Analyses of Acoustic Backscatter Signal with Artificial Neural Network for Continuous Monitoring of Suspended Sediment

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Abstract

Traditional sampling methods are restrictive for spatial and temporal monitoring of suspended sediment in river. Application of these methods is simple but it is required labor intensive to collect sample and the other process. Recently, with the technological advances in computer and electronic science, the use of new technological methods has recently gained importance. These methods are commonly based on the spreading of sound or light in water. Acoustic methods involve propagating sound at around the Megahertz frequency range through the water column. Sediment in suspension will divert a portion of this sound back to the transducer. Since the acoustic backscatter system is an indirect method, an inversion algorithm is required for determining of sediment concentration with using measured backscattered signal strength. Because of the complexity of the phenomena, a soft computing method artificial neural network (ANN) which is the powerful tool for input output mapping can be used for estimating sediment concentration. This experiment was carried out under laboratory conditions and all measurements were conducted in the vertical sediment tower which was built to obtain a homogeneous suspension of sediments. About 60 different sediment concentrations (between 0.1 and 6.0 g/l) were prepared with natural sediment material which was sieved and prepared two groups as smaller than 50 micron and 50-100 micron radiuses. ABS measurements were taken during 90 minutes for all treatments. In addition the obtained data set was distinguished as 70% for testing and 30% for training purposes to establish ANN model. On the basis of the comparisons, the results show that ANN model was found to be reasonable alternative and, ANN model could be employed successfully in estimating sediment concentration from backscatter signal. This study showed that acoustic method can be improved with new algorithms of further ANN model studies.

Keywords: Artificial neural network, Acoustic backscatter systems, Suspended sediment,

I. INTRODUCTION

The suspended sediment yield is the crucial parameter for hydrological studies and has spatial and temporal variability depending on many factors such as the hydraulic characteristic of the stream, properties of the catchments, and the climatic regime of the area and the presence of vegetation. Correct measurement of sediment load is crucial for designing and management of water resources projects to get the economical life of the facilities. The sediment load carried by river may lead to reduction in useful storage of a dam and blockage in water inlet. Transportation of sediment load not only causes decrease in economical life of facilities but also harm agricultural areas. Measurement of sediment concentration in a river for long term requires taking periodic water samples and it is necessary for specific studies to monitor sediment concentration such as along the entire storm hydrograph to predict loads [1, 2].

Application of traditional method is simple but intensive labor is required to collect and process. Besides, this method is restrictive in its capability to represent spatial and temporal profiles of suspended sediment concentration. For this reason, the use of acoustics to measure sediment has gained increasing acceptance within the sedimentological community over the past two decades [3, 4, 5, 6, 7]. The application of acoustics to the measurement of suspended sediments has been validated by many laboratory, field and theoretical studies.

The acoustic method involves the spreading of sound (0.5 MHz -5.0 MHz) through the water column. Short bursts of high frequency sound are transmitted by a transducer are directed towards the measurement volume. Sediment in suspension will divert a portion of this sound back to the transducer. The strength of the backscattered signal is used to calculation of sediment concentration. The arrangement is illustrated in figure 1. The backscatter amplitude depends on the concentration, particle size, and acoustic frequency. This can be exploited by using multiple frequencies to determine both particle size and concentration. The strong signal from the bed can be used to measure the bed forms. Acoustic devices measure the concentration in a range-gated vertical profile of 1-2 m in depth [8, 9, 10].

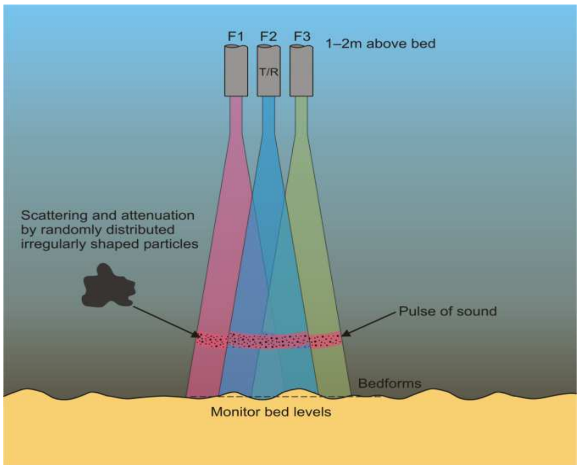

Figure 1. The acoustic beam an ABS transceiver and the scattering from particles.

