International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:2, No:3, 2008

Decision Support System for Flood Crisis Management using Artificial Neural Network

Muhammad Aqil, Ichiro Kita, Akira Yano, and Nishiyama Soichi

***Abstract*—**This paper presents an alternate approach that uses artificial neural network to simulate the flood level dynamics in a river basin. The algorithm was developed in a decision support system environment in order to enable users to process the data. The decision support system is found to be useful due to its interactive nature, flexibility in approach and evolving graphical feature and can be adopted for any similar situation to predict the flood level. The main data processing includes the gauging station selection, input generation, lead-time selection/generation, and length of prediction. This program enables users to process the flood level data, to train/test the model using various inputs and to visualize results. The program code consists of a set of files, which can as well be modified to match other purposes. This program may also serve as a tool for real-time flood monitoring and process control. The running results indicate that the decision support system applied to the flood level seems to have reached encouraging results for the river basin under examination. The comparison of the model predictions with the observed data was satisfactory, where the model is able to forecast the flood level up to 5 hours in advance with reasonable prediction accuracy. Finally, this program may also serve as a tool for real-time flood monitoring and process control.

***Keywords*—**Decision Support System, Neural Network, Flood Level

I. Introduction

RIVER management is undoubtedly a challenging field of operational hydrology, and a huge literature has been developed in years. Modeling of flood dynamics is performed not only to provide a warning system as a technical way to reduce flood risks but also assist in managing reservoir operation particularly during the drought periods. In the past, prediction of river flood was mainly performed using conceptual and deterministic models [1]. Recently, artificial neural network has gained an increasing popularity for modeling nonlinear systems.

Artificial neural network (ANN) is an empirical modeling tool that has an ability to identify underlying highly complex relationship from input-output data only. This empirical modeling tool is designed to emulate the human pattern recognition function through parallel processing of multiple inputs. Neural network operate like a black box model, requiring no detailed information about the system. Instead, they learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data [2]. The advantages of neural networks over the traditional methods are the ability to handle large amounts of noisy data from dynamic and nonlinear systems, especially when the underlying physical relationships are not fully understood [3]. There are many different types of neural networks architectures and topologies, and among them, feed forward network has recently gained popularity as an emerging and challenging computational technology [4]. Feed forward networks are the most common form applied in hydrology due to the simple framework.

Neural network technology have provided many promising results in modeling complex nonlinear systems, and successful applications of this artificial intelligence in the field of hydrology and water resources modeling have been widely reported, such as for river flow forecasting [5]-[8], rainfall forecasting [9]-[12], groundwater modeling [13]-[16], and rainfall-runoff simulation [17]-[20]. A comprehensive review of the application of neural network to hydrology can be found in the ASCE Task Committee [21] and in Maier and Dandy [22].

In this paper, a decision support system is developed involving a neural network decision-making method and applied to monitor the flood level dynamics in a river basin. The decision-support system was developed for use in estimating a one-step and multi-step ahead prediction of hourly flood level dynamics.

II. Artificial Neural Network

ANN is a parallel and dynamic system of highly interconnected interacting parts based on neurobiological models. Here the nervous system consists of individual but highly interconnected nerve cells called neurons. These neurons typically receive information or stimuli from the external environment. Similar to its biological counterpart, ANN is designed to emulate the human pattern recognition function through parallel processing of multiple inputs i.e. ANN have the ability to scan data for patterns and can be used to construct non-linear models.

Feed forward neural network (FFNN) is widely used for the

Manuscript received December 16, 2005. This work was supported in part by the Ministry of Education, Culture, Sports, Science and Technology, Japan.

Muhammad Aqil is with the Graduate School of Agricultural Sciences, Tottori University, Tottori 680-8573 Japan (e-mail: akilshimane@gmail.com).

Ichiro Kita, Akira Yano are with the Faculty of Life and Environmental Science, Shimane University, Shimane, Matsue 690-8504 Japan.

