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Effective Operation of Reservoir and Sediment Bypass Tunnel Considering Inflow Prediction of Water and Sediment

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Abstract

Reservoir sedimentation has been an important issue at dams in the world. Evacuating sediments with sediment bypass tunnels, which allow sediments from upstream of reservoirs to pass through the reservoirs without being captured by the reservoirs, is expected to be an effective countermeasures. This paper aims at discussing issues and potential approaches for effective operation of the reservoir and sediment bypass tunnel considering water and sediment inflow prediction during flood conditions for sediment management. Potential availability of satistical approaches including artificial intelligence techniques are also discussed for better prediction of sediment inflows.

Keywords: reservoir operation, bypass tunnel, inflow prediction, AI, optimization

1 Introduction

Reservoir sedimentation has been an important issue for reservoir management since it decreases the available capacity of the reservoir and consequently brings a decrease in the efficiency of the reservoir. Effective sediment management is therefore needed for sustainable use of reservoirs. As one of the countermeasures against reservoir sedimentation, sediment bypass tunnels (SBTs) have been installed at some reservoirs. This measure is considered as one of the effective solutions to overcome reservoir sedimentation issues because it can pass some of inflowing sediments through SBT without letting them come into the dam reservoir during flood events. It is, however, important to operate the SBT in an effective way so that the reservoir can divert as much sediment as possible during flood events under various restrictions related to reservoir operation such as flood control and water recovery for water supply or power generation.

In order to develop an effective method to minimize the amount of sediment entering reservoirs, an approach for adaptive operation of the reservoir and SBT considering real-time sediment inflow prediction is discussed in this paper. Statistical approaches and issues for real-time sediment inflow prediction including artificial intelligence (AI) techniques are discussed for reservoirs with steep catchments that have quick rainfall-runoff responses such as Japanese reservoir catchments in order to bring out an enhanced capability of the SBT to divert sediment to the downstream of the reservoir. Potential approaches are also discussed for real-time optimization of operation of the reservoir and SBT considering the sediment inflow prediction.

2 SBT Operation Considering Real-time Sediment Inflow Prediction

A large part of sediment is yielded and transported to reservoirs during flood events. Predicting sediment inflow to reservoirs under flood conditions can contribute to more efficient decision making on operation of reservoirs or SBTs. Water inflow prediction is also important for real-time optimization of sediment discharge operation by reservoirs to decide an appropriate timing and volume of water release in light of reservoir storage capacity or water recovery requirement. Ideally speaking, operation of reservoirs and SBTs can be optimized in advance of a flood if water and sediment inflow predictions for the entire period of the flood are given with a certain accuracy. However, predictions for the coming hours can also improve decision making on operation of SBTs at many reservoirs as it gives the timing of increase or decrease in sediment inflow to some extent.

Most reservoirs located in the upstream mountain area where the sediment yield is usually active compared to the downstream have small catchments, largely ranging from 100 km^2 to 300 km^2. For these reservoirs, the travel time of water (and suspended sediment, SS) from the most upstream part of the catchment to the reservoir often becomes one to three hours. In this case, rainfall prediction is also needed to predict water and sediment inflow for the coming hours that is longer than the travel time. The flow diagram on optimization in operation of a reservoir and SBT considering real-time predictions in this case is shown in Fig. 1. For rainfall prediction, one can utilize operational rainfall forecast products which are usually provided by meteorological authorities, while one can develop a short-term rainfall prediction model tailored to the target reservoir catchment considering those operational meteorological forecasts. In either case, operational forecasts can provide a first good estimation of rainfall in the future.

Some new forecasting technologies have also been introduced in the field of operational numerical weather forecasts in recent years. One of them is ensemble forecasting. An ensemble forecast is composed of a set of numerical weather forecast simulations (called as ensemble members), which are respectively conducted with different initial conditions to reduce the effect of errors contained in imperfect observation or model representation. Ensemble forecasts can provide not only the predicted values but also information on the degree of uncertainty contained in the forecast by considering the dispersion of each ensemble members. Forecasts are usually provided in a form of the ensemble prediction when the temporal range of the forecast is long, where prediction uncertainty tends to be great. For example, Japan Meteorological Agency provides forecasts with a long forecast range but coarse temporal resolution, such as one-week forecast or one-month forecast.

