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Foundations for
Global Water Security and Resilience:
Knowledge, Technology and Policy

Application of Deep Learning and Soft Computing Methods for Prediction of Increased Sediment Load Inflow in Reservoirs Owing to Climate Change

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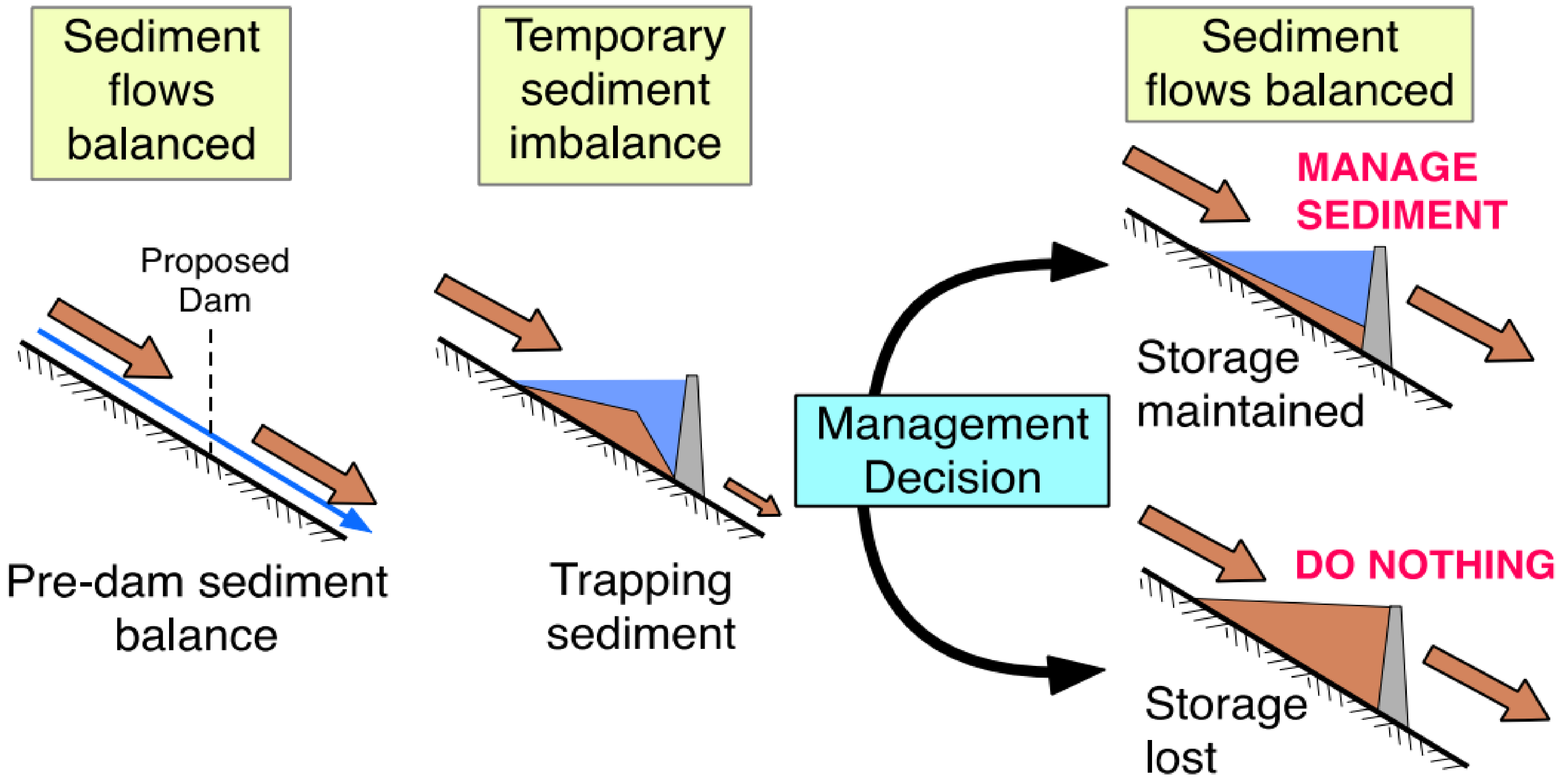
Research Phases

1. Introduction and Literature Review

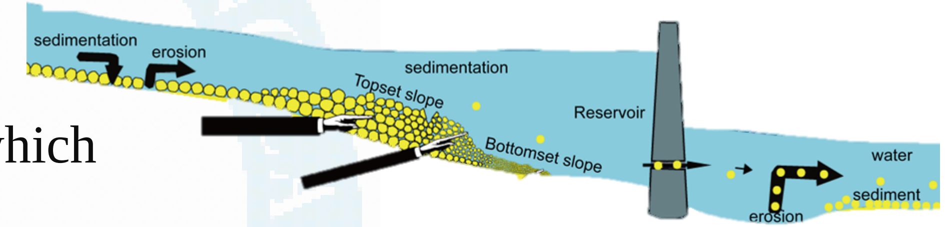


Alternative transitions from pre-impoundment to post-impoundment sediment equilibrium. To maintain long-term reservoir storage is a management decision (*Morris, GL, 2020*)

1. Introduction and Literature Review

1.1. Reservoir Sedimentation

- When river flows in still water of reservoir, it loses its velocity and sediment carrying capacity.
- Riverbed rises due to sediment deposition, which result in storage loss.
- Global annual reservoir storage loss due to sedimentation ranges 0.1–2.3%, with an average value of approximately 1% (*Wisser et al. 2013*).



