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An Overview of Machine Learning Techniques for Sediment Prediction †

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Abstract: Most hydrological and water resources researchers prioritize the development of an accurate sediment prediction model. Several conventional techniques have failed to accurately predict suspended sediment. Because of the intricacy, non-stationarity, and nonlinearity of sediment movement behavior in streams and rivers, many techniques fall short. Over the last several years, there have been meaningful theoretical improvements in the understanding of machine learning approaches, vis a vis strategy for the implementation of their processes and uses of the technique for practical and hydrological issues. To produce the desired output, machine learning models and other algorithms have been employed to predict complicated nonlinear connections and patterns of huge input parameters. This paper examines a few key works of the literature on sediment transport prediction while focusing on a variety of machine learning applications. Sediment transport models aided by machine learning have attracted a growing number of researchers in recent years. As a result, they must gain in-depth knowledge of their theory and modeling methodologies. Furthermore, this chapter includes an overview of the machine learning technique and other developing hybrid models that have produced promising outcomes. This overview also includes various examples of successful machine learning applications in sediment prediction.

Keywords: machine learning techniques; artificial neural network; sediment transport prediction; suspended sediment

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1. Introduction

The understanding of river hydraulics is important in water resources, which is why hydraulic and hydrological practitioners have been advancing knowledge in sediment conveyance in rivers and streams for several decades. Sediment, erosion, and deposition modify the hydraulic shape of the channel, potentially increasing flood frequency and causing navigation issues due to excessive deposition. Human activities, such as soil erosion and other anthropogenic actions, are contributing to the increased movement of river sediment. Additionally, these activities are also reducing the flux of sediment to the coastal zone by retaining it in reservoirs [1]. The estimation of sediment transport rates in rivers and streams holds significant importance in various aspects such as erosion, sedimentation, management of flooding, enduring morphological assessment, and other purposes. Sediment samples collected physically arguably provide the most precise data for understanding river sediment dynamics and transport [2]. There are a number of techniques utilized for this purpose including depth integration and isokinetic samplers [3], which constitute substantial representation of the water column in a river cross section [4].

Similarly, larger particles such as gravels and cobbles moving along the riverbed are measured using the pressure difference bedload and thereafter the sediment concentration processed in the laboratory using the procedures as described by the American Society for Testing and Materials, 2000 [5].

Over the past few decades, there has been extensive research leading to the development of numerous models for sediment transport. Regrettably, there is often doubt regarding the accuracy of these models, with many real-world situations yielding prediction errors deemed unacceptably high. References [6–8] and other researchers have diligently examined and documented the effectiveness of these models. Drawing from these observations, it is plausible to assert that the movement of sediment is an immensely intricate process that defies representation through a deterministic mathematical framework [9].

Emerging modeling paradigms, such as machine learning (ML), have been observed in recent times. ML pertains to the field of study that focuses on the creation and refinement of models capable of acquiring knowledge and making predictions via the analysis of empirical data. This development has created novel prospects for modeling processes that lack sufficient knowledge to establish a pertinent mathematical framework or possess insufficient data to calibrate a suitable model. ML is currently being employed in nearly all scientific disciplines as a substitute or supplement to the conventional physically based process modeling methodology. It utilizes a variety of modeling methodologies and techniques, encompassing artificial neural networks (ANNs), decision trees, fuzzy logic, support vector machines, genetic programming, Bayesian networks, and other pertinent techniques [1].

