IMPROVEMENT OF ANN MODEL OF TASTE-AND-ODOR EVENTS IN KAMAFUSA RESERVOIR

Tohoku University Student Duong Hai THUAN
Tohoku University Member Makoto UMEDA
Tohoku University Fellow Member Hitoshi TANAKA

1. INTRODUCTION

Kamfusa Reservoir is the main drinking water resources to the Sendai city, with a population of more than one million, by supplying 37.5% of the city total water demand. Thus its water quality is of high importance in terms of domestic water supply. However, Kamafusa Reservoir has long been suffered from taste-and-odor problems since 1971 as the reservoir started functioning. The cause of the problem was identified as a species of cyanobacteria, *Phormidium tenue* at that time. The overgrowth of the algae was considered as a result of the high nutrient load from farm land in the basin.

The occurrence of taste-and-odor problem is often accompanied with eutrophication in the water resources. However, taste-and-odor has been reported to happen without trend and/or seasonal variation. Thus taste-and-odor still remains a challenging problem in water quality management.

The occurrence of taste-and-odor events were identified by estimation the level of off-flavor compounds such as 2-methylisoborneol (MIB) and/or geosmin in water sources, which are produced by certain species of cyanobacteria. There are two ways of measuring the level of MIB and/or geosmin. One is to make use of continuous direct measurement of MIB and/or geosmin. The other is to use a predictive model which adopts other water quality parameters that correlate to the level of MIB and/or geosmin. The advantage of the second method is that those parameters are often easier to measure than MIB and/or geosmin itself. Multiple linear regression (MLR) and artificial neural network (ANN) were mostly applied to the problem. However, ANN has been proven more useful than MLR in dealing with nonlinear problems similar with the occurrence of taste-and-odor problem.

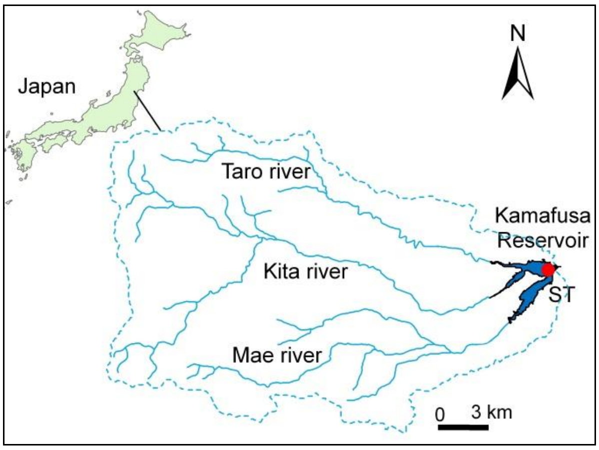

Fig.1 Kamafusa reservoir and location of sampling station

2. METHODS

2.1 Data acquisition

In this study, all data were taken at sampling station ST shown in **Fig.1**. Discrete data of MIB and cells count of *Phormidium* were synchronized with six continuous data of water temperature, turbidity, electricity conductivity (EC), Chl-a, pH, and DO, obtained from CWQM in order to extract appropriate data set. Finally, we have obtained 434 data points from 3/26/2001 through 3/2/2011 for the analysis.

2.2 Data analysis

Firstly, MLR was applied to identify most influential factors to generation of MIB from the six parameters of CWQM data as well as cells count of Phormidium. This examination showed that EC and pH were independent with MIB concentration. On the other hand, Chl-a, DO, and cells count of Phormidium were in significant correlation with MIB. Hence, a judgment was done that those three parameters are the major factors influencing on temporal variation of MIB concentration. A three-layer feed-forward neural networks with back propagation learning was constructed in the second step. In order to avoid the over-fitting in the final model, we minimize the number of nodes in the hidden layer based on an empirical formula proposed by Fletcher and Goss. Early stop was also applied by using several criteria such as mean square error (MSE) larger than a fixed value, maximum of epoch, or the different of MSE between two epochs. Additionally, based on the viewpoint of the events prediction problems that how to estimate the total days has MIB concentrations are higher than the threshold level. We applied root mean square error of the total taste-and-odor days for early stop criteria condition.

The data were divided into 2 sets, from 3/26/2001 to 1/1/2007 with 276 data points for training phase, and from 1/1/2007 to 3/2/2011 with 158 data points for validation phase.

3. RESULTS AND DISCUSSIONS

Fig.2 shows the comparison between the observed data (the top frame graph) and the computed concentration (the middle and bottom graph) of MIB in the reservoir. The first half of the period from 2001 to 2007 shows the training stage of ANN computation, and the second half is the validation. During this period, four major events of MIB increase were observed in 2001, 2003, 2005 and 2008. Besides, minor events of increase were also found in 2006, 2007, 2009, and 2010, during which the level of MIB concentration was high enough to be detectable by the human sense of taste and smell.

