Development of DeepSWING Method ~ Water Inflow prediction in Mountain Tunnel Excavate Using Data Assimilation and Deep Learning

Moritada Mori*1 Toru Yasuda*2
Tomofumi Koyama*3 Satoshi Nishiyama*4

Summary

The SDA-SWING method is a simplified method for water inflow prediction in mountain tunnel excavation. We extended the SDA-SWING method, which is based on one-dimensional well formulas, to three dimensions and incorporated data assimilation methods and deep learning to improve the feedback of excavating information and the accuracy of future prediction.

We named this method the DeepSWING method and confirmed the effectiveness of this method by simulating it using actual excavating records.

Keywords: tunnel excavation, predicting spring water inflow, data assimilation, deep learning

1 Introduction

In mountain tunnel construction, detailed design is generally based on geological characteristics obtained from preliminary investigations. Due to its geographical conditions, Japan has a very complicated geological composition, with well-developed faults and fissures. Therefore, construction of mountain tunnels rarely progresses as expected from prior assumptions, and the actual geological distribution is monitored by face observation and various measurements during construction, and the construction method is reviewed in a timely manner. Particularly in Japan, rivers are short and steep, the amount of rainfall is twice the world average, and the groundwater level is high. NATM (New Austrian Tunneling Method), which is generally used in mountain tunnel construction, is premised on the constant drainage from the tunnel. Moreover, when evaluating the impact of tunnel excavation on the surrounding groundwater environment, the groundwater behavior must be predicted by local evaluation of the construction area and considering the entire basin as part of the water environment system. This aspect is one of the most challenging to control.

Various methods have been proposed and used in practice for controlling the conventional groundwater behavior associated with tunnel excavation. However, particularly in three-dimensional and quasi-three-dimensional seepage flow analyses, the analysis time is long because the model is divided into numerous elements. In addition, there is a high degree of freedom in modifying hydraulic constants using observed values, and the accuracy of the modification tends to depend on the skill of the engineer, that make it difficult to implement in real time at the actual site.

Therefore, the SDA-SWING method was developed to quickly predict the amount of spring water by automatically reflecting the observed data during construction to the hydrogeological model using a sequential data assimilation (SDA) [1), 2), 3), 4)] method, based on a simple well equation. This method is intended for landsides with small fluctuations in spring water, where rock properties were known to be almost uniform from the geological survey. However, this method adopts Bear's equation[5)], which is a type of well equation that assumes the Dupuit quasi-uniform flow as the governing equation. This poses a problem as it inherently incorporates analysis errors associated with modeling due to the heterogeneity of the ground. Additionally, the system that reflects the actual results of the already-excavated sections in the non-excavated sections is simple, and there is a problem with the accuracy of future predictions.

To solve the aforementioned problems, we extended the SDA-SWING method to consider the three-dimensional flows and introduced deep learning[6),7)] to improve the analysis accuracy by predicting the geological information of the non-constructed

*1 Research & Development Institute (Takenaka Civil Engineering & Construction Co., Ltd.), Dr. Eng.
*2 Transportation Infrastructure Div, Pacific Consultants Co., Ltd., Dr. Eng.
*3 Prof., Dr. Eng., Faculty of Societal Safety Sciences, Kansai University
*4 Prof., Dr. Eng., Graduate School of Environmental and Life Science, Okayama University

section using the results of the already-excavated section as training data. We named this new analytical method as DeepSWING method. This study describes the overview of the DeepSWING method and the results of applying this method to construction data from actual tunnel construction.

2 Overview of the SDA-SWING method

2.1 Basic equations

The SDA-SWING method is an evaluation method that focuses on mountain tunnel construction, targeting the rock masses where the physical rock engineering properties in geological surveys are almost uniform, and there is little fluctuation in the amount of spring water inflow. It sequentially corrects a hydrogeological model, predicts the amount of spring water inflow, and reflects the prediction results in excavation based on the observed spring water inflow amount at the tunnel entrance. During construction, as shown in Fig. 1, based on the observed amount of spring water inflow at the tunnel entrance, future spring water inflow amount at the tunnel entrance is predicted from previous short-term data, and the observed amount of spring water inflow at the tunnel entrance is used to repeat the correction of the hydraulic conductivity, which is a hydraulic constant, to improve the accuracy of predictions and evaluations. In the analysis, as shown in Fig. 2, the unit slice volume obtained by dividing the excavation target section at equal intervals in the longitudinal direction of the tunnel is used as the target. The unit slice volume is a simplified hydrogeological model in which physical property values are constant for each divided section, and the length of the divided section is generally 20m, which is a guideline for one week's worth of excavation progress.