2. Conventional Sediment Estimation Approach

The sediment rating curve (SRC) has been widely used and arguably considered the conventional approach for sediment estimation and prediction. The technique establishes estimation of suspended sediment concentration via a correlation between discharge and sediment concentration. In this method, discharge serves as a surrogate variable encompassing the cumulative impact of all mechanisms influencing erosion and the transport of sediment within the river system [10]. Typically, rating curves are expressed as power functions, and their general form is represented as follows:

$$S = aQ^b \tag{1}$$

where:

S = suspended sediment concentration (mg/L)

Q = river discharge (m^3/s)

a and b = regression coefficients

Variations in the behavior of rating curves are evident across diverse rivers, primarily attributed to the correlation observed between suspended sediment concentration and discharge across varying orders of magnitude. This relationship is contingent on the geographical location. The widespread acceptance of sediment rating curves stems from their facile establishment, requiring a distinct and comparatively modest dataset [10]. Additionally, these curves can be formulated by utilizing turbidity data calibrated with suspended sediment data, serving as a surrogate variable for suspended sediment concentration, particularly in scenarios where only a restricted number of sediment samples are accessible.

3. Machine Learning Approaches

ML has been effectively employed in various applications within the field of water resources engineering. For instance, ML techniques have been successfully utilized in hydrology, as demonstrated in the ASCE 2000 study. ML has also been applied to water system control, water quality evaluations, and the establishment of stage–discharge relations, among other areas. The application demonstrates that ML does not produce original insights into the underlying process. Instead, it utilizes existing knowledge of the process to choose input and output parameters. It then employs contemporary regression techniques to enhance the correspondence between the observed data and the model's predictions. The subsequent text provides a comprehensive depiction of the machine learning algorithm. The aim is to establish a functional relationship between a set of input vectors and their corresponding target output vectors, using a provided collection of input vectors and target output vectors. The input vector x gives rise to the target vector z through the function f, but the specific function f is not known:

$$z = f(x) \tag{2}$$

The objective of the algorithm is to recognize or learn the function f. We employ an ANN as a function approximation approach, among others highlighted in the subsections below [11].

3.1. Artificial Neural Network (ANN)

Artificial neural networks (ANNs) serve as computational tools for data processing and modeling and are commonly employed for tasks such as estimation, forecasting, pattern recognition, optimization, and the exploration of relationships among intricate variables. According to [12], ANNs are characterized as massively parallel distributed information processing systems, displaying performance features reminiscent of the neural networks in the human brain. Derived as a generalization of mathematical models inspired by human cognition or neural biology, ANNs adhere to principles outlined by [13], including: (i) information processing by individual elements referred to as neurons; (ii) signal transmission between nodes through connecting links; (iii) association of each connection link with a weight representing its strength; and (iv) application of a nonlinear transformation, known as an activation function, by each node to determine its output signal. The distinguishing capability of ANNs lies in their capacity to learn the relationships between inputs and outputs from examples without physical intervention. Additionally, ANNs possess the remarkable ability to discern patterns between input and output variables without requiring supplementary explanations [14]. In the domain of hydrology, hydraulics, and water resources management, ANNs have found successful application in tasks such as flood forecasting, groundwater level prediction, and rainfall-runoff estimation.

The most prevalent type of artificial neural network (ANN) employed in sediment prediction research is the multilayer perceptron. This ANN architecture is composed of multiple layers, including an input, one or more hidden layers, and an output. Each layer is made up of artificial neurons, also referred to as nodes. In the input layer, data are fed into the network through a node, with each node typically corresponding to an input variable. The hidden layer comprises several different nodes determined through a combination of experience, empirical formulas, and systematic study. The number of nodes in the output layer of an ANN may differ based on the number of variables that require prediction. Information transmission within the network, from the input layer through the hidden layer, and ultimately to the output layer, involves a sequence of transformations carried out by transfer functions at each node. These transfer functions introduce nonlinearity into the ANN [15].

In the context of sediment transport prediction, where numerous parameters purportedly influence sediment discharge or concentration, researchers have investigated the impact of varying input variables on the performance of ANN predictive models.

3.2. Genetic Expression Programming (GEP)

Gene expression programming (GEP), akin to genetic algorithms (GAs) and genetic programming (GP), operates as a genetic algorithm, employing populations of individuals selected based on their fitness and introducing genetic variation through one or more genetic operators [16] The distinguishing feature among these three algorithms lies in the nature of the individuals they employ: GAs utilize linear strings of fixed length (chromosomes), GP employs nonlinear entities of varying sizes and shapes (parse trees), and GEP encodes individuals as linear strings of fixed length (the genome or chromosomes), which are subsequently expressed as nonlinear entities of diverse sizes and shapes, such as simple diagram representations or expression trees [16].