Nishiyama Soichi is with the Faculty of Agriculture, Yamaguchi University, Yamaguchi 753-8515 Japan.

input/output pair mapping of qualitative relationship due to its capability of approximating nonlinear model functions [11]. The FFNN has a parallel and distributed processing structure. In general, it is composed of three layers: an input layer, which is used to present data to the network; an output layer, which is used to produce an appropriate response to the given input; and one or more intermediate layers, which are used to act as a collection of feature detectors. The network topology consists of a set of nodes (neurons) connected by links and usually organized in a number of layers. Each node in a layer receives and processes weighted input from a previous layer and transmits its output to nodes in the following layer through links. Each link is assigned a weight, which is a numerical estimate of the connection strength. The weighted summation of inputs to a node is converted to an output according to a transfer function (typically a sigmoid function). A schematic diagram of a three-layer FFNN is shown in Fig. 1.

Fig. 1 shows the y output that is transformed from the I inputs (x_1, x_2…, x_i,…, x_I) through the hidden layer with J neurons. The output of the neural network, y, can be computed as follows:

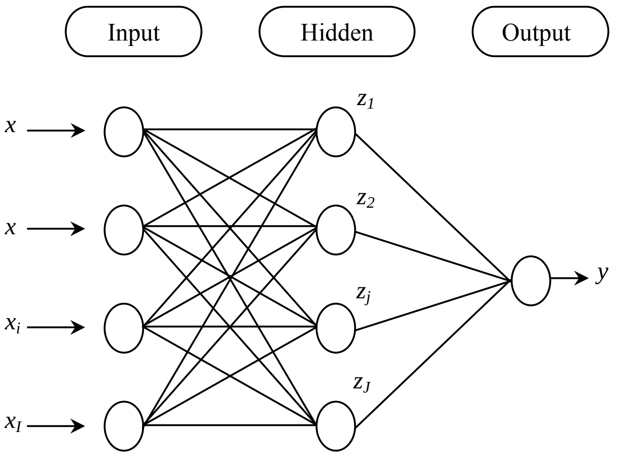

Fig. 1. A three-layer feed forward neural network.

$$y = f_y\left(\sum_{j=1}^{J} z_j . w_j + w_o\right) \tag{1}$$

With $z_j = f_z\left(\sum_{i=1}^{I} x_i . w_{ij} + w_{oj}\right)$ (2)

where z_j is the output value of the j-th hidden node, w_j are the weights between nodes of the hidden and output layer, w_{ij} are the weights between input and hidden layer, w_o is the bias for neuron y, w_{oj} is the bias for neurons z_j, f_y and f_z are the activation functions, which are normally nonlinear functions. Sigmoid shape activation functions are normally defined as:

$$f(\zeta) = \frac{1}{1+e^{-\zeta}} \tag{3}$$

There are so many types of algorithms available for training a network, and selection of an algorithm that provides the best fit to the data is required. The Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix [23]. When the performance function has the form of a sum of squares, the Hessian matrix can be approximated as follows:

$$H = J^T J \tag{4}$$

and the gradient can be computed as:

$$G = J^T e \tag{5}$$

where J is the Jacobian matrix, which contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like weight update:

$$x_{k+1} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e \tag{6}$$

where x indicate the weights of neural network, and μ a scalar that controls the learning process. Note that when parameter μ is large, the above expression approximates gradient descent with a small step size while for a small μ the algorithm approximates the Newton's method. By adaptively adjusting the parameter Newton's method, the Levenberg-Marquardt can maneuver between its two extremes – the gradient descent and the Newton's algorithm. The Levenberg-Marquardt algorithm is very efficient for training small to medium-size networks.

III. Model Development

A. Input Vector Selection

A potentially critical issue in applying an extrapolative prediction method in river stage management is the choice of input variables. The parameters that need to be selected in the input variable are determined by two statistical methods, i.e. autocorrelation (ACF) and partial autocorrelation (PACF) between the variables. The ACF and PACF are generally used to gather information about the autoregressive process of the data series [24]. The number of antecedent river stage that should be included in the input variables are usually determined by placing a 95% confidence interval on the autocorrelation and partial autocorrelation plots.

