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ABSTRACT

A deep neural network (DNN) model for runoff analysis is proposed. The DNN model is developed by extending hierarchical neural network (HNN) based on the deep learning and is applied to the runoff analysis. Prediction accuracy of DNN model is then compared with that of HNN model. From the comparison results, it is found that the prediction accuracy of DNN model is higher than that of HNN model.

KEY WORDS: Runoff analysis; Neural network; Deep learning

INTRODUCTION

Runoff analysis is very important for water management and water use. Generally, it is difficult to model the relation between rainfall and discharge because of its high nonlinearity. For the representation of nonlinearity, the neural network modeling is useful. Hsu et al. (1995) applied a hierarchical neural network (HNN) model to the runoff analysis and demonstrated its applicability. Even apart from this, there have been many works on runoff analysis using HNN model (e.g., Isobe et al., 1994; Abe et al., 2000; Tsukiyama et al., 2003; Seki et al., 2013).

However, increase or addition of layers to obtain more general representation leads to vanishing gradient and overfitting. Recently, deep learning methods (LeCun et al., 2015) are proposed. In this study, a deep neural network (DNN) model, which is an extended HNN based on the deep learning, is applied to the runoff analysis and is validated its effectiveness.

HNN AND DNN

The neural network is a nonlinear mathematical model which imitates biological nervous systems. A representative neural network model is HNN model, which is a three-layer feed forward neural network model consisting of input, hidden and output layers as shown in Fig. 1. In the HNN model, the output in *j*-th layer is described as follows.

$$f(u_j) = \frac{1}{1+\exp(-u_j)} \tag{1}$$

$$u_j = \sum_{i=1}^{n} w_{ij} x_i - \theta_j \tag{2}$$

where $f(u_j)$ is output value in *j*-th layer, x_i is input in *j*-th layer, w_{ij} is weight coefficient, θ is threshold value, n is the number of unit in *i*-th layer. The training procedure is used the back propagation error algorithm (Rumelhart et al., 1986).

DNN model is a HNN model which has more than two hidden layers. In order to avoid the gradient vanishing, the layer-wise pre-training is employed (Bengio, 2006). For the problem of overfitting, the number of training run is limited based on the early-stopping technique (Kamishima et al., 2015).

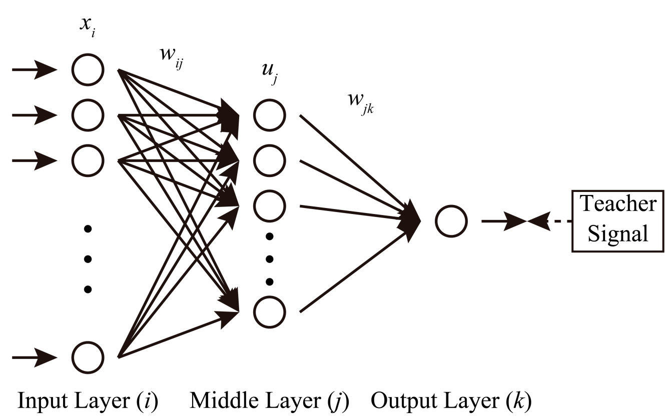

Fig. 1 HNN model

STUDY AREA

The target area in this study is Shigenobu River basin, Ehime prefecture, Japan as shown in Fig. 2. Shigenobu River is 36 km length and flows into Seto Inland Sea. The basin area is 445 km^2 and 70% of the basin is covered by forest. The alluvial fan, Dogo Plain, is formed in the downstream basin. The average annual rainfall in the plain is approximately 1,300 mm year^{-1}, which is less than that of Japan (1,700 mm year^{-1}).

The daily discharge and rainfall are observed at the observatory of Deai (N33° 48' 21'', E132° 43' 31'') and Matsuyama (N33° 49' 18'', E132° 44' 22''), respectively. Those data can be obtained from Water Information System (Ministry of Land, Infrastructure, Transport and Tourism).

APPLICATION OF DNN

A DNN model, which consists of one input layer, two middle layers, and one output layer and outputs daily discharge from daily rainfall as input, is developed as shown in Fig. 3. The daily discharge data is used as the teacher signal. Generally, daily discharge depends on daily rainfall before several days. Thus, daily rainfall before 10 days is used as input data based on the hyeto and hydro graph at the observatory of Matsuyama and Deai. While the number of units in two middle layers can be arbitrary determined, it is beyond the purpose of this study. Thus the number of units in two middle layers are set as seven and five in this study.

In order to validate effectiveness of DNN model developed, the calibration and verification results are compared with those of HNN model. The training (calibration) period is set from 2001 to 2005, and prediction (verification) period is from 2006 to 2010 in this study. Parameters used in the learning is summarized in Table 1.

