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A Review on Applications of Artificial Intelligence-Based Models to Estimate Suspended Sediment Load

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Abstract *Undeniably application of Artificial Intelligence (AI) has grown increasingly through past years. Hydrology also has its portion of utilization of AI-based models. Among different parts of hydrology, Suspended Sediment Load (SSL) estimation plays an important role since SSL can cause trouble in water resources engineering and environmental procedures. Therefore, employing AI-based models would cause more precise consequences. Recently proposed hybrid models provided more accurate prediction. These models employ AI-based models too, but in comparison, hybrid models forecast phenomena more accurate than sole AI-based models. It is because hybrid models can deal with non-stationary data. In this paper, advantages and disadvantages of both AI-based and hybrid models in the field of SSL modeling are discussed in the details.*

Index Terms— *Artificial Intelligence, Hybrid models, Suspended sediment load.*

I. INTRODUCTION

Estimates of sediment load are required in a wide spectrum of hydro-environmental issues such as the design of dams, transport of sediment and determination of the effects of the watershed management and environmental impact assessment. The physical based models are created based on the simplified partial differential equations of flow and sediment flux as well as some unrealistic simplifying assumption for flow and empirical relationships for erosive effects of rainfall and flow. They are highly sophisticated and complex models that have the advantage of having components that correspond to physical processes and being theoretically capable of taking into account the spatial variation of catchment properties as well as uneven distribution of precipitation and evapotranspiration. The sophistication and complexity of the model should, however, be keyed to utilizable information about the catchment characteristics and density and frequency of the available input data. Sediment computation methods provide rough estimates since the sediment amount is not only dependent on flow condition but also some other factors like drainage basin characteristics. Therefore, the hydrologic conditions and basin characteristics change both temporally and spatially and difficulties arising in determination of their effects have encouraged the employment of other type of models such as black box models for estimating suspended sediment. Black box models are divided generally as linear and non-linear and in particular artificial intelligence-based (AI) methods are currently used as new generation of black-box models for the modeling non-linear hydrological processes like sediment.

In this paper, some very commonly used AI-based approaches for prediction and forecasting river and watershed sediment load are addressed. The methods include Artificial Neural Network (ANN), Genetic Programming (GP) and Support Vector Machine (SVM) as AI-based models, Adaptive Neuro-Fuzzy Inference System (ANFIS), WANN (Wavelet-ANN) and WNF (wavelet Neuro-Fuzzy) models as hybrid models. For this purpose, at first a brief description of each method is presented and thereafter the related conducted studies are cited.

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II. APPLICATION OF ANN FOR SEDIMENT MODELING

An ANN is an information processing paradigm that is inspired by the way human brain processes information. The two major structural constituents of a brain are neurons and synapse. Neurons are information processing units and synapses are elementary structural and functional units that mediate the interaction between neurons. Haykin [1] defined ANNs as parallel distributed processors made up of simple processing units, which are capable of acquiring and storing experiential knowledge and making it available for use. There are different kinds of ANNs that are able to perform various tasks. Feed-Forward, Kohonen and Hopfield networks are some of the most recognized ANNs among others. A Feed-Forward ANN consists of information processing nodes or neurons organized in layers. There is no feedback between layers of a Feed-Forward ANN. Every neuron or node in a layer is connected to all nodes in the previous layer using synaptic or connection weights. Synaptic weights having different strengths encode the knowledge of a network [2].

ANNs have been developed as generalizations of mathematical models of human cognition or neural biology based on the assumptions that [2]:

i. Information processing occurs at many simple structures called neurons.

ii. Signals are passed between neurons over connection inks.

iii. Each connection link has an associated weight, which, in a typical neural net, multiplies the signal transmitted.

iv. Each neuron applies an activation function (usually nonlinear) to its net input (sum of weighted input signals) to determine its output signal.

v. A neural network is characterized by: (a) its pattern of connections between the neurons (called its architecture), (b) its method of determining the weights on the connections (called its training, or learning algorithm), and (c) its activation function.

vi. Whatever distinguishes ANNs from other approaches to information processing provides an introduction to both how and when to use neural networks. ANN can be applied to a wide variety of problems, such as storing and recalling data or patterns, classifying patterns, performing general mappings from input pattern to output patterns, grouping similar patterns, or finding solutions to constrained optimization problems. Each neuron has an internal state, called its activation or activity level, which is a function of the inputs it has received. Typically, a neuron sends its activation as a signal to several other neurons. It is ANN research stagnated after the publication of machine learning research by Minsky and Papert [3]; they discovered two key issues with the computational machines that processed neural networks:

i. The first issue was that single-layer neural networks were incapable of processing the exclusive-or circuit.

ii. The second significant issue was that computers were not sophisticated enough to effectively handle the long run time required by large neural networks.

Also key in later advances was the back propagation (BP) algorithm which effectively solved the exclusive or problem [4]. Architecture of such a network is shown in Figure 1.

