COMBINING RAINFALL-RUNOFF MODELS FOR ENSEMBLE STREAMFLOW PREDICTION

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1 INTRODUCTION

Introduced in 1970's, ESP (Ensemble Streamflow Prediction) became a key part of the advanced hydrologic prediction system for the National Weather Service in the United State. In Korea, Kim et al. (2001) introduced ESP as an alternative probabilistic forecasting technique for improving the water supply outlook. More recently, Jeong and Kim (2002) successfully applied the same technique to a one-month ahead inflow forecasting for Chungju multipurpose dam in Korea. In their study, it was emphasized that systematic (or modeling) error dominates in the winter and spring (i.e. dry seasons) while random (or meteorologic) error dominates in the summer (i.e. wet season). They suggested that the rainfall-runoff used model used in their ESP study should be improved to obtain more accurate probabilistic inflow forecasts, which is the objective of the present study.

To improve the output series of a rainfall-runoff model, one generally has to analyze all the model components and to devise better alternatives for some components that may degrade the model performance. This type of improvement strategy, however, requires considerable effort and time. The present study proposed an alternative way to improve the model performance: Rather than modifying the model itself, the model output (i.e. the simulated runoff series) is adjusted by using the exogenous information. In this study, we assumed another rainfall-runoff model so that another series of the simulated runoff would be available as the exogenous information. This study then attempted to improve the simulated runoff series of the first model by "combining" with the simulated runoff series of the second model. In other words, two (or more) independently calibrated rainfall-runoff models were combined to improve their simulation accuracy.

Since first introduced by Bates and Granger (1969), combining methods have been studied and applied for economic forecasting. In hydrologic forecasting or simulation studies, however, few paid attention to this topic. McLeod et al. (1987) reported the first experiments dealing with the combination of river flow forecasts, but no further significant study has been made since then. McLeod et al. (1987) made several forecasts of a monthly river flow from time series and conceptual rainfall-runoff models and combined the forecasts based on the forecast error covariance. They found significant improvements in forecast performance when forecasts from different models were combined.

In this study, we attempted to make a broader review of combining methods that have been commonly used in economic forecasting than McLeod et al. (1987) did and compared performance of the combining methods though a hydrologic example. Note that the combining

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theory described in the following section can be applied to both cases of forecasting and simulating hydrologic time series.

2 COMBINING METHODS

If several, generally different forecasts are available to a forecaster, she/he has to choose one particular forecasted value or series. Alternatively, one can combine the forecasts in an effort to take advantage of the strengths of each model because each has its own particular strength and weakness (McLeod et al., 1987). If there are m forecasts available, the combined forecast F_c would be

$$F_c = \sum_{i=1}^{m} \lambda_i F_i \qquad (1)$$

where F_i is the i th forecast and λ_i is weight for the i th forecast. Each forecast F_i is typically given from a model, but may be given from an unknown source. The simplest way to obtain a combined forecast would probably be to take the average of F_i with equal weight $1/m$ (Simple Average (SA) method). If we can consider the statistical properties of the forecasts and their errors as described in the following sections, better accuracy may be obtained.

3 COMBINING METHODS USING STATISTICAL TECHNIQUES

3.1 Variance-Covariance (Var-Cov) method

The Var-Cov method combines forecasts to minimize the variance of the forecast errors. Bates and Granger (1969) demonstrated how two unbiased forecasts (F_1 and F_2) can be combined to produce a new forecast that is more accurate than either forecast. If there are two unbiased forecasts and y is the common forecast variable between them, the two forecasts can be written as

$$\begin{aligned} y_t &= F_{t,1} + z_{t,1} \\ y_t &= F_{t,2} + z_{t,2} \end{aligned} \qquad (2)$$

where z_1 and z_2 are the forecast error, which have means of zero, variances σ_1^2 and σ_2^2 respectively, and covariance σ_{12}. The optimal combined forecast F_c is calculated by determining the weights, λ_1 and λ_2 in Eq. (3) which has a constraint, $\lambda_1 + \lambda_2 = 1$.

$$F_{t,\mathrm{c}} = \lambda_1 F_{t,1} + \lambda_2 F_{t,2} \qquad (3)$$

Substituting Eq. (2) to Eq. (3) and then expecting it, we can minimize the variance of the combined forecast error with respect to λ_1 and λ_2 given by

$$\begin{aligned} \lambda_1 &= \frac{\sigma_2^{\,2} - \sigma_{12}}{\sigma_1^{\,2} + \sigma_2^{\,2} + 2\sigma_{12}} \\ \lambda_2 &= \frac{\sigma_1^{\,2} - \sigma_{12}}{\sigma_1^{\,2} + \sigma_2^{\,2} + 2\sigma_{12}} \end{aligned} \qquad (4)$$

The values of the variances and covariance of the forecast errors are unknown and have to be estimated from a sample of observations.

