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REVIEW OF APPLICATION OF SOFT COMPUTING METHODOLOGY IN RIVER MODELLING, PREDICTION AND MANAGEMENT

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ABSTRACT

Algorithms relying mostly on traditional approaches and methodologies can rarely model the complexity of uncertainty in processes taking place within the river hydraulic structural system. This review of literatures is based on 30 publications randomly selected on the applications of soft computing methodologies in modelling different processes in different rivers around the world as published from the year 2008 to 2018 spanning an interval of 10 years. The technique used, authors name, where published and date of publication were presented in tabular form and the most adopted model, the results achieved were compared and conclusions of the most optimized methods was drawn. ANFIS stands out as the best techniques due to its ability to incorporate the potential of both Artificial Neural Networks (ANN) and Fuzzy Logic (FL) in the modelling of a highly non-linear, dynamic and complex system such as river hydrodynamics in an efficient manner. This work proved to be a resourceful guide to researchers working in the area of river modelling for different purposes as well as revealing the trend of development in the use of soft computing for River modelling in recent times. It is suggested that developing countries were the adoption of soft computing methodologies are still at low ebb should look into and intensify effort in the areas of using soft computing in solving their water resources related challenges for better management. ANFIS seems to be more favoured above others in our consideration. Statistical mean from the study shows 2.23 while the standard deviation is 948.79.

Key Words: ANN, Genetic Algorithm, Fuzzy Logic, ANFIS, River Modelling, Soft Computing

1.0 Introduction

The evolution of soft computing (SC) dated back to 1981 when Lotfi A. Zadeh published a paper titled: "*Theory of Soft Data Analysis*". Soft Computing or Computational Intelligence (CI) as is also often called basically includes: Artificial Neural Networks (ANN), Fuzzy Logic Systems (FLS) and Genetic Algorithms (GA) which are new, advanced information processing techniques that exhibit characteristics closely associated with human intelligence [29]. In summary, SC, as put by [54], simply refers to a collection of methodologies designed to model and enable solutions to real-world problems which would have been difficult if not impossible to model mathematically at varied scale whilst its main aim being to exploit the tolerance for imprecision, uncertainty, approximate reasoning similar to that of human beings.

When a system under consideration becomes more varied and more complex, [29] no single methodology suffices to deal with it. This is particularly true of what may be called information-intelligent systems, systems that form the core of modem technology. To conceive, design, analyse, and use such systems, it is necessary to frequently adopt the totality of tools that are available. Among such tools are the techniques centered on fuzzy logic, Neurocomputing, evolutionary computing, and related methodologies integrated to form a better model with more refined and acceptable result [29].

River modelling is a very tasking work, because most of the processes involved are non-linear in nature. For instance, sediment, pollutant or dissolved chemical modelling may not follow the one dimensional advection-diffusion equation used in classical method. Monitoring and prediction of rainfall pattern in a place and the change in climate over time which are the major factors responsible for most of the river system variability are areas where soft computing takes the lead and more preferable over the conventional methods as data needed are multifaceted for proper modelling, prediction and/or management. Therefore, soft computing approach is very important in water resources since it can handle most of these processes without problem as emphasized by this work.

For ANN, the module works based on mathematical principle, such as calculus, regression, polynomial, etc. For instance, equations 1 and 2 show how this can be demonstrated.

$$f(x) = y \tag{1}$$

This is a case of "universal approximator", because ANN can learn to approximate an unknown function f (x) = y between any input x and any output y, assuming they are related at all for instance (by correlation or causation). In the process of learning, a neural network finds the right (f), or the correct manner of transforming (x) into (y). Given also the chain rule in calculus by Artificial Intelligence [62] which states that:

$$\frac{dy}{dx} = \frac{dz}{dy} * \frac{dy}{dx} \tag{2}$$

Applying this rule in the ANN feedforward network, the relationship between the net's error and a single weight will look something like this; Artificial Intelligence [64].

$$\frac{dError}{dWeight} = \frac{dError}{dActivation} * \frac{dActivation}{dWeight}$$

For Fuzzy logic, the operation (rules) applied are described as follows: Let µA and µB be the membership functions for fuzzy sets A and B. The most used operations for OR and AND operators are max and min, respectively. For complement (NOT) operation, Equation 3 is used for fuzzy sets.

$$\mu_{\hat{A}}(x) = 1 - \mu_A(x) \tag{3}$$

For an Adaptive Neuro-Fuzzy Inference System (hybridization) model, it is considered to be a universal "estimator" if X is used to denote a random variable corresponding to the observed data, the estimator (itself treated as a random variable) is symbolized as a function of that random variable, $\hat{\theta}(X)$. The estimate for a particular observed data value x (i.e. for $X = x$) is then $\hat{\theta}(x)$, which is a fixed value. Often an abbreviated notation is used in which $\hat{\theta}$ is interpreted directly as a random variable, but this can cause confusion [28].