ANNs were employed by a number of diverse fields of engineering including water resources engineering. In the hydrological forecasting context, recent experiments have reported that ANNs may offer a promising alternative for rainfall-runoff modeling [5], [6], [7], [8], [9], streamflow prediction [10], [11], [12], reservoir inflow forecasting [13], as well as suspended sediment estimation [14], [15], [16], [17], [18], [19], [20], [21]. Jain [14] used a single ANN approach to establish sediment- discharge relationship and found that the ANN model could perform better than the rating curve. Tayfur [15] developed an ANN model for sheet sediment indicated that the ANN could perform as well as, in some cases better than, the physically based models.

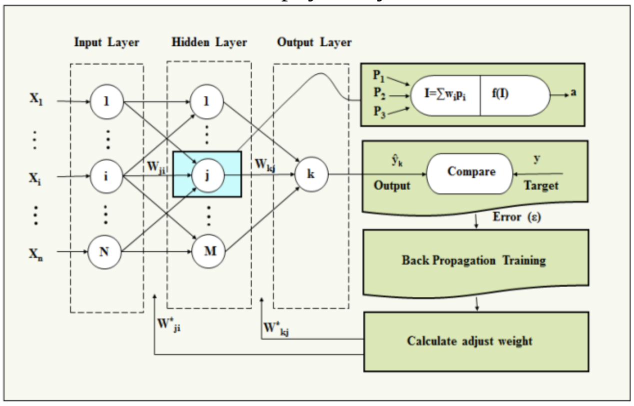

Fig. 1. A three-layered feed-forward neural network with BP training algorithm

Cigizoglu [16] investigated the accuracy of a single ANN for estimation and forecasting daily suspended sediment load. Kisi [17] used three different ANN techniques for daily suspended sediment concentration prediction and indicated that multi-layer perceptron could show better performance than the radial basis neural networks and generalized regression neural networks. Kisi [18] developed an ANN model for modeling suspended sediment load and compared the ANN results with those of the rating curve and multi-linear regression methods. Cigizoglu and Kisi [19] developed some methods to improve ANN performance in suspended sediment estimation. Nourani [20] employed ANNs for sediment load forecasting of Talkherood River mouth. ANN was introduced as non-linear black box model interpolator tool that is used for modeling suspended sediment load. The obtained results were compared with the results of two other classic methods (i.e., linear regression and rating curve methods) in order to approve the efficiency and ability of the proposed method. Also, Nourani et al. [21] Proposed two semi distributed ANN-based models for estimation of suspended sediment load. In both models, a three-layer perceptron neural network was trained considering various combinations of input and hidden neurons and the optimum architectures of the models were selected. The obtained results demonstrated that the predicted sediment load time series by both models are in satisfactory agreement with the observed data.

A common criticism of neural networks is that they require a large diversity of training for real-world operation. This is not surprising, since any learning machine needs sufficient representative examples in order to capture the underlying structure that allows it to generalize to new cases.

III. APPLICATION OF ANFIS FOR MODELING SEDIMENT LOAD

The Adaptive Neuro-Fuzzy Inference System (ANFIS), first introduced by Jang [22], is a universal approximator and, as such, is capable of approximating any real continuous function on a compact set to any degree of accuracy [23]. Thus, in parameter estimation, where the given data are such that the system associates measurable system variables with an internal system parameter, a functional mapping may be constructed by ANFIS that approximates the process of estimation of the internal system parameter. Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions. Jang [22] introduced architecture and a learning procedure for the fuzzy inference systems (FIS) that uses a neural network learning algorithm for constructing a set of fuzzy if-then rules with appropriate membership functions (MFs) from the specified input-output pairs. There are two approaches for FIS, namely Mamdani [24] and Sugeno [25]. The differences between these two approaches arise from the consequent part. Mamdani's approach uses fuzzy MFs, whereas Sugeno's approach uses linear or constant functions (Fig.2). The ANFIS is functionally equivalent to fuzzy inference systems [23]. Below, the hybrid learning algorithm, which combines gradient descent and the least-squares method, is introduced and the issue of how the equivalent fuzzy inference system can be rapidly trained and adapted with this algorithm is discussed (Fig.3). As a simple example, a fuzzy inference system with two inputs x and y and one output z is assumed. The first-order Sugeno fuzzy model, a typical rule set with two fuzzy If-Then rules can be expressed as [26]:

Rule 1: If $\mu(x)$ is A_1 and $\mu(y)$ is B_1; then

$$f_1 = p_1 x + q_1 y + r_1 \qquad (1)$$

Rule 2: If $\mu(x)$ is A_2 and $\mu(y)$ is B_2; then

$$f_2 = p_2 x + q_2 . y + r_2 \qquad (2)$$

The resulting Sugeno fuzzy reasoning system is shown in Fig. 2. Here, the output z is the weighted average of the individual rules outputs and is itself a crisp value. The corresponding ANFIS architecture is shown in Fig. 2. Nodes at the same layer have similar functions. The output of the i th node in layer l is denoted as O_i^1.

