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Real-Time Forecasting of Water Levels Using Adaptive Neuro-Fuzzy Systems

D. K. Gautam*, K. P. Holz*, Z. Meyer**

*Brandenburg University of Technology at Cottbus, Germany
**Technical University of Szczecin, Poland

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Abstract

Real-time forecasting of high water levels at the mouth section of the Odra river is important for the safety conditions of shipping, shipyard works, river banks protection, flood control and overall management of aquatic environment in the area. While numerical hydrodynamic models offer one possible solution, such models require forecasting of all boundary conditions and forcing data, calibration of model parameters and are often too complex and time consuming. These models are not very suitable for real-time forecasting where fast solutions are required to provide adequate lead time. Simpler approaches offered by artificial intelligence methods such as artificial neural networks and fuzzy rule-based systems are thus becoming more attractive and promising alternatives. These methods provide a fast, sufficiently good and low-cost solution. In this paper, an application of Adaptive-Network-Based Fuzzy Inference System (ANFIS) is presented for real-time forecasting of water levels at Police on the mouth section of the Odra river.

Notations

A	–	Fuzzy set
ANFIS	–	Adaptive-Network-Based Fuzzy Inference System
ARMAX	–	Autoregressive Moving Average with eXogeneous input
ARX	–	Autoregressive with eXogeneous inputCCF Cross-Correlation Function
d	–	Pure time delay of the system
DC	–	Determination coefficient
FIS	–	Fuzzy Inference System
h	–	Water level
k	–	Prediction horizon
m	–	Order of exogeneous input
MPE	–	Mean percent error

n	–	Order of autoregressive input
O, y	–	Output
P	–	Atmospheric pressure
PBIAS	–	Percent bias
RMSE	–	Root mean square error
u, v, W	–	Wind speed
w	–	Firing strength of rule
X	–	Input
α	–	Consequent parameters
μ	–	Membership value
φ	–	Regressor vector

1. Introduction

Real-time forecasting of high water levels at Police, Świnoujście and other places in the mouth section of the Odra river is very important for flood control, river banks protection, safety conditions for shipping, shipyards work and overall management of water systems in the region.

The mouth section of the Odra river has strong sea influence on water levels and flows. The sudden high increases of water surface in the sea during the passage of a low atmospheric pressure area (cyclone) over the region generates the so-called "storm tides". These *barotropic waves* propagate upstream in the river network and significant increase in water levels occur resulting in widespread flooding and destruction of the shores of Szczecin bay.

Usually the storm tides are accompanied by northerly winds. West winds (NW, W, SW) are predominating, however, the strongest blow from the north. South winds are minimal. In Szczecin area, one may notice a clear wind canalization concentration along river valley and an increase of wind velocity above the river with respect to velocity over lands (Meyer 1995).

These winds produce additional effects, so-called *wind backwaters*. It also results in increase of water levels. The phenomenon of wind backwater occurs when water flowing down encounters the wind blowing against it and in consequence wind shear stress at surface takes place. The surface flow velocity and mean flow velocity in the river decreases. In order to maintain a constant flow, the water depth increases. Intense wind may sometimes result a surface back stream flow.

The effect of astronomical tide is negligible. However, the passage of a low atmospheric pressure system accompanied by strong winds (N, NW) generates *storm surges*. The rising waves due to storm surges produce most frequently much higher and more dynamic changes of water levels and outflows in the river network of Odra than the passage of a typical flood wave from an upstream section of the river.

Simplified analytical formula for quatitative description of water level changes depending on atmospheric pressure changes can be found in Meyer and Ewertowski (1996a, b). Meyer and Ewertowski (1996a, b) have proposed different models of atmospheric pressure changes such as the step function model, exponential model of pressure distribution and general function of atmospheric pressure distribution. Using these functions, solution for water level changes and flow velocity can be obtained in a straight channel. However, these analytical models are not very suitable in real cases where a numerical hydrodynamic model is mainly used.

The numerical hydrodynamic model for the Odra river network which incorporates the influence of air pressure changes in time and space and wind shear stress at the free water surface, has also been developed at the Technical University of Szczecin. This model needs initial conditions, boundary conditions (water level at downstream and discharge at upstream), wind field data and atmospheric pressure changes. The two model parameters i.e. Manning's coefficient and wind drag coefficient, should be determined by model calibration. This model is very useful to calculate the water levels and flows at different time and space in all cross-sections for every branch of the Odra river network. However, this model is not very suitable for real-time forecasting of water levels, as it requires forecasting of all boundary conditions, wind field data and atmospheric pressure changes to carry out the forecast forward in time and is very complex and time consuming.