A one-dimensional unsteady flow, as shown in Fig. 3, is considered in each unit slice volume to predict the tunnel spring water inflow and groundwater level drop range due to excavation and correct the hydraulic conductivity. In other words, it is assumed that a tunnel with a diameter sufficiently smaller than the ground size is constructed in the aquifer on the horizontal bedrock. The groundwater level, which is constant initially, gradually decreases with time after excavation from directly above the tunnel. The groundwater flow is a two-dimensional unsteady flow in this case. However, the SDA-SWING method predicts the amount of water inflow per unit length of one unit slice volume and the extent of groundwater table lowering by replacing the groundwater flow with Bear's equation based on Dupuit's quasi-uniform flow assumption shown in Eqs. (1) – (3).

$$\frac{h^2-{h_0}^2}{{H_0}^2-{h_0}^2}=\frac{x}{R_{(t)}} \tag{1}$$

$$R_{(t)}=\left[k\frac{({H_0}^2-{h_0}^2)}{2\varepsilon}\left(1-e^{-\frac{6\varepsilon t}{\lambda e(H_0-h_0)}}\right)\right]^{\frac{1}{2}} \tag{2}$$

$$q_{(t)}=k\frac{({H_0}^2-{h_0}^2)}{2R} \tag{3}$$

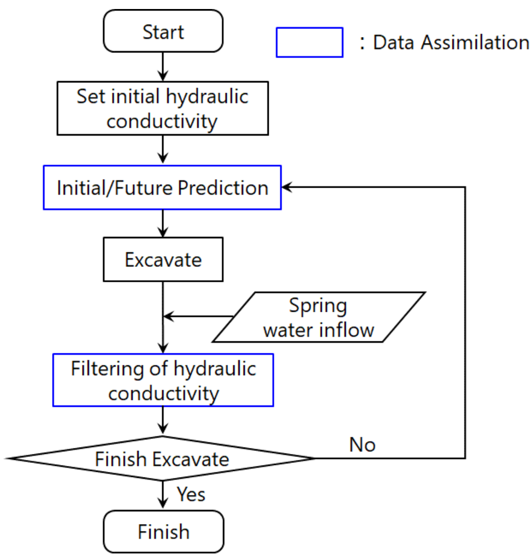


Fig.1 Processing flow of SDA-SWING method

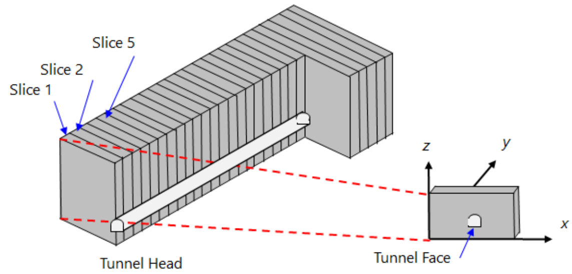


Fig.2 Unit slice volume of SDA-SWING method

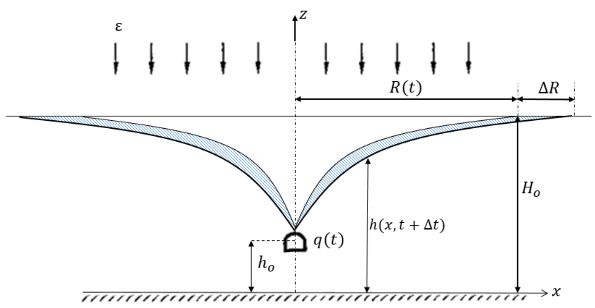


Fig.3 Groundwater flow caused by tunnel excavation

Where,

t : Elapsed time after unit slice volume excavation (d)
k : hydraulic conductivity (m/d)
ε : rainfall permeability (m/d)
λ_e : porosity, H_o : initial groundwater level (m)
h_o : distance from impermeable base to tunnel base (m)
q : amount of spring water inflow per unit slice volume (m^2/d)
R : groundwater level drop range (m)

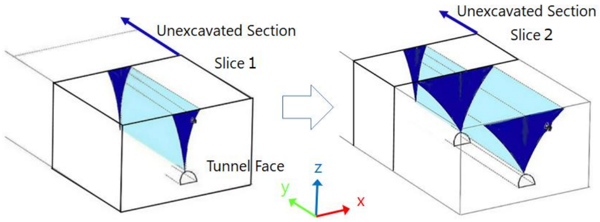


Fig.4 Extent of groundwater level caused by tunnel excavation

The rainfall permeability ε in Eq. (2) is obtained from the ratio of the base runoff to the actual rainfall by constructing a four-stage tank model[8] that considers the ground surface as one basin. The various parameters of the tank model are set based on the amount of rainfall and the flow rate of nearby rivers during a certain period before construction starts. For predicting the river discharge influenced by the tunnel spring water inflow, it is assumed that the aquifer flowing into the river and the aquifer flowing into the tunnel are integrated. The calculation is performed by subtracting the amount of tunnel spring water inflow calculated by the SDA-SWING method from the river discharge predicted for the excavation period by the tank model that identifies the measured river discharge before excavation.

