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Artificial Neural Network for Predicting Flood : A Review

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ABSTRACT

Flood disaster continues to occur in many countries around the world and cause tremendous casualties and property damage. An Artificial Neural Network (ANN) is a flexible approach which gives very promising results. Unfortunately, the inability to predict beyond the limits of the training range was found to be a serious limitation of this approach. Therefore, the accuracy of prediction is not significantly improved by a single output model.

Keywords : Flood prediction, Artificial Neural Network, Biological Neuron, Fuzzy Logic Model

I. INTRODUCTION

Flood is a natural event or occurrence where a piece of land or area that is usually dry land suddenly gets submerged under water. Some floods can occur suddenly and recede quickly, others take days or even months to build and discharge. When floods happens in an area that people live, the water carries along objects like houses, bridges, cars, furniture and even people. It can wipe away farms, trees and many more heavy items. Flood occurs at irregular intervals and varying sizes, duration and the affected area. It is important to note that water naturally flows from high areas to low lying areas that means low lying areas may flood quickly before it begins to get to higher grounds. Flooding is extremely dangerous and has the potentials to wipe away an entire city, coastline or area and cause extensive damage to lives and property. The hazard of flooding is an annual phenomenon that has displaced millions every year worldwide and claimed lives and properties (Bronstert, 2003). The main cause of flood is the hydrological conditions of discharge of heavy rain fall and the enormous water. The other associated cause is metrological condition, that is, untimely cycle and storm. The planning, that is, poor drainages, high siltation in river, breaching of the embankments, spilling of floodwaters over them also contributes to the flooding situation. The geographical condition, that is, flows of water from neighboring states, flow of river across the state, and the topographical condition up to some extent are the factors of flooding condition (Patra, 2008).

Nigeria experiences floods every year especially flash floods and dams related floods during the raining season. However, each disaster seems to get worst leaving a larger impact than the previous (Bariweni et al, 2012 and Etuonovbe, 2011). NEMA (2012) states that in 2012, the intensity with which the floods came left the affected areas in a tragic state. The flood displaced over 2.1 million Nigerians leaving them homeless. Hundreds of lives were lost and properties including hundreds of thousand hectares of farmlands wash away. The most widespread of any hazard, floods can arise from abnormally high precipitation, storms surges from tropical storms, dam – bursts and rapid snow melts or even bursts water mains. The majorities of floods are harmful to human (Etuonovbe, 2011). Floods can overwhelm a village or city in a matter of moments. But with an early warnings system, vulnerable communities can be armed with the information and preparations it takes to keep a threat from turning into a tragedy. Good predictions and warning saves lives. With only a few minute notices of a tornado or flash flood, people can act to protect themselves from injury and death. Predictions and warnings can also reduce damage and economic losses. When notice of an impending disaster can be issue well in advance as it can for some riverside floods, wildfires and hurricanes, property and natural resources can be protected.

ANNs were first introduced in water resources research for their use to predict monthly water consumption and to estimates occurrences of floods. Since then ANNs have been used for a number of different water resources application which includes time – series prediction for rainfall forecasting, rainfall – runoff processes and river salinity, modeling soil and water table fluctuation, pesticide movement in soils, water table management and water quality management (Parson, 1999). The use of ANN is a popular data driven technique that has been frequently applied to a broad range of fields. An ANN is able to handle non – linearity and automatically adjust to new information while generally requiring little computational efforts (Rietjes and de Vos, 2008). ANNs are widely accepted as powerful ways of modeling complex non – linear and dynamics systems for which there are large amount of sometimes noisy data (Chen et al., 2002).

Statement of the problems

Flood situation is a troublesome situation which occurs almost every year (Priyadarshinee, Sahool, & Mallick, 2015). The problems encountered due to flooding comprises loss of numerous lives and huge destruction of properties every year, destruction of social, economic, as well as the agricultural activities of the communities residing around the water areas or channels. Also, when there is flood, it leads to the outbreak of diseases due to the accumulation of wastes from industrial chemicals deposited in the areas and lack of adequate information / publicity or awareness and improper dissemination of warning messages to the communities at risk leads to huge loss of lives of the people as well as to the communities and government authorities. Hence, this research work aimed to predict flood using artificial neural network taken into consideration of historic data.

Significance of the study

A flood prediction model can play a key role in providing relevant information of possible impending flood disaster in populated locations. Good flood prediction can help reduced the damages caused by flood in risk prone areas by informing decision – makers ahead of time of the disaster by given correct and adequate information to the people living around the risk prone areas for quick and timely evacuation. It will help to monitor and detect water flow levels of the rivers as well as to report any warning dangers to the emergency response team for quick and timely intervention of people residing in the risk prone areas. Communities that are within the risk prone areas need to be properly and effectively informed about the flood disaster immediately after the received of the warning prediction. This will help the authorities to minimize the huge amount of money spend on re – settling of victims of flood disaster and discourage people from blocking water channels and avoid building on water ways. It will also help the authority to expand water channels so as to contain the amount of water during the raining season.