Artificial intelligence methods such as artificial neural networks and fuzzy rule-based systems are offering promising alternative for such real-time forecasting and control problems. The domain of artificial intelligence is gradually entering in the field of water resources management. The main advantage of these techniques is that they can be set up in considerably less time and the model response can also be obtained fast, thus reducing the cost. Although these models give little insight into the physical processes, they provide a sufficiently good, low-cost solution. Another advantage of these methods is that they are extremely effective on handling dynamic, non-linear and noisy data, especially when the underlying physical relations are highly complex and not fully understood. These methods offer a more flexible, less assumption dependent and self-adaptive approach to modelling complex, non-linear and dynamic systems. Moreover, these models representing complex, empirical part can be plugged into the conventional numerical models thus resulting in a hybrid model (See and Openshaw 1998, Boogaard and Kruisbrink 1996).

The application of artificial neural networks and fuzzy rule-based systems as a modelling tool in the field of hydrology and hydraulics is a relatively new area of research, although some studies have already been conducted to some extent in the field of hydrology and these studies have generated considerable enthusiasm. Intensive research has been carried out by Minns (1998), and Minns and Hall (1996) for the modelling of rainfall-runoff processes by applying neural networks.

Until now, artificial neural networks have been applied for rainfall modelling (Luk et al. 1998, French et al. 1992), derivation of unit hydrograh (Lange 1998), modelling of time series (Gautam and Boogaard 1998), urban runoff prediction (Sincak et al. 1998), estimation of annual runoff (Sajikumar and Thandaveswara 1996), real-time flash flood forecasting (Khondker et al. 1998) and regional flood frequency analysis (Hall and Minns 1998).

This paper considers the application of hybrid neuro-fuzzy approach for real-time forecasing of water levels. The proposed approach is explained in more detail in Section 2. Sections 3 and 4 describe the case study and present the results from an application to data from the station Police at the mouth of the River Odra in Poland. Some conclusions are presented in the final Section.

2. Adaptive-Network-Based Fuzzy Inference System

Adaptive-Network-Based Fuzzy Inference System (ANFIS) is a hybrid neuro-fuzzy system for function approximation proposed by Jang (1993). It is a fuzzy inference system implemented in the framework of adaptive networks and represents a Sugeno-type fuzzy system in a special five-layer feedforward network architecture (Fig. 1). In Sugeno-type fuzzy system, the output of each rule is a linear combination of input variables plus a constant term, and the final output is the weighted average of each rule's output. The rules are of the form:

$$R_r: \text{ If } x_1 \text{ is } A_1^{(r)} \wedge \ldots\ldots \wedge x_p \text{ is } A_p^{(r)} \text{ then } y_r = \alpha_0^{(r)} + \alpha_1^{(r)} x_1 + \ldots\ldots + \alpha_p^{(r)} x_p \quad (1)$$

ANFIS provides an effective method for tuning the membership functions. The rule base itself should be generated either directly from expert knowledge or from data or by a combination of both. To generate the rules from observed data, a clustering method such as subtractive clustering can be employed (Chiu 1994). Subtractive clustering is an efficient method for estimating the cluster centers which can be used as the basis for identifying initial fuzzy inference system (FIS) for ANFIS training. It considers each data point as a potential cluster center and calculates the measure of potential for a data point based on its distances to all other data points. A data point with many neighbouring data points will have a high potential value. After the potential of every data point has been computed, the one with the highest potential is selected as the first cluster center and the potential of each data point is revised by subtracting an amount of potential from each as a function of its distance from the first cluster center. Then that with the highest remaining potential is selected as the second cluster center and the potential of each data point is further reduced according to its distance from the second cluster center. The process is repeated until all cluster centers have been found (see Chiu 1994). The value of cluster centers can be used to define Gaussian type membership function for the rule's antecedent part and the rule's consequent part can be determined by least-squares estimation method. In this

