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Complementary Modeling Approach for Estimating Sedimentation and Hydraulic Flushing Parameters Using Artificial Neural Networks and RESCON2 Model

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ABSTRACT

Accurate prediction of reservoir sediment inflows ($\mathbf{M_{in}}$) and adaptation of feasible sediment management strategies pose challenges in water engineering. This study proposed a two-stage complementary modeling approach for comprehensive reservoir sediment management. In the first stage, artificial neural network-based models provide real-time $\mathbf{M_{in}}$ predictions using water inflow, water head, and outflow as input parameters. In the second stage, the parameter estimation method of the RESCON model is applied to hydraulic flushing in a reservoir. This approach was applied to the Sangju Weir and Nakdong River Estuary Barrage (NREB) in South Korea. Results from the RESCON model revealed that hydraulic flushing was effective for sediment management at both the Sangju Weir reservoir and the NREB approach channel. Efficient flushing at the Sangju Weir required a flushing discharge of 100 m^3/s for 6 days and 40 m of water head. Efficient flushing at the NREB required a flushing discharge of 25 m^3/s for 6 days with 1.8 m of water-level drawdown. The proposed approach is expected to prove useful in reservoir sediment management.

1. Introduction

Sediment transport is a significant aspect of fluvial processes as it is closely related to river morphology. The sediment load produced by the erosion of geological features in a watershed is transported by water streams to rivers, lakes, and eventually to seas further downstream (McLean et al., 1999). The sediment-carrying capacity of rivers depends on stream power, bed shear stress and bedforms, rainfall intensity, and land-use characteristics of the watershed (McLean et al., 1999; Kang et al., 2001; Eaton and Church, 2011). All rivers in the world carry a sediment load and are therefore considered bodies of flowing sediment (Vercruysse et al., 2017). When a sediment-laden river flows into the still waters of a reservoir, it loses velocity and subsequently its sediment-carrying capacity. The sediment carried by rivers settles in a reservoir, resulting in its storage loss (Jiahua and Morris, 1992; Lu et al., 2012). The rate of reservoir sedimentation is controlled by reservoir geometry, operating rules, capacity and inflow, and the density of current formation (Mahmood and Mundial, 1987; Jiahua and Morris, 1992; Schleiss et al., 2016). The proportion of sediment load trapped in a reservoir over time, trap efficiency, is a function of the kinetic energy and type of sediment (Trimble and Wilson, 2012).

All water-impounding structures including large dams, barrages, and power plants suffer from sedimentation. The global annual loss of reservoir capacity due to sedimentation ranges from approximately 0.5% to 1% of available reservoir volume, although it can reach 5% in some cases (Dominik et al., 2013). Sedimentation in reservoirs formed by hydraulic structures such as barrages and weirs poses a significant risk as a heightened riverbed not only limits water storage, but leads to breaches of embankments during flood events (Gebhardt et al., 2019; Noseda et al., 2019). The processes associated with reservoir sedimentation are complex and their physics are not yet fully understood (Schleiss et al., 2016).

Prediction of the mean annual total sediment inflow mass

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($\mathbf{M_{in}}$) into a reservoir is crucial to estimating the useful life of the reservoir and to selecting effective sediment management measures (Hillebrand et al., 2016; Hao et al., 2017). Hydrographic surveys and sediment rating curves are traditional approaches for predicting reservoir sedimentation, but both are associated with substantial inaccuracies and limitations (Furnans and Austin, 2008; Heng and Suetsugi, 2013; Bussi et al., 2017). Previous research has identified various methods of linking sediment inflow with hydraulic parameters, geometric parameters, and sediment characteristics (Chang, 1992; Sear, 2002). However, these methods tend to be site-specific and cannot be applied universally. Physical hydrological models, including the Soil and Water Assessment Tool (Neitsch et al., 2011), the Erosion Productivity Impact Calculator (Williams, 1989), and the Water Erosion Prediction Project (Flanagan et al., 2007), can model sediment and nutrient transport in catchments and reservoirs. The application of physical models is often event-based and requires extensive bathymetry, topography, and hydrologic data.

Artificial neural networks (ANNs) and other computing and machine-learning (ML) models have been applied recently to predict river and reservoir sediment inflows (Choubin et al., 2018; Khosravi et al., 2018; Malik et al., 2019; Samet et al., 2019). ANNs have successfully modeled suspended-sediment concentration (Lafdani et al., 2013; Huang et al., 2019; Rajaee and Jafari, 2020) and predicted sediment-loads (Pektas and Cigizoglu, 2017; Khan et al., 2019). Safari et al. (2016) used ANNs to model flow velocity associated with incipient sediment deposition. Rahman and Chakrabarty (2020) used ANNs with various training algorithms and transfer functions to simulate sediment transport in an alluvial river. Numerous other ANNs applications have been developed for use in hydraulics (Zounemat-Kermani et al., 2020), surface water hydrology (ASCE, 2000a, 2000b), and groundwater hydrology (Bharti et al., 2017; Zhang et al., 2019). Idrees et al. (2021) evaluated six ML techniques and developed suspended sediment load (SSL) inflow prediction models, in which the ANN-based model has been found best for SSL inflow prediction in a reservoir.

Methods of countering sedimentation for sustainable use of reservoirs include sediment routing, sluicing, dredging, and flushing (Mahmood and Mundial, 1987; Tigrek and Aras, 2011; Schleiss et al., 2016). The REServoir CONservation (RESCON) model was developed by the World Bank to assess the feasibility of various sediment management techniques (Palmieri et al., 2003). A newer version of the model (RESCON2), which includes sustainability factors and hydrological uncertainties associated with climate change, was introduced recently. Huang et al. (2015) applied the RESCON model to assess sediment management of the Sanmenxia Reservoir in China. Garcia (2019) found that the RESCON2 model could predict a feasible sediment management strategy accurately. Idrees et al. (2019) developed a parameter estimation method for efficient sediment flushing in a dam reservoir using the RESCON model.

Sediment flushing involves increasing the flow velocities of a reservoir, followed by a lowering of water levels depending on site conditions, to erode and transport sediment deposits through low-level outlets (Lai and Shen, 1996). Sediment flushing has proven to be an effective method of countering and managing reservoir sedimentation worldwide (White, 2012). However, the associated complexity of morphological processes requires extensive knowledge and study of onsite constraints (Atkinson, 1996). Research and application of ANNs and the RESCON model to reservoir-sediment deposition and removal strategies, and complex sediment flushing processes in particular, are still deficient.

The purpose of this paper is to predict $\mathbf{M_{in}}$ upstream of dams and consider sediment flushing as a possible sediment management strategy. The concept of a two-stage complementary-modeling approach was put forward based on a machine-learning ANNs and the RESCON2 model. The specified objectives of this study are 1) to propose a complementary-modeling approach that combines ANNs with the RESCON model for sediment management behind weirs; and 2) to demonstrate the performance of the new approach to sediment management by applying it to multiple hydraulic structures on the Nakdong River, South Korea.

The present work utilizes the robustness, parallelism, and nonlinear mapping ability of ANNs for reservoir-sediment inflow prediction and extends its application to RESCON modeling to achieve superior sediment management in run-of-river hydraulic structures. To the best of author's knowledge, this is the first attempt to integrate a data-driven ANNs model and the empirical RESCON model in reservoir-sediment management. The comprehensive approach proposed in this study is expected to provide guidelines to improve sediment management in dam reservoirs.