Effect of floods disaster

Floods are the most frequently natural hazards globally (Verdin, 2002), and the hazard of flooding can be divided into primary, secondary and tertiary effects. The primary effects of floods are those due to direct contact with the flood water velocities resulting in floods as the discharge velocity increases. Secondary effects such as disruption of infrastructure and services and health impacts, while the tertiary effects are viewed as the long – term changes that occur, for instance, changes in the position of river channels (Nelson, 2010). Previous year's flooding have been the most costly disasters in terms of property and human casualties. These floods cause great losses and damages that also have devastating socio – economic, hydrological and climatic tertiary effects (Varoonchotikul, 2003). In 2012, the intensity with which the floods came left the affected areas in a tragic state. The flood displaced over 2.1 million Nigerians leaving them homeless. Hundreds of lives were lost and properties including hundreds of thousand hectares of farmlands wash away (NEMA, 2012). The most widespread of any hazard, floods can arise from abnormally high precipitation, storms surges from tropical storms, dam – bursts and rapid snow melts or even bursts water mains. The majorities of floods are harmful to human (Etuonovbe, 2011). In terms of lives lost and property damaged, floods are just behind tornadoes as the top natural disaster. In United States, flood damages totaled $8.41 billion in 2011. There were 113 flood – related deaths. Floods can affect any area to some degree and whenever rain falls, flooding can occur. The top five deadliest floods in world history occurred when the Huang He (Yellow) River in China exceeded its banks. The yellow silt that provoked the river's name can pile up higher than the land around it, causing the water to spill out of its causeway and onto the flat land surrounding it. In an effort to control the damage, the Chinese government built channels, dams and dikes to moderate the flow. The deadliest flood came in 1931 when between 1 and 4 million people were killed. Thirty – four thousand square miles (88,000sq km) of land were flooded leaving 80 million people without homes. In 1887, natural flooding claimed between 1 and 2 million lives. Strategic military flooding of the river top the third and fourth deadliest spots. In 1642, approximately 300,000 people died to flooding, famine and plague when the Ming governor of Kaifeng ordered his men to break dikes along the river in an attempt to drown rebels assaulting his city. In 1938 the river was again used as a defensive weapon to halt the advance of invading Japanese troops, killing nearly a million people. The worst dam collapse in history occurred in 1975 when significant rainfall following a typhoon assaulted the Banqiado dam on the Ru River in China (Nola Taylor Redd, 2017).

Factors affecting floods

The meteorological factors that affects flood includes (wind speed and direction, temperature, humidity, rainfall and solar radiation), hydrological (terrain slope, land use, vegetations, soil types, soil moisture) (DPLG, 2008 & Smith, 2001). Occurrence of flooding is determined by weather, hydrology, topography, run – off and urban infrastructures such as roads and buildings. Flood forecasting provides a basis for warning and to inform decision – makers and those in the path of floods in order to reduce flood damages which is normally measured in economic terms. Flood damage refers to all varieties of detrimental effects caused by flooding (Messner & Meyer, 2005, McCarthy et al., 2007).

Related works on Different types of Flood Prediction Techniques

Flood prediction is a complex process influenced by geographical location, rainfall, soil type and size of catchments that affect river water level. Floods cannot be prevented but damaged can be reduced by proper planning. According to Sparks et al, (1998), there are three main approaches in used for flood risk prediction which includes statistical techniques, models and maps and the monitoring of water and ice levels. Statistical techniques is use to determine the likelihood, frequency and intensity of water discharge causing flooding, models and maps are used to determine and visualize the extent of possible flooding, abnormal amounts of rainfall and sudden large water discharge that can be monitored to provide short term flood prediction (Alho, 2009). Weerts and Beckers (2009) constructed a frame work named Uncertainty Framework for flood and storm surge forecasting. It is built around procedural and operational constraints. The framework is said to help in deciding which method and which part of the model chain it is most suitable to increase the accuracy or quantifying the predictive uncertainty of the flood forecast.