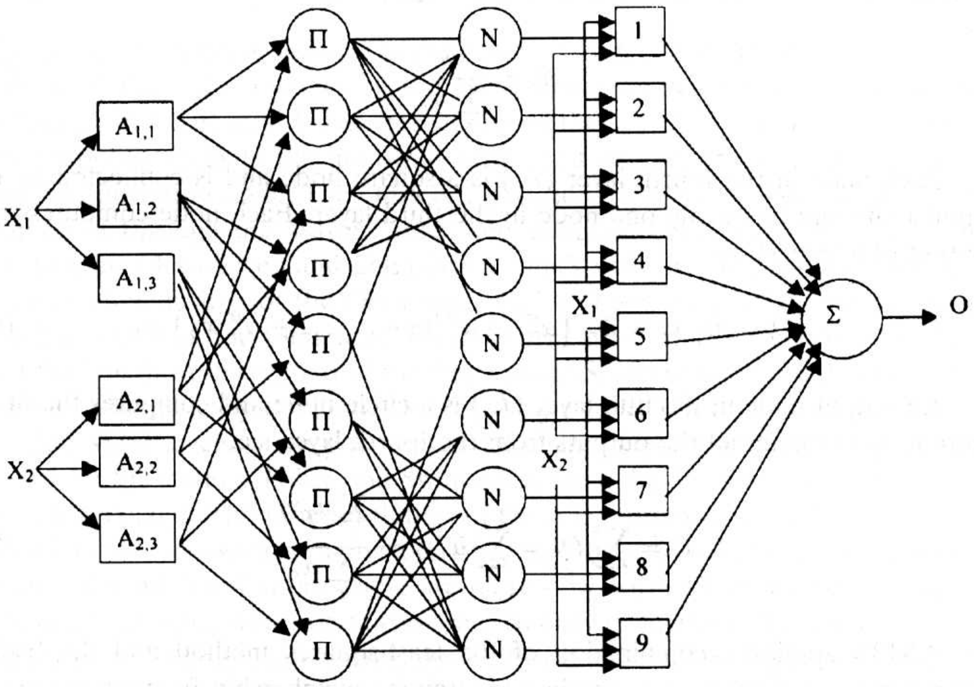

Fig. 1. Structure of ANFIS (adopted from Jang 1993)

way, an initial fuzzy inference system for ANFIS training can be obtained. ANFIS then adjusts only the parameters of membership functions of the antecedents and the consequent.

The ANFIS network structure contains p input units and five layers. Each node in the first layer (L_1) is a square (adaptive) node and stores the parameters of membership functions associated with each input. The number and type of membership function must be specified or can be generated using subtractive clustering. Commonly used membership functions are Gaussian curve, generalized bell shape, sigmoidal, triangular and trapezoidal membership functions. Each node is connected to exactly one input unit and computes the membership degree of the input value obtained.

Each node in the second layer (L_2) denoted by Π in Fig. 1 is a circle (fixed) node which multiplies the degrees of membership to determine the degrees of fulfilment (firing strength),w_r for the rule represented by R_r, i.e.,

$$w_r = \mu_{A_1^{(r)}} \times \mu_{A_2^{(r)}} \times \ldots\ldots \times \mu_{A_p^{(r)}} \tag{2}$$

Each node in the third layer (L_3) denoted by N in Fig. 1 is a circle node and is connected to all the rules in the second layer and computes the relative degree of fulfilment (also known as normalized firing strengths) for each rule R_r given by

$$\overline{w}_r = \frac{w_r}{\sum_r w_r} \tag{3}$$

Each node in the fourth layer (L_4) is a square node and is connected to all input units and to exactly one node in the third layer. Each node computes the output of a rule R_r by

$$O_r = \overline{w}_r . y_r = \overline{w}_r . \left(\alpha_0^{(r)} + \alpha_1^{(r)} x_1 + \ldots\ldots + \alpha_p^{(r)} x_p\right) \tag{4}$$

An output node in the fifth layer (L_5) is a circle node and computes the final output by summing all the outputs from the fourth layer, i.e.

$$O = \sum_r O_r = \sum_r \overline{w}_r y_r = \frac{\sum_r w_r y_r}{\sum_r w_r} \tag{5}$$

ANFIS applies a combination of the least-squares method and the back-propagation gradient descent method for training membership function parameters. Backpropagation is used to learn the antecedent parameters, i.e. the membership functions parameters, and least-squares estimation (LSE) is used to determine the coefficients of the linear combinations in the rules' consequents. Detailed description of training algorithm can be found in Jang (1993), Jang et al. (1996), Nauck et al. (1997).

The learning procedure suggested by Jang has the following steps (Nauck et al. 1997):

1. Propagate all patterns from the training set and estimate the optimal consequent parameters by an iterative least mean square procedure while keeping the antecedent parameters fixed.
2. Propagate all patterns again and modify the antecedent parameters using backpropagation while keeping the consequent parameters obtained before fixed.
3. If the error measure undergoes four consecutive decreases, then increase the learning rate by 10%. If the error measure undergoes two consecutive combinations of an increase followed by a decrease, then decrease the learning rate by 10%.
4. Stop if the training error goal is achieved or the designated number of training epoch is reached, otherwise continue with step 1.

