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Prediction of erosional rates for cohesive sediments in annular flume experiments using artificial neural networks

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Abstract

Artificial neural network is used to predict development of suspended sediment concentration in annular flume experiments on cohesive sediment erosion. Natural sediment for the experiments was taken from the River Rhine and subjected to a consecutive increase in the bed shear stress. The development of the suspended particulate matter (SPM) was measured and then utilized for artificial neural network training, validation, and testing, including independent testing on new data sets. Several network configurations were examined, in particular, with and without autoregressive input. Additionally, relative importance of auxiliary physical-chemical parameters was analyzed. Artificial neural network with autoregressive input showed very high precision in the SPM prediction for all independent test cases achieving average mean squared error 0.034 and regression value 0.998. It was found that for an abundant training sample, the SPM parameter itself is enough to obtain high quality prediction. At the same time, physical-chemical parameters may provide some improvement to the artificial neural network prediction in cases that comprise values unprecedented in the training sample.

Key words: annular flume, artificial neural network, sediment erosion

INTRODUCTION

Estimating suspended sediment concentration is important for proper management of riverbanks, estuaries, and reservoirs, evaluation of land use, and measuring sediment-related nutrients and contaminants (Minella *et al.* 2008). Moreover, resuspension of the polluted sediments requires careful assessment to quantify availability of the potentially threatening substances not only in benthic environment, but also in surrounding water column and their subsequent transport (Knott *et al.* 2009). Despite high engineering and managerial demand in accurate models of sediment transport dynamics, analytical formulations for cohesive sediments are currently lacking (Black *et al.* 2002). As model-based forecasting methods require further enhancement, data-driven approaches, in particular, artificial neural networks (ANN), may be of interest. ANN are capable of modeling sediment transport with accuracy, as reported in the literature (Buyukyildiz & Kumcu 2017), and require relatively low computational effort.

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Jain (2001) introduced ANN as a tool for prediction of suspended sediment concentration in rivers based on time series data of river stage, discharge, and sediment concentration. The author showed that ANN outperforms conventional curve-fitting approaches and displays better correspondence with the observed data. Nagy *et al.* (2002) used ANN to predict natural sediment discharge in rivers. The authors maintain that the neural networks can be successfully applied for the sediment transport in cases where direct methods fail. Cigizoglu & Kisi (2006) examined how data preliminary processing influences ANN efficiency for prediction of suspended sediment in rivers. In subsequent work, Kisi (2008) studied an influence of data pre-processing and different training algorithms on the ANN performance for suspended sediment estimation. The results of the study demonstrate ANN trained with Levenberg–Marquardt and conjugate gradient training algorithms outperform ANN trained with gradient descent training algorithm in suspended sediment estimation. Alp & Cigizoglu (2007) used feed-forward back-propagation and radial basis function in ANN to simulate suspended sediment load of the Juniata River, Pennsylvania and compared the obtained results with a multi-linear regression approach. Rainfall and flow were used as input variables. Rai & Mathur (2008) utilized ANN to obtain rainfall–runoff-sediment yield from watersheds. Analysis of different ANN structures and the different combinations of input variables revealed that a best-fit ANN model produces the sedimentographs closer to the observed one in comparison to the linear transfer function model. Wang *et al.* (2009) applied ANN to estimate suspended sediments' concentration in a bay area in China. The results demonstrate significantly higher accuracy in neural network prediction than in that of regression analysis. Maanen *et al.* (2010) developed an artificial neural network to predict the depth-integrated alongshore suspended sediment transport rate using water depth, wave height and period, and alongshore velocity as input variables. The authors show that relative influence of the input variables can be additionally studied and conclude that wave height removal from the input data set improves ANN prediction abilities, whereas alongshore component of velocity has the largest explanatory power. Oehler *et al.* (2012) combined ANN with boosted regression trees to study near-bed suspended sediment concentration in nearshore zone using water depth, wave-orbital semi-excursion, wave period, and bed-sediment grain size as inputs. Across the range of variability present in the data set, the utilized algorithms dominate other commonly used predictors, for example, Nielsen's predictive formula (Nielsen 1986). Hassan *et al.* (2015) employed ANN to estimate weekly sediment load based on discharge and temperature data. Makarynskyy *et al.* (2015) estimated suspended sediment concentration in marine areas. Currents and waves modeled by deterministic numerical models were used as ANN inputs. The authors identified the appropriate number of inputs and their best combination to achieve satisfactory performance while reducing computational effort to train the network. Moridnejad *et al.* (2015) used ANN to assess suspended sediment concentration based on satellite remote sensing imagery. Buyukyildiz & Kumcu (2017) compared several machine-learning algorithms (support vector machine, three types of ANN, and two types of adaptive network based fuzzy inference systems) in their ability to model and predict suspended sediment load for a real-world case. All three types of ANN showed the highest performance ratings for specific input combinations. It should be mentioned, however, that the best performance in this study was achieved by the support vector machine with determination coefficient 0.868 (in comparison to ANN results ranging 0.859–0.866); although ANN was able to achieve high performance for several input combinations, which speaks in favor of the method.