This method has been conducted successfully under laboratory and field conditions by several investigators. Results showed that sediment concentration and particle size can be measured relatively non-intrusive, with high spatial and temporal resolution with acoustic backscatter systems [7, 11]. Since the acoustic backscatter system is an indirect method of measurement, an inversion algorithm is required for determining of sediment concentration with measured backscattered signal strength. The acoustic backscatter equations provide the basis for the development of such an algorithm [12, 13].

The acoustic properties of different natural sediments vary and depend on many parameters such as size, shape, mineralogy and distribution of those parameters in the sample. By using the approximated acoustic parameters, such as form function and cross-section, obtained for a particular type of scatters like glass spheres or quartz sand, the inversion algorithm can lead to erroneous results if the actual sediment differs from the approximation in mineralogy and shape. Although backscattering signal has been applied to the study of sediment transport processes for a number of years, there are still problems in using the backscattered signal to measure suspended sediment parameters. To address this problem different alternative approaches to the iterative implicit formulation are investigated using new inversion [14].

Because of the complexity of the acoustic algorithm, a soft computing method artificial neural network (ANN) which is the powerful tool for input output mapping can be used for estimating sediment concentration. The developing of ANN technology has provided may favorable results in the many hydrological studies and has been widely applied for complex nonlinear models. Reference [15] investigated the abilities of neural network approaches to model the stremflow-suspended sediment relations. Reference [16] used water discharge and turbidity as input parameters for ANN model to estimate sediment concentration. Reference [17] used ANN model which was developed to predict the depth-integrated alongshore suspended sediment transport rate using 4 input variables; water depth, wave high and period and alongshore velocity, and reported that use of an ANN approach can result in the development of generalized models of suspended sediment transport. Similarly ANN has been used for a wide range of different learning-from-data applications and input–output correlations of non-linear processes for sediment prediction [18, 19, 20, 21, and 22].

In this study, new powerful sediment measurement method, acoustic backscattering system (ABS), was used at laboratory condition and it was aimed to enrichment it with ANN models by removing complexity of the acoustic algorithm. In addition turbidity values were considered as alternative input value for ANN.

II. Materials and Methods

This experiment was carried out at laboratory conditions and measurements were conducted in a sediment tower, which consisted of a 0.90 m vertical tube with a diameter of 0.45 m and with mixing and re-circulating units. The main objective of the tower's design was to obtain a homogenous suspension of sediments through the depth. Homogeneity was maintained with continuous mixing during the measurement process. The suspended sediment solutions were prepared with natural sediment material to get similar river conditions. Two sediment size groups (<50 micron and 50-100 micron) were produced by sieving and about 60 different sediment concentrations (between 0.1 and 6.0 g/l) were conducted in sediment tower.

The four frequency acoustic backscatter system (AQUAscat-L) developed by the Aquatec Group, was operated in transceiver mode at 0.5, 1.0, 2.0 and 3.9 MHz [23]. The transducers were mounted near the top of the tower and their beams were directed vertically downwards. The system measured the backscattered signal at 0.01 m intervals and once per second during a three minute period for each treatment.

The turbidity measurements were made simultaneously with a Seapoint Turbidity Meter, which measures the scattered light (880nm) at 15–1500 to the axis of the light beam from a small volume within 5 cm2 of the sensor window. This sensor is factory adjusted for consistent responses to the Formazin Turbidity Standard measured in Formazin Turbidity Units (FTU) and has linear output for 0-750 FTU with 2% deviation

A. Acoustic algorithm

The portion of sound beam sent to water is reflected by sediment towards transducer depending upon concentration, particle size, and sound frequency. The strength of the backscattered signal can be converted of sediment concentration, *M*, [7, 24, 11].

$$M = \left\{\frac{V_{rms}\psi\ r}{k_s k_t}\right\}^2 e^{4r(\alpha_w+\alpha_s)}$$

$$k_s = \frac{f}{\sqrt{a_s\rho_s}} \qquad \alpha_s = \frac{3\chi M}{4a_s\rho_s} \tag{1}$$

where, V_{rms} is the recorded voltage from the transducer, ψ accounts for the departure from spherical spreading within the transducer nearfield, r is the range from the transceiver, k_t is calibration constant, and k_s is a function of the scattering properties of the sediment. α_w is the water absorption and relatively straightforward and its dependence upon water temperature and salinity. α_s is the particle attenuation, a_s is the particle radius of the sediment, and ρ_s is the sediment grain density. The normalized total scattering cross section, χ, and the form function, *f*, can be determined for sandy sediment. Reference [13] evaluated four decades of published data on the acoustic scattering properties of suspensions of sandy sediments. These data were reformulated in terms of the usual acoustic scattering nomenclature that is the normalised total scattering cross-section and the form function, based on a sphere scattering model.

$$\chi = \frac{0.29x^4}{0.95+1.28x^2+0.25x^4} \tag{2}$$

$$f = \frac{x^2\left(1-0.35\,e^{-((x-1.5)/0.7)^2}\right)\left(1+0.5\,e^{-((x-1.8)/2.2)^2}\right)}{1+0.9x^2} \tag{3}$$

where, $x=k.a_s$; k is the wave number of the sound and equal to $2\pi f_r /c$, c is speed of sound in water and f_r is transducer frequency.

