



Rainfall estimation and real-time reservoir operation with neural network and fuzzy inference

T. Kojiri, K. Ito & S. Sakakima

*Department of Civil Engineering, Gifu University,
1-1 Yanagido, Gifu, Japan*

Abstract

The aim of this study is to propose the real-time decision support system of storage reservoir introducing the advanced artificial intelligent methodologies of the neural network and the fuzzy theory.

1 Introduction

Typhoon have historically caused heavy rainfall and serious disasters in Japan and Southeast Asian countries. Though more meteorological data on typhoon has been collected through modern technologies of air observation, satellite, weather radar and other monitoring systems, the disaster damage was not reduced. One reason is that the prediction of typhoon movement is too difficult because of the complexity of meteorological conditions. Another reason is that flood control system is not sufficient for disaster prevention because of it's uncompleted construction and inefficient management. So, we want to establish the real-time prediction and control system of typhoon course and hyetograph with neural network. Then the release will be decided through neural run-off model and release decision model.

2 TYPHOON FORECAST

The considered typhoon course is defined in the area from 120° to 145° east longitude and from 20° to 40° north latitude, and expressed through two-dimensional space whose elements consist of 1×1 mesh. The simple

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perceptron model [4] with one hidden layer is applied. The number of input and hidden layer elements are changeable to four stages according to the position of present typhoon; namely, the first stage has 45 units from 20° N to 25° N, the second one has 60 units from 20° to 30° N, the third one has 75 units from 20° to 35° N and the fourth one has 90 units from 20° to 40° N. The number of output elements is equal to the representative typhoon courses and the output denotes the similarity of the present typhoon to the representative one. The typhoon course is predicted through the following fuzzy inference concept [5];

$$tp(t+t') = \frac{\sum \{ftyp(bi) rety(bi, t+t')\}}{\sum ftyp(bi)} \quad (1)$$

where, $ftyp(bi)$ is the similarity of representative typhoon bi , $rety(bi, t+t')$ is the typhoon position at time $t+t'$ and t is the present time. On the other hand, the physical relation of velocity and atmosphere pressure without friction is formulated as follows [1];

$$\delta u(t) / \delta t = -\delta p(t) / \delta x / \rho + 2\omega \sin(nl(t)) v(t) \quad (2)$$

$$\delta v(t) / \delta t = -\delta p(t) / \delta y / \rho + 2\omega \sin(nl(t)) u(t) \quad (3)$$

where, ρ is the atmosphere density, $u(t)$ is the velocity to east, $v(t)$ is the velocity to north, $p(t)$ is the atmosphere pressure, ω is the angular velocity of earth and $nl(t)$ is the typhoon position on north latitude. Combining two predicted results of neural network and physical model, we infer the typhoon position in future as follows;

$$prety(t+t') = \{tp(t+t') + R(t') enl(t+t')\} / (1 + R(t')) \quad (4)$$

$$R(t') = 0.8^{t'-1} \quad (5)$$

where, $R(t')$ is the weighting function against the physical model and $enl(.)$ means the two-dimensional typhoon position. The rainfall amount is also inferred through the similarities of representative typhoons and hyetographs. The fuzzy membership functions of hyetograph is defined as follows;

$$fms(bi, t1) = \{-dis(bi, t1) + AH\} / AH \quad (6)$$

$$dis(bi, t1) = \min_{t1} \max_t \{ rhye(t) - ohye(bi, t1) \}. \quad (7)$$

Here, $rhye(t)$ is the present hyetograph, $ohye(bi, t1)$ is the representative hyetograph of typhoon bi and AH is the parameter. To consider the extraordinary storm, the representative hyetograph is modified into the following one;

$$ohye'(bi, t1) = \{1 + (sign) dis(bi)\} ohye(bi, t1). \quad (8)$$

Here, $(sign)$ denotes the sign of $(rhye(t) - ohye(bi, t1))$. As the fidelity of hyetograph is represented as multiplication of similarity of typhoon by hyetograph, the future hyetograph is predicted through the fuzzy inference with height method as,

$$prehye(t+t') = \frac{\sum \{ ftyp(bi) fms(bi) ohye'(bi, t+t') \}}{\sum ftyp(bi) fms(bi)}. \quad (9)$$