Layer 1: Every node i in this layer is an adaptive node with node function [26]:

$$O_i^1 = \mu A_i(x) \qquad for\ i = 1,2 \tag{3}$$

or

$$O_i^2 = \mu B_{i-2}(x) \qquad for\ i = 3,4 \tag{4}$$

Where x (or y) is the input to the i th node and A_i is a linguistic label (such as "low" or "high") associated with this node. In other words, O_i^1 is the membership grade of a fuzzy set A ($= A_1, A_2, B_1$, or B_2) and it specifies the degree to which the given input x (or y) satisfies the quantifier A. The membership functions for A and B are generally described by generalized bell functions, e.g. [26]:

$$O_i^1 = \mu A_i(x) = \frac{1}{1 + [(x - c_i)/a_i]^{2b_i}} \tag{5}$$

Where {a_i, b_i, c_i} is the parameter set. As the values of these parameters change, the bell-shaped function varies accordingly, thus exhibiting various forms of membership functions on linguistic label Ai. In fact, any continuous and piecewise differentiable functions, such as commonly used triangular-shaped membership functions, are also qualified candidates for node functions in this layer (Jang, 1993). Parameters in this layer are referred to as premise parameters. The outputs of this layer are the membership values of the premise part.

Layer 2: Every node in this layer multiplies the incoming signals. For instance [26]:

$$O_i^2 = w_i = \mu A_i(x) \mu B_i(y) \qquad i = 1,2 \tag{6}$$

Each node output represents the firing strength of a rule.

Layer 3: In this layer, the nodes labeled N calculate the ratio of the i th rule's firing strength to the sum of all rules' firing strengths. The outputs of this layer are called normalized firing strengths [26]:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \tag{7}$$

Layer 4: This layer's nodes are adaptive with node functions where $\overline{w}$ is the output of layer 3, and { p_i, q_i, r_i }are the parameter set. Parameters of this layer are referred to as consequent parameters [26]:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{8}$$

Layer 5: This layer's single fixed node labeled Σ computes the final output as the summation of all incoming signals [26]:

$$O_i^5 = \sum_{i=1} \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{9}$$

Thus, an adaptive network which is functionally equivalent to a Sugeno first-order fuzzy inference system is created. More information on ANFIS can be found in Jang [22]. Fuzzy membership functions can take many forms, but simple straight-line functions are often preferred. Triangular membership functions are often selected for practical applications. Two or three membership functions to the NF models were found enough for modeling suspended sediment and bed load sediment. Kisi [18] applied neuro-fuzzy and neural network techniques for estimating suspended sediment. Kisi [27] proposed evolutionary fuzzy models for suspended sediment concentration estimation. Cobaner et al. [28] applied ANFIS and ANN approaches to estimate suspended sediment load using hydro-meteorological data. Rajaee et al. [29] proposed hybrid wavelet and neuro-fuzzy model for daily suspended sediment modeling. Suspended sediment load estimated by this technique was closer to the actual data than the others. Also, the model could be employed to simulate hysteresis phenomenon, while sediment rating curve method was incapable of doing that.

As a criticism, ANFIS is a complex method in comparison to other adaptive fuzzy systems, for this reason in some cases; it can not be easily used. In cases mentioned below application of the ANFIS can be recommended:

i. Degree of Sugeno systems of zero or 1,
ii. If only one output is concerned,
iii. There must be no common rule,
iv. Weights of the rules must equal to unit.

Applying ANFIS as an alternative approach to predict the functional relationships of sediment transport causes more accurate results. The results show that the recommended network can more accurately predict the measured bed-load and suspended load data when compared to an equation based on a regression method or ANN and other networks. Membership function parameters of the system are set using back propagation training method.

