Journal of Epidemiology and Community Health J Epidemiol Community Health, 2006; 60: 543-550. doi:10.1136/jech.2005.038539.
18. Berman, M.G., Jonides, J., Kaplan, S. *The cognitive benefits of interacting with nature*. Psychological Science, 2009; 19(12): 1207-1212.
19. Bullinaria, J. A. Biological Neurons and Neural Networks, Artificial Neurons. Neural Computation: Lecture, 2012; 2.
20. Carpenter, G.A, Grossberg, S. and Rosen, D.B. Fuzzy ART: "*Fast Stable Learning and Categorisation of Analog Patterns by an Adaptive Resonance System*". Neural Networks, 1991; 4: 759-771.
21. Centres for Disease Control and Prevention Public health conceptual data model, *US department of health and human services public health service*, Available from: www.cdc.gov/nedss/DataModels/phcdm.pdf [Accessed 3 Dec, 2015], 2000.
22. Craun, G. F., *Gunther F.* Craun and Associates, Staunton, *Virginia The importance of waterborne disease outbreak surveillance in the United States* Ann Ist Super Sanità, 2012; 48(4): 447- 459 447.
23. Chun Xiang C., Duo Chun W., Biao K., Biao J., Biao 1, YunFei X. And Xiao Wen L. *District Prediction of Cholera Risk in China based on environmental factors Preventive Medicine Hygienics*, 2013; 58(23): 2798-2804.
24. Corner R.J., Dewan1 A. M. and Hashizume M. *International Journal of Health Geographics,* http://www.ij-ealthgeographics.com/content/12/1/13 doi:10.1186/1476-072X-12-13, 2013.

25. Dom, R.M., Kareem, S.A., Aabidin, a., Kamaruzaman, a. and Kajindran, a. the prediction of aidssurvival: a data Mining Approach Analysis with Fuzzy Model., *IEEE Transactions on Systems, Manand Cybernetic,* 2009; 12(6): 1982: 903 – 907.
26. Edwards, D. D. Trouble waters in Milwaukee. WHO Regional Epidemiology: Man and Disease, 1993; 93-109.
27. Ekiye, E. and Luo Zejiao Water quality monitoring in Nigeria; Case Study of Nigeria's industrial cities. *[Journal of American Science, 2010*; 6(4): 22-28]. (ISSN: 1545-1003).
28. Fenwick, A. *Waterborne infectious diseases- Could they be consigned to history*? Science, 2006; 313: 1077-1081.
29. Ganiyu, R.A. *Modelling And Simulation of Multi-Phase Traffic Light Controlled Intersections Using Tine Coloured Petrinets* an Unpublished PhD., 2011.
30. Gleick P. H., Dirty Water*: Estimated Deaths from Water-Related Disease 2000-2020,* Pacific Institute Research Report, 2002.
31. Hamed M. M., Khalafallah M. G., Hassanien E. A. *Prediction of wastewater Treatment plantperformance using artificial neural networks.* Environ. Model. Soft, 2004; 19: 919-928.
32. Hill, G., Horstkotte, E. & Teichrow, J. *Fuzzy-C development system – users' manual*, Togai Infralogic, 30 Corporate Park, Irvine, CA 92714, USA, 1990.
33. Hopkins, R. S., Gaspard, G. B., Williams, F. P., Karlin, R. J, Cukor, G., and Bladlow N. R *A community waterborne gastroenteritis outbreak: evidence for rotavirus as the agent*. Am J Public Health, 1984; 74: 263-265.
34. Idowu, P. A. Development of a Web Based Geo-spatial Environmental Health Tracking System for Southwestern Nigeria. *I.J. Information Technology and Computer Science,* 2012; 7: 61-71. (http://www.mecs-press.org/) DOI: 10.5815/ijitcs.2012.07.08.
35. Ifabiyi, I.E. Spatial distribution and performance of water pumps in the rural areas of Kaduna State, Nigeria before the Second Republic. *European Journal of Social Sciences*, 2011; 25(3): 15-25.
36. Innocent, P.R. "*Fuzzy Symptoms and a Decision Support-Index for the Early Diagnosis of Confusable Diseases*", Proceedings of the RASC Conference, Centre for Computation Intelligence, Dept of Computing Science. De Montfort University Liecester, 2000; 125-138.