Next, the procedure for predicting the amount of spring water inflow is explained. First, slice 1, which is the unit slice volume that is subject to excavation, enters the analysis range as excavation progresses, as shown in Fig. 4. Here, we refer to the unit slice volumes starting from the tunnel entrance as Slice 1, Slice 2, and Slice 3 in sequential order. Additionally, the SDA-SWING method uses Bear's equation, which is a well equation, and the groundwater level drops to a level just above the tunnel at the same time as the excavation, as shown in Fig. 3. Bear's equation is based on one-dimensional unsteady flow and cannot consider two- or three-dimensional flows; hence, slice 1 is the only unit slice volume in which the groundwater level drops. In other words, water level drop after slice 2, which is the unit slice volume in front of the face, is not considered. When the excavation progresses to slice 2, the groundwater level of slice 2 drops to a level just above the tunnel. By repeating this cycle, the analysis range accumulates successive unit slice volumes as the tunnel is excavated. In other words, the predicted value of the tunnel entrance spring water inflow amount can be obtained by summing the spring water inflow amount generated in all the unit slice volumes.

2.2 Overview of the data assimilation method

The SDA-SWING method adopted the ensemble Kalman filter (EnKF), which is a sequential data assimilation method, as an automatic correction method for hydraulic conductivity. Hydraulic constants, such as hydraulic conductivity, obtained from geological surveys are input to each unit slice volume as the initial condition, and the hydraulic conductivity is corrected sequentially based on the observed value of spring water inflow at the tunnel entrance.

The following is the explanation of the procedure of EnKF in the SDA-SWING method. In EnKF, when correcting the state vector based on the observation vector for an unknown state space model, a combination of state vectors that can reproduce the observed value is searched under the assumption that the state and observation vectors each contain noise (v_T, w_T). Additionally, assuming that there is no time update f_T of the state model and only system noise is included, the system model is as shown in Eq. (4).

$$x_{T|T-1} = x_{T-1|T-1} + v_T \tag{4}$$

The state vectors of the SDA-SWING method are three soil constants: hydraulic conductivity k, porosity λ_e, and average rainfall permeability ε. However, system noise was applied only to the hydraulic conductivity k, which has a particularly large effect on the analysis results, among the state vectors. Next, the observation vector is the observed value Q of the amount of spring water inflow at the tunnel entrance. Additionally, in EnKF, accuracy is higher when the probability distribution of the state vector is closer to the Gaussian distribution, whereas it is generally known that the logarithmic value of the hydraulic conductivity follows the Gaussian distribution. Therefore, it was decided to give system noises to the logarithm of the hydraulic conductivity.

Here, if the time required for excavation of one unit slice volume is set as m, and the total amount of spring water inflow from the unit slice volume of the already-excavated section at time T is $Q'_{(T)}$, then the state-space model of this method during slice (j) excavation is expressed as shown in Eqs. (5), (6), and (7). Note that the hydraulic conductivity k was converted to a logarithmic value, as shown in Eq. (5).

$$x^{j}{}_{T|T-1} = x^{j}{}_{T-1|T-1} + v_T \quad ※x_{T-1|T-1} = \log_{10} k_{T-1|T-1} \tag{5}$$

$$y_T - Q'_{(T)} = h_{T-m(j-1)}\left(x^{j}{}_{T|T-1}\right) + w_T \tag{6}$$

$$Q'_{(T)} = \sum_{n-1}^{j-1} h_{T-m(n-1)}\left(x^{n}{}_{T}\right) \tag{7}$$

For the above state-space model, the hydraulic conductivity is corrected at the stage when the tunnel entrance spring water inflow amount is observed. Additionally, the spring water inflow from the unit slice volume after excavation converged to a steady flow within several hours or weeks. Therefore, after securing a slice width (= 20 m) that allows the excavation period to converge to a steady flow, EnKF processing was applied only during excavation. After excavation, the hydraulic conductivity that reproduces the spring water inflow amount best at the tunnel entrance for the unit slice volume during excavation was back calculated (filtered) and set to a constant value. Subsequently, future prediction was conducted using the back calculated hydraulic conductivity. As shown in Fig. 5, the future prediction accuracy is improved by repeating successive filtering and future prediction for the observed values of the tunnel entrance spring water inflow amount.

