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Sediment transport analysis in water management system using optimized neural framework

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Abstract

In a water management system, sediment prediction is considered a complex process. Conventional sediment prediction techniques are less precise. The sediment predictions through artificial intelligence analysis possess more prediction characteristics than the conventional approaches. One of the divisions of artificial intelligence is the deep learning technique. In this investigation, the deep learning technique is combined with the neural network approach for predicting the sediment parameters of the water management system using a novel Hyena Deep Neural Sediment Framework (HDNSF). Prime contributions are initially, the parameter of the water management system is provided as input to the approach, then the shear stress and transportation stage of the sediments are determined and the outcomes are generated. Thereafter, the mean velocity of the sediment particles, total sediment load, and the rate of total transported sediment are determined for the river system. The outcomes of the water management system are predicted to consist of transported sediment load and rate of transported sediments. Along with that, the determination coefficient of the prediction system is also evaluated. The outcomes of the prediction system and the determination coefficient of the prediction system are compared with recent studies such as Ant Colony Optimization Fuzzy Inference System (ACOFIS), Adaptive Neuro-Fuzzy Inference System (ANFIS), Least Square Support Vector Machine (LS-SVM), and Group Method of Data Handling (GMDH). A plain river water management system is analyzed, including its characteristics. At the end of fifth month, peak sediment load transport and sediment rate was recorded. The peak sediment load was 124695 tons/day and the peak sediment transport rate was 19636m^3/s. The coefficient of determination of the proposed HDNSF technique is 0.982.

Keywords: Deep neural network, Transported sediment load, Water management system, Hyena optimization, Sediment load prediction

1. Introduction

Major rivers in the world are self-originated, and streams and sediment transport develop the paths they trace. With consideration to the natural channels, the channel's depth and breadth directly impact the flow of water and natural material that makes the boundary with the channel [1]. Usually, the high load sediments are seen in rivers that possess soft materials in correlation with rivers that have bedrock exposed [2]. This is because the bottom and sides of the channel are where the sediment load originates [3]. In the current days, the water and suspended sediments affect the water quality and the life of the aquatic creatures [4]. The riverbeds' most important and complex process is sediment transport [5]. It is necessary to understand the nature of the process and the sediment qualities in the river courses to establish the provident management of the water system [6]. Most of the necessary construction projects on the riverbank are research areas, and there will always be questions about the erosion process of sediment particles' transportation and sediment technique [7]. Hence, there is a need for riverbank stability analysis, which mainly depends on the sedimentation erosion in the riverbank [8]. The sedimentation processes in the riverbanks are considered a necessary parameter [9]. The action of water will transport the eroded sedimentation particles, moving along the river's orientation and settling in the delta region [10].

Additionally, the construction locations are mostly near the rivers or will be constructed near the water available areas [11]. This course of water can minimize the stable slope in the riverbanks adjacent and thus by raising the load on the bed and the colloidal transport particles with turbidity [12]. The load of suspended sediment and the bed load are the two types of sediment load seen in the rivers [13]. The suspended sediment load is again classified into wash load and load of suspended bed material [14]. The wash load in sediments is obtained from the fine fractions of grain particles of the soil from the surface of the rain catchment [15]. The primary variation between the load of suspended bed material and the runoff-washed load material is that the runoff-washed load material can be controlled and the suspended bed load material is not controlled [16]. It is controlled with the help of the water-transferring capacity in the river. The suspension particles in the flow are sediment particles of very fine size in the wash load [17]. Considering the load by suspended bed load materials and the bed load, the wash load possesses transport law of different formats [18]. The wash load is considered a sub-division of the suspension load in which the particles are much smaller than the suspension load particles. Hence, the transportation parameter varies from the other two load criteria [19].

The transported wash load rate mainly depends on the catchment rate from the upstream of the river [20]. The suspended load on the riverbed can be managed by the hydraulic analysis of river systems [21]. Most of the sediment load on the river system is the sediment by runoff. The samples are collected from the rivers in the analysis process, and the rainfall condition is not considered [22].

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This is because the wash load in the transported sediment is neglected on the sediment-suspended load. The rate of transported sediments is calculated from the variables in the hydraulic analysis of the river. The sedimentation process and the erosion process will occur consistently in the river system during the flow of water [9]. The process of erosion, transportation, and sedimentation of the river sediment particles will affect the residential, research, and commercial buildings near the river one way or another [23]. Hence, the sediment transport analysis is a necessary parameter in the water management system along the river's path. The primary aim of this investigation is to deliver a precise and effective sediment transport prediction system using a deep neural network. Recently, deep networks have been utilized in different applications like convolutional neural models for water quality prediction [24], Alzheimer's disease diagnosis by convolutional neural model [25, 26], etc.; here, it is utilized for sediment prediction applications.

Recent regression rules were adopted for this water sedimentation process, but the lack of a tuning process does not support every run without any manual interpretation [27]. A discrete wavelet with a nonlinear random function [28] was established for the river basin study for the sediment load prediction, but it could not support linear data. In another case, the review was performed with artificial intelligence [29] to predict the sediment load from the review data, which could show the average outcome. Considering all these methods, the present proposed system has incorporated the hybrid features based on the neural and the optimization constraints that is deep neural system with hyena model. It is considered as the novelty of the work. Due to the optimal features, the present system is flexible for every situation in predicting the sediment load from the river basin data.