The synergy between chromosomes (replicators) and expression trees (phenotype) in GEP necessitates an unambiguous translation system, converting the language of chromosomes into the language of expression trees (ETs). The structural organization of GEP chromosomes, as elucidated in this study, establishes a genuinely functional genotype/phenotype relationship. Any modification made in the genome consistently yields syntactically correct ETs or programs, owing to the diverse set of genetic operators developed to introduce genetic diversity in GEP populations, which unfailingly generates valid ETs. Consequently, GEP stands as an artificial life system, firmly established beyond the replicator threshold, capable of adaptation and evolution. The merits of GEP, drawn from observations in nature, are notable, with simplicity being paramount. The chromosomes are uncomplicated entities: linear, compact, relatively small, and amenable to genetic manipulation (replication, mutation, recombination, transposition, etc.) [17]. In contrast, the ETs exclusively manifest the characteristics of their respective chromosomes; they serve as the entities subjected to selection, and based on fitness, they are chosen for reproduction with modification. During reproduction, it is the chromosomes of the individuals, not the ETs, that undergo replication with modification and are passed on to the succeeding generation. These characteristics render GEP highly versatile, surpassing existing evolutionary techniques. Notably, in the most intricate problem addressed in this study—the evolution of cellular automata rules for the density-classification task—GEP—outperforms GP by more than four orders of magnitude [11].

3.3. Bayesian Network (BN)

BNs are a type of probabilistic estimation technique that addresses conditional probabilities establishing connections between variables, albeit in a discretized manner. Statistical operations encompass several techniques, such as marginalization, which involves integrating across a specific portion of a broader distribution. This approach utilizes the available data to define restrictions and make inferences [18]. The utilization of Bayesian networks (BNs) presents a robust approach for the quantification of intricate relationships among variables and the derivation of statistical inferences, as highlighted by [19]. This modeling framework offers numerous advantages, including a minimal requirement for sample size, explicit elucidation of uncertainty, lucid visualization of variable interdependencies, facile integration of expert knowledge, and dynamic engagement with new data and decision tools, as underscored by [20–22]. Owing to these merits, BNs demonstrate proficiency in addressing complex systems, leading to their widespread application in environmental modeling, as evidenced by [20–22].

3.4. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFISs are commonly employed in the field of environmental and hydrology engineering to effectively tackle nonlinear challenges pertaining parameters like rainfall, inflow, and dam water stage. The architecture of the fuzzy system comprises three primary components, namely the fuzzifier, the fuzzy dataset, and defuzzifier. Fuzzification involves the conversion of data into vectors, which are subsequently utilized in the fuzzy database. On the other hand, the defuzzification process entails the conversion of the vector back into its original form, representing actual data. The fuzzy database is partitioned into two distinct components, namely the fuzzy rule base and inference system. The fuzzy rule basis is identified using an if–then conditional statement. There are three main variants of fuzzy interface systems, namely Sugeno's, Tsukamoto's, and Mamdani's, categorized based on the specific interface operation exhibited by their if–then rules. The approach proposed by Sugeno is characterized by its compactness and computational efficiency. As a result, it yields crisp outputs without wasting much time and theoretically inflexible defuzzification process associated with Mamdani's technique [23].

Neuro-fuzzy systems, which amalgamate artificial neural networks (ANNs) with fuzzy systems, offer the distinct advantage of facilitating a straightforward conversion of the final system into a set of if–then rules. The fuzzy system can be conceptualized as a neural network structure, wherein knowledge is distributed across connection strengths. Research and applications in neuro-fuzzy inference strategies underscore the benefits of hybrid systems in various domains, such as leveraging existing algorithms designed for artificial neural networks (ANNs) and the direct adaptation of knowledge articulated through a set of fuzzy linguistic rules [24].