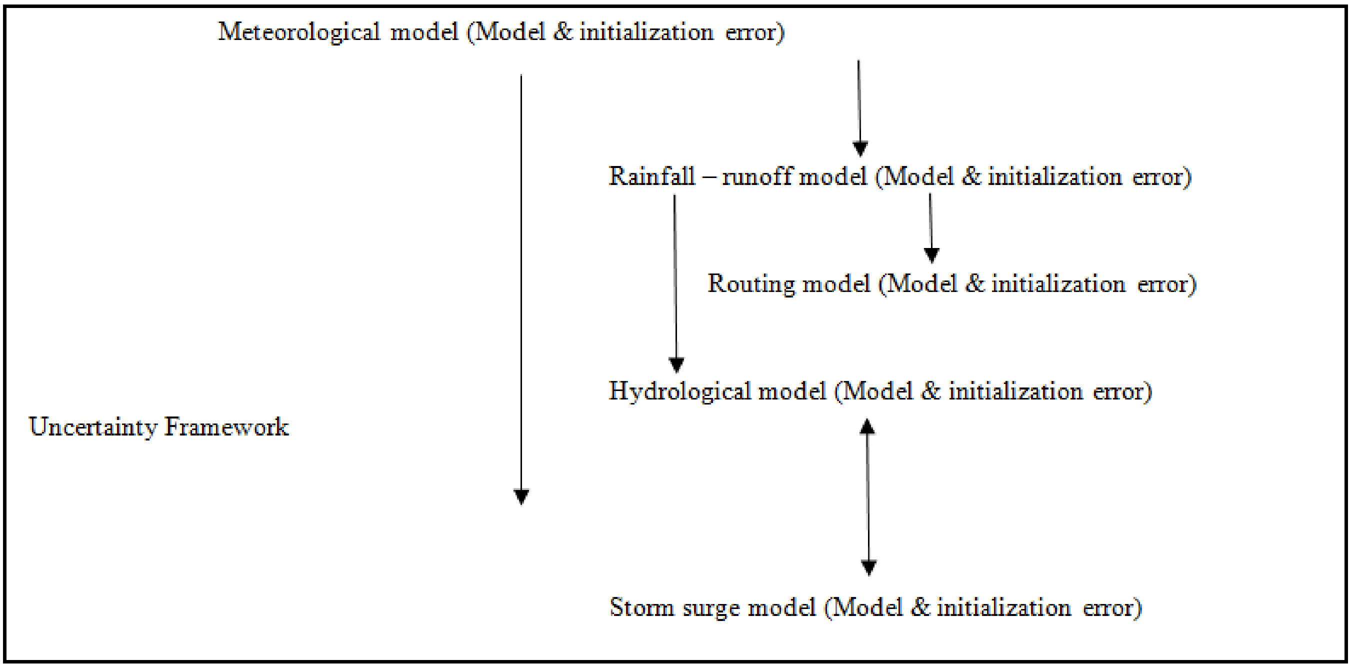

Figure 1

Uncertainty is divided into three parts in model used for flood forecasting: Input boundary conditions for the prediction, Initial condition of the area or model and behavior of the model during the prediction stage. Zhang, Zhou, Xu and Watanabe (2003) designed a national integration system using remote sensing, geographical systems, the Global Positioning System and other technology for monitoring and evaluation flood disasters in China. The main roles of the system cover three periods: Before, during and after flooding. Zhang et al (2003) states that before flooding, the system can be used to calculate the distribution of areas at high risk by comparing historical floods height with digital elevation model data, estimate social and economic losses under different alternatives for decision making or flood routing based on social and economic databases and models, suggest the best alternatives for population withdrawal from area at risk and suggest the best alternatives for storing and transporting flood prevention materials. During flooding, the agency can dynamic monitoring of flooded areas, estimate the expansion of flooded area according to meteorological and hydrological forecasting and optimizing the transport of materials for disaster relief. After flooding, the system can be used to calculate the actual losses in different administrative and such information allows government agencies to determine relief funds and for insurance by proving comprehensive spatial information, the system supports various efforts in rebuilding, such as planning water conservation facilities and selecting areas of new towns.

DPLG (2007) states that early warning flood systems can be implemented in order to provide effective warning for natural disasters that can be caused by floods. This can be accomplished by the combination of technologies such as GIS, remote sensing and ICT that translate data into useful information and make this information accessible to the role players and communities at risk. Flood cannot be prevented but damage can be reduced by proper planning. Flood prediction is a complex process influenced by geographical locations, rainfall, soil type and size of catchments that affect river water level. Forecasting models such as Quantitative Flood Forecasting (QFF) and Barros and Kim (2001) says that ANNs has been developed and implemented in different locations to help in weather forecasting over the past decades. Some of the existing data sources used in flood modeling are: Radar information systems, stream and rain – gauge networks and hydrograph analysis, linear statistical models and non – linear time series analysis and prediction.