For GAs it does not require derivatives but just an "evaluation function" (i.e. a fitness function) [30]. It can be applied in both linear and non-linear cases, for instance: Given a function y = *f*(x) for example, the step to solve this with the model are highlighted as follows

- (i) pick a point x^0
- (ii) compute the gradient $\nabla f(x^0)$
- (iii) step along the gradient to obtain $x^1 = x^0 + \alpha \nabla f(x^0)$
- (iv) repeat until extreme is obtained, then stop the process [30].

The integration of ANN and FL with GAs aims at overcoming the limitation of individual techniques through hybridization or fusion, leading to hybrid intelligent systems (HIS) [44]. [1] concluded that the fuzzy models (ANFIS) are used because of their flexibility in modelling of nonlinear phenomena such as rainfall–runoff.

This paper seeks to address the application of soft computing in water resources related matters and the limitations and strengths inherent in the considered methodologies. The aim is to provide handy information to researchers who are interested in using soft computing methods for their work as well as providing them with information suitable in selecting the best method of their choice.

2.0 Soft Computing Methodologies

Soft Computing consists of several computing paradigms basically consisting of core of soft computing system, namely Fuzzy set (for knowledge representation via fuzzy If-then rules), Neural Networks(for learning and adapting) and Genetic Algorithms(for evolutionary computation) [54].

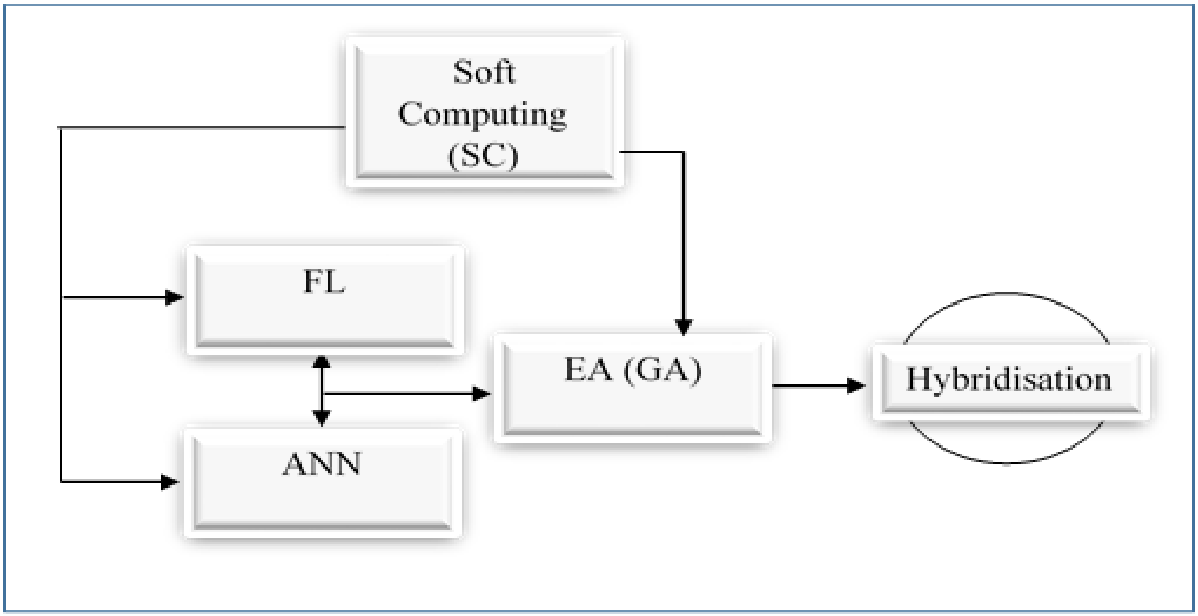

Figure 1: Core of soft computing system

2.1.1 Artificial Neural Networks

ANN as one of the soft computing methodology in the field of river modelling, prediction and management has been dealt with extensively by various researchers [2, 5, 6, 7 [41-42]; [21, 26, 35, 38, 48, 51, 68]; [57-58].

A data-driven technique that has gained significant attention in recent years is an Artificial Neural Network (ANN) modelling [16]. In many fields, ANNs has proven to be good at simulating complex, non-linear systems. Figure 2 shows ANN architecture.

