Short-term Water Level Prediction using Different Artificial Intelligent Models

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Abstract—Artificial intelligent models (AIMs) have been successfully adopted in hydrological forecasting in a plenty of literatures. However, the comprehensive comparison of their applicability in particular short-term (i.e. hourly) water level prediction under heavy rainfall events was rarely discussed. Therefore, in this study, the artificial neural networks (ANN), support vector machine (SVM) and adaptive neuro fuzzy inference system (ANFIS) were selected for comparison. A study case in Yaojiang watershed, southeast China was selected for demonstration. The forecasting models were compared in terms of (i) using different lags as modeling inputs; (ii) using training datasets of heavy rainfall events only and all years; (iii) performance in multistep ahead (i.e. from 1 hour to 6 hours) forecasting; and (iv) performance in peak values and all values. The results showed that ANN model trained with datasets sampling from the duration of heavy rainfall performed better than that in using all datasets (including baseflow). The 1- to 4-hour ahead forecasting based on previous 2-hour inputs is the suggested modeling scenario. ANFIS showed better ability of avoiding information noise with different lags of inputs. SVM is relatively more robust during peak values under extreme typhoon events. Overall, this study shed some lights on the best practices in using various artificial intelligent methods for prediction of hourly water level with different model settings. Further studies were desired to issue the early warning with the availability of short-term flash flood forecasting.

Keywords—*flash flood; artificial neural networks; support vector machine; adaptive neuro fuzzy inference system; water level*

I. INTRODUCTION

Flash flood is one of the uppermost natural disasters which greatly affect the assets safety, infrastructure interruptions, and agricultural production. Various engineering (e.g. building dams and managing reservoirs) and non-engineering (e.g. flood forecasting and early warning) measures have been developed for flash flood mitigation [1-3]. Out of which, the short-term flood forecasting (e.g. water level) is essential to provide sufficient hydrological information for rational decision

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making. To improve flash flood forecasting, in terms of either prediction accuracy or lead time, is therefore important [4].

Over the past decades, artificial intelligent methods (AIMs) have received much enthusiasm in hydrological forecasting due to their superiority of easy-to-development, nonlinear fitting capability, and avoiding detailed data and knowledge for modeling. A plenty of successful application were reported in literatures [5-14]. Particularly in short-term forecasting, Ayalew et al. [6] demonstrated the success of artificial neural networks (ANN) in predicting of magnitudes and the time to peak discharge under flood events. Tiwari and Chatterjee [7] employed wavelet bootstrap ANN for hourly water level time series forecasting. Chang et al. [8] used recurrent neural networks to predict 10- to 60-min-ahead water level. Yu et al. [9] applied support vector machine (SVM) to hourly flood stage forecasting, and gave a sensitivity analysis on different lags of input variables, confirming that the forecasting is not sensitive to the lags so convenient and practical method is preferred. Lin et al. [10] developed a two-stage flood forecasting model using SVM to improve the accuracy of rainfall-runoff prediction for 1 to 6 hours ahead, especially the peak flows. Chen et al. [11] showed the practical potential in using adaptive neuro fuzzy inference system (ANFIS) for hourly rainfall-runoff modeling.

Among the various AIMs, Nayak et al. [12] illustrated that ANFIS outperformed ANN in hourly river flow forecasting with relatively longer lead time. Mukerji et al. [13] optimized the weights using genetic algorithm (GA) in ANIFS model and found that adaptive neuro-GA integrated system had better performance than ANN and ANFIS in hourly rainfall-runoff forecasting. Chen et al. [14] proposed an evolutionary fuzzy inference model, which combines fuzzy inference model with GA and genetic programming (GP), setting the number of fuzzy inference rules based on the number of typhoon flood events and adjusting the parameters according to the characteristics of flood events.

However, the comparison of ANN, SVM and ANFIS in short-term rainfall-runoff forecasting under various modeling setting is still limited. Particularly, their applicability to predict hourly water level under heavy rainfall is rarely discussed.