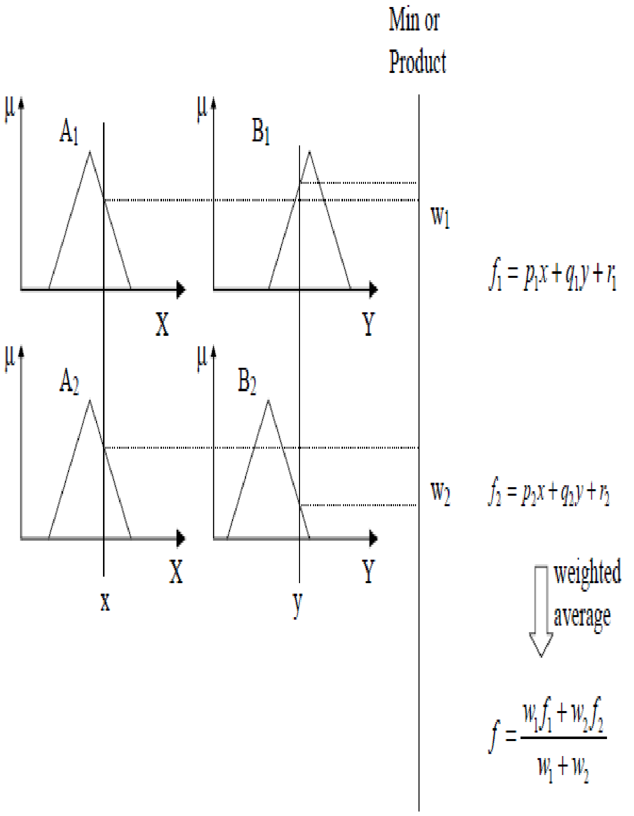

Fig. 2. Two- input first- order Sugeno fuzzy model with two rules

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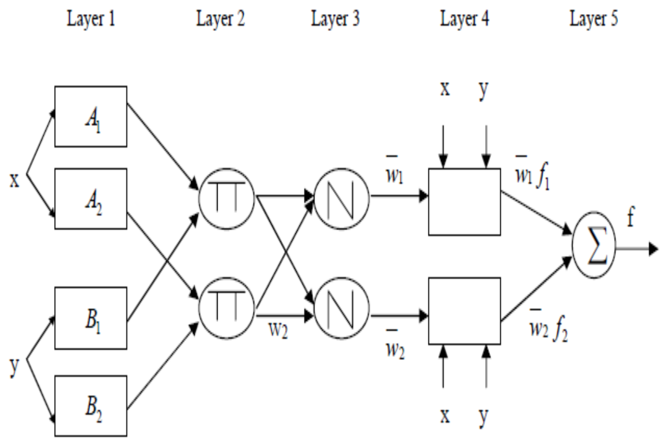

Fig. 3. Equivalent ANFIS architecture

IV. GP FOR SEDIMENT MODELING

During recent decades, some black box models based on artificial neural networks have been developed but these type of models are implicit that can not be simply used by other investigators. Therefore it is still necessary to develop an explicit model for the discharge–sediment relationship. In artificial intelligence, genetic programming (GP) is an evolutionary algorithm-based methodology inspired by biological evolution to find computer programs that perform a user-defined task. Essentially GP is a set of instructions and a fitness function to measure how well a computer has performed a task. It is a specialization of genetic algorithms (GA) where each individual is a computer program. It is a machine learning technique used to optimize a population of computer programs according to a fitness landscape determined by a program's ability to perform a given computational task. In 1954, GP began with the evolutionary algorithms first used by Nils Aall Barricelli applied to evolutionary simulations. In the 1960s and early 1970s, evolutionary algorithms became widely recognized as optimization methods [30]. Later GP-related work grew out of the learning classifier system community, which developed sets of sparse rules describing optimal policies for Markov decision processes. The first statement of modern "tree-based" GP (that is, procedural languages organized in tree-based structures and operated on by suitably defined GA-operators) was given by Cramer; this work was later greatly expanded by John R. Koza, a main proponent of GP who has pioneered the application of GP in various complex optimization and search problems. GP is a generalization of genetic algorithms (GAs), starts with an initial population of randomly generated computer programs composed of functions and terminals appropriate to the problem domain [31]. The functions may be standard arithmetic operations, standard programming operations, standard mathematical functions, logical functions, or domain-specific functions. Depending on the particular problem, the computer program may be boolean-valued, integer-valued, real-valued, complex-valued, vector-valued, symbolic-valued, or multiple-valued. The fundamental steps of GP are schematically presented in Figure 4.

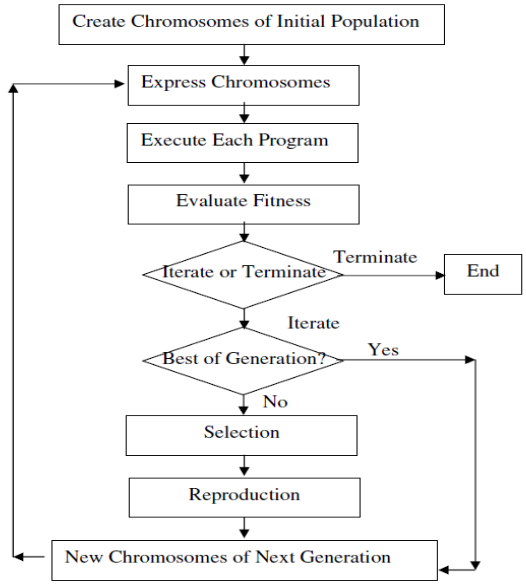

Fig. 4. Flowchart of gene expression programming

Five stages are employed in GP to solve a problem [30]:

I. Initialize a population of programs,
II. The randomly generated programs with the higher fitness will "win" and must be copied to the next generation. There are several different types of selection used in GP such as roulette-wheel selection, tournament, and ranking,
III. The two winner programs (GP solution) are then copied and transformed probabilistically by exchanging parts of the winner programs with each other to create two new programs (crossover) and randomly changing each of the winner program to create new program. A function can only replace a function, a terminal can only replace a terminal and an entire sub tree can replace another sub tree (mutation),
IV. Replace the "loser" programs in the population with the transformed "winner" programs. The winners of the selection remain in the population unchanged,
V. Repeat steps 2-4 until a program is developed that predicts the behavior properly. The fitness function, fi, of an individual program, i is expressed by [39]:

$$f_i = \sum_{j=1}^{n} \left(R - \left| P_{(ij)} - T_j \right| \right) \quad (10)$$

Where R is the range of selection, $P_{(ij)}$ is the value predicted by the individual program i for fitness case j and T_j is the target value for fitness case j.

