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# OPTIMIZATION OF NEURAL NETWORK ARCHITECTURE AND TRANSFER FUNCTIONS FOR RAINFALL-RIVERFLOW MODELLING

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*Artificial Neural Network (ANN) architecture and transfer functions had become as essential as the network training algorithm. This study presents the optimization of neural network architecture that were driven by the biological cell division architectures together with products of two window type localized sigmoidal (biradial) transfer functions on Oyun River modelling to determine their suitability for rainfall-riverflow modelling. Hydro-meteorological data used for the model study includes seasonal river discharge and rainfall values. Two ANN models with three different hidden layers each for mitosis and meiosis feed-forward architecture were developed. The ANN1 models with Mitosis Feed-Forward Neural Network Architecture (MiFFNNA) has $R^2$ values ranged from 80.07% to 96.74% and 76.12% to 92.40% for model calibration and validation while the MSE and RMSE values ranged from 0.040 to 0.560 and 0.190 $m^3/s$ to 0.750 $m^3/s$ respectively. The ANN2 models with Meiosis Feed-Forward Neural Network Architecture (MeFFNNA) has $R^2$ values ranged from 92.68% to 99.57% and 89.34% to 95.45% for model calibration and validation while the MSE and RMSE values ranged from 0.468 to 0.024 and 0.698 $m^3/s$ to 0.154 $m^3/s$ respectively. The results revealed that the ANN models using meiosis feed-forward architecture and window type sigmoidal transfer functions is simulate better and promising to be a good approximator for rainfall-riverflow modelling. Further combination of new transfer functions with the biologically inspired neural network architecture and their application to hydrological modelling should be encouraged.*

# INTRODUCTION

Rainfall-riverflow processes account for one aspect of hydrologic cycle that is characterized by a continuous movement of water leaving the earth's surface and eventually returning in the form of precipitation. Hydrologic modelling is a prerequisite for operational flood risk management (Schumann, 2011). Hydrologic modelling typically relate the known input (hydro-meteorological) to the unknown output (riverflow).

Recently, artificial neural network has become a powerful tool in the hands of hydrologists for hydrologic modelling, flood forecasting, etc.

Artificial Neural Network (ANN) has been successfully applied across an extraordinary application domains (Varoonchotikul, 2003). However, knowledge regarding artificial neural network modelling using biologically inspired architecture and new transfer functions remains highly pertinent as this study intends to shed more light on the potential of a biologically inspired architecture and new transfer function that is capable and flexible enough of approximating feature space with small adaptive weight.

Karim (2009) demonstrated ANN's ability as a universal approximator when applied to complex systems that may be poorly described or understood using mathematical equations. Features that makes artificial neural network a better modelling tool includes its ability to solve problems where it is effectively impossible to get primary data as in the case of groundwater chemistry (Gumrah *et al.*, 2000), where processes are highly non-linear and spatially and temporally variant (Islam and Kothari, 2000), artificial neural network handles incomplete, noisy and ambiguous data.

Smith (2001) describes neural network as "a form of multiprocessor computer system" with simple processing neurons, a high degree of interconnection, simple scalar messages and Adaptive interaction between elements.

Adaptive systems of the Artificial Neural Network (ANN) (Duch and Jankowski, 1999) type were initially motivated by the parallel processing capabilities of the biological brains, however, studies have shown that the processing elements and the architectures used in artificial neural networks have little in common with biological architectures. Expert's holds the opinion that neural network architecture and transfer functions that would fully behave like the biological systems would approximate better functions with minimal inputs and computational cost. Form l990's scientist have been trying to develop a neural network architecture within the domain of multilayer perceptron that would be fully biologically inspired. A breakthrough in this would be a great contribution in the world of artificial intelligent. In view of the above, this study developed neural network models using neural network architecture that are inspired by the biological cell division structures, window type localized sigmoidal transfer function and c3sep training algorithm.

Artificial neural network transfer functions determine the way signals are processed by the network individual neurons. Also, transfer function enables the tessellation of the parameter space in the most flexible ways using the lowest number of adaptive weight. There are numerous transfer functions among which are sigmoidal transfer function, hence, sigmoidal transfer functions are more frequently used in hydrologic modelling but is not flexible enough to describe an arbitrarily shaped density distributions of the multi-dimensional input space with small adaptive weights (Pallav, 2003).

The objectives of this study was to optimize and apply a neural network architecture that are inspired by the biological cell division architectures and a window type localized sigmoidal (biradial) arbitrarily shaped density distributions of the multidimensional input vector on Oyun River with a view of establishing their effects on rainfall-riverflow modelling using some hydro-meteorological inputs. The results obtained from this study will provide large-scale information on the development and application of the biologically inspired neural network architecture and new transfer functions that will serves computational cost and are quite flexible enough to describe an of establishing their effects on rainfall-riverflow modelling using some hydro-meteorological inputs. The results obtained from this study will provide large-scale information on the development and application of the biologically inspired neural network architecture and new transfer functions to rainfall-riverflow modelling and also will serve as a guide on integrated land and water resources modelling.

## HYDROLOGICAL MODELLING OF OYUN RIVER

Artificial neural networks were driven by the highly interconnected parallel processing capabilities of the biological brains to approximate unknown function from the space of inputs X to the space of outputs Y = FW(X).

The performance of a trained neural network depends largely on the network architecture, the transfer functions and the learning algorithm. From the statistical point of view, an adaptive systems should approximate the density of joint probability p(X;Y) or the posterior probability p(Y;X) of the input-output values. Recent emphasis on the application of neural network for hydrologic modelling are commonly based on the network learning algorithms forgetting the great importance of the network architectures and transfer functions.