International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:2, No:3, 2008

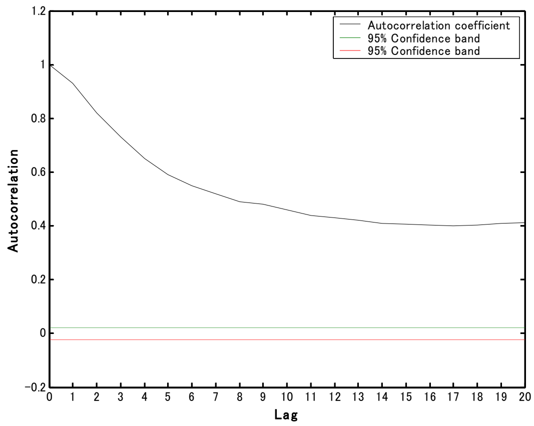

Fig. 2 Autocorrelation plot of the data series

The ACF and the corresponding 95% confidence intervals of the river stage series for lag 0 to lag 20 is presented in Fig. 2. Similarly, the PACF and the corresponding 95% confidence intervals of the river stage series are presented in Fig. 3. The ACF (Fig. 2) showed a significant correlation at 95% confidence level interval up to 14-h of river stage lag. In addition, the PACF showed significant correlation up to lag of 3 (3-h). Result of correlogram plots of the data series shown in Figs. 2 and 3 imply that incorporating the antecedent values up to lag 3-h can best represent the process in the catchment area under examination. Therefore, in this study three antecedent values of river stage are selected as input for modeling river stage.

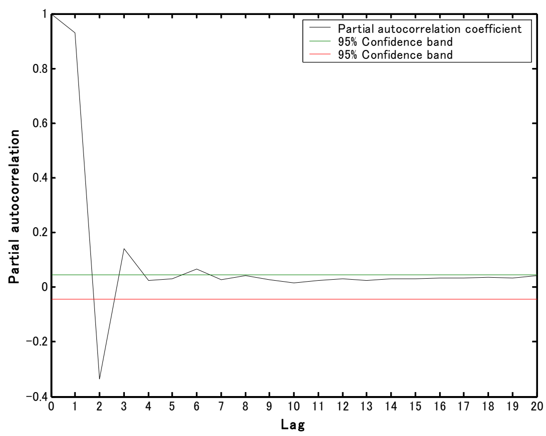

Fig. 3 Partial autocorrelation plot of the data series

B. *ANN Model Development*

The network architecture that is employed uses a multilayer perceptron network. The network has three layers including input layer, output layer and hidden layer. A single hidden layer was used in this study, and the number of neuron in the hidden layer was identified using a trial and error procedure by varying the number of hidden layer neurons from 2 to 10 with an increment of 2. The output layer had one neuron corresponding to the predicted river water level. A tan-sigmoid activation function was used for the hidden layer, and a linear transfer function for the output layer. Levenberg-Marquardt algorithm was used to train the network. The optimal network architecture for each model was selected from the one which resulted in minimum error and best correlation in the data set. The effect of changing the number of hidden neurons on the root mean square error (RMSE) of the data set is shown in Fig. 3. As can be seen from Fig. 3that the effect of the number of neurons assigned to the hidden layer has a little effect on the performance of the feed forward model. As could be concluded from Fig. 3, the use of three or four neurons gives the lowest prediction error in the testing data set. Therefore a Levenberg-Marquardt-FFNN with 4 input neurons, 4 hidden neurons and 1 output neuron (4-4-1) was adopted as the best structure combination to capture the relationship inherent in the data under consideration.

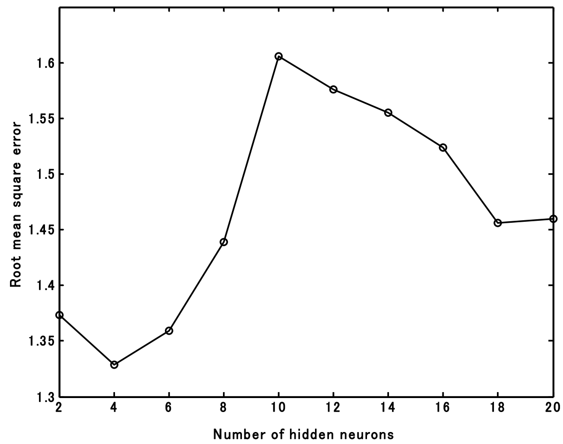

Fig. 4 Effect of changing the number of nodes on network performance

C. *Case Study and Data Description*

The ANN configuration described in Section III.B is illustrated with its application to the management of the Cilalawi river basin in Indonesia (Fig. 5). Cilalawi river basin is located in the Purwakarta Regency, West Java Indonesia. The total drainage area of the river basin is approximately 6,017.58 km^2. The climate of the catchment is generally dry, except during the monsoon months from December to April. It has an annual precipitation depth of 3,000 mm in the mountainous area and 2,500 in the lowland and normally 70% falls during rainy season whereas 30% falls during dry season. Water resources in the Cilalawi river basin are operated and managed by Perum Jasa Tirta II (PJT II), a public corporation formed in 1967.