They are, however, planning to soon introduce an ensemble forecasting technique into a shorter operational forecast by a meso scale model (MSM), which currently provides a prediction for the coming 39 hours with one-hour time resolution eight times a day. This can also be considered useful for robust decision making on reservoir sediment release operation. It is therefore a challenge for improved reservoir sediment release operation to

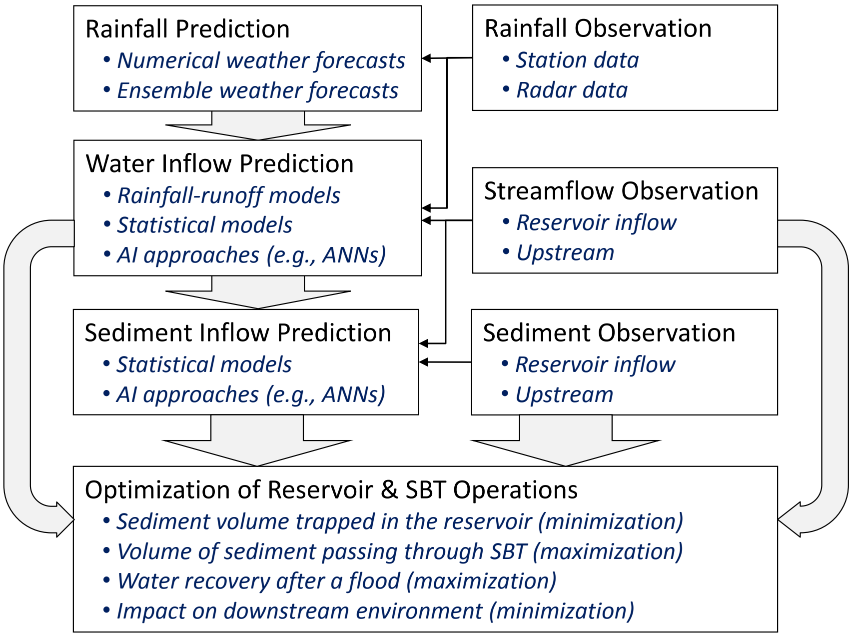

Fig.1 Flow Diagram of Reservoir and SBT Operations Considering Real-time Sediment Inflow Prediction

incorporate these new rainfall forecast approaches into sediment inflow prediction.

Water inflow prediction can be conducted considering rainfall prediction and observation. Sediment inflow prediction can also be conducted mainly based on observation of streamflow and sediment runoff as well as water inflow prediction. These processes are described in more detail in the following chapter. Real-time operation of reservoirs and SBTs can then be optimized for the target operation objectives with consideration of water and sediment inflow predictions. Potential problems for optimization of SBT operation could be minimization of sediment volume trapped in the reservoir when water storage volume is small and water storage recovery is needed for water use or hydropower objectives. In this case, the reservoir needs to store a required volume of water for water storage recovery, at the same time as decreasing sediment volume coming into the reservoir. Especially for the reservoir where more sediment discharge occurs in the early stage of a flood in its catchment, water storage recovery should be conducted in the end of a flood where the sediment amount in inflow water is relatively small. Real-time inflow prediction can contribute to decide the appropriate timing to conduct sediment discharge by the SBT and to start water storage recovery by providing the possible time series of water and sediment inflows during the flood event. Another potential optimization problem is the minimization of impacts of sediment discharge from the reservoir or SBT on the downstream environment. Relatively clear water sometimes needs to be added to attenuate water released from the SBT when highly turbid water is passing through the SBT. In that case, release of relatively clear water from the reservoir can contribute to decrease the concentration of sediment materials in the downstream river water, which can contribute to securing the downstream river environment.

3 Sediment Inflow Prediction

When developing a sediment inflow prediction model, a physical based model can be a potential candidate. Considering the calculation time which must be short enough to be applied to real-time prediction, employing statistical models, which usually require short computation time, is a good option for sediment inflow prediction. Historically, several approaches have been developed for statistical sediment inflow prediction. They can largely be categorized into three typical approaches: sediment rating curves (SRCs), regression models including multi-linear regression (MLR) models, and artificial neural networks (ANNs). Two of these statistical approaches for sediment inflow prediction, namely, MLR models and ANNs, are discussed in the following part of this chapter. As many studies focus on suspended loads as the target of the sediment transport or inflow prediction (e.g., Cobaner *et al.*, 2009), the suspended sediment concentration (SSC) in inflowing water is considered as the target predictand in the following discussion.