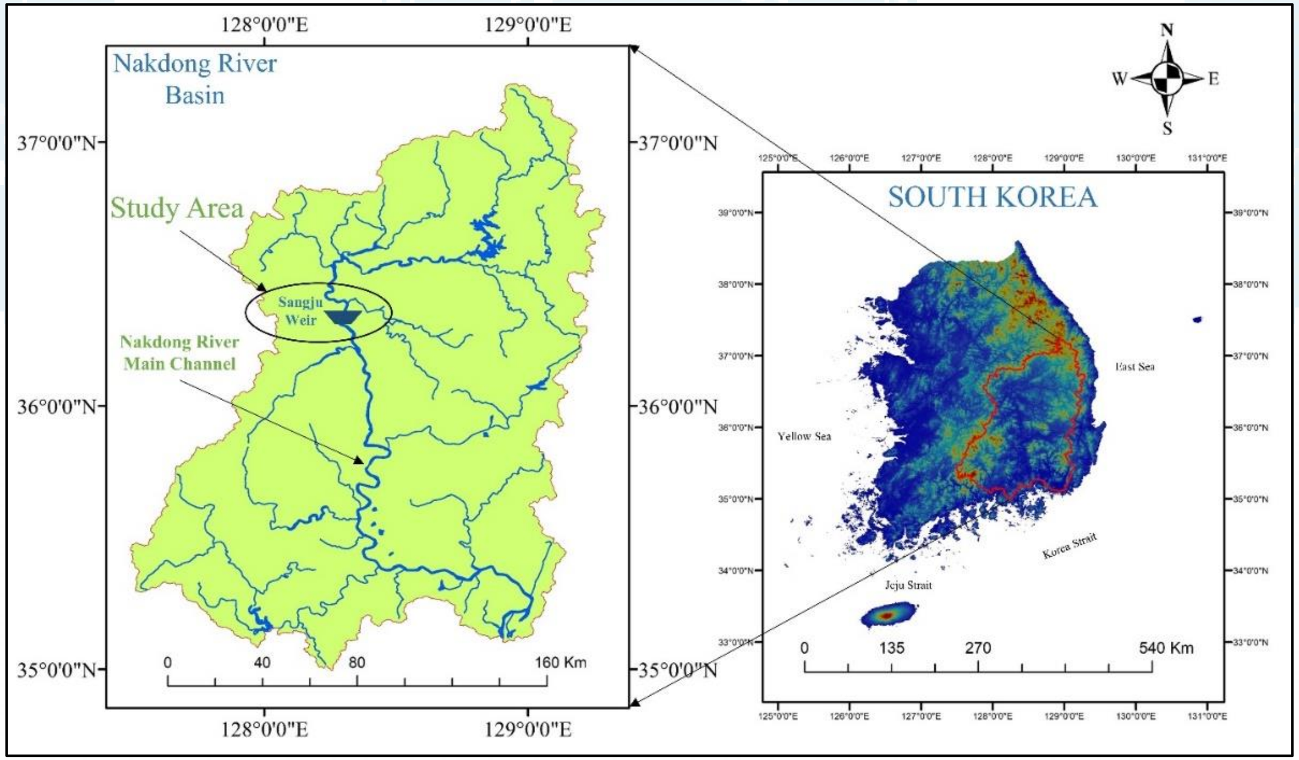
- Sediment deposition in river decrease the flood carrying capacity which result in the increasing of inundation area (*Nazir et al. 2016*).

1.2. Sedimentation Problem in Nakdong River, South Korea

- The construction of eight consecutive weirs along the Nakdong River changed the erosion and sedimentation patterns after the Four Major River Restoration Project (FMRRP).
- **Sangju Weir (SW)** is the uppermost of these eight weirs on Nakdong river.
- Current operating rules at Sangju weir are ambiguous and completely ignores the sedimentation issue (*Kim et al. 2017*).

1. Introduction and Literature Review (*Contd.*)

- Significant sediment deposition has been observed upstream of Sangju Weir since it started operating.
- The reservoir operation rules of Sangju Weir focus on provision of high-water stage throughout the year, which aggravate the sedimentation deposition (*Kim et al. 2017*).
- Mechanical dredging has been performed yearly to counter sedimentation, which is very expensive, time consuming, and labor-intensive option (*Kim et al. 2017; Kim and Julien 2018*).



1. Introduction and Literature Review (*Contd.*)

1.3. Reservoir Suspended Sediment Load (SSL) Inflow Estimation

- Hydrographic surveys and sediment rating curves (SRC) are traditional approaches for prediction of reservoir sedimentation, but these are associated with substantial inaccuracies and limitations (*Furnans and Austin, 2008; Heng and Suetsugi, 2013; Gianbattista et al., 2017*).
- Previous researchers reported various methods linking sediment inflow with hydraulic parameters, geometric parameters, and sediment characteristics (*Bogen et al., 2003; Costa, 2016*).
- These methods are mostly site-specific and do not have universal application.
- Physically-based hydrological models including Soil and Water Assessment Tool, SWAT (*Neitsch et al., 2011*), Erosion Productivity Impact Calculator, EPIC (*Williams, 1989*), Water Erosion Prediction Project, WEPP (*Flanagan et al., 2007*) permit modelling of sediment and nutrient transport in catchments and reservoirs.
- The application of physical models is often event-based and require extensive field data of bathymetry, topography, and hydrologic parameters.

1. Introduction and Literature Review (*Contd.*)

1.4. Machine Learning (ML) Models for Reservoir Sedimentation

- Machine learning (ML) models have been applied successfully around the globe in recent reservoir sedimentation and fluvial sediment transport studies.
- Aytek and Kişi (*2008*) proposed genetic programming (GP) approach to form an explicit relationship between SSL and water discharge.
- Lafdani et al. (*2013*) investigated artificial neural networks (ANN) and support vector machine (SVM) models to predict daily SSL in Doiraj River, Iran.
- Kumar et al. (*2015*) used an ANN model for rainfall-runoff-sediment modelling using TRMM-3B42 rainfall estimates as input variable.
- Zhao et al. (*2017*) quantified the impact of climate change and anthropogenic factors on sediment load by coupling the dynamic water balance model (DWBM) with ANN.
- Khosravi et al. (*2018*) quantified hourly sediment load inflow using stand-alone and hybrid ML models at Adean catchment, Chile.

