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AN ENSEMBLE APPROACH FOR TYPHOON RUNOFF SIMULATION WITH PERTURBED RAINFALL FORECASTS IN TAIWAN

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Under the background of demand for accurate and reliable flood forecasting, various methodologies are used to model floods. However, not all the phases of the hydrograph can be predicted by any models, even though the global optimum may be reached. In order to exploit the distinct information provided by different models, an ensemble approach is proposed to improve the forecasting accuracy and reliability. The ensemble precipitation estimates from a Weather Research Forecasting (WRF) model were used to as inputs to model the rainfall-runoff process in Taiwan. A Dynamic Evolving Neural-Fuzzy Inference System was applied to combining the predictions of the ensemble members based on the forecasting performance for different water levels of the combined members. Using sophisticated models to address the performance of different runs is shown to be a potential way to improve the accuracy of flood forecasting.

INTRODUCTION

Taiwan is vulnerable to typhoons and typhoon-related floods. Building an accurate flood forecasting system is necessary for policy makers to prevent the flood damages as well as to make use of the flood resource. The rainfall-runoff models rely on the rainfall forecasting, which is quite sensitive to small errors in the initial state. Producing more forecasting with perturbed initial conditions can be an approach to reduce the uncertainties [1], but it will be hard to decide which flood forecasting will be reliable. Hence, this study will emphasize on the approach to combining the predicted water levels from these members to provide a more reliable ensemble forecasting.

METHODOLOGY

Then Ensemble model used in this paper is the Dynamic Evolving Neural-Fuzzy Inference System or DENFIS [2]. Combining the reasoning ability of fuzzy system and parameters learning of neural network, DENFIS clusters the input vectors into different clusters within the maximum of the cluster radius. This threshold of the cluster radius Dthr will determine the number of the clusters to be created. The fuzzy membership functions depend on the cluster centers, input vectors and Dthr. The offline mode of DENFIS is used for ensemble purpose in this paper, which globally optimizes the resulting clusters by adjusting the cluster centers to minimize the objective function:

$$J = \sum_{j=1}^{n} J_j = \sum_{j=1}^{n} \left(\sum_{x_i \in c_j} \| x_i - C_{c_j} \| \right) \tag{1}$$

Subject to $\| x_i - C_{c_j} \| \leqq Dthr$

Where i =1,2,…,p; j =1,2,…,n. So the summation of the distance from all the input vectors to the corresponding cluster centers is minimized.

A one-way coupled hydrometeorological approach has been used to predict the water levels for Lanyang basin in Taiwan from 11th May 2012 to 4th Nov 2013. The rainfall forecasting with different perturbed initial conditions from the ensemble meteorological modeling system was used to drive the physically distributed hydrological model WASH123D [1]. In this study, the water levels forecasting of the operational runs with six-hour interval from 15 members were used as inputs to the ensemble model DENFIS. The event from 21st Sep 2013 to 24th Sep 2013 including consecutive two operational runs was used as the test data.

Data PRE-PROCESSING

DENFIS model is trained with the values of member forecasts for ensemble forecasts, so the time order is not necessary for training in this study. The data used to train the model was divided into two equally sized subsets after random permutation. The model was trained on one data set and validated on the other one in parameter learning to avoid over-fitting.

Instead of directly importing the data into the ensemble model, all the fifteen members were evaluated in terms of the forecasting performance for different water levels to decrease the effects from poor members (Low: below 3.5 m; Medium: between 3.5 m and 5.8m; High: above 5.8 m). After ranking the fifteen members, three strategies were used to select the members to be used besides the test using all the members (Rank1: the best member in the three water levels; Rank2: the best two members in the three water levels; 1L2M3H: Address more on medium and high water levels). The selected members for ensemble purpose were listed in Table 1:

Table 1. Selected Members for Ensemble Model

Strategy	Selected Members					
Rank1	1	11	13			
Rank2	1	4	7	11	13	14
1L2M3H	1	4	11	13	14	

Results

For the same input selection, the ensemble model produced less training error with smaller Dthr but the model which over-fits the training data cannot generalize the data patterns. So the distance threshold Dthr was identified through trial and error until the lowest validation RMSE was found before over-fitting. The results of the optimal values of Dthr for different input selection and the corresponding RMSE for training, validation and test were shown in Table 2. Among all the input selections, the ensemble results with more address on medium and high input water levels produced the best result with RMSE 0.33m. The improvement of the input selections over directly importing all the members is not significant, which can be explained by the DENFIS model allocating less weight to those poor members.