2. Materials and Methods

2.1 Study Site Description

The Four Rivers Restoration Project (FRRP) was launched in South Korea in 2009 to improve flood control, drought relief, and the ecological restoration of rivers. Significant sediment deposition has been observed upstream of weirs and near the confluence of river tributaries after completion of the FRRP in 2012 (Jun and Kim, 2011). Sangju Weir is the uppermost of eight consecutive weirs on the Nakdong River (Fig. 1). It was chosen for this study because it represents sedimentation problems, and recent reports addressed this sedimentation issue. The Naesung and Yeong streams as tributaries contribute significantly to annual sediment inflow into the Sangju Weir. Due to ambiguous operating rules at the Sangju Weir, severe sediment deposition occurs in the reservoir, leading to significant annual dredging costs. Kim (2016) developed an integrated reservoir sedimentation estimation procedure for reservoir sedimentation estimates at the Sangju Weir. Kim et al. (2017) presented a multi-criteria decision analysis and devised new operating rules for the Sangju Weir to counter the sedimentation problem without affecting hydroelectric power generation, water supplies, or flood control. Kim and Julien (2018) conducted long-term analyses to determine hydraulic

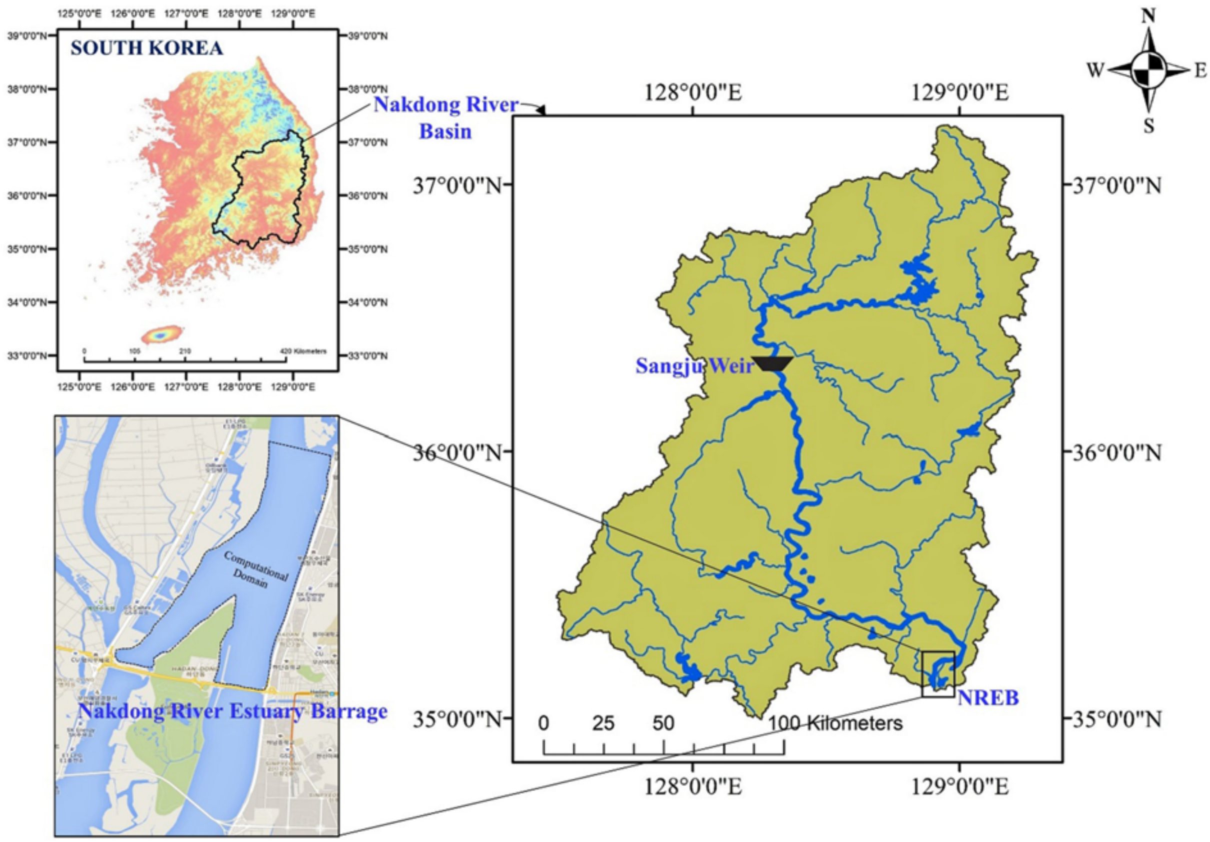

Fig. 1. Nakdong River basin and Location of the Sangju Weir and NREB on the Nakdong River Main Channel

thresholds for mitigating sedimentation problem at the Sangju Weir.

Nakdong River Estuary Barrage (NREB) was constructed in 1987 to prevent intrusion of saltwater from the sea into the river (Fig. 1). The cross-sectional length of the main body of NREB is 2,230 m, comprising a 510 m gated section, and a 1,720 m closed wall. The gated section includes six main gates, four control gates, one lock for navigation, and a tidal outlet in the right bank. Recently, three main gates and two control gates were added to the closed-wall section to improve flood control (Williams et al., 2013). The approach channel of NREB is affected by sedimentation and dredging is performed annually up to 3 km from the barrage to maintain flood-conveyance capacity. The height of sediment deposits must be kept below 1.0 m for effective flood control (Kim et al., 2014). Ji et al. (2011) combined sediment-flushing curves at NREB with flow duration curves to assess the feasibility of sediment flushing. Park et al. (2013) studied the effectiveness of sediment dredging operations in flood mitigation in the NREB approach channel. After performing numerical modeling of sediment control scenarios at the NREB, Ji et al. (2016) concluded that sediment flushing combined with channel contraction considerably reduces the height of sediment deposits.

Daily inflow (m^3/s), water stage (m), and outflow (m^3/s) data for the Sangju Weir reservoir were collected from the Water Resources Management Information System (WAMIS, http://www.wamis.go.kr). The reservoir inflows ranged from 6 m^3/s to 410 m^3/s, with high seasonal inflow peaks recorded in July and August. The long-term sediment inflows at Sangju Weir reservoir have been estimated by applying the integrated reservoir sedimentation estimation procedure (IRSEP). Kim (2016) developed the IRSEP which estimates reservoir sediment inflow based on flow duration and sediment rating curve (FD/SRC), and the series expansion of the modified Einstein point procedure (SEMEPP). The sediment inflow is then multiplied by trap efficiency (T_e) to estimate sediment deposition. The study area includes three gauging stations for the Sangju Weir: Hyangseok station on Naesung Stream, Jeomchon station on Yeong Stream, and Waegwan station on the main Nakdong River. The FD curves and SRC's were produced by Kim (2016) at head of three streams: 1) Naesung Stream (Hyangseok station); 2) Yeong Stream (Jeomchon station); and 3) Nakdong River (Waegwan station). A representative FD curve was obtained and the SRC's at three stations were combined to predict long-term sediment yield at the Sangju Weir reservoir. The SEMEPP correction factor was applied to get the total sediment load inflows at Sangju Weir reservoir. Because the Sangju Weir began operating in 2012, eight years (2012 – 2020) of data were considered in this study. The representative sediment rating curve relationship for the Sangju Weir reservoir site is