Cousin and Savic [32], Drecourt [33], applied GP to rainfall-runoff modeling. Babovic et al. [34] applied GP to sedimentary particle settling velocity equations. Harris et al. [35] studied velocity predictions in compound channels with vegetated floodplains using GP. Dorado et al. [36] studied prediction and modeling of the rainfall-runoff transformation of a typical urban basin using ANN and GP. Giustolisi [37] determined Chezy resistance coefficient in corrugated channels using GP. Rabunal et al. [38] determined the unit hydrograph of a typical urban basin using GP. Nourani et al. [21] proposed a hybrid wavelet-Genetic programming model to optimize ANN modelling of rainfall-runoff process. Hakimzadeh et al. [40] applied GP to simulate dam breach hydrograph and peak out flow discharge.

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Different studies have been conducted for sediment modeling using GP approach. Babovic [41] used experimental flume data utilized by Zyserman and Fredsoe [42] and expressed a new formulation for bed concentration of suspended sediment. Kizhisseri et al. [43] used GP methodology to explore a better correlation between the temporal pattern of fluid field and sediment transport by utilizing two datasets; one from numerical model results and other from Sandy Duck field data. Aytek and Kisi [44] in their study proposed GP as a new approach for the expressed formulation of daily suspended sediment-discharge relationship. They compared expressed models obtained using the GP with rating curves and multi-linear regression techniques in suspended sediment load estimation. They used the daily stream flow and suspended sediment data from two stations on Tongue River in Montana as case studies. Their results indicated that the proposed GP formulation performed quite well compared to sediment rating curves and multi-linear regression models and was quite practical for use. Kisi and Guven [45] developed a machine code-based GP for suspended sediment concentration estimation. The accuracy of the GP was compared with those of the adaptive NF, ANN and rating curve models. The daily stream flow and suspended sediment data from two stations, Rio Valenciano and Quebrada Blanca, in USA were used for the model simulations. The comparison results indicated that the GP model performed better than the NF, ANN and rating curve models.

V. APPLICATIONS OF SVM FOR MODELING SEDIMENT LOAD

The original SVM algorithm was invented by Vladimir N. Vapnik and the current standard incarnation (soft margin) was proposed by Vapnik and Cortes [46].In machine learning, SVMs are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into the same space and predicted to belong to a category based on which side of the gap they fall on. In addition to performing linear classification, SVMs can efficiently perform non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

The main relationship for statistical learning process is as follows [47]:

$$y = f(X) = \sum_{i=1}^{M} W_i \phi_i(X) = W\phi(X) \tag{11}$$

Where the output of the model is the part of linear M and the converter is shown by the nonlinear model of φ(). This equation is converted as the below for using SVM model [47]:

$$y = f(X) = \left\{ \sum_{i=1}^{N} W_i K(X_i, X) \right\} - b \tag{12}$$

Here K is the Kernel function, W_i and b are parameters of the model, N the total number of learning patterns and X_i data vector for network learning and X is an independent vector. The parameters of the model are determined with maximizing the objective of function. The general structure of an SVM is shown in Fig. 5. SVM use some of the specific kernel functions which convert the input vector as the input data from nonlinear function in this model. Selection of an appropriate kernel function is a complex stage and often standard kernel function is used.

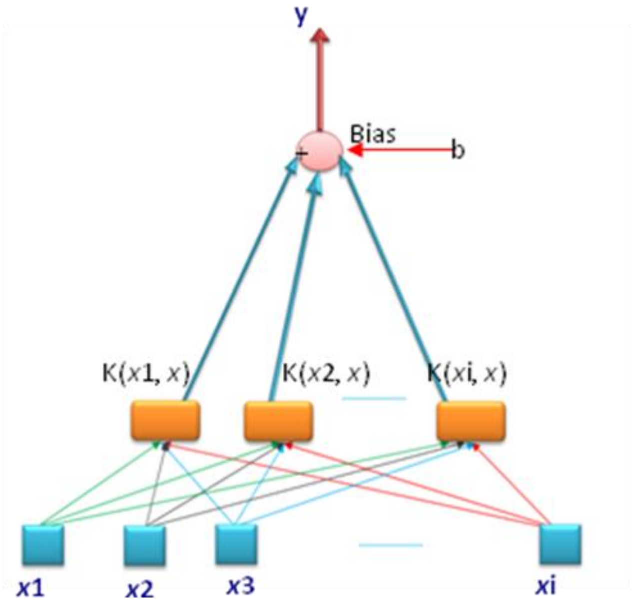

Fig. 5. Structure of SVM model [48]

Until now, many techniques have been proposed for prediction of SSL. However, due to the complexity of SSL transportation mechanism and non-linear behavior of effective hydrologic parameters, such techniques do not have enough precision [49]. Recent experiences concerning hydrological forecasts have shown that artificial neural networks and support vector machines can be proper alternatives to predict SSL carried by the river [16], [17], [18], [20], [50], [51], [52]. Bhattacharya et al. [53] and Azamathulla et al. [54] used machine learning approach to predict load transport. Jie and Yu [55] estimated suspended sediment load using ANN and SVM models in Kaoping river basin located in southern Taiwan. The result showed that SVM outperforms the ANN model. Cimen [56] used SVM with Gaussian radial basis function kernel in order to estimate suspended sediment concentration for two rivers located in the USA. Results indicated that SVM model can estimate sediment without producing negative values. Kisi [57] used Least Square Support Vector Machine (LSSVM) to model discharge-suspended sediment relationship. Results showed that the LSSVM model is able to produce better results than the ANN models. LSSVM and ANN models were found to be better than the SRC model for the upstream station.