2 RAINFALL AND RUN-OFF PREDICTION

Regarding to the rainfall echoes, in other words, the intensities of rainfall cells as the two-dimensional feature image, we introduce the optical flow technique [2]. The movement of image is decided by minimizing the changing volume of image through the following equations;

$$\left\{ \frac{\delta^2 vx(t)}{\delta x^2} + \frac{\delta^2 vx(t)}{\delta y^2} \right\} + \left\{ \frac{\delta^2 vy(t)}{\delta y^2} + \frac{\delta^2 vy(t)}{\delta y^2} \right\} \rightarrow \min \quad (10)$$

subjected to

$$\frac{\delta f}{\delta x} vx(t) + \frac{\delta f}{\delta y} vy(t) + \frac{\delta f}{\delta t} = 0 \quad (11)$$

Here, $vx(t)$ and $vy(t)$ are the decision variables in this non-linear optimization problem. The identified variables $vx(t)$ and $vy(t)$ are shifted forward to time $t+1$. The updated velocities and the new location of rainfall echoes are predicted. As this predicted feature image seems to include the updated rainfall characteristics, the predicted hyetograph can be modified again. Assuming that the prediction accuracy of rainfall radar is equal to the ratio of considered area to image area, we infer the newly predicted hyetograph

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among typhoon and rainfall predictions as follows;

$$prehye'(t+t2) = \frac{fms'prehye(t+t2)delsrd(t+t2)}{fms'+dels} \quad (12)$$

where, fms' is the fidelity of typhoon expressed with $fms(bi)$, $dels$ is the assumed predicted accuracy of rainfall radar, $rd(t+t2)$ is the predicted rainfall through the optical flow of equation (10) in weather radar. The storage function model on run-off process [3] is introduced and formulated as follows;

$$\frac{SB(t) - SB(t-1)}{dt} = fa RA(t) - q(t) \quad (13)$$

$$SB(t) = Kq(t)^P. \quad (14)$$

Here, $SB(t)$ is the conceptual storage volume depth with run-off time lag in the basin, fa is the run-off coefficient, $RA(t)$ is the averaged rainfall depth in the basin from time $t-1$ to t , $q(t)$ is the run-off discharge depth with time lag, and K and P are parameters. If the storage volume depth is calculated at time t and the rainfall at time $t+1$ is predicted, the storage volume and the discharge at time $t+1$ are estimated. To identify the optimal values of K and P , the neural network is structured as shown in Figure 1, where the input layer consists of three units; namely the constant value ($=1$), the discharge and the difference between predicted discharge and observed one, and the hidden layer has two units. As the teacher's signal for output is the storage volume depth at time t and the response function is given as 10^x , the back

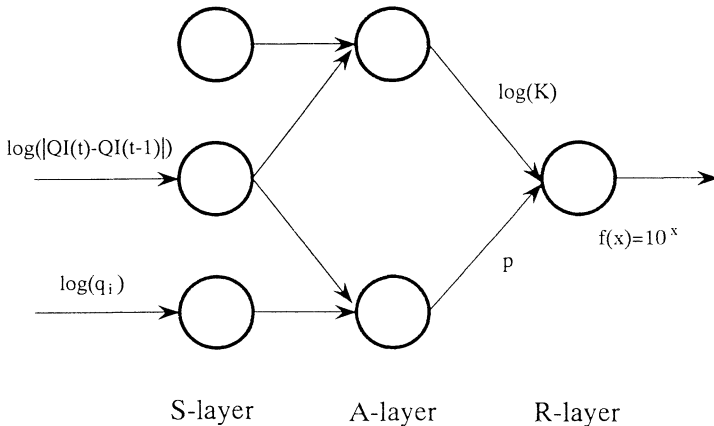


Figure 1: Neural network modeling of run-off process



propagation algorithm is carried on and the optimal storage volume depth is obtained at every time.

3 RESERVOIR OPERATION

Operator can control the dam gate against flood by considering the predicted hydrograph and the predicted reservoir state. The reservoir operation system is managed by using three neural networks as follows;
Sub-network I, Typhoon position

Elements of nine input units denotes the present position of typhoon, six hour ahead position and twelve hour ahead position which expresses three different levels. With nine hidden units, three output units meaning that typhoon is (i) approaching, (ii) passing and (iii) gone are structured.

Sub-network II, Inflow feature

The neural network on inflow feature consists of seven input units depending on the predicted deviation from the present time to six hour ahead, seven hidden units and three output units representing the inflow features; namely the increase, the decrease and the peak.
Sub-network III, Reservoir state

Input layer on reservoir state has five units according to the storage level and output layer has three units representing the logical level of changing release. The teacher's signal is modified through the information on typhoon position or hydrograph feature; namely smaller, medium and bigger. We set the following four cases to decide the teacher's signal.