The linear regression was carried out to determine relationship between measured sediment and computed sediment acoustic method. These relationships were evaluated by using determination coefficient (R^2) and root mean squared error (RMSE).

B. Application of artificial neural networks (ANN)

ANN was performed for modeling sediment concentration with ABS and Turbidity values, based on the procedures given by [25]. Fort his aim, Neural Network Toolbox for MATLAB (R2010b, licensed to Bilal CEMEK) software was used. The input parameters were ABS and Turbidity values and output parameter was sediment concentration (Fig. 2). Different network topologies and (with single or double hidden layer) number of neurons were used. In addition, single input parameter was performed to obtain easy alternative for sediment measurement. Each neural network model for all input alternatives was trained starting from 100 up to 500 with increments of 100. The all measured data set was distinguished as 70% for training and 30% for testing purposes to establish ANN model. Finally ANN models were evaluated by using R^2 and root mean squared error (RMSE).

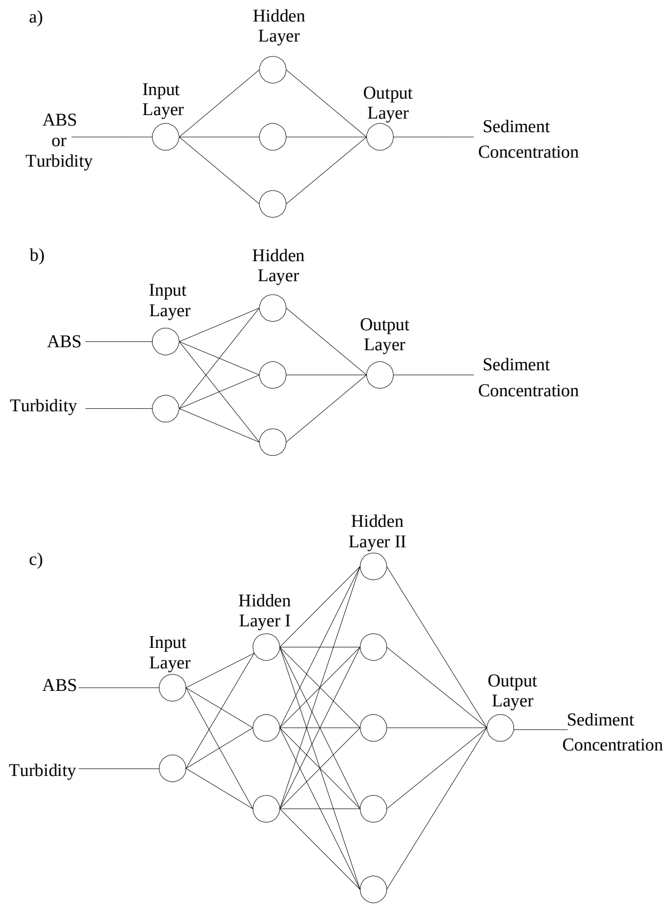

Figure 2. Structures of artificial neural network models used in sediment concentration estimation.

III. Result and Discussion

ABS algorithm results

The average acoustic backscattering signal and turbidity values for each known sediment concentration were given Fig. 3. Measurements were conducted for 4 different frequencies but 2 MHz frequency was considered at this study due to the best response sediment of concentration levels. The linear regression analyses result between measured sediment and computed sediment with ABS were presented Fig. 4 with R^2 and RMSE values. Although reasonable R^2 value (0.938 and 0. 947) was obtained for 50-100 micron sediment group (b and c), a significant R^2 (0.383) was not produced for <50 micron sediment group (a)