1. Introduction and Literature Review (*Contd.*)

- Malik et al. (*2019*) evaluated the performance of different ML models for suspended sediment concentration (SSC) modeling using the gamma test in the Godavari River basin, India.
- Huang et al. (*2019*) applied a numerical model in combination with ML models to predict half-hourly SSL in the Shi-Men reservoir, Taiwan.
- Chang et al. (*2020*) proposed an outflow sediment concentration forecasting model by integrating ML approaches and time series analysis for density current venting in reservoirs.

1.5. Reservoir Sediment Management

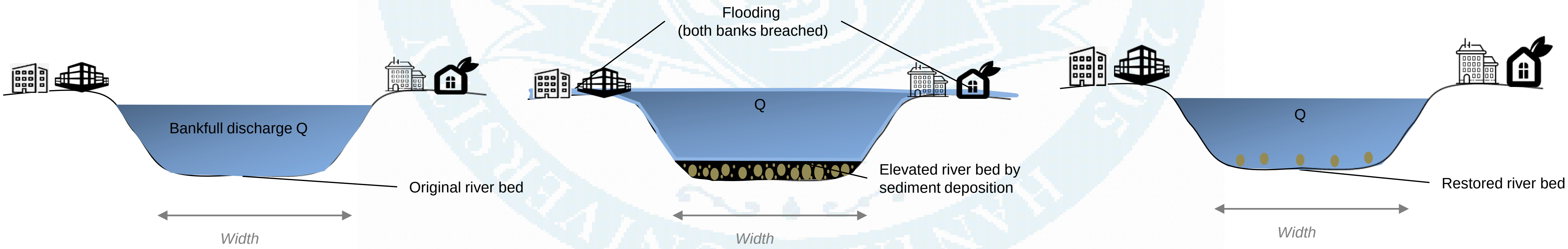
- Various methods to counter sedimentation for sustainable use of reservoirs use have been reported including sediment routing, sluicing, dredging, and flushing (*Mahmood and Mundial, 1987; Tigrek and Aras, 2011; Schleiss et al., 2016*).
- **Sediment flushing** involves the increase of flow velocities in the reservoir, followed by lowering of water level depending on site conditions, to erode and transport the sediment deposits through low-level outlets (*Lai and Shen, 1996*).

1.7. Limitations of Previous Studies

- In previous studies, mostly streamflow has been chosen solely as input variable of ML models to predict sediment inflows (*Aytek and Kişi 2008; Kumar et al. 2015; Malik et al. 2019*).
- Khosravi et al. (*2018*) used three parameters including streamflow, water temperature, and electric conductivity as input variables for three ML models to predict SSL.
- None of these studies consider incorporating reservoir operation parameters such as dam outflow and water stage for SSL predictions.
- Hence the research and application of ML models for reservoir SSL studies remain deficient.
- Furthermore, these studies evaluated and compared the performance of up to three ML models simultaneously for SSL inflow predictions.
- A comprehensive study is required on evaluation of mainstream ML models for SSL inflow predictions and linking it with reservoir operation parameters.

1. Introduction and Literature Review (*Contd.)*

- Sediment flushing has been proven successful worldwide to counter and manage reservoir sedimentation.
- However, the complexity of morphological processes requires extensive knowledge and study of onsite constraints for the success of flushing operation.
- A technique is required to calculate sediment flushing parameters of flushing discharge, duration, frequency, and drawdown at a dam site.
- Research and application of ML techniques and RESCON model on reservoir sediment deposition and removal strategies, especially complex sediment flushing processes, are still deficient.



(a) River flow conditions at regime

(b) Sediment deposition and rise in river bed, resulting in flooding

(c) Flow conditions restored by sediment flushing

2. Identification of Research Gaps

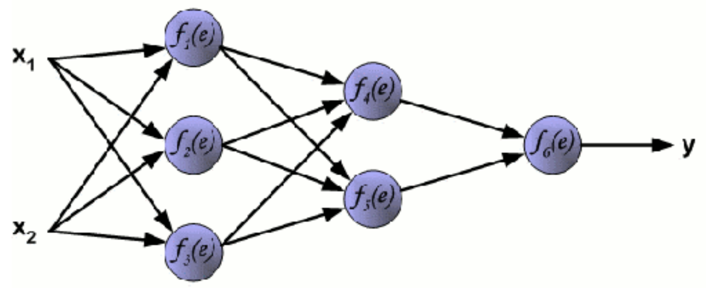
- For reservoir sedimentation studies, mean annual SSL inflow is a crucial input.
- Owing to the complexity and stochastic nature of sedimentation, accurate prediction of reservoir SSL inflow is challenging.
- Research and application of ML modelling for reservoir sedimentation are still deficient.
- It is imperative to utilize the robustness, parallelism, and nonlinear mapping ability of ML modelling for reservoir SSL prediction.
- Further, extending its application to the RESCON modelling approach is imperative to achieve better sediment management in run-of-river hydraulic structures.

3. Objectives of Current Study

- To apply various machine learning models for real-time reservoir SSL inflow prediction using reservoir operation and climate variables.
- To analyze and compare the predictive performances of ML models based on statistical evaluation criteria.
- To demonstrate the performance of the ML models by its application on Sangju Weir, South Korea.