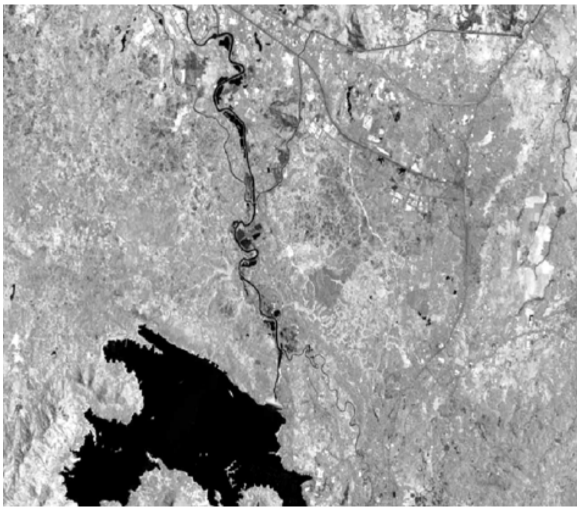

Fig. 5 Satellite image of the river (acquired on Sep 4 2005)

The continuous hourly water level data were measured from year 2002-2003, and separately used to train and validate the model. The whole data set was composed of 9000 hourly data sets, and divided into two subsets: a training subset includes 5000 data sets and the testing subset that has the remaining 4000 data sets. The training data set is used for model development and parameter estimation, whereas the verification data set is used to validate the model.

IV. Continuous Flood Level Simulation

A decision support system is developed involving a neural network decision-making method and applied to the water level forecasting in the Cilalawi river basin in Indonesia. The decision support system is found to be useful due to its interactive nature, flexibility in approach and evolving graphical feature and can be adopted for any similar situation to predict the water level. Fig. 6 presents the sample screen of the main module of the decision support system.

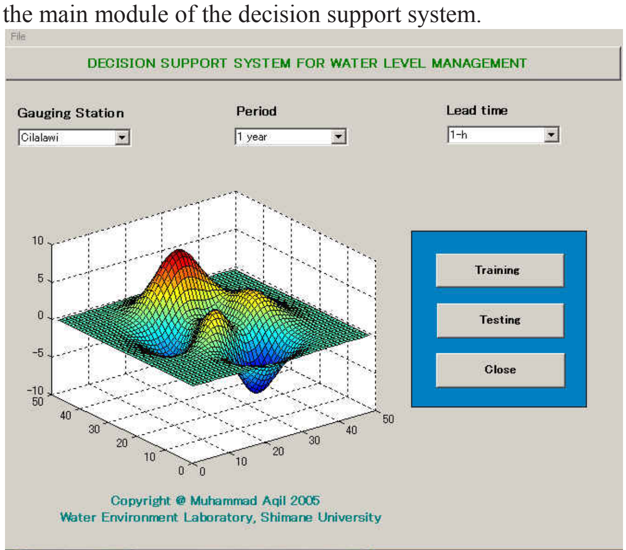

Fig. 6 Sample screen of the main module

The training period was considered for the first 5000 data sets and the last of the data was used for testing the model. The input layer consisted of 3 nodes representing the water level values at *t*, *t-1*, and *t-2*. and the output layer consisted of a single node representing the flow value at *t+1*. A Levenberg-Marquardt-FFNN with 4 input neurons, 4 hidden neurons and 1 output neuron (4-4-1) was adopted to evaluate the competence of the network. During the network training, prediction models were generated from historical data, which was provided and was combined with another parameter to deliver the results. Performance of the model was compared with the actual data using two performance criteria.