An adaptive network, as implied by its nomenclature, comprises nodes and directional links, with its overall input–output behavior dictated by a collection of adjustable parameters that interconnect the nodes. The adaptive system employs a hybrid learning algorithm to identify parameters specific to Sugeno-type fuzzy inference systems. This entails the utilization of a combination of the least-squares method and the back-propagation gradient descent method for training the parameters of fuzzy inference system (FIS) membership functions to replicate a given training dataset. The learning process unfolds in two principal phases. During the forward phase, consequent parameters ascertain the least squares estimate, while in the backward phase, error signals—representing derivatives of the squared error with respect to each node output—propagate backward from the output layer to the input layer. In this backward pass, the premise parameters undergo updates through the gradient descent algorithm. The learning or training phase of the neural network is a dynamic process aimed at determining parameter values that sufficiently align with the training data. The adaptive neuro-fuzzy inference system (ANFIS) training employs alternative algorithms to minimize training error, with a combination of the gradient descent and least squares algorithms facilitating an efficient search for optimal parameters. A key advantage of this hybrid approach is its accelerated convergence, attributed to the reduction in search space dimensions inherent in the backpropagation method [25].

4. Hybrid Machine Learning Models

Aside from the commonly used machine learning techniques, researchers have suggested and used innovative techniques for sediment prediction. [26] pioneered the use of support vector machines (SVMs) in sediment prediction. SVMs were tested on three Malaysian rivers with promising results. The use of fuzzy logic and genetic algorithms has taken center stage in sediment prediction; numerous techniques, including the adaptive neuro-fuzzy inference system and its variants with fuzzy c-means clustering, have been applied, providing good predictions. Some prior works, such as [27], use ANNs paired with neuro-fuzzy models to estimate sediment concentration. These combinations or hybrids have been shown to produce accurate sediment estimates and are therefore recommended for use.

5. Machine Learning Applicability in Sediment Prediction

Assessment of water body sediment concentration or load is frequently regarded as an important component of watershed sediment behavior. To forecast the sediment concentration from streamflow measurements, empirical techniques such as the creation of simple linear or multiple regression models and sediment rating curves have been frequently employed over time. These procedures are still used today to provide estimates of sediment concentrations. Other methodologies, such as physically based, data-driven, and conceptual models, have been deduced and employed. Due to the laborious data collection process and intricate interconnections related to sediment movement, the utilization of data-driven algorithms may present a more suitable approach for predicting sediment [28,29]. The utilization of machine learning and genetic programming is gaining acceptance among specialists due to the nonlinear correlation shown between sediment concentration, discharge, and other variables. Various algorithms have been effectively modeled and employed in the prediction of sediment conveyance in rivers over a period. These algorithms utilize multiple hydro-meteorological parameters and previous sediment data as inputs to estimate the concentration of suspended sediment or the load of suspended sediment [30,31].

In practical applications, it is usual to employ a combination of river discharge, rainfall, and other hydrological variables as input parameters in ML models for suspended sediment concentration (SSC) or suspended sediment load (SSL) modeling. Rainfall and river discharge serve as input variables for the prediction of suspended sediment as in [18,19]. Several other factors such as river stage, catchment features, temperature, turbidity, and climate parameters are used as input variables in modeling sediment concentration; for instance, a research work [2] used an ANN to predict sediment rating curve variables with satisfactory results. Similarly, ref. [32] predicted SSL in an ungauged catchment using catchment characteristics and climate parameters as input. Additionally, in West Azerbaijan, Iran, the Bayesian neural network was used by [33] to estimate sediment discharge and results compared with the ANN estimate showed that BN had superior accuracy with the highest correlation coefficient. On the other hand, ref. [34] employed the genetic expression programming technique to predict SSL and concluded that the model is capable of predicting SSL accurately. Ref. [35] modeled daily SSC for Eel River in California by using an ANFIS, FCM, ANN, and evolutionary fuzzy (EF), which is a combination of fuzzy logic and a genetic algorithm called a hybrid model. A comparison of their performance reveals that the EF model outperforms the ANFIS, FCM, and ANN. In terms of hybrid models, ref. [36] combined continuity equation and fuzzy pattern recognition, denoted as a hybrid double feedforward neural network, to predict daily SSL, resulting in efficient estimates. Likewise, ref. [37] used another hybrid model known as the Classification And Regression Tree (CART) algorithm to successfully predict sediment with good estimates compared to the ANN, SVM, and ANFIS.