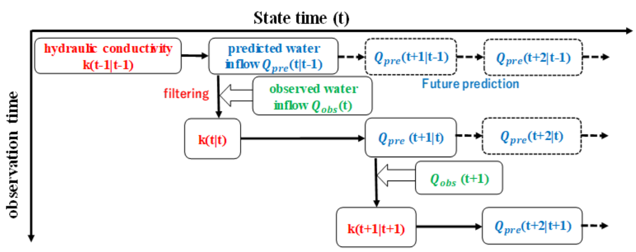


Fig.5 Procedure for updating spring water prediction using SDA-SWING method

In the SDA-SWING method, EnKF is applied to the spring water inflow phenomenon in individual excavation slices, and the time T in the equation is the elapsed time in the slice, which is different from the progress of the excavation slice. As a result, the hydraulic conductivity of the new excavation slice used for future prediction remained at the initial value, and the actual excavation performance could not be reflected in the future prediction accuracy. Therefore, the initial hydraulic conductivity of each slice after slice 3 is given as the average value of the hydraulic conductivity that was set to a constant value before slice 2 to reflect the results of the already-excavated section and improve the prediction accuracy for future excavation sections.

2.3 Issues with the SDA-SWING method

In the SDA-SWING method, the amount of spring water inflow is determined according to Bear's equation. Hence, as the excavation progresses and the overburden increases, the water catchment area expands, which inevitably increases the amount of spring water inflow at the tunnel entrance. A countermeasure for this is the incorporation of a feedback mechanism for already-excavated sections using average values. However, in actual rock masses, the geological features often change in a complex manner, and it is expected that the average value alone is insufficient to reflect the changes in the geological information of the non-excavated sections. Additionally, since the data assimilation method is used, the observed values other than parameters that constitute the observation equation must be treated as noise in the model, and no feedback can be provided for other observed values.

Furthermore, the well equation is applied independently to each slice in the SDA-SWING method. As shown in Fig. 6, the groundwater level did not decrease in the non-excavated section slice ahead of the face, and as each slice accumulates in the analysis range as the excavation progresses, the water level drops for the first time from the elapsed time zero (day), resulting in a large drop in the groundwater level. However, for the actual phenomenon, the groundwater level drops in advance due to the flow in the depth direction in front of the face, and it is expected that the amount of spring water inflow will not change significantly during excavation. The only consideration for the planar direction is the one-dimensional flow in the face plane direction, which assumes Dupuit quasi-uniform flow. This prediction method contains an error due to the flow in the vertical direction

3 Overview of the DeepSWING method

To resolve the issues described in the previous section, we developed the DeepSWING method, which includes two improvements to the SDA-SWING method. This section provides an overview of these improvements.

3.1 Improvement (1): Extension of flow dimensions

Generally, a two-dimensional seepage flow analysis must be conducted to consider the vertical water flow in the flat well problem. However, Nishigaki et al. proposed a simplified equation (hereinafter referred to as the “Nishigaki’s equation”) for flow rate and catchment area under steady flow conditions, based on Bear's equation and modified to consider water flow in both horizontal and vertical directions. When this equation was incorporated into Bear’s equation, Eqs (2) and (3) were modified as follows:

$$R_{(t)} = 1.22\left[\left(\frac{k}{\varepsilon}\right)^{\frac{1}{2}} - 1\right] H_0 \left[1 - \left(\frac{h_0}{H_0}\right)^2\right] \cdot \alpha_{(t)} \quad (8)$$

$$q_{(t)} = 0.72 {H_0}^{-1} k\left({H_0}^2 - {h_0}^2\right)\left(\frac{k}{\varepsilon}\right)/\alpha_{(t)} \quad (9)$$

$$\alpha_{(t)} = \left[\left\{1 - e^{-\frac{6\varepsilon t}{\lambda e(H_0 - h_0)}}\right\}\right]^{\frac{1}{2}} \quad (10)$$

Additionally, to consider the flow in the depth direction, it was assumed that the water level drop range in front of the face was the same as that in the plane direction of the face, as shown in Figs. 6 and 7. The groundwater level in the non-excavated section within the groundwater level drop range at time *t* and distance *y* (m) in the longitudinal direction of the tunnel from the unit slice volume during excavation is expressed by Eq. (11) from Bear’s equation.

$$h_{0y} = \sqrt{\frac{y}{R_{(t)}}\left({H_0}^2 - {h_0}^2\right) + {h_0}^2} \quad (11)$$

Then, Eq. (11) is used to obtain Eq. (12), which is the amount of spring water inflow per unit time/length in the unit slice volume in front of the face.

$$q_{(t)} = \frac{0.72 {H_0}^{-1} k\left({H_0}^2 - {h_{0y}}^2\right)\left(\frac{k}{\varepsilon}\right)^{-0.35}}{\left[1 - e^{-\frac{6\varepsilon}{\lambda e(H_0 - h_{0y})}}\right]^{\frac{1}{2}}} \quad (12)$$