Toth, Brath & Montanari (2000) emphasize that numerical weather prediction models, such as timely use of remote sensing observation, for example, radar data and satellite images, allows the issue of short – term forecast (Xue et al., 2000). Although the output from satellite and radar images provides useful information on precipitation patterns, they do not usually provide a satisfactory assessment of rain intensities. Radar detection is difficult in mountainous regions because of elevation and altitudes effects (Toth et al., 2000). Radar imagery forecasting technique show higher accuracy than model forecasts within 6 – 7 hours of the time of the radar image. Seal, Raha, Maity, Mitra, Mukherjee and Naskar (2012) presented a forecasting model designed using wireless sensor networks (WSN). This model helps to predict flood in rivers using simple and fast calculations to provide real time results and save the lives of people who may be affected by the flood by ringing an alarm. They used multiplied variable robust linear regression which is easy to understand, simple and cost effective in implementation and is speed efficient. It has low resources utilization and yet provides real time predictions with reliable accuracy. The model is independent of the number of parameters, that is, any kind and any number of parameters may be added or removed based on the on – site requirements. The rise in water level is represented by using a polynomial from which the exceeding of the flood line in the near future can be determined. They used time multiplier function is used to only decide the time interval between two successive readings. In their model, the central node is mentioned but it is not taken into account. The model is only predicting the flooding situation and warning people about flood by ringing the alarm but it has no role in preventing the flooding situation.

Review of Related Literatures on ANNs

Tan,.T., G.K.K.,Liong, .S.Y., Lim, T.K., Chu, J. and Hung, T. (2008) combined two models of ANN and SVM in order to come out with a new model called Reward Learning Ensemble [RLENSemble]. One model will learn the problem while the other will learn from the error of its counterpart. SVM is the first model subsequently followed by ANN using MLP. Error produced by SVM will be in the input for the MLP. Output produced from MLP will be taken as final prediction. RLEnsemble is the one with the highest accuracy in predicting the rainfall pattern in Singapore. Pang, B. and Liang, Y. (2011) develops a non – linear perturbation model adopting ANN (NLPM – ANN) and the results are compared to ANN and also linear perturbation model (LPM). The model recognized that seasonal hydrological behavior is very important source of information in flood forecasting as incorporated in the model and it shows that the NLPM – ANN obtain better simulation results that ANN by 2.7%, while results compared to LPM is higher by 6.32%. Mandal et. al. (2005) employed ANN model, namely Multi – Layer Perceptron (MLP) using back – propagation network technique and used delta rule for tracing. Environmental parameters used in the research are temperature, humidity, underground water level, precipitation and wind speed. They found out that underground water level is the most significant parameter for the prediction model. Simulations used for this model is NeuroSolutions v 4.0 has resulted in 97.33% of given overall prediction accuracy.

Ayalewa et. al. (2007) adopted three – layer back – propagation ANN model for real – time flood forecasting in Omo River, Ethiopia. Floods in Omo river are sudden non – linear and of short duration. The research uses sigmoid function which is commonly used for hydrological studies and magnitude and time – to – peak change were the two important parameters used in the research work. Comparisons of observed and forecasted runoff values for training and testing for all models showed little discrepancies. Rosmina Bustami, Nabil Bessail, Charles Bong and Suhaila Suhaili (2007) carried out a research on ANN for precipitation and water level predictions of Bedup River. The research aimed to improve water level predictions at Bedup River with estimations made to absent precipitation data using ANN. They used back propagation of ANN to predict both missing precipitation and water level. ANN model developed in the study successfully estimates missing precipitation data of a recorder in Bedup River, Sarawak with 96.4% accuracy. Predicted values of precipitation were then used to forecast.

John Wei – Shan Hu, Yi – Chung Hu and Ricky Ray – Wei Lin (2012) conducted a study on oil prices, that is, to accurately forecast prices of crude oil futures by adopting three popular neural networks methods which includes Multilayer Perceptron, the Elman recurrent neural network and recurrent fuzzy neural network. Their experimental result shows that the use of neural network to forecast the crude oil futures prices is appropriate and consistent learning is achieved by employing different training times. They found out that in most situations, learning performance can be improved by increasing the training time. They discovered that the RFNN has the best predictive power and MLP has the worst predictive power among the three underlaying neural networks. In their finding under the ERNNs and RFNNs, the predictive power improves when increasing the training time, exceptional case involved in BPNs suggesting that the predictive power improves when reducing the training time and they concluded that RFNN out – performed the other two neural networks in forecasting crude oil future prices.

