Combined use of Finite element method and Neural Networks for the prediction of pore pressure change

Mebruk M.N.[1], Kunio Watanabe[2] and Shinji Takeuchi[3]

[1]*Member of JSCE, M. Eng., Geosphere research Institute, Saitama University (Shimo Okubo 255, Sakura-ku, Saitama, Japan)*

[2]*Member of JSCE, Dr. of Eng., Professor, Geosphere research Institute, Saitama University (Shimo Okubo 255, Sakura-ku, Saitama, Japan)*

[3]*Member of JSCE, M. Eng., Tono Geoscience Center, Japan Atomic Energy Agency (1-64, Yamanonichi, Akeyo, Mizunami, Gifu, Japan)*

Precise prediction of pore pressure change due to the construction of underground structures is very important to monitor and manage the groundwater flow. Most current approaches to pore pressure prediction involve the use of numerical models like finite element method (FEM). However, for accurate prediction, these techniques need a lot of effort for detail hydrogeologic investigation, which is costly in usual case. In this study a technique of combining FEM and feed forward neural networks (FNN) were developed for more precise pore pressure prediction using limited and incomplete hydrogeologic data obtained around the Mizunami underground research laboratory (MIU) construction site, Japan. The results show the successful application of the method.

Key Words: *FEM, FNN, monitoring of pore pressure, MIU*

1. INTRODUCTION

Monitoring of pore pressure change is an effective tool to properly evaluate the change of groundwater flow system due to any construction work in underground. Numerical models like finite element method (FEM) are the most common methods for analyzing pore pressure changes. Spatial and/or temporal variability of aquifer parameters, boundary conditions, and initial conditions can be assigned across the numerical model domain. While this constitutes a powerful modeling advantage, it also presents a challenge of overcoming aquifer parameter uncertainty, which ultimately result in model prediction errors. On the other hand, artificial neural network (ANN) developed with exhaustive pore pressure and construction data, can achieve excellent predictive accuracy at specific field locations. Exhaustive data implies paired input-output data that contain the possible future maximum and minimum data values. Getting such exhaustive construction data is a challenge for the application of ANN in such cases. Many studies show successful application of ANN models in the field of groundwater simulations. Daliakopoulous et al.[1)] use feed forward neural network (FNN), recurrent neural network (RNN) and radial basis function (RBF) and trained these models with three different algorithms (Levenberg-Marquardt (LM), Gradient Descent and Bayesian Regularization) to forecast groundwater levels in Greece. They concluded that FNN trained with LM algorithm was the most efficient. Other ANN applications in the field of groundwater used FNN trained by error back propagation[2), 3)]. Gokmen et al.[3)] compares the results of FEM and ANN for the analysis of flow through Jeziorsko Earth fill Dam in Poland and reports the adequacy and competitiveness of ANN against FEM for predicting seepage through an earth fill dam. In an effort to combine the relative advantages of numerical model and ANN, a new modeling approach called FEM-FNN is presented in this study. In this model, to create the exhaustive data needed for developing ANN, several patterns of pore pressure changes were calculated by FEM for a simplified hydrogeologic conceptual model by changing the hydrogeologic parameters. Then a FNN model was constructed to predict the actual pore pressure change using these FEM results as inputs. FEM-FNN modeling approach was applied to monitor the pore pressure change caused by the construction of two shafts of Mizunami underground research laboratory (MIU), Japan. This approach, beside avoiding costly hydrogeologic studies it creates exhaustive data for the application of FNN method which ultimately predicts precise pore pressure values.

2. GROUNDWATER FLUCTUATION IN THE MIU SITE

MIU site is located in Mizunami city, Gifu prefecture, Japan (see **Fig. 1**). A research project for establishing techniques for investigating the geological environment, and to develop applicable engineering techniques in deep underground[4] is now going on in MIU. Two circular 1,000 m length vertical shafts (6.5 m diameter Main shaft (MS) and 4.5m diameter Ventilation shaft (VS)), are now under construction. The two vertical shafts have been excavated in fractured sedimentary rock and basement rock composed of fractured granite[5].