6. Discussion

The procedures employed for sediment transport measurement within a watershed typically commence with the assessment of suspended sediment levels at critical points in the river network. Furthermore, the examination of sediment concentration serves as a means to infer details regarding the variability of sediment events, offering a foundation for the quantification of sediment yield and load. Assessments can derive suspended sediment concentrations through diverse methods, encompassing direct sampling, water quality sampling, and indirect surrogate measurements such as turbidity. Additionally, advanced techniques involving the utilization of sensors like acoustic Doppler current profilers, remote sensing, laser diffraction, and optical backscatter are employed [38]. Some sediment studies introduce an additional element, such as the characterization of sediment composition, to categorize sediment sources utilizing the sediment fingerprinting technique [39].

Monitoring sediment transport is an arduous task requiring significant resources and labor. Consequently, numerous sediment studies resort to modeling techniques to estimate or forecast sediment transport and discharge. Modeling approaches encompass traditional empirical relationships, such as the suspended sediment rating curve and the universal soil loss equation (USLE). Recent advancements have seen the emergence of physically based models designed to replicate various catchment sediment processes, encompassing the simulation of sediment transport, hillslope processes, and riverbank erosion [40]. Notably, there is a heightened focus on data-driven models in studies where the estimation of suspended sediment load takes precedence. These models encompass diverse methodologies, including multiple linear regression, artificial neural networks, genetic programming, adaptive neuro-fuzzy inference systems, Bayesian methods, and several others. However, these methods are characterized by some merits and demerits (as presented in Table 1). The sediment rating curve is a traditional and widely used method in hydrology for predicting sediment transport based on streamflow. Its simplicity and ease of application make it an attractive choice, especially in regions with limited data availability. However, SRCs are known for their limitations in capturing complex nonlinear relationships and are highly dependent on the assumption of stationarity. The reliance on historical data may hinder the adaptability of SRCs in dynamically changing environments.

Table 1. Comparison of some selected sediment prediction techniques.

Technique	Merit	Demerit
Sediment Rating Curve (SRC)	Effective in low-data regions Historical data utilization Widespread applicability	Assumption of stationarity Inability to capture nonlinearities Challenges in urbanized catchments
Artificial Neural Network (ANN)	Nonlinear pattern recognition Adaptability to complex relationships Ability to learn from data	Data-intensive training requirements Dependence on training data quality Risk of overfitting
Genetic Expression Programming (GEP)	Automatic discovery of mathematical relationships Effective in capturing nonlinear relationships Model transparency and interpretability	Sensitivity to parameter settings Dependency on population size Complexity in rule extraction
Bayesian Network (BN)	Model transparency through graphical representation Applicability to multivariate systems Effective in handling incomplete information	Dependency on accurate prior information Limited applicability in dynamic systems Challenges in learning structure from data
Adaptive Neuro-Fuzzy Inference System (ANFIS)	Handling of uncertainties Hybridization of neural networks and fuzzy logic Effective in modeling nonlinear relationships	Dependency on quality of training data Sensitivity to parameter tuning Dependency on quality of training data

On the other hand, ANNs have gained popularity in sediment prediction and estimation because of their ability to model complex relationships and adapt to nonlinear patterns. The approach's effectiveness is contingent upon the availability of extensive datasets for training, and the potential for overfitting poses a challenge, especially with limited data. Additionally, the non-availability of a physical mathematical model or equation can make it difficult to interpret and understand the underlying processes governing its predictions.