The prime focus of this research is to deliver a water management parameter prediction system using an optimized DNN technique. This is because the DNN approaches possess higher prediction ability than other techniques in complex problem computations. Then, the mean velocities of the sediment particles are determined. Thereafter, by utilizing the sediment particle's mean velocity and the initialized parameters, the total sediment load and the rate of total transported sediments are determined using the proposed HDNSF approach. In the end, the coefficient of determination of the prediction system is also determined.

The remaining portion of the investigation is as follows, the second part contains the recent related works about sediment transport in the water management systems and their problem statement. The third part contains the proposed methodology for overcoming the complexities in the second part. The fourth part contains the results and discussions of the proposed approach in the water management system, together with their comparisons, and the fifth part concludes the study with future work.

2. Related work

As per the study, to offer the best sediment performance, the issues of the sediment transport should be determined [30]. Sediment trapping and sediment dredging are the main parameters discussed in the river. Regulatory optimization is implemented in the project to manage the above main parameters. By implementing the above technique 70%, lesser sediment load is obtained compared to the initial design parameters. The sediment deposition is also minimized by 33% from the initial primary design. In other case, random forest hybrid model is utilized to predict the suspended sediment load [31] based on regression rules. In the dam's downstream side, suspended sediment particle plays a crucial role in the design life on the dam's downstream side. The Seonath River basin is considered for this investigation. The model implemented was an iterative optimizer with random forest and another iterative optimizer with pace regression. Both models have been implemented in the river basin for 35 years. The key metrics of the process in terms of determination coefficient, absolute mean error, and root mean square error are determined. The functioning of the model is enhanced by 27% through the utilization of optimizations. Evaluating the quantitative impact of soil influence and the discharge of sediments in conserving the water management system was inevitable [32]. The sediment discharge is determined for the last 6 decades. The mean sediment discharge is reduced by 81.1%. When the soil erosion degree is at 32%, the outcomes indicated marginal sediment reduction of zero and when the degree exceeds 50%, the sediment discharge is minimal. The functional sediment connectives are soft and the structural sediment connectives are hard [33]. Hydrological transport [34] of sediment regimes in the intermittent rivers of the Mediterranean Most studies utilize structural sediment connectives as the priority features of sediment transport management.

For the better-suspended sediment concentration predictions, hybrid neural models were designed with the control system [35]. The nonlinear autoregressive network model incorporates exogenous inputs and a framework for data pre-processing. Multigene genetic programming is employed for detailed scaling, while wavelet transformation is used for time series decomposition. The model exhibits the best prediction performance with a mean coefficient of determination rise of 7.7%–38.6% and a decrease of 15.1%–54.5%. The limitation is relying on a single dataset affects the model's generalizability. The Artificial neural network (ANN) is hybrid with optimization algorithms such as genetic, Particle swarm (PS), and Imperialist Competitive [36]. The hybrid of these models demonstrates better detection accuracy than the existing ANN, but the hybrid of PS with ANN demonstrates poor prediction accuracy. An adaptive neuro-fuzzy inference system (ANFIS) and group method of data handling (GMDH) models with butterfly and firefly (BF) optimization algorithms [37] are executed to estimate the volumetric concentration of silt in sewage systems. However, the combination of BF enhanced ANFIS performance and significantly enhanced GMDH's performance. The disadvantage is that utilizing multiple algorithms increases computational complexity. Furthermore, the Wavelet transformations [38] extract and split down the rainfall and runoff cycles into time series sub-signals. The post-processed data is then used as the training set for neural networks to forecast the sediment model. The results demonstrate that the wavelet transform model effectively improves the model's accuracy. Though the model performs better, it faces challenges in highly dynamic environments. The ANN model faces limitations due to overfitting and results in poor performance by obtaining high RMSE, MAE, and R^2 [39].

The research focuses on factors that affect the flow and transport of sediments in the river system since these parameters affect the quality and nutrients necessary for the river ecosystem. The high resolution data, the stream flow, and the sediments' concentration are utilized to quantify the runoff. The rainfall, flow of the stream, and the variables in the sediments are utilized to access the suspended sediments. The Burger River has a maximum concentration of suspended sediments, validated against maximum discharge. The Carapelle River has a higher coefficient of annual runoff with the intermittence of lower flow. Under this condition, the majority of the annual yield of sediment is transported. This study provides details about spatial format prediction as well as sediment transport intensity in the river basins.

2.1 Problem statement

An excess of sediment may cause problems for the severely silted reservoir below the dam, such as altered aquatic organisms and the possibility of algal blooms. From the other end of the bandwidth, a dam discharge might result in a sharp rise in downstream flows.

The bed substance, building behind bars, and additional habitat regions can be refreshed if the discharge is managed. Flooding may arise from an unregulated release or dam removal, which would move the spilled silt downstream beyond what is necessary.

The sediment transport is a complex process in the water management system. Measuring sediment transport is difficult, particularly in rivers and streams with gravel beds and gentle gradients. Because of their intricate hydrodynamics, morphology dynamics, and sedimentological procedures, high-gradient rivers present a special set of difficulties for forecasting of sediment transport.