The excavation has started in Feb. 2005. This excavation had been stopped on Oct. 27, 2005 due to the inflow of fluoride-rich groundwater in to the shafts. The concentration of the fluoride was greater than Japanese environmental standard. After the construction of water treatment facility, the accumulated groundwater in the shafts was pumped out and the excavation has started again[5] on Feb. 20, 2006 (see **Fig. 2**).

The surface topography around the MIU construction site is mountainous having relatively steep slopes (slope gradient 25%-35%). The ground surface is generally sloped from Northeast to Southwest. Meteorological data measured within MIU site show precipitation is highest during four months of summer (June to September) and reaches almost above 200mm/month and during December to February it is as low as 50mm/month. The average annual precipitation is about 1550mm[6].

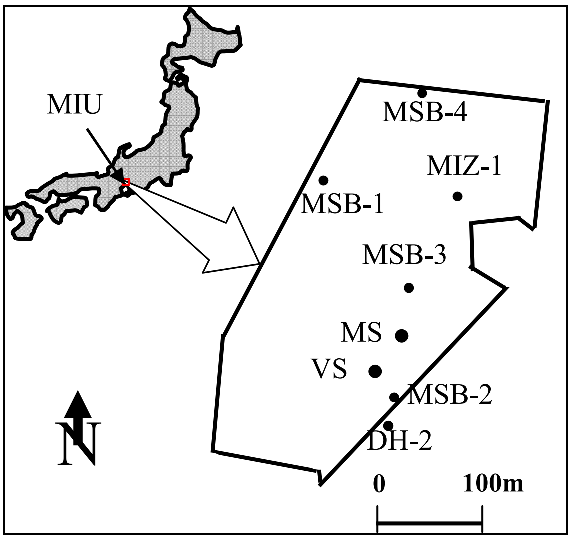

Fig. 1 MIU site area, Shafts and boreholes location

Six boreholes MSB-1, MSB-2, MSB-3, MSB-4, MIZ-1 and DH-2 (see **Fig. 1**) have been drilled for monitoring the groundwater flow during the excavation. Continuous monitoring of pore pressure heads have been performed in DH-2, MSB-1 and MSB-3 boreholes[7]. There are five and twelve pressure sensors at different depths in MSB-1 and DH-2 boreholes respectively. **Fig. 2** illustrates the observed pore pressure changes in DH-2 and MSB-1 boreholes together with the excavation and water level data in both main and ventilation shafts from Jan. 1, 2005 till Mar. 31, 2006. The pore pressure changes at 17.4m, -11.4m, -25.2m, -52.5m & -268.5m above mean sea level (amsl) in DH-2 and 72.5m & 56.8m amsl in MSB-1 are displayed