3.2 Regression method

Granger and Ramanthan (1984) proposed a combining forecast method using a regression equation, given by

$$F_c = \beta_0 + \beta_1 F_1 + \beta_2 F_2 + z_t \qquad (5)$$

The Regression method is identical to the Var-Cov method, if F_1 and F_2 are unbiased forecasts, the sum of β_1 and β_2 is one, and the intercept term β_0 is zero. The role of the constant term β_0 in Eq.(5) is to correct for any bias in the forecasts.

3.3 Switching Regression (SR) method

The SR method was suggested with an assumption, in which the lagged forecast error from the alternative forecast models may be useful in combining the forecasts (Deutsch et al., 1994). Using the sign of the lagged forecast error, the following two combination equations were proposed:

$$F_{t,c} = I(t \in I_1)(\lambda_1 F_{t,1} + \lambda_2 F_{t,2}) + (1 - I(t \in I_1))(\lambda_3 F_{t,1} + \lambda_4 F_{t,2}) \qquad (6)$$

$$(1)\ z_{t-1,1} \geq 0, \qquad t \in I_1$$

$$(2)\ z_{t-1,2} \geq 0, \qquad t \in I_1$$

where $I(t \in I_1) = 1$ when $t \in I_1$.

3.4 Sum of Squared Error (SSE) method

The properties of the forecast error may vary over time so that using the fixed weight method such as the Var-Cov and the Regression methods may produce poor combined forecasts. The SSE method was suggested to overcome this problem (Granger and Newbold, 1977), which is

$$\lambda_{t,1} = \frac{\sum_{h=t-1}^{t-v} (z_{h,2})^2}{\sum_{h=t-1}^{t-v} (z_{h,1})^2 + \sum_{h=t-1}^{t-v} (z_{h,2})^2}, \qquad \lambda_{t,1} + \lambda_{t,2} = 1 \qquad (7)$$

$$F_{t,c} = \lambda_{t,1} F_{t,1} + \lambda_{t,2} F_{t,2}, \qquad (8)$$

where the v is the number of previous forecast errors employed to calculate weights. The SSE method uses only the most recent data while the combining methods described above use all the available data to estimate the weights.

4 COMBINING METHODS USING ARTIFICIAL NEURAL NETWORKS

4.1 ANN Error Correction (EC) method

If a streamflow forecast model exists and its past forecast errors (z_{t-1}, …) are available, the model error can be forecasted using the pattern recognition task with ANN (Artificial Neural Network) as shown in Eq.(9):

$$\hat{z}_t = ANN((I_{t-1}, I_{t-2}, ...), (R_{t-1}, R_{t-2}, ...), (E_{t-1}, E_{t-2}, ...), (z_{t-1}, z_{t-2}, ...), ...) \qquad (9)$$

where I is streamflow, R is rainfall and E is evaporation.

The forecasted value of the model then can be updated using the ANN forecasted error obtained in Eq. (9)

$$F_{t,c} = F_t + \hat{z}_t \qquad (10)$$

In other words, the combining forecast value ($F_{t,c}$) can be calculated with a model's forecast value (F_t) and a forecast error ($\hat{z}_t$).

4.2 ANN Combining method

If there are several forecasts ($F_{t,1}$, $F_{t,2}$, …) and their past forecast values for training ANN are available, the combined forecast can be obtained by ANN such that

$$F_{t,c} = ANN((F_{t,1}, F_{t,2}, F_{t,3}, ...), (R_{t-1}, E_{t-1}, ...)) \qquad (11)$$

In Eq. (11), $R_{t\text{-}1}$ and $E_{t\text{-}1}$ represent the hydrologic states at the forecast time that summarize the antecedent hydrologic condition in a basin being considered.

4.3 Case Study

The combining methods described above were applied to simulate monthly inflows at the Daechung dam in Keum River, Korea. The Daechung dam is a multipurpose dam, mainly supplying water and controlling floods. Since 2001, the Korea Water Resources Corporation has been developing an ESP system for probabilistic river forecasting for the Keum River basin. The observed inflow data of the dam from 1981 to 1995 were used to calibrate the combining equations and the most recent 6 years from 1996 to 2001 were used to evaluate the performance of the combining methods.

5 RAINFALL-RUNOFF MODELS

There already exists a conceptual rainfall-runoff model for the Daechung dam basin, called TANK. Having three tanks, TANK simulates the net stream discharge as the sum of the discharges from the side orifices of the tanks.