$$Q_s = 2.66Q^{1.507}. \tag{1}$$

For the NREB, the approach channel, 3 km upstream of the barrage was considered in this study for computations. The Samrangjin station on the Lower Nakdong River is the closest to the NREB. Detailed records of hydrologic data at Samrangjin station are available online and can be retrieved from the WAMIS website. Sediment characteristics and time series of sediment-load inflow at the NREB for 2008 – 2020 were retrieved from Kim and Lee (2019). The sediment rating curve relationship for the NREB approach channel is

$$Q_s = 10.47Q^{0.96}. \tag{2}$$

2.2 Artificial Neural Networks

ANNs possess a nonlinear mapping ability because the networks "learn" as the connection weights adjust and can perform particular modeling. A typical structure of ANNs consists of three types of highly interconnected layers: an input layer (input vectors are introduced to the network), a hidden layer (data processing), and an output layer (outputs are produced and presented), as shown in Fig. 2. Although numerous architectures of ANNs have been proposed, the feed-forward model with an error back-propagation (BP) supervised learning algorithm is the most popular for hydrology and water resources. A BP-ANNs model was used in this study to predict $\mathbf{M}_{in}$ at the Sangju Weir reservoir and NREB approach channel.

2.3 RESCON Model

The RESCON Model was developed in 2003 by the World Bank to assess water resource infrastructures and implement life-cycle management. The underlying algorithm of RESCON

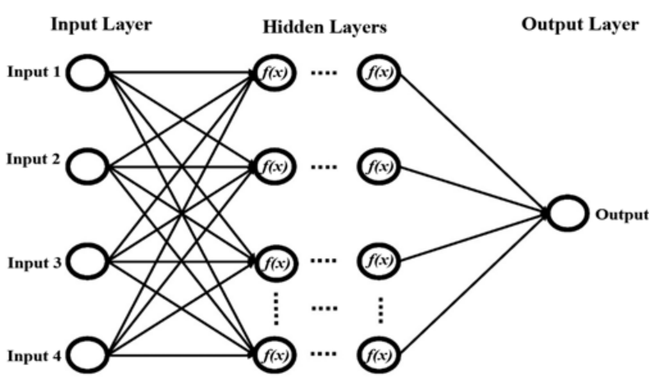

Fig. 2. Conceptual Framework of ANNs with Multiple Hidden Layers

involves evaluating different sediment management techniques by computing feasibility indicators with support of engineering relationships (Kawashima et al., 2003; Palmieri et al., 2003). A new version of the RESCON model, "RESCON2" released in 2017, has enhanced abilities to evaluate advanced sediment management strategies. RESCON2 assesses flushing operation efficiency and onsite applicability using dimensionless indicators developed by Atkinson (1996), namely sediment balance ratio (SBR), long-term capacity ratio (LTCR), drawdown ratio (DDR), flushing width ratio (FWR), top width ratio (TWR), and sediment balance ratio at full drawdown (SBRd).

The SBR is the ratio of sediment mass flushed to the total sediment mass deposited annually into the reservoir. The LTCR is the ratio between the area of the reservoir that can be sustained over the long term by flushing and the total area of the reservoir. Both the SBR and LTCR are basic criteria that need to be satisfied for successful flushing operation. The constraints in the onsite application of flushing operation are assessed based on the DDR, FWR, TWR, and SBRd. The water level that can be drawn down during flushing is expressed by the DDR. A flushing channel is usually formed in the reservoir during a flushing operation, and the FWR is the ratio between the flushing channel width and the bottom width of the reservoir. The TWR is the ratio between top width of the scoured valley formed by flushing to the actual top width of dam body. The successful flushing operation requires that SBR > 1, LTCR ≥ 0.5, DDR ≥ 0.7, SBRd > 1, FWR > 1, and TWR = 1 – 2.

2.4 Complementary Modeling

A flowchart of the methodology for this research is displayed in Fig. 3. A new approach to comprehensive analysis of sediment deposition and application of sediment flushing operation at weirs was developed in this study. The proposed new approach comprises two stages. Stage 1 involves the prediction of $\mathbf{M}_{in}$ with the ANNs. In stage 2, sediment data, along with geometric data and water characteristics of the reservoir, are used to set up the RESCON2 model to study the feasibility of various flushing options. The developed approach is illustrated in Fig. 4 and can be described by the following process:

1. Select the hydrologic and hydraulic variables to be used as input vectors for ANNs model development. Collect long-term historical data for each variable along with a historical record of reservoir sediment inflow to be used as the target