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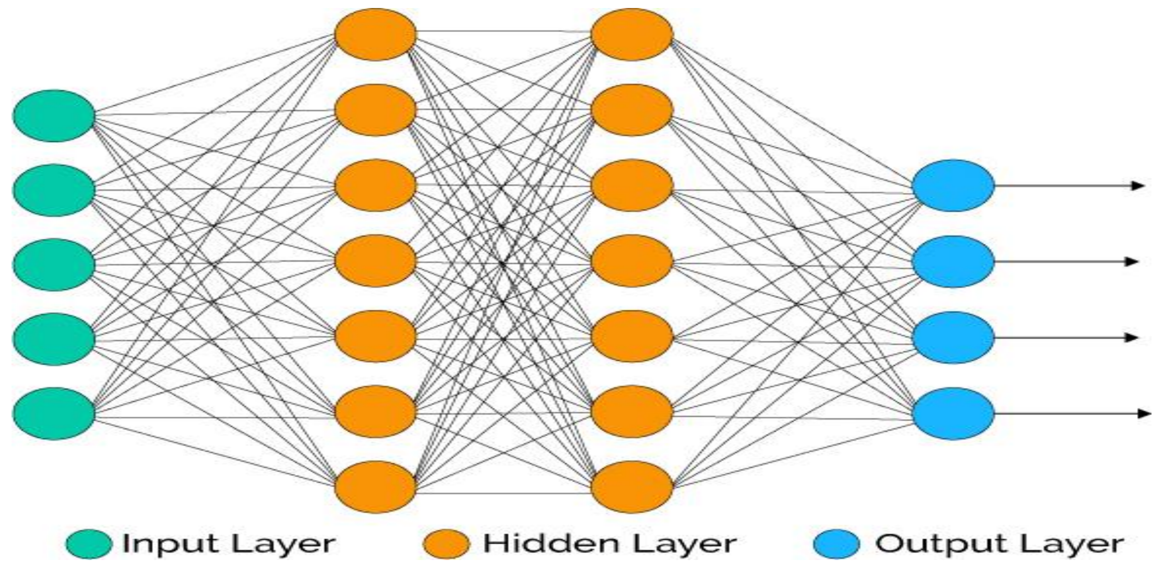

Figure 2: ANN architecture. Source: [65]

This module works by supplying input data like (average depth, river velocity, river discharge, rainfall, tide etc.) to the computer for simulations using some collections of algebraic variables and mathematical models linking them in a hidden layer running in the computer background to produce an output which is able to mimic the real life scenario such as pollutant fate in a river, rainfall model for a particular river reach and so on [13]. The connections between one layer and another are usually represented by weight (an assign number), which can be either positive (if one layer excites another) or negative (if one layer suppresses or inhibits another). This is further explained by [13] that the higher the weight, the more likely influence one layer or unit has on the other. The neural network is regarded as an iterative learning process in which input data cases are given to the network one at a time and weights associated with input interconnection are adjusted each time [49].

2.1.2 Limitation of ANN

Limitation of ANN can be seen while choosing the number of hidden layers and hidden nodes so much so that as the number of connections approaches the number of training samples, generalization decreases. Furthermore, initialization of weights, as random initialization can cause problems with the training set. Neural Network's output, precision is often limited to least squares errors; the training time required is quite large; the training data has to be chosen over the entire range where the variables are expected to change [11, 29].

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2.1.3 Enhancing ANN performance using evolution algorithms

Many of the problems associated with ANN can be addressed with EA (Topology selection, parameter selection and training are the most common) areas where success has been made [11]. This unit work by applying a random search algorithm that simulates natural selection and evolution. It searches the total solution space and can find the optimal solution globally over a domain. This begins as soon as an initial population has been randomly generated, the algorithm evolves through three operators of (selection, crossover and mutation) to improve the percentage of ANN accuracy in a model [49].

2.2. Fuzzy logic

Fuzzy logic has been around since the mid-1960s reported by [46]; however, it was not until the 70s that a practical application was demonstrated. Fuzzy logic systems are well suited to handling nonlinear systems and systems that have multiple inputs and multiple outputs. Any reasonable number of inputs and outputs can be accommodated by fuzzy logic. It also works well especially when the system in question cannot be modelled easily by conventional approach [29, 46].

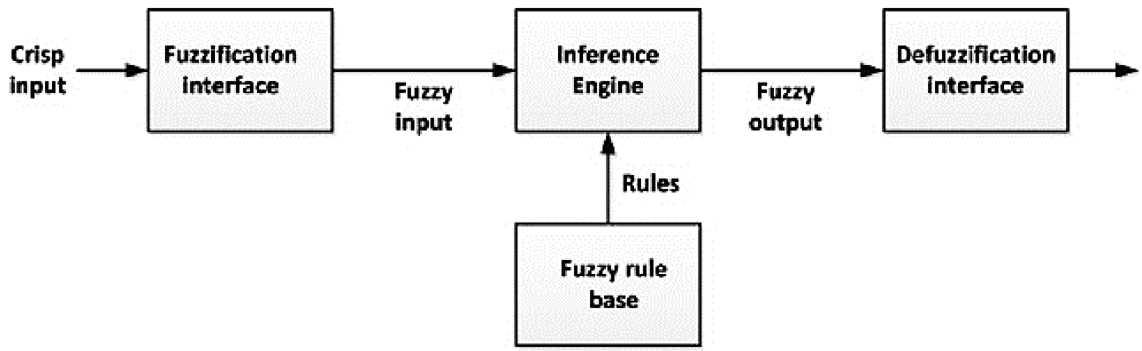

Figure 3: FL system architecture Source: [18]

The design and implementation of a fuzzy logic system begin with a set of membership functions for each (input) and a set for each (output). A set of rules then applies to the membership functions to yield a “crisp” output value [46, 29, 32].

This unit function by applying logic rules (IF-THEN rule) in obtaining the partial truth between true and false values which can be compared with Boolean logic halving ranges between 0 and 1 in conjunction with system employing linguistic variables (non-numeric values) such as age, temperature, pressure, salinity etc. with their relative degrees (Low, Medium or High) being managed by the membership function [33, 27].