We developed an additional rainfall-runoff model by using the Ensemble Neural Networks (ENN). Combining the outputs of several member models, ENN can significantly improve generalization performance because the generalization error of the final predictive model is controlled by combining the outputs. (Note that "ensemble" of ENN is not at all related with the "ensemble" of ESP and also "combining" in ENN is independent of "combining" in the combining methods.) The ENN model in this study employed a simple ensemble method known as bootstrap aggregation (Breiman, 1996). The bootstrap aggregation group the available data into a training data set and a test data set. The training data set is used to generate an ensemble of member models and the subset is drawn at random with replacement from the training set. The bootstrap aggregation is advantageous because it reduces the variance, or instability of the ANN. The ENN rainfall-runoff model calibrated in this study used one hidden layer with ten hidden nodes, consisting of the following ten input variables:

$$\hat{I}_t = ENN((R_t,\ R_{t-1},\ R_{t-2},\ R_{t-3}),\ (E_t,\ E_{t-1},\ E_{t-2},\ E_{t-3}),\ (I_{t-1},\ I_{t-2})) \qquad (12)$$

6 APPLICATION OF COMBINING METHODS

The TANK and the ENN rainfall-runoff models were used to simulate the 5-year monthly inflows from 1996 to 2001 for Daechung dam. The simulated series from TANK ($F_{t,1}$) and ENN ($F_{t,2}$) were then combined by using the combining methods shown in Table 1. In Table 1, SR(1) and SR(2) indicate the use of (1) the sign of the lagged simulation error of TANK ($z_{t\text{-}1,1}$) and (2) the sign of the lagged simulation error of ENN ($z_{t\text{-}1,2}$), respectively.

In the SSE method, the choice of the v can have a significant impact on the estimation of the weight and consequently, on the combining results. Therefore, in this study v = 1, 2, 3, 6, 9, and 12 were tested and $v = 2$ was found to produce the minimum root mean square error.

In ANN EC method, the simulated inflow with TANK ($F_{t,1}$) was updated with the forecasted error $\hat{z}_{t,1}$ which was simulated with ENN using the rainfall (R_t, R_{t-1}, R_{t-2}, R_{t-3}), evaporation (E_t, E_{t-1}, E_{t-2}, E_{t-3}), with the inflow of Daeching dam (I_{t-1}, I_{t-2}, I_{t-3}) and with the lagged TANK models errors ($z_{t-1,1}$, $z_{t-2,1}$, $z_{t-3,1}$). The ENN model has 30 member models and each member model has 1 hidden layer and 10 hidden node numbers.

The ANN combining method also used the ENN technique using the input variables of the simulated inflows from TANK ($F_{t,1}$) and ENN ($F_{t,2}$). This study also tested the additional input variables such as the monthly rainfall (R_t) and evaporation (E_t), but they had little impact on the combined inflow.

Table 1. Combining Equations

Method	Combining Equation	Note
SA	$F_{t,c} = 0.5F_{t,1} + 0.5F_{t,2}$	
Var-Cov	$F_{t,c} = 0.193F_{t,1} + 0.807F_{t,2}$	
Regression	$F_{t,c} = -0.817 + 0.330F_{t,1} + 0.670F_{t,2}$	
SR (1)	$F_{t,c} = I(t \in I_1)(0.353F_{t,1} + 0.647F_{t,2}) + (1 - I(t \in I_1))(0.095F_{t,1} + 0.905F_{t,2})$	$z_{t-1,1} \geq 0,\ t \in I_1$ $I(t \in I_1) = 1$
SR (2)	$F_{t,c} = I(t \in I_1)(0.379F_{t,1} + 0.621F_{t,2}) + (1 - I(t \in I_1))(0.140F_{t,1} + 0.860F_{t,2})$	$z_{t-1,2} \geq 0,\ t \in I_1$ $I(t \in I_1) = 1$
SSE	$\lambda_{t,1} = \dfrac{\sum_{h=t-1}^{t-2}(z_{h,2})^2}{\sum_{h=t-1}^{t-2}(z_{h,1})^2 + \sum_{h=t-1}^{t-2}(z_{h,2})^2}$ $F_{t,c} = \lambda_{t,1}F_{t,1} + \lambda_{t,2}F_{t,2}$	$v = 2$ $\lambda_{t,1} + \lambda_{t,2} = 1$
ANN EC	$\hat{z}_{t,1} = ENN((I_{t-1},\ I_{t-2},\ I_{t-3}),\ (R_t,\ R_{t-1},\ R_{t-2}, R_{t-3}),\ (E_t,\ E_{t-1},\ E_{t-2},\ E_{t-3}),\ (z_{t-2,1},\ z_{t-2,1},\ z_{t-3,1}))$ $F_{t,c} = F_{t,1} + \hat{z}_{t,1}$	hidden layer no.: 1 hidden node no.: 10
ANN combining	$F_{t,c} = ENN(F_{t,1},\ F_{t,2})$	hidden layer no.: 1 hidden node no.: 8

7 PERFORMANCE OF COMBINING METHODS

Table 2 shows the Bias and RMSE (Root Mean Square Error) of the two rainfall-runoff (TANK and ENN) models and the combining methods. Between the two rainfall-runoff models, ENN always performed better than TANK except during one season. Among the combining methods, the Var-Cov, Regression, SR (1), and SR (2) methods reduced the annual Bias against ENN. The Regression method gave an annual Bias of zero, but the biases of the Regression method in spring and autumn were greater than those of ENN. To conclude, some combining methods improved ENN in Bias, but ENN generally showed excellent performance in Bias.