37. Ibrahima, *et al Mapping and predicting waterborne diseases in Nouakchott (Mauritania*): improving public health interventions by using integrated geospatial models *Geospatial Health*, 2013; *8(1): 53-63.*

38. Ismail, Z., and Efendy, R., "Enrolment forecasting based on modified weight fuzzy time series". *Journal of Artificial Intelligence*, 2011; *4(1)*: 110-118.
39. Jang, J.S.R. and Gulley, N. "*Fuzzy Logic Toolbox*", The Math Works Inc., 24 Prime Park Way Natick, Mass. 01760-1500, 1995.
40. Jantzen, J, Axer, H, & Diedrich, G.K "*Diagnosis of Aphasia Using Neural and Fuzzy Techniques"*, jj@iau.dtu.ak, Dept of Automation bldg 326, DK 2800 Kongens Lyngby, Denmark, 2002.
41. Johnson, J.Y.M.; Thomas, J.E.; Graham, T.A.; Townshends, I.; Byrne, J.; Selinger, L.B.& Gannon V.P.J., *Prevalence of Escherichia coli 0157:H7 and Salmonella spp. in surface waters of Southern Alberts and its relation to manure source*. Canadian J. Microbiol., 2003; 49: 326-335.
42. John, R. I, and Innocent, G Type-2 *Fuzzy Sets and Neuro-Fuzzy Clustering of Radiographic Tibia Images*, Proceedings of the 7th International Conference Fuzzy Systems, FUZZIEEE, 1998; 1373-1376.
43. Juang, C. F and Lin, C. T "*An Online Self Constructing Neural Fuzzy Inference Network and its Applications*", IEEE transactions on Fuzzy Systems, 1998; 6(1): 12-32.
44. Kavanagh, N.J. *The demand for water: policy issues and empirical evidence*. /. *Instn Wat. Engrs*, 1967; 21(3): 305-314.
45. Keller, J.M. and Hunt, D.J. "*Incorporating fuzzy membership functions into the Perceptron algorithm, in Fuzzy models for pattern recognition*" (Bezdek and Pal, 1992), 1985; 468-474.
46. Koepke A. A., Longini I.M., Halloran M. E., Jon W, and Minin V.N. Predictive Modeling of Cholera Outbreaks in Bangladesh *The Journal of Chemical Physics*, .arXiv:1402.0536v1, 2014; 106(494): 440-451.
47. Khanale, P.B., and Ambilwade, R.P., A Fuzzy Inference System for Diagnosis of Hypothyroidism. *Journal of Artificial Intelligence*, 2011; 4(1): 45-54.
48. Kuncheva, L.I and Steimann, F. "*Fuzzy Diagnosis in Medicine, Artificial Intelligence in Medicine",* Elsevier Science, 1999; 16: 121-128.
49. Lamikanra, A. & Okeke, I.N. *A study of the effect of the urban/rural divide on the incidence of antibiotic resistance in Escherichia coli.* Biomed. Lett., 1997; 55: 91-97.
50. Lee, S. C. and Lee, E.T. "*Fuzzy neural networks, in Fuzzy models for pattern recognition*" (Bezdek and Pal, 1992), 1975; 448-467.
51. Lenntech B.V. *The United Nations World Water Development Report 'Water for people Water life'*, 2014; 102-106.

52. Linkens, D.A., and Mahfouf, M., The Intelligent Systems in Biomedicine Laboratory in the Department of automatic Control and Systems Engineering at the University of Sheffield, UK. *Artificial Intelligence for Medicine*, 2001; 21: 171- 176.
53. Lin, C. T. and. Lu, Y. C. "*A neural fuzzy system with linguistic teaching signals*", IEEE Transactions Fuzzy Systems, 1995; 3(2): 169-189.
54. Malowany, J.I., Butany, J. Pathology of sickle cell disease. *Seminars in Diagnostic Pathology*, 2012; 29(1): 49-55.
55. Mishra, N., Jha, P. (2014) Framing Fuzzy Rules using Mamadani Model for Effective Sickle Cell Diagnosis. *International Journal of Engineering Sciences and Research Technology*, June 2014: 3(6): 389-396. ISSN: 2277-9655.