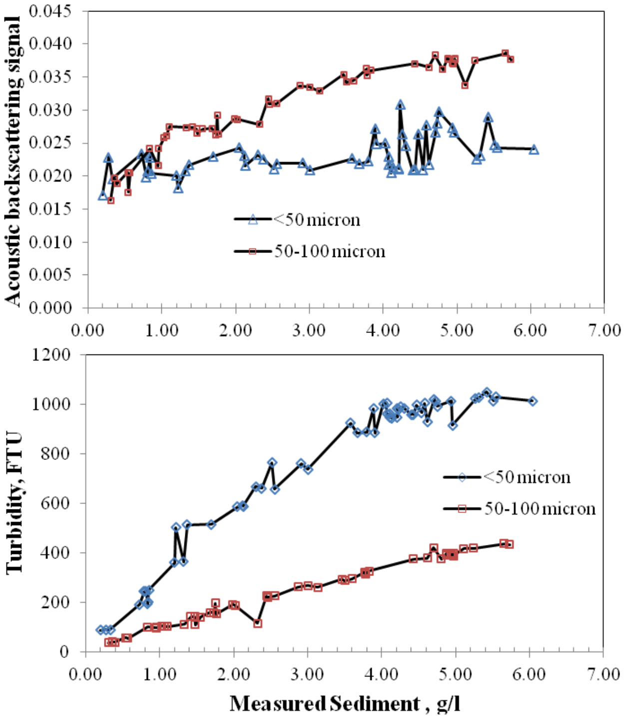

Figure 3. The average acoustic backscattering signal and turbidity values

Clay existence in the sediment solution has negatively effect on ABS. Similar results were reported by several researchers. This problem is essentially related the shape of sediment material [26] and some coagulation based on clay material which were occurred suspicious backscattering signal [27]. This situation is occurred some restriction to use acoustic method for clay content conditions.

A calibration constant, k_t, was used for single point calibration which was obtained for a known sediment concentration (0.500 g/l) before taking measurements (Fig 4 (b)). Although reasonable R^2 value (0.938) was obtained for this alternative but RMSE value (2.890) was higher than expected. Therefore multipoint (low, mid and high) calibration equation was used to get better results (Fig. 4 (b)).

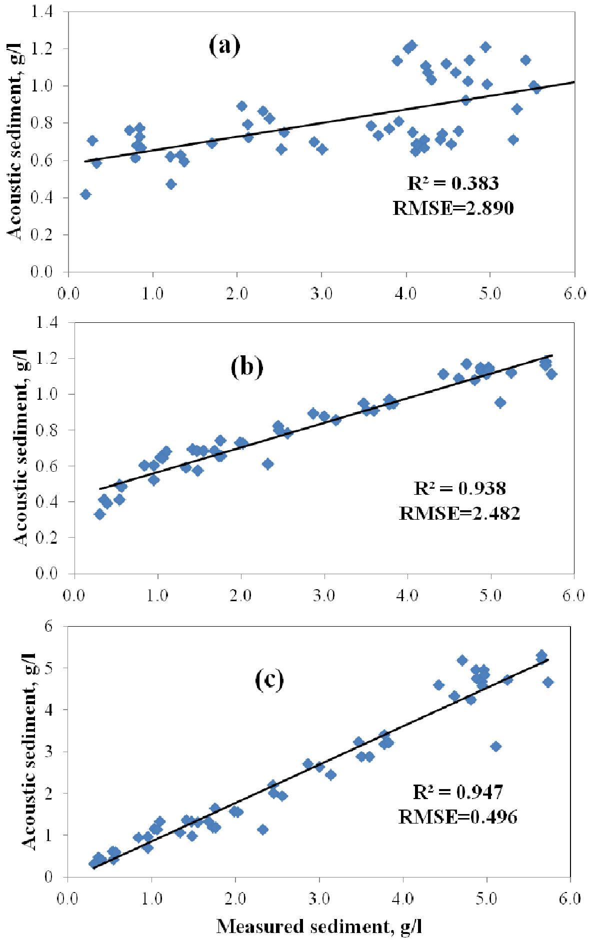

Figure 4. Regression analyses between measured sediment and acoustic sediment. <50 micron sediment group (a), 50-100 micron sediment group (b and c), b: single point calibration, c: multipoint calibration

ANN results

Statistical parameters of ANN models (R^2 and RMSE) were considered to determine the best model (TABLE I and II). Firstly ABS values for <50 micron group were not produced reasonable sediment concentration with any ANN model ($R^2 <$ 0.40), and it wasn't considered for discussion. This weak relationship between ABS and sediment, which can be explained with clay content in sediment, was not improved with ANN. Therefore turbidity values was considered single input to estimate sediment concentration and the highest R^2 (0.969) and the lowest RMSE (0.397) values were obtained using the ANN1for testing. The using of ABS input with turbidity was not improved the relation statistical parameters.