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For the downstream station, however, SRC model outperformed the LSSVM and ANN models. In the second part of the study, the models were compared to each other in estimation of downstream suspended sediment data using data from both stations. It was found that the LSSVM model performed slightly better than the ANN models and both models performed much better than the SRC model.

VI. APPLICATION OF HYBRID AI-BASED MODELS FOR MODELING SEDIMENT LOAD

Although AI methods have been used extensively as useful tools for prediction of hydrological variables, they may also include some drawbacks to deal with non-stationary data. Therefore, some hybrid modeling approaches which include different data-preprocessing and combine techniques have been also developed to increase generalization capability of sole AI-based methods. Approaches for dealing with non-stationary characteristics of data are not as highly generated, nor as well proved, as those for hydrological prediction problems. In the last years, there has been an interest in hybrid modeling techniques. Here, some of such hybrid models employed in sediment modeling are presented.

Combined Wavelet-Artificial Neural Network (WANN) model has been widely used in recent years to forecast hydrological and hydrogeological phenomena. The neuro-wavelet models are obtained by combining two methods, ANN and wavelet transform. WANN models, based on wavelet analysis and ANN, have been proven effective for modeling nonlinear and non-stationary time series signals. A non-stationary signal can be decomposed into a certain number of stationary signals by wavelet transform. Then, ANN is combined with wavelet transform to improve the prediction accuracy [58]. During recent years, wavelet transform has become a useful method for analyzing such as variations, periodicities, trends in hydrological time series. Partal and Cigizoglu [50] used neuro-wavelet technique for forecasting river daily suspended sediment load. Kisi [59] proposed neuro-wavelet models for estimating daily suspended sediment estimation. The WANN was developed by combining two methods, ANN and discrete wavelet transform. The WANN and ANN models were tested by applying to different input combinations of daily streamflow and suspended sediment load data of two stations on Tongue river in Montana. The comparison results indicated that the discrete wavelet transform could increase the accuracy of ANN model in suspended sediment load estimation. Rajaee et al. [49] applied ANN and Wavelet conjunction model to predict River suspended sediment load. Nourani et al. [60] conjugated threshold based wavelet de-noising approach and ANN to forecast suspended sediment load. Results revealed that chosen mother wavelet and resolution level directly affect the prediction results. On the other hand, the threshold value, as well as so-called factors, is another challenging issue. According to obtained result high values of threshold didn't mean accurate result and after a specific threshold value the reduction in performance of the model was occurred. Result presented that this procedure extensively enhanced accuracy when modeling streamflow-SSL process.

Wavelet analysis, which gives information in both time and frequency domains of the signal, also presents considerable knowledge about the physical form of the data. Neuro-fuzzy modeling is another method that refers to the approach of applying deferent learning algorithms developed in the neural network literature to fuzzy modeling or a fuzzy inference system (FIS). Wavelet analysis and artificial intelligent approaches (such as FIS and NF) are indicated to be suitable when applied individually to environmental and water resources problems. Recently, there has been a growing interest in combining methods. Rajaee et al. [29] combined wavelet and neuro-fuzzy model to predict daily suspended sediment load. The cumulative suspended sediment load estimated by this technique was closer to the actual data than the other ones. Also, the model could be employed to simulate the involved hysteresis phenomenon, while sediment rating curve method was incapable with this issue.

VII. CONCLUSION

Recently, conducted studies in hydrology indicated that Artificial Intelligence-based models (AI) and hybrid models are efficient. Employing Artificial Neural Network (ANN) for modeling suspended sediment load leads to acceptable results, but in past few years more attentions are paid to apply hybrid models. Genetic Programming (GP) also eventuates applicable results, but most of studies show that ANN is more powerful tool than GP. Employing Support Vector Machine (SVM), shows accurate results than other approaches; especially, when using selected kernels. No coincidence, application of hybrid models leads to better results in comparison with sole AI-based models. Preprocessing of data and handling non-stationary data are the main reasons of such results.

