ニューラルファジーシステムによる流域における水供給量の予測モデル
A neural fuzzy system approach to modeling a prediction of water supply from local source in a river basin

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1 Introduction

Over the past few decades, intelligent computation methods, which include artificial neural networks, fuzzy logic, etc., have been adopted in water resources forecasting studies as a powerful alternative modeling tools (Delft, 2000). These methods offer advantages over conventional modeling, including the ability to handle large amounts of noisy data from dynamic and nonlinear systems, especially where the underlying physical relationships are not fully understood (Openshaw and Openshaw, 1997). Neuro-fuzzy system, which combine neural networks and fuzzy logic have recently gained a lot of interest in research and application. The neuro-fuzzy approach added the advantage of reduced training time due not only to its smaller dimensions but also because the network can be initialized with parameters relating to the problem domain. Such results emphasize the benefits of the fusion of fuzzy and neural network technologies as it facilitates an accurate initialization of the network in term of the parameters of the fuzzy reasoning system. A specific approach in neuro-fuzzy development is the adaptive neuro-fuzzy inference system (ANFIS), which has shown significant results in modeling nonlinear functions. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion. In the present paper, the advantage of neural fuzzy system in modeling water supply time series in a river basin was examined, and illustrated by a case study of water supply forecasting from the small rivers (called local source).

2 Model development

A first order Takagi-Sugeno fuzzy inference system is identified by two main step procedure: the first step used subtractive clustering algorithm integrated with a linear squares estimation algorithm for initial identification of fuzzy inference system (FIS), the second step used an ANFIS model for optimizing of initial identified FIS. The identification of the optimal neural fuzzy model consists of two distinct steps: (1) determination of cluster centers to establish the number of fuzzy rules and the rule premises, and (2) identification of the consequent parameters. A subtractive clustering technique was first applied to determine the number of rules and antecedent membership functions. The cluster information obtained from subtractive clustering are then used to determine the initial number of rules and antecedent membership function, that is for identifying the FIS. Once a fuzzy model for a class is identified, an ANFIS network equivalent to the model can be built. The network is then trained using the hybrid learning algorithms such that the desired response is achieved. The final fuzzy inference system (FIS) model would ordinary be the one associated with minimum training error. The modeling procedure was applied for water management in a river basin through forecasting of half-monthly water supply from local source. The average water supply data from local source during the period of 1989 to 2003 were collected and prepared for further training and testing of the model. To ensure that the numbers of data records are sufficiently large to provide confidence in the forecasting results, water year (from 1 January to 31 December) was divided into 24, half-month periods. It means that 24 different models had to be built to predict the whole year. The model performance during the training and testing periods were examined by: (1) root mean square error, (2) mean average error and (3) coefficient of correlation.

3 Result and discussion

Different neural fuzzy system parameters were adopted during the training process of ANFIS, and for each combination of parameters, a model was built and trained. To predict the water supply for

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the whole year, as many as 24 different models have been developed. For each model, 264 out of 360 data pairs were used for training purpose, while the remaining 96 data pairs were used for testing. Having tried many combinations of r_a and initial step size, the optimal value obtained ranged from 0.2 to 0.5 and 0.1 to 0.2 for r_a and initial step size respectively. The combination of r_a and initial step size resulted in approximately 4 to 10 rules for each model. The parameters of the membership function were then optimized in the learning process through gradient descent method whereas the consequent parameters were calculated using a linear least squares method. Training was performed until either an error goal of 0.01 is reached, or maximum of 200 epochs is obtained. The final values of model parameters obtained after training, were then used as the optimal parameter combination for testing the networks. Testing of the networks was done using the remaining 96 data pairs (half-monthly data during year 2000-2003). The results obtained for half-month prediction using neural fuzzy system performed a better prediction of the supply peaks that occurred in the early and late periods of the year. However, neural fuzzy model overestimates water supply during the low supply series that occurred from the end of September to the beginning of October. This forecasting error is probably due to the supply variation during those periods experience great variances.

In order to show the potential of the neural fuzzy system model, multiple linear regression analysis based prediction that is used by the PJT II is also presented. The comparison of the predictions accuracy using neural fuzzy system and multiple linear regression analysis is fully summarized in Table 1. By comparison, the forecast result show that the yield of forecasting using neural fuzzy system model is significantly improved compared to results of multiple linear regression. It is evident from Table 1 that the neural fuzzy outperforms the multiple linear regression analysis in terms of all statistical performance indices. A significant improvement is observed for the neural fuzzy model i.e., in modeling the flow during the supply peaks, which occurred in the early and late periods of the year while multiple linear regression model failed in producing a good result. The model performance analysis using neuro-fuzzy model yielded the value of RMSE, MAE and CORR are 20.10, 18.75% and 0.83% respectively. Meanwhile, the value of RMSE, MAE and CORR using multiple regression analysis are confined to 31.95, 44.62% and 0.66 respectively. The results indicate how well the neuro-fuzzy learned the events it was trained to recognize, and the degree to which this model can generalize its training to forecast events not included in the training process.

Table 1. Forecasting performance of models for one step ahead forecasting

Performance	Local source		
	RMSE	MAE (%)	CORR
Neuro-fuzzy model	20.10	18.75	0.83
Multiple linear regression	31.95	44.62	0.66

4 Conclusion

The potential of neural fuzzy system for modeling and prediction of water supply time series in a river basin has been presented. The presented methodology was applied to water management in Citarum river basin, and its performance accuracy was evaluated in terms of root mean square error, mean average error and coefficient of correlation. The results indicate that the neural fuzzy system model applied to the water supply prediction seems to have reached encouraging results for the river basin under examination. The neural fuzzy system outperforms the multiple linear regression analysis in terms of all statistical performance indices. A significant improvement is observed for the neural fuzzy model i.e., in modeling the flow during the supply peaks, which occurred in the early and late periods of the year while multiple linear regression model failed in producing a good result. The highly encouraging results of forecasting indicate the potential of neuro-fuzzy approach for modeling water supply time series. However, the developed neuro-fuzzy model was, in some cases more sensitive for changes in conditions and susceptible to failure when working outside the training data.

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