4. Artificial Neural Networks – An Overview

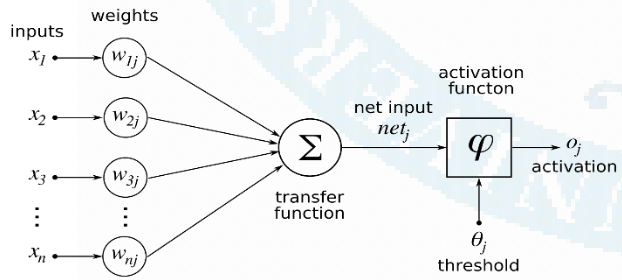
- Artificial Neural Networks (ANNs) are parallel, nonlinear computational framework consisting of highly interconnected neurons.
- The working of ANNs is inspired by working of actual human brain.
- ANNs possess certain advantages over other statistical models.
- Black-box properties → no prior knowledge of process is required.
- Nonlinear activation function → enables it to model complex problems.
- Highly robust and adaptable.
- Application of ANN in Water Recourses Engineering problem gained popularity in recent past.
- Utilization of ANN for optimum reservoir operation, especially reservoir sediment erosion and deposition is promising research area.
- In this study, ANNs are employed for sediment deposition simulation at Sangju weir, South Korea.



4. Application of ANN for Simulation of Sediment Deposition

Workflow of Present Research

- Firstly, the input variables were defined for ANN which affect the sedimentation most: reservoir stage, inflow and release.
- Graphical data was available for these variables. Digitization software was employed for data acquisition.
- Daily reservoir sedimentation data of year 2014 (From IRSEP in Kim et. al. (2018)) was used as target variable.
- ANN was created and configured with 3-6-1 framework typically used in water resources engineering problems.
- The network was trained with daily (365) values of the year 2014 of the variables.
- The effects of different training algorithms, activation function, and number of hidden neurons were investigated.



Defining Input Variables and Target Variable

Input Data Collection

Reservoir Sedimentation Data Acquisition

Create and Configure the Network

Train and Validate the Network

Use the Network for Simulating Sediment Deposition

5. Adaptive Neuro-Fuzzy Inference System (ANFIS)

- An ANFIS is an adaptive neuro-fuzzy mapping algorithm based on TSK* fuzzy inference system [11].
- ANFIS offer the combined advantage of both ANN (optimization capability, learning capability, and connectionist structure) and fuzzy logic (IF-THEN rule base) in a single framework.
- A typical ANFIS network has two identifiable parts: premise, and consequence parts.
- The architecture of ANFIS consists of 5 layers (Fig 4).
- The first layer, named ***fuzzification layer*** receives the input and determines associated membership function.
- Second layer, the ***rule layer*** determines the firing strength of the rules.
- Third, the ***normalization layer*** normalized the determined firing strengths.
- Fourth layer takes the input in the form of normalized values and the set of consequence parameter.
- The last layer takes the defuzzificated values and returns the output of structure.
- In this study, eight (8) membership functions have been used and evaluated to compute sedimentation at Sangju weir.

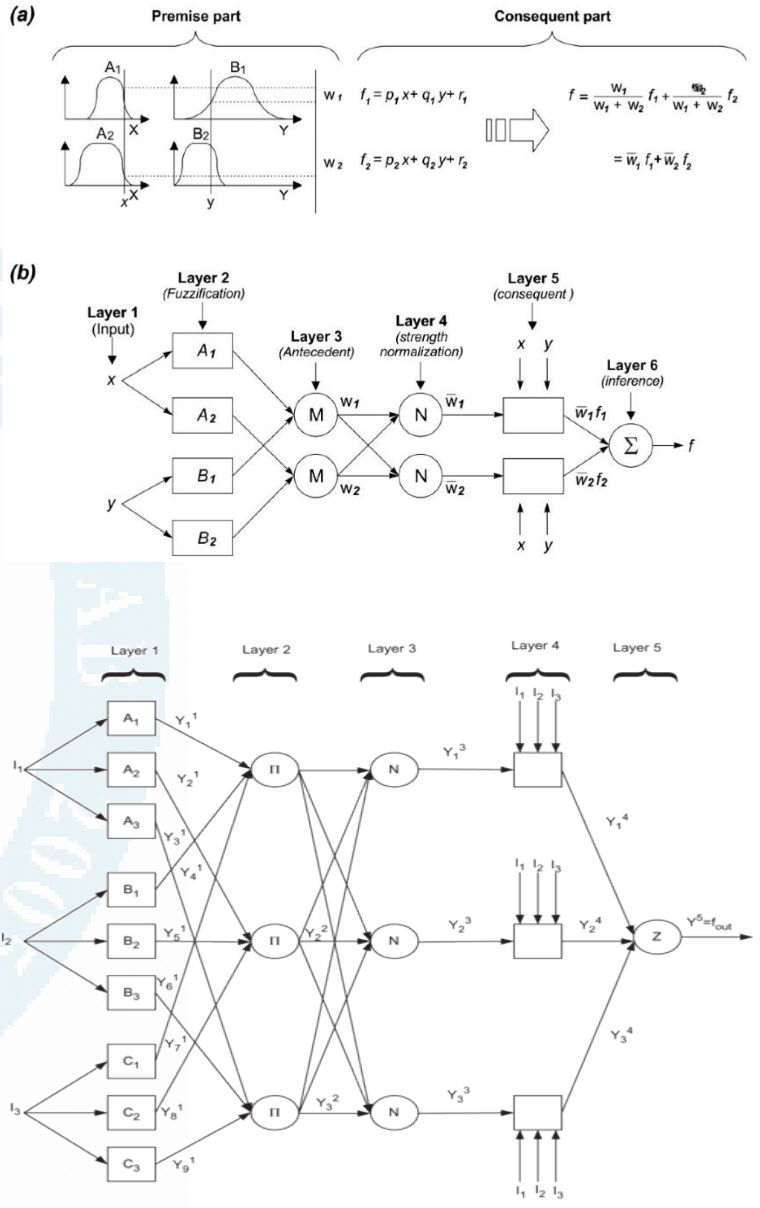
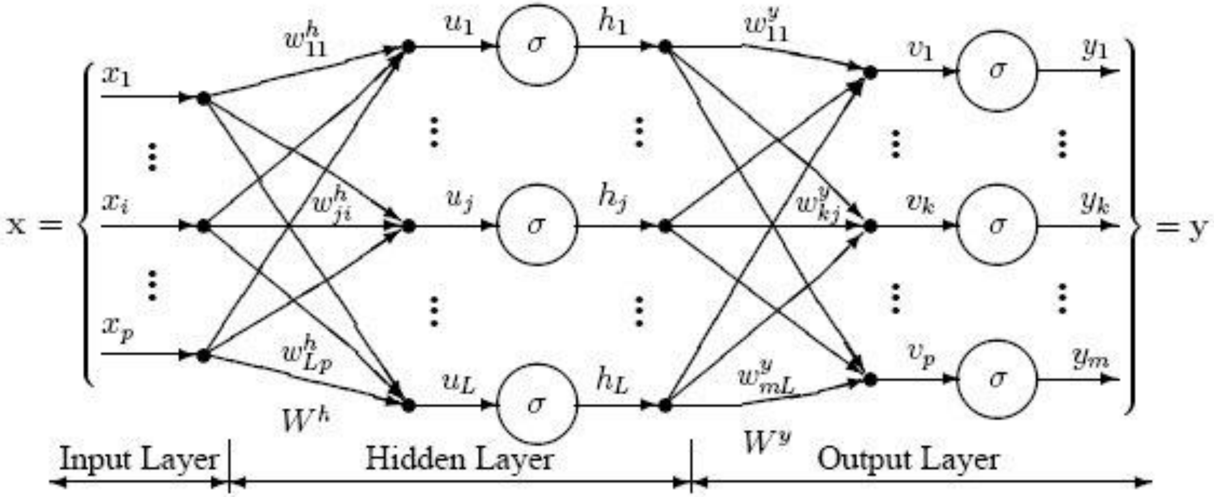