Since the erosion in the bed of the river affects the stability of the nearby structures, (e.g building constructions) by causing landslides, collapses or infrastructure damage. This eroded particle of sediments suspends the river water and affects the quality of water and nutrients required for the survival of the river ecosystems. The prediction of the transported sediment in the riverbed is a necessary consideration when constructing structures near the river. These sediment transport prediction models in the form of equations have been carried out to date. The actual and original values differ depending on the environmental conditions of the water management system. This research aims to deliver a DNN model for predicting the sediment transport parameters in the water management system. The DNN model effectively predicts the outcomes through the water management system's pre-trained optimized characteristics data. The water sedimentation structure is exposed in Figure 1.

Water atoms go along the current in identically, forming straight lines in laminar motion. The laminar motion is a feature of shallow, extremely slow-moving fluid, which is rare. It is typical of movements in extremely viscous "fluids," such as icy glacier ice or low-water mud flows.

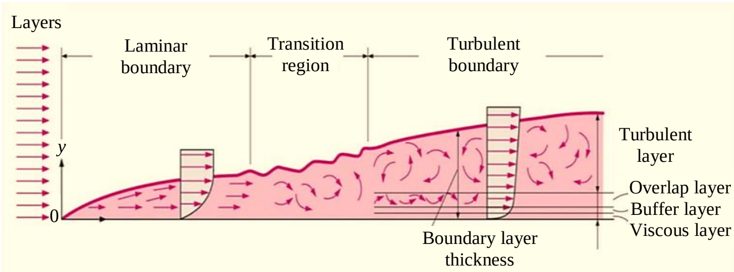

Figure 1 Water sediment transport

The complicated motion caused by water droplets is what defines turbulent flow. In addition to moving forward, towards the ground, and upwards in spurts, molecules can travel backwards. Since nearby molecules travel in distinct patterns and an additional dye mix into water's surface extremely fast, there is much combining in the flow process. Most of the atmosphere and water motions are turbulent, at least partly. Because it facilitates grain movement and attempts to prevent it from circulating for longer, disturbance is crucial for sediment transport.

Both laminar and turbulent flow properties can be found in transitional flows. For instance, colour does blend into the flow, though it might take some time.

3. Proposed methodology

Initially, the required parameters of the water management system are initiated in the HDNSF approach. The HDNSF is optimized to predict the parameters of the water management system and the required parameters such as critical velocity, fall velocity of the sediments, etc. Necessary from the initialized parameters are also optimized in the optimization memory of the HDNSF approach. At first, the shear stress in the sediments and the transportation stage of the sediments are identified based on their conditions.

Thereafter, the volumetric concentrations of the sediments are determined based on the conditions of the sediments. From the volumetric concentrations, the mean flow velocity of the sediments is evaluated. The total load of sediments in the water management system is determined using the mean flow velocity. Then, the sediment transport rate of the water management system is predicted by implementing the total sediment load. In the end, the coefficient of determination of the prediction system is also determined. Then, the outcome parameters are compared with the recent prediction models like ACOFIS, ANFIS, LS-SVM, and GMDH, which are implemented in the same platform, and their performance is compared. The process of the suggested methodology is represented in Figure 2.

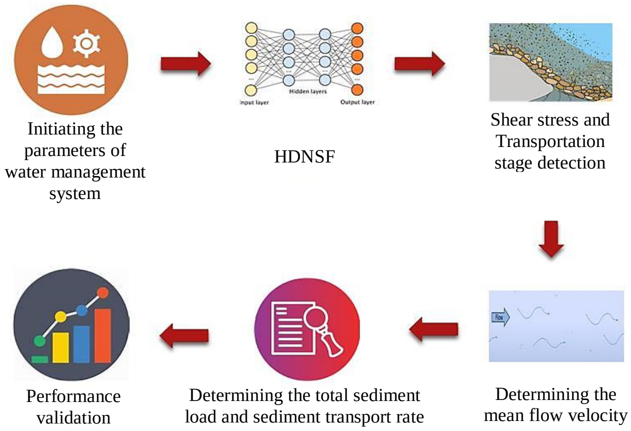

Figure 2 Proposed Methodology

3.1 Hyena Deep Neural Sediment Framework (HDNSF)

The HDNSF has the merits of hyena optimization and deep neural networks in predicting sediment particle transportation in water management systems. This HDNSF is initiated in the sediment transport system prediction for its effectiveness and lower error rate. The proposed approach is trained and optimized to predict the parameters of the water management system. The input parameters are initially assigned to the HDNSF as expressed in the Eqn. (1). Here, d_{50} is the medium sediment variable, those values are defined in case study.

$$I_p = \{d_{50}, H_r, E_s, \gamma_{se}, \gamma_{wa}, u_c, c_y, g, W, \varepsilon_b, \alpha, V\} \tag{1}$$

Where, H_r is the hydraulic radius, E_s is the energy slope of the water management system, γ_{se} is the unit weight of sediments, γ_{wa} is the unit weight of water, u_c is the critical velocity, c_y is the volumetric sediments concentration, W is the sediments fall velocity, V is the velocity average concerning flow, ε_b is the coefficient of efficiency, α is the shear force ratio among the tangential and normal direction in the water management system. The parameters such as the critical velocity of the flow and sediment fall velocity are determined from the other initialized sub-parameters. The fitness function is activated for determining the shear stress (ϕ) in the sediments of the water management system on both the normal and tangential directions are determined using Eqn. (2).

$$\phi = \left(\frac{\gamma_{se} - \gamma_{wa}}{\gamma_{wa}}\right)\frac{d_{50}}{H_r E_s} \tag{2}$$