Here, *q(t)* varies with the distance *y* from the tunnel face. Therefore, as shown in Fig. 6, *q(t)* is calculated for the slice of the water level drop section in front of the face, and the total amount of spring water inflow *Q* is obtained by adding the slices. Consequently, unlike the conventional SDA-SWING method, the groundwater level in the unit slice volume that is newly analyzed

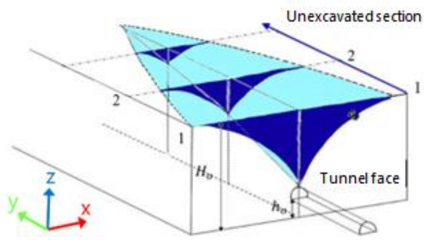


Fig.6 Water level drops in front of tunnel face

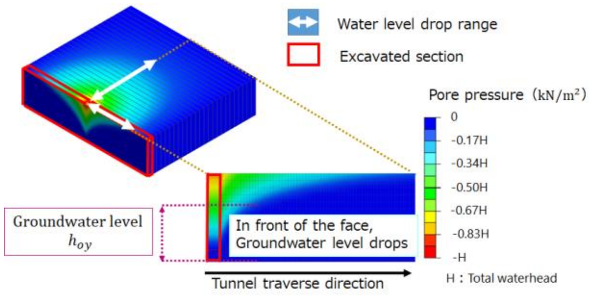


Fig.7 Range of groundwater level in DeepSWING method

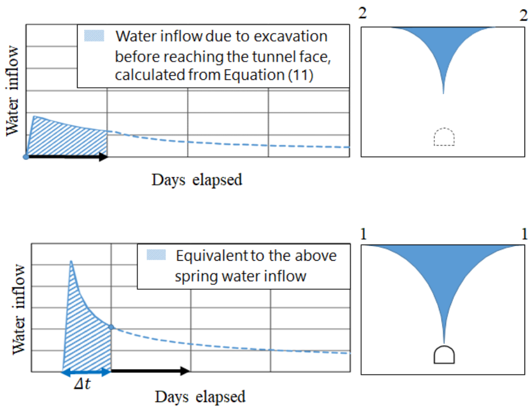


Fig.8 Changes in water inflow and groundwater levels caused by tunnel excavation

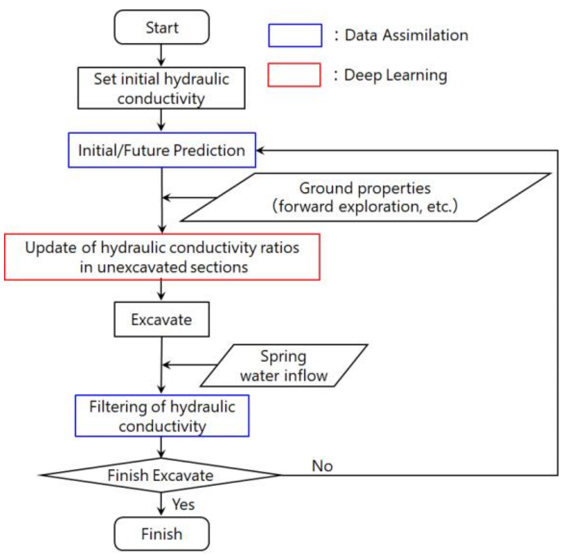


Fig.9 Processing flow of DeepSWING method

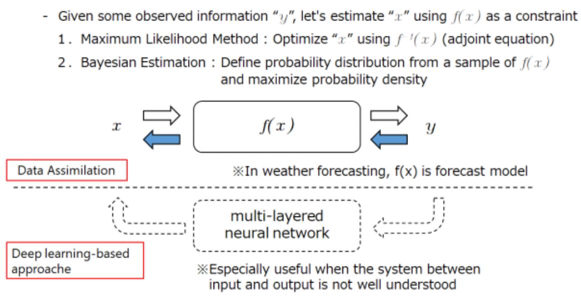


Fig.10　Difference between data assimilation and deep learning[10)]

as the excavation progresses has already decreased due to the prior excavation. Specifically, as shown in Fig. 8, the elapsed time ⊿t which is equivalent to the advance amount of spring water inflow is calculated, and when the face is reached, the spring water inflow amount is obtained with $q(t+⊿t)$ as the start time. This makes it possible to calculate the spring water inflow rate considering the three-dimensional flow in a simulated manner.