Fig. 6: Structure of a typical ANFIS network

*TSK = Tagaki-Sugeno-Kang

6. Multi-layered Perceptron (MLP)

- ANN structures with more than two hidden layers are referred to as deep nets.
- MLP is a very popular deep learning technique which is composed of hidden layers followed by dropout layers.
- The dropout layers assist in avoiding overfitting by bringing a transferability to network (Rynkiewicz, 2019).



7. Comprehensive Evaluation of Machine Learning Models for Suspended Sediment Load Inflow Prediction in Reservoir

Dataset Preparation

Parameter	Unit	Statistical properties					
		Maximum	Minimum	Mean	SD	Kurtosis	Skewness
Complete dataset							
Q	m^3/s	410.429	5.939	72.258	57.443	9.065	2.752
T	℃	29.272	-2.611	15.235	8.807	-1.310	-0.250
Q_{out}	m^3/s	1456.101	0.039	82.435	148.591	8.345	5.815
H	m	47.506	45.097	47.079	0.241	3.923	-5.786
SSL	tons/day	910.817	800.117	897.147	7.495	3.877	-5.786
Training data							
Q	m^3/s	410.429	5.939	72.258	57.444	9.068	2.752
T	℃	28.277	-2.611	15.052	8.769	-1.322	-0.265
Q_{out}	m^3/s	1456.101	0.039	82.435	148.596	8.360	5.816
H	m	47.506	45.992	47.079	0.269	3.938	-5.787
SSL	tons/day	910.817	835.145	897.150	7.490	3.861	-5.779
Testing data							
Q	m^3/s	410.311	6.286	72.258	57.474	9.121	2.756
T	℃	29.272	0.953	15.964	8.927	-1.305	-0.202
Q_{out}	m^3/s	1456.063	0.039	82.435	148.673	8.563	5.825
H	m	47.113	45.097	47.011	0.216	3.888	-5.781
SSL	tons/day	910.795	800.117	897.145	7.498	3.891	-5.769

7. Comprehensive Evaluation of Machine Learning Models for Suspended Sediment Load Inflow Prediction in Reservoir

Performance Indicators

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_{pre} - Y_{obs}\right|$$

- Mean absolute error (MAE)
- Willmott index (WI)
- Pearson correlation coefficient (PCC)

$$\mathrm{WI} = 1 - \left[\frac{\sum_{i=1}^{n}\left(Y_{pre} - Y_{obs}\right)^2}{\sum_{i=1}^{n}\left(\left|Y_{pre} - \overline{Y_{obs}}\right| + \left|Y_{obs} - \overline{Y_{obs}}\right|\right)^2}\right]$$

$$\mathrm{PCC} = \frac{\sum_{i=1}^{n}\left(Y_{obs} - \overline{Y_{obs}}\right)\left(Y_{pre} - \overline{Y_{pre}}\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_{obs} - \overline{Y_{obs}}\right)^2 \cdot \sum_{i=1}^{n}\left(Y_{pre} - \overline{Y_{pre}}\right)^2}}$$

7. Comprehensive Evaluation of Machine Learning Models for Suspended Sediment Load Inflow Prediction in Reservoir

Selection of best input combination

Input variables: Q, T, H, Q_{out}
Target variable: SSL

- 1) SSL = f (Q)
- 2) SSL = f (Q_{t-1})
- 3) SSL= f (Q, T, H, Q_{out})
- 4) SSL = f (Q_{t-1}, T_{t-1}, H_{t-1}, $Q_{out(t-1)}$)
- 5) SSL = f (Q, Q_{t-1}, T, T_{t-1}, H, H_{t-1}, Q_{out}, $Q_{out(t-1)}$)