The GEP is a symbolic regression methodology that evolves mathematical expressions to represent sediment transport relationships. GEP's ability to generate explicit equations enhances model transparency, aiding in the understanding of underlying processes. Notably, GEP performance may be sensitive to parameter settings, and its application may be limited in cases where the sediment transport process involves intricate nonlinearities. In addition, the BN provide a probabilistic framework for modeling sediment transport, incorporating uncertainties and dependencies. The explicit representation of probabilistic relationships enhances model interpretability. The method has some drawbacks, including requirement of prior knowledge for constructing reliable probability distributions, and the effectiveness is contingent on the availability of accurate prior information.

Furthermore, the ANFIS is known as a combination or hybrid model with the strength of fuzzy logic and neural networks. Providing a hybrid prowess for sediment prediction, its ability to incorporate expert knowledge and handle uncertainties is advantageous. ANFIS models may be sensitive to parameter tuning, and the effectiveness is contingent on the appropriate selection of fuzzy rules. The interpretability of the fuzzy rules, while better than ANNs, may still pose challenges.

In light of the advantages and drawbacks outlined for each method discussed in this section and Table 1, researchers and practitioners should carefully evaluate the distinctive characteristics of the study area, data availability, and the desired level of model interpretability when opting for a sediment prediction approach. The selection process should be informed by the specific requirements and limitations inherent in the given application. There is a clear imperative for further research to focus on the development of integrated approaches that capitalize on the strengths of various methods, aiming to bolster the accuracy and robustness of sediment prediction models.

7. Conclusions

The manuscript presents an overview of ML techniques applied to sediment prediction, addressing the complexities inherent in sediment transport within river systems. Traditional sediment estimation approaches, exemplified by the sediment rating curve (SRC), have proven effective in low-data regions with widespread applicability. However, challenges such as the assumption of stationarity and limitations in capturing nonlinearities hinder their adaptability, especially in urbanized catchments. The integration of ML techniques, such as artificial neural networks (ANNs), genetic expression programming (GEP), Bayesian networks (BNs), and adaptive neuro-fuzzy inference systems (ANFISs), presents a paradigm shift in sediment prediction. These approaches demonstrate remarkable capabilities in handling nonlinear relationships, automatic discovery of mathematical patterns, model transparency, and effective adaptation to complex environmental variables.

The ANNs, particularly the multilayer perceptron, stand out for their prowess in nonlinear pattern recognition, making them valuable tools in predicting sediment-related variables. Similarly, GEP showcases its strengths in automatic discovery of mathematical relationships, effective capturing of nonlinearities, and model transparency. The BN presents model transparency through graphical representation, making it suitable for multivariate systems and effective in handling incomplete information. The technique is not devoid of some drawbacks related to accurate prior information, limited applicability in dynamic systems, and dependency on the quality of training data need careful consideration.

Hybridization of neural networks and fuzzy logic has emerged as a powerful tool for modeling nonlinear relationships. While effective in capturing intricate patterns, it demands careful parameter tuning and is sensitive to the quality of training data. In the context of hybrid machine learning models, the integration of support vector machines, fuzzy logic, and genetic algorithms has provided promising results, offering accurate sediment estimates. This innovative approach, as seen in the works of [26,27,36], signifies the potential for further advancements in sediment prediction research.

The applicability of machine learning in sediment prediction, demonstrated through a range of hydro-meteorological parameters and hybrid models, signifies a promising avenue for future research. The ability to effectively model sediment transport over time using diverse algorithms has the potential to revolutionize our understanding and prediction capabilities in this critical domain. As we move forward, continued interdisciplinary collaboration and advancements in machine learning techniques will play a pivotal role in enhancing the accuracy and reliability of sediment prediction models.

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