Afterward, the transport stage parameters of the sediments are determined based on the functional relation between the critical velocity and the bed shear velocity. Then the second fitness function is initiated for determining the transport stage of the sediment particles as shown in Eqn. (3).

$$T_s = \left(\frac{u^2 - u_c^2}{u_c^2}\right) \tag{3}$$

If the value of T_s is positive then it indicates that the sediment particle is in the transportation stage occurs. If the T_s value is zero or negative the sediment particles are considered as in the rest stage. Where bed shear velocity $u = (g^{0.5}/C)$, C is the constant determined using Eqn. (4).

$$C = 18log\left(\frac{12H_r \times d_{50}}{3}\right) \tag{4}$$

The third fitness function is initiated to determine the mean sediment transport velocity in the water transport system using Eqn. (5).

$$u_m = \frac{1}{\int_0^h c_y.dy}\int_0^h c_y.u.dy \tag{5}$$

By implementing the outcomes obtained from the third fitness function to the fourth fitness function, the total load of sediments is determined by using Eqn. (6) for the mean velocity of sedimentation particles.

$$P_t = \left(\frac{\gamma_{se}}{\gamma_{se} - \gamma_{wa}}\right) \times \left(\frac{W\varepsilon_b}{u_m \tan\alpha} + 0.01\right) \times \gamma_{wa}.H_r.E_s.V \times \left(\frac{u_m}{W}\right) \tag{6}$$

For every total load of sediments on the particular location of points, the fifth fitness function is triggered to determine the rate of sediment transport by executing Eqn. (7).

$$\psi = \frac{P_t}{\gamma_{se}}\left(\frac{\gamma_{wa}}{\gamma_{se} - \gamma_{wa}}\right)^{0.5}\left(\frac{1}{d_{50}^3 g}\right)^{0.5} \tag{7}$$

In the end, the outcomes of the water distribution system are obtained as output as illustrated in Eqn. (8).

$$O_p = (\phi, u_m, T_s, P_t, \psi) \tag{8}$$

Initially, the input parameters of the water management system, such as hydraulic radius, energy slope, unit weight of sediments, unit weight of water, concentration of volumetric sediments, critical velocity, fall weight of sediments, average flow velocity, coefficient of efficiency, and shear force ratio are initialized in the HDNSF approach. Then, the sediment particles' shear stress and transportation stage are determined. After that, the sediment particle's mean velocity, total sediment load, and sediment transport rate are determined for the sediment particles in the riverbed. Then, the coefficient of determination in the prediction system is determined. Ultimately, the outcomes correlate with the recent models to validate the study. By precisely executing the above steps, the robustness of the proposed model can be obtained. The Flow chart of the proposed approach is defined in Figure 3.

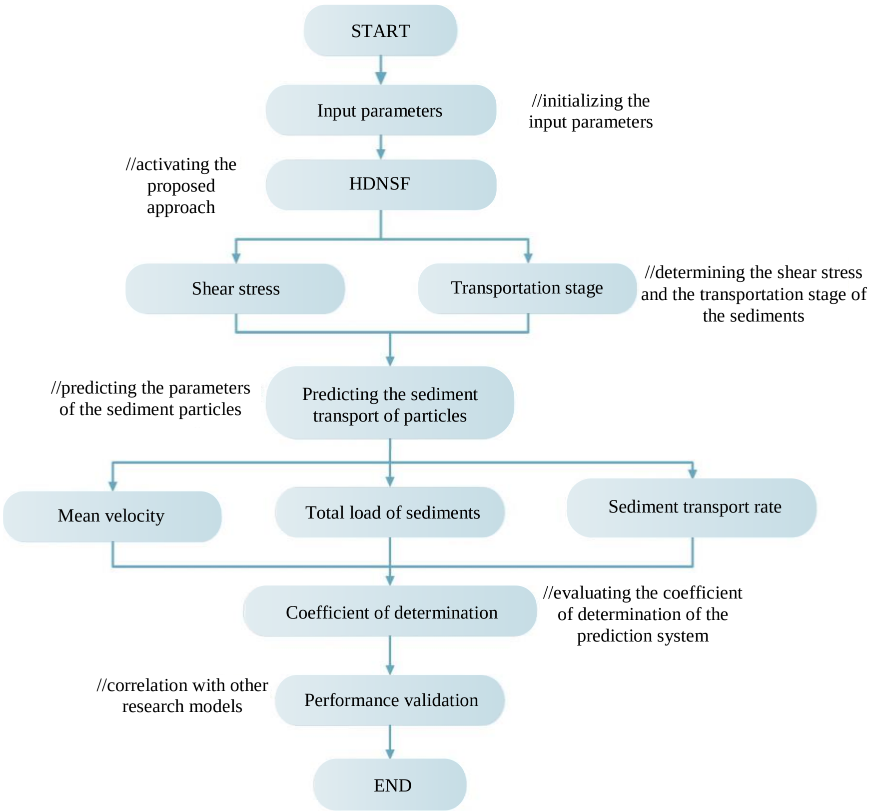

Figure 3 Flow chart of the proposed approach

4. Result and discussions

The sediment transport analysis of the water management system was carried out in the MATLAB R2023a software running on Windows 10. The Matrix Laboratory is the abbreviation for MATLAB, which is a high-level computational software utilized to analyze data in a matrix format. It is considered an optimum tool for prediction analysis in the Department of Science and Mathematics [40]. The MATLAB application uses matrix operations and functional arrays to predict the outcome of work in more exact mannar [38]. Along with that, it implements the natural format of computational mathematics. MATLAB analyses algorithm errors, plots graphical data, and computes scientific analysis. In this investigation, the parameters in the water management system are initialized in the HDNSF approach in the MATLAB environment. Then the shear stress and the transportation stage parameter are determined. Then, the sediment particle's mean velocity, total sediment particle load, and sediment transport rate are determined.