The presented study uses a data-driven approach to predict suspended matter concentration from a series of experiments in an annular flume (Döring *et al.* 2015). In addition to bed shear stress regiment and contaminant presence in the solid and in the fluid phase, a set of physical-chemical parameters, such as water temperature, pH value, electrical conductivity, redox potential, and water hardness were measured in the experiments, and their relative importance for accurate ANN prediction was studied. The obtained results are evidence of a very high performance of nonlinear autoregressive neural network with external input in suspended particulate matter (SPM) values' prediction. In

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general, trained ANN is able to predict SPM based on the previous values of SPM only, or based on SPM values and essential external parameters such as bed shear stress and contaminant's presence. External parameters alone are not sufficient for good prediction; however, in cases that comprise values beyond those present in a training sample, they can be beneficial, presumably, since irregular values of certain parameters are reflected in other parameters.

METHODOLOGY

Annular flume experiments

Thirteen sediment erosion experiments were conducted in an annular flume facility at the Institute for Hydraulic and Water Resources at RWTH Aachen University (see Figure 1). The flume consists of a circular glass channel (width, 0.25 m; radius of the circle, 1.5 m) and a coaxial hanging plexiglas lid (Schweim 2005). Channel and lid rotate in opposite directions to produce an endless flow. Natural sediment from the River Rhine in Koblenz-Ehrenbreitstein at river-kilometer 591 was subjected to gradual resuspension triggered by step-wise increase in bed shear stress by 0.1 N/m^2 every 3 hours in the course of 18 hours. Turbidity (from which SPM is calculated), water temperature, pH, oxygen content, redox potential, and electrical conductivity were continuously measured in the annular flume every third of a second during the course of experiments using an external measurement unit (Döring *et al.* 2015). Additionally, at the beginning of each bed shear stress step, samples were taken by interactive half-automatic sampling unit and water hardness and SPM were measured.

Figure 1 | Annular flume experimental setup: (1) glass channel, (2) measurement unit.

Turbidity was measured using transmitting light technology. Based on the turbidity measurement, particulate matter was calculated. After calibration, deviation of less than 10%, on average, was reached for SPM. Measurement of the chemical-physical parameters was implemented in an external measurement unit, which is continuously flown through. In the measurement unit, the following sensors were installed during the experiments: pH (SenTix), oxygen content (FYA640O2, Ahlborn), electrical conductivity (FYA641LFP1, Ahlborn), and redox potential (FY96RXEK, Ahlborn). The O_2 probe features a temperature sensor for observation of water temperature. Logging of the parameters was operated with the Multiparameter logger Almemo 2690-8.

In seven cases out of 13, the natural sediments were additionally spiked with either cadmium chloride ($CdCl_2$), or permethrin ($C_{21}H_{20}Cl_2O_3$), or both substances. In four cases, artificial control over

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natural pH reduction was performed. The overview of the experimental conditions is given in Table 1, columns (a)–(e).

Table 1 | Annular flume experiments overview

Case (a)	Name (b)	Sediment type (c)	Contaminant (d)	pH reduction (e)	Use for ANN (f)
1	E1	Natural	Native	No	All except for 1 outlier
2	E1c (E1 replicate)	Natural	Native	No	First 7.41 hours
3	E1d (E1 replicate)	Natural	Native	No	All except for 1 outlier
4	E1e (E1 replicate)	Natural	Native	No	Not used
5	E2	Natural	Native	Yes	Not used
6	E2b (E2 replicate)	Natural	Native	Yes	Not used
7	E3	Natural	Permethrin	No	Not used
8	E3b (E3 replicate)	Natural	Permethrin	No	First 7.86 hours
9	E3c (E3 replicate)	Natural	Permethrin	N	All except for 10 outliers
10	E4	Natural	Permethrin	Yes	First 9 hours
11	E5	Natural	Cadmium chloride	No	All except for 1 outlier
12	E6	Natural	Cadmium chloride	Yes	Not used
13	E9	Natural	Cadmium chloride and permethrin	No	All except for 153 outliers

Data-driven approach

ANN proved their wide applicability and effectiveness in the estimation of complex nonlinear relations, including applications in hydrology (Govindaraju & Rao 2013). ANN is an information processing system that adapts its internal structure in correspondence with input–output training data sets and then can be used for output parameters' prediction. The best results are achieved for the test cases that lie in the range of the training data. Extensive coverage of ANN basic principles and applications is provided in the literature (e.g., Patterson 1998; Govindaraju & Rao 2013; Karayiannis & Venetsanopoulos 2013; Yadav *et al.* 2014).