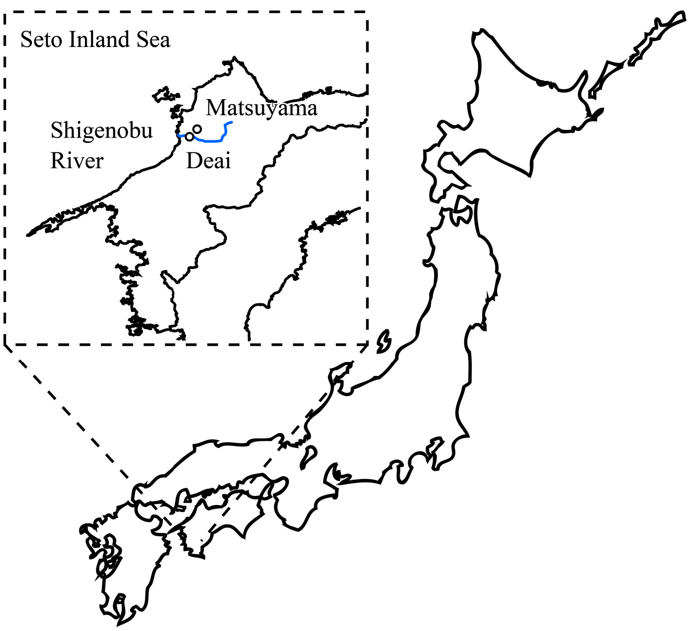

Fig. 2 Study area

APPLICATION RESULTS

In order to compare the calibration and verification results of DNN model with those of HNN model, the root mean square errors (RMSE) are firstly summarized in Table 2.

From Table 2, it is found that accuracy of DNN model are higher than that of HNN model by 20% to 45% and 10% to 35% in the calibration and verification, respectively.

Next, the scatter diagrams for the calibration result of both DNN and HNN model are shown in Figs. 4 and 5 in order to investigate the reproducibility of the models in detail.

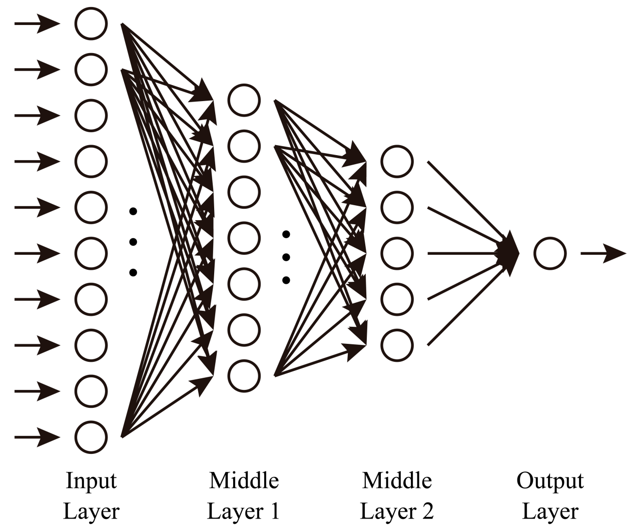

Fig. 3 DNN model

Table 1 Parameters used in the present study

Item	Value
Number of data sets	1,816
Learning rate	0.75
Decay factor	0.80
Number of learning runs	50,000

Table 2 RMSE in DNN and HNN model

		DNN	HNN
Calibration results	2001	7.70	14.04
	2002	5.25	8.30
	2003	9.99	12.44
	2004	8.54	13.70
	2005	4.88	5.44
Verification results	2006	32.33	48.67
	2007	29.46	32.77
	2008	11.68	17.93
	2009	20.04	26.74
	2010	19.83	25.87

