A NEURAL NETWORK APPROACH TO RAINFALL-RUNOFF MODELLING

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INTRODUCTION

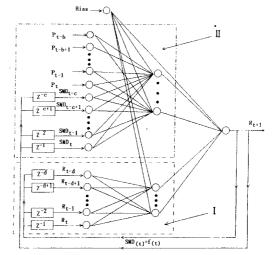
Rainfall-runoff modelling is a hot topic for hydrologists from the beginning of hydrological studies. Since the end of the last century, numerous models of rainfall-runoff transformation have been developed. In this study, a new approach identified with a neural network structure is proposed for catchment rainfall-runoff modelling, with considerations of both the foundations of the neural network and the conceptions of the real hydrological system. In comparison with other existing models, this model is founded without employing any other hydraulic or hydrological fundamental equation except a simple physical sound equation of water balance in a catchment, and any physical assumption associated with the catchment is not necessary. Thus no parameter inside the model needs to be calibrated and determined manually. It is a partial intelligence-based model which, through the selflearning progress, can be trained to adapt itself to the environment (i.e. the catchment system), and thus can be utilized for purposes such as flood prediction subsequently.

NEURAL NETWORK

The modern era of neural networks (NN) is said to have begun with the pioneering work of McCulloch and Pitts in 1943, with the original purpose of information storage and computing by neuronal processes found in nature. However, the NN's applications were not widespread until the publication of the Back-propagation (BP) method developed by Rumelhart in 1986. Many of the applications, like the work here, are based on some form of a BP network. The distinguished features of the NN is, by providing a manner close to human perception and recognition, it has the capacity to generate solutions to complex problems that are beyond formal description or definition, and the models they can build are non-linear and do not require mathematical equation. As a result, for handling complicated natural problems, the NNs are considered as an excellent predictive tools replacing traditional techniques like multiple regression analysis, and has been used productively in a wide range of fields particular in recent years.

NEURAL NETWORK ARCHITECTURE PROPOSED FOR RAINFALL-RUNOFF MODELLING

The complication of the runoff formation and concentration makes it impossible for a catchment system to be signified simply by a standard BP structure. Because the relationship between the rainfall and runoff is neither a simple pattern (runoff process) by pattern (rainfall process) problem due to, for example, the existence of the control of the initial soil moisture deficit, or a direct point (runoff) by point (rainfall) reflection due to reasons such as the reality of the time lag from rainfall to runoff. Hence, based on the consideration of real transformation of rainfall to runoff, a new NN architecture for representing the catchment system is proposed as displayed in Fig. 1. The model is made up of two self-governing parts within the input and hidden layer. The first part can be physically considered as the phase of runoff concentration with only the input of runoff Fig.1 The NN Architecture for Rainfall-runoff Modelling



(R) itself, while the second part is the phase of runoff formation, wherein the time series inputs of rainfall (P) and soil moisture deficit (SMD) interact in a non-linear way to generate the net rainfall adding to the first phase. These two parts operate together in parallel to produce a final output of runoff. During the training process, conduct the computation in cycles, this output result is immediately fed back as the runoff input into the input layer of the part I of the model, and as SMD input into the input layer of part II of the model after recomputation with the equation of water balance in a catchment.

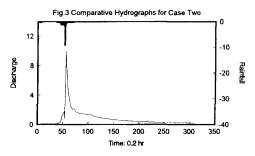
APPLICATION OF THE MODEL

With a time interval of 0.2 hour, five rainfall-runoff processes form a small catchment with an area of 4.47 km² are applied for examining the performance of the model. Two of them with single-peaked hydrograph are selected for training procedure, while another three are used for verification. The results are shown in Table 1. Where R and DC are correlation coefficients and determination coefficients respectively. Fig. 2 to Fig. 4 are comparative hydrographs for case one, two and three.

Table 1 The results of model performance

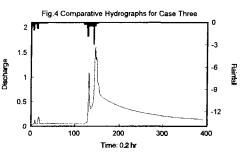
Objective	Storm Cases	R	DC
Training or Calibration	Case 1 (1989,7,25) Case 2 (1990,7,25)	0.971 0.977	0.826 0.897
Testing and Verification	Case 3 (1990,8,11) Case 4 (1990,7,28) Case 5 (1991,7,21)	0.914 0.888 0.922	0.827 0.759 0.843

Fig.2 Comparative Hydrographs for Case One Calculated Observed -5 -10 Time: 0.2 by



CONCLUSION

The neural network is a relative new technology, and the improvements are being made rapidly. Thus, as a new approach for analyzing rainfall-runoff relationships, this model, which is chiefly based on the fundamentals of the neural network, is far from being mature, although the achievement here demonstrates qualified results. More data from different catchments with various conditions are needed to inspect this model. However, what we can conclude is that the neural network has a great potentials for handling complicated natural problems. Due to its easy



operation and efficient performance, the model proposed here can be considered as a new superior procedure or alternative for rainfall-runoff modelling. The initial success of the model indicates a bright future for further applications.

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