4.1 Case study

To show the performance of the novel HDNSF model, different testing cases were considered that are explained in the following section. Discussing the other test cases were mentioned in terms of case study. A plain river water management system is considered in this case study to have characteristics of depth of flow as 0.2 to 10m, the average breadth of the river as 100m, and the flow velocity as 0.58 to 1.7 m/s [41]. Acceleration due to gravity is taken as 9.81 m/s^2, energy slope variation is considered as 0.041632 to 0.01874, the length of the river in the analysis is considered as 40km, the flow is considered as unsteady and turbulent [42], d50 of the sediment is taken as 0.3 to 0.35 µm [43]. The unit weight of water is considered as 1000 kg/m^3, the unit weight of sediments is taken as 1800 to 2000 kg/m^3, the sediments are considered as lower river sand, and the season is considered as winter because the suspended sediment flux is maximum in winter season [44]. The critical velocity in the initial stage and the velocity in the fall of sediments are evaluated by the HDNSF approach through the relation between the sediment particle size and flow velocity in the water management system. The volumetric sediments' concentration is 0.094 to 0.344g/l [18]. The volumetric sediment concentration for a particular strip region is analyzed in the HDNSF approach, and then, based on the integral limit from 0 to the height of the top surface, the overall mean velocity in the sediments is calculated in the transportation stage. The ratio of the normal shear stress and the tangential shear stress provides the value of α in the river system.

4.1.1 Total sediment load

Sediment load in the water management system is the amount of load transported by the system from one location to another within the given duration. In the case of a water management system, the duration is considered in days, and the unit of the total load of sediments is considered in tons/days. In this analysis, a duration of six months is considered. The total sediments are measured with an interval gap of each month. The graph is plotted against total load sediments vs. days, and the graphical representation of the results is shown in Figure 4. For the prediction, a sediment database that contains 4017 data samples was considered. Moreover, the proposed system was processed in the range of 20%testing and 80% training. In that dataset, the sediment load is considered for 6 months [45]. Hence, the present study sets the prediction interval for six months.

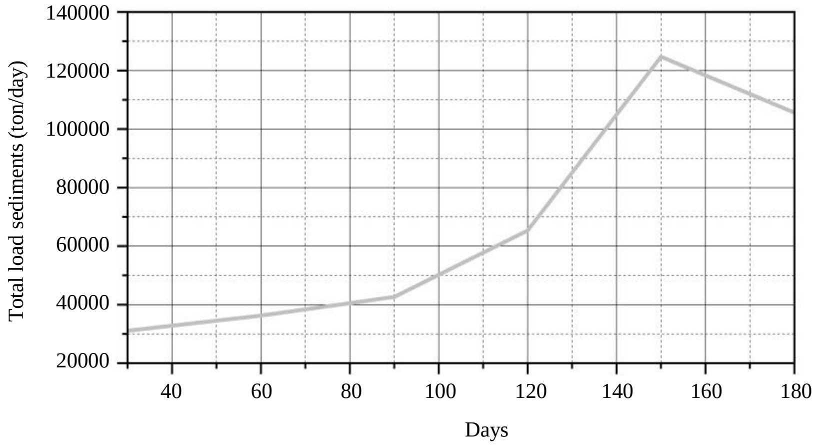

Figure 4 Total load sediments vs Days

Initially, the total load of sediments in the plain river water management system at 30 days was 31056 tons/day. At the end of two months, the total load sediments were 36289 tons/day; at the end of three months, the total load sediments shifted was 42669 ton/day, at the end of four months, the total load sediments were 65329 ton/day, at the end of five months the total load sediments was 124695 ton/day. This is the maximum total load of sediments shifted in the water management system. Here, each month is considered as 30 days. At the end of six months, the decrease in the total load sediments is 105638 ton/day.

The sediment load decreases in the analyzed plain river water management system after six months. Once the optimum amount of sediment is transported, the shear stress in the sediments will be able to withstand the water flow until the change in the velocity or the behaviour of sediment particles occurs in the plain river system.

4.1.2 Total sediment transport rate

The rate of total transported sediments is the amount of sediments discharged from one point to another within a particular duration. Here, the duration is defined in seconds, and the number of sediments is shifted to a one-meter cube of sediments. The sediment transport rate details the amount of sediments shifting in a particular water management system. The total sediment transport rate vs. the days in one-month intervals for an overall period of 6 months is determined using the HDNSF approach, and the outcomes are illustrated in graphical form in Figure 5.

At one month's end, the total transported sediments rate was 6582 m^3/s. At the end of two months, the rate of total transported sediments in the system was 9584 m^3/s. At the end of three months, the rate of total transported sediments was 14692 m^3/s. At the end of four months, the rate of total transported sediments was 16582 m^3/s, at the end of five months, the rate of total transported sediments was 19636 m^3/s, and at the end of six months, the rate of total transported sediments was 17642 m^3/s, it is visualized in Table 1.

