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Dam operation support system utilizing Artificial Intelligence (AI)

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ABSTRACT: In Japan, droughts and flood damages caused by abnormal heavy rain have occurred frequently due to the influence of climate change, so flexible operation that maximizes the function of the existing dam is required. With the change of social situation, efficient dam operation by only a few operators is required. On the other hand, in recent years, with the improvement of the processing capacity of computers, the utilization of artificial intelligence (AI) is becoming widespread. By recreating the dam operation made by using human intelligence by computer, it is expected to improve efficiency and speed up process judgment. Here, in order to realize the advanced flood routing in dams by only a few operators, we studied the dam operation support system utilizing artificial intelligence (AI).

RÉSUMÉ: Au Japon, sécheresses et inondations causées par des pluies anormalement abondantes sont de plus en plus fréquentes en raison de l'influence du changement climatique. Il est par conséquent indispensable de pouvoir opérer de façon flexible en exploitant au maximum les fonctions des barrages existants. La baisse des naissances, le vieillissement de la population et la réduction des dépenses de travaux publics ont par ailleurs conduit à une diminution du nombre de dirigeants expérimentés et de cadres.D'un autre côté, les progrès réalisés ces dernières années au niveau de la capacité de traitement des ordinateurs ont contribué à l'extension de l'utilisation de l'intelligence artificielle (IA).En reproduisant de manière numérique les opérations auparavant effectuées par l'intelligence humaine, il devrait être possible d'améliorer l'efficacité des tâches et d'accélérer la prise de décision.Afin de permettre à un nombre réduit d'opérateurs de procéder à une gestion performante des inondations, nous avons réalisé des recherches sur les systèmes d'aide à l'exploitation des barrages basés sur l'intelligence artificielle.

1 OUTLINE OF TARGET BASIN AND DAM OPERATIONS

1.1 *Kitakami river basin and characteristics of floods*

The target Kitakami River has a shape of "bird's wing" with its branches flowing to the east and west from the main river as the center (Figure 1). The basin area of the river is about 10,150 km^2 (4th largest in Japan), and the length of mainstream is about 249 km (5th longest in Japan). Mediumsized cities, such as Morioka City and Ishinomaki City, lie around the river. The population in the basin stands at about 1.48 million, and the asset value in the estimated flooded area is about 9.36 trillion yen. The area around Kozenji Temple in Ichinoseki is prone to flooding since the river becomes narrower downstream.

Moreover, the gradient of the river from the narrow part to the river mouth suddenly becomes gentle, which blocks the flow of water downstream. For this reason, the water overflows at the narrow part and its upstream, resulting in flooding damages. Another feature of the basin is the heavy snowfall, which also causes flooding in spring when the snow melts.

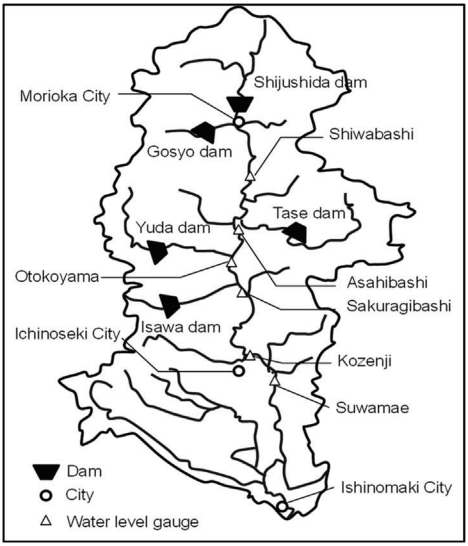

Figure 1. Kitakami river basin map.

2 FLOOD CONTROL MEASURES AND 5 DAMS

In the Kitakami River flood control plan, water control is made using levees, dam reservoirs, and anti-flood ponds to reduce the damage caused by flooding. Specifically, it is assumed that 13,000 m^3/s of water flows down at Kozenji Temple if there are no dams and anti-flood ponds, of which the plan aims to adjust 4,500 m^3/s (March 1973 plan) with dams and anti-flood ponds. Based on this scheme, five dams were built at Kitakami River, namely Ishibuchi Dam in 1953, followed by the sequential completion of Tase Dam, Yuda Dam, and Shijusida Dam, then Gosyo Dam in 1981.

Shijushida Dam was built based on the plan of 1953. After that, Isawa Dam was completed as the redevelopment of Ishibuchi Dam (March 2014) (Table 1).

Table 1. Dam data.