56. Mathworks Fuzzy Logic Toolbox™ User's Guide, The Math Works, Inc. Natick, US., 2011.
57. Montosi E., Montosi S., Porporato A., and Montanari A. *An ecohydrological model of malaria outbreaks Correspondence to:* E. Montosi Published in Hydrol. Earth Syst. Sci. Discuss.: 5 March 2012Hydrol. Earth Syst. Sci., 2012; 16: 2759–2769, www.hydrol-earth-syst-sci.net/16/2759/2012/.
58. Mudundulu, P *Water Borne Diseases: A Cry of a Trapped Community. Community and Regional Planning Program*: Student Projects and Theses *University of Nebraska-Lincoln*, 2011.
59. Nauk, D. and Kruse, R. "*A Neuro Fuzzy Controller Learning by Fuzzy Error Propagation* in Proceedings of Conference of the North American", Fuzzy Information Proceedings Society afips'92, Mexico, 1992; 388-397.
60. Nzeakah, G. *Nigeria in the light of UNDP index*. Sunday Punch, November, 2006; 19: 19.
61. Nguyen, H.T and Wlaker, E.A *A First Course in Fuzzy Logic*, CRC Press Inc. London, 1996.
62. Obeagu, E.I., Ogbuabor, B.N., Ikechukwu, O.A., Chude, C.N. *Haematological parameters among sickle cell anemia patients' state and haemoglobin genotype AA individuals* at Michael Okpara University of Agriculture, Umudike, Abia State, Nigeria. *International Journal of Current Microbiology and Applied Sciences*, 2014; 3(3): 1000 – 1005, ISSN: 2319-7706.
63. Obot, O.U. "*A Neuro-Fuzzy Expert Synjmstem Model for the Diagnosis and Therapy of Cardio-ocular Diseases*". Unpublished Ph. D Thesis, Federal University of Technology Akure, 2007.

64. Oguntoke, O. *Assessment of Blood and Urine lead levels of some pregnant women residing in Lagos, Nigeria*". Environmental Monitoring Assessment, 2009; 170: 67-474.
65. Okeke, I.N.; Abiodun, O.A.; Byarugaba, D. K.; Ojo, K.K. & Opintan, J. A. *Growing problem of multidrug-resistant enteric pathogens in Africa*. *Emerg. Infect. Dis.*, 2007; 13(11): 1640-1646.
66. Olajuyigbe, A.E. *Some factors impacting on the quantity of water used by households in a rapidly urbanizing state capital in south western Nigeria*. J. Sustainable Dev. in Afr., 2010; 12(2): 322-337.
67. Rahman, G.A.; Abubakar. A.M., Johnson, A.W. & Adeniran, J.O. *Typhoid ileal perforation in Nigerian children*: An analysis of 106 operative cases. Pediatr. Surg. Int., 2001; 17: 628-630.
68. Pao, Y.H. "*Adaptive Pattern Recognition and Neural Networks*", Addison Wesley Patterson and Robichaud (1996). Managing Your Health, 1989; *16-17-25*.
69. Peter H. Gleick *Dirty Water: Estimated Deaths from Water-Related Disease* 2000-2020, Pacific Institute for Studies in Development, Environment, and Security• www.pacinst.org, 2000; 3/12.
70. Papageorgiou, E. I., Papandrianos, N. I., Apostolopoulos, D., and Vassilakos, P., *Complementary use of Fuzzy Decisoin Trees Decision Making in Medical Informatics*, International Conference on Bio Medical Engineering and Informatics. BMEI, 2008; 1: 888-892.
71. Revell AD, Ene I, Duiculescu D, Wang D Youie M, Pozniak A, Montaner J,Larder A. *The use of computational model to predict response to HIV therapy for clinical cases in Rmania*. GERMS., 2012; 2(1): 6-11.