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2.2.1 Limitation of FL

[32], highlighted the limitations inherent in using Fuzzy Logic Systems to include: Comprehensibility, Parsimony, Modularity, Explainability, Uncertainty, Parallelism and Robustness. Drawbacks of basic Fuzzy Logic rules as noted also by [53] is in the combination of membership functions as the minimax rule for conjunctive (AND) and disjunctive (OR) reasoning due to the fact that they are not robust enough when compare to the way human reasoning can be perfectly mimicked. The minimax rule is definitely not the way, the rule also fails to ascribe the same importance to all factors taken part in the combination process. Optimization of FL [32] can mean that a change made to MF will also require a corresponding change in the rules, a change in the rules may require also that a change be effected in the MF, each parameter or choice taken affects the others and multi-parameter optimization could also cause a problem.

2.2.3 Enhancing FL performance using evolution algorithms

Having identified the major drawbacks in section 1.1.2, application of Evolution Algorithms (EA) or Genetic Algorithms (GAs) to FL can help overcome in most cases the effect of these inherent drawbacks/weaknesses. EA are well suited to solving combinatorial problems since most of the problems of FL are combinatorial in nature (MF parameters, MF/rule interdependencies). Application of EA has been done mostly in three different ways, namely: (i). optimizing MF, (ii) optimizing rules, and (iii) optimizing the whole system [32].

The function of GA built-in in Fuzzy logic is to generate information about its current performance at each iteration of the GA, as is passed onto the Fuzzy logic controller (FLC) where the information will be processed and a recommendation for how the GA parameters should be altered in order to achieve more optimal execution will be made. Four critical components that support the FLC are given by a rule-base, a fuzzification unit, an inference engine, and a de-fuzzification unit.

2.3 Genetic algorithms (GAs)

A genetic algorithm (GA) is a search-based technique for systems optimization used in computing to find true or approximate solutions to optimization and search problems. They are categorized as global search heuristics and belong to a particular class of evolutionary algorithms (EA) that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover [59, 52, 23].

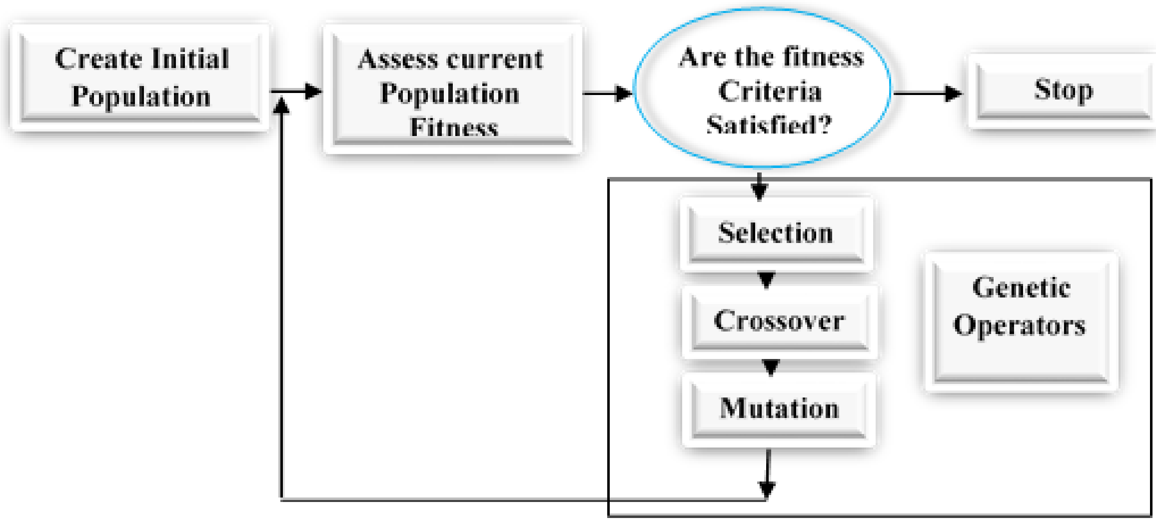

Figure 4: Genetic Algorithms Architecture modified from [14].

The unit comprises of a "fitness function" that is the function that the algorithm is trying to optimize [24, 34]. It tests and quantifies how "fit" each potential solution is and it is a pivotal part of the algorithm components. For example, if *f* is a non-negative fitness function, then the probability that chromosome C_{53} is chosen to reproduce might just be represented as:

$$C_{53} = \left| \frac{f(C_{53})}{\sum_{i=1}^{N_{Pop}} f(C_i)} \right|$$

Each candidate solution is encoded as an array of parameter values, a process that is also found in other optimization algorithms [22, 24, 61]. Let a problem at hand has *N-par*. dimensions for instance, then each chromosome can be encoded as an *N-par*. element array chromosome = (p_1, p_2... p_{Npar}) [24].

where each p_i, is a particular value of the i^{th} parameter [22, 24, 61]. It is left for the genetic algorithm programmer devise means of how to translate the sample space of candidate solutions into chromosomes. One approach available to do this is to convert each parameter value into a bit of binary string (sequence of 1's and 0's), then concatenate the parameters end-to-end like genes in a DNA strand to create the chromosomes.