3.1 MLR models

A MLR model for prediction of sediment inflow can be described as follows:

$$y(t) = a_0 + \sum_k a(k) \cdot x(k,t) + \varepsilon(t) \qquad [1]$$

where, $y(t)$ is SSC of inflow water at time step t, a_0 is a constant term, $a(k)$ is a coefficient for variable k which are selected as a predictor, $x(k, t)$ is the value of variable k for time step t, and $\varepsilon(t)$ is an error term for estimation of the prediction model for SSC in inflow water. Although MLR models can represent only linear statistical relations between explaining and objective variables, they usually have more stable model response than non-linear models even if the amount of statistical data used in modelling is small. Therefore, MLR models are often employed for sediment inflow prediction when model calibration data is limited. Their prediction results are also considered as a bench mark when the performance of non-linear models are evaluated (Chutachindakate *et al.*, 2009).

3.2 Artificial Neural Networks

An ANN is a network model inspired by the functioning of the brain and biological nervous systems (Tokar *et al.*, 2000). Because of its capability for modeling non-linear relationships between input and output data, ANNs have been employed for modeling hydrological and hydraulic processes (French *et al.*, 1992; Dawson *et al.*, 1998). Studies on estimation of sediment amount or concentration in the river water by use of ANNs have also been increasing in last two decades. Nagy *et al.* (2002) developed ANN models for estimation of sediment load concentraion in rivers with physical parameters related to river flows or river channels. Cobaner *et al.* (2009) also employed ANN models to simulate SSC of the river water with one-day time resolution. ANNs have also been applied to the short-term prediction of sediment yield during the flood or storm event (Rai *et al.*, 2008; Chutachindakate *et al.*, 2009; Nohara *et al.*, 2013).

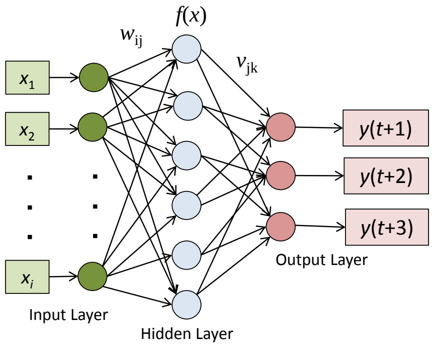

Fig.2 A conceptual example of feed forward type ANNs with three layers.

Although various types of ANNs have been proposed including layer typed networks and mutually connected ones, standard multi-layer feedforward models are often employed for sediment inflow prediction (see also Fig. 2). In typical conventional multi-layer ANN models, input and output values of the units in layer *h* are respectively calculated from the output values fo the precedent layer (layer *h*-1) as the following equations:

$$u_m^h = \sum_j w_{jm}^{h-1,h} o_j^{h-1} \qquad [2]$$

$$o_m^h = f(u_m^h + \theta_m^h) \qquad [3]$$

where u_m^h is the input value to unit *i* in layer *h*, $w_{jm}^{h-1,h}$ is a weight parameter of the connection between unit *j* in layer *h*-1 and unit *m* in layer *h*, o_m^{h-1} and o_i^h are respectively the output of unit *j* in layer *h*-1 and that of unit *m* in layer *h*, θ_m^h is the offset of unit *m* in layer *h*, *f*(·) is a response function of the unit in the middle (hidden) layers, which is often defined as a sigmoid function described as the following equation:

$$f(x) = \frac{1}{1+\exp(-2x/u_o)} \qquad [4]$$

where u_o is a coefficient. Adjustment of the weight parameters of connection between units in the adjacent layers is often conducted in an iterative manner. When the number of layers is three, the backpropagation algorithm is often employed for this training process, and adjustment is carryied out so as to minimize the following value:

$$E_\tau = \sum_p E_p = \sum_p \sum_n (T_{pn} - O_{pn})^2 / 2 \qquad [5]$$

where O_{pn} is the output of unit *n* in the output layer for training pattern *p*, T_{pn} is the desired output signal which is also called as supervisory signal and normally derived from observed data to be estimated for unit *n* for training pattern *p*, E_p is the integrated error of estimation for the desired output values for training pattern *p*, and E_τ is the total training error for all training patterns.

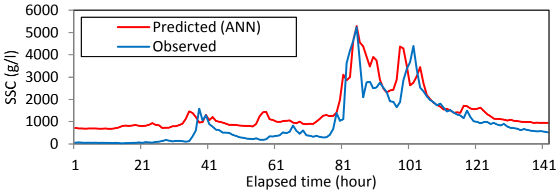

Fig.3 An example of prediction results of SSC at the Miwa Reservoir two hours ahead by an ANN model.

An example of prediction results of SSC in inflow water is shown in Fig. 3. The prediction results of SSC in inflow of the Miwa Reservoir in the central Japan for the flood event that occurred on July 10th, 2010 (Nohara *et al.*, 2013). The figure shows the prediction result of SSC two hours ahead when predicted from three-hour accumulated rainfall by the current hour and values of inflow and SSC at the current hour. It can be seen in Fig.3 that the ANN model could predicted the first peak value of SSC including its timing, while it could not predict the timing of the second peak and low SSC conditions perfectly. The model, however, represented the increase and decrease of SSC during the flood event in a large sense, which can also be helpful for real-time operation of reservoirs and SBTs.