3. Study Area and Data

The Szczecin region is situated in the north-western part of Poland in the mouth section of the Odra river along the Baltic coast. Szczecin city is an important industrial and port city. It has free access to the sea from the north. The Odra river supplies water to the industrial plants and also serves as a communication and transportation track. The Odra is a navigable river on a 717 km long section, connected through the Warta, Noteć and Bydgoski canal with the Vistula and through the Odra-Spree and Odra-Havel canals with the German river network. Total catchment area of the Odra river is 118611 m^2, with 105961 m^2 in Poland which is 89.3% of the total area. The total length of the river course is 866.2 km and the length of the section of the Świnoujście-Szczecin fairway is 27 km. Figure 2 shows schematically the mouth section of the River Odra.

The water levels, atmospheric pressure changes and wind field data were obtained for the stations Police and Świnoujście from the Maritime Institute Branch Szczecin, Poland. The time resolution of these measurements is 10 minutes.

It has been shown from a previous study that the seasonal changes are observed in annual wind distribution. There are more slow north winds during summer. In spring and autumn, wind conditions are extremely diversified. The strongest winds appear in the winter season from the north-western sector. These winds are the reason for storm surges arising in the sea, which propagate upstream the Odra river and thus cause the wind backwater (Pluta 1998). Based on this fact, the winter season (Jan.-Mar.) data for 1996 and 1997 were taken for this study. The data set were divided into training, checking and test subsets. January and February, 1997 data were chosen for training the model and March, 1997 data were provided as the checking data set to prevent model *overfitting*. February, 1996 data were used for testing the model's performance. The statistical characteristics of the target (output) vectors for each data set are given in Table 1.

The statistical characteristics of the test set suggest that it contains extreme high water levels with high degree of variability (standard deviation). Hence, the model should extrapolate to estimate these extremes.

Table 1. Statistical characteristics of target vectors

Data set	Number of patterns	Mean	Standard deviation	Maximum	Minimum
Training set	8478	495.61	17.03	555.10	458.90
Checking set	4446	515.94	14.36	540.90	468.70
Testing set	4086	518.98	23.56	592.20	487.30

The correlation analysis was performed on the training set data to evaluate the correlation of water levels at Police with the atmospheric pressure changes and wind speeds. The wind direction was implicitly taken into account by resolving