To utilize annular flume experimental data, a preliminary analysis was performed to determine any inconsistencies or mistakes present in them. To assess the data, both the physical-chemical parameter measurements and the resulting continuous and sampled SPM were plotted and visually evaluated. Several measurements had to be removed from the data pool due to one or more issues, namely: (1) inconsistency between continuous measurements and sample measurements; (2) incorrect measurements in one or more physical-chemical parameters; and (3) unexpected values (outliers). Examples of incorrect measurements include negative pH, pH $= 20$, negative oxygen concentration, conductivity measurements unexpectedly dropping to zero. Figure 2 illustrates an example comparison between continuous and sample SPM for two cases. For case E1 (Figure 2(a)), general agreement between the continuous and sample measurements is evident. An outlier at 3.2×10^4 s is removed as inconsistent with the rest of the data (based on visual analysis). For case E1e (Figure 2(b)), continuous and sample measurements are inconsistent, especially after 4.3×10^4 s; in addition, pH measurements are negative, which results in the case being excluded from further analysis. A summary of the decision regarding each experiment is given in Table 1, column (f). More detailed information for each case is provided in the Supporting materials (SM, Table S1). Consequently, more than 12,000 data points were acquired, including resulting SPM concentration for combinations of bed shear stress, sediment contaminant, and pH value with an additional four physical-chemical parameters measured (water temperature, electrical conductivity, redox potential, and water hardness). Data range for each parameter is provided in Table 2. Artificial contaminant's presence or absence was

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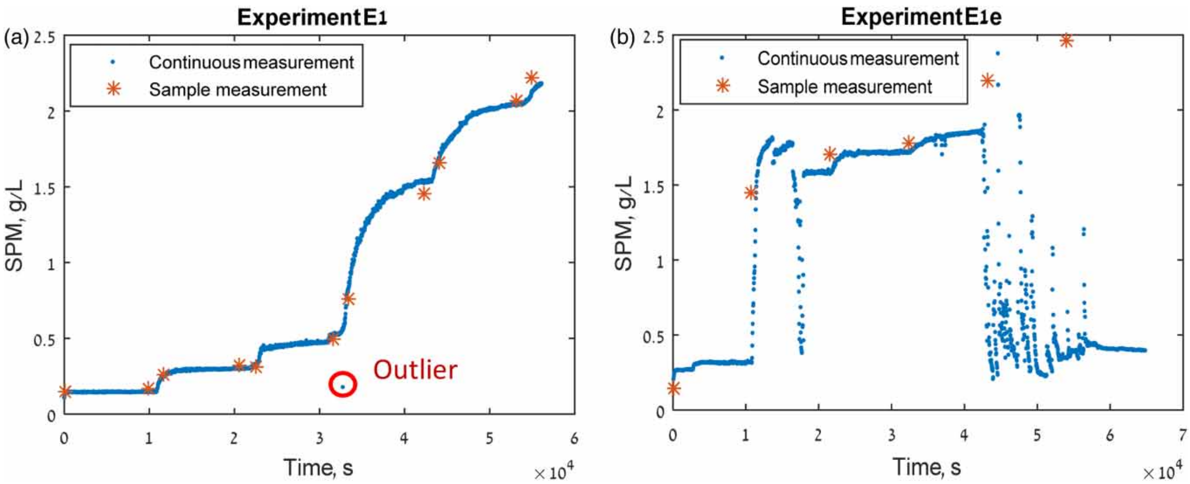

Figure 2 | SPM concentrations in course of the experiments for cases (a) E1, (b) E1e, continuous and sample measurements.

Table 2 | Input and output parameters' data range

Case	Name	Contaminant	Bed shear stress N/m^2	Temperature °C	pH	Conductivity S/m	Redox mV	Water hardness 10 mg CaO/l	Resulting SPM g/l
1	E1	0	0.1–0.6	22.3–23.2	7.17–7.27	0.3–0.3	−17.9–73.6	6.7–7.5	0.11–2.18
2	E1c	0	0.1–0.3	20.6–20.9	7.16–7.22	0.32–0.33	−185.2–25.8	6.67–7.99	0.22–0.78
3	E1d	0	0.1–0.6	18.4–19.1	7.11–7.2	0.36–0.39	−26.1– − 18.9	7.3–10.6	0.00–2.09
4	E3b	1	0.1–0.4	17.8–18.5	7.05–7.11	0.34–0.41	−30.3– − 21.4	8.00–8.99	0.09–1.99
5	E3c	1	0.1–0.6	18.6–19.3	7.00–7.85	0.38–0.43	−77.7– − 32.6	6.2–7.59	0.15–1.45
6	E4	1	0.1–0.4	21.8–22.5	5.16–7.65	0.35–0.41	−2.5–8.7	7.5–8.9	0.19–0.69
7	E5	2	0.1–0.6	20.8–21.6	7.14–7.23	0.33–0.35	−213.9–10.5	6.7–7.6	0.03–5.98
8	E9	3	0.1–0.6	20.7–22.0	7.17–7.3	0.32–0.37	−167.8–90.8	6.5–7.59	0.00–2.34

encoded as follows: 0 – no contaminant, 1 – cadmium chloride, 2 – permethrin, 3 – both substances together.

