Modeling of 3D Isotropic Distribution of Hydraulic Conductivity using Neural Network

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Abstract: In most natural condition, hydraulic conductivity distribution is heterogeneous and anisotropic that is affected by local lithological condition, such as rock porosity and rock joint distribution. Therefore, the more porous of lithology the more hydraulic conductivity number it gets. In the previous study, spatial hydraulic conductivity distribution is modeled using Kriging with the aid of SeGMS software. Three dimensional (3D) hydraulic conductivity distributions in sedimentary rocks, which are isotropic and heterogeneous, can be used for groundwater flow modeling. This paper discusses the modeling 3D hydraulic conductivity distribution using Neural Network (NN). The hydraulic conductivity as a target value is trained segmentally from its position in x, y, z coordinate using NN. Numbers of nodes and hidden layers will be affected by complexity of the data. Geological validation and cross validation show that NN can be applied for modeling the spatial hydraulic conductivity distribution.

Keywords: hydraulic conductivity, Neural Network (NN), modeling spatial distribution.

I. INTRODUCTION

THE main parameter in groundwater flow modeling is hydraulic conductivity (K). Generally, one lithological layer is assumed consists of one value of K to simplify groundwater modeling. In fact, the value of K can vary widely in one layer. Furthermore, layer that became desaturated is even more difficult to analyze. Fractured rock has higher degree of heterogeneity and complexity than the sedimentary rock. Hence, modeling groundwater in real condition cannot simply use one K value in one layer. Spatial distribution of K can be done by interpolating the site data. Cahyadi et al (2014), successfully modeled K value spatial distribution using Kriging method with SeGMS software [4]. This paper is devoted to pursue Cahyadi et al (2014) on modeling K value using Artificial Neural Network (ANN) method.

A. Application of ANN in Spatial Modeling

Artificial Neural Network (ANN) is composed by simple elements operating in parallel. In nature, the connections between elements largely determine the network function. ANN can be trained to perform a particular function by adjusting the values of the connection (weights) between elements. The training itself is adjusting weights so that a particular input leads to a specific target output [6].

In past decades, ANN is applied in various spatial studies. For example, Zeissler and Hertwig., 2011 used ANN for generating 2D map of soil contamination in Saxony (Germany) [2]. Demyanov, Kanevsky., et al 2015; applying ANN with residual Kriging for 2D map of climate study [5].

II. CASE STUDY

Hydraulic conductivity data is used in this study, which is measured from 34 samples. In addition, those samples are acquired from bore holes, located in north Sulawesi, using constant head method. Lithological condition from this site consists of sediments, volcanic rocks and quarter alluvial deposits. There are 2 aquifer systems, shallow aquifer in alluvial deposits and clay layer, and deep aquifer in fractured-rock lithology.

III. ANN ARCHITECTURE AND INTERPOLATION METHOD

A. Proposed Custom ANN

The custom ANN consists of 1 input layer with size 3 (x,y,z location of data), 2 hidden layers with 9 nodes from input layer and 1 nodes to output layer, and 1 output layer (log K-training).

Fig. 1. Custom neural network architecture.

The first hidden layer uses log-sigmoid (logsig) transfer function, which is : $\text{Logsig}(n) = 1/(1 + \exp(-n))$. The second hidden layer uses pure linear transfer function, thus every result is summed linearly. Levenberg-Marquardt algorithm (trainlm) is used in training algorithm.

B. Several ANN Performance Result

For architecture performance test, those all 34 data are trained using several MATLAB ANN training algorithm and custom ANN. The R^2 between logK-data and logK-training for each ANN algorithm as shown in Table II :

TABLE I
 R^2 VALUE OF ACTUAL VS. PREDICTED DATA USING SEVERAL MATLAB NEURAL NETWORK ALGORITHM [7] AND PROPOSED CUSTOM ANN

Fitnet		Feedforwardnet		Custom ANN	
Method	R^2	Method	R^2	Method	R^2
traintrainlm	0.00794	trainlm	0.5195	Trainlm	0.88777
traintrainbr	0.00000	trainbr	0.0000		
traintrainbfg	0.01292	trainbfg	0.0632		
traintrainrp	0.36818	trainrp	0.2182		
traintrainscg	0.27478	trainscg	0.3161		
traintraincgb	0.13991	traincgb	0.1288

Fig. 2. Spatial model from trained custom ANN.