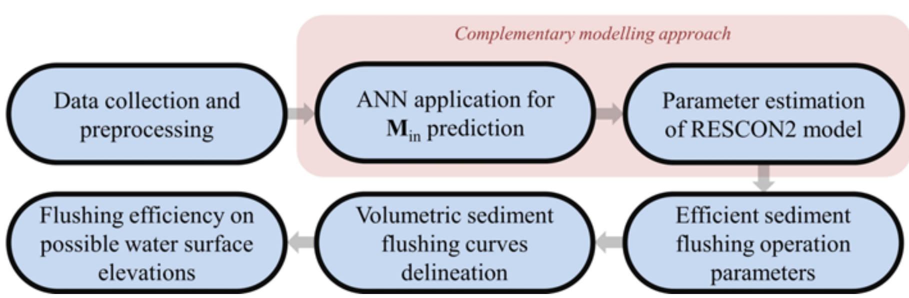

Fig. 3. Primary Flowchart of Methodology for This Study

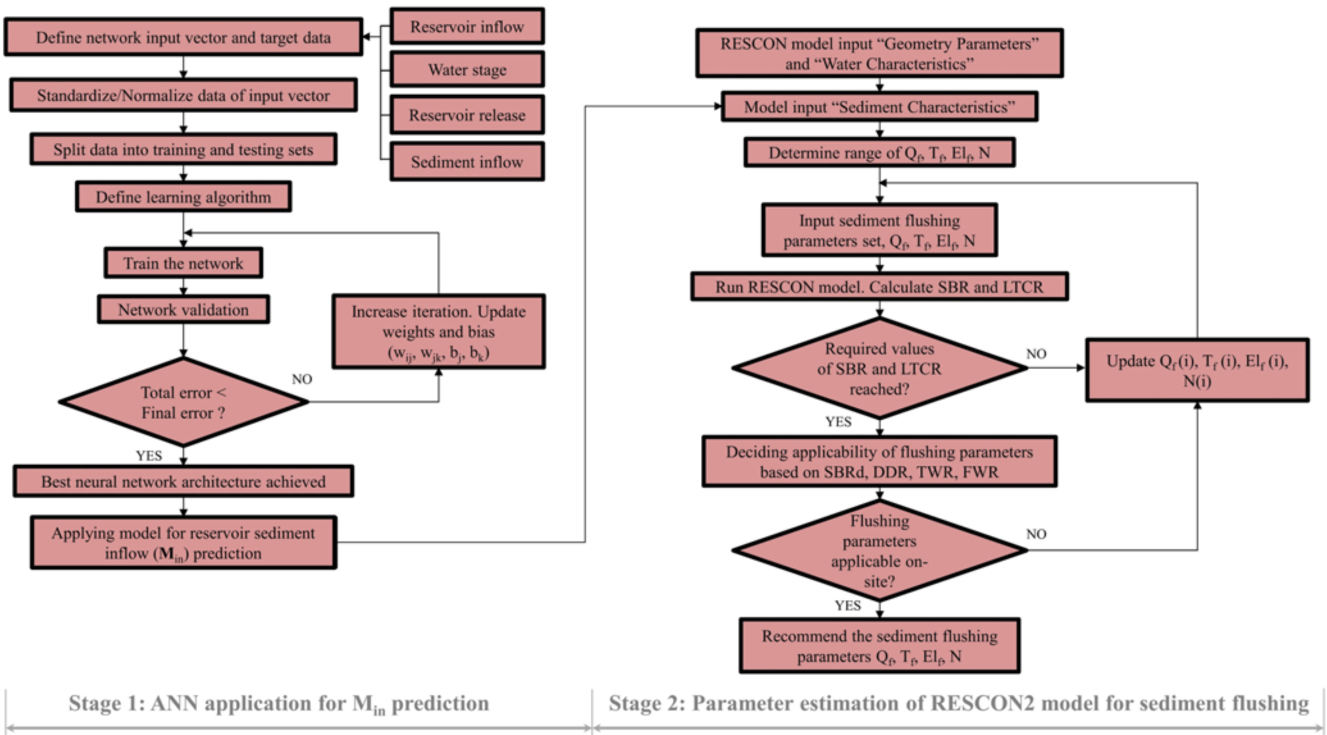

Fig. 4. Flowchart of a Two-Stage Complementary Modeling Approach for Comprehensive Reservoir Sediment Management

variable.

2. Perform input-data normalization. Data normalization is recommended for faster training of the ANNs model and to bring data attributes within a common scale.
3. Train the ANNs model until the best model architecture is achieved.
4. Apply the ANNs model to predict $\mathbf{M_{in}}$ into the reservoir.
5. Setup the RESCON2 model by feeding in the predicted $\mathbf{M_{in}}$ and other sediment characteristics, along with dam and reservoir geometry data, hydrologic data, and removal parameters.
6. Input the initial estimates of sediment flushing parameters and run the model.
7. The RESCON2 model uses the SBR and LTCR as the main criteria to be met for efficient sediment flushing. If the required values for both indicators are achieved, proceed to the next step. Otherwise, construct a new set of sediment flushing parameters, and repeat from step 6.
8. The sediment flushing parameters may or may not be applicable to the reservoir site. The onsite applicability can be evaluated in RESCON2 based on the DDR, FWR, TWR, and SBRd. Observe the achieved values and evaluate the practicality of the sediment flushing parameters. Recommend the parameters if the required values of indicators are achieved. Otherwise, fabricate a new set of sediment flushing parameters and repeat from step 6. Repeat the process until the sediment flushing parameter is optimized based on flushing efficiency indicators.

3. Application

3.1 ANNs Input Selection and Data Pre-processing

The studies related to applications of ML models for sediment inflows estimations (Lafdani et al., 2013; Malik et al., 2019) attempted to mimic the SRC approach and used only water inflow as an input variable, with sediment inflow as the target variable. Khosravi et al. (2018) used three input variables for three ML models to predict sediment inflow. We have also used three input variables sediment inflow prediction including the daily reservoir water inflow (Q), water stage (H), and reservoir release (R). These parameters greatly influence sediment inflow ($\mathbf{M_{in}}$) and deposition in reservoirs (Khosravi et al., 2018; Samet et al., 2019; Rahman and Chakrabarty, 2020), $\mathbf{M_{in}}$ was used as a target variable in this study. Although ANNs can accommodate data in any range, a saturation effect may make the applied model sensitive to inputs within a narrow range. To move the data into a comparable range, data were normalized in [–1, +1] using Eq. (3). The target variable was used in the natural state:

$$X_{normal} = \left[\frac{X_0 - X_{min}}{X_{max} - X_{min}}\right] \times 2 - 1 \, . \tag{3}$$

When modeling with heuristic approaches, sediment inflow at the current day is reportedly influenced by values of input parameters at previous time-steps (Khan et al., 2019; Kumar et al., 2019; Samet et al., 2019). A Gamma test was performed for all input parameters at both the Sangju Weir and NREB sites with up to two time lags (Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-1}, R_{t-2}). All possible input combinations are presented in Table 1 for both

Table 1. Identification of Most Significant Input Combination for Sediment Inflow at the Sangju Weir and NREB Based on the Gamma Test

Model	Input parameters	Gamma test statistics			
		Mask	Γ	SE	V_{ratio}
Sangju Weir					
SW M1	$Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-1}, R_{t-2}$	111,111,111	0.0966	0.0021	0.5461
SW M2	$Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-1}, R_{t-2}$	011,111,111	0.0968	0.0026	0.5455
SW M3	$Q_t, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-1}, R_{t-2}$	101,111,111	0.0976	0.0028	0.5474
SW M4	$Q_t, Q_{t-1}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-1}, R_{t-2}$	110,111,111	0.0973	0.0019	0.5514
SW M5	$\mathbf{Q_t, Q_{t-1}, Q_{t-2}, H_{t-1}, H_{t-2}, R_t, R_{t-1}, R_{t-2}}$	**111,011,111**	**0.0962**	**0.0021**	**0.5497**
SW M6	$Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-2}, R_t, R_{t-1}, R_{t-2}$	111,101,111	0.0970	0.0024	0.5452
SW M7	$Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, R_t, R_{t-1}, R_{t-2}$	111,110,111	0.0964	0.0027	0.5522
SW M8	$Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_{t-1}, R_{t-2}$	111,111,011	0.0972	0.0030	0.5484
SW M9	$Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-2}$	111,111,101	0.0964	0.0029	0.5462
SW M10	$Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-1}$	111,111,110	0.0967	0.0029	0.5542
NREB					
NREB M1	$Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-1}, R_{t-2}$	111,111,111	0.0744	0.0058	0.3583
NREB M2	$Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-1}, R_{t-2}$	011,111,111	0.0772	0.0055	0.3324
NREB M3	$Q_t, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-1}, R_{t-2}$	101,111,111	0.0744	0.0052	0.3254
NREB M4	$Q_t, Q_{t-1}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-1}, R_{t-2}$	110,111,111	0.0747	0.0057	0.3541
NREB M5	$Q_t, Q_{t-1}, Q_{t-2}, H_{t-1}, H_{t-2}, R_t, R_{t-1}, R_{t-2}$	111,011,111	0.0746	0.0057	0.3589
NREB M6	$Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-2}, R_t, R_{t-1}, R_{t-2}$	111,101,111	0.0748	0.0061	0.3219
NREB M7	$Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, R_t, R_{t-1}, R_{t-2}$	111,110,111	0.0756	0.0056	0.3472
NREB M8	$Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_{t-1}, R_{t-2}$	111,111,011	0.0753	0.0054	0.3347
NREB M9	$\mathbf{Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-2}}$	**111,111,101**	**0.0742**	**0.0052**	**0.3564**
NREB M10	$Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-1}$	111,111,110	0.0750	0.0059	0.3512