Therefore, the objective of this study is to apply ANN, SVM and ANFIS in short-term flood forecasting (i.e. water level) particularly under heavy rainfall events. A real-world study case in Yaojiang watershed, southeast China was selected for demonstration. The performances of these models under modeling scenarios of using different lags as inputs and being trained with different samples were compared. Their performances in terms of prediction of peak values and all values were also analyzed.

II. METHODOLOGY

A. Artificial Neural Networks (ANN)

ANN consists of a large number of parallel processing neurons, working independently and connecting to each other by weighted links [15]. It is capable of simulating complex nonlinear system due to its ability of self-learning, self-adaption and generalization. The feed forward neural network (FFNN), with one input layer, one or more hidden layer and one output layer, is employed in this study.

BP algorithm, firstly introduced by Rumelhart [16], is employed for training. It consists of two processes, including (i) forward propagation of input signal from input layer to get simulating output; and (ii) backward propagation of error signal from output layer to adjust the connection weights automatically. The global error could be calculated as [23]:

$$E = \frac{1}{2N} \sum_{l=1}^N \sum_{j=1}^M (s_j^l - t_j^l)^2 \quad (1)$$

where M is the number of output variables, N is the number of training patterns, s are simulated values, t are observed values, j are neurons in the output layer, and l are training patterns. In backward propagation of error signal, the weights and biases are adjusted accordingly and automatically using:

$$\mathbf{v}_{i+1} = \mathbf{v}_i - \mathbf{r}_i \mathbf{g}_i \quad (2)$$

where $\mathbf{v}$ are vectors of weights and biases, $\mathbf{r}$ are vectors of learning rate, $\mathbf{g}$ are vectors of gradient, and i is the time step of training.

B. Support Vector Machines (SVM)

SVM tries to find an optimal separating hyperplane to divide the samples into two groups through maximizing the distance between them [17, 18]. It is widely adopted in solving regression and classification problems. When the samples are generally linear separable, slack factor and penalty factor are introduced into the optimization equations. Otherwise, original sample space is transferred into a higher dimensional feature space through kernel function, where samples become linear separable.

In this study, Radial Basis Function (RBF) is employed as kernel function, which is given as:

$$K(x, x_c) = \exp\left(-\frac{\|x - x_c\|^2}{2\sigma^2}\right) \quad (3)$$

where x_c is the center position and σ is the width parameter.

For support vector regression problems, the regression function that fits the relationship from the input vector to the output vector can be written as:

$$f(\mathbf{x}) = \mathbf{w}^T \phi(\mathbf{x}) + b \quad (4)$$

where $\mathbf{x}$ is the input vector, $\phi(\cdot)$ is the transition function, $\mathbf{w}$ is a vector of weights, and b is the bias.

Based on the principal of structural risk minimization (SRM), regression problems can be expressed as the following optimization problems [18]:

Minimize

$$Z(\mathbf{w}, b, \xi, \xi^*) = \frac{1}{2} \mathbf{w}^T \mathbf{w} + C \sum_{i=1}^{N_d} (\xi_i + \xi_i^*)$$

subject to

$$y_i - \mathbf{w}^T \phi(\mathbf{x}) - b \leq \varepsilon + \xi_i$$

$$\mathbf{w}^T \phi(\mathbf{x}) + b - y_i \leq \varepsilon + \xi_i^*$$

$$\xi_i, \xi_i^* \geq 0, \quad i = 1, 2, \dots, N_d$$

where y are the predicted values, N_d is the number of training data, ε is the error tolerance, $C > 0$ is a user-defined parameter that balances the model complexity and empirical error, and ξ and ξ^* are slack factors that specify the upper and the lower fitting errors, respectively. It could be solved using duality theory and Lagrange multipliers [24].

C. Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS combines the advantages of ANN and FIS. It expresses the algorithm in fuzzy language and can adjust the parameters of fuzzy rules and membership functions automatically during training and learning process.

A typical ANFIS model consists of two inputs, one output and five layers, with two fuzzy inference rules as follows:

$$\text{if } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } B_1 \text{ then } f_1 = p_1 x_1 + q_1 x_2 + r_1 \quad (6)$$

$$\text{if } x_1 \text{ is } A_2 \text{ and } x_2 \text{ is } B_2 \text{ then } f_2 = p_2 x_1 + q_2 x_2 + r_2 \quad (7)$$

where A and B are fuzzy subsets, output f is the linear combination of individual rules, x are the inputs, and p , q and r are linear coefficients.