Table 2. RMSE of Ensemble Outputs for Different Input Selection

Input Selection	Dthr	Training RMSE (m)	Validation RMSE(m)	Test RMSE(m)
All Members	0.13	0.39	0.42	0.39
Rank1	0.09	0.52	0.53	0.35
Rank2	0.09	0.48	0.50	0.34
1L2M3H	0.11	0.46	0.48	0.33

For the test data, Member 12 produced the lowest RMSE over the consecutive runs. The ensemble forecasts from DENFIS (1L2M3H) were compared with Member 12 for the test data in Figure 1.

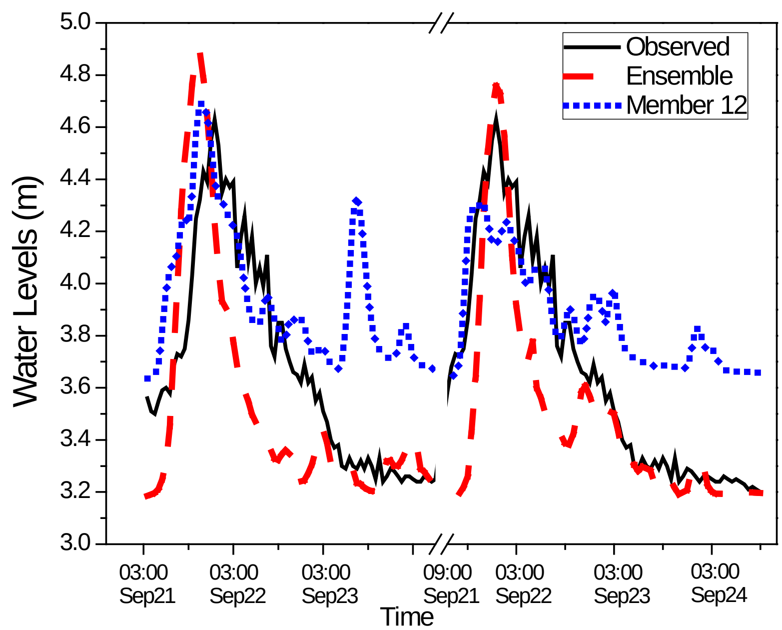

Figure 1. Comparison of the Ensemble forecasts with Member 12 for the test data.

From Figure 1, the curve of the observed water levels in the second run was shifted 6 hours forward compared with that in the first run because the starting time of the second run was six hours later. Even though Member 12 performed the best among all the fifteen members, the errors increased when the operational run started nearer to the peak time. This error increase may result from the computational instability in weather forecasting. To the contrary, the ensemble model performed slightly better in the second run.

Other criteria such as percent error in peak (PEP) [3] and percent bias (PBIAS) [4] were also selected in this paper to evaluate the ensemble model and the members. The percentage error at peak time (noted as PE) and the peak time difference (noted as PT) were also calculated. The results were shown in Table 3. The mean and stand deviation values of the observed water levels for the two runs were 3.68m and 3.66m, 0.41m and 0.42m. The ensemble model produced much closer results than those of Member 12 and the low stand deviation of Member 12 indicated the weakness that failed to depict the hydrological response for the test data. PBIAS and PEP described the percentage error from overall and maximum values respectively.

The positive values indicate overestimation and the negative values indicate underestimation. Except for the PEP in the first run, ensemble model performed better especially for the peak values in the second run. PT describes the time difference of the peak between the predictions and the observed water levels, which defines the negative values as early warning. The ensemble results in the second run produced the lowest error at peak time and warned the peak at the correct time. For the percentage error at observed peak time (PE), the ensemble results improved a lot in the second run comparing to the deterioration of Member 12.

Table 3. Evaluation of the forecasts of the Ensemble model and Member 12 for the consecutive two runs of the test data

	First run		Second run	
Criteria	Ensemble	Member 12	Ensemble	Member 12
Mean	3.54 m	3.95 m	3.49 m	3.86 m
Stand Deviation	0.46 m	0.28 m	0.39 m	0.20 m
PBIAS	-3.81%	7.24%	-4.64%	5.61%
RMSE	0.37	0.39	0.28	0.33
PEP	5.54%	1.32%	2.79%	-6.91%
PE	-8.51%	-4.97%	2.79%	-10.41%
PT	-4 h	-4 h	0 h	-3 h

In addition, the ensemble results showed better performance in the second run to predict the peak values, while the performance of Member12 is worse when the operational run is near the peak time.

FURTHER WORK

Due to the limitation of the operational water level forecasts from all the fifteen members, it is unlikely to analyze whether there exist any patterns in different runs now. With more data collected by the operational forecasting system, further study is possible on the more sophisticated ensemble approach exploiting the changes of the performance in different operational runs.

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