



Suspended sediment concentration forecasting at downstream water intake during reservoir desilting operation

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Abstract

Three to four typhoons affect the hydrological condition of Taiwan river watershed annually. Each typhoon carry out huge rainfall quantity and intensity to induce soil erosion activity on hillsides and affect the turbidity of raw water in reservoirs. Based on reservoir desilting operation for sustainable water resources, abundant sediment would be released to downstream river, especially on suspended fine sediment. The suspended sediment concentration forecasting is crucial at the water intake downstream of the dam for water resource management. In this study, an effective suspended sediment concentration forecasting is investigated for public water management. The study adopts an artificial intelligence, namely multilayer perceptron (MLP), to yield suspended sediment concentration forecasts for 1- to 3-h lead time. Then, the corrected forecasts of suspended sediment concentration can be obtained by an autoregressive (AR) model. The results reveal that after correcting, the accuracy of suspended sediment concentration forecasting is improved.

Keywords: suspended sediment concentration, drinking quality of water, multilayer perceptron, autoregressive model, forecasting

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1. Introduction

The study adopts multilayer perceptron (MLP) to yield suspended sediment concentration forecasting for 1- to 3-h lead time, and then uses an autoregressive (AR) model to correct suspended sediment concentration forecasting. The study area is at YuanShan weir which is important to supply water for two millions people living at Taoyuan city and New Taipei City. The input variables for MLP are suspended sediment concentration of YuanShan weir and Afterbay weir located at upstream. The MLP model would be trained via corss-vaildation with nine typhoons which are from 2008 to 2016 as show in Tab. 1.

Tab. 1: Typhoon evets from 2008 to 2016.

No.	Event	Start time	End time
1	Typhoon Fung-wong	2008/07/27	2008/07/29
2	Typhoon Sinlaku	2008/09/12	2008/09/17
3	Typhoon Jangmi	2008/09/28	2008/10/01
4	Typhoon Morakot	2009/08/06	2009/08/10
5	Typhoon Soulik	2013/07/12	2013/07/17
6	Typhoon Trami	2013/08/21	2013/08/24
7	Typhoon Soudelor	2015/08/07	2015/08/12
8	Typhoon Dujuan	2015/09/28	2015/09/30
9	Typhoon Megi	2016/09/26	2016/09/28

2. Methodology

2.1 Multilayer perceptron (MLP)

The MPL is belong to feedforward artificial neural network. The MLP, at least, is constituted of an input layer, a hidden layer, and an output layer as shown in Abb. 1. The neural network is trained through supervised learning. Therefore, the MLP model would be trained based on nine typhoon events via cross-validation.

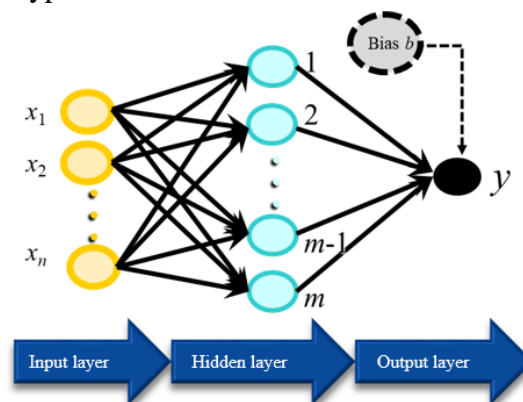


Abb. 1: Multilayer perceptron structure with input, hidden, and output layer.

2.2 Autoregressive (AR) model

After outputting suspended sediment concentration forecasting via MLP, the next step is to correct forecasting of concentration via AR model as shown in Eq. (1). First, the errors between observations and simulations of concentration are derived from Eq. (2). Then, the parameters of AR model can be derived from the errors with a least-squares method. After deriving parameters of AR model, the AR model can produce forecast errors. Finally, the corrected simulations can be derived by adding forecast errors to simulations.

$$E_t = \theta_0 + \theta_1 E_{t-1} + \dots + \theta_p E_{t-p} + \varepsilon_t \quad [1]$$

$$E_t = C_o - C_s \quad [2]$$

where θ_0 is constant, $\theta_1, \theta_2 \dots \theta_n$ are the parameters, and ε_t is white noise. The E_t is error between observations and simulations of concentration. C_o is observed sediment concentration, and C_s is simulated sediment concentration. The results of AR model are shown in Tab. 2.

Tab. 2: The results of AR model and MLP.

Lead time (hour)	Model	RMSE (ppm)	MAE (ppm)	CE	CC
t+1	MLP	4622.79	1157.21	0.74	0.86
	AR(1)	3930.16	1086.78	0.81	0.90
	AR(2)	3527.13	1072.68	0.85	0.92
	AR(3)	3405.32	1038.28	0.86	0.93
	AR(4)	3321.37	1035.84	0.86	0.93
t+2	MLP	5802.97	1630.71	0.58	0.76
	AR(1)	5891.64	1549.89	0.57	0.76
	AR(2)	5727.23	1647.69	0.59	0.77
	AR(3)	5728.04	1650.31	0.59	0.77
	AR(4)	5747.78	1751.75	0.59	0.77
t+3	MLP	5478.22	1914.44	0.63	0.80
	AR(1)	4834.64	1418.08	0.71	0.85
	AR(2)	4580.07	1430.95	0.74	0.86
	AR(3)	4399.69	1437.39	0.76	0.87
	AR(4)	4098.87	1449.85	0.79	0.89

3. Conclusion

According to Tab. 2, the results reveal that after correcting by AR model, the performances, including RMSE, MAE, CE, and CC, of forecasting to suspended sediment concentration are improved. For the 1-h lead time, the AR(4) performs better than the others. The scores of RMSE, MAE, CE, and CC improved from 4622.79 ppm to 3321.37 ppm, from 1157.21 ppm to 1035.84 ppm, from 0.74 to 0.86, and from 0.86 to 0.93, respectively. For the 2-h lead times, the AR(2) and AR (1) performs better on RMSE (5727.23 ppm) and MAE (1549.89 ppm) than the others, respectively. Except for AR(1) model, the CE and CC of AR(2), AR(3), and AR(4) are the same results as 0.59 and 0.77, respectively. For the 3-h lead times, the AR(4) performs better on RMSE (4098.87 ppm),

CE (0.79), and CC (0.89) than the others obviously. However, the AR(1) performs better on MAE (1418.08 ppm) than the AR(4), including AR(2) and AR(3). With the above evidences, the AR model can significantly improve suspended sediment concentration forecasting. Therefore, the corrected forecast of suspended sediment concentration via AR model can be implemented.

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