Dam name	Shijushida	Gosyo	Tase	Yuda	Isawa
Date of construction	1968	1981	1954	1964	2013
Basic area [km^2]	1,196	635	740	583	185
Total storage capacity [10^3 m^3]	47,100	65,000	146,500	114,160	143,000
Planned flood flow rate [m^3/s]	1,350	2,450	2,700	2,200	2,250
Discharge Method	Fixed rate fixed volume	Fixed rate fixed volume	Fixed volume	Fixed volume	Natural adjustment

3 PROBLEMS WITH DAM OPERATIONS

On August 9, 2013, a flood volume exceeding the planned inflow flowed into Gosyo Dam, seriously affecting the appropriate operations of the dam. The characteristics of the flood included an hourly rainfall exceeding 100 mm at the Harukiba Observatory and the hourly rainfall of 40 mm or more continuing for five hours, causing concentrated heavy rain in a short time. As a result, in about eight hours from the start of the rain, the peak flow rate reached 3,733 m^3/s, exceeding the planned inflow of 2,450 m^3/s significantly. In addition,

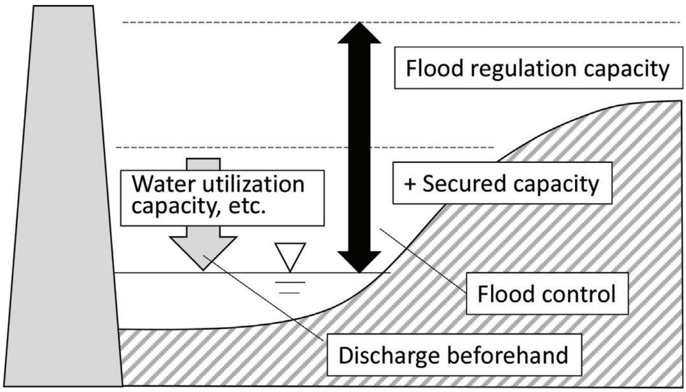

Figure 2. Example of flexible operations.

flood damage caused by abnormal torrential rains is frequent due to the influence of climate change, such as the second largest flood recorded at Tase Dam in August 2016.

At some of the five dams, operations to discharge some of the water for utilization before the start of a flood for flood control is performed to prevent fatal flood damage. Even in Japan, flexible operation that utilizes such dam functions are sought (Figure 2). But since these operations rely on the technical skills and judgment power of dam operators, they are rarely used.

4 OUTLINE OF DAM OPERATION SUPPORT MODEL IN THIS STUDY

In this study, learning data is created based on the data used for dam operations and the actual data of the dam outflow. Based on the learning data, a model capable of predicting the dam outflow is constructed using the neural network (Hiromasa 2016). The accuracy of the model that has already been constructed based on the flood in May 2018 will be examined. For shallow type neural network models, we decided to learn from actual data. With the model, actual condition and prediction factor data are input to evaluate the dam outflow, which is the output value.

5 ANALYSIS USING NEURAL NETWORK MODELS

5.1 *Calculation conditions*

5.1.1 *Learning data*

The learning data used in this study was based on the factor data obtained in real time used by dam operators to judge dam outflow and the outflow three hours after the current time, which is the result of judgment. Learning data used is the one hour pitch data between 2013 to 2017 including flooding in August 2013. Since Isawa Dam is a perforated dam, called natural adjustment dam, gate operation cannot be used. Thus learning and prediction are not performed.

Factor data included "dam inflow" between 12 hours before and present, "dam water level," "dam outflow," "water level of dam downstream," "current flooding period (flood period, non-flood period)," and "predicted inflow" between present and 24 hours ahead. In the actual dam operation, the prediction results of the flood prediction system is used as the judgment material of dam operations. Since the data on past predicted inflow is not accumulated, the actual inflow in the future is replaced as predicted inflow. To enable real time operations, it is assumed that some of learning data includes actual missing data due to power outage and failure of the water level meter.

5.1.2 *Learning method*
The learning method for the conventional artificial neural network models (ANN) adopted was a general neural network model. To correct the weighting of the hierarchical neural network (backpropagation), the sigmoid function was adopted to avoid over reaction. The number of intermediate neuron layers was decided to be 10, and the number of learning was set at 10,000.