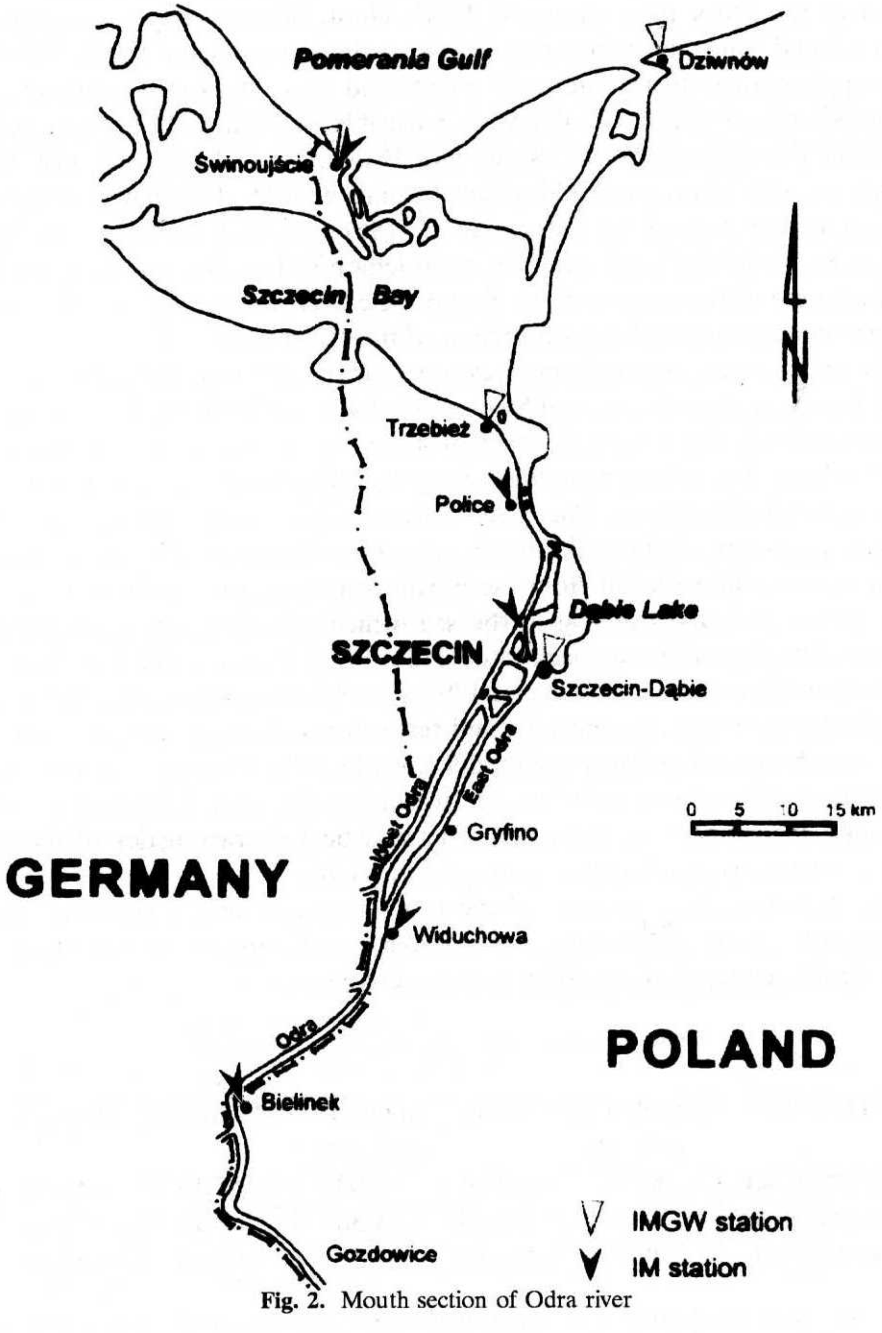

Fig. 2. Mouth section of Odra river

the wind speed into two components, $u = W.\cos\phi$ and $v = W.\sin\phi$, where W is the wind speed and ϕ is the wind direction. Table 2 shows the cross-correlation functions of water levels at Police with atmospheric pressure (P) and wind speed (u, v) for training set data.

Table 2. Cross-correlation function (CCF) of water levels at Police with different inputs

Inputs	P	u	v
Instantaneous CCF	−0.0848	0.1491	−0.0321
Maximum CCF	−0.6482	0.1971	0.2297
Lags	274	77	−187

The autocorrelation function (Fig. 3) of the water levels at Police for Jan.-Feb. 1997 shows that the water levels are highly autocorrelated and the autocorrelation function is exponentially decaying indicating the persistence and low order autoregressive process.

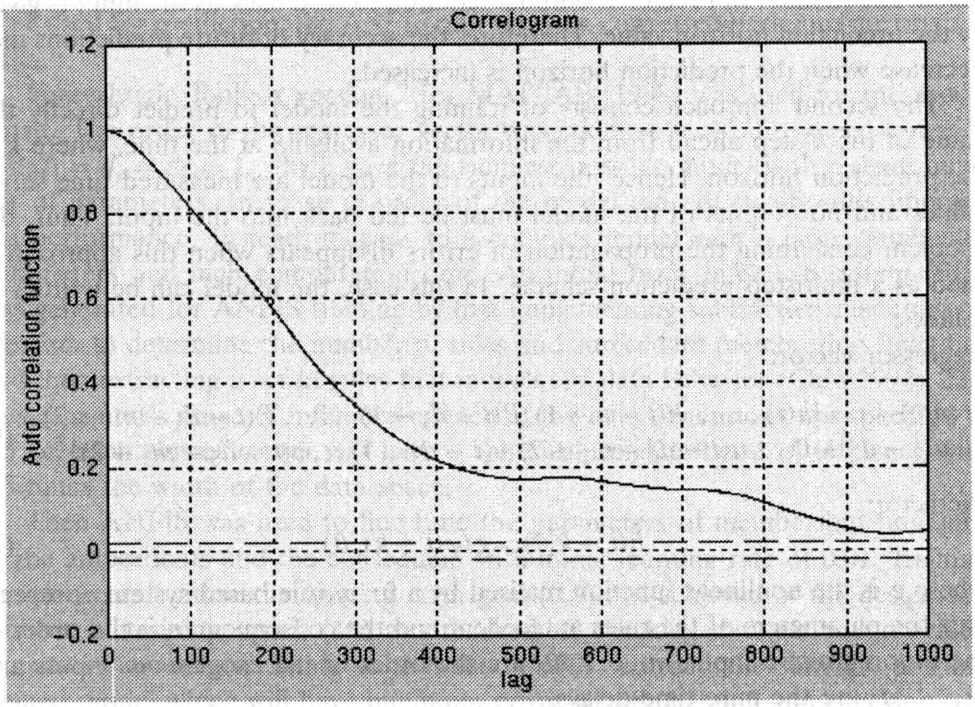

Fig. 3. Auto-correlation function of the water levels at Police

Table 2 shows that the water levels at Police are strongly and negatively correlated with the atmospheric pressure with peaks at lags 274. The significant cross-correlation functions for positive lags indicate that passage of low pressure causes storm surges. A similar analysis for N-S component of wind speed at Police (u) shows that the water levels have a fair positive correlation with wind speed with peaks at lags 77 indicating that increase in wind speed causes a rise in water level. At extreme individual events of storm surges, the correlations are even greater.