REFERENCES

1. S.S. Haykin. (1999). Neural networks: a comprehensive foundation. Prentice Hall, University of Michigan, United States.
2. F.G. Bekele. (2007). Integrated modelling System for multi- objective management of ecosystem services in a watershed. University of Carbondale. United States.
3. M.L. Minsky, S.A. Papert. (1969). Perceptrons: An introduction to computional geometry. The MIT Press, Cambridge, MA.
4. P.J. Werbos. (1975). Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences.
5. A.Y. Shamseldin. (1997). Application of a neural network technique to rainfall-runoff modelling. J. Hydrol. 199. pp. 272–294.
6. R.J. Abrahart, L. See, E. Kneale.(1999). Applying saliency analysis to neural network rainfall-runoff modelling. Proceedings of the 4th International Conference on Geocomputation, Fredericksburg, Virginia. USA, 25-28 July.
7. A.S. Tokar, P.A. Johnson. (1999). Rainfall-Runoff Modeling using artificial neural networks. J. Hydraul Eng. 4(3). pp. 232–239.
8. D.P. Solomatine, K.N. Dual. (2003). Model trees as an alternative to neural networks in Rainfall-runoff modelling, Hydrol. Sci. J. 48(3). pp. 399–411.
9. O. Giustolisi, D. Laucelli. (2005). Improving generalization of artificial neural networks in rainfall-runoff modelling. Hydrol. Sci. J. 50(3). pp. 439–457.
10. H.K. Cigizoglu. (2003). Estimation, forecasting and extrapolation of acceleration data by artificial neural networks. Hydrol. Sci. J. 48(3). pp. 349–361.
11. H.K. Cigizoglu, O. Kisi. (2005). Flow Prediction by three Back Propagation Techniques Using k-fold Partitioning of Neural Network Training Data. Nord. Hydrol. 36(1). pp. 1–16.
12. O. Kisi, H.K. Cigizoglu. (2007). Comparison of different ANN techniques in river flow prediction. Civ. Eng. Environ. Syst. 24(3). pp. 211-231.
13. S.K. Jain, A. Das, D.K. Srivastava. (1999). Application of ANN for reservoir inflow prediction and opreation. J. Water. Res. Pl. 125(5). pp. 263–271.