(i) When the typhoon is approaching to Japan and the hydrograph is not steady, the release is calculated with the optimization approach of the dynamic programming.

(ii) When the typhoon is nearly located to Japan and the inflow shows the peak, the release is equal to the minimum volume for predicted hydrograph.

(iii) When the typhoon is gone and the discharge is decreasing, the release is derived from the volume of previous time.

(iv) Otherwise, the release is decided to be equal to the inflow. For each case, the tuning volume of teacher's signal is assumed from the range of 0.8 to 1.2. These processes of modification is executed at every time iteratively.

4 APPLICATION OF PROPOSED METHODOLOGIES

The basic information of considered basin and reservoir are listed below;

<i>Basin area</i>	: 471 km ²
<i>Flood control capacity of reservoir</i>	: 11,000,000 m ³
<i>Design high water</i>	: 1,400 m ³ /sec

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As we have only seven historical typhoons, all of data were regarded as the representative ones. Figure 2 shows the comparison of predicted typhoon courses with and without weather map. The circle means the present position of the considered typhoon. The former predicted result expresses the higher accuracy because of introduction of physical process on typhoon movement.

Figure 3 shows the predicted hyetographs and hydrograph. The predicted hyetograph with radar information is modified to be smaller than that without radar. In this case, the historical typhoons seem to have bigger hyetograph. In the same figure, the predicted hydrograph is expressed with circle and bigger than the observed one. The identified run-off parameters K and P were unsteady. It is the reason that the neural network for K and P does not include the time hysteresis of input units for rainfall sequence. If the better parameters would be identified, the better discharge would be predicted. Figure 4 shows the operational results of storage reservoir. The initial storage was set as empty. As the neural network for typhoon position announced the typhoon approach at 16-th time stage, the release was changed from the increasing type of storage to constant type of storage. At 38-th time stage, the release of $482.9 \text{ m}^3/\text{sec}$ for flood control was taken through the dynamic programming because of prediction of bigger inflow. Then, from

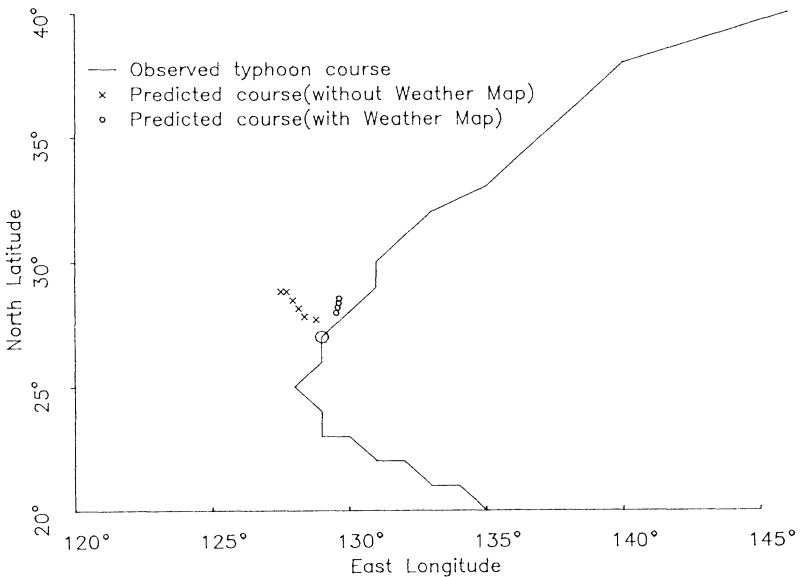


Figure 2: Comparison of predicted typhoon courses with and without weather map



47-th to 51-th time stage, the neural network estimated that the peak discharge would come within these six hours and the release of $700.0 \text{ m}^3/\text{sec}$ was taken for flood control with peak cut strategy.