Keywords: Kamafusa reservoir, Taste-and-odor problem, MIB, artificial neural network
Tohoku University, 6-6-06 Aoba, Sendai 980-8579, Japan. Tel & Fax: +81-22-795-7451

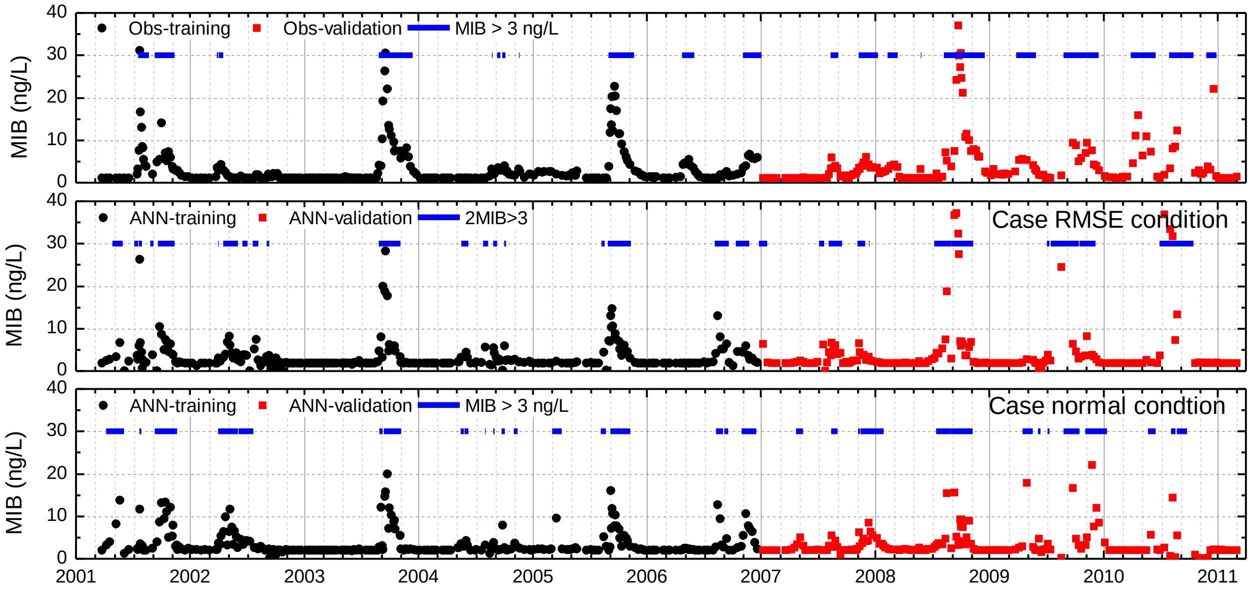

Fig. 2 Results of ANN model of MIB concentration in the reservoir (middle and bottom) compare to those of the measurement (top). The middle panel shows the results of ANN model with new criteria condition and the bottom panel shows those with normal condition. The first half of the period from 2001 to 2007 is for the training phase and the second half from 2007 to 2011 is for validation phase. The blue lines at the level of 30 ng/L show the period when MIB is higher than 3 ng/L, which is a criteria of special treatment in the plant using activated carbon as measures against off-flavor problem.

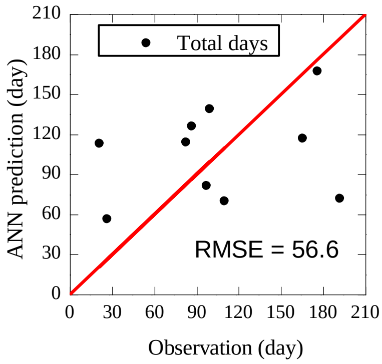

Fig.3 Comparison between observation and ANN prediction of the total day with MIB concentration larger than 3 ng/L.

In some case of MIB increase, results with RMSE of total taste-and-odor day condition show more accuracy than those with ANN traditional condition. The prediction by the model is in good agreement with the measurement on the whole. However, underestimations by the model are found in quite high rise of MIB. The computation results around 20 ng/L at most during the events when about 30 ng/L were observed. In a viewpoint of precise prediction of concentration, the modeling here could be evaluated as insufficient accuracy.

4. CONCLUSION

In this study, predictive model for intermittent occurrence of taste-and-odor in Kamafusa Reservoir has been developed. The model employs ANN and the correlation between off-flavor compound of MIB and input data from CWQM as well as cells count of Phormidium.

The model is not able to yield accurate concentrations of MIB at higher ranges. However, the model is almost successful in prediction of MIB increase events. The ANN model applied new criteria condition shown better results. In terms of practical use in preparation of off-flavor occasions, the method proposed in this study successfully reproduces the periods when MIB concentration is higher than the threshold (3 ng/L) for taste-and-odor treatment in water treatment plant.

5. ACKNOWLEGEMENTS

The authors would like to gratefully acknowledge the Kamafusa Dam Officer for providing us the data for model simulation. The first author was supported by Vietnamese Government Scholarship during this study.

REFERENCES

Westerhoff, P.: Seasonal occurrence and degradation of 2-methylisoborneol in water supply reservoirs, Water research, Vol.39, pp.4899-4912, 2005.

Sugiura, N.: Assessment for the complicated occurrence of nuisance odours from phytoplankton and environmental factors in a eutrophic lake, Lakes and Reservoirs: Research and Management, Vol.9, pp.195-201, 2004.

Dzialowski, A. R.: Development of predictive models for geosmin-related taste and odor in Kansas, USA, drinking water reservoirs, Water research, Vol.43, pp. 2829-2840, 2009.

Fletcher, D. and Goss, E.: Forecasting with neural networks An application using bankruptcy data, Information and Management, Vol.24, pp.159-167, 1993.