study sites. The first combination consisted of all nine inputs; the second combination consisted of eight inputs, with the first input masked as 0. The procedure was repeated for the other combinations, with the input corresponding to the 0 mask excluded from model input parameters. Physically, the response timing of sediment inflow ($\mathbf{M_{in}}$) to input parameters may be lagged due to various controlling factors like slope of basin and stream, vegetation cover, soil type, etc. The variables Q, H, R, and their time lags are the base quantities in all models (M1 – M10). Any combination of these inputs can influence the $\mathbf{M_{in}}$, depending on various onsite hydrological and hydrodynamic factors. Obviously, without analysis, it is hard to determine what combination of inputs is most influencing on a particular site. Hence, as a part of our methodology, we proposed constructing different input vector combinations for each reservoir first using all variables (M1), and then masking the variables one by one (M2 – M10). The masked input is excluded from the input vector and does not play any role in $\mathbf{M_{in}}$ prediction. The M1 model is therefore the only model that includes nine inputs and all other models (M2 – M10) have eight inputs. The criteria for the selection of a model is to have the least value of all Gamma-test statistics, including gamma score (Γ), standard error (SE), and V_{ratio} (Malik et al., 2019). The SE reflects the reliability of the Γ, and V_{ratio} is the measure of the predictability of output from applied input. Smaller values for both SE and V_{ratio} are desirable. Table 1 reveals that for the Sangju Weir site, the combination SW M5 had the smallest score of Gamma-test statistics. The variation of Γ ranged from 0.0962 to 0.0976, the SE from 0.0021 to 0.0029, and V_{ratio} from 0.5422 to 0.5542. For the NREB site, the combination NREB M9 performed the best, with the smallest Gamma-test statistic. The Γ range was from 0.0742 to 0.0756, the SE from 0.0052 to 0.0061, and V_{ratio} from 0.3219 to 0.3589. The achieved combinations of input variables for both the sites are shown in Eqs. (4) and (5), and were applied as input vectors of the ANNs model for $\mathbf{M_{in}}$ prediction:

$$\text{SW M5: } \mathbf{M_{in}} = f(Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-2}, R_t, R_{t-1}, R_{t-2}), \tag{4}$$

$$\text{NREB M9: } \mathbf{M_{in}} = f(Q_t, Q_{t-1}, Q_{t-2}, H_t, H_{t-1}, H_{t-2}, R_t, R_{t-2}). \tag{5}$$

3.2 Reservoir Sediment Inflow Prediction by ANNs

An ANNs architecture with 10 hidden neurons reportedly exhibits the best performance in reservoir sedimentation problems (Samet et al., 2019). An ANNs model with a feed-forward network and a BP learning algorithm was used with the Levenberg-Marquardt (LM) training function. The long-term historical records of input variables (Q, H, R) and target variable ($\mathbf{M_{in}}$) for the Sangju Weir and NREB were collected. The whole dataset was split into two sets with homogeneous statistical properties (mean, standard deviation); 80% of the data was used for the training and 20% for the testing.

The input variable combinations SW M5 and NREB M9 were used to train the ANNs for the Sangju Weir and NREB,

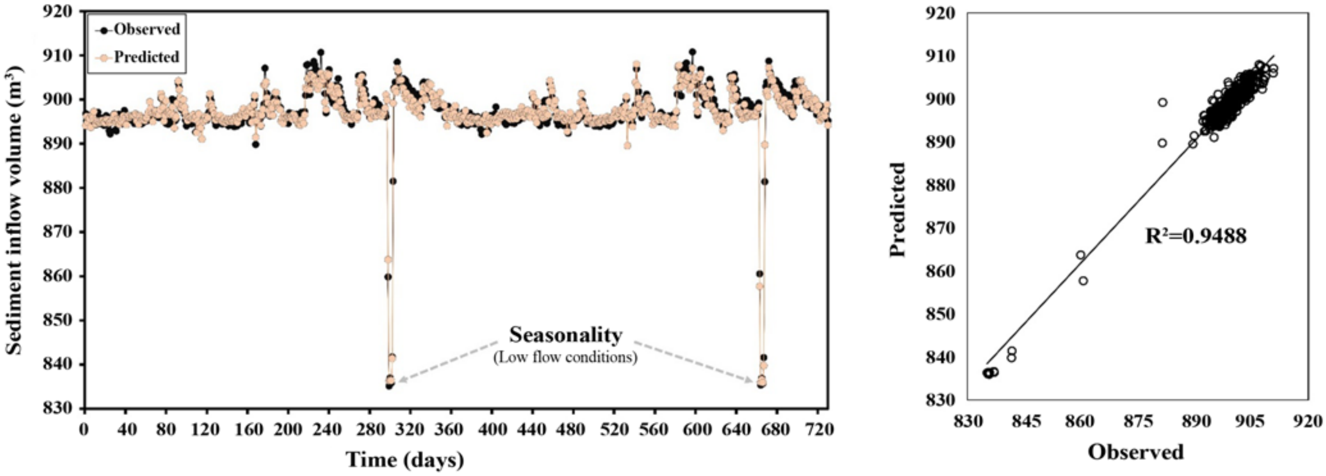

Fig. 5. Sediment Inflow Simulations at the Sangju Weir Reservoir during Testing Period of ANNs Model: (a) Observed and Simulated Sediment Inflows, (b) Scatterplot of Sediment Inflow Simulations

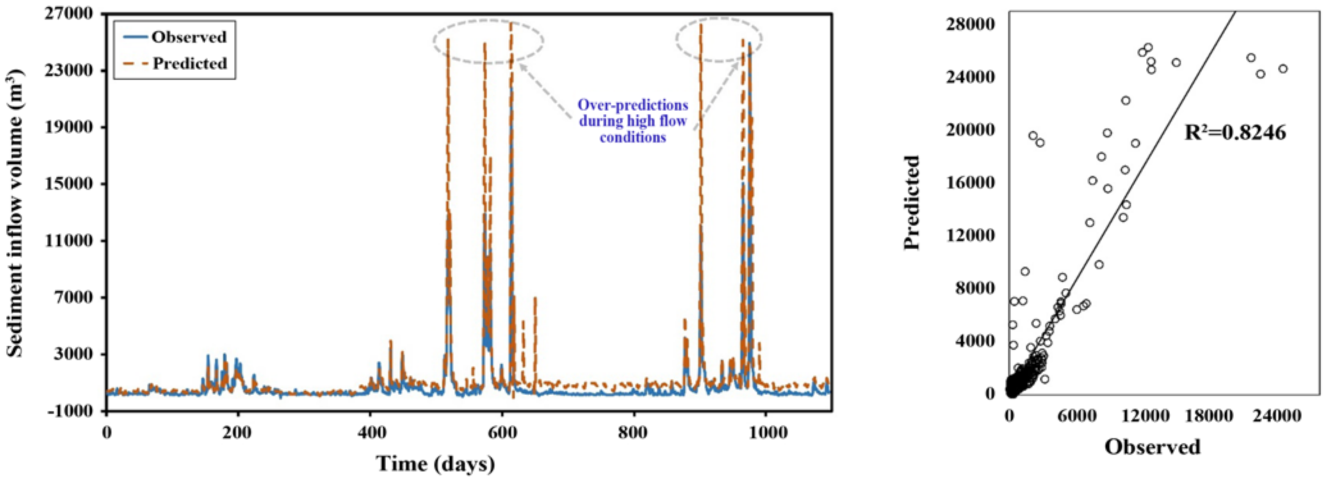

Fig. 6. Sediment Inflow Simulations at the NREB Approach Channel during the Testing Period of ANNs: (a) Observed and Simulated Sediment Inflows, (b) Scatterplot of Sediment Inflow Simulations