2.3.1 Limitation of genetic algorithms

[63] Confirmed that although a GAs holds the ability of searching the global optimum solution to a complex problem, but the inherent drawback is the fact that it may not

necessarily lead to the best possible solution owing to its limitation in local searching capability.

2.4 Hybrid System

The application of more than one methodologies in solving a particular problem is referred to as hybridization. A genetic algorithm-based artificial neural network (ANN-GA) model and a genetic algorithm-based Fuzzy Logic model (FL-GA) are both possible hybrid integration of ANN and GA algorithms as well as FL and GA algorithms which in most cases are known for their best performance combining the weaknesses and strengths of both soft computing modelling tools of ANN and FL [64, 27]. Hybridization of techniques also has the advantage that it is easier to think of alternative solutions to the same problem. If there are several possibilities for the structure and the search methods, many more pairings of technologies are possible, and problem solving becomes easier. Hybridization of fuzzy logic, neural networks and genetic algorithms has led to the creation of a perspective scientific trend known as soft computing [11]. Adaptive Neuro-Fuzzy Inference System (ANFIS) is also a hybrid system from which several other systems have been combined to give a better result for example by: [40, 7, 27].

Example of a hybrid system include the following: ANFIS with SVM, ANFIS with Meta-Heuristic Algorithm, ANFIS with Classic, Recurrent, and Modified Recurrent (C-ANFIS, R-ANFIS MR-ANFIS) integration, ANFIS with Genetic Fuzzy System (ANFIS-GFS), differential evolution (ANFIS-DE), ant colony optimization (ANFIS-ACO), wavelet (WANFIS) etc. But researchers in different fields always improve on the existing models by adopting mathematical manipulations with respect to their field's peculiarity for a more robust and refined output. This they do by comparing the result obtained from using the non-hybrid model types.

3.0 Methodology of the Review

This review captured a total number of 30 publications in literature from different authors around the world in the area of applications of soft computing methodologies in river modelling, maintenance and management. Online materials, books and journal in related area were sourced and carefully selected at random to meet the purpose for which the review is intended. These materials were selected because they addressed the challenges and common issues being faced in water resource management and hydraulic engineering structural studies for effective river sustainability [62]. Subsequently, the focused area by each of the papers was a very important consideration in selecting the reviewed papers. The review considered papers that touch the major global factors (Table 1, column 4 – focused area) that affect the river drive in any part of the world, this measure is taken in order to ensure whichever model

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is considered the most optimal and appropriate to be used anywhere in the world irrespective of its spatial location and the prevailing environmental condition.