Sulafa .Hag Elsafi (2014) conducted a study at Dongola Station in Sudan using artificial neural network as a modeling tool and validated the accuracy of the model against actual flow. The ANN model was formulated to simulate flows at a certain location in the river reach based on flow at upstream locations. Different procedures were applied to predict flooding by the ANN. Readings from stations along the Bluealide, white Nile, main Nile and River Atbara between 1965 and 2003 were used to predict the likelihood of flooding at Dongola station. The analysis indicated that ANN provides a reliable means of detecting the flood hazard in the River Nile. Ramli, Fazlina, Abdmanan and Zainazian (2012) stated that flood water level prediction has long been the earliest forecasting problems that have attracted the interest of many researchers. Accurate prediction of flood water level is extremely importance as an early warning system to the public to inform them about the possible incoming flood disaster. Using the collected data at the upstream and downstream station of a river, they propose a modeling of flood water level at downstream station using back propagation neural network (BPN). In order to improve the prediction values, an extended kalman filter was introduced at the output of the BPN. The introduction of extended kalman filter at the output of BPN shows significant improvement to the prediction and tracking performance of the actual flood water level.

Artificial Neural Network (ANNs)

ANN is a part of artificial intelligence and it is an area of computer science which is related in making computers behave more intelligently. ANN process data and exhibit some intelligence and they behave exhibiting intelligence in such a way like pattern recognition, learning and generalization. ANN is a programmed computational model that aims to replicate the neural structure and functioning of the human brain. ANNs are systems of interconnected neurons. Neurons or cells are the basic building blocks of brains which are the biological neural networks.

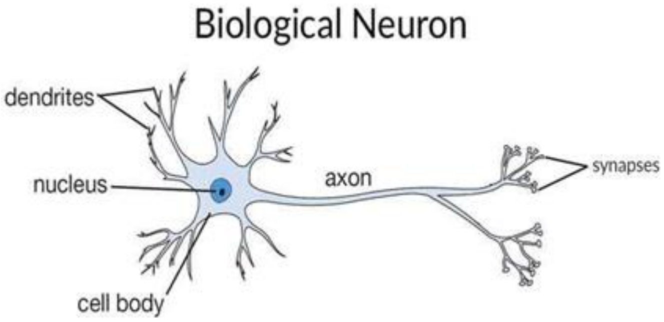

Figure 2

ANNs are the computational tools which were modeled after brains. It is made up of an interconnected structure of artificially produced neurons that function as pathways for data transfer. Some of the areas researchers are designing ANNs to solve a variety of problems include pattern recognition, prediction, optimization, associative memory and control. ANNs are described as the second best way to form interconnected neurons. ANNs are used to model brains and also to perform specific computational tasks. A successful ANN application will have the capability of character recognition.

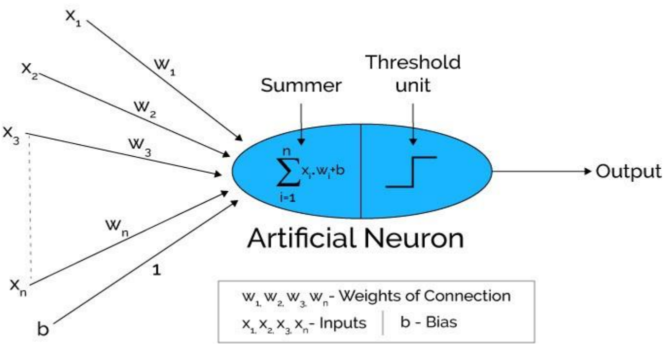

Figure 3

A computing system is made up of a number of simple, highly interconnected processing element and they process information to external input with their dynamics state response. A neuron has the ability to produce a linear or non – linear response. A non- linear ANN is made by the interconnection of non – linear neurons. Non – linear systems have inputs which will not be proportional to output. ANN is developed with a systematic step – to – step procedure which optimizes a criterion commonly known as the learning rule. The input / output training data is fundamental for the network as it communicate the information that will be necessary to discover the optimal operating point. ANN is a system and this system is a structure which receives an input, processes the data and provides an output. The input in data array will be wave sound, a data from an image file or any kind of data can be represented in an array. Once an input is presented to the neural network (NN) required target response is set at the output and from the difference of the desired response along with the output of real system an error is obtained. The error information is fed back to the system and it makes many adjustments to their parameters in a systematic order which is commonly known as learning rule. This process is repeated until the desired output is accepted. It is observed that the performance hinges heavily on the data so the data need to be pre – processed with third party algorithms such as DSP algorithms.