In this study, the Gaussian membership function is employed in the first layer, given as:

$$\mu_A(x) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (8)$$

where c is the position of peak value, and σ is the shape parameter.

Active degree of each rule is calculated in the second layer by multiplying incoming signals, and normalized in the third layer. Weighted result of each rule is calculated in the fourth layer and summarized in the fifth layer, producing the final output as:

$$y = \sum_i \bar{w}_i f_i = \bar{w}_1 f_1 + \bar{w}_2 f_2 \quad (9)$$

where $\bar{w}_i$ is the normalized result of each rule, the proportion in all rules, and y is the final output.

III. CASE STUDY

The study area of Yaojiang watershed is selected for demonstration (Fig. 1). It is located in eastern Zhejiang Province of China between 120°55' and 121°38'E and 29°53' and 30°11'N. It has a drainage area of 3306 km², which is an important plain of agricultural production characterized with a subtropical monsoon climate. Its main stream with the length of 106 km originates from Xiajialing in Dalan Town. The number of raining days ranges from 120 to 200 per year. The annual mean precipitation is 1525.5mm. More than 70% of rain falls between from April to September. Zhangting Station, as the representative typical station of main stream, is selected in this study for demonstration. The water level varies from -1.34 m to 3.03m, with an average of 0.94m.

Heavy rainfall (e.g. total precipitation for consecutive 24 hours is more than 50mm) is the most significant driven factor for flash flood in this study area. During heavy rainfall period hourly rainfall has strong uncertainty and flash flood responses to it quickly and complicatedly. Firstly, hourly meteorological and hydrological datasets under heavy rainfall events were extracted and analyzed. Totally 1,068 samples during 2007-2012 were selected for training, and 608 samples during 2013-2014 were used for verification. Then the training datasets were linearly normalized from -1 to 1 before feeding to model for training.

Fig. 1. Map of study case

IV. APPLICATION AND RESULTS

In applying ANN, tansig function is used as transfer function in hidden layers, and purelin function in output layer; Levenberg-Marquardt algorithm is employed in BP training, and gradient descent algorithm with momentum term in BP learning. The number of nodes in hidden layer is set as $\log_2 n$ (i.e. through trial and error, n is the number of input variables). Radial Basis Function (RBF) is used as kernel function in SVM

model. The penalty parameter c and kernel function parameter g are specified using K-fold Cross Validation (K-CV), to avoid underfitting and overfitting. Fuzzy c-means (FCM) is used to preprocess normalized data before ANFIS training. In this study, the initial FIS structure has three rules and each input pattern is related to three clusters generated by FCM. The Gaussian function is employed as membership function for input nodes, and linear function for output nodes.

In this study, NC , $RMSE$ and R^2 are used as performance indicators for comparison, which are defined as [19]:

$$NC = 1 - \frac{\sum_{i=1}^n (Q_i^t - Q_i^s)^2}{\sum_{i=1}^n (Q_i^t - \bar{Q}^t)^2} \quad (10)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Q_i^t - Q_i^s)^2} \quad (11)$$

$$R^2 = \left[\frac{\sum_{i=1}^n (Q_i^t - \bar{Q}^t)(Q_i^s - \bar{Q}^s)}{\sqrt{\sum_{i=1}^n (Q_i^t - \bar{Q}^t)^2} \sqrt{\sum_{i=1}^n (Q_i^s - \bar{Q}^s)^2}} \right]^2 \quad (12)$$

where Q_i^t are observed values at time i , Q_i^s are predicted values at time i , $\bar{Q}^t$ is the average of observed values, and $\bar{Q}^s$ is the average of predicted values. A smaller value of $RMSE$ and larger value of R^2 mean the better performance of models. Performance of models is compared in terms of peak values (e.g. water level higher than the warning critical value of 1.8 m) and all values.