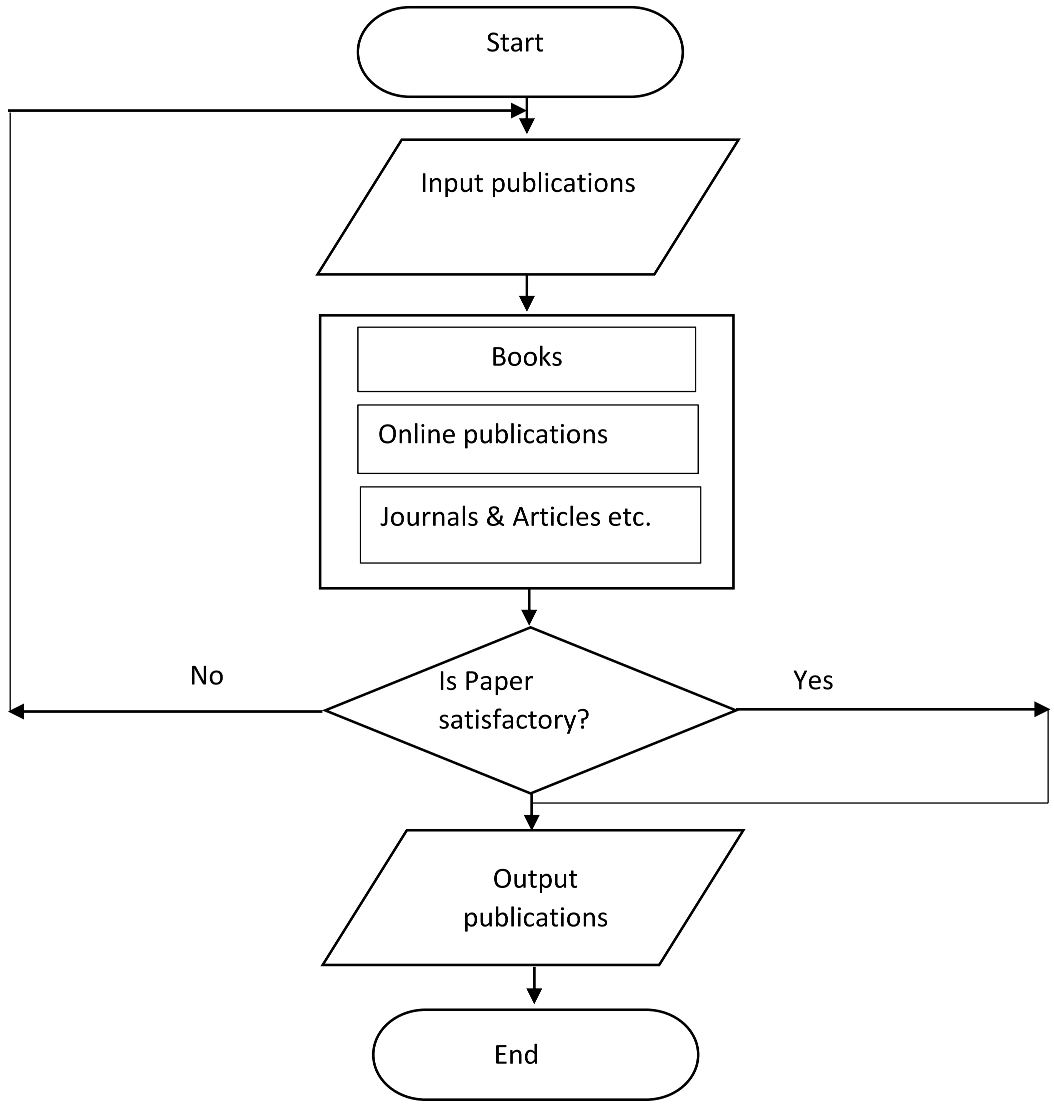

Figure 5: Flow chart of the methodology

Table 1: List of publications in the area of water resources modeling and management

Author(s)	Paper Tittle	Technique Used	Focus Area	Where Published	Frequency	Cumulative Frequency	Results/ Findings
[7]	Streamflow Prediction of Karuvannur River Basin Using ANFIS, ANN and MNLR Models	Artificial neural network (ANN), adaptive neuro-fuzzy inference systems (ANFIS) and multiple nonlinear regression (MNLR)	Streamflow Prediction	Elsevier	1	1	ANFIS model predicts daily flow more accurately compared to ANN and MNLR models.
[50]	Development of Artificial Neural-Network-Based Models for the Simulation of Spring Discharge	ANN and MLR	Simulation of Spring Discharge	Journal of Advances in Artificial Intelligence	1	2	ANN performed better than MLR
[42]	A Comparison of Artificial Neural Networks for Prediction of Suspended Sediment Discharge in River- A Case Study in Malaysia	Two (ANN) types: Radial Basis Function (RBF) Network and the Multi-Layer Feed Forward (MLFF)	Prediction of Suspended Sediment Discharge	International Journal of Civil and Environmental Engineering	1	3	The RBF network model provided slightly better results than the MLFF network model in predicting suspended sediment discharge. .
[40]	Evaluation of different types of artificial intelligence methods to model the suspended sediment load in Tigris River	(ANFIS), in addition to two different kinds of (ANN) i.e. feedforward and radial basis networks	Suspended sediment load	MATEC .	1	4	ANFIS model outperform the other methods

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[55]	Pollutant source identification model for water pollution incidents in small straight rivers based on genetic algorithm	basic genetic algorithm (BGA) and analytic solution	Pollutant source identification	Springer	1	5	basic genetic algorithm (BGA) excellently identified pollutant source
[19]	Artificial intelligence-based approaches for multi-station modelling of dissolve oxygen in river	Adaptive neuro fuzzy inference system (ANFIS); Feed forward neural network (FFNN)	Multi-station modelling of dissolve oxygen	Global J. Environ. Sci. Manage	1	6	ANFIS model predicted better than FFNN model.
[2]	Computational Modeling of Pollution Transmission in Rivers	Numerical method and artificial neural network (ANN)	Pollution Transmission in Rivers	Springer	1	7	ANN model improved the L D Coefficient prediction accuracy for pollution simulation
[6]	Comparison of different methods for reconstruction of instantaneous peak flow data	ANN, FL, and GA and Regression (REG)	Reconstruction of instantaneous peak flow data	Auto Soft Journal	1	8	ANFIS reconstructs instantaneous peak flow values with the highest accuracy among the four tested methods.
[66]	Bayesian Regression and Neuro-Fuzzy Methods Reliability Assessment for Estimating Streamflow	Neuro-Fuzzy and Bayesian Regression	Streamflow estimation	(MDPI)/ Journal/ Water	1	9	BR model outperformed ANFIS models at global and local scales
[60]	A comparative study of adaptive neuro fuzzy inference System (ANFIS) and multiple linear regression (MLR) for Rainfall-runoff modelling	ANFIS and MLR	Rainfall-runoff modelling	International Journal of Science and Nature	1	10	ANFIS model is better than the MLR models in estimation of daily runoff for Arpa River.