Types of ANNs

Most of the ANNs have some resemblance with more complex biological counterpart and are very effective at their intended tasks like segmentation or classification.

i. **Feedback ANN**: In this type of ANN, the output goes back into the network to achieve the best evolved results internally. The feedback feed information back into itself and is well suited to solve optimization problems. Feedback ANNs are used by the internal system error corrections.
ii. **Feed forward ANN**: It is a simple neural network consisting of an input layer, an output

layer and one or more layers of neuron. Through evaluation of its output by reviewing its input, the power of the network can be notice base on group behaviors of the connected neurons and the output is decided. The main advantage of feed forward ANN is that it learns to evaluate and recognize input pattern.

iii. **Classification – Prediction ANNs**: This is the subset of feed forward ANNs and the classification prediction ANN is applied to data mining scenarios. This network is trained to identify particular patterns and classify them into novel pattern which are new to the network.

Applications of ANNs

ANNs are used in the following fields:

i. In the field of solar energy for modeling and design of a solar steam generating plant.
ii. ANNs are used in system modeling such as implementing complex mapping and system identifications.
iii. ANNs are used for the estimation of heating loads of buildings, parabolic – trough collector's intercept factor and local concentration ratio.
iv. ANNs are used in diverse applications in control, robotics, pattern recognition, forecasting, medicine, power systems, manufacturing, optimization, signal processing and social / psychological sciences.
v. ANNs are also used in prediction of airflows in a naturally ventilated test room and for the prediction of the energy consumption of solar building.
vi. They are able to handle noising and incomplete data and also able to deal with non – linear problems.
vii. They are used in ventilating and air conditions systems, refrigerators, modeling, etc.

An ANN application provides an alternative way to tackle complex problems as they are among the newest signals processing technologies. ANNs offers real solutions which are difficult to match with other technologies. ANNs based solution is very efficient in terms of development, time and resources.

Advantages of ANNs

ANNs can perform tasks in which a linear program cannot perform, when an element of the neural network fails, it can continue without any problem by their parallel nature, ANNs does not need to be reprogrammed as its learns itself, it can be implemented in an easy way without any problem, as adaptive, intelligent systems, neural networks are robust and excel at solving complex problems. NNs are efficient in their programming and scientists agree that the advantages of using ANNs outweigh the risks.

Benefits of ANNs

ANNs are flexible and adaptive, are used in sequence and pattern recognition systems, data processing, robotics, modeling, etc, and ANNs acquires knowledge from their surroundings by adapting to internal and external parameters and they solve complex problems which are difficult to managed, it generalizes knowledge to produce adequate response to unknown situations, ANNs is flexible and have the ability to learn, generalize and adapts to situations based on its findings. Non - linearly, i.e, this function allows the network to efficiently acquire knowledge by learning. Also, an artificial neural network is capable of greater fault tolerance than a traditional network, and ANNs is based on adaptive learning.

Artificial Neural Network (ANN) Models

i) Back Propagation Neural Networks Model (BPNN)
ii) Probabilistic Neural Networks Model (PNN)
iii) Recurrent Fuzzy Neural Network model (RFNN)
iv) Fuzzy Logic Network Model (FLN)

v) Generalized Regression Neural Network Model (GRNN)

Back Propagation Neural Network (BPNN)

According to Shah and Trivedi (2013) BPNN is a supervised algorithm in which error difference between the desired output and calculated output is back propagated. The procedure is repeated during learning to minimize the error by adjusting the weights thought the back propagation of errors. As a result of weight adjustments hidden units set their weights to represent important features of the task domain. BPNN consists of three layers: Input layer, Hidden layer and Output layer. Number of the hidden layers depends upon the complexity of the problem. Learning of BPNN is a two-step process:

i. **Forward propagation**: Depends upon the inputs and current weights, outputs are calculated. For such calculations, each hidden units and output unit calculates net excitation which depends on values of previous layer units that are connected to the unit in consideration, weights between the previous unit and unit in consideration and threshold value on the unit in consideration. This net excitation is used by activation function which returns calculated output value for that unit. This activation function must be continuous and differentiable. There are various activation functions which can be used in BPNN but sigmoid is widely used and is defined as

$S_c(x) = 1/1+c^{-cx}$

ii. **Back propagation error**: Error is calculated at this step by difference between the targeted output and actual output of each unit. This error is back propagated to the previous layer, that is, hidden layer. For each unit in the hidden layer N, error at that node is calculated. In similar way, error at each node of previous hidden layer, that is, N – 1 is calculated. These calculated errors are used to correct the weights so that the error at each output unit is minimized forward and backward steps are repeated until the error is up to the expected level.