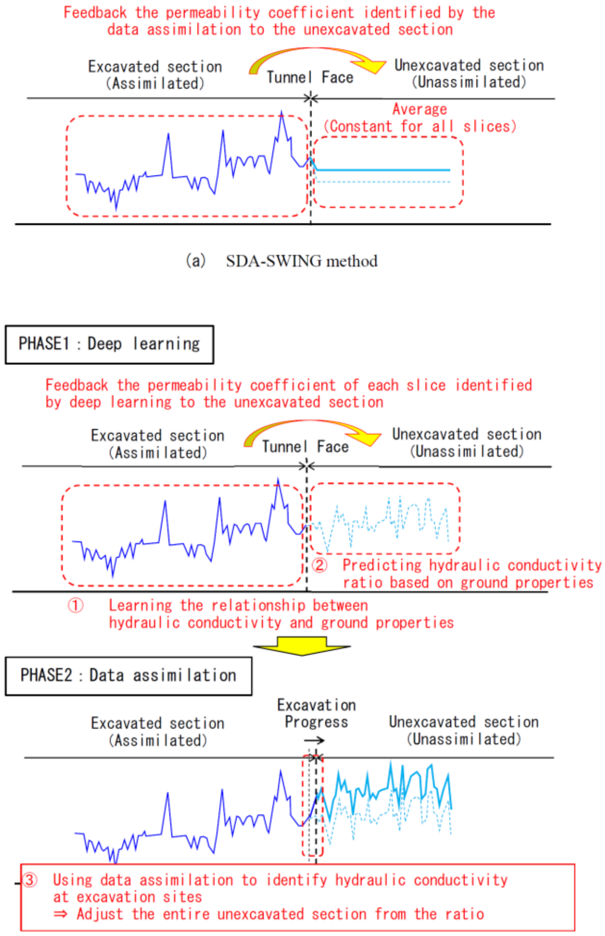
3.2 Improvement (2): Introduction of deep learning

Deep learning was introduced as a method for predicting the hydraulic conductivity of a non-excavated section based on actual data from an already-excavated section. Fig. 9 shows the overall calculation flow. The DeepSWING method is implemented by inserting deep learning processing into data assimilation processing.

As shown in Fig. 10, in normal deep learning, the relationship between the observation vector given in advance and the state vector associated with it is used as training data. The observation vector for any arbitrary state vector is calculated by internal processing called a neural network, enabling prediction. Therefore, neural networks in deep learning play the role of the observation and state equations in data assimilation. Hence, if there is enough training data for parameters and samples, data assimilation is unnecessary, and the solution can be obtained directly by deep learning.

Additionally, in data assimilation, all explanatory variables (i.e., rock mass features) other than the parameters that constitute the observation equation were treated as noise; in contrast, with deep learning, correlations with observation vectors can be considered for all explanatory variables.

However, the observation equation is a simulation model of physical laws in nature that has been clarified through repeated trial and error by various researchers, and they have a certain degree of accuracy. If all these are discarded and deep learning is conducted using only training data, then it is expected that a massive amount



(a)　SDA-SWING method

(b)　DeepSWING method

Fig.11　Procedure for identification of hydraulic conductivity

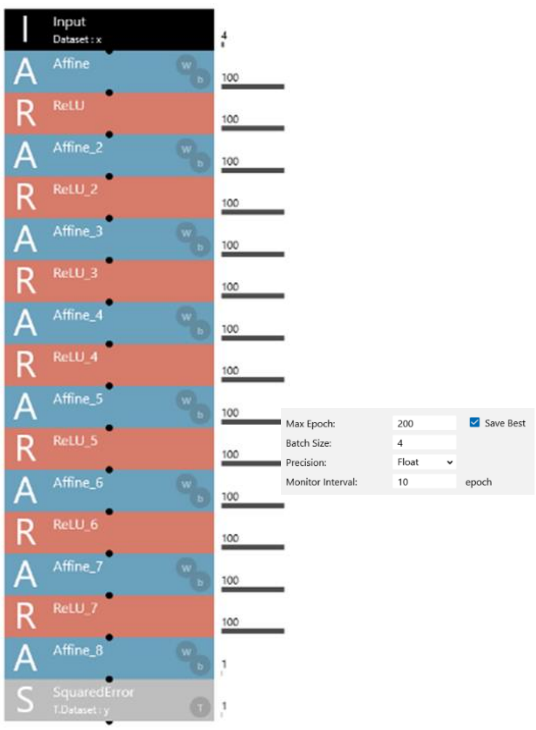


Fig.12　Deep learning configuration

of training data will be required to make accurate predictions.

Therefore, we used the following identification procedure to establish both methods.