[12]	Using artificial neural network (ANN) for prediction of sediment loads, application to the Mellah catchment, northeast Algeria	Multilayer Perceptron (MLP) neural networks	Sediment loads	Journal of Water and Land Development	1	11	ANN Model produced satisfactory agreement between observed and predicted data
[48]	A new approach for modeling suspended sediment: Evolutionary fuzzy approach	EF, ANN and ANFIS-FCM	Suspended sediment modeling	Hydrology and Earth System Sciences	1	12	EF model provided better accuracy than ANN and ANFIS-FCM.
[56]	Optimizing ANFIS for sediment transport in open channels using different evolutionary algorithms	3- Hybrid ANFIS: ANFIS-GA, ANFIS-DE and ANFIS-PSO.	Sediment transport in open channels	Journal of Applied Research in Water and Wastewater	1	13	Hybrid models: ANFIS-GA, ANFIS-DE and ANFIS-PSO performed better than general ANFIS. But ANFIS-PSO supersede all
[58]	Daily Suspended Sediment Discharge Prediction Using Multiple Linear Regression and Artificial Neural Network	MLR and ANN	Suspended Sediment Discharge Prediction	Journal of Physics	1	14	MLR performed better than ANN
[31]	Comparison of fuzzy inference systems for streamflow prediction	ARMA, and Two fuzzy Inference type (Mamdani and Takagi-Sugeno)	Streamflow prediction	Hydrological Sciences Journal	1	15	ARMA outperforms both Mamdani and Takagi-Sugeno (fuzzy Inference) in terms of error criteria
[37]	Simultaneous optimization of clustering and fuzzy IF-THEN rules parameters by the genetic algorithm in fuzzy inference	FIS, GA, ANFIS and Coastal Engineering Manual	Wind-driven waves in marine environment	Journal of Hydroinforma tics	1	16	The developed model outperforms the ANFIS model and (CEM) method to estimate the function representing

	system-based wave predictor models.						the generation process of the wind-driven waves.
[5]	Improving one-dimensional pollution dispersion modeling in rivers using ANFIS and ANN-based GA optimized models	ANN, ANFIS, ANFIS-GA, ANN-GA, multiple linear regression (MLR), and empirical equation	Sediment/ pollutant dispersion prediction in open-channel flows	Springer/ J. Environmental Science and Pollution Research (JESPR)	1	17	hybrid numerical-intelligence model is more accurate than the other classical methods for sediment/pollutant dispersion prediction in open-channel flows
[51]	River water modelling prediction using multi-linear regression, artificial neural network, and adaptive neuro-fuzzy inference system techniques	MLR, ANN and ANFIS	Dissolve oxygen Prediction (DO)	Elsevier/ (J. Procedia Computer Science)	1	18	ANFIS outperform others
[68]	Time series modeling of biochemical oxygen demand at the upstream catchment of Feitsui Reservoir, Taiwan	ANN, ARIMA and ANFIS	Biochemical oxygen demand (BOD)	J. of Hydrology Research	1	19	ANFIS model identified at each sampling station is superior to the respective ARIMA and ANN models.
[15]	Forecasting streamflow by combination of a genetic input selection algorithm and wavelet transforms using ANFIS models.	ANFIS, Wavelet Transform and GA	Streamflow forecasting	Journal Hydrological Sciences Journal	1	20	GA and wavelet methods improved the two ANFIS model: subtractive (Sub)-ANFIS and fuzzy C-means (FCM)-ANFIS.
[26]	Ensemble of ANN and ANFIS for Water Quality Prediction and Analysis - A Data Driven Approach	ANN, ANFIS	Water Quality Prediction and Analysis	J of Telecommunication, Electronic and	1	21	Ensemble of ANN and ANFIS model shows significant improvement in prediction performance

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				Computer Engineering			as compared to the individual models.
[57]	Prediction of water quality of Euphrates river by using Artificial neural network model (spatial and temporal study)	ANN and MRA	Prediction of water quality	International Research Journal of Natural Sciences		22	ANN could explain the variability of the TDS of water in Euphrates river with more efficiency and outperform Statistical technique in forecasting
[63]	Artificial neural network modeling of dissolved oxygen in reservoir	(ANN), (BPNN), (ANFIS) and (MLR)	Dissolve oxygen (DO) estimation	Springer/ (J. of Environmenta l Monitoring Assessment)	1	23	ANN perform better than MLR. ANFIS model is better than the BPNN model for predicting the DO values.
[36]	The Study of Artificial Neural Network (ANN) Efficiency with Neuro-Fuzzy Inference System (ANFIS) in Dissolved oxygen Simulation of River Water	ANN and ANFIS	Dissolve oxygen (DO) Simulation	Bulletin of Environment, Pharmacology and Life Sciences	1	24	Analogy between model 1-4 with model 5-8), neuro-fuzzy network showed an absolute superiority to the similar neural models.
[10]	An ANFIS-based approach for predicting the bed load for moderately sized rivers	ANFIS	Bed load prediction	Elsevier	1	25	(ANFIS) network can more accurately predict the measured bed-load data when compared to an equation based on a regression method.