respectively, with $\mathbf{M}_{in}$ as the target variable. The trained models were used to simulate the $\mathbf{M}_{in}$ in the testing period; the results are shown in Figs. 5 and 6, respectively. The overall shapes of the observed and predicted $\mathbf{M}_{in}$ graphs are in close agreement, except for the extreme values, with the models tending to over-predict the $\mathbf{M}_{in}$ values for both the Sangju Weir and NREB. Quantitative assessment of modeling results was based on the performance indicators of mean squared error (MSE) and Willmott Index (WI), while simulated accuracies of the models were assessed by pooled average relative error (PARE). The values of these indicators obtained during training and testing periods for both sites are supplied in Table 2. The MSEs for the Sangju Weir and NREB sites were 0.948 and 0.826, respectively, during testing periods, reflecting a low level of discrepancies in $\mathbf{M}_{in}$ measurements at both sites. A low level of model prediction error was observed for simulations at both sites as WI values were closer to unity. The PARE values of 6.32 and 5.97 at the Sangju Weir and NREB quantified simulative accuracy.

Table 2. Results of Applying ANNs for Mean Annual Sediment Inflow Prediction and Performance Indicators

Performance Indicators		Sangju weir	NREB
Testing	MSE	0.948	0.826
	WI	0.987	0.894
Observed sediment inflow volume (m^3/year)		425,000	169,417
Predicted sediment inflow volume (m^3/year)		398,144	159,298
PARE (%)		6.32	5.97

3.3 Parameter Estimation of RESCON2 Model for Sediment Flushing

The RESCON2 model was set up by feeding in data for reservoir geometry, hydrological data, and sediment characteristics at both sites. All model input data are listed in Table 3. For the Sangju Weir, the operating rules required maintaining a near-constant water stage of 47 m throughout the year, although a water stage

Table 3. Input Data for the RESCON2 Model for the Sangju Weir and NREB

Serial No.	Symbol	Parameter description	Sangju weir	NREB
Reservoir geometry				
1.	W_{bot}	Representative reservoir bottom width at the dam location	355 m	250 m
2.	SS_{res}	Representative side slope of reservoir	1.5	1.0
3.	ELOWL	Maximum pool elevation of reservoir	47.8 m	3.0 m
4.	Elbmin	Minimum reservoir bed elevation at dam site	36.0 m	0.8 m
5.	EL_f	Water surface elevation during flushing	[47 m, 37.2 m]	[3m, 0.8m]
6.	ncomp	No. of reservoir compartments	5	13
7.	L	Reservoir/approach channel length	15,570 m	3,800 m
8.	h	Available head up to:	11 m	2.2 m
Hydrological data				
9.	MAR	Mean annual reservoir water inflow	2,996 MCM	1.38 MCM
10.	Cv	Coefficient of variation of annual run-off volume	0.21	0.21
11.	Twater	Representative water temperature in the reservoir	16	14
Sediment characteristics				
12.	rd	Specific weight of in-situ reservoir sediment (bulk density)	1.50 tonnes/m^3	1.20 tonnes/m^3
13.	$\mathbf{M_{in}}$	Mean annual total sediment inflow mass	39,8144 m^3	169,144 m^3

of 37.2 m had also been reported in a low-flow season. The average annual water inflow was 2,996 million cubic meters (MCM), which corresponded to a water inflow discharge of 95 m^3/s. The ranges in water-level elevation during flushing (El_f = 47 m to 37.2 m) and flushing discharge (Q_f = 95 m^3/s to 190 m^3/s) for flushing simulations were adopted. The flushing frequency (N), i.e., complete years between two flushing operations, should be 1.0 for successful flushing operation. Different combinations of Q_f and El_f were added to the RESCON2 model, and the model was run for each combination with a variable time of flushing (T_f). The volume of sediment flushed was calculated in each run and the volumetric sediment flushing curves were drawn as a function of time for the Sangju Weir, as shown in Fig. 7(a). The same procedure was adopted for the NREB site with sediment flushing parameters for Q_f of 10 m^3/s to 35 m^3/s and for El_f of 2.8 m to 0.8 m. The RESCON2 was set up and run with site-specific data for the NREB and time-dependent volumetric sediment flushing curves were obtained, as shown in Fig. 7(b).

The flushing curves were compared with $\mathbf{M_{in}}$ at both sites to approximate the required flushing time under different discharges. At the Sangju Weir, flushing the sediment volume equal to $\mathbf{M_{in}}$, would take approximately 28 days under low-flow conditions, and 5 to 15 days under high-flow conditions (Fig. 7(a)). For the NREB site, the low-flow conditions required a substantial amount of time (> 12 days) to flush a sediment volume equivalent to $\mathbf{M_{in}}$ (Fig. 7(b)). The volumetric sediment-flushing curves for both sites indicated that flushing could be practical if high-flow conditions prevailed, i.e., during flooding season. At the screening level, a Q_f of 100 m^3/s and a T_f of 6 days for the Sangju Weir site, and a Q_f of 25 m^3/s and T_f of 6 days for the NREB were selected.

The water stage during flushing (El_f) is critical for the success of flushing operations. The two indicators of flushing operation, SBR and LTCR, were calculated at the Sangju Weir by applying Q_f = 100 m^3/s, T_f = 6, and N = 1, and El_f was varied between 47 m and 37.2 m. Likewise, at the NREB site, the flushing feasibility indicators were calculated by applying Q_f = 25 m^3/s, T_f = 6 days, N = 1 and El_f = 2.8 m to 0.8 m. The results are displayed in Fig. 8

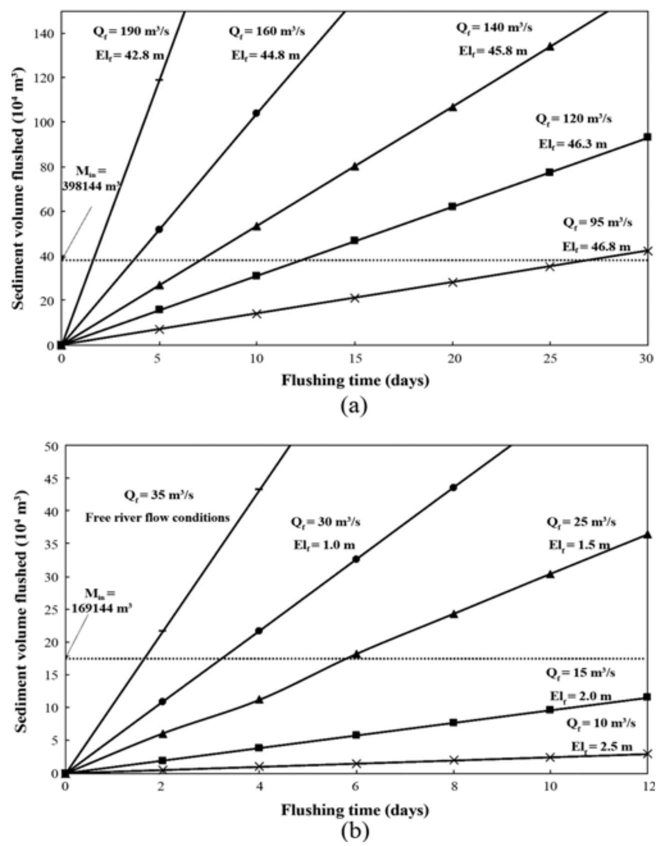

Fig. 7. Volumetric Sediment Flushing Curves for: (a) The Sangju Weir Reservoir, (b) The NREB Approach Channel