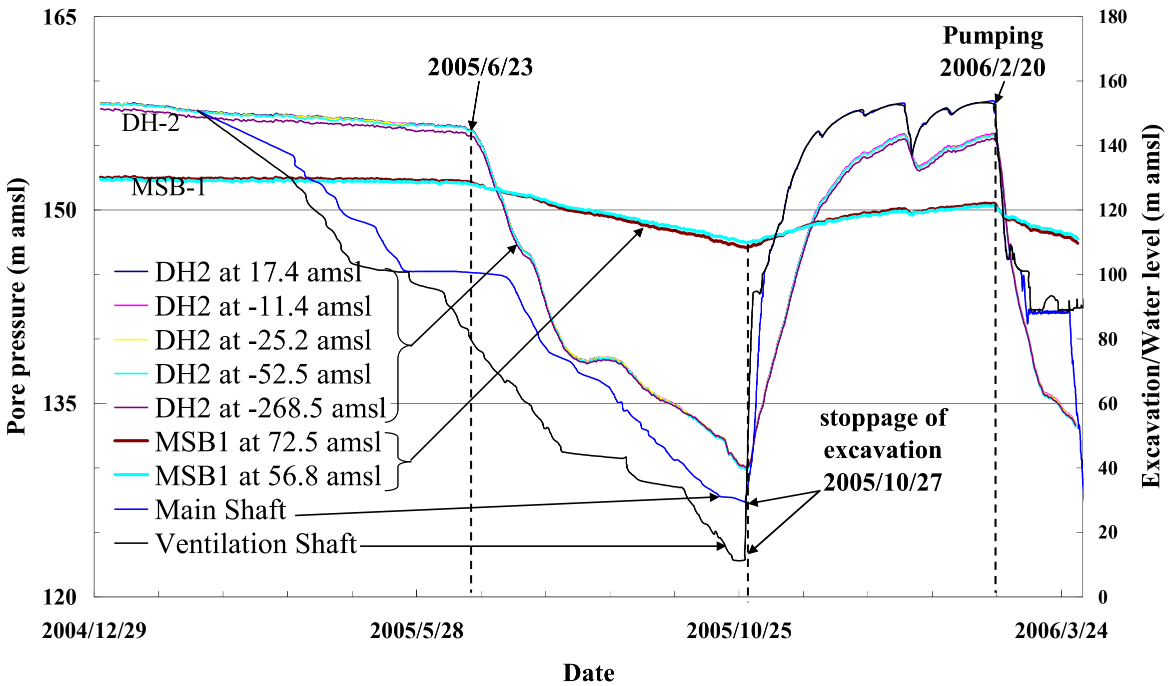

Fig. 2 Observed pore pressure in DH-2 and MSB-1, excavation and water level in MS and VS

in **Fig. 2**. The sensors in MSB-1 are located in the sedimentary rock and sensors in the DH-2 are located in granite rock.

3. THE FEM -FNN MODEL

(1) Model structure

In this model as a first step, a three dimensional conceptual hydrogeologic model is constructed and boundary conditions are given. In the second step, groundwater flow analysis is conducted by FEM for the conceptual model with assuming N combination of hydrogeologic parameters like horizontal and vertical hydraulic conductivities and specific storage. At this step N different trends of temporal change of pore pressure corresponding to the N hydrogeologic parameters are obtained. As the third step FNN analysis is performed using the FEM results as inputs. This step will find parameters of the FNN model like learning rate, momentum factor, synaptic weights that will best fit the observed pore pressure data. Finally pore pressure change in future is predicted using the optimized FNN model parameters and FEM results. The structure of the FEM-FNN model is schematically illustrated in **Fig. 3.**

(2) The FEM model

The groundwater table around MIU site is shallow and the rock is almost saturated except at the top of the sedimentary rock[4]. The shafts have been excavated in deep saturated fractured rock mass. Therefore three dimensional saturated groundwater flow model was adopted to analyze the pore water pressure change. A three dimensional FEM code, called TAGSAC, developed in Geosphere research institute of Saitama university is adopted for the analysis. The code is developed based on Galerkin FEM.

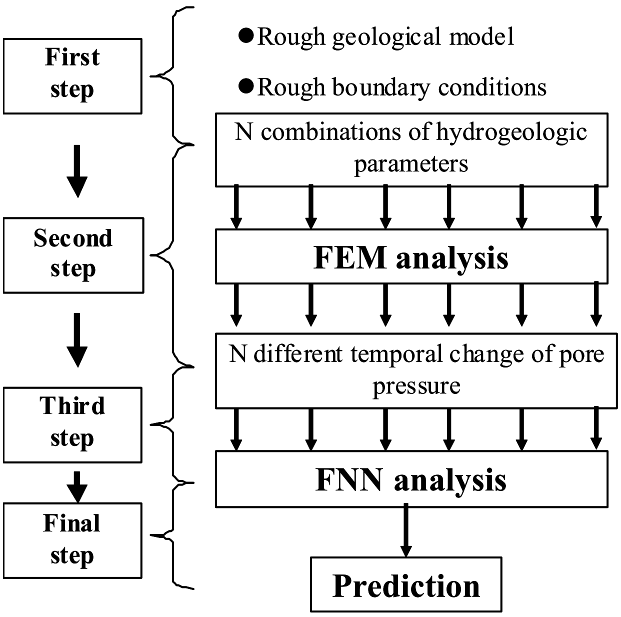

Fig.3 Structure of FEM-FNN model

The site is essentially composed of sedimentary and granite rocks[5), 7), 8)]. The measured pore pressure trends in DH-2 and MSB-1 boreholes have shown a drastic change around June 23, 2005 (see **Fig. 2**). Moreover the observed pore pressure trends in MSB-1 and DH-2 boreholes are different. These differences may be due to the sensor locations in MSB-1 borehole are in low permeable sedimentary rock while those in DH-2 are in higher permeable granite rock. Therefore, in this study, a two layer model as illustrated in **Fig. 4** is adopted as the conceptual hydrogeologic model. To include the natural hydraulic boundaries like rivers and groundwater divides nearby MIU, the analyzed domain was extended beyond the site boundary as shown in **Fig. 4.**

Hydraulic conductivity and specific storage measured for the rock of this site widely distributed[8), 9)]. For the reason, different combination of horizontal and vertical hydraulic conductivities and specific storage were assumed to form the hydrogeologic models.