The neural network architectures as applied in hydrologic modelling before now are selected on the basis of the developer's knowledge or by trial and error methods. However, this study considered creating a neural network architecture that are driven by the biological processes of cell division architecture which will serve computational cost while offering a better simulation. Studies has shown that Islam *et al.* (2014) optimized a neural network architecture using a genetic algorithm for electrical load forecasting.

There are two functions that determine the way signals are been processed by network neurons. These include the activation function I(x) which determines the total signal a neuron receives and the output function o(I), which determine neuron's signal processing. These two functions put together determine the values of the network outgoing signals. The combination of the activation and the output functions offers the transfer function o(I(**x**)). The transfer function is however defined by the *N*-dimensional input space. The transfer functions can be local if its values are significantly different from zero in a finite area of the input space; otherwise the function is non-local.

Before now the use of sigmoidal transfer functions had become popular among hydrologists when solving hydrologic problems, this may be due to its commonly believed that the activity of biological neurons follows such sigmoidal transfer function and also it is continuously differentiable. Neither the sigmoidal or Gaussian transfer functions that are commonly used for hydrologic modelling is flexible enough to describe an arbitrarily shaped decision borders in multi-dimensional input space using a small number of adaptive weight. Nevertheless, no study have shed more light or investigate the combination and use of new transfer functions in rainfall-riverflow modelling. Thus, this study tends to show the potential hidden in the use of biologically inspired neural network architecture and a new transfer function (biradial) for rainfall-riverflow modelling.

# RESEARCH METHODOLOGY

## Study Area and Data Collection

The study area for the application of the optimized neural network architecture and the new transfer function, Oyun River, lies in the sub-humid climatic zone. Oyun River is about 20 km to Ilorin the Kwara State capital. It has an estimated terrain elevation of 370 m above sea level and lies on Longitudes 4°30’ East and Latitude 8°26’N (Awu *et al*., 2016). Rain normally starts falling in April and stop late October, with June and September recording the highest rainfall values while the dry season lasts from November to March. The mean annual rainfall values of the study area is about 1700 mm while the mean monthly maximum and minimum temperature values in the basin are 31°C and 29°C respectively with the highest temperature values recorded in the months of February through April. The potential evapo-transpiration of the area is between 1500 mm to 1700 mm per annum (Manta *et al*., 2010). Figure 1 shows the catchment area of Oyun river basin enclosed within the thick black.

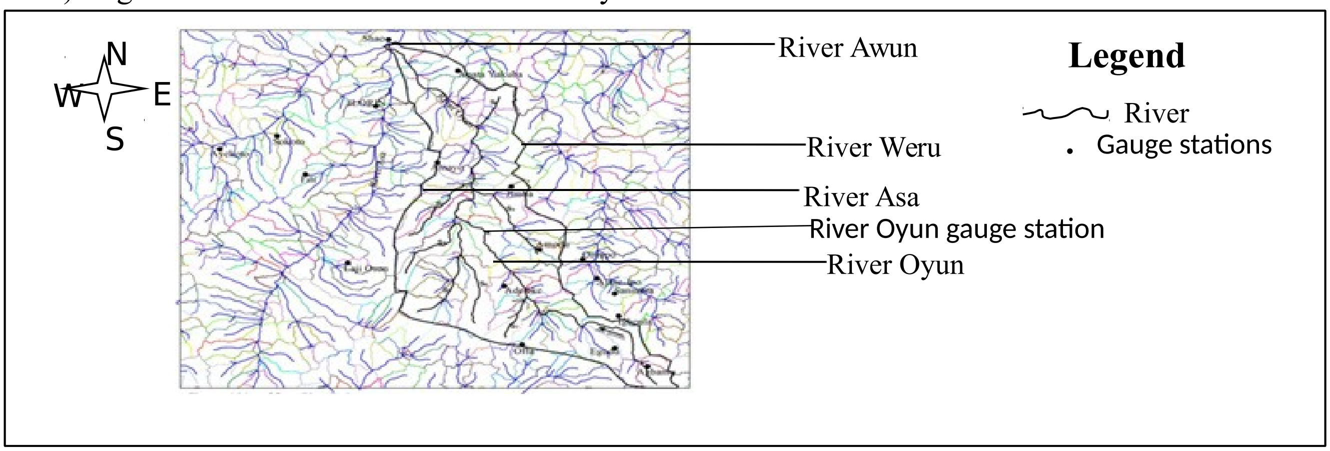


Figure 1: Catchment Area of Oyun River (Awu *et al*., 2016)

Oyun River catchment is a relatively small catchment with elongated narrow shape and non-steep slope of 830 km$^2$, 0.57%, 0.46 and 0.35 for basin area, slope, elongation and circulatory ratio respectively, which contributed to relatively slower draining of water into the river (Awu *et al*., 2016). The application of the biologically inspired neural network architecture and new transfer function on rainfall-riverflow modelling was based on the hydro-meteorological data collected from Meteorological Unit of the Land and Water Engineering Department of the National Centre for Agricultural Mechanization (NCAM), Ilorin. NCAM is located at km 20 Ilorin-Lokoja Highway, Ilorin, Kwara State, Nigeria.

The hydro-meteorological data collected includes seasonal river discharge and rainfall values. The hydro-meteorological data were divided into two sets: the calibration set and the validation set. The calibration set was based on a historical data consisting of 80% of the total data while the validation set was based on futuristic data consisting of 20% of the total data (5-fold cross validation method was used). The main reason of dividing the data into three sets is to avoid overfitting the model. The neural network used in this study is based on code I adapted from David Miller's C++ neural network tutorial (http://www.millermattson.com/dave/?p=54) into visual basic for better understanding.