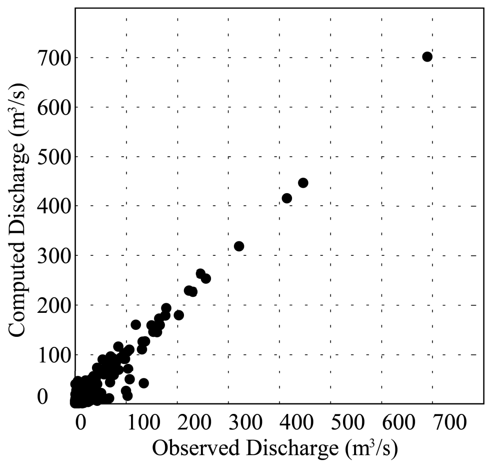

Fig. 4 Scatter diagram for calibration result of DNN model

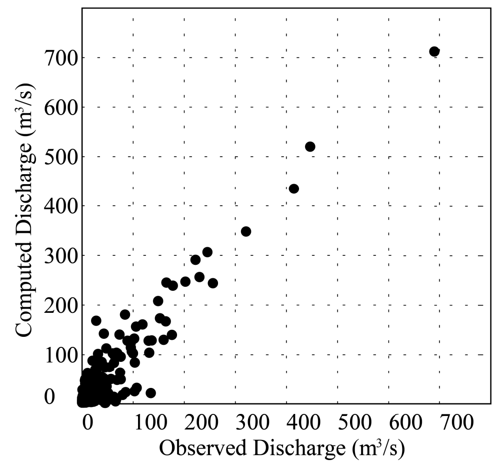

Fig. 5 Scatter diagram for calibration result of HNN model

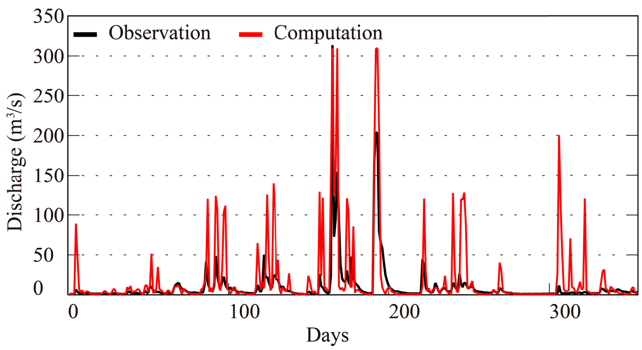

Fig. 6 Verification result for 2006 by DNN model

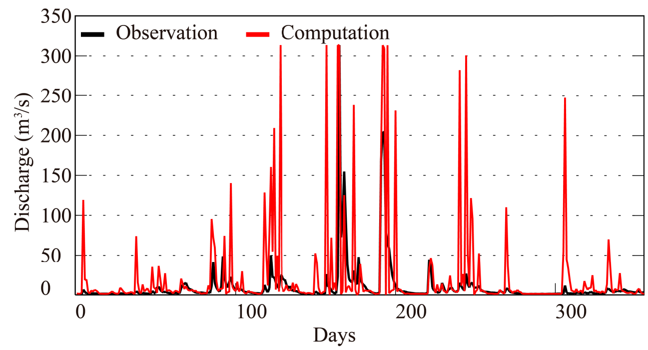

Fig. 7 Verification result for 2006 by HNN model

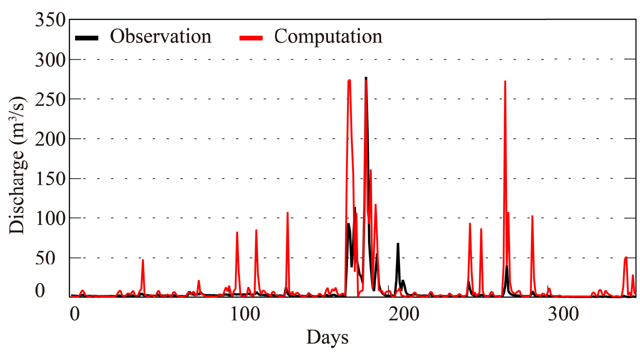

Fig. 8 Verification result for 2007 by DNN model

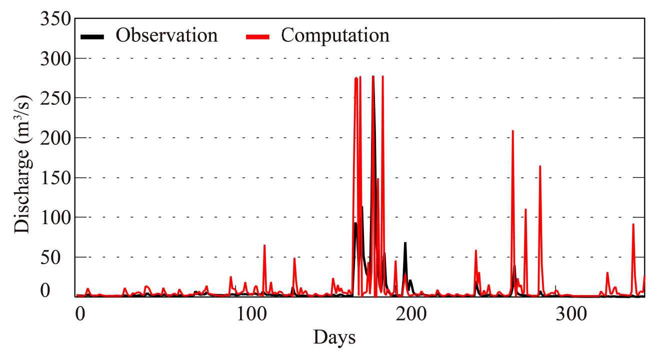

Fig. 9 Verification result for 2007 by HNN model

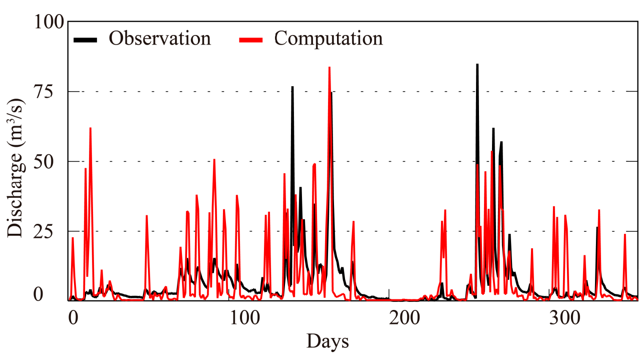

Fig. 10 Verification result for 2008 by DNN model

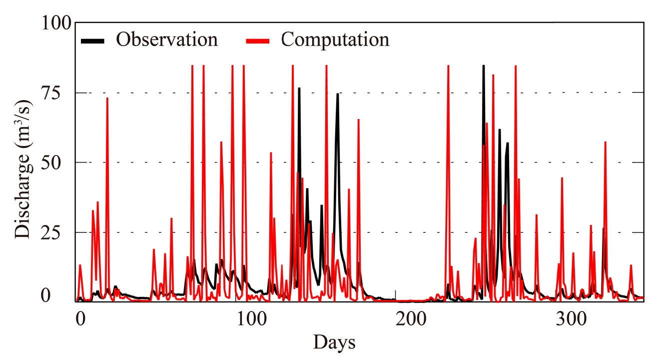

Fig. 11 Verification result for 2008 by HNN model

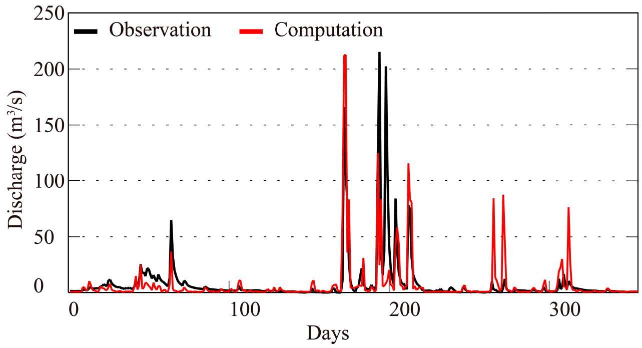

Fig. 12 Verification result for 2009 by DNN model

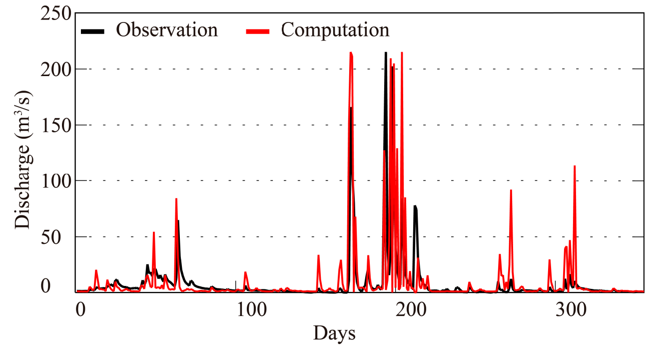

Fig. 13 Verification result for 2009 by HNN mode