Model	Performance indicators	Input combination				
		1	2	3	4	5
ANN	MAE (tons/day)	112.31	131.22	33.11	19.52	**18.21**
	RMSE (tons/day)	140.21	114.45	30.41	22.37	**20.76**
	PCC	0.52	0.54	0.81	0.73	**0.92**
ANFIS	MAE (tons/day)	232.51	167.25	58.21	34.85	**22.41**
	RMSE (tons/day)	151.44	114.45	84.51	29.43	**20.76**
	PCC	0.43	0.48	0.79	0.77	**0.88**
RBFNN	MAE (tons/day)	245.62	131.22	73.11	57.21	**28.75**
	RMSE (tons/day)	222.35	114.45	30.41	22.37	**20.76**
	PCC	0.49	0.56	0.83	0.66	**0.87**
GP	MAE (tons/day)	332.58	358.88	**29.54**	55.84	39.33
	RMSE (tons/day)	261.54	297.78	**30.41**	48.44	49.21
	PCC	0.31	0.29	**0.84**	0.66	0.84
SVM	MAE (tons/day)	201.68	131.22	87.61	**49.52**	67.77
	RMSE (tons/day)	197.85	114.45	30.41	**22.37**	80.26
	PCC	0.41	0.56	0.83	**0.95**	0.82
DL	MAE (tons/day)	487.78	368.76	**119.54**	187.43	151.29
	RMSE (tons/day)	392.67	297.78	**141.61**	148.36	187.44
	PCC	0.29	0.34	**0.78**	0.61	0.69

7. Comprehensive Evaluation of Machine Learning Models for Suspended Sediment Load Inflow Prediction in Reservoir

Model Architecture:

ANN

- The number of neurons in hidden layer of ANN determines its architecture.
- Increasing the number of hidden neurons does not always result in increasing performance of network.
- Usually a trail-and-error procedure is adopted for determination of number of hidden neurons.
- For this study, the number of neurons in hidden layer was varied from 2-12.

ANFIS

- Training ANFIS involves selecting number of membership function (MF), output MF type, optimization method, and number of epochs.
- Studies in literature debate on importance of MF type selection for attaining optimized ANFIS performance.
- In this study, eight input MFs were utilized. The ‘constant’ output MF type was used, and ‘hybrid’ training FIS optimization method was employed.
- For all eight input MF types, the number of epochs were increased persistently until the error became constant.

7. Comprehensive Evaluation of Machine Learning Models for Suspended Sediment Load Inflow Prediction in Reservoir

MLP

- MLP is a widely used deep learning technique which has been applied in this study for sediment deposition modelling.
- The suitable architecture of the model is adopted based on trial-and-error method.
- For this study, 8-layered fully connected network was adopted with one input and output layer, three hidden layers, and three dropout layers.
- Three hidden layers contained 100, 50, and 20 number of neurons, respectively.
- The rectified linear unit (ReLU) activation function was used which has increased application in recent years for deep neural nets due to its abilities to avoid saturation of gradient.
- Each of the three hidden layers were followed by one dropout layer having dropout rate 0.3, 0.2 and 0.1, respectively.
- The application of dropout layer assists in avoiding overfitting in deep net applications and the dropout rate defines the percentage of neurons inactivated in feed-forward pass.

7. Comprehensive Evaluation of Machine Learning Models for Suspended Sediment Load Inflow Prediction in Reservoir

Results

ANN

- The results for testing data are shown in Fig.7 with all three performance indicators.
- Best performance was seen with ten hidden neurons and after that the performance of network started decreasing.
- The transfer function for output layer is ‘purelin’ because the target data in its natural state was used.
- Hence, 4-10-1 network architecture was used for simulation, and three training functions were employed for comparison.
- It was observed the Levenberg-Marquardt (LM) algorithm has minimum value of MSE for both training and testing data, as shown in Table 1.
- The WI values for all simulations fall near the ideal value of 0.5.
- The PCC values in the Scaled Conjugate Gradient (SCG) and Bayesian Regulation (BG) application were similar, but the WI indicator showed slightly better results for SCG.
- It was concluded based on performance indicators that using LM algorithm yielded best possible result for sedimentation problem.

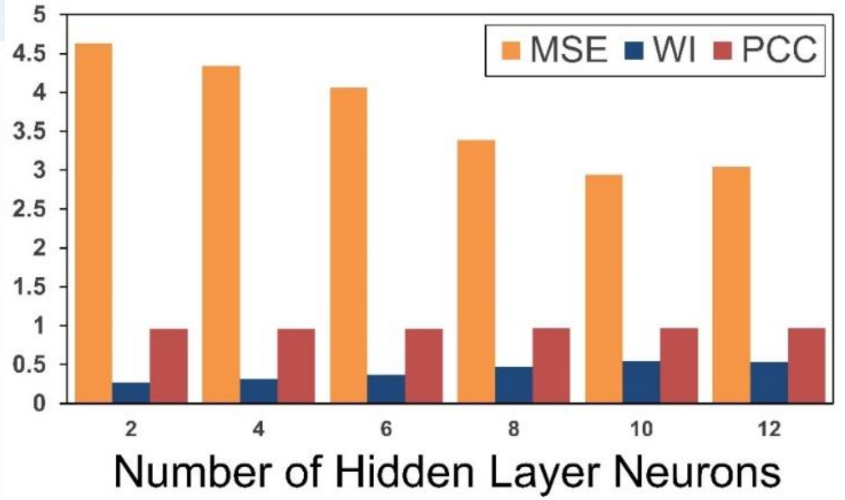


Figure l ANN architecture selection based on performance indicators

Table 2 l ANN results utilizing different transfer functions

Transfer Function	Training Data			Testing Data		
	MSE	WI	PCC	MSE	WI	PCC
Levenberg-Marquardt	2.945	0.541	0.973	3.221	0.511	0.959
Scaled Conjugate Gradient	3.232	0.498	0.971	4.729	0.464	0.955
Bayesian Regularization	3.252	0.495	0.971	4.994	0.469	0.947

7. Comprehensive Evaluation of Machine Learning Models for Suspended Sediment Load Inflow Prediction in Reservoir

Results

ANFIS

- The resulting performance indices values for each MF are shown in Fig. 8.
- The results revealed that 'trainmf' MF produced fixed course values; thus, it can be discarded for modelling this problem.
- The 'gbellmf', 'dsigmf' and 'psigmf' showed best performance based on MSE criteria.
- However, slightly better values for 'psigmf' MF were obtained for WI and PCC criteria.
- Hence, the ANFIS with 'psigmf' input MF type was declared best for modelling sediment deposition.