A. Comparison of ANN trained with samples in different periods

Fig. 2 shows the comparison of ANN models trained with datasets in different periods in prediction of 1- to 6-hour ahead water level. The $RMSE$ of ANN trained with samples representing heavy rainfall period is between 0.017 and 0.172 m for peak values, and that is between 0.029 and 0.176 for all values. Regarding NC , R^2 and $RMSE$, the accuracy of ANN models trained with heavy rainfall samples decreases with the increasing of hourly steps ahead. The acceptable performance (NC more than 0.889, R^2 more than 0.903, and $RMSE$ less than 0.113 m for peak values) could be achieved for 1- to 4- hours ahead forecasting.

Generally, ANN models trained with samples in heavy rainfall performs better than those trained with all data points. From Figs. 2d to 2f, the differences in performance are not obvious between the models trained with samples representing different periods. It might be the reason that a global performance indicator mitigates the problem. On the contrast, from Figs. 2a to 2c, the superiority is obvious in prediction of peak values. It thus has practical meanings in establishing the flood early-warning system and emergency response.

Fig. 2. Performance of ANN models trained with datasets representing different periods

B. Comparison among ANN, SVM and ANFIS

Fig. 3 shows the performance (i.e. *RMSE*) of 1-, 3- and 6-hour ahead forecasting using ANN, SVM and ANFIS trained with previous 1- to 12-hour water levels and rainfalls. It could be observed that ANN, SVM and ANFIS models all perform well in using previous 2-hour water levels and rainfall as inputs. The *RMSE* ranges from 0.017 to 0.049 m, from 0.074 to 0.086 m and from 0.135 to 0.194 m for 1-, 3- and 6-hour ahead peak value forecasting, respectively.

The SVM has the most prominent variation in terms of *RMSE* for peak values (from 0.042 to 0.283 m for 1-hour ahead; 0.077 to 0.333 m for 3-hour ahead; 0.135 to 0.390 m for 6-hour ahead). Comparatively, ANFIS is relatively robust for peak value prediction in using different lags as inputs (the value of *RMSE* is from 0.016 to 0.026 m for 1 hour ahead, and 0.086 to 0.116 m for 3 hours ahead). The same characteristics could be observed in using these models for predicting all values, thus are not discussed in detail. It implies that ANFIS has the capability of avoiding information noise and thus robust for practical application.

Fig. 3. Performance using different lags as inputs with data in heavy rainfall period

Figs. 4a to 4c show the predicted time series water level in using various models under Feite Typhoon occurred from October 6th 1:00 to 9th 2:00 in 2013. It is the heaviest typhoon event during 2007-2014, leading to maximum hourly water level of 3.03m. All of the models perform well in 1-hour ahead forecasting, but slightly worse in 3-hour ahead forecasting.

Figs. 4d to 4f show the forecasting results under Fenghuang Typhoon occurred from September 22nd 0:00 to 23rd 17:00 in 2014. Three models perform similarly, and achieve acceptable accuracy in 1- and 3-hour ahead forecasting.

It is observed that three models perform well during rising limb of water level, but worse during peak values, especially in 3- and 6-hour ahead forecasting. SVM seems a little more robust, for it performs stably during peak values, while ANN predicted values are relatively fluctuating and lower than observation, and ANFIS predicted values are comparatively higher. Comparing two events, error is likely to be larger when the rainfall intensity is stronger, and the underestimate of ANN and SVM and the overestimate of ANFIS become more obvious as well. Therefore, it provides practical reference for flash flood forecasting and decision making under extreme typhoon events.

Fig. 4. Hourly water level prediction in using ANN, SVM, ANFIS under Feite (a-c) and Fenghuang (d-f) Typhoon events

V. CONCLUSIONS

The artificial intelligent models, including ANN, SVM and ANFIS, were applied to hourly water level forecasting, with a study case in Yaojiang watershed. The performances of ANN trained with samples representing different periods were compared in terms of peak values and all values. The results showed that ANN using samples in heavy rainfall period performed better than that in using all data values. 4-hour ahead forecasting based on previous 2-hour inputs is the suggested modeling scenario for ANN, SVM and ANFIS. With different lags of inputs, ANFIS performed better in avoiding information noise. Under extreme typhoon events, SVM showed relative robustness during peak values. Further studies are still required to appropriately issue the early warning with the availability of the short-term flash flood forecasting.

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