4. Application of ANFIS

There are two approaches to building the prediction model for the purpose of multistep prediction of water levels at Police. The first approach consists of training the model for the purpose of one-step prediction and using it in a recurrent form by feeding back the predicted output as an input for the next prediction. The main disadvantage of this approach is that the parameter set has been obtained with the purpose of one-step prediction. During the training phase, the model captures the relation between the actual observations of the original time series. However, when the model is used for multistep prediction by feeding back the predicted outputs of previous time steps, the errors which occur for the predicted outputs are propagated and the quality of the future prediction will be affected by them. The number of predicted outputs required to feed back as the input is given by the prediction horizon value. Therefore, the accuracy of future predictions may decrease when the prediction horizon is increased.

The second approach consists of training the model to predict directly the value of the k-step ahead from the information available at the time, where k is the prediction horizon. Hence, the inputs to the model are measured time series values and no outputs of the model must be fed back into the input. Thus, the problem concerning the propagation of errors disappears when this approach is used as a multistep prediction scheme. In this case, the model can be written as follows:

Regressor vector:

$$\begin{aligned} \varphi(t+k) = [h(t) \ldots\ldots h(t-n+1)\ P(t-d_1+1) \ldots\ldots P(t-d_1-m_1+2) \\ u(t-d_2+1) \ldots u(t-d_2-m_2+2)\ v(t-d_3+1) \ldots v(t-d_3-m_3+2)]^T \end{aligned} \tag{6}$$

Predictor:

$$\hat{h}(t+k|\theta) = g(\varphi(t+k), \theta) \tag{7}$$

where g is the nonlinear function realised by a fuzzy rule-based system, θ represents the parameters of the rules antecedent and the consequent, n is the order of the *autoregressive* input, $m_1, \ldots, m_3$ are the order of the *exogeneous* inputs and $d_1, \ldots, d_3$ are the pure time-delays.

A disadvantage of this approach is that the inputs to the model may not contain sufficient information about the time series in order to predict that instant. That is, the input vector may be very distant in the time from the prediction horizon, and it may not have any relation with that instant. In this case also, the accuracy of future predictions decreases as the prediction horizon increases. Another disadvantage is that the same model cannot be used for different values of k and thus a separate model must be constructed for each k-step prediction.

In this application, the second approach was employed. The input vector may consist of present and past values of water level and several delayed values of atmospheric pressure and wind speed at Police and ouput vector consists of water level at Police at the time $t + k\Delta t$. The forecast lead time given by $k\Delta t$ depends on the practical requirements such as to issue warning and take necessary safety measures. To evaluate the degree of accuracy of forecast for different prediction horizons, k was varied from 18 (3 hours) to 144 (24 hours).

Since the training set data were not of the same order of magnitude and had different units, all data set were normalized prior to analysis so that they will have zero mean and unity standard deviation i.e. the scaled value was then given by

$$y_{jp} = \frac{x_{jp} - \overline{x}_p}{\sigma_p} \tag{8}$$

where $\overline{x}_p$ and σ_p are the mean and standard deviation of the p variable. These normalized patterns were employed for training the ANFIS. After the ANFIS were used for prediction, the ANFIS outputs were converted back into the original units.

Fuzzy Logic Toolbox version 2 for MATLAB (1998) was used for the experiment. The order of the regressor vector was taken as $n = 1$, $m_1 = m_2 = m_3 = 1$ and $d_1 = d_2 = d_3 = 1$, which gave the simplest possible model with a small number of parameters. Increase in order of the model did not significantly improve the performance. Instead, it leads to a complex model with a large number of parameters and high computation time. An initial fuzzy inference system (FIS) was generated for ANFIS training by first implementing subtractive clustering on the data to determine the number of rules and antecedent membership functions and then extracting a set of rules that models the data behavior (Chiu 1994). The cluster center's range of influence in each of the data dimensions was specified to 0.5 i.e. each cluster center will have a spherical neighborhood of influence with 0.5 times the width of the data space.

Then ANFIS was used to fine tune the parameters of membership functions of the antecedents and the consequent with initial learning rate of 0.01. Training was done until either the training error goal (0.0) was achieved or the designated number of training epoch (10) was reached. A checking data set was provided to prevent model overfitting so that the ANFIS returned the simplest possible trained model which will have minimum error in both training and checking set.

3-hour forecast:

An initial fuzzy inference system (FIS) was generated for 3-hour forecast by implementing subtractive clustering which resulted three sets of rules with a three Gaussian membership function for each input for the antecedent part of the rule.