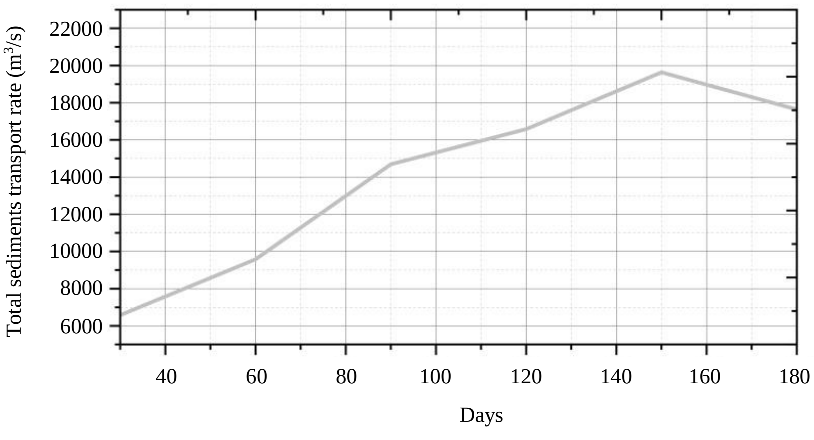

Figure 5 Total sediment transport rate vs Days

4.1.3 Coefficient of determination

The R^2 value, which is the determination coefficient, provides the amount of prediction by the proposed approach for a particular duration. The coefficient of determination for both the total sediment load and the rate of total transported sediments are merged in the analysis for the definite duration. The coefficient of determination of the proposed approach vs. the analyzing duration in days is shown in Figure 6 and Table 1.

The coefficient of determination at the end of the one-month prediction was 0.912, and the value decreased in the second-month prediction to 0.936, and the third-month prediction was 0.957. The coefficient of determination for the fourth-month prediction was 0.964, and at the end of five months, the coefficient of determination was 0.982. In the final sixth-month prediction, the coefficient of determination was 0.976, as defined in Table 1.

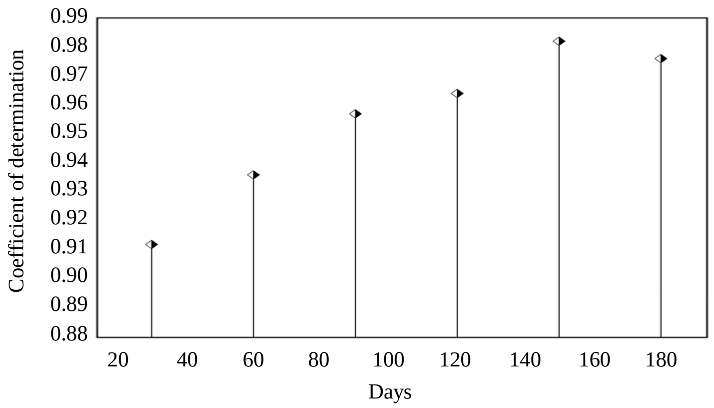

Figure 6 Coefficient of determination vs days

Table 1 Overall outcomes predicted by the proposed approach

Days	Total Sediment transport load (ton/day)	Sediment transport rate (m^3/s)	Coefficient of determination (R^2)
30	31056	6582	0.912
60	36289	9584	0.936
90	42669	14692	0.957
120	65329	16582	0.964
150	124695	19636	0.982
180	105638	17642	0.976

The overall parameters of the proposed system are shown in Table 1. In which the column 1 gives the days of prediction. Column 2 provides the total sediment load on that particular day. Column 3 provides the rate of sediment transport concerning column 1. The fourth column provides the coefficient of determination in the proposed approach for evaluating total sediment load and sediment transport rate.

4.2 Comparisons

For validating the sediment transport analysis by utilizing the HDNSF approach in the water management system. The proposed model is correlated with recent prediction techniques in water management systems. The coefficient of determination of the proposed approach is correlated with the Ant Colony Optimization Fuzzy Inference System (ACOFIS), Adaptive Neuro-Fuzzy Inference System (ANFIS) [45], Least Square Support Vector Machine (LS-SVM), and Group Method of Data Handling (GMDH) [46]. The sediment transport rate of the proposed model is compared with the Adaptive Neuro Fuzzy Inference System (ANFIS) and Ant Colony Optimization Fuzzy Inference System (ACOFIS) [45]. The correlations are carried out in an orderly and sequential manner, with accurate results from the HDNSF approach.

4.2.1 Total sediment transport rate

The total sediment transport rate obtained in the proposed HDNSF system is correlated with the ANFIS and ACOFIS sediment load prediction systems. The ANFIS system possesses the advantages of both adaptive Neuro technology and a fuzzy inference system. The ACOFIS system has the merits of both Ant lion colony optimization and Fuzzy Inference system [45]. The proposed approach implements the HDNSF in an optimized manner to predict the total sediment transport rate.