TABLE I. COMPARISON BETWEEN MEASURED AND ESTIMATED SEDIMENT CONCENTRATION BY ANN MODELS (FOR < 50 MICRON)

Inputs	ANN models	Structure	Training data set			Testing data set		
			Epoch	R^2	RMSE	Epoch	R^2	RMSE
Turbidity	ANN1	1-3-1	100	0.980	0.225	100	0.949	0.403
			200	0.983	0.209	200	**0.969**	**0.397**
			300	0.967	0.292	300	0.934	0.441
			400	0.977	0.242	400	0.948	0.413
			500	0.967	0.292	500	0.936	0.441
	ANN2	1-3-5-1	100	0.964	0.306	100	0.934	0.444
			200	0.993	0.131	200	0.924	0.527
			300	0.987	0.183	300	0.928	0.479
			400	0.991	0.155	400	0.935	0.439
			500	0.984	0.206	500	0.929	0.452
Turbidity ABS	ANN1	2-3-1	100	0.935	0.413	100	0.934	0.476
			200	0.967	0.293	200	0.834	0.723
			300	0.971	0.272	300	**0.942**	**0.417**
			400	0.961	0.318	400	0.940	0.425
			500	0.969	0.287	500	0.940	0.432
	ANN2	1-3-5-1	100	0.979	0.233	100	0.930	0.486
			200	0.992	0.139	200	0.928	0.467
			300	**0.998**	**0.067**	300	0.935	0.438
			400	0.996	0.105	400	0.935	0.438
			500	0.993	0.115	500	0.935	0.436

TABLE II. COMPARISON BETWEEN MEASURED AND ESTIMATED SEDIMENT CONCENTRATION BY ANN MODELS (FOR 50-100 MICRON)

Inputs	ANN models	Structure	Training data set			Testing data set		
			Epoch	R^2	RMSE	Epoch	R^2	RMSE
ABS	ANN1	1-3-1	100	0.925	0.504	100	0.900	0.548
			200	0.928	0.495	200	0.900	0.548
			300	**0.934**	**0.478**	300	**0.917**	**0.521**
			400	0.926	0.488	400	0.915	0.524
			500	0.914	0.526	500	0.903	0.546
	ANN2	1-3-5-1	100	0.905	0.533	100	0.894	0.583
			200	0.898	0.579	200	0.883	0.617
			300	0.912	0.505	300	0.896	0.585
			400	0.911	0.503	400	0.891	0.593
			500	0.917	0.499	500	0.895	0.574
Turbidity ABS,	ANN1	2-3-1	100	0.994	0.135	100	0.973	0.309
			200	0.992	0.153	200	0.969	0.323
			300	0.992	0.152	300	0.972	0.305
			400	0.993	0.142	400	**0.973**	**0.297**
			500	0.960	0.360	500	0.969	0.322
	ANN2	1-3-5-1	100	0.995	0.123	100	0.971	0.290
			200	0.997	0.098	200	0.969	0.323
			300	0.999	0.052	300	0.956	0.376
			400	0.999	0.056	400	0.936	0.439
			500	0.997	0.088	500	0.958	0.394

For the second sediment group (50-100 micron), ABS values were used as single input for ANN model and the highest R^2 (0.917) and the lowest RMSE (0.521) values were obtained using the ANN1 model for testing. Although acoustic algorithm has better results than ANN model for similar input condition, but it should be considered that; many parameters (such as; sediment, water and acoustic devices parameters, as in (1 and 3)) were used for acoustic algorithm apart from ABS values. This situation is occurred some complexity and is required expertise of user. This is main disadvantages for acoustic method [28]. But ANN model seems uncomplicated and reasonable with using just ABS values.

Turbidity values has a good relationship with sediment concentrations at both of sediment groups but the using of ABS input with turbidity was not improved the relation statistical parameters the highest. Therefore turbidity values can be used a single input parameter for estimate sediment concentration and can be considered as an alternative method for acoustic measurements.

IV. CONCLUSION

The acoustic method, especially with glass scattering equation, works well for calculating soil sediment in laboratory and river conditions. It is known that scattering properties become more complex especially with different particle sizes high sediment concentrations [27, 29]. This study results showed that the method has potential for continuous and reliable sediment measurements as long as appropriate multipoint calibration approaches are used. First of all, more promising results of this study is that acoustic method can be facilitate with ANN model which is the powerful tool for input output mapping. A single input parameter, ABS, was used for ANN model at this study and reasonable results were obtained to estimate sediment concentration. In sight of this study results, further ANN studies can be conducted with alternative inputs such as; particle size, shape or density and water properties, as a result more accurate models can be derived.

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