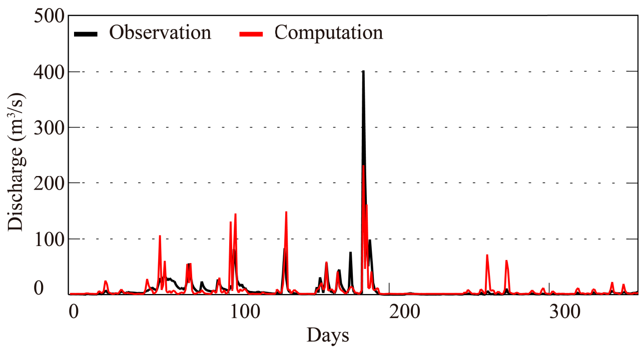

Fig. 14 Verification result for 2010 by DNN model

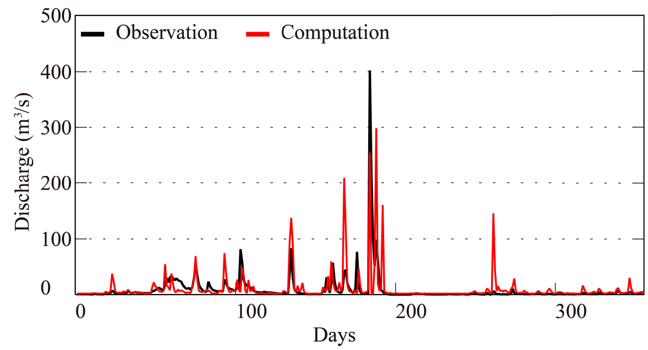

Fig. 15 Verification result for 2010 by HNN mode

From Figs. 4 and 5, it is found that both DNN and HNN model can reproduce the large discharge with high accuracy while it is difficult to reproduce the low-water discharge. The difference in the model accuracy is the reproducibility of the low-water discharge.

Finally, the verification results of both DNN and HNN model are shown through Figs. 6 to 15.

From Figs. 6 to 15, it is found that the reproducibility of peak discharge is improved by using DNN model.

CONCLUSIONS

A DNN model is applied to runoff analysis and is compared prediction accuracy with that of HNN model. From the results, it is found that the DNN model could reproduce the observed discharge with higher accuracy than HNN model.

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