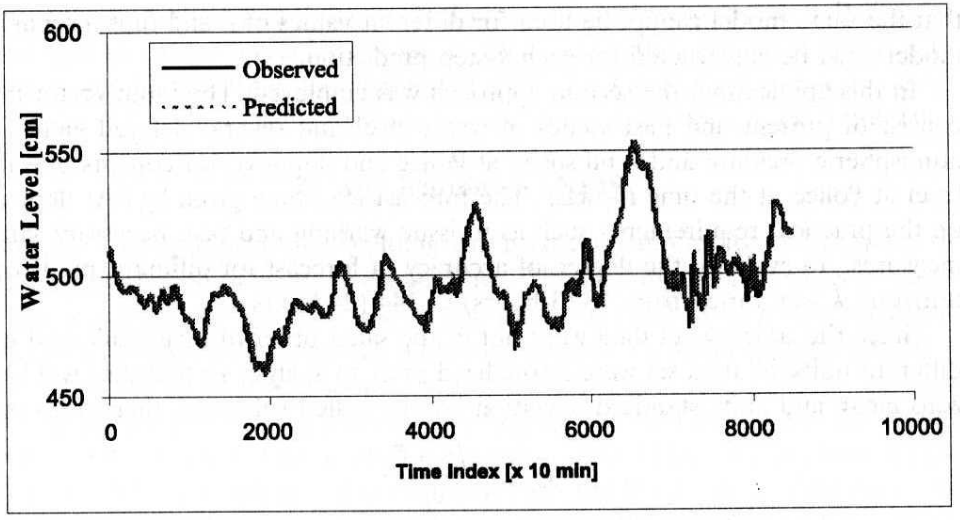

Fig. 4. Observed and predicted hydrograph for training set

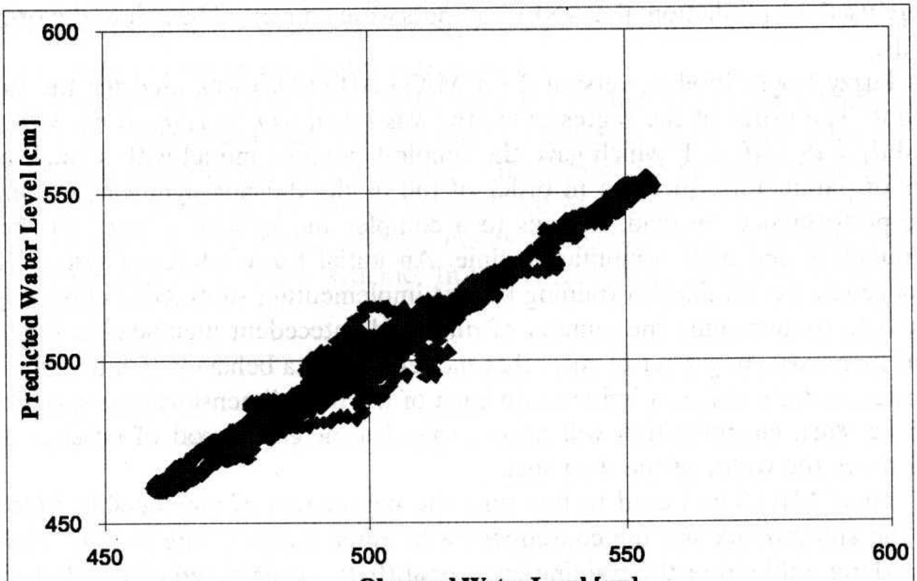

Fig. 5. Scatterplot of water levels for training set

The FIS was then trained using ANFIS to forecast the water levels at Police 3-hours ahead. Figure 4 shows the time series plot of target water levels and predicted water levels. From this figure, it is obvious that the ANFIS outputs conform well with the target water levels. Figure 5 shows the scatterplot of target water levels against ANFIS outputs. The scatterplot of target against predicted water levels also shows good performance during training with correlation coefficient 0.9892.

Then the set model has been employed to predict water levels on test set data. Figure 6 shows the time series plot of observed and predicted water levels during testing and Figure 7 shows the scatterplot of target water levels against ANFIS output. These figures clearly show the good capability of ANFIS to forecast water levels 3-hours ahead. The model was quite capable of reproducing the hydrograph and the correlation coefficient between the observed and predicted water levels was 0.9971. An interesting point to note is that the model is even capable of predicting the extreme high water levels which were not present in the training set.