In fact, this ANN model was developed (trained) with a limited number of historical flood data because of data availability. In this case, the nonliniearlity in the input-output relationships cannot be represented by ANN models well, and the performance of ANN models could be limited, even below that of MLR models. Therefore, it would be better to employ a MLR model as a sediment inflow prediction model instead of ANN models when data for model calibration is limited. This could be a criterion which should be used for sediment inflow prediction model, linear models or nonlinear models such as ANNs.

3.3 Discussions

As described in the previous section, one of the challenges in using ANNs for sediment inflow prediction is data scarcity. The scarcity in data for calibrating the network limits the performance of an ANN to represent the complex relationship between input and output data. This data scarcity can often happen because not a few river basins do not have monitoring stations for sediment transport, and because the number of historical flood events occurred in the same river catchment is limited even though monitoring stations for sediment transport are installed. As an ANN model usually needs a lot of datasets of input and output variables to adjust a number of parameters, i.e., weight parameters of connections among units between the adjacent layers, a lot of observation data corresponding to input and output variables (e.g., rainfall, inflow, SSC) are needed.

An approach to overcome this problem is to use empirical relationships between input and output variables to supplement insufficient model calibration due to data scarcity.

For instance, one can use sediment rating curves (SRCs) to enhance sediment inflow

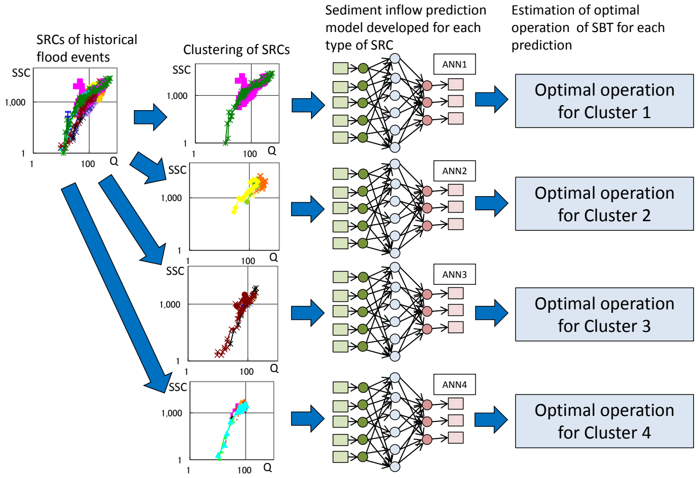

Fig.4 Real-time SBT operation using ANN prediction models developed for each cluster of flood SRCs.

prediction by ANNs. In this approach, SRCs of historical flood events in the target river basin are classified into representative clusters according to the shape of SRC, and an ANN is respectively developed for each cluster of SRC to model the time series characteristics of sediment transport in the river during those flood events in that cluster (see also Fig. 4). This can relax the non-linearity of input-output relationships and improve the performance of ANNs, because time series characteristics of relations between river discharge and SSC, which is to be modeled by each ANN, are simplified thanks to the clustering before making input data. Other AI techniques such as fuzzy clustering (Bezdek, 1981) can also be employed for the clustering process to incorporate the non-crisp classification and to derive an aggregated operation policy from each operation guidance optimized for each clusters of SRC.

Thanks to the recent advancement in ANN techniques, more complex non-linear relationships between input and output data can be modelled by ANNs in recent years. Since new training algorithms that can overcome the drawback of backpropagation algorithm (local optimality, vanishing gradient problem) have been established, deep neural networks or convolutional neural networks (Krizhervsky *et al.*, 2012) have been applied to model the complex input-output relationships in many fields. These new AI techniques can also have a great potential for improved modelling of sediment transport which can enhance sediment transport prediction. Generative adversarial networks (Goodfellow *et al.*, 2014) can also be considered to have a potential to be applied to artificially generate flood event data for training of ANNs to resolve data scarcity problem.

4 Conclusions

Approaches and potential effectiveness of adaptive operation of the reservoir and SBT considering real-time sediment inflow prediction were discussed. AI techniques including ANNs have a potential to provide further advancement in real-time sediment inflow predictions, which can sophisticate operation of the SBT and reservoir during flood periods. Further studies are therefore needed for establishment of more effective reservoir and SBT operations introducing the newly developed soft-computing techniques.

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