## Neural Network Architecture Driven by Biological Cell Division Architectures

Different neural network architectural approaches may be used to search for best system approximation. Before now, the architectures used in artificial neural networks have little in common with biological structures and could be responsible for yet-to-breakthrough in a neural network development that behave exactly like biological counterpart. Neural network architecture can be in the form of feed-forward or recurrent architecture that consist several processing elements known as neurons that are arranged in layer by layer basis. In this study a feed-forward neural network architecture that was driven by the biological cell division architectures was considered.

Typically, there are two types of biological cell division architectures namely: mitosis and meiosis cell division architectures. Mitosis is a form of eukaryotic cell division that produces two daughter cells whereas meiosis produces four daughter cells as shown in Figure 2.

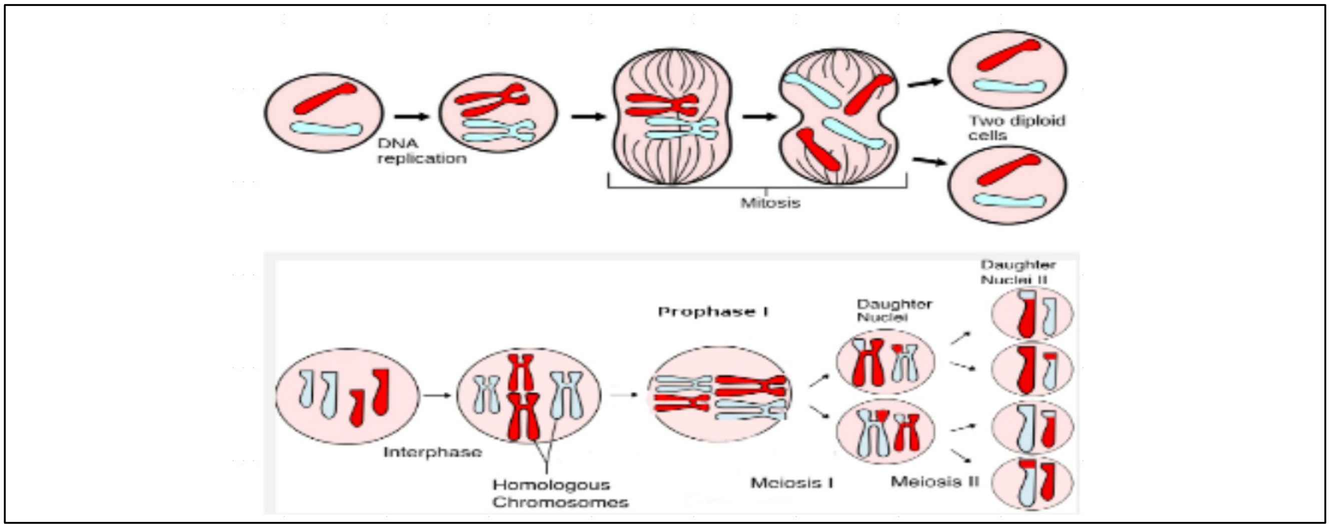


Figure 2: Biological Mitosis and Meiosis Cell Division Architectures (source: http://bio1510.biology.gatech.edu)

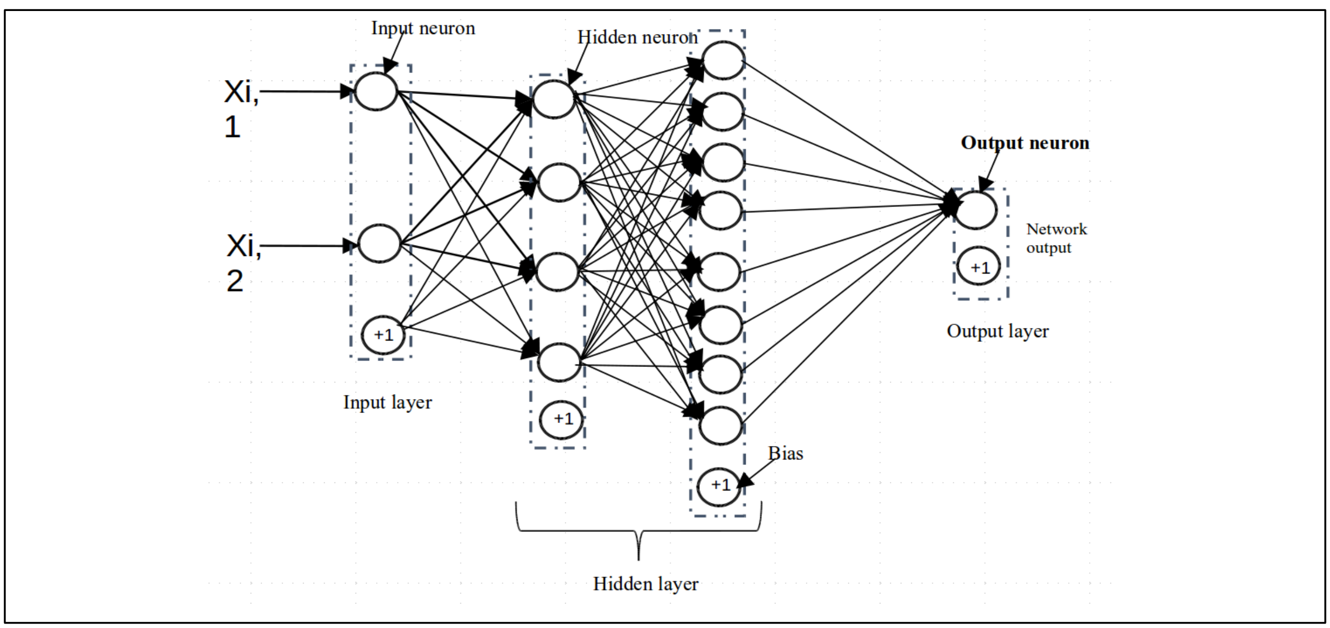


Figure 3: Schematic Diagram of a Mitosis Feed-Forward Neural Network Architecture (MiFFNNA)

Adopting the cell divisional architectures into a feed-forward architectures having two input parameters, firstly into mitosis structure and secondly into meiosis structure (Figures 3 and 4).