The comparison between the predicted and actual flow values at training phase was satisfactory, and ANN can catch the low and peak flood level dynamics with a good generalization. During the training stage, the MAPE and RMSE resulted were 1.010 % and 4.421 respectively. The final values of model parameters obtained after training, were then used as the optimal parameter combination for multiple-step ahead forecasting. In this particular case, the predicted outputs were feed back into the networks to predict more values. The decision support system was develop to forecasts up to 5-h water level in advance, in a recursive way. It is to be noted that as the number of steps ahead increases, it is expected that the prediction error variance should also increase. The values of the performance indices of the model for multi-step ahead forecasting is presented in Table II. This can be observed in Table II in which the MAPE is small for forecasts 1-h and 2-h ahead (1.029 and 1.667% respectively). However, once the period of short-term predictability is over, the reconstructed model starts to move away from the actual data. The results indicated that the performance of the proposed model is much better when predicting the near future, but it decreased gradually when predicting larger lead times.

TABLE I
STATISTICAL PARAMETER USED TO TEST THE MODEL

Statistical parameter	Expression
Mean absolute percentage error (MAPE)	$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{Q_i^p - Q_i^o}{Q_i^o}\right\rvert x100$
Root mean square error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Q_i^o - Q_i^p\right)^2}{n}}$

TABLE II
PERFORMANCE OF THE MODEL DURING THE TESTING PERIOD

Testing period	MAPE (%)	RMSE
1-h ahead	1.029	4.616
2-h ahead	1.667	7.409
3-h ahead	2.390	9.005
4-h ahead	2.928	10.258
5-h ahead	3.388	11.013

In order to obtain a brief picture of the general performance of the decision model, we also provide the sample screen of the hydrographs of observed water level against 1-h, 3-h, and 5-h prediction in advance. Figs. 8 through 10 indicate a good agreement between the observed and computed flood level at shorter lead times. The computed value at 5-h lead-time produces satisfactory result, where the ANN model resulted in the MAPE<3.468% and RMSE<11.122 cm. It is clearly indicated in Figs. 8 through 10 that the high water level is predicted higher than the actual data, especially for lead-time of 5-h in advance. This error is probably due to the result of error accumulation at previous time steps, which is increase as the increase of lead-time. Therefore, our next task should rather give more importance to the model's ability in multi-step-ahead predictions.