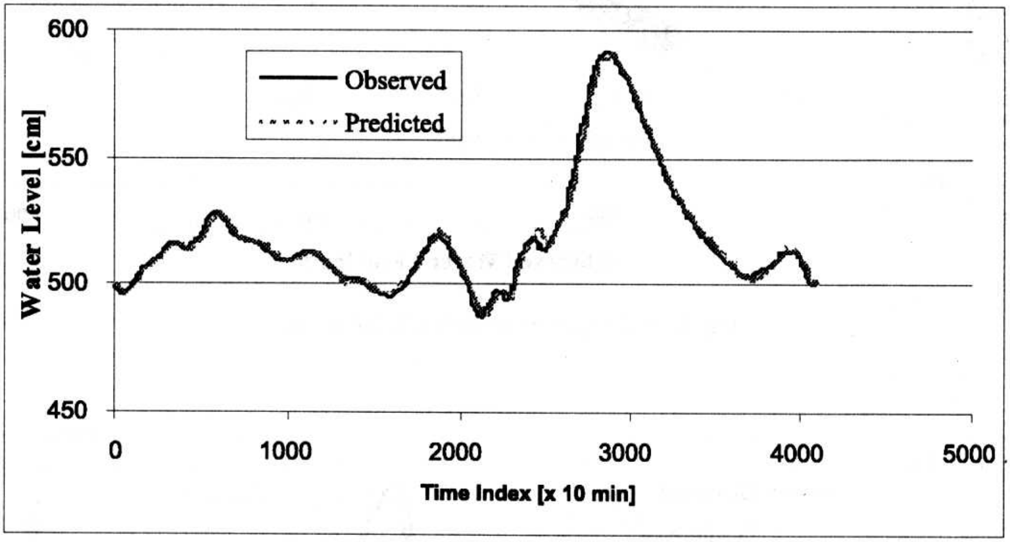

Fig. 6. Observed and predicted hydrograph for test set

6, 12 and 24-hour forecast:

Initial FIS structures were generated for 6, 12 and 24-hour forecasts using a subtractive clustering method which resulted in only two Gaussian type membership functions for each input and two rules in these cases. The ANFIS was then employed to train the FIS to forecast the water level at Police 6, 12 and 24 hours ahead. Figs. 8, 9 and 10 show the time series plot of observed and predicted water levels for the test set. The plots show the degraded performance of the model as the prediction horizon increases. As the prediction horizon increases, ANFIS becomes bias and the peak water levels are underestimated and predicted late.

Table 3 presents the performance of the model measured in terms of root-mean square error (RMSE), mean percent error (MPE), percent bias (PBIAS) and determination coefficient (DC) for different prediction horizons during both

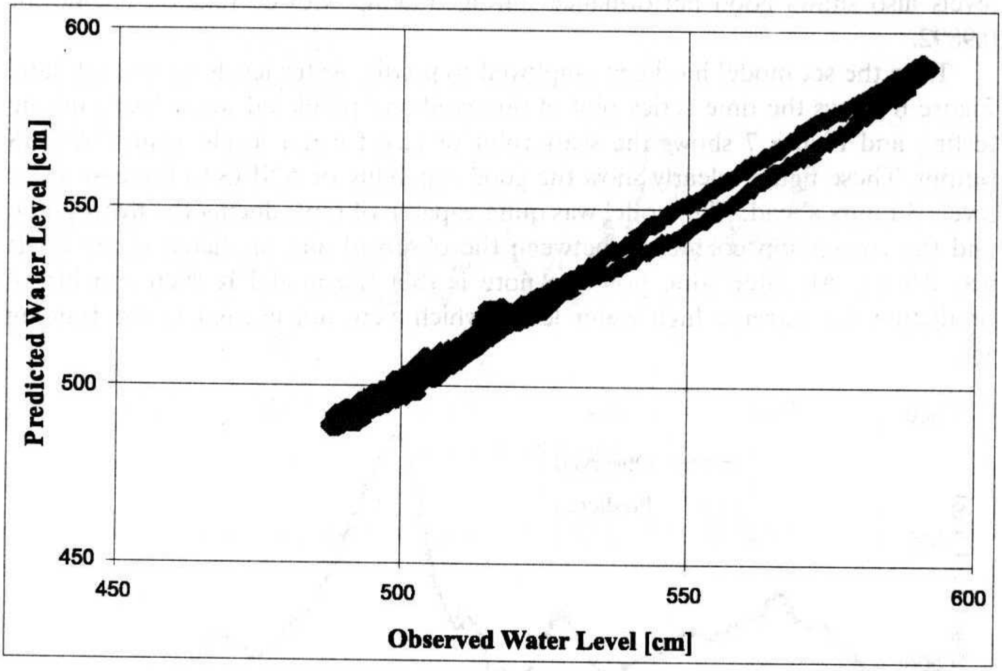

Fig. 7. Scatterplot of water levels for test set