For RMSE that incorporates both systemic and random errors, all the combining methods were superior to either TANK or ENN. The annual RMSE was best improved with the SSE method, a time-varying combining method. In winter, RMSE of SSE was close to that of ENN, but in summer and autumn SSE performed much better than ENN. In spring, the ANN EC method performed the best among the combining methods, but, in winter, this method performed worse than the ENN model. However, ANN EC was always superior to TANK, and this fact suggested that ANN EC was valid as a correction technique for the TANK model.

Table 2. Bias and RMSE of the rainfall-runoff model and combining methods

	method	year	spring	summer	autumn	winter
Bias	TANK	5.57	-7.17	4.28	19.85	5.31
	ENN	-1.52	-6.00	-0.73	0.41	0.24
	SA	2.02	-6.58	1.77	10.13	2.78
	Var-Cov	-0.15	-6.22	0.23	4.16	1.22
	Regression	0.00	-7.20	0.11	6.01	1.10
	SR (1)	-0.47	-6.24	-2.17	4.55	1.99
	SR (2)	0.11	-6.28	0.13	5.80	0.79
	SSE	1.57	-7.41	2.63	8.52	2.52
	ANN EC	-2.93	1.86	-3.77	-5.44	-4.37
	ANN Com	3.66	-6.52	8.99	7.65	4.52
RMSE	TANK	35.89	13.87	59.48	32.80	18.61
	ENN	29.17	16.58	47.42	29.15	5.60
	SA	27.53	14.01	47.13	22.95	9.27
	Var-Cov	27.23	15.35	45.60	24.94	5.29
	Regression	26.81	15.02	45.60	22.99	6.46
	SR (1)	26.57	15.67	43.01	26.07	7.04
	SR (2)	26.87	15.13	44.91	24.83	5.12
	SSE	25.36	14.98	42.11	23.22	5.99
	ANN EC	26.15	8.50	42.64	26.38	12.22
	ANN Com	26.39	15.81	44.09	23.47	6.45

Fig 1 shows the errors of the TANK model, ENN model, and SSE method that performed the best in the annual criteria. In most cases, the SSE errors were smaller than those of Tank or ENN model.

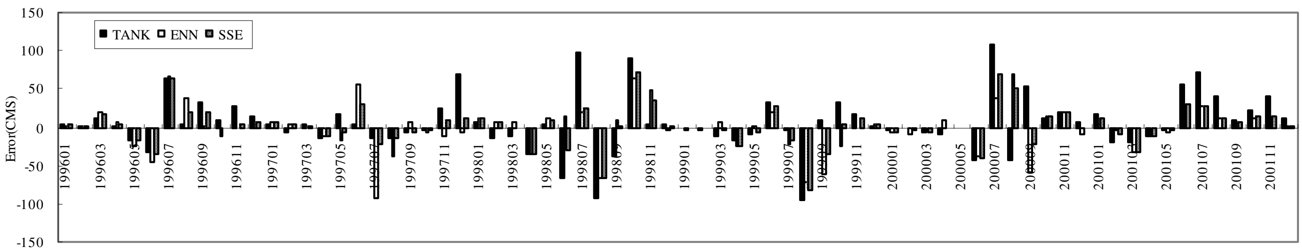

Fig 1. Simulation Errors of TANK model, ENN model, and SSE method.

8 CONCLUSION AND FUTURE STUDY

This study developed a new rainfall-runoff model, called ENN, for simulating monthly inflow of the Daecheong dam in Korea. The simulated inflow series from ENN was combined with that from the existing model, called TANK. Seven combining methods were tested with respect to Bias and RMSE of the simulated errors. This study found that in general ENN was better than TANK, and the Regression and SSE methods gave the best Bias and RMSE, respectively.

This study aimed to improve the accuracy of the ESP probabilistic forecasting for the Daecheong dam. The ESP system currently being developed by KOWACO uses TANK as a rainfall-runoff model. As the future study, therefore, the ENN model and the combining methods studied in this article should be incorporated into the current ESP system to increase the overall forecasting capability of the ESP system.

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