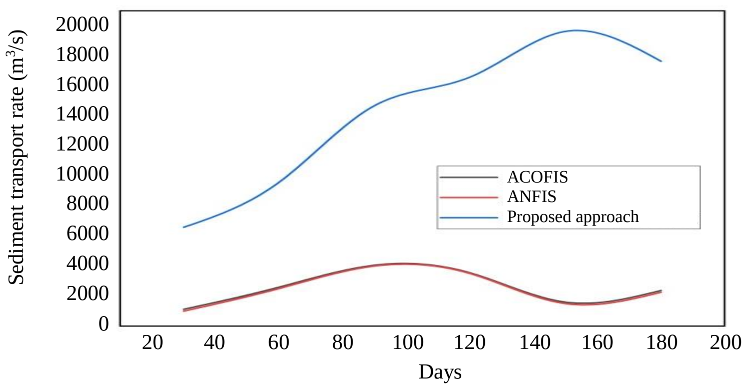

Figure 7 Comparison of different sediment transport rate prediction systems

The correlation graph with different days for the proposed HDNSF approach with the ACOFIS and ANFIS system is shown in Figure 7 and Table 2, where the range of sediment transport rate of the ANFIS varies between 1000 m^3/s to 4000 m^3/s. Initially, the value rose at the end of one month, and the peak sediment transport rate was at the 90th day. Then, there is a decrease until the 150th

day, and the value slightly increases on the 180th day. The ACOFIS graphical representation also follows the same pattern as the ANFIS in predicting sediment transport rate. This happens due to the similar execution of the neural fuzzy system; the fuzzy rules in any system have provided the common decision, which tends to gain a similar outcome.

Table 2 Sediment transport rate of recent models with the proposed approach

Sediment transport rate (m^3/s)			
Days	**ACOFIS**	**ANFIS**	**Proposed**
30	1123	1000	6582
60	2596	2500	9584
90	4056	4000	14692
120	3545	3500	16582
150	1600	1500	19636
180	2370	2250	17642

The value of the proposed approach is 6582 m^3/s at the end of one month and the peak sediment transport rate was observed on the 150th day, which was 19636 m3/s; in the end, the sediment transport rate was 17642 m^3/s. The proposed approach predicts that the sediment transport rate will be higher for the provided plain river model than for the ANFIS and ACOFIS prediction systems. Finally, the sediment loads after 6 months period is given in Figure 8 and Table 3 with sediment rates.

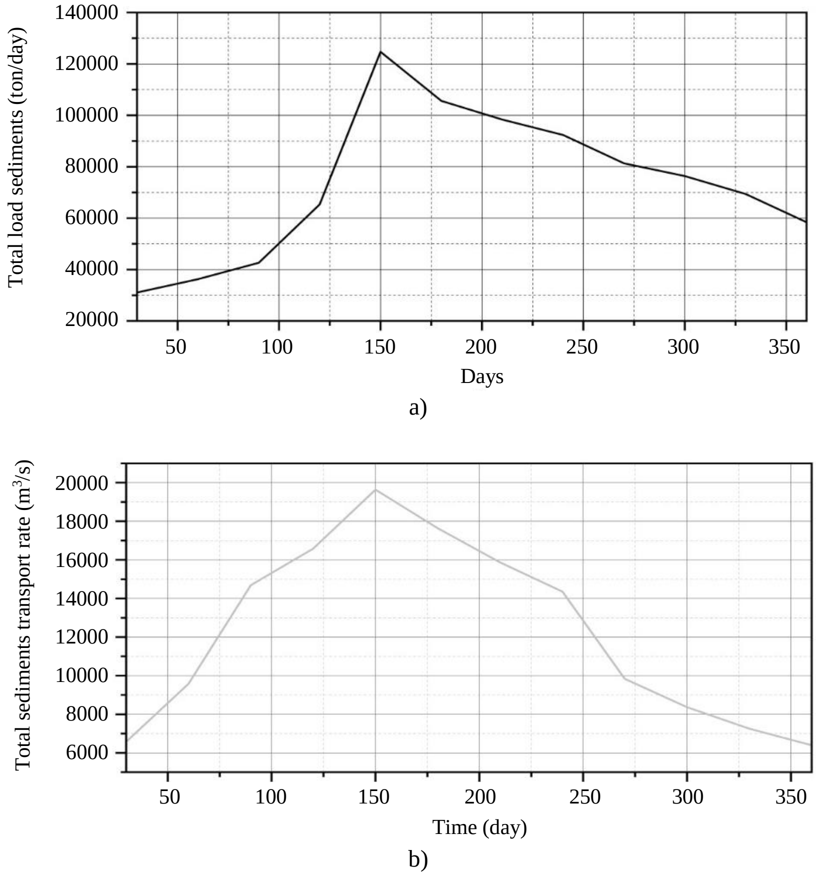

Figure 8 Sediment analysis: a) Total load sediments vs. Days, b) Rate of total transported sediments (m^3/s)

Table 3 Total load of sediments predicted by the proposed approach

Days	**Total load sediments (ton/day)**	**Rate of total transported sediments (m^3/s)**
30	6582	31056
60	9584	36289
90	14692	42669
120	16582	65329
150	19636	124695
180	17642	105638
210	15872	98369
240	14359	92356
270	9835	81336
300	8369	76358
330	7258	69385
360	6399	58398

4.2.2 Coefficient of determination

The R^2 value, which is the determination coefficient of the proposed approach, is correlated with ANFIS, ACOFIS [33], LS-SVM, and GMDH [46]. The LS-SVM approach is a statics technique used to predict water management systems' characteristic parameters. A learning model evaluates the data to identify patterns and categorize parameters. The GMDH is a mathematical multi-parameter algorithm to predict water management system parameters.