The boundary condition on the ground surface is set as a free seepage face and a recharge rate of 0.28mm/day[9)] that is an average infiltration rate estimated in the vicinity of Tono Mine (located about 5km north-west of MIU) was given. Constant head equal to the average water level of the Toki and Hiyoshi rivers is given for the nodes representing the rivers. For the nodes representing the mountain ridges, a constant head is also given. The constant head value on the ridge was determined by Eq.(1), which formulates the relationship between surface elevation (*SE*) in m amsl and the water level (*WL*) observed in boreholes around the study area[8)].

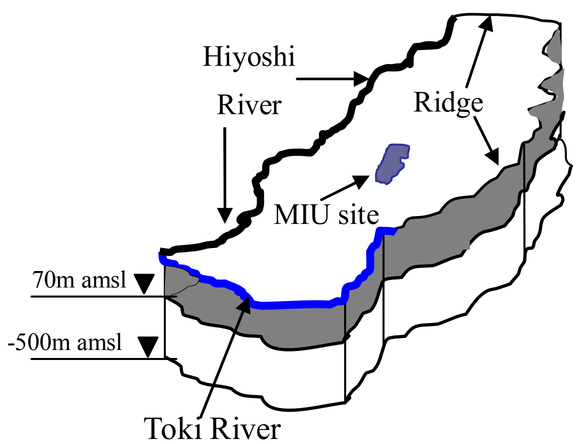

Fig. 4 Analyzed area and **c**onceptual hydrogeologic model assumed

$$WL = 0.8619 * (SE) + 18.5 \quad (1)$$

Bottom boundary assumed at -500 m amsl was set as a no-flow boundary. Because the minimum excavation level in the analysis period was 29.5m amsl in main shaft and 11.4m amsl in ventilation shaft, the effect of this level of the bottom boundary on the groundwater flow pattern might be minimal. A no flow boundary may represent a groundwater divide or a streamline[10]. Therefore the side of the entire model domain is assumed as no flow boundary to represent a streamline created by the groundwater divide along the rivers and ridges.

Transient boundary conditions have been given on the shafts walls. Groundwater level in the shaft was equal to the bottom of the shaft during excavation; hence constant head equal to this level is given for the nodes at the bottom. During water level recovery in the shafts, the transient water level variation is given as the changing constant head value for the nodes at the bottom of the shafts.

In the FEM analysis, at first, arbitrary combinations of vertical (K_V) and horizontal (K_H) hydraulic conductivities were given in the two layer hydrogeologic model. Then a steady state pore pressure distribution was calculated for predicting the initial pore pressure distribution before shafts construction begins. Measured pore pressures at certain depth of DH-2 and MSB-1 boreholes before shaft excavation were compared with the calculated values. K_V and K_H values of the two layers having better approximation were selected. By using the selected K_V and K_H values a transient FEM simulation was analyzed. In this transient FEM analysis the specific storage (Ss) value was adjusted to approximate the measured pore pressure trend at DH-2 and MSB-1 boreholes due to the shafts construction.

18 different hydrogeologic models were used to approximate the pore pressure trends shown in **Fig. 2**, of which 9 are for DH-2 and the other 9 are for MSB-1 pore pressure trend approximation. 3 hydraulic parameters (K_V, K_H and Ss) for both layers, totally 6 hydraulic parameters are given for each hydrogeologic model. **Table 1** summarizes the range of parameter values given for both boreholes pore pressure trends approximation. The top layer mainly represents the sedimentary rock while the bottom layer represents the granite basement.