5.2 *Calculation Results*

5.2.1 *ANN*
We predicted the outflow of the dam up to 3 hours at 3 hour pitch by the learning model (Figure 3), sorted out the mean error (Table 2) and correlation coefficient (Table 3). The

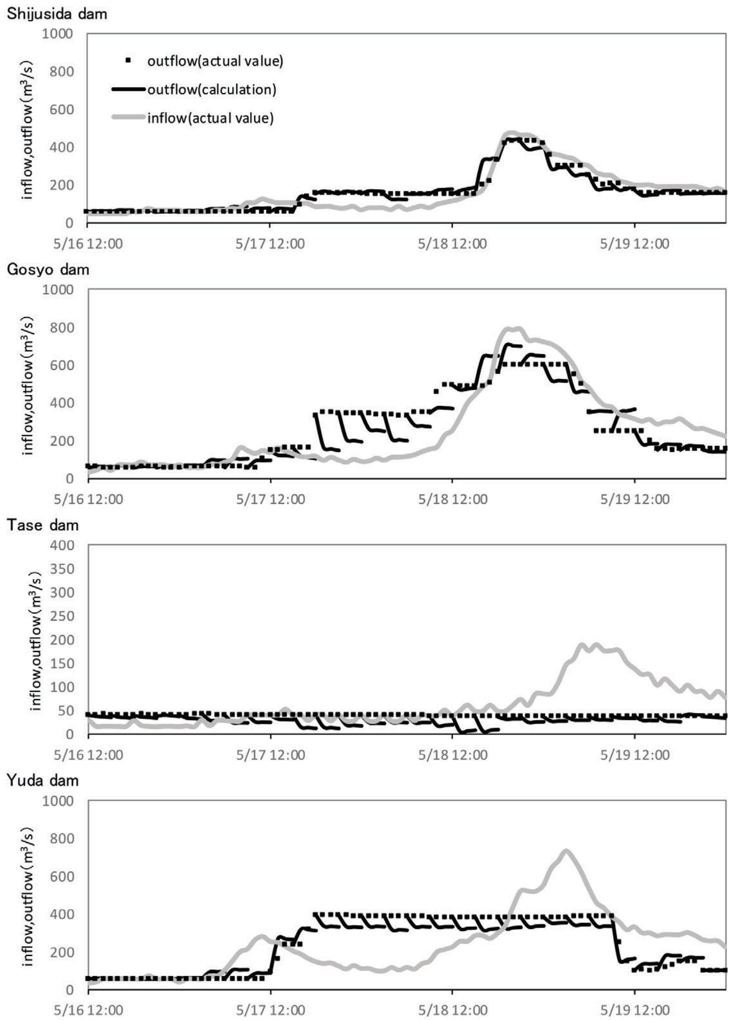

Figure 3. ANN based prediction results.

Table 2. Average outflow error between actual value and calculation.

Dam name	Shijushida	Gosyo	Tase	Yuda
1 hour later [m^3/s]	26	59	11	42
2 hour later [m^3/s]	19	61	12	36
3 hour later [m^3/s]	32	50	6	28

Table 3. Correlation coefficient between actual value and calculation.

Dam name	Shijushida	Gosyo	Tase	Yuda
1 hour later	0.92	0.92	0.16	0.96
2 hour later	0.97	0.91	0.17	0.99
3 hour later	0.98	0.89	0.15	0.98

outflow prediction result based on the ANN is essentially accurate except for Gosyo Dam, because the mean error is less than 50 m^3/s and correlation coefficient is more than 0.9. It is thought that the accuracy was poor for the dam because the flooding during the snowmelt period was an unexperienced flood.

5.2.2 *Problems in model construction*

One of the problems in model construction is that accuracy cannot be improved due to the lack of teacher data. The object of this study is to predict dam outflow at the time of flooding. There is not enough learning data for unexperienced large scale floods due to recent climate changes.

Therefore, in addition to the ANN, learning data is created by deep learning (Factor Variation Auto encoder, Factor VAE). Factor VAE is a method of deep learning. It is a method of automatically generating various types of flood patterns by performing adversarial learning based on past learning data (Hyunjik et al. 2018). This is to give versatility to the unexperienced flood patterns.

6 CONCLUSIONS

The prediction results of dam outflow by the ANN model confirmed the accuracy to be high in the experienced flood pattern. On the contrary, accuracy was poor for unexperienced floods, as observed in the case of Gosyo Dam. The dam operation support system based on AI instantaneously shows the recommended dam outflow values by learning the past discharge performance of dam administrators and its judgment material. In addition to supporting reliable routine operation, the system also makes use of dam reservoir capacity as much as possible to reduce damages at downstream rivers and support judgment in advanced operations. We hope that this system will be used for more efficient and effective dam operations.

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