Dynamic time series prediction was performed by nonlinear autoregressive ANN with external input (NARX), meaning that to predict SPM concentration at time t, past d values of SPM concentration itself along with past d values of other parameters are used (see Figure 3). The number of hidden neurons and number of delays d were fine-tuned to achieve the best fit. Of eight cases, seven were used for ANN training, validation, and testing (internally randomized during the training procedure), and then the eighth case served as an independent test to check ANN performance on a

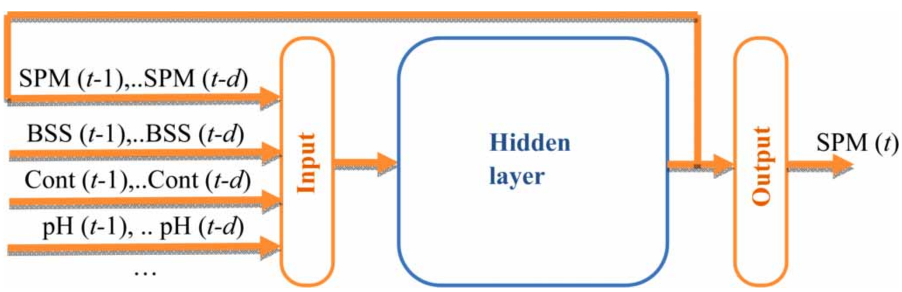

Figure 3 | NARX scheme (input parameters: SPM – suspended particulate matter, BSS – bed shear stress, Cont – contaminant).

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completely new set of data. Build-in NARX from Matlab Neural Network Toolbox (Matlab 2015) was used; the number of layers and neurons for each configuration were found by trial and error.

RESULTS

First, the ANN was trained, validated, and tested with all seven input parameters, delay of 2 and 10 hidden neurons. Example training results for all cases except for E1d are given in Figure 4. Mean squared error (MSE) and regression (R) values are evidence of a very high correspondence between the measured and predicted values. Major mismatching between the values is associated with discontinuity in the data (both initially present in measurements, for example, in case E1c, see SM, Figure S1(b) and acquired in the construction of the combined training sample). Then, the trained ANN was tested on a new data set, case E1d. Figure 5 displays ANN performance for different network configurations: ANN(2,5) with delay 2 and 5 hidden neurons and two equivalent networks ANN(2,10) and ANN2(2,10) with delay 2 and 10 hidden neurons that differ only in training. Each training generates a different neural network due to different initial conditions and sampling, but the predicted values follow the pattern of actual measurements with high precision and consistency for slightly different ANN configurations.

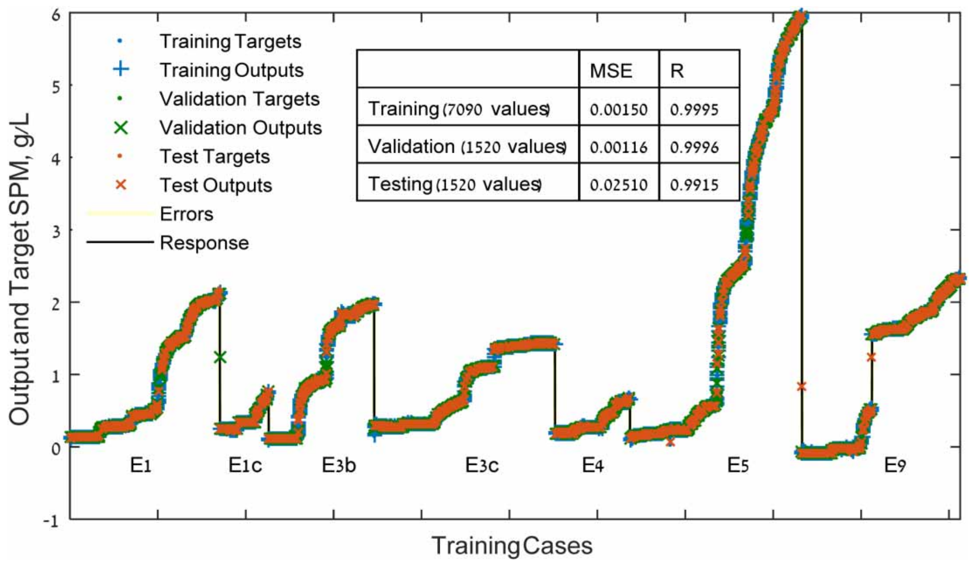

Figure 4 | Training results.

Some influence of the number of hidden neurons can be noticed. In general, more hidden neurons may lead to overfitting (Sheela & Deepa 2013), that is, during the training, very high precision is achieved due to capturing the smallest interrelation, whereas for the test, less precise results are expected due to overrating of the noise component of an input signal. Statistical test (two-sample t-test, each group contains results of ten ANN runs) reveals significant difference in MSE (p-value 0.028) and R (p-value 0.011) between the results obtained for 5 and 10 hidden neurons with better results corresponding to the lower value.