- The rock mass is sliced in the excavation direction, and a two-dimensional well model that considers the tunnel position is created. The observation vector is set to the tunnel entrance spring water inflow amount Q, and the state vector is set to the hydraulic conductivity k.
- An explanatory variable (rock mass characteristics, etc.) is set for each slice. The objective variable is set as the hydraulic conductivity k of each slice.
- Forward and inverse analyses are used according to the data assimilation procedure to update the state vector in the excavation target slice from the observed values. Additionally, the ratio α of the hydraulic conductivity for each rock type obtained by deep learning, which will be described later, is used to update state vectors for all rock types other than the excavation target slice.
- The correlation between the objective and explanatory variables is obtained by deep learning, and the ratio α of the objective variable for each rock type in the non-excavated section is updated each time the explanatory and objective variables are updated.

Fig. 11 shows an image of the aforementioned identification procedure. The SDA-SWING method averages the identified hydraulic conductivity in the already-excavated section and feeds it back to the non-excavated section. In contrast, the DeepSWING method implements feedback to the non-excavated section by combining deep learning and data assimilation using the correlation between the identified hydraulic conductivity and various rock mass characteristics as training data, which enables a more detailed prediction of the distribution of hydraulic conductivity.

The SONY Neural Network Console was used for the implementation of the deep learning part, and as shown in Fig. 12, we adopted a multi-layer perceptron model with 100 × 7 nodes and a ReLU-type activation function.

4 Application of the DeepSWING method to actual tunnels

4.1 Overview of tunnel construction

Table 1 shows an overview of the tunnel construction, and Fig. 13 shows a geological cross-section. Most of the basement rocks in the tunnel project area are composed of Neogene Itoi Formation Kaburagi volcanic rocks, and it is primarily composed of decayed andesitic lava, which changes to tuff breccia as excavation progresses.

The boundary between the two rock types is a stream-like topography, and a river with a base discharge of 50–300 L/min flows, which is, however, with a small overburden of 50 cm. Therefore, as shown in Photo 1, we used high-density polyethylene pipes of φ 1000 during construction to divert the river and installed a protective embankment of H = 2.0 m using cement-based ground improvement soil. Additionally, due to the land acquisition, it was impossible to start construction from the tunnel entrance; hence, a separate tunnel was installed, and excavation was started from the position of TD = 110 m. Furthermore, drilling energy surveys were conducted every 30 m in front of the face using the DRISS[11] to detect unexpected fracture zones in advance. In the actual construction, the effects of the above countermeasures were demonstrated, and the rock mass was more homogeneous than expected; hence, the construction was completed without any sudden spring water inflow.

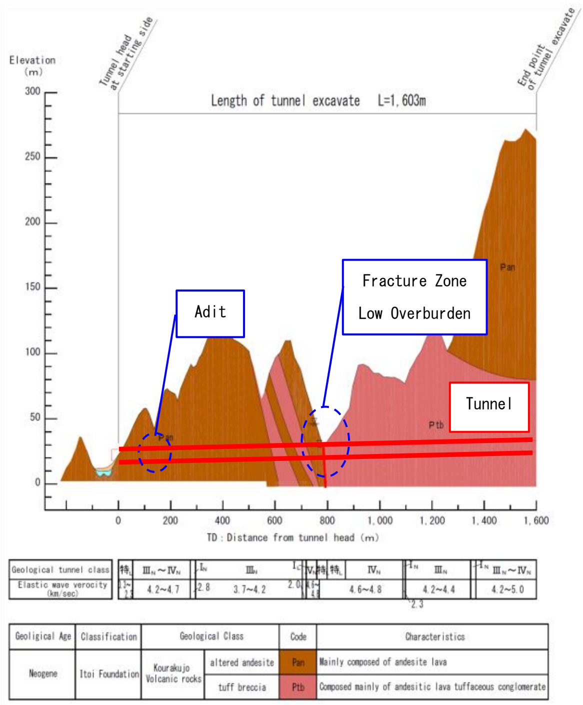


Fig.13　　Vertical section map for geology

Table 1 Tunnel construction overview

Construction name	Hokuriku Shinkansen Fukui Tunnel No. 2 Construction
Length	1.6 km
Inner cross-sectional area	75 m^2
Maximum overburden	Approx. 240 m
Support type	NATM
Excavation method	Upper half advanced bench cut method
Rock type	Tuff breccia, propylite lava

Table 2 Relationship between rock types and porosity

Lithology	Weathering extent	Porosity
Propylite	Somewhat weathered	0.1
Tuff breccia	Fresh	0.05
Fracture zone	Low compacted soil	0.6

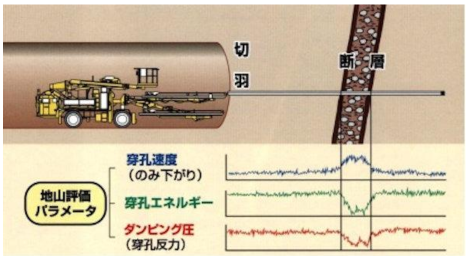


Fig.14 DRISS overview[11)]

4.2 Verification of prediction accuracy

Fig. 15 shows the explanatory variables used in the DeepSWING method. Four explanatory variables were used to correlate with the hydraulic conductivity: overburden, porosity, elastic wave velocity, and drilling energy. Of these, overburden and elastic wave velocity were set based on the survey results (topographical and seismic surveys) at the time of design, and the drilling energy was set as the value obtained by DRISS during construction. The rock mass porosity was determined as shown in Table 2, with reference to the geological profile and the literature[12)].