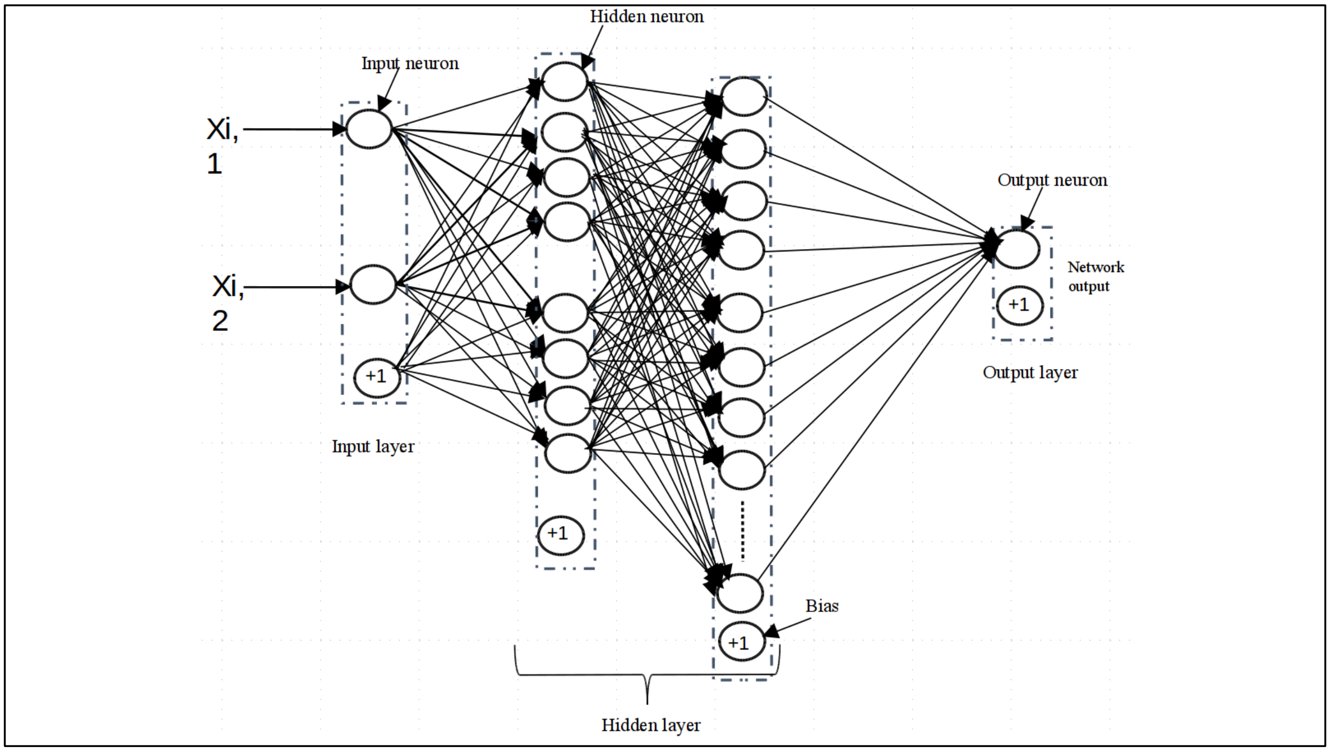


Figure 4: Schematic Diagram of a Meiosis Feed-Forward Neural Network Architecture (MeFFNNA)

The processing of a single neuron is shown in Figure 5.

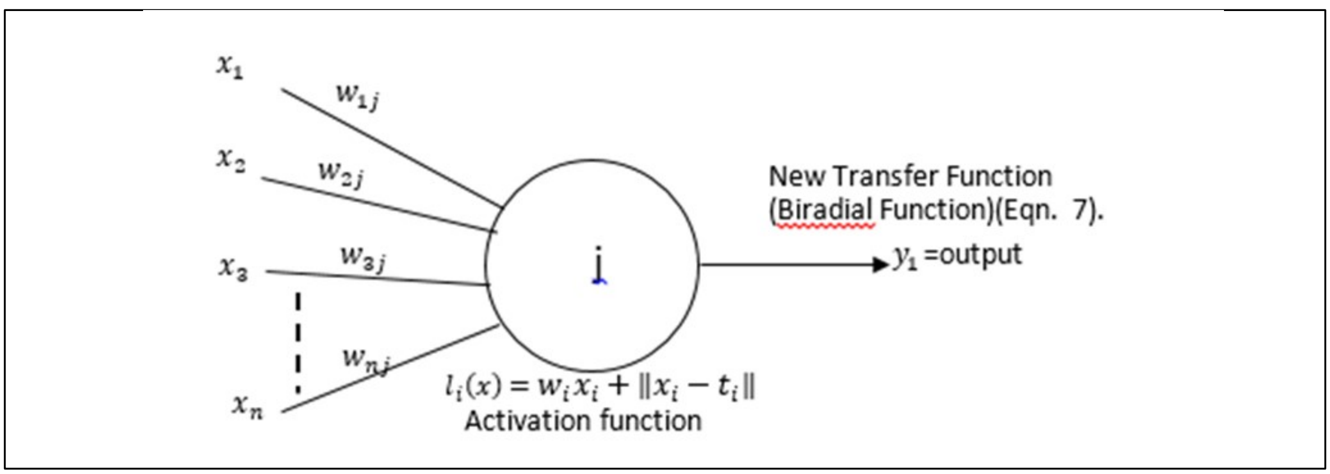


Figure 5: Activation of a single neuron (Modified from Debes *et al*., 2005)

In Mitosis Feed-Forward Neural Network Architecture (MiFFNNA), every neuron in the preceding layer is accountable for two neurons in the succeeding layer while in Meiosis Feed-Forward Neural Network architecture (MeFFNNA), every neuron in the preceding layer is accountable for four neurons in the succeeding layer respectively. The signal processing in neural network starts from the first hidden layer.