Parameters of BPNN

Shah and Trivedi (2012) outlined the criteria which affects the performance of BPNN as:

i. Learning rate
ii. Initial weights
iii. Number of hidden units
iv. Overtraining and early stopping criteria
v. Number of learning samples
vi. Activation function
vii. Normalization of the outputs

Advantages of BPNN

i. Support high speed classification
ii. Can be used for linear as well as non – linear classification
iii. Supports multi – class classification

Challenges of BPNN

i. Training time for BPNN is high
ii. BPNN suffers from local minima
iii. Structure of BPNN is complex.

Probabilistic Neural Network Model (PNN)

Cheung and Cannons (2002) states that PNN is predominantly a classifier, that is, it map any input pattern to a number of classification and can be forced into a more general function approximation. It is an implementation of a statistical algorithm called kernel discriminate analysis in which the operations are organized into a multilayered feed forward network with four layers as;

i. Input layer
ii. Pattern layer
iii. Summation layer
iv. Output layer

Advantages of PNN

i. Fast training process, that is, orders of magnitude faster than back propagation.
ii. An inherently parallel structure
iii. Guaranteed to converge to an optimal classifier as the size of the representative training set increases and has no local minimal.
iv. Training samples can be added or removed without extensive retraining.

Disadvantages of PNN

i. Not as general as back propagation
ii. Large memory requirement
iii. Slow execution of the network
iv. Requires a representative training set

Recurrent Fuzzy Neural Network Model (RFNN)

Predryc (2005) and Aliev, B. Fazlollahi, and Aliev (2004) outline fuzzy function as a function whose values are fuzzy numbers. Let f be a fuzzy function $\mu_{f(x)}$ denotes the membership function of the fuzzy number f(x), for $0 < \alpha \leq 1$, $f_+^{\alpha}(x)$ will denote sup {z ε dom($\mu_{f(x)}$): $\mu_{f(x)}$ (z) $\geq \alpha$ and $f_-^{\alpha}(x)$ will denote inf{z ε dom($\mu_{f(x)}$) : $\mu_{f(x)}$ (z) $\geq \alpha$. Functions $f_+^{\alpha}(x)$ and $f_-^{\alpha}(x)$ are level functions of f. A fuzzy subset A of R^n is defined in terms of its membership function $\mu_A(x) : R^n \rightarrow [0,1]$ for each α ε (0,1) the α – level set $[\mu_A(x)]^{\alpha}$ of a fuzzy set A is the subset of points x ε R^n with membership values $\mu_A(x)$ of at least α, that is, $[\mu_A(x)]^{\alpha}$ = {x ε R^n : $\mu_A(x) \geq \alpha$. FNN approach has become a powerful tool for solving real – world problems in the area of forecasting, identification, control, image recognition and others that are associated with high level of uncertainty (Akhmetov, Dote and Ovaska, 2001). This is related with the fact that the FNN paradigm combines the capability of fuzzy reasoning in handling uncertain information and the capability of pure neural networks in learning from experiments.

Advantages of RFNN

i. It allows automation of design of fuzzy rules and combined learning of numerical data as well as expert knowledge expressed as fuzzy IF – THEN rules (Aliev, Fazlollahi, & Aliev, 2004).
ii. FNN may have smaller network size and be faster in convergence speed as compared with ordering NN. FNN are oriented for real – world problems that are inherently uncertain and imprecise (Aliev, Fazlollahi, and Vahidov,2001).

Generalized Regression Neural Network (GRNN)

Celikoglu and Cigizoglu (2007), states that GRNN is a variation of the redial basis neural networks which is based on kernel regression networks. A GRNN does not require an iterative training procedure as back propagation network. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. In addition, it is consistent that as the training set size becomes large, the estimation error approaches zero with only mild restriction on the function. GRNN consists of four layers: input layer, pattern layer, summation layer and output layer. The number of input units in input layer depends on the total number of the observation parameters. The first layer is connected to the pattern layer and in this layer each neuron presents a training pattern and its output. The pattern layer is connected to the summation layer. The summation layer has two different types of summation which are a single division unit and summation units. The summation and output layer together perform a normalization of the output set.

Fuzzy Logic Model

According to Mellit, (2008) fuzzy logic process uses the concepts of a pure fuzzy logic system where the fuzzy rule base consists of a collection of fuzzy IF – THEN rules. The fuzzy inference engine uses these fuzzy IF – THEN rules to determine a mapping from fuzzy sets in the input universe of discourse. Under the fuzzy set theory, elements of a fuzzy set are mapped to a universe of membership values using a function theoretic form belonging to the closed interval from 0 to 1. Hasan et al., (2009) states that fuzzy logic are very useful in modeling complex and imprecise systems and fuzzy set theory is a powerful tool and its applications have rapidly increased with establishing its utility in numerous areas of the scientific world. The fuzzy logic possibility and its degree of effect due to the ambiguous input variables are considered by some as being generated in the human mind and is often referred to as expert knowledge. This expert knowledge is the accumulation of knowledge and ideas as a result of the expert's experience in a particular system, hence decision making processes may be considered as fuzzy expression perceived by the expert.