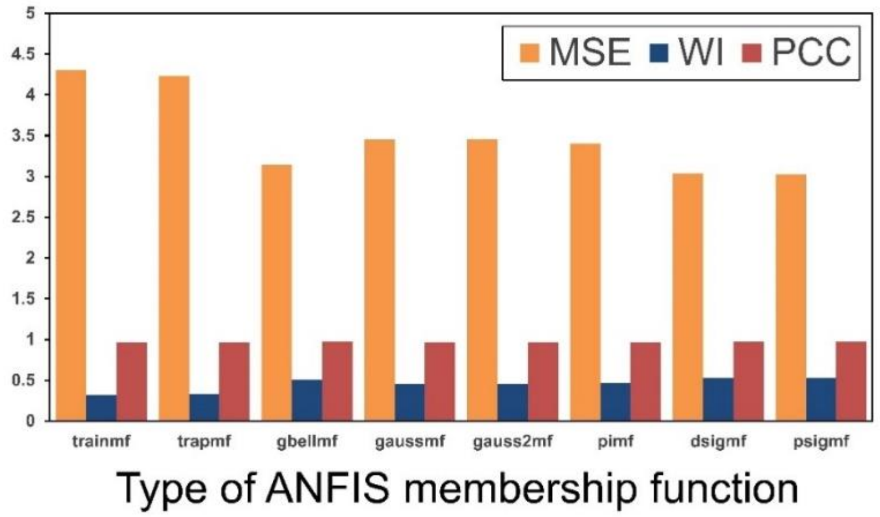


Figure 8 l Effect of different ANFIS membership functions on model performance

7. Comprehensive Evaluation of Machine Learning Models for Suspended Sediment Load Inflow Prediction in Reservoir

Results

- For the comparison of three models, the best performing architecture of each model and their performance indicators are shown in Table 3.
- It was concluded that the ANN model with one hidden layer was most efficient in capturing the relationship of reservoir operation and climate change variables with sediment deposition rate.
- The MLP model consisted of multiple hidden layers yet performed poorly.
- Figure 4 consisted of annual sediment deposition in the reservoir observed during the testing period (2017-2019) and its simulation results using all three models.
- All the models tend to over-predict the amount of sediment deposition in 2017 and 2018 while MLP showed over-prediction in 2019.
- The fact observed here that soft computing models tend to over-predict the sediment deposition is also reported by previous researchers (Emamgholizadeh & Demneh, 2018; Kumar et al., 2019; Malik et al., 2019).
- This is because generally the sedimentation data is highly variable, and it is likely that training and testing datasets have different distributions.

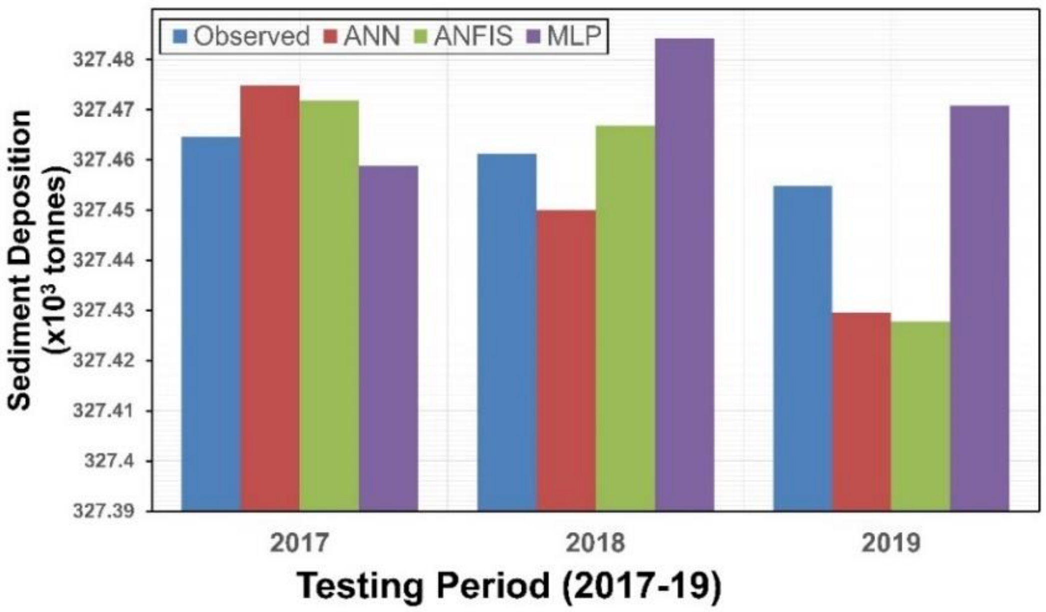


Figure 9 | Performances of models for simulating sediment deposition in testing period