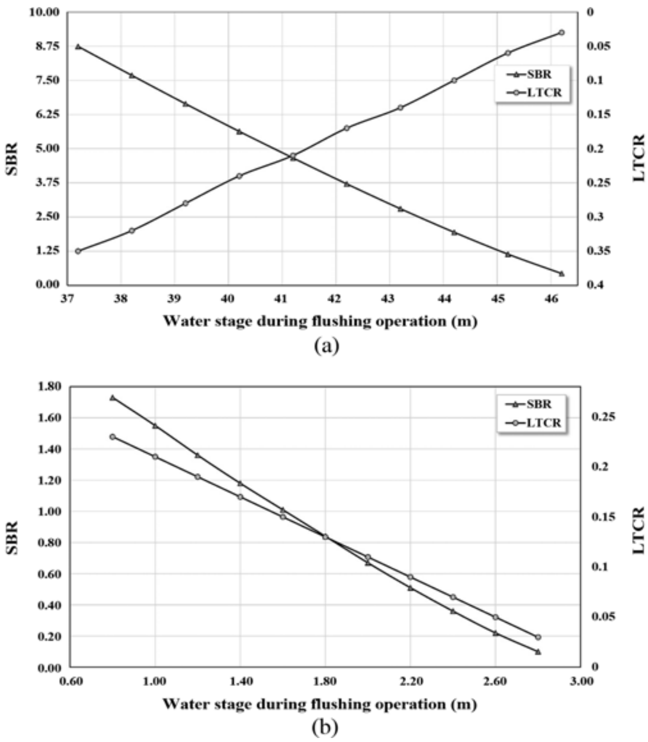

Fig. 8. The SBR and LTCR as Functions of El_f, Keeping Other Flushing Parameters Constant at: (a) The Sangju Weir, (b) The NREB Approach Channel

for both sites. For the Sangju Weir, when $El_f = 47$ m, the SBR = 0.41 and LTCR = 0.03, which implies that if flushing were to be performed on a regularly kept level, it would remove only 41% of incoming sediment, with 3% of original storage maintained in the long term. Similarly, at the approach channel of the NREB, low flushing efficiency (SBR = 0.05, LTCR = 0.03) was observed when a high stage of water was applied. The observed were consistent at both sites, and $El_f = 40$ m for the Sangju Weir and $El_f = 1.2$ m are recommended.

Sediment flushing is a complex operation and successful implementation is dependent on multiple onsite constraints. The RESCON2 model quantifies feasibility indicators such as the DDR, SBRd, FWR, and TWR, as explained in section 2.3. These indicators are functions of reservoir geometry, channel width formed during flushing, and water availability for flushing. Their values as computed by the RESCON2 for the Sangju Weir and

Table 4. Indicators of Constraints in Efficient Flushing Operation Calculated by the RESCON2 Model at the Sangju Weir and NREB

Indicator	Required value in RESCON2	Obtained value	
		Sangju weir	NREB
DDR	>0.7	0.71	0.80
SBRd	>1.0	8.74	1.78
FWR	>1.0	0.88	0.79
TWR	>1.0	1.02	1.11

Table 5. Recommended Values of Sediment Flushing Parameters

Parameter	Symbol	Suggested value	
		Sangju weir	NREB
Flushing discharge	Q_f	100 m^3/s	25 m^3/s
Duration of flushing after complete drawdown	T_f	6 days	6 days
Water stage during flushing operation	El_f	40 m	1.2 m
Number of complete years between flushing operation	N	1	1

NREB sites along with their required values are displayed in Table 4. The DDR, SBRd, and TWR criteria were comfortably met at both sites. The TWR criteria were marginal at both sites, which was due to the simplified reservoir geometry assumed by the RESCON2. The parameters of efficient flushing are therefore recommended for both Sangju Weir and NREB sites, and are supplied in Table 5.

4. Discussion

Sedimentation in a reservoir behind a weir threatens the flood-carrying capacity and depletes storage volume. Accurate prediction of sediment load carried by rivers into an artificial reservoir and its proper management is crucial for the sustainable use of a reservoir. Flushing sediment through a reservoir using the hydraulic force of flowing water is suitable but quite complex. A new and complementary approach was put forward in this study to predict mean annual sediment inflow and suggest parameters for efficient flushing. The case studies of Sangju Weir and NREB were discussed for the practical application of a complementary approach for sediment management. This study constitutes an effective contribution toward a comprehensive sediment risk management strategy for dam and reservoir operation.

Data-driven artificial intelligence models have proven their ability to mimic complex natural phenomena in suspended-sediment modeling. ANNs-based models have been applied effectively to suspended-sediment simulations and certain advantages over other data-driven techniques have been observed. The ANNs model was therefore adopted for reservoir sediment inflow prediction behind weirs in this study. Application of various data pre-processing analyses such as normalization, sensitivity analysis, and statistical analysis have been reported. In this study, an ANNs model with selected input vectors and data pre-processing predicted sediment inflow patterns with a high degree of accuracy at both study sites. Generally, close agreement was achieved between observed and predicted daily sediment inflow datasets based on well-established performance indicators.

The sediment inflow data sampling is a very capital-intensive task and hence has financial constraints which make long-term data collection impractical. Historically, the SRC technique has been applied to past streamflow records to construct long-term