Artificial Neural Network Architecture

A typical neural network contains a large number of artificial neurons called units arranged in a series of layers. A typical artificial neural network comprises of different layers which includes: Input layer, Hidden layer and Output layer.

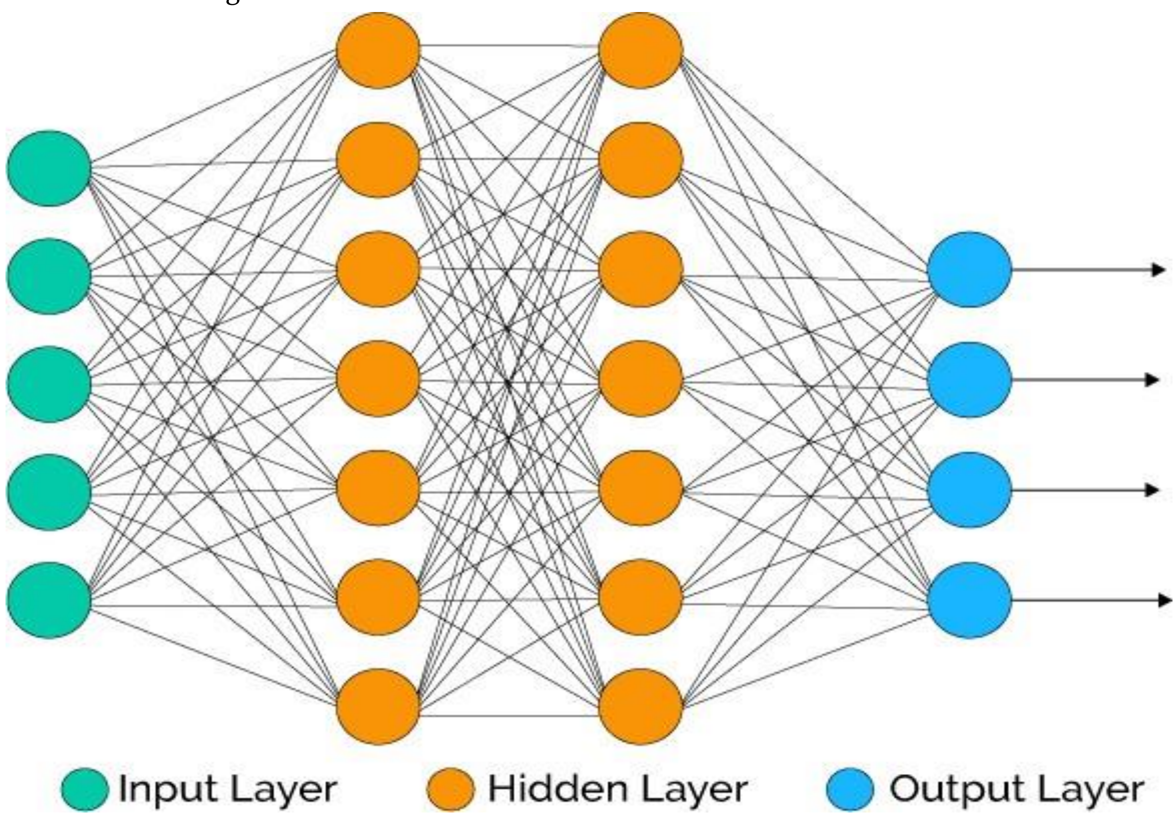

Figure 4

i) **Input layer**: It contains those units (artificial neurons) which receive input from the outside world on which network will learn, recognize about or otherwise process.
ii) **Hidden layer**: These units are in between input and output layers. The job of hidden layer is to transform the input into something that output unit can use in some way.
iii) **Output layer**: It contains units that respond to the information about how it's learned any task.

Most neural networks are fully connected that means to say each hidden neuron is fully connected to the every neuron in its previous layer (input) and to the next layer (output) layer. Other popular neural networks includes: Single layer Perceptron, Redial network (RBN), Multi-Layer Perceptron, Recurrent Neural network, LSTM Recurrent neural network, Hopfield network and Boltzmann Machine.

II. CONCLUSION

The ability to provide sufficient advance warning of flood occurrence is fundamental to reducing the potentially disastrous effects of floods. Sufficient advance warning time may save lives by giving flood plain residents time to remove themselves and their possession to safety environment. ANN has the room to extrapolate, the attention may be concentrated on the ability to predict one or more times steps ahead.

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