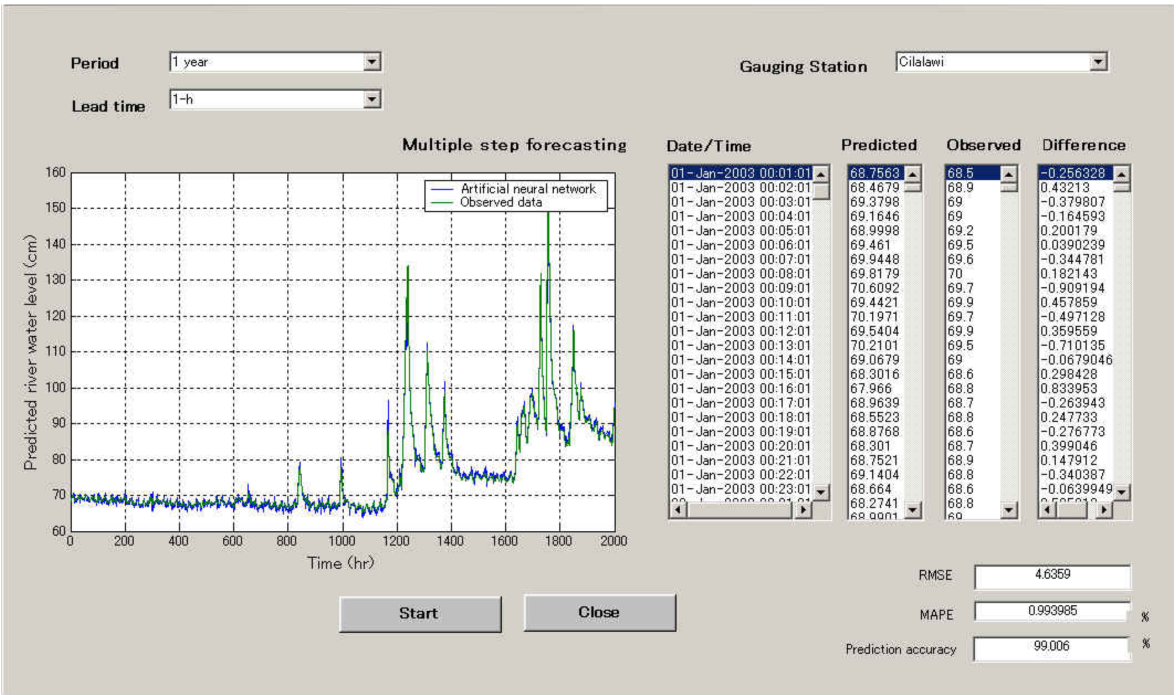

Fig. 7 Sample screen of the prediction result for 1-h ahead

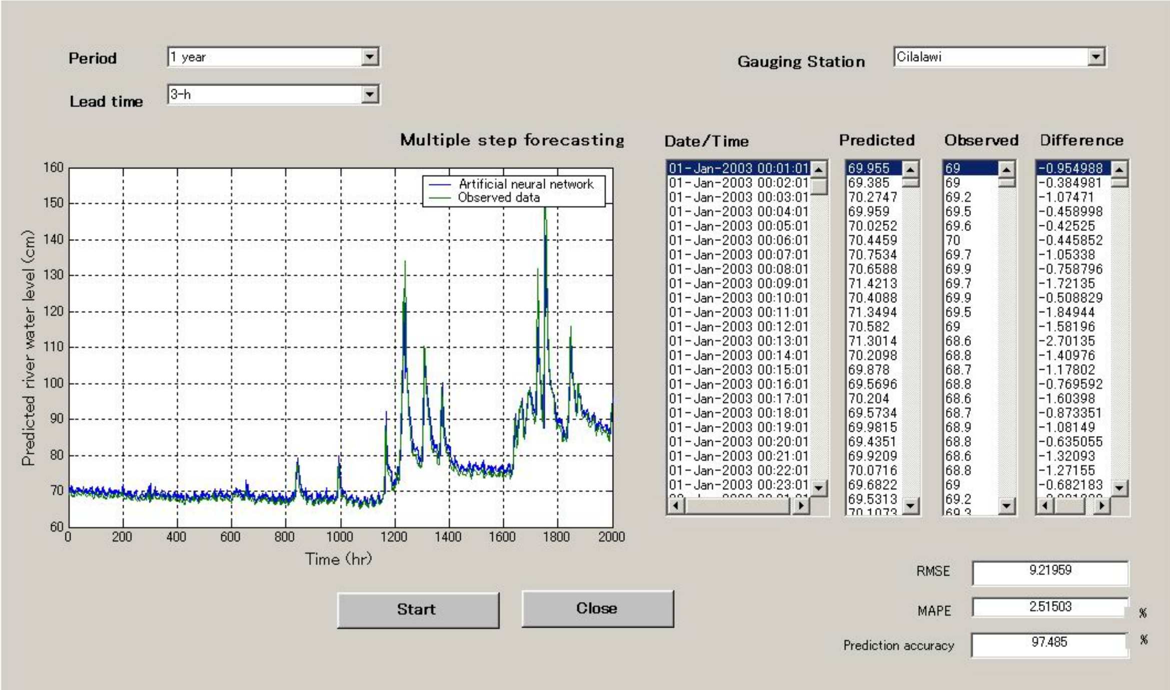

Fig. 8 Sample screen of the prediction result for 3-h ahead

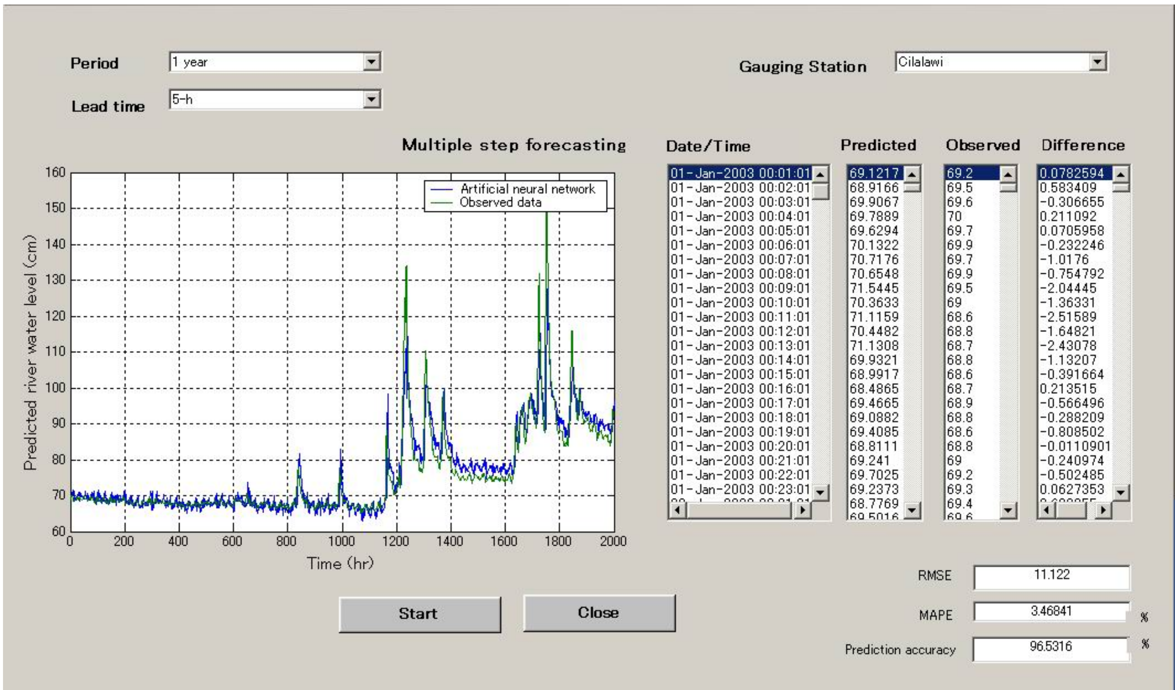

Fig. 9 Sample screen of the prediction result for 5-h ahead

V. Conclusion

In this study, a decision support system is developed involving a neural network decision-making method and applied to the flood level forecasting. The algorithm was developed in a decision support system environment in order to enables users to process the data. The decision support system is found to be useful due to its interactive nature, flexibility in approach and evolving graphical feature and can be adopted for any similar situation to predict the flood level.

The main data processing includes the gauging station selection, input generation, lead-time selection/generation, and length of prediction. This program enables users to process the flood level data, to train/test the model using various inputs and to visualize results. The program code consists of a set of files, which can as well be modified to match other purposes. This program may also serve as a tool for real-time flood monitoring and process control. The running results indicate that the decision support system applied to the flood level seems to have reached encouraging results for the river basin under examination. The comparison of the model predictions with the observed data was satisfactory, where the model is able to forecast the flood level up to 5 hours in advance with reasonable prediction accuracy. Finally, this program may also serve as a tool for real-time monitoring and process control.

ACKNOWLEDGMENT

The authors would like to extend grateful thanks to Perusahaan Umum Jasa Tirta II (PJT II), West Java Indonesia for the cooperation and assistance during the data collection exercise. In a special way the authors wish to acknowledge Mr. Andri Sewoko assistance in providing the data on which this research was based.