In which the ANFIS system has a coefficient of determination of 0.963. Both the LS-SVM and the GMDH system have a coefficient of determination of 0.94 [46], The ACOFIS system has a coefficient of determination of 0.826 [45], and the proposed approach has a coefficient of determination of 0.982. The statistics are illustrated in Table 4.

Table 4 Coefficient of determination of the different water management systems

Techniques	Coefficient of Determination (R^2)
ANFIS	0.963
LS-SVM	0.94
GMDH	0.94
ACOFIS	0.826
Proposed	0.982

The proposed approach has a higher coefficient of determination than the other approaches because the proposed approach initially determines the shear stress and transportation stage of the sediment particles. Then it predicts the water management system's total sediment load and total sediment transport rate [47].

4.3 Statistical analysis

The skewness in the sediment particles, along with their standard deviations in the riverside along with the river, is illustrated in Figure 9. A total of 10 sets of points are considered in the analysis in the initial point where the sediment particles start the transportation stage in the river. The standard deviation in the sediment transport point ranges between 0.3 and 0.6. The maximum and minimum skewness values lie between 1 and -0.2. The dune term denotes the sediment particles near the shore.

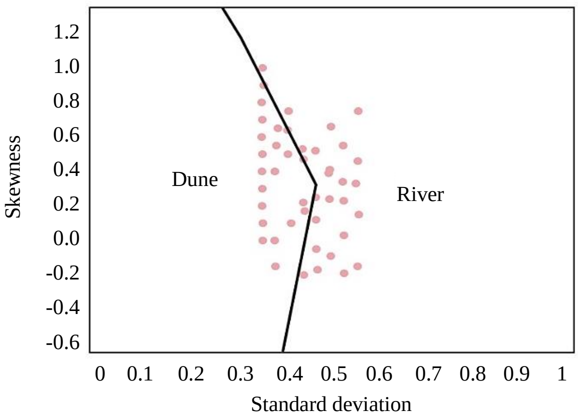

Figure 9 Skewness and standard deviation in the plain river sediment

The mean, standard deviation and skewness in the initial transportation stage point are plotted and illustrated in Figure 10. The maximum skewness point was seen at 0.36. The sediment transport particles and their mean and standard deviations in the particular point are used to determine the maximum skewness of the specific shore.

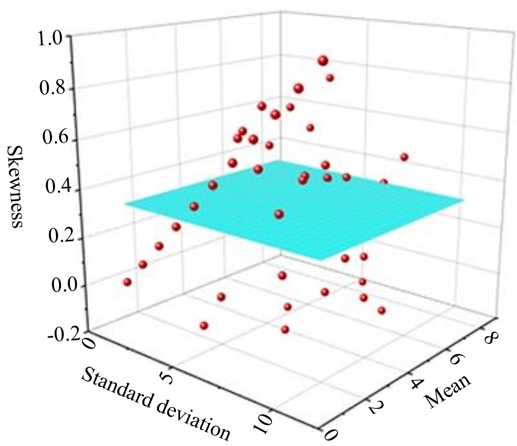

Figure 10 Statistical analysis of sediment transport in three dimensions

The reason for gaining the finest outcome is the tuned deep neural system; here, the deep nets were tuned by the hyena fitness to gain the finest prediction outcome. The desired results of the water management sediment attributes were imported and stored in the hyena memory; while running the optimization process, the optimal best solution-finding process was iterated continuously till the desired outcome was met. Thus, the hybrid model attained the finest outcome compared to traditional models. Moreover, the results were reproducible using the following link (GitHub - FeralFlows/SedSim: A river basin simulation model for sediment, water, and hydropower).

The sediment is the most dominant feature of the water management system. Also, the water in rivers or dams has several impacts [48] due to seasonal and pollution reasons. Based on the watershed scales, there are different management practices [49] under the river basin in this decade.

4.4 Advantages

The system's key advantage is predicting the water management attributes more accurately. The presence of optimal features reported the finest performance in every trail. This is due to finding the finest solution; the optimization function can iterate continuously until the desired finest outcomes are gained.

5. Conclusion

The proposed HDNSF approach initially predicts the sediments' shear stress and transportation stage by the implemented initialized parameters. The parameters are predicted for a period interval of one month, and the duration of prediction is six months. The peak values of the parameters are observed at the end of five months. The total sediment load evaluated at the end of five months was 124695 tons/day, and the rate of total transported sediments was 19636 m^3/s. After five months, the values of total sediment transport and the rate of the total transported sediments in the prediction system are decreased for the plain river water management system. The rate of total transported sediments in the proposed approach is higher than the other compared models. The coefficient of determination of the proposed approach is 0.982, which is a 19.7% higher prediction than the other compared models. The inclusion of flow characteristics and frictional parameters of the sediments in the analysis makes this approach a finite and efficient analysis prediction system in the future. The system's limitation is that it does not validate the sediment rate at different seasons. Also, due to the fixed optimal behaviour, the sediment rate curve was differed based on the different seasonal parameters [50]. So, analyzing the sediment rate for different seasonal conditions with Daubechies wave curve will afford the finest, most accurate outcome by the wide and lower range of wave curve [51-53]. Hence, the future study's performance analysis will be done with the support of Daubechies wave, which will give exact improvement outcomes.

6. References

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