The same analysis was performed for each test case, i.e., ANN was trained, validated, and tested on the constructed sequences that consist of all cases except one, and then additionally tested on this one remaining case. The resulting MSE and R values are presented in Table 3. The slight decline in performance features cases that contain data outside the training data range or have discontinuous data. For example, cases E5 and E9 are the only cases that have contaminant values 2 and 3, respectively.

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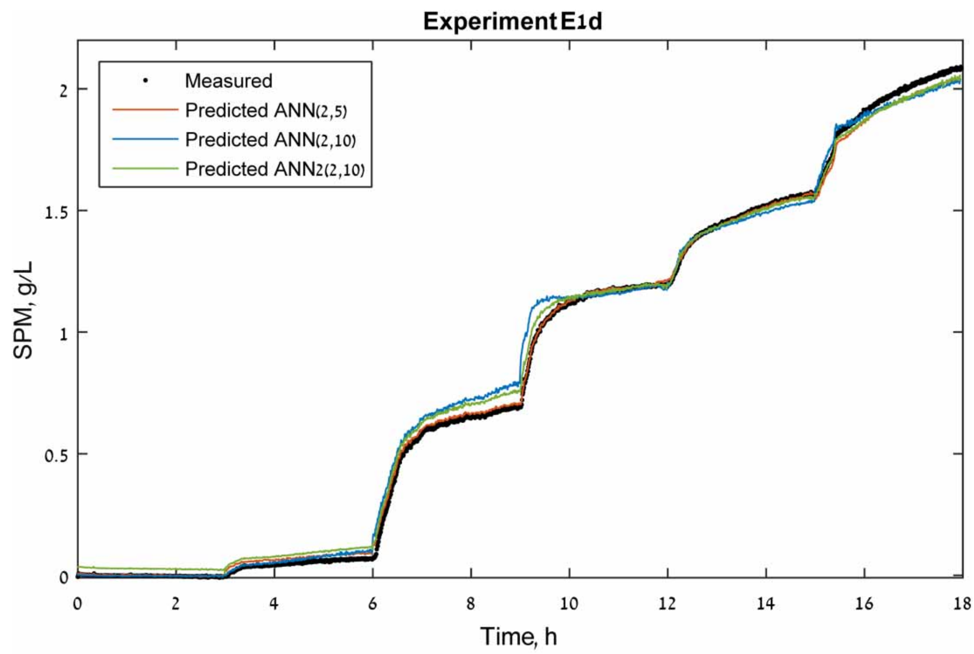

	MSE	R
ANN(2,5)	0.00044	0.9998
ANN(2,10)	0.00189	0.9985
ANN2(2,10)	0.00116	0.9997

Figure 5 | ANN configuration: test results for case E1d.

Table 3 | ANN performance on new data cases

	MSE	R
Test case E1	0.0036	0.999
Test case E1c	0.0001	0.998
Test case E1d	0.0004	0.999
Test case E3b	0.0008	0.999
Test case E3c	0.0001	0.999
Test case E4	0.0014	0.998
Test case E5	0.2584	0.995
Test case E9	0.0061	0.999

Hence, if one of these cases serves as a test case, no data in the training pool have the corresponding contaminant value. Yet, the largest discordance is observed for case E5 that is characterized by the highest final SPM concentration (see Table 2).

Sensitivity to input parameters

Number of parameters

To check how input parameters influence ANN performance, additional tests were performed. For cases E4 and E5 as independent test cases separately, training and testing were performed with various input parameters configurations, as described in Table 4.

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Table 4 | ANN performance for different combinations of input parameters

	Input parameters	Case E4 Average R in 10 trials	Case E5 Average R in 10 trials
Setup 1	All 7 input parameters	0.998	0.968
Setup 2	2 parameters: bed shear stress and contaminant	0.999	0.963
Setup 3	3 parameters: bed shear stress, contaminant, and pH	0.998	0.969
Setup 4	3 parameters: bed shear stress, contaminant, and conductivity	0.999	0.971
Setup 5	4 parameters: bed shear stress, contaminant, pH, and conductivity	0.999	0.980
Setup 6	5 parameters: bed shear stress, contaminant, pH, temperature, and conductivity	0.998	0.962

In addition to setup 1, which includes all available parameters as input, five configurations were constructed that include two to five parameters in different combinations. For independent test case E4, good fit was further improved by input reduction (p-value = 0.026, significant difference in regression parameter for setup 2 in comparison with setup 6). Contrasting that, for independent test case E5, initially, slightly poorer results were not advanced with input reduction. Moreover, only two input parameters produce slightly less good fit (p-value 0.049, significant difference in regression parameter for setup 2 in comparison with setup 6). The best performance from a sample of 10 for two- and seven-input configurations is given in Figure 6. This agrees with the assumption that lower results for case E5 as an independent test case are connected to the fact that final SPM in this case is unprecedented in the training data pool (and exceeds the highest value in the training data pool by 155%).