## New Transfer Functions

The activation and output functions are the two functions when combined will give network transfer functions. The sigmoidal activation function shown in Equation 1 (Debes *et al*., 2005), is used in neural network models not only because of their biological motivations, but due to their contours of constant value I(**x**) = const that are defined by hyperplanes.

$$I_i(x)=\sum_{j=0}^{N} W_{ij} X_j(1) \tag{1}$$

where $I_i$ is the total activation function, $W_{ij}$ is the connection strength and $X_j$ is the neuron signals. Statistically, the activation functions are classified into inner products as a method based on discrimination using hyperplanes for tessellation of the input space and the distance based methods on clusterization in which similarities are calculated using some kind of a distance measure as shown in Equations 2 and 3 (Duch and Jankowski, 1999).

Inner product activation function: $I(x;w) \propto w^T . x$ (2)

Distance based activation function: $I(x;t) \propto \|x-t\|$ (3)

Before now, studies have shown that researchers uses either the inner product or distance based activation functions as a stand-alone activation function in their neuron processing, but this study considered using a new activation function that was driven from linear combination of the final vector components of the inner product and the distance based activation function to represent complex decision borders as shown in Equation 4 (Figure 6)

$$I_i \propto w_i x_i + \|x_i - t_i\| \tag{4}$$

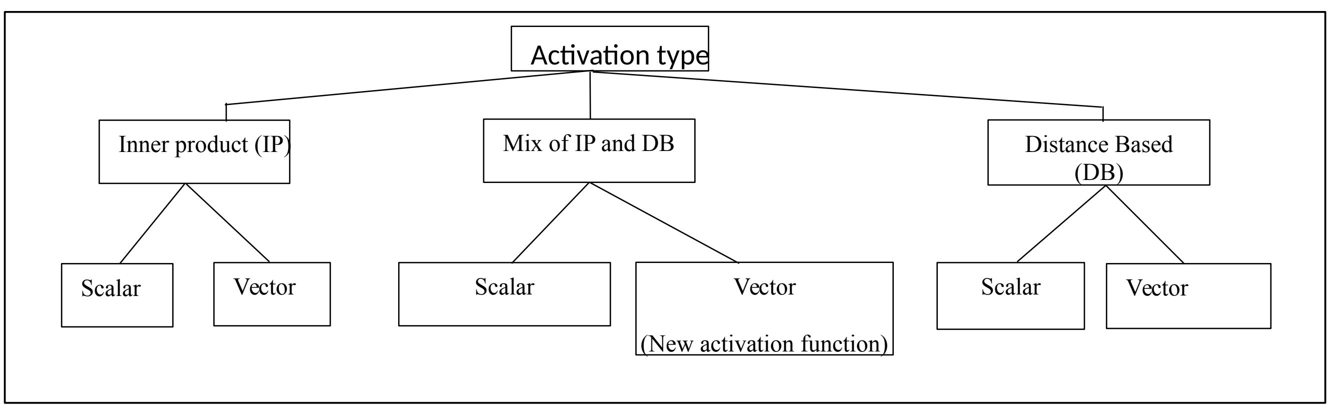


Figure 6: Taxonomy of activation function (Source: Duch and Jankowski, 1999)

Likewise, the output functions of sigmoidal type (Equation 8) are not only natural from the statistical point of view but are also a good squashing functions for unbounded activation. Sigmoidal output functions have non-local behavior. Hence, this study considered the use of a products window type transfer function (new transfer function) and the adoption of a new algorithm “c3sep algorithm” proposed by Growchoski *et.al* (2008) for rainfall-riverflow modelling. The window type transfer function (new transfer function) was based on arithmetic operation functions that don’t have exponential functions, this will make the neuron processing faster and save computational cost. Since calculation of exponents in logistic output function is much slower than the simple arithmetic operations other functions of sigmoidal shape such as window type transfer function are hereby used to speed up computations.

However, the new transfer function (Equation 7) used in this study is a products of two simple window type localized sigmoidal functions (Equation 5).

$$\delta(x)(1-\delta(x)) \tag{5}$$

After normalization the form becomes Equation (6)

$$\frac{\delta(x+b)-\delta(x-b)}{\delta(b)-\delta(-b)} \tag{6}$$

Growchoski *et.al* (2007) uses the window type localized sigmoidal functions to train his neural network using traditional error minimization algorithm. He found out that the new transfer functions is flexible, producing decision regions of arbitrary shapes for approximations. The general form of the window type localized sigmoidal functions is shown in Equation 7 (Growchoski *et.al* (2008).

$$G(x;t,b,s)=\prod_{i=1}^{B}\delta\left(e^{s_i}.\left(x_i-t_i+e^{b_i}\right)\right)\left(1-\delta\left(e^{s_i}.\left(x_i-t_i-e^{b_i}\right)\right)\right) \tag{7}$$

where: $\delta(x)=\frac{1}{(1+e^{-x})}$ (8)

The first sigmoidal factor in the product is growing for increasing input $x_i$ while the second is decreasing, localizing the function around $t_i$. Shape adaptation of the density $Gi(x;t,b,s)$ is possible by shifting centers *t*, rescaling *b* and *s*. Exponentials $e^{s_i}$ and $e^{b_i}$ are used instead of $s_i$ and $b_i$ to prevent oscillations during learning procedure. Figures 7, 8 and 9 are schematic diagrams of sigmoidal transfer functions and products of window type localized sigmoidal functions (new transfer function). The products of logistic sigmoidal functions is known as biradial transfer function.