Table 1 Range of parameters obtained

parameter	Layer		min	max
Hydraulic conductivity (m/s)	Top	K_V	5.0E-11	1.0E-9
		K_H	1.25E-7	3.5E-6
	Bottom	K_V	5.0E-6	5.0E-5
		K_H	1.0E-7	1.0E-6
Specific storage	Top		1.5E-5	9.0E-5
	Bottom		1.2E-6	1.5E-5

(3) The FNN model

A three layer FNN model composed of an input, a hidden and an output layers and trained by back propagation algorithm have been adopted. We have used the 18 FEM simulation results as input to FNN model, therefore the total number of input nodes are 18. There is no standard method to select the number of hidden layer and hidden nodes; trial and error methods are usually employed. After careful consideration one hidden layer with 7 hidden nodes were found to be suitable in present study for both boreholes pore pressure analyses. The output layer has only one node to represent the measured pore pressure. The number of nodes for input, hidden and output layer (including the biased nodes at input and hidden layer) of the finally selected FNN model was 19, 8 and 1 respectively. **Fig. 5** illustrates the architecture of the FNN model selected. The suffix b refers to the biased node.

The pore pressure trends calculated by FEM are given to the nodes of input layer and send the respective input value to all hidden nodes. At any hidden layer node, information received from all input nodes and bias node of input layer are multiplied by hidden-input synaptic weights (SWs) and summed up. The summed up input is then acted upon by sigmoid logistic non-linear activation function. The result is then forwarded from each hidden node to output layer node. Similarly, information received from all hidden layer nodes

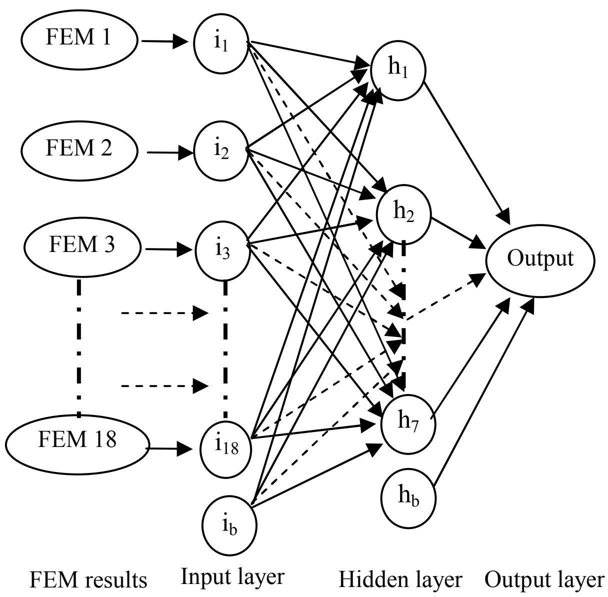

Fig. 5 Architecture of FNN model adopted

and bias node of hidden layer are multiplied by output-hidden SWs and summed up and then acted upon by the sigmoid logistic activation function. Values at the output node are then compared with the measured pore pressure trend. Mean square error (MSE) is calculated at output layer, and if MSE is within acceptable limit the process is terminated otherwise feed backward pass is carried out for updating of SWs by using back propagation equation (Eq.(2))

$$w_{oh}(new) = w_{oh}(old) + \eta\delta_o p_o + \alpha[\Delta w_{oh}(old)]$$
$$\delta_o = (t_o - p_o)\times(p_o)\times(1-p_o) \qquad (2)$$

In Eq.(2) w_{oh} is the SW value joining output and hidden layer nodes, subscript "*o*" denotes output layer node and "*h*" denotes hidden layer node. $\Delta w_{oh}(old)$ is the previous weight change of the respective SW (w_{oh}). p_o is the computed value of output layer node. t_o the measured pore pressure value. η is the learning rate and α is the momentum factor.

The SWs between input and hidden layer nodes are also updated in a similar manner. Appropriate selection of parameters of η and α are also very important for successful training of FNN models. After trial calculations as η and α values 0.001 and 0.9 were selected respectively.

In order to avoid over fitting problem in back propagation algorithm it is now standard practice to use cross validation approach[1),11)]. In cross validation approach a dataset is divided into three portions: training, validation and test sets, the former is used for the training of the model, validation set is used to avoid over fitting and the test set is used to check the accuracy of trained model.