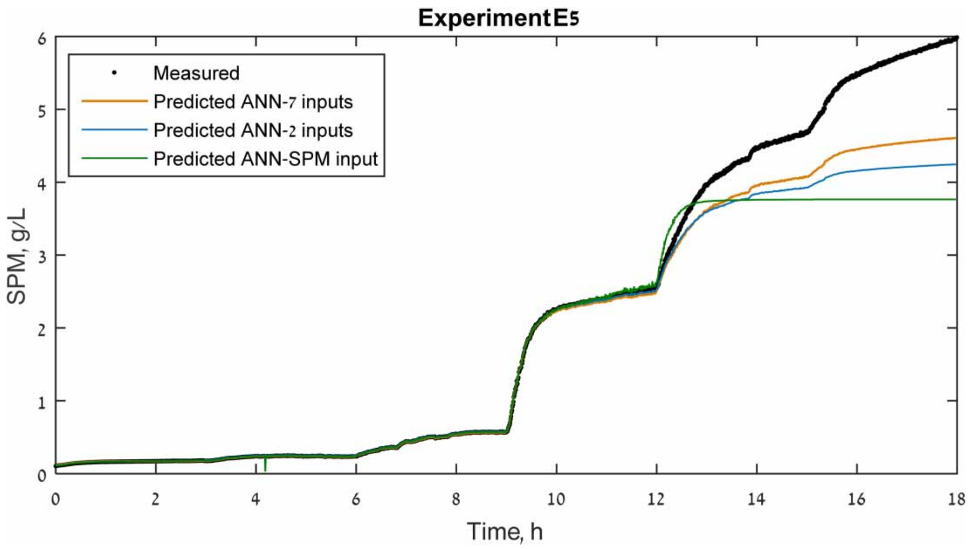

Figure 6 | Number of input parameters: ANN results for test case E5.

Thus, for the size of input vector, the following observations could be made:

(1) For cases whose input parameters range within training data limits, additional input parameters can be surplus or even interfere.

Additionally, an ANN trained on less input parameters has broader application, for example, it can be utilized in cases where some input data are corrupted. In fact, for the annular flume experiments' database, case E2 was removed from consideration in the above analysis due to defective pH data. Although, if an ANN utilizes two inputs only (bed shear stress and contaminant presence), it can

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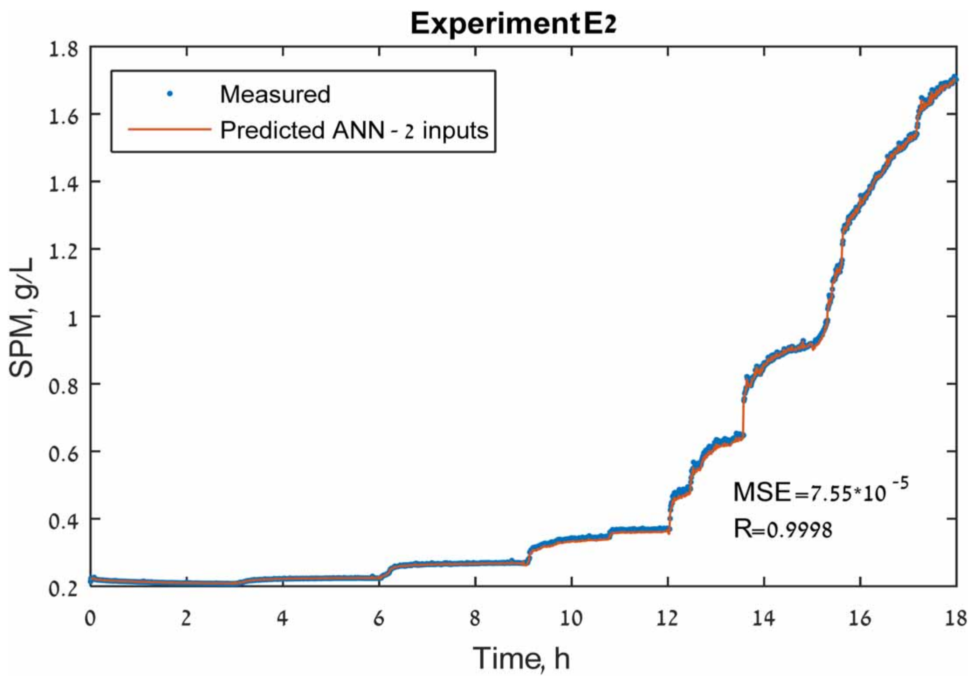

Figure 7 | Number of input parameters, sufficiency of two input parameters: ANN results for test case E2.

be used for the case E2. ANN trained with two inputs was tested on case E2 and showed very high performance (see Figure 7).

(2) For cases whose input parameters fall beyond the training data range, additional parameters can be helpful to obtain better results.

Indeed, contaminant addition (cases E5, E9) may influence erosion rate, but additionally it influences pH and electrical conductivity. Thus, combined input of a larger number of parameters may be more successful in obtaining better fit, since the additional parameters undertake explanatory function for the unprecedented values in other input parameters. This approach should be utilized with caution; rather, efforts to construct wider training sets should be made.