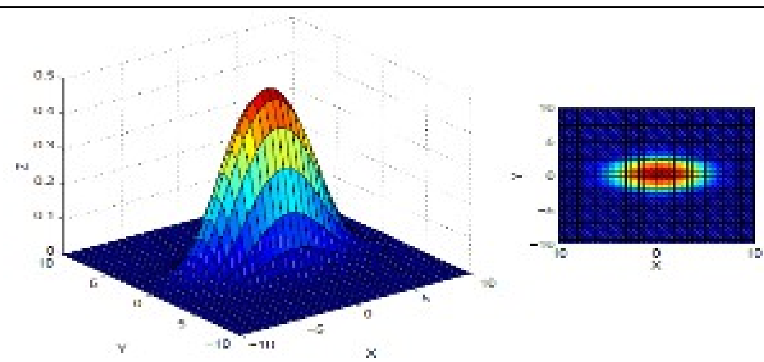

Figure 7. Sigmoidal transfer function (Source: Duch and Jankowski, 1999).

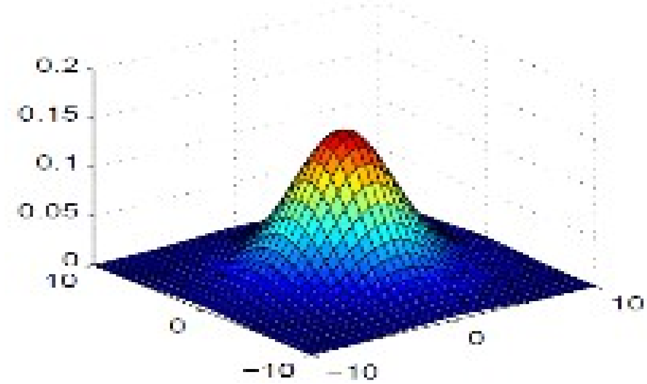


Figure 8. Window type transfer function (New transfer function) (Source: Duch and Jankowski, 1999).

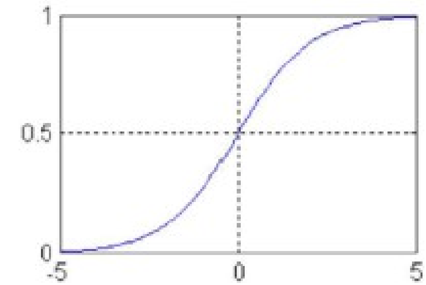


Figure 9. Sigmoidal transfer function fitted (Debes et al., 2005)

**Application of the Optimized Neural Network Architecture and New Transfer Functions to Rainfall-Riverflow Modelling**

This study proposed and apply optimized neural network architecture that are driven by biological cell division structures and window type localized sigmoidal transfer functions (new transfer function) on rainfall-riverflow modelling. The neural network used c3sep training algorithm as proposed by Growchoski et al. (20108). They were applied to a feed-forward multilayer perceptron (FFMLP) network for rainfall-riverflow modelling of Oyun River catchment using the seasonal river discharge and rainfall values that had occurred earlier at times $t_{-n}$. A feed-forward multilayer perceptron is a structure of a neural network that has being proven to be the best neural network structure for hydrological modelling (Shamseldin, 2010). In multilayer perceptron, there exists between the input and output layers, the hidden layer. There can be one or more hidden layers with many neurons that can be varied to adapt to the complexity of the relationships between input and output variables. Information is transmitted through the connections between neurons in layer-by-layers basis with the aid of connections called synaptic weights (Awu *et al*., 2016). The input layer receives input information and feed-forward same through the output layer which produces output information. The number of neurons in the input layer and the output layer were determined by the number of input and output parameters as shown in Figures 3 and 4.

Each neuron computes a linear combination of the inputs vector using new activation function (combination of inner product and distance based activation functions) from the connections feeding into them using Equation 4.

The linear combined activation functions are transformed using the new transfer function (biradial transfer function) shown in equation 7. However, the output obtained serves as an input to next neurons in the next layer. The output signal can then be interpreted as the response of the artificial neural network to the given input stimulus (Awu *et al*., 2016).

Training of the network was aimed to determine the main control parameters of the artificial neural network. The processes of estimating these parameters are known as neural network learning. The training type used in this study was basically supervised training. In supervised training, the network compares the network generated values with the target values. The training algorithm used for the network was adopted from the proposed c3sep algorithm by Growchoski *et al.* (2008). The error resulting from the comparison is computed using equation 9. The network was trained under 2000 iterations

$$E(x)=\frac{1}{2}\sum_{x}(y(x)-c(x))^2+\lambda_1\sum_{x}((1-c(x))y(x))-\lambda_2\sum_{x}c(x)y(x) \tag{9}$$

where $c(x)=\{0,1\}$ is the input vector (x) and $y(x)=\sum\widetilde{G}(x)$ is the actual network output. All the synaptic weights in the network were randomized between $\pm 0.5$, learning rate of 0.4 and momentum of 0.5. The first term in Equation 9 is the sum-of-squares error function (equation 10), whereas the second and third terms in Equation 9 are the penalty $\lambda_1$ and reward $\lambda_2$ factor respectively. As the penalty factor increases the reward factor decreases the total error for the input vectors $x_i$ from the $c(x_1)=1$ class that fill into cluster of the vectors from the opposite class 1.

$$E=\frac{1}{2}\sum_{n}\sum_{k}\{y_k(x^n)-t^n{}_k\}^2 \tag{10}$$

where $t^n{}_k$ is the target value for output neuron *k* when the network is presented with input vector $x^n$.