7. Comprehensive Evaluation of Machine Learning Models for Suspended Sediment Load Inflow Prediction in Reservoir

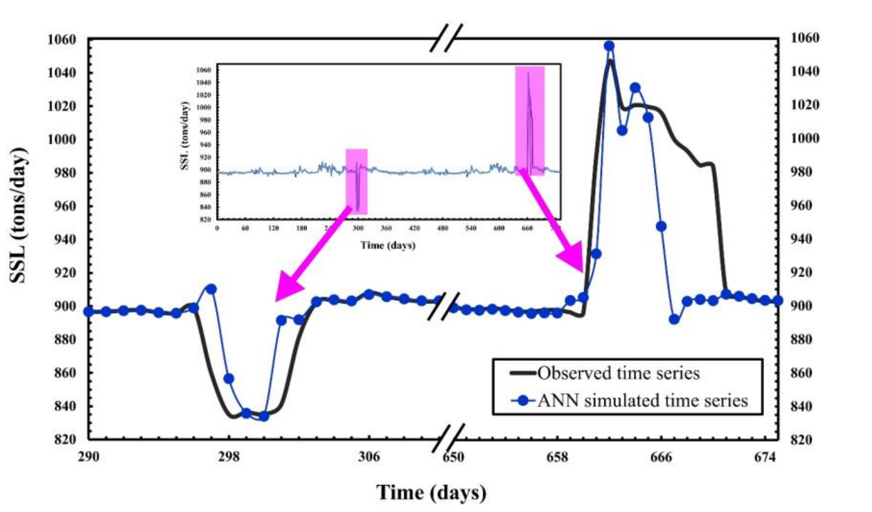
- It is evident from Table 2 that application of all three models at the testing stage showed a decreasing trend in performance.
- These results also reflect the variable effects of changing climate on the sediment deposition because the reservoir water inflow and water temperature were different in training and testing periods.
- Whilst data applied for training has been observed to optimally train ANN with single hidden layer, the performance of ANFIS and MLP was inferior because of larger data requirement for training of their complex architectures.
- It is recommended to apply deep learning to solve this particular type of problem only when substantial data is available ; application of ANN with single hidden layer is recommended for smaller datasets.

Table 3 I Comparison of best performing architectures of three models

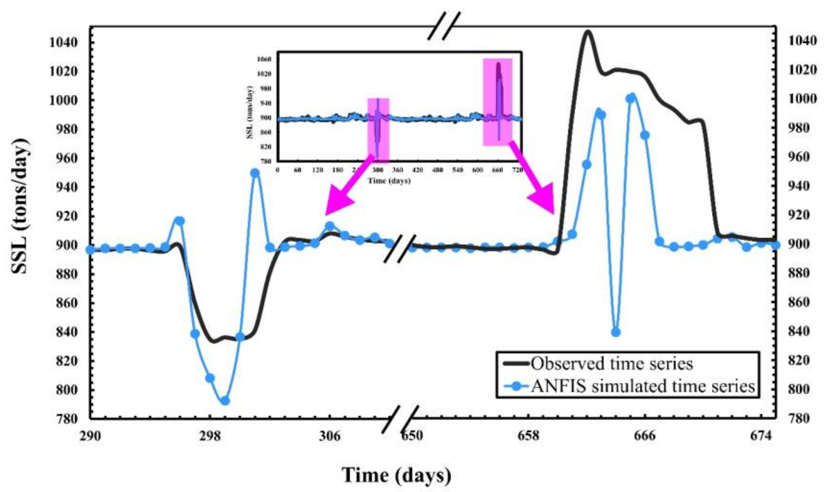
Model	Training			Testing		
	MSE	WI	PCC	MSE	WI	PCC
ANN (4-10-1)	2.945	0.541	0.973	3.221	0.511	0.959
ANFIS (MF: psigmf)	3.022	0.529	0.971	2.954	0.498	0.944
MLP (4-100-50-20-1)	4.521	0.475	0.955	4.822	0.418	0.916

7. Comprehensive Evaluation of Machine Learning Models for Suspended Sediment Load Inflow Prediction in Reservoir

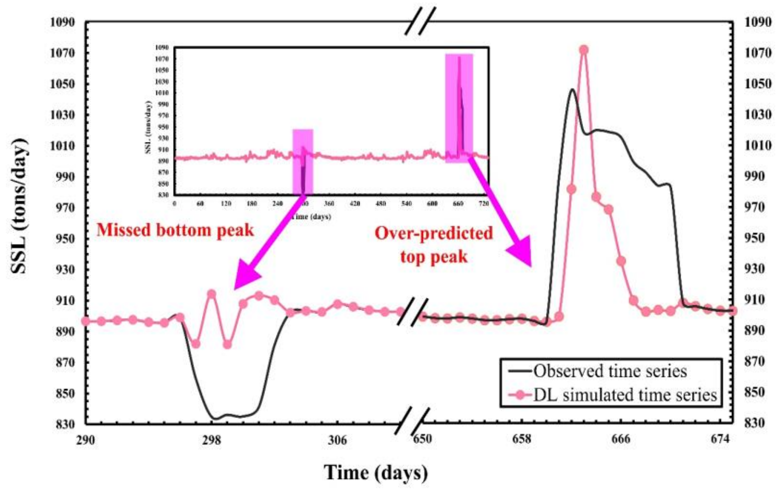
Results



ANN



ANFIS



MLP

8. Conclusions

- This study was carried out to inspect the potential of ANN, ANFIS, and MLP in simulating sediment deposition at Sangju Weir, South Korea.
- Input combination of reservoir water temperature, inflow, water stage, and outflow were used to develop soft computing models while the reservoir sediment deposition rate was the target variable.
- The estimates of ANN, ANFIS and MLP were compared with observed sedimentation using MSE, WI, and PCC and performance indicators.
- The results indicated that ANN, ANFIS, and MLP were able to predict reservoir sedimentation rate with reasonable degree of accuracy. ANN model with 4-10-1 architecture and LM transfer function gave the best performances in training and testing periods.
- Eight membership functions for ANFIS were employed and their performance hierarchy was psigmf > dsigmf > gbellmf > pimf > gauss2mf > gaussmf> trapmf > trainmf.

8. Conclusions

- MLP model with three hidden layers and three dropout layers was the less efficient than ANN and ANFIS models.
- The outcomes of this study are useful to model increased reservoir sedimentation rates as the impact of climate change.
- ANN, ANFIS and MLP employed here are data-driven models, hence the outcomes of these methods need to be verified using more data.
- The scope of the present study can be broadened by applying a more diverse set of input variables.
- It is also recommended to expand the scope of this work in future research by coupling the parameter estimation methodology with quasi-steady or unsteady flow simulation models.
- Scope of the ML modelling comparative study can be expanded with the application of more associated input variables for SSL inflow prediction and comparison with physically-based modeling studies.
- The applicability of the SSL modelling approach can be extended by the integration of quasi-steady or unsteady water and sediment flow simulation models.

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Thank You!

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