Importance of SPM as an input parameter

ANN was also tested in nonlinear input–output mode without autoregressive input (SPM at time t was predicted based on bed shear stress, contaminant, temperature, pH, electrical conductivity, water hardness, and redox potential at times $t-1, t-2, \ldots, t-d$).

In this configuration, ANN showed good results on the training sample, but for the independent test case, the prediction was insufficient: average performance parameters for ten runs are MSE = 1.53 and R = 0.53 for case E1d served as the independent test case. Example training and independent testing results are illustrated in Figure 8.

Finally, ANN was trained and tested on SPM data only, without external parameters, producing nonlinear autoregressive (NAR) model. In this implementation, very high prediction precision was achieved as well. For example, for test case E1d, average performance parameters in ten ANN runs are R = 0.999 and MSE = 0.00003. Interestingly, for test case E5, ten runs average R = 0.965 and MSE = 0.807. Illustration of one of the runs is given in Figure 6 (lower line). Thus, the NAR model corroborated with previously drawn conclusions that the unprecedentedly high SPM level for case E5 during late stages of the experiment are significantly less accurate based on previous values of SPM only, or based on

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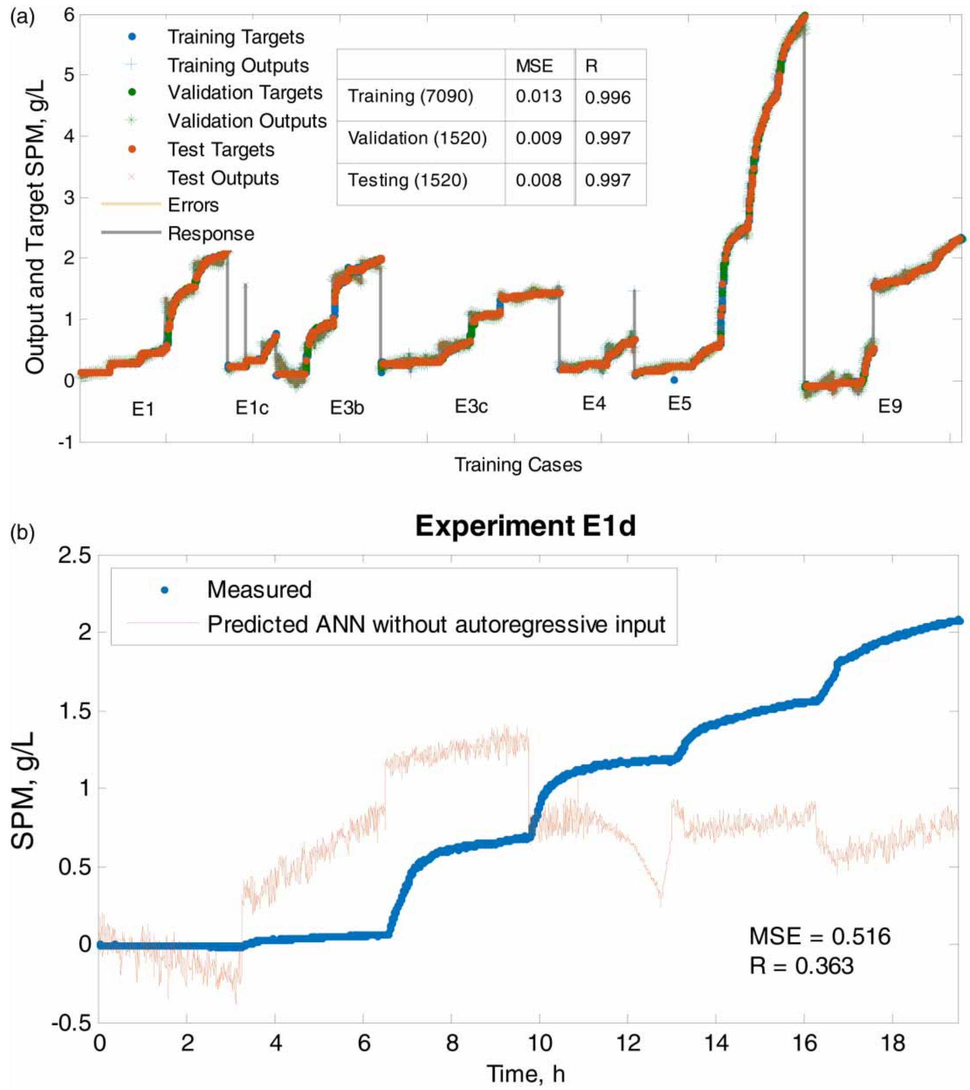

Figure 8 | Importance of SPM as an input: ANN without autoregressive input (a) training samples, (b) independent testing.