Normalization of the data set is highly essential to enable the network outputs to remain within the range of the network output function and also for all data to receive equal treatment during training as well as to enhance the efficiency of the network training algorithm. The significance of data normalization should not be underestimated. In this study, the data were normalized with respect to the range of all values between 0 to 1 using equations 11:

$$N_k=\frac{R_k-Min_k}{Max_k-Min_k} \tag{11}$$

where: $R_k$ is the real value applied to neuron k, $N_k$ is the normalization value calculated for neuron k.

**Statistical Model Evaluation**

The statistical measurements used to evaluate the performance of the artificial neural network models in this study include: the coefficient of multiple determination ($R^2$), the mean squared error (MSE), and the root mean squared error (RMSE) (Equations 12, 13, and 14 respectively (Abrahart et al., 2005)).

$$R^2 = \frac{\sum_{i=1}^{n} \left(Q_i - \acute{Q}\right) - \left(\hat{Q}_i - \grave{Q}\right)^2}{\sqrt{\sum_{i=1}^{n} \left(Q_i - \acute{Q}\right)^2 \sum_{i=1}^{n} Q_i - \grave{Q}^2}} \tag{12}$$

$$MSE = \frac{\sum_{i=1}^{n} \left(Q_i - \hat{Q}_i\right)^2}{n} \tag{13}$$

$$RMSE = \frac{\sqrt{\sum_{i=1}^{n} \left(Q_i - \hat{Q}_i\right)^2}}{n} \tag{14}$$

where: $Q_i$ are the *n* modelled flows, $\hat{Q}_i$ are the *n* observed flows, $\acute{Q}$ is the mean of the observed flows and $\grave{Q}$ is the mean of the modelled flows.

The $R^2$ model efficiency criterion as suggested by Nash and Sutcliffe is closely linked to the least-squares objective function being expressed as the sum of the squares of the differences between the models estimated and observed discharge. The $R^2$ criterion in essence, is a global measure of the performance of the substantive model relative to that of the original model. These are correlation statistics that measure the goodness of fit of modelled data with respect to observed data. Abrahart *et al*. (2005) reported that $R^2$ ranges from –1 (perfect negative correlation), through 0 (no correlation) to +1 (perfect positive correlation), also, that mean squared errors (MSE) provide a good measure of the goodness-of-fit at high flows, while root mean squared errors (RMSE) provide a more balanced perspective of the goodness of fit at moderate flows.

## DISCUSSION OF RESULTS

This study deals with the optimization and application of the neural network architecture that are biologically inspired by the cell division architectures, linear combination of the inner product and distanced based activation functions, products of window type localized sigmoidal transfer function and c3sep training algorithm on rainfall-riverflow modelling of Oyun River. The products of window type transfer function (new transfer function) which is based on arithmetic operation functions don’t have exponential functions, this made the neuron processing faster and save computational cost. The artificial neural network (ANN) models used were based on the architecture of the Feed-Forward Multilayer Perceptron (FFMLP). The neural network architecture used were driven by the biological cell division architectures of mitosis and meiosis cell division architectures. Two ANN models utilizing the feed-forward architecture for mitosis and meiosis architectures were developed. Each ANN model were trained for three different hidden layers. Every neural network model uses seasonal river discharge and rainfall values as their external input. The network performance were evaluated for the 3 different hidden layers for mitosis and meiosis feed-forward neural network architectures respectively as shown in Table 2 and 3.

Table 1. Number of neurons contained in the 3 different hidden layers for mitosis and meiosis feed-forward neural network architecture.

| Description | ANN 1 (mitosis architecture) | ANN 2 (meiosis architecture) |
|---|---|---|
| 1st hidden layer | 4 | 8 |
| 2nd hidden layer | 8 | 32 |
| 3rd hidden layer | 16 | 128 |

The results of the coefficient of multiple determination ($R^2$), the mean squared error (MSE) and the root mean squared error (RMSE) are shown in Tables 2 and 3.

Table 2. The $R^2$, MSE and RMSE efficiency values ANN 1model (mitosis architecture).

| Description | 1st Hidden Layer | 2nd Hidden Layer | 3rd Hidden Layer |
|---|---|---|---|
| Calibration $R^2$ (%) | 80.07 | 82.03 | 96.74 |
| Validation $R^2$ (%) | 76.12 | 78.75 | 92.40 |
| MSE | 0.56 | 0.59 | 0.04 |
| RMSE ($m^3/s$) | 0.75 | 0.70 | 0.19 |

Table 3. The $R^2$, MSE and RMSE efficiency values ANN 2 model (meiosis architecture).

| Description | 1st Hidden Layer | 2nd Hidden Layer | 3rd Hidden Layer |
|---|---|---|---|
| Calibration $R^2$ (%) | 92.68 | 98.19 | 99.57 |
| Validation $R^2$ (%) | 89.34 | 94.08 | 95.45 |
| MSE | 0.486 | 0.025 | 0.024 |
| RMSE ($m^3/s$) | 0.698 | 0.159 | 0.154 |

As observed in Tables 2 and 3, all the developed artificial neural network models performed very well as their $R^2$ values were very close to +1 which infer a perfect positive correlation. Generally, it was observed from Table 2 and 3 that $R^2$ values varied from one decimal places both for calibration and validations respectively and increases as the hidden layer increases. The modeled results showed that ANN 2 that uses, meiosis feed-forward architecture with 3 hidden layers performed better with $R^2$ value of 99.57**%** and 95.45% for calibration and validation than other ANN models. The ANN1 model with mitosis structure has $R^2$ values ranged from 80.07% to 96.74% and 76.12% to 92.40% for model calibration and validation while the MSE and RMSE ranged from 0.040 to 0.560 and 0.190 $m^3/s$ to 0.750 $m^3/s$ respectively. The ANN2 model with meiosis structure has $R^2$ values range from 92.68% to 99.57% and 89.34% to 95.45% for model calibration and validation while the MSE and RMSE ranged from 0.468 to 0.024 and 0.698 $m^3/s$ to 0.154 $m^3/s$ respectively. Generally, ANN2 models that uses Meiosis feed-forward multilayer architecture performed better than ANN1 models that uses mitosis feed-forward multilayer architecture (Figure 10 and 11). From the neural network architecture, it was observed that the meiosis feed-forward neural network architecture (MeFFNNA) has almost double neurons in every hidden layer when compared to the mitosis feed-forward neural network architecture (MiFFNNA). This could have been responsible for a better simulation performance by meiosis feed forward neural network architecture (MeFFNNA).