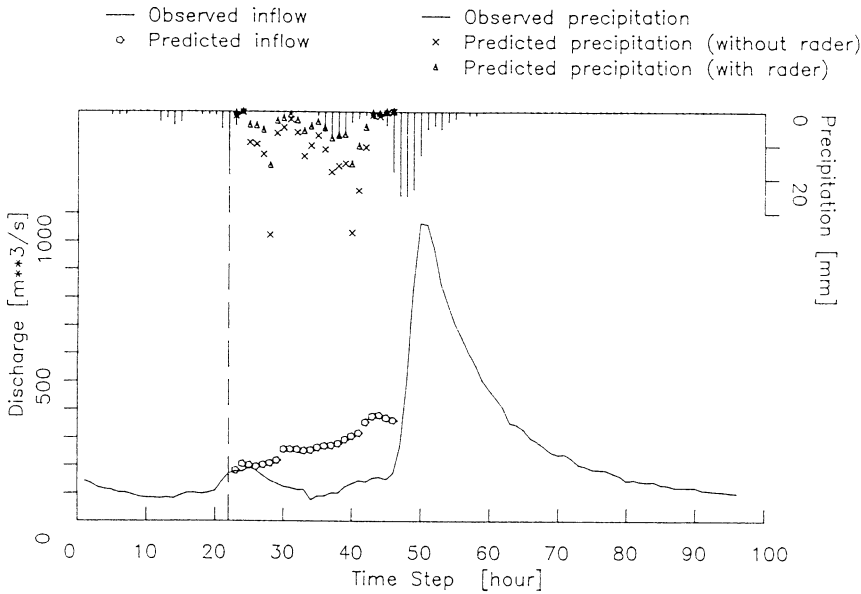


Figure 3 :Predicted results of precipitation and discharge

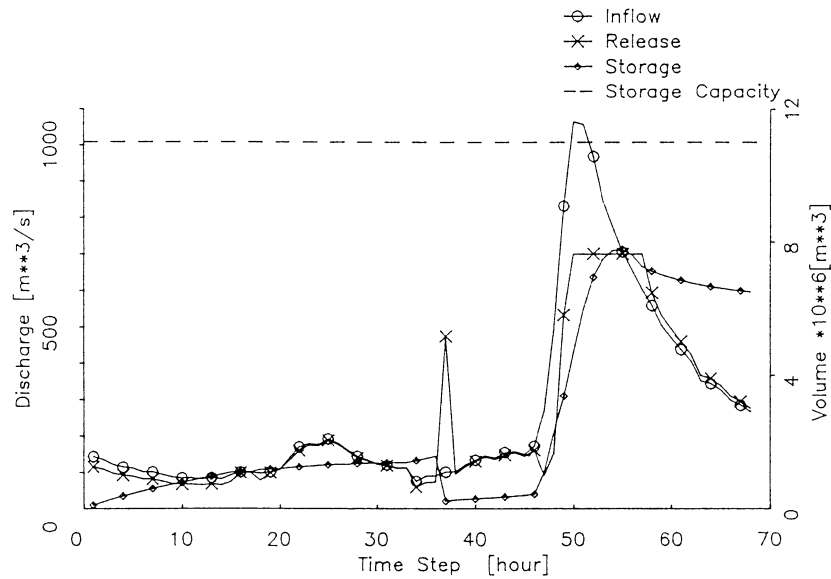


Figure 4 :Control results of reservoir operation



5 CONCLUSIONS

We have discussed the rainfall and run-off prediction and the real-time reservoir operation by using the neural network for calculation time and control accuracy. Those availability was verified through the application on real reservoir. To sum up, the following results were obtained;

i) Typhoon course were predicted through the neural network which worked in the designed analyzing space. Combining the physical process of typhoon movement whose information was gained from the weather map and the predicted course, we inferred the modified typhoon course through fuzzy theory.

ii) Hyetograph was also inferred among the predicted typhoon courses through the fuzzy theory. To introduce the other meteorological information, the rainfall echoes of weather radar was analyzed and the rainfall intensity was predicted with the optical flow concept. Then the hyetograph was modified with the both predicted results.

iii) Hydrograph was calculated while the parameters of run-off model were identified with neural network. The predicted accuracy of discharge was not sufficient in this application. If we set more input units for discharge, we will get more better results considering the non-linearity of run-off process.

iv) Reservoir operation was performed by handling the output information of our previous systems. Depending on the combination of such information, we could decide the release as three levels; namely the inflow level, the optimized level and the design flood level. The tuning operation with neural network was executed to decide the optimal solution of release by considering all of flood information.

REFERENCES

1. Ganpo, K. *Updated Numerical Forecast*, Chijin Publishing Company, 1981, pp.10-11.
2. Hunahisa, Y. *Pattern Recognition*, Kyoritu Publishing Company, 1991, pp.136-139.
3. Kojiri, T., Ikebuchi, S. and Yamada H. Basinwide flood control system by combining prediction and reservoir operation, *Stochastic Hydrology and Hydraulics*, 3, 1989, pp.31-49.
4. Rosenblatt, F. The perceptron : A probabilistic model for information storage and organization in the brain, *Psychol., Rev.*, 65 [6], 1958, pp.3-54.
5. Sugeno, M. *Fuzzy Control*, Nikkan Kogyo Newspaper Co., LTD, 1988, pp.67-109.