14. S.K. Jain. (2001). Development of integrated sediment rating curves using ANNs. J. Hydraul. Eng. 127(1). pp. 30–37.
15. G. Tayfur. (2002). Artificial neural networks for sheet sediment transport. Hydrol. Sci. J. 47(6). pp. 879–892.
16. H.K. Cigizoglu. (2004). Estimation and forecasting of daily suspended sediment data by multi-layer perceptrons. Adv. Water. Resour. 27: 185-195.
17. O. Kisi. (2004). Multi-layer perceptrons with Levenberg – Marquardt optimization algorithm for suspended sediment concentration prediction and estimation. Hydrol. Sci. J. 49(6). pp. 1025–1040.
18. O. Kisi. (2005). Suspended sediment estimation using neuro-fuzzy and neural network approaches. Hydrol. Sci. J. 50(4). pp. 683–696.
19. H.K. Cigizoglu, O. Kisi. (2006). Methods to improve the neural network performance in suspended sediment estimation. J. Hydrol. 317. pp. 221–238.
20. V. Nourani. (2009). Using artificial neural networks (ANNs) for sediment load forecasting of Talkherood River mouth. J. U. E. E. 3(1). pp. 1–6.
21. V. Nourani, O. Kalantari, A. Baghanam. (2012). Two Semidistributed ANN-Based Models for Estimation of Suspended Sediment Load. J. Hydraul. Eng. 17(12). pp. 1368–1380.
22. J.S.R. Jang. (1993). Adaptive-network-based fuzzy inference system. IEEE, Man, and Cybernetics. 23(3). pp. 665–685.
23. J.S.R. Jang, C.T. Sun, E. Mizutani. (1997). Neuro-Fuzzy and Soft Computing. Prentice Hall. ISBN 0-13-261066-3. pp. 335–368.
24. E.H. Mamdani, S. Assilian. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. Int. J. Man-Mach. Stud. 7(1). pp. 1–13.
25. T. Takagi, M. Sugeno. (1985). Fuzzy identification of systems and its applications to modelling and control. Int. J. Man-Mach. Stud. 15(1). pp. 116–132.
26. V. Nourani, O. Kisi, M. Komasi. (2011). Two hybrid Artificial Intelligence approaches for modeling rainfall–runoff process. J. Hydrol. 402. pp. 41–59.
27. O. Kisi. (2009). Evolutionary fuzzy models for river suspended sediment concentration estimation. J. Hydrol. 372. pp. 68–79.
28. M. Cobaner, B. Unal, O. Kisi. (2009). Suspended sediment concentration estimation by an adaptive neuro-fuzzy and neural network approaches using hydrometeorological data. J. Hydrol. 367. pp. 52–61.
29. T. Rajaee, S.A. Mirbagheri, V. Nourani, A. Alikhani. (2010). Prediction of daily suspended sediment load using wavelet and neuro-fuzzy combined model. Int. J. Environ. Sci. Technol. 7(1). pp. 93–110.
30. O. Mohamad Rezapour, T. Shui, A.A. Dehgani. (2010). Review of genetic programming in water resource engineering. AIBAS. 4(11). pp. 5663–5667.
31. D.E. Goldberg. (1989). Genetic Algorithms in Search, Optimization and Machine Learning. Addison-Wesley, Reading, Mass.
32. N. Cousin, D.A. Savic. (1997). A rainfall-runoff model using genetic programming. Centre for Systems and Control Engineering. Report No. 97/03, School of Engineering, University of Exeter, Exeter, United Kingdom. p. 70.
33. J.P. Drecourt. (1999). Application of neural networks and genetic programming to rainfall-runoff modeling. D2K Technical Report 0699-1-1, Danish Hydraulic Institute. Denmark.
34. V. Babovic, M. Keijzer, D.R. Aguilera, J. Harrington. (2001). Automatic Discovery of Settling Velocity Equations. D2K Technical Report. D2K-0201-1.
35. E.L. Harris, V. Babovic, R.A. Falconer, (2003). Velocity predictions in compound channels with vegetated floodplains using genetic programming. JRBM. 1(2). pp. 117–123.
36. J. Dorado, J.R. Rabunal, A. Pazos, A. Rivero, J. Santos. (2003). Prediction and modelling of the rainfall-runoff transformation of a typical urban basin using ANN and GP. Eng. Appl. Artif. Intel. 17. pp. 329–343.
37. O. Giustolisi. (2004). Using genetic programming to determine Chezy resistance coefficient in corrugated channels. J. Hydro. Inform. 6. pp. 157–173.
38. J.R. Rabunal, J. Puertas, J. Suarez, D. Rivero. (2007). Determination of the unit hydrograph of a typical urban basin using genetic programming and artificial neural networks. Hydrol. Process. 21. pp. 476–485.
39. V. Nourani, M. Komasi, M. Alami. (2012). Hybrid Wavelet–Genetic Programming Approach to Optimize ANN Modeling of Rainfall–Runoff Process. J. Hydraul. Eng. 17(6). pp. 724–741.
40. H. Hakimzadeh, V. Nourani, A. Amini. (2013). Genetic Programming Simulation of Dam Breach Hydrograph and Peak Outflow Discharge. J. Hydraul. Eng. 10.1061/(ASCE)HE.1943-5584.0000849.
41. V. Babovic. (2000). Data mining and knowledge discovery in sediment transport. Compute -Aided. Civ. Inf. 15(5). pp. 383–389.
42. J.A. Zyserman, J. Fredsoe. (1994). Data analysis of bed concentration of suspended sediment. J. Hydraul. Eng. 120(9). pp. 1021-1042.
43. A.S. Kizhisseri, D. Simmonds, Y. Rafiq, M. Borthwick. (2005). An Evolutionary computation approach to sediment transport modeling. In: Fifth International Conference on Coastal Dynamics. Barcelona. Spain.
44. Aytek, O. Kisi. (2008). A genetic programming approach to suspended sediment modelling. J. Hydrol. 351. pp. 288–298.
45. O. Kisi, A. Guven. (2010). A machine code-based genetic programming for suspended sediment concentration estimation, Adv. Eng. Softw. 41. pp. 939–945.
46. V. Vapnik, C. Cortes. (1995). Support Vector Networks, Machine Learning. 20. pp. 1–25.
47. E. Kakaei, A. Moghddam Nia, A. Ahmadi. (2013). Daily suspended sediment load prediction using artificial neural networks and support vector machines. J. Hydrol. 478. pp. 50–62.
48. V. Vapnik. 1998. Statistical Learning Theory. Wiley, New York.
49. T. Rajaee, V. Nourani, M. Zounemat-Kermani, O. Kisi. (2011). River suspended sediment load prediction: Application of ANN and wavelet conjunction model. J. Hydraul. Eng. 16(8). pp. 613–627.
50. T. Partal, H.K. Cigizoglu. (2008). Estimation and forecasting of daily suspended sediment data using wavelet-neural networks. J. Hydrol. 358. pp. 317–331.
51. O. Kisi, I. Yuksel, E. Dogan. (2008). Modelling daily suspended sediment of rivers in Turkey using several data-driven techniques. Hydrolog. Sci. J. 53 (6). pp. 1270–1285.
52. Y.M. Zhu, X.X. Lu, Y. Zhou. (2007). Suspended sediment flux modeling with artificialneural network: an example of the Longchuanjiang River in the UpperYangtzeCatchment, China, Geomorphology 84. pp. 111–125.
53. B. Bhattacharya, R.K. Price, D.P. Solomatine. (2007). Machine learning approach to modelling sediment transport. J. Hydraul. Eng. 133(4). pp. 440–450.
54. H. M.D. Azamathulla, A. A.B. Ghani, C.K. Chang, Z. Abu Hasan, N.A. Zakaria. (2010). Machine learning approach to predict sediment load - a case study. Clean-SoilAir Water. 38 (10). pp. 969–976.
55. L.C. Jie, S.T. Yu. (2011). Suspended sediment load estimate using support vector machines in Kaoping River basin. IEEE Trans. Consum. Electron. 459. pp. 1750–1753.
56. M. Cimen. (2008). Estimation of daily suspended sediments using support vector machines. Hydrol. Sci. J. 53. pp. 656–666.
57. O. Kisi. (2012). Modeling discharge-suspended sediment relationship using least square support vector machine. J. Hydrol. 456. pp. 110–120.
58. H.C. Zhou, Y. Peng, G.H. Liang. (2008). The research of monthly discharge predictor corrector model based on wavelet decomposition. Water. Resour. Manag. 22. pp. 217–227.
59. O. Kisi. (2010). Daily suspended sediment estimation using neuro-wavelet models. Int. J. Earth. Sci. 99. pp. 1471–1482.
60. V. Nourani, A. Yahyavi Rahimi, F.H. Nejad. (2013). Conjuction of ANN and threshold based wavelet de-noising approach for forecasting suspended sediment load. Int. J. Manag. Inf. Tech. 3(1). pp. 9–26.

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