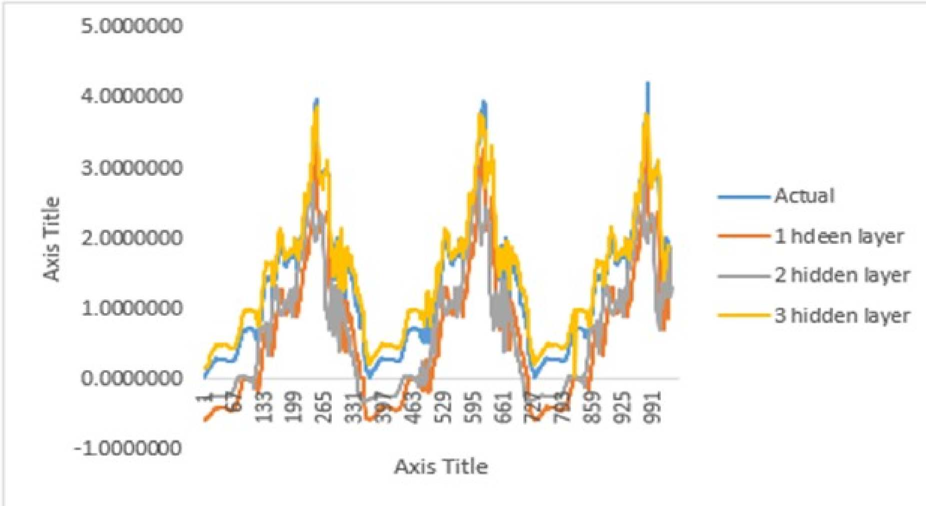


Figure 10. ANN1 (Mitosis structure) model.

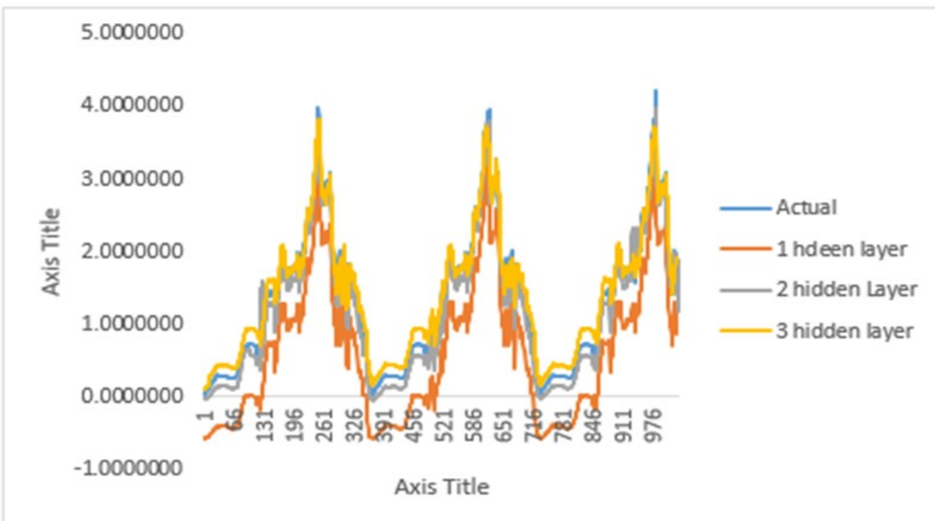


Figure 11. ANN2 (Meiosis structure) model.

## CONCLUSION AND RECOMMENDATION

Artificial neural network modelling for Oyun River were developed using an optimized neural network architecture that were driven by biological cell division architectures and a products window type localized sigmoidal (biradial) transfer functions. A c3sep algorithm was used in the network training. The neural network learning from statistical point of view requires approximation of the complicated density and flexible transfer functions that are as important as good architectures and learning algorithm. From the study a new activation function derived from linear combination of inner products and distance based function were used together with biradial output functions. Their application on rainfall-riverflow modelling was to evaluate its application suitability. The greatest advantage of the new transfer function comes from their separability which is the most disadvantage of sigmoidal function. The new transfer functions used in this study contain 3N-dimensional parameters per one unit and are flexible in representing various probability density. The optimized neural network architecture and the new transfer function was tested on a rainfall-riverflow modelling for Oyun River. The developed ANN models was based on the function and structure of a feed-forward multilayer perceptron.

Generally, the results reveals that the biologically inspired neural network architecture of meiosis performed better than the mitosis structure and the new transfer function is promising to be a good approximator, since error noticed in the comparison of actual and modelled output is very minimal. It is therefore concluded that the biologically inspired neural network architecture and the new transfer function can be applied for rainfall-riverflow modelling not only for Oyun River but for any small to medium river catchment globally, provided the neural network is well-trained.

The results obtained from this study will provide large-scale information on the application of the biologically inspired neural network architecture and new transfer functions to rainfall-riverflow modelling and also serve as a guide to governments, agencies for better policy and decision making for integrated land and water resources modelling.

It is recommended that, further combination of new transfer functions with the biologically inspired neural network architecture and their application to hydrological modelling should be investigated.

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