II -315 Artificial Neural Network: An Application to the Runoff Analysis in Tono Area

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1. Introduction

Artificial Neural Network (NN) models have been used for analyzing rainfall runoff phenomena(Hsu et al.,1995, Minns and Hall,1996 etc). Although those NN models have shown potential for simulating runoff, on account of their not using catchment state variables or properties, they have the limitations that they can hardly serve in the management problem to assess effects of any catchment changes. In the present study, we have focused on the formulation of NN model, in a way it utilizes the catchment state variable-soil moisture data, thus moving a step forward in making such black box type model a possible tool for management problem.

2. Modeling Approach

Three layer feed forward network based on back propagation algorithm was adopted for our purpose. The network consisted of an input layer consisting of node(s) representing various input(s), the hidden layer consisting of many hidden nodes, and an output layer consisting of an output. Inherently a trial and error process, the selection of number of hidden nodes is, however, often guided by some available heuristics and experiences with modeling. In order to speed up the training process, two parameters namely, learning and momentum parameters are also utilized. Again, the selection of such parameters is case specific and has to be decided based on the response of network starting with some benchmark heuristics. Input data are often normalized with suitable methods. The output data is usually normalized in the range of 0.1 and 0.9. Once the data is trained and tested it is denormalized again. A typical 3 layer network with single output is shown in Fig. 1. Figure 2 shows one typical hidden node where two functions namely, activation and transfer take place.

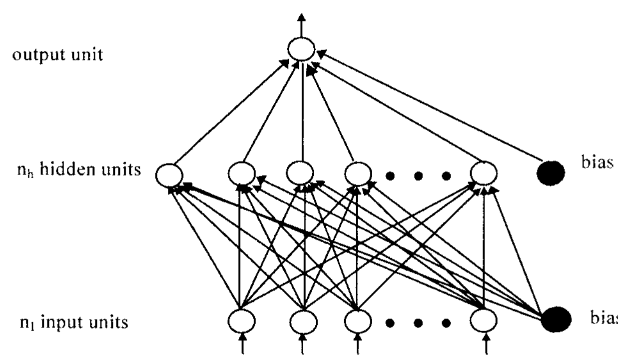

Fig. 1 Typical BPNN Model Structure

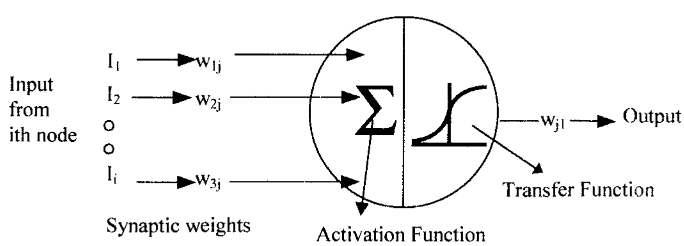

Fig. 2 A Typical Diagram of j[th] Neuron of Hidden Layer

3. Application

We extended our model to a small mountainous catchment(≦12 ha)located in Gifu Prefecture. In order to search which input parameters govern the discharge, we considered many possible NN models based on different combinations of input types. The input considered for the model consisted of soil moisture data at different location namely midslope(M) and downslope (D) at different depths and past rainfall events. Table I shows the input parameters(where Δt =10 minutes) and the efficiency(Nash and Sutcliffe, 1970) of the four typical cases out of many considered in the present study. The result showed that the model that utilizes soil mositure data at the downslope location at 40 cm depth can be considered as the best model among the considered ones. The model that utilized past discrete rainfall events

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fared poorly, but the one that utilized the near surface soil moisture[at 20 cm depth at D location(20D)] performed relatively better. Figure 3 shows typical result of the three cases. The advantage offered by 40 D soil moisture is that, it represents the integrated effect of whole upslope area. As such, any changes in the upslope catchment area will be reflected as changes in the soil moisture in terms timing and magnitude and in the dominant runoff generation processes. Consequently, the relationship found in undisturbed catchment with prior application of NN model will not hold in the changed context, thus imparting the model the ability of assessment.

Table I: Model Name, Input Parameters and Efficiency Index(EI)

Model Name	Inputs	Training Phase EI	Testing Phase EI
NN1	(t-Δt) 40D soil moisture	0.935	0.714
NN2	(t-4Δt) 40M soil moisture	0.565	0.612
NN3	(t-Δt)20D soil moisture	0.943	0.701
NN4	(t-Δt, t-2Δt, t-3Δt,t-4Δt) rainfall values	0.907	0.64

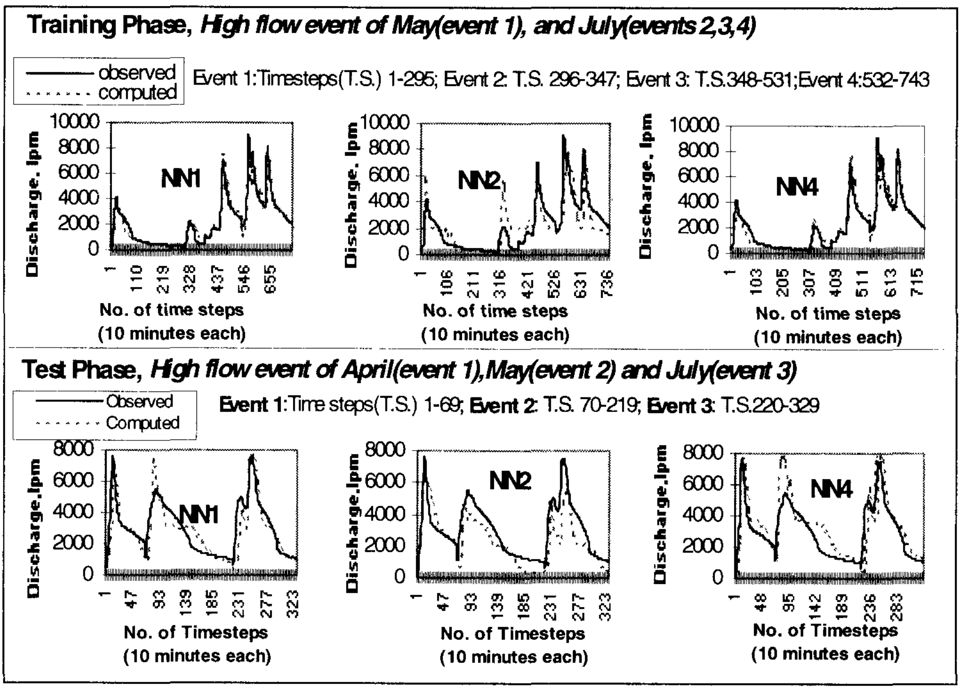

Fig. 3 Comparison Between Observed and NN Computed Discharges

4. Conclusions

Models were formulated for a real catchment, using back propagation NN algorithm with different inputs and their combinations . The result showed precipitation data as input did not improve the result, and soil moisture at D location at 40 cm depth was most important as reflected by efficiency index and graphical comparison plots. As the formulated model uses information from within the catchment, it can be considered to be useful in the assessment of the effect of land use changes along with forecasting uses.

References

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