Although the R^2 result is quite good, 3D model from custom ANN with 34 data gives poor presentation as shown above. Subsequently, groundwater flow modeling using this result can lead to wrong analysis. This is caused by the complexity of the data that is not distributed normally with high number variance of log K.

C. Proposed Interpolation: Segmented Training

Segmented training is a training method that creates several ANN network for lesser range of data, which means reducing complexity of data to be trained by ANN and only applied to small limited range of input data. This idea is like modeling many limited space to construct global model. In this study, original data is sorted by depth (Z) then custom ANN is trained for first 6 upper data to model log K distribution from depth 0 m until the 6th data depth. Furthermore, a new custom ANN is trained for data number 2-7. This applies, continuously until last the step of last custom ANN that trains the data number 29-34. Z (depth) segmented training is selected because in every Z segment, the data is distributed normally in XY plane. Total custom ANN will be 29 simple networks function that can be used to model log K distribution for each range custom ANN input.

The final process of segmented training combines the entire segment to create total model from all the data by averaging value of each data position from each affected segment ANN model.

IV. RESULTS AND DISCUSSIONS

The final model result as shown below.

Fig. 3. Spatial model combined from all custom ANN segments, east to west view

Regression analysis was performed to check correlation between actual and predicted results. From regression analysis below, there is 1 result, which has a huge number of differences between actual and predicted result. This is due to the data from bore hole 4, there are 2 data that is too close in distance but so much differ in value, and lead to false training.

Fig. 4. Regression between actual and predicted data.

V. CONCLUSIONS

Model from segmented custom ANN training gives better presentation than non-segmented custom ANN training. Standard or non-segmented ANN can be trained to get best performance of error, along with increasing complexity that can give extreme change of predicted value in close spatial distance. We must aware of this complexity, good performance between actual data and predicted data do not guarantee the quality of all predicted data in space. To reduce the complexity and also preventing such an extreme change, segmented training with lesser data input for training can be used. Sometimes, reducing the data for training still does not result good performance. According to R^2 validation result for segmented custom ANN training method, it can be concluded that this method is quite good for modeling of spatial distribution. Another method for segmentation can be developed for further study to get better result.

VI. ACKNOWLEDGMENT

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VII. REFERENCES

- [1] Iskandar I., Koike K., "Distinguishing potential sources of arsenic released to groundwater around a fault zone containing a minesite", *Environ Earth Sci* (2011), pp. 595-608.
- [2] K. Zeissler and Th. Hertwig, "Artificial Neural Network Instead of Kriging? A Case Study with Soil Contamination of Complex Sources," *Landwirtschaft und Geologie, Dresden* 2011.
- [3] Suhasini V. Kottur and S.S. Mantha, "An Integrated Model using Artificial Neural Network (ANN) and Kriging for Forecasting Air Pollutants using Meteorological Data," *International Journal of Advanced Research in Computer and Communication Engineering Vol. 4, Issue 1*. (2015), pp. 146-152.
- [4] Cahyadi, T. A., Notosiswoyo, S., Widodo, L. E., Iskandar, I., dan Suyono, (2014): Distribusi sebaran konduktivitas hidrolik dari hasil uji akuifer – constant head permeabilitas pada batuan sedimen secara heterogen, *Prosiding TPT Perhapi XXIII, Makasar, Indonesia*, pp. 352-360. DOI 10.17605/OSF.IO/AF8SN
- [5] V. Demyanov, M. Kanevsky, S. Chernov, E. Savelieva, and V. Timonin, "Neural Network Residual Kriging Application for Climatic Data," *Journal of Geographic Information and Decision Analysis*, vol. 2, no. 2 (1998), pp. 215-232.
- [6] D.K.H. Lim, P.K. Kolay, "Predicting Hydraulic Conductivity (k) of Tropical Soils by using Artificial Neural Network (ANN)," *Unimas E-Journal of Civil Engineering, Vol. 1: issue 1* (2009).
- [7] Matlab R2013 Documentation (2013)