72. Simsion, G. C., and Witt, G. C., *Data modelling essential*. 3 of America, Elsevier ed., United States, 2005.
73. Sharareh, R.N., and Xiao-Jun, Z., *Fuzzy Logic Approach to Predict Outcome of Tuberculosis Treatment Course Destination*. Proceedings of the World Congress on Engineering and Computer Science, Volume II WCECS, October San Francisco, USA, 2009; 20-22.
74. Siganos, D. & Stergiou, C. Artificial Neural Networks in Medicine Su, Chou and Lai, U. (1999); "Self-Generating Neuro-Fuzzy System Through Reinforcement", IEEE Trans on Systems, Man and Cybernetics, 2000; 323-328.
75. Simmons, G.M. *Potential sources of faecal coliforms in tidal inlets*. Proceedings of the Interstate Seafood Seminar, 1994; 49-67.

76. St. Louis M. and Hess J. "*Climate Change: Impacts on and Implications for Global Health.*" Am J Prev Med, 2008; 35(5).
77. Sugeno, M. "*Fuzzy Identification of systems and its applications to modeling and control*", IEE Trans. Systems, Man & Cybernetics, 1985; 15(1): 116-132.
78. Sulzberger, S.M, Tschichloy-Gurman, NN. and Velstli, S.J FUN; "*Optimization of Fuzzy Rule Based Systems using Neural Networks*", In Proceedings of IEEE conference on Neural Networks, San Fransico, 1993; 312-316.
79. Sani A. Fakai, M. O. Ibrahim, A. Danbaba Deterministic Mathematical Model Of Cholera, Predicting Chances Of Its Outbreak *International Journal of Scientific and Technology research,* 2013; 2(4). issn 2277-8616. 19 ijstr©2013 www.ijstr.org.
80. Tagaki, T.& Sugeno, M. "*Derivation of Fuzzy Control Rules from Human Operators Control Actions",* Proceedings of the IAFC Symposium of Fuzzy Logic Information. Knowledge Representation and Decision Analysis, 1983; 55-60.
81. Thang, K. F., *MATLAB implementation of Neural* and *Neuro-Fuzzy Approaches for Short-Term Electricity Demand Forecasting*, International Conference on Power System Technology. 21-24 November. Singapore. 2004.
82. Tsutsui, T., and Arita, S., Fuzzy logic Control of Blood Pressure through effleurage anaesthesia. *Journal of Clinical Monitoring*, 1994; 10: 110-117.
83. UNICEF, WHO *Progress on drinking water and sanitation* - 2012 update, NY, USA, 2012.
84. Warren, J., Beliakov, G., and Van der, Z. B., Fuzzy Logic in Clinical Practice Decision support System. *Proceedings of the 33rd Annual Hawaii International Conference on System Science*, 2000; 10: 4-7.
85. Wellems, T.E., Hayton, K., Fairhurst, R.M. The impact of malaria parasitism: from corpuscles to communities. *Journal of Clinical Investment*, 2009; 119(9): 496-505.
86. WHO/UNICEF *Joint Monitoring Programme for Water Supply and Sanitation*, 2010.
87. William, G *Epidemic disease control*. Nigeria Bulletin of Epidemiology, 1991; 1(1): 3-8.
88. West, M., and Fowler, J., (2003). *Developing high quality data models*, Available from: www.matthew-west.org.uk/documents/princ03.pdf *[Accessed 22 Nov, 2015]*, 1991.
89. Ong, K, Fung, C. C. & Myers, D. "An Integrated Neural Fuzzy Approach with Reduced Fuzzy Rules for Well Log Analysis". *International Journal of Fuzzy Systems*, 2002; 4(1): 592-599.

90. World Health Organisation / United Nations Environment Programme *Pollution and Health;* World Health Publication, Geneva. World Commission of Environment and Development (1998): Our Common Future**.** Oxford University Press, Oxford, 1997.
91. Zimmermann, H.J. *Fuzzy set theory-and its applications*, second edn. Kluwer, Boston (1.ed. 1991).World Health Organization (WHO) Website. http://www.who.int/en/ (Accessed 27 March 2009), 1993.
92. Zolnoori, M., Zarandi, M, and Moin, M., Fuzzy Rule base Expert System for Evaluation Possibility of Fata Asthma. *Journal of Health Informatics in Developing Countries*, 2010; 171-184.