REFERENCES

[1] Q. Duan, S. Sorooshian, and V.K. Gupta, “Effective and efficient global optimization for conceptual rainfall runoff models,” *Water Resour. Res*., vol. 28, pp. 1015–1031, 1992.
[2] A. W. Minns, and M.J. Hall, “Artificial neural networks as rainfall-runoff models,” *Hydrol. Sci. J.*, vol. 41, pp. 399-418, 1996.
[3] S. Openshaw, and C. Openshaw, ”*Artificial Intelligence in Geography,”*, Chichester : John Wiley & Sons Ltd, 1997.
[4] T. Y. Pan, and R. Y. Wang, “State space neural networks for short term rainfall-runoff forecasting,” *J. Hydrol*., vol. 297, pp. 34–50, 2004.
[5] C. E. Imrie, S. Durucan, and A. Korre, “River flow prediction using artificial neural networks: generalisation beyond the calibration range,” *J. Hydrol*., vol. 233, pp. 138–153, 2000.
[6] T. S. Hu, K. C. Lam, and S. T. Ng, S.T, “River flow time series prediction with a range-dependent neural network,” *Hydrol. Sci. J*., vol. 46, pp. 729–745, 2001.
[7] D. N. Kumar, K. S. Raju, T. Sathish, T, “River Flow Forecasting using Recurrent Neural Networks,” *Water Resour. Mgmt*., vol.18, pp. 143–161, 2004.
[8] A. Jain, K. P. Sudheer, and S. Srinivasulu, “Identification of physical processes inherent in artificial neural network rainfall–runoff models,” *Hydrol. Process*. vol. 118, vol. 571–581, 2004.
[9] K. Hsu, H. V. Gupta, and S. Sorooshian, “Artificial neural network modelling of the rainfall–runoff process,” *Water Resour. Res*., vol. 31, pp. 2517–2530, 1995.
[10] R. Kuligowski, and A. P. Barros, “Localized precipitation forecasts from a numerical weather prediction model using artificial neural networks,” *Wea. Forecast*., vol. 13, pp. 1195–1205, 1998.
[11] K. C. Luk, J. E. Ball, and A. Sharma, “An application of artificial neural networks for rainfall forecasting,” *Math. Computer Mod*., vol. 33, pp. 683–693, 2001.
[12] M. C. P. Rami´rez, H. F. C. Velho, and N. J. Ferreira, N.J, “Artificial neural network technique for rainfall forecasting applied to the Sa˜o Paulo region,” *J. Hydrol*., vol. 301, pp. 146–162, 2005.
[13] R. S. Ranjithan, D. E. Eheart, and J. H. Garrett, “*Application of neural network in groundwater remediation under conditions of uncertainty*,” in *New Uncertainty Concepts in Hydrology and Water Resources*’, edited by Z. W. Kundzewicz, 133–144, Cambridge University Press, New York, 1995.
[14] C. C. Yang, S. O. Prasher, R. Lacroix, S. Sreekanth, N. K. Patni, and L. Masse, L, “Artificial neural network model for subsurface-drained farmland,” *J. Irrig. Drain. Eng*. vol. 123, pp. 285–292, 1997.
[15] P. Coulibaly, F. Anctil, R. Aravena, and B. Bobe´e, “Artificial neural network modeling of water table depth fluctuations,” *Water Resour. Res*. vol. 37, pp. 885–896, 2001.
[16] I. N. Daliakopoulos, P. Coulibalya, and I. K. Tsanis, “Groundwater level forecasting using artificial neural networks,” *J. Hydrol*. vol. 309, pp.229–240, 2005.
[17] C. W. Dawson, and R. L. Wilby, “A comparison of artificial neural networks used for rainfall-runoff modeling,” *Hydrol. and Earth Syst. Sci.,* vol. 3, pp. 529-540, 2000.
[18] A. S. Tokar, and P. A. Johnson, “Rainfall-runoff modelling using artificial neural Networks,” *J. Hydrol. Eng.* Vol. 4, pp. 232–239, 1999.
[19] S. Riad, J. Mania, L. Bouchaou, and Y. Najjar, “Predicting catchment flow in a semi-arid region via an artificial neural network technique,” *Hydrol. Process*. vol. 18, pp. 2387–2393, 2004.
[20] P.C. Nayak, K.P. Sudheer, D.M. Rangan, and K.S. Ramasastri, “Short-term flood forecasting with a neurofuzzy model,” Water Resour. Res. vol. 41, pp. 2517–2530, 2005.
[21] ASCE Task Committee, “Artificial neural networks in hydrology,” *J. Hydrol. Eng.* vol. 5, pp. 115–123, 2000.
[22] H. Maier, and G. Dandy, “Neural networks for the predictions and forecasting of water resources variables: review of modeling issues and applications,” *Environ. Modelling and Soft.*, vol. 15, pp. 101–124, 2000.
[23] H. Demuth, and M. Beale, “*Neural Network Toolbox for Use with MATLAB, Users Guide, Version 3,”*. The MathWorks, Inc., Massachusetts, 1998.
[24] K. P. Sudheer, A. K. Gosain, and K. S. Ramasastri, “A data-driven algorithm for constructing artificial neural network rainfall–runoff models,” Hydrol. Process. vol. 16, 1325–1330, 2002.