SPM, shear stress, and contaminant parameters. For any other cases that served as a test case, SPM data exclusively are sufficient to obtain very close correspondence between measurements and ANN predictions with R on the order of 0.999 and MSE on the order of 10^{-4}. Additionally, the ANN autoregressive model was compared to a simple autoregressive model (Matlab function *ar*) of order 1, meaning that SPM at time t was predicted based on SPM value at time $t-1$. For case E2, the simple autoregressive model fitted to measurements taken within the first 14.4 h of the experiment was used to predict the SPM values in the next 3.6 h. The resulting regression coefficient is $R = -0.93$, meaning the model fails to predict further trend in SPM. In fact, only high order autoregressive models give satisfactory results (autoregressive model of order 50 results in $R = 0.99$); however, further investigation of these models lies beyond the scope of this study.

To test the hypothesis that physical-chemical parameters can improve ANN predictions for outstanding cases, two input configurations were compared: only SPM as the input and SPM with physical-chemical parameters that were not deliberately controlled in the experiments (water temperature, pH, redox potential, electrical conductivity, and water hardness, but not bed shear stress and contaminant presence). For independent testing case E5, the first input configuration results in the average MSE in 20 runs equal to 0.760 and $R = 0.967$. The second input configuration results in the average $MSE = 0.694$ and $R = 0.982$ in 20 runs. While no significant difference in MSE was

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found, regression parameter in the latter case is stronger (two-sample t-test, p-value = 0.012). Thus, physical-chemical parameters may provide some improvement to the ANN prediction in cases that comprise values unprecedented in the training sample.

DISCUSSION

Different configurations of ANN were tested on several sets of input parameters to predict SPM concentration and compare it with SPM concentration measured in a series of annular flume experiments. Among the eight available experiments, seven served for initial ANN training, validation, and testing, whereas the remaining experiment provided an independent testing. For readers' convenience, a summary of the conducted analysis is given in Figure 9.

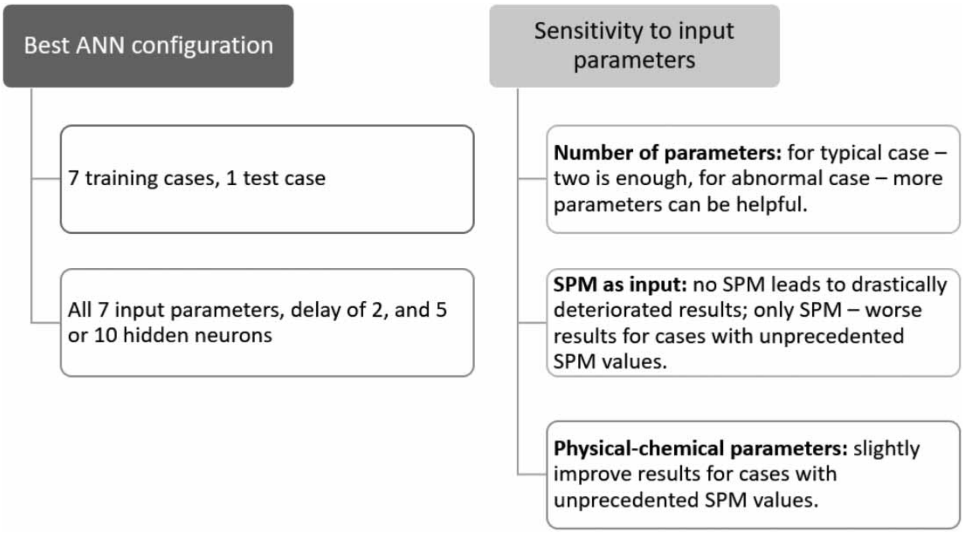

Figure 9 | Analysis summary.

This procedure proved to be very useful in demonstration of the core differences in performance of ANN of different configurations. In particular, while excellent results were achieved in initial training-validation-testing procedure for all configuration and all cases, ANN without autoregressive input, i.e., without SPM as an input parameter, failed to correctly predict SPM concentration in independent testing.

With autoregressive input, ANN was capable of successfully predicting SPM in independent testing with average R = 0.998 and average MSE = 0.034. Best results were obtained for cases that fall within the training data range. These results are substantially higher than previously reported in the literature. The network showed particular sensitivity to the uncommon values of SPM (case E5). In this case, additional physical-chemical parameters can contribute to better model performance. In other cases, SPM alone is sufficient for accurate prediction.

High precision of the modeled levels of SPM in comparison with the measurements is governed by the nature of the training sample. More specifically, all experiments were conducted in controlled conditions with bed shear stress steadily rising in equal steps within equal time intervals and resulting in a similar pattern of sediment resuspension and corresponding SPM concentrations. To obtain meaningful results for resuspension of cohesive sediments in natural streams, special focus should be put on collecting relevant data for ANN training. This study shows comparative irrelevance of physical-chemical parameters such as water temperature, electrical conductivity, redox potential, and water hardness for good ANN prediction. For new cases that fall within training sample data

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range, SPM itself was sufficient for obtaining very good prediction ($R = 0.99$, $MSE \sim 10^{-5}$). On the other hand, in an unprecedented case, they may be of certain value (stronger regression parameter R, statistically significant with *p*-value 0.012). Consequently, for a real-world case, it is recommended to include physical-chemical parameters as ANN inputs.

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