The maximum range of sigmoid logistic function is between 0 and 1. The input data is therefore required to be normalized in between these two limits. However, the data was rescaled in effective range of 0.0 to 0.9 to accommodate occasionally occurring extreme pore pressure values.

Starting values of SWs also significantly affect the generalization capability of FNN model. Trial and error method is most commonly used to select the starting SW vector values. After several trials with different combinations of starting SW vector values, values initialized in the range of ±1.0 were selected for MSB-1 and ±3.0 for DH-2 borehole pore pressure analyses.

4. RESULTS AND DISCUSSION

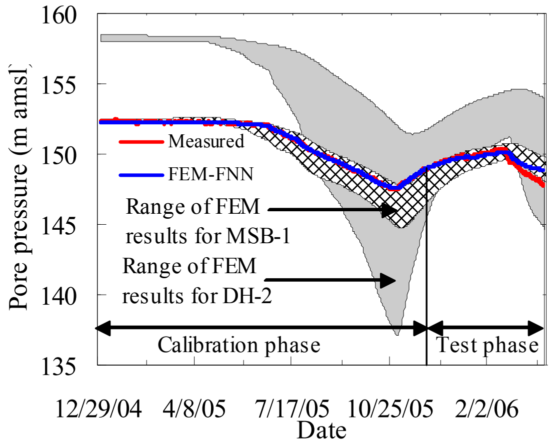

Fig. 6 Results for 56.8m sensor in MSB-1

While discussing the results of FEM-FNN model both training and validation sets are taken and called it as calibration phase. Three types of measures of the goodness of fit have been used to check the performance of the FEM-FNN model; these are coefficient of efficiency (CE), coefficient of determination (CD), and the root mean square error (RMSE). CD and CE tend to one and RMSE tend to zero for perfect prediction[12)].

For both bore holes 1 hour interval data from Jan.1, 2005 till Mar.31, 2006 were used. After neglecting some faulty measured data points 75% of the total data points were used for calibration and 25% for testing of FEM-FNN model. The result of the model for 56.8m amsl sensor in MSB-1 and -52.5m amsl sensor in DH-2 are shown in **Fig. 6** and **Fig. 7** respectively. In these figures the range of FEM results to approximate pore pressure trends at 56.8m amsl sensor in MSB-1 and -52.5m amsl sensor in DH-2 with using hydraulic parameters in the range shown in **Table 1** are also depicted.

In calibration phase, the value of CE, CD and

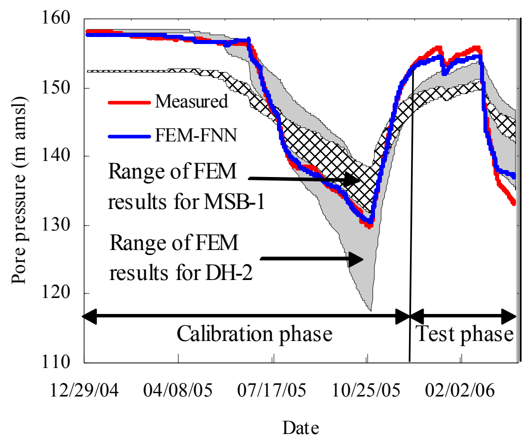

Fig. 7 Results for -52.5m sensor in DH-2

Table 2 CE, CD and RMSE for DH-2 and MSB-1 at different test phase periods

Borehole		DH-2			MSB-1		
Indicators		CE (-)	CD (-)	RMSE (m)	CE (-)	CD (-)	RMSE (m)
Test phase	1	0.999	1.05	0.068	1.000	1.01	0.017
	7	0.997	1.11	0.191	0.998	0.94	0.051
	15	0.992	1.19	0.385	0.996	0.91	0.068
	30	0.976	1.37	0.801	0.990	0.87	0.091
	60	0.973	1.41	0.874	0.978	0.84	0.113
	114	0.976	1.41	1.425	0.908	1.56	0.359

RMSE were 0.998, 1.003 and 0.411m for DH-2 and 0.999, 1.003 and 0.049m for MSB-1 pore pressure data fitting respectively. These results indicate the models were calibrated successfully. This calibrated FNN model was used to validate the pore pressure prediction in the test phase. The validation was performed by changing the test phase periods for the next 1 day to 114 days after the end of the calibration phase. The CE, CD and RMSE for different test phase periods can be seen in **Table 2**.