Fig. 16 shows the results of using the SDA-SWING and DeepSWING methods to predict the amount of spring water inflow at the tunnel entrance after TD = 700 m based on the identification results up to that point. In the SDA-SWING method, the hydraulic conductivity in the predicted section was set as a constant value using the average hydraulic conductivity of the already-excavated section; however, in the DeepSWING method, the fine changes in the hydraulic conductivity were set according to the rock mass conditions, with reference to the drilling energy value. Additionally, in the SDA-SWING method, the amount of spring water inflow at the tunnel entrance, particularly after TD = 1200 m, was overestimated as the overburden rapidly increased. This is because the amount of spring water inflow in the observation equation increased as the overburden increased. In contrast, the DeepSWING method processed the trend of the already-excavated section by deep learning to learn that the amount

(a) Completion of river diversion and protective embankment excavation

(b) Completion of installation of protective embankment

Photo 1 Tunnel protection for low ground cover area

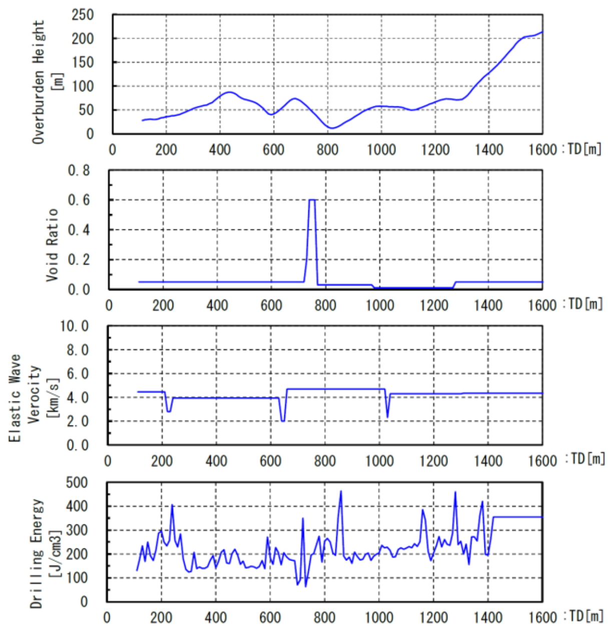


Fig.15 Explanatory variables in deep learning

of spring water inflow is constant even if overburden increases, and as a result of automatically setting the hydraulic conductivity to be small in inverse proportion to the overburden, it did not show any spring water inflow regardless of overburden, yielding a highly accurate prediction that captures the characteristics of the actual tunnel entrance spring water inflow amount. However, the hydraulic conductivity identified by the SDA-SWING and DeepSWING methods differs from the observed values obtained by in-situ permeability tests and other methods, and data assimilation includes modeling errors associated with observation equations and deep learning.

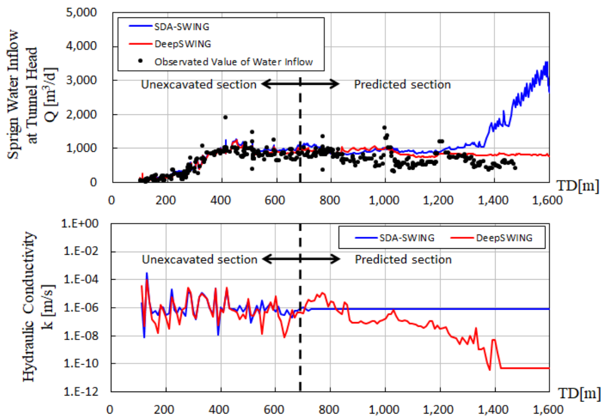


Fig.16 Analysis result for SDA-SWING/DeepSWING method

5 Conclusion

We developed the DeepSWING method to improve future prediction accuracy. The method involved two improvements to the SDA-SWING method, which is a groundwater impact assessment method for mountain tunnel construction. Additionally, we applied this method to the construction data obtained in actual tunnel construction and confirmed that the future prediction accuracy of the tunnel entrance spring water inflow amount was improved. We hope that this method will help establish groundwater information-based construction methods in mountain tunnel construction.

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