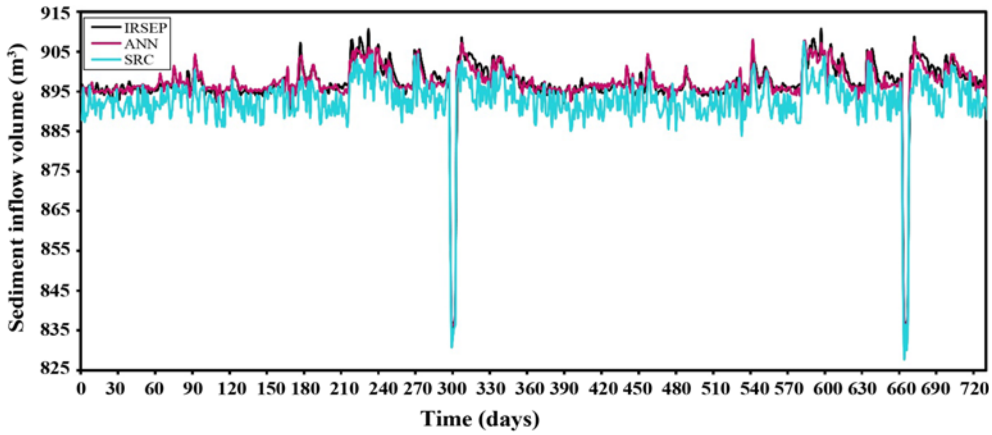

Fig. 9. The Comparison of Sediment Inflows Quantified by IRSEP, ANN-Based Model, and SRC Model at Sangju Weir

sediment load inflow time series. The SRC describes sediment load as a function of river water inflow only. The sediment inflow time series (2012 – 2020) at the Sangju Weir reservoir was developed by using the SRC method and also by following the IRSEP (Kim, 2016). The results of IRSEP (observed data), ANN model (predicted results), and SRC model (established sediment inflow prediction method) for the ANN testing period at Sangju Weir are displayed in Fig. 9. A close agreement is evident from Fig. 9 among IRSEP and ANN-based predicted values of sediment inflow volume. Hence, the ANN-based model showed superior performance than the SRC model, and this finding is well-aligned with recent findings of Emamgholizadeh and Demneh (2019).

At the Sangju Weir, the present operating rule curves required a water stage near 47 m to be maintained throughout the year for hydroelectric power production and to mitigate drought conditions. The sediment inflows at the weir site remained close to a range of 890 m^3/day to 910 m^3/day, as shown in Fig. 5(a). Two significant edges in the figure correspond to low streamflow during the winter season, when sediment inflows dropped to 830 m^3/day. Kim et al. (2017) performed a multi-objective analysis of the sedimentation behind the Sangju Weir and recommended drawing down the water level to 44.5 m before a flood season. The threshold values suggested by Kim and Julien (2018) to balance hydroelectric power production and dredging were a stage of 43.6 m and a discharge threshold of 600 m^3/s. This study suggested drawing down the water level to achieve an El_f of 40 m before a flood season and maintaining a Q_f of 100 m^3/s for at least six days. The gates should then be opened fully to pass the flood and the reservoir should be filled in the later part of the flood to maintain a water stage of 47 m. Examination of the volumetric flushing curves revealed that sediment deposition during the flood can be avoided by keeping the water stage as low as possible. These outcomes agree closely with the findings of Kim et al. (2017) and Kim and Julien (2018).

At the NREB approach channel, directly application of sediment management measures such as hydraulic flushing can be challenging because the downstream tidal effect makes maintaining the water level difficult. The mean annual sediment inflow mass considerably decreased following construction of eight consecutive weirs on the Nakdong River under the FRRP. After assessing the feasibility of sediment flushing at the NREB, Ji et al. (2011) reported that 54% of the annual dredged volume could be removed by hydraulic flushing. Park et al. (2013) recommended using natural flushing in combination with intentional sluicing for sediment management at the NREB. Ji et al. (2016) reported that sediment flushing in combination with channel contraction was effective at the NREB. This study found that hydraulic flushing was a feasible sediment management measure at the NREB to achieve the parameters stated in Table 5. The ANNs-based model successfully captured the lower or intermediate values of sediment inflow volume (Fig. 6). The higher sediment inflows in the 500 – 600 day and 900 – 1,000 day ranges were over-predicted because of the data-driven nature of the ANNs. ANNs performance decreased with higher values of sediment inflows, which were all predicted to be near 25,000 m^3/day. Precautions must be taken against the opening of barrage gates at high tide, as this can result in saltwater intrusion. Opening the gates at low tide to achieve a flushing discharge Q_f of 25 m^3/s with an El_f of 1.2 m for six days' results in efficient flushing operation.

After calculating the parameters of efficient sediment flushing, Huang et al. (2015) declared that sediment flushing is the most feasible solution. To identify an effective sediment management strategy, Garcia (2019) advocated the incorporation of accurate estimates of reservoir sediment inflow in the RESCON model. A parameter estimation method using the RESCON model for efficient sediment flushing was proposed by Idrees et al. (2019). A major limitation associated with these studies is that no mechanisms for predicting annual sediment inflows were provided. The present study aimed to overcome this limitation by applying a complementary modeling approach to mean annual sediment inflow prediction and calculation of parameters of efficient flushing. However, certain limitations must be taken into consideration which are associated with the ANN-based modelling approach. Being intrinsically data-driven, ANN-based modelling is programmed to fit target data as much as possible without any physical basis.

Moreover, the prediction models derived from ANNs analysis for both the sites would not apply to other rivers having different hydrological conditions.

Climate change is characterized by temperature variations that affect rainfall patterns and consequently streamflow (Q) from a watershed to a reservoir. This research utilized Q as part of the input vectors to build ANNs-based sediment inflow prediction models. An ANNs model can be applied to study variations in sediment inflow during extreme disasters due to climate change, but with some limitations. Sediment inflow prediction from the ANNs resulted in satisfactory results on annual scales, but the model tended to over-predict sediment inflow on a daily scale, particularly during high-flow conditions. Because measurement of sediment inflow volume is complicated, it is difficult to obtain sediment inflow data at finer temporal resolutions. Furthermore, sedimentation data are highly variable in space and time due to the intrinsic complexity of the processes involved. It is likely that training and testing datasets will follow different distributions, which may explain the over-prediction. As the sedimentation data are highly dependent on streamflow, it may be possible to improve the predictive ability by developing different models for rainy and dry seasons.

5. Conclusions

A complementary modeling approach was proposed to predict mean annual sediment inflow ($\mathbf{M_{in}}$) and estimate parameters of efficient flushing for sediment management at weirs and barrages. The proposed complementary approach involved the application of the ANNs for predicting $\mathbf{M_{in}}$ and estimating RESCON model parameters for sediment flushing. Daily inflow, water stage, and reservoir release were used as input variables, and significant input combinations for the ANNs were selected based on Gamma-test statistics. A complementary approach was implemented at the Sangju Weir reservoir and estuary barrage of the Nakdong River to demonstrate the approach. The ANNs efficiently mapped the nonlinear relationship of the chosen input variables, with annual sediment inflows at both sites. $\mathbf{M_{in}}$ of 398,144 m^3 and 159,298 m^3 were predicted for the reservoir of Sangju Weir and the approach channel of NREB, respectively. The RESCON2 model was run with observed sediment characteristics, reservoir geometry data, and water characteristics. For efficient flushing operation at the Sangju Weir, water discharge of 100 m^3/s was applied to gate operation, with a water surface elevation of 40 m to be maintained for six days. At the NREB approach channel, a discharge of 25 m^3/s had to be achieved for six days, with a water surface elevation of 1.2 m. For flushing to be effective, it must be applied every year, at the start of the flooding period, with maximum possible water drawdown. Application of annual hydraulic flushing with the achieved criteria at both sites can help avoid consolidation of sediment deposits and keep sediment delta in a favorable position. The presented two-stage complementary approach was found to be useful for comprehensive sediment management studies of water diversion structures. The proposed approach inherits limitations from the daily resolution of data and the RESCON2 model framework, which assumes simplified reservoir geometry and steady-state flow conditions. The scope of the present study can be extended by the application of quasi-steady or unsteady water and sediment flow simulation models.

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