It has been reported that models having CE values above 0.9 are very satisfactory, in between 0.8-0.9 are fairly good and below 0.8 are unsatisfactory[6)]. According to this criterion the FEM-FNN model shows very satisfactory result for every test phase period shown in **Table 2**. The improvement of the proposed model results in terms of RMSE, CE and CD statistics with decreasing test period, suggest that the shorter the forecasting period the better the performance of the proposed modeling approach.

5. CONCLUSIONS

A combination of FEM and FNN model (FEM-FNN) was developed for the prediction of the pore pressure change at MIU site; Japan. The measures of goodness of fit obtained for different test periods are very satisfactory and are more improved with decreasing the test period length. This can clearly indicate the application of the model in pore pressure prediction. Of course, this model needs exhaustive measured pore pressure trends for optimization of the FNN parameters.

In monitoring and management of pore pressure changes in fractured rock aquifers, when uncertainty in hydrogeologic parameters estimation and/or the scale of interest make the mathematical and conceptual modeling approaches like discrete fracture network or equivalent porous medium is difficult to apply, this combined model can be used.

Finally, although the dynamicity of the groundwater flow pattern in MIU project area is complex due to construction of shafts, the FEM-FNN modeling approach have shown very good result. Therefore this modeling approach would also improve the results of numerical models when it is applied in case of other groundwater managements.

REFERENCES

1) Daliakopoulous IN, Coulibaly P. and Ioannis KT: Groundwater level forecasting using artificial neural networks, J. Hydrology 309: pp.229-240, 2005.
2) Gautam M.R., Watanabe K. and Saegusa H.: Analysis of hydraulic pressure fluctuation in deep geological formations in Tono area, Japan using artificial neural networks, Journal of Hydrology, 284, pp.174-192, 2003.
3) Gokmen Tayfur, Dorota Swiatek, Andrew Wita, and Vijay P. Singh: Case Study: Finite Element Method and Artificial Neural Network Models for Flow through Jeziorsko Earth fill Dam in Poland, J. Hydraulic Engineering., Volume 131, Issue 6, pp.431-440, 2005.
4) Japan nuclear cycle development institute: Master Plan of the Mizunami Underground Research Laboratory Project, Japan, JNC Technical Report, JNC TN7410 2003-001, 2002.
5) Takeuchi S., Takeuchi R., Salden W., Saegusa H., Arai T. and Matsuki K.: Hydrogeological conceptual model determined from baseline and construction phase groundwater pressure and surface tilt meter data at the Mizunami Underground Research Laboratory, Japan, Proceedings of the 11th International Conference, ICEM2007, 2007.
6) Sohail A., Watanabe K. and Takeuchi S.: Stream flow forecasting by artificial neural network (ANN) model trained by real coded genetic algorithm (GA)- A case study when the role of groundwater flow component in a surface runoff is small, journal of Groundwater hydrology, 48(4) pp.233-262, 2006.
7) Goto J, Ikeda K, Kumazaki N, Mukai K, Iwatsuki T. and Hama K.: Working Program for Shallow Borehole Investigations, Japan Tono Geoscience Center, Japan Nuclear Cycle Development Institute, JNC TN7400 2002-005, 2002.
8) Kumazaki N., Ikeda K., Goto J., Mukai K., Iwatsuki T. and Furue R.: Synthesis of the Shallow Borehole Investigations at the MIU Construction Site, Japan Tono Geoscience Centre, Japan Nuclear Cycle Development Institute, JNC TN7400 2003-005, 2003.
9) Japan nuclear cycle development institute: Mizunami Underground Research Laboratory Project Results from 1996-1999 (Revised edition), JNC Technical Report, JNC TN7400 2003-004, 2001.
10) Marry P.A. and William W.W: Applied groundwater modeling, USA, Academic Press limited, pp 97-145, 1992.
11) Shamseldin A.Y: Application of a neural network technique to rainfall runoff modeling, J. Hydrol 199, pp.272-294, 1997.
12) Spitz Karlheinz and Joanna Moreno: A practical guide to groundwater and solute transport modeling, USA; John Wiley & Sons Inc, pp.201-270, 1996.

(Received September 30, 2008)