[21]	Adaptive neuro fuzzy inference system for classification of water quality status	ANFIS and ANN	Water quality status	Journal of Environmental Sciences	1	26	ANFIS outperformed ANN in testing of samples
[17]	Discharge Modelling using Adaptive Neuro - Fuzzy Inference System	ANFIS and MLR	Discharge Modelling	International Journal of Advanced Science and Technology	1	27	ANFIS models, predicted better results than MLR
[39]	Discharge Forecasting By Applying Artificial Neural Networks At The Jinsha River Basin, China	AR, ANN, FFBPNN, GRNN and RBFNN	Discharge Forecasting	European Scientific Journal	1	28	ANN outperformed AR but FFBPNN showed the best applicability, compared to other techniques.
[4]	Flood forecasting using ANN, Neuro-Fuzzy, and Neuro-GA models	ANN, Neuro-Fuzzy and Neuro-GA	Flood forecasting	Journal of Hydrologic Engineering	1	29	ANFIS and ANN model perform similarly in some cases, but ANFIS model predicts better than the ANN model in most of the cases.
[20]	Prediction and optimization of runoff via ANFIS and GA.	ANFIS and GA.	Prediction and optimization of runoff	Elsevier/ (Alexandria Engineering Journal)	1	30	ANFIS shows better result with 3-inputs than 2-inputs and GA based evolutionary optimizer was used to identify when runoff is maximum.

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Table 2: Statistical representation of the considered soft computing methodology

S/No	Methodology	Weight (x)	Frequency (f)	fx	x-x'	| x-x'|	(x-x')^2	f(x-x')^2
1	ANFIS	3	15	45	42.8	42.8	1831.84	27477.60
2	ANN	2	7	14	11.8	11.8	139.24	974.68
3	GAs	1	1	1	-1.2	1.2	1.44	1.44
4	BR	1	1	1	-1.2	1.2	1.44	1.44
5	E/Fuzzy	1	1	1	-1.2	1.2	1.44	1.44
6	MLR	1	1	1	-1.2	1.2	1.44	1.44
7	Ensemble ANN	1	1	1	-1.2	1.2	1.44	1.44
8	Ensemble ANFIS	1	1	1	-1.2	1.2	1.44	1.44
9	ARMA	1	1	1	-1.2	1.2	1.44	1.44
10	Wavelet	1	1	1	-1.2	1.2	1.44	1.44
Sum Total		13	30	67				28463.80

$$Mean(\bar{x}) = \frac{\sum fx}{f} = \frac{67}{30} = 2.23$$

$$SD(\sigma) = \sqrt{\frac{\sum f(x-\bar{x})^2}{\sum f}}\sqrt{\frac{28463.80}{30}} = 948.79$$

4.0 Discussion

From Table 2, Weight of one (1) was attached to the entries which has only one number of occurrence (frequency), weight of two (2) was attached to the entries having the frequency of (7) while weight three (3) was attached to the entries with highest frequency of (15). Measure of central tendency was used for analyzing the occurrence of the various soft computing methods that were reviewed in the work. It can be observed that the data shows tendency of researchers clustering around the ANFIS method, this may likely signifies that the method produce the best optimal results than the rest of the methods considered in the review. However, a high value of standard deviation was computed for the dataset which indicates that the values in the dataset are farther away from the mean, and denotes that the data are spread out. Likewise, the considered literatures were compared by visual inspection to determine the most viable optimization model in river quality modelling based on the authors' findings. ANFIS has fifteen (15) outstanding performance above other models followed by ANN with seven (7), GAs, Bayesian Regression, Evolutionary Fuzzy, Multi-Layer Regression, ARMA, Wavelet and Essemble ANN and Ensmble ANFIS has one (1) entry each. The submission here did not portray a rule of thumb but rather, our judgment is based on the scope of the thirty (30) number of literatures randomly consulted. Therefore, this submission may be subjected to criticism and further investigation anyway, but for the time being this happens to be the true representation of what we have at hand. ANFIS seems to be more favoured above others in our consideration. Statistical mean from the study shows 2.23 while the standard deviation is 948.79 which is used to measure the deviation, variability or dispersion with respect to the computed mean. All of the models, except ANFIS and ANN, show a high level of disparity as indicated in column 2 of Table 2.

5.0 Conclusion

Thirty (30) published papers in river modelling, monitoring, prediction, forecasting and management have been considered in this review, most importantly in the area of soft computing methodologies, applications and the evolving hybridization of two or more core systems of soft computing (ANN and FL) in the quest for a better result in the area of the river modelling, monitoring, forecasting and sustainable management of this dynamic environment coupled with its inherent peculiarities. It can be inferred from the results of this review that among the river modelling, monitoring prediction forecasting and management models, ANFIS and ANN are the most widely used. It could be concluded that they probably yield the most optimal results as compared to other models. More also, this paper can help researchers working in this particular area of interest to have handy information at a glance for onward confirmation of the best river optimization model that could be used before venturing deep into their main work.

From the paper consulted, modelling pollutant and various hydrodynamics processes using soft computing methodologies seems to be on the low ebb as most publication from developing countries are still scanty and scarce. It is therefore suggested that more attention be directed toward that area, especially in the developing countries where analytical method is still prevalent. Adaptive system can also be improved upon when combine with genetic algorithms for better result.

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