DDDPおよびNNによる貯水池群の総合的管理方針の策定について -タイ・メクロン川流域の事例研究-

On deriving a general operating policy of a multiple reservoir system using DDDP and NN - A case study in the Mae Klong system, Thailand -

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1 Introduction

An artificial neural network (ANN), sometimes referred to as just a neural network (NN), is originally studied in the framework of artificial intelligence (AI) that attempts to imitate functioning of information procession in a human's brain. A NN functions through the creation of connections between processing elements which function as the equivalent of neurons. These connections are weighted such that the particular inputs will produce the desired outputs. NNs are applicable when the relationship between the inputs and outputs exists and is very complex that is known to depend on several factors and the interaction of those factors is not well known.

Recently, the dynamic programming neural network (DPN) model was proposed by Raman and Chandramouli (1996) to derive a general operating policy of a single reservoir. The method was extended to multiple reservoir operation by Chandramouli and Raman (2001). The DPN model scheme is divided into three phases that consists of a dynamic programming (DP) algorithm, a NN algorithm, and a simulation model. The optimization results obtained from the DP are supplied as the training patterns to the NN to derive a general operating policy. After the training process, the trained network is used in a simulation model to assess its performance. In the present study the concept of the DPN as implemented in Raman and Chandramouli (1996) and Chandramouli and Raman (2001) is adopted but a combination approach of a genetic algorithm (GA) and a discrete differential dynamic programming (DDDP) as proposed in the work of Tospornsampan *et al*. (2005) is adopted in this study to derive a set of optimal training patterns instead of a deterministic DP used in the original papers.

GAs are search algorithms based on the mechanics of natural selection and natural genetics. GAs perform a multi-directional search by maintaining a population of potential solutions. The DDDP is an iterative technique in which the recursive equation of the DP is used to search for an improved trajectory among the discrete states (called 'corridors') in the neighborhood of a trial trajectory. Basically, instead of searching the entire feasible sets of discrete states as in the conventional DP, the DDDP approach examine only a small fraction of the total feasible states and narrow down successively to a near optimal solution. Since the corridor size becomes smaller as the iteration process proceeds, the DDDP approach can lead to a closer optimal solution.

A genetic algorithm (GA) is used to search for the initial trial trajectories for the DDDP, which is the most difficulty step in implementing the DDDP. By using different initial trial trajectories obtained from the GA, the DDDP can provide different optimal operating policies having the same objective function values. As a result, different alternative of the training sets can be served to the NN in order to investigate its performance as well as the operating policies obtained in the simulation phase. The performance of the DDDP-NN model developed in this study is demonstrated through application to a case study of a multiple reservoir system called the Mae Klong system in Thailand.

2 Application to Mae Klong System

The Mae Klong River Basin is located in the west of Thailand, covering the total area of 30,800 km^2. Two major large-scale multi-purposes dams: the Srinagarindra Dam and the Vajiralongkorn Dam, and the Mae Klong diversion dam are constructed in the basin. Figure 1 shows schematic diagram of the system.

The dams in this basin are operated together to serving multi-purposes for irrigation, hydropower generation, domestic and industrial water supply, recreation and salinity control. The major water requirements from this basin are occupied by those from the Greater Mae Klong Irrigation Project (GMKIP). The objective function used to evaluate the system performance is to minimize the expected GMKIP demand deficit over a year after all other requirements have been fulfilled.

Fifteen years of monthly statistical data from

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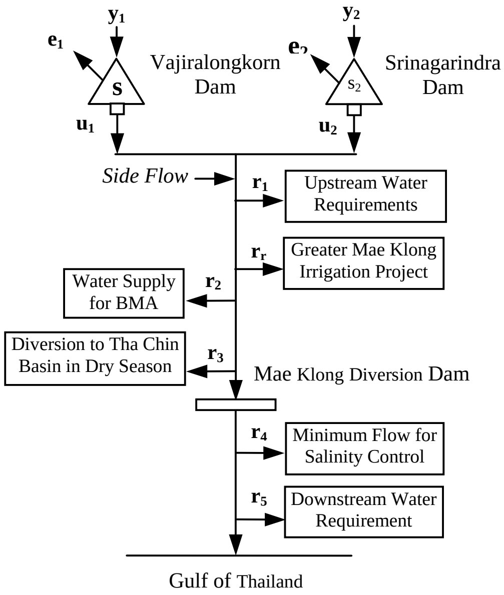

Figure 1: Diagram of Mae Klong System

1986-2000 are selected for the study. Thirteen years of data (1986-1998) are used to derive the optimal operating policies by the GA-DDDP and to train the network by the NN. Two years of data (1999-2000) are used to evaluate the performance of the NN in the simulation model. The simulation model is applied to the networks simultaneously together with the training process. Each time after the weights are updated, the network is then evaluated by the simulation model to investigate its performance while the training process proceeds.

The input pattern is composed of 9 variables of the two initial storages, the two inflows, the two losses, the side flow, the GMKID demand, and the sum of other demands. The output pattern is composed of two variables of releases from two reservoirs. The activation function used in the hidden layer is the sigmoidal function while the linear function is used in the output layer. The error assessments used to evaluate the performance of the ANN in this study are the root mean square error (RMSE), the mean absolute percentage error (MAPE), and the correlation coefficient (r).

3 Results and Discussions

After trial and error procedure, the network is finally designed with 9 input nodes, 90 hidden nodes, and 2 output nodes that allowed to train for 3,000 iterations. It takes about 3 minutes 15 seconds to execute on the Athlon 64 3200+ PC at 2.2 GHz. Several sets of input-output pattern derived from the optimization results are given to the network and trained by the backpropagation (BP) algorithm with a number of different initial random weights. It is found from the simulation results that a feasible operating policy is not always achieved by the best trained networks because the operating policies obtained from the best-trained networks often violate the system constraints. However, many networks that are not the best-trained network provide promising feasible operating policies in the simulation stage. Details of the three selected compromising optimal operating policies during two years of simulation are summarized in Table 1. The selection was based on the results of the training stage and the simulation model that the networks provide low error prediction values in the training procedure and feasible simulation results in which the operating policies do not violate the system constraints.

4 Conclusions

The results obtained in this study indicate that the combination model of GA-DDDP and NN performs satisfactorily on deriving a reservoir general operating policy. The general operating policy obtained by this method is considered tentative and can be changed again after some periods of operation that the additional reservoir data are collected. It is worthy of further investigation for other applications for different problems. Further applications of the method to the real-time operation can be expected.

References

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Table 1: Results of optimal networks obtained from the simulation model

Networks	Training results			Total Irrigation deficit (MCM)	Deficit month (Month)	Average deficit/month (%)[1/]
	RMSE	MAPE	r			
1	7.1299	2.0154	0.9995	790.5490	7	18.9401
2	10.4578	2.6221	0.9988	313.5668	6	11.0329
3	10.8395	2.6830	0.9989	505.1204	8	12.6814

1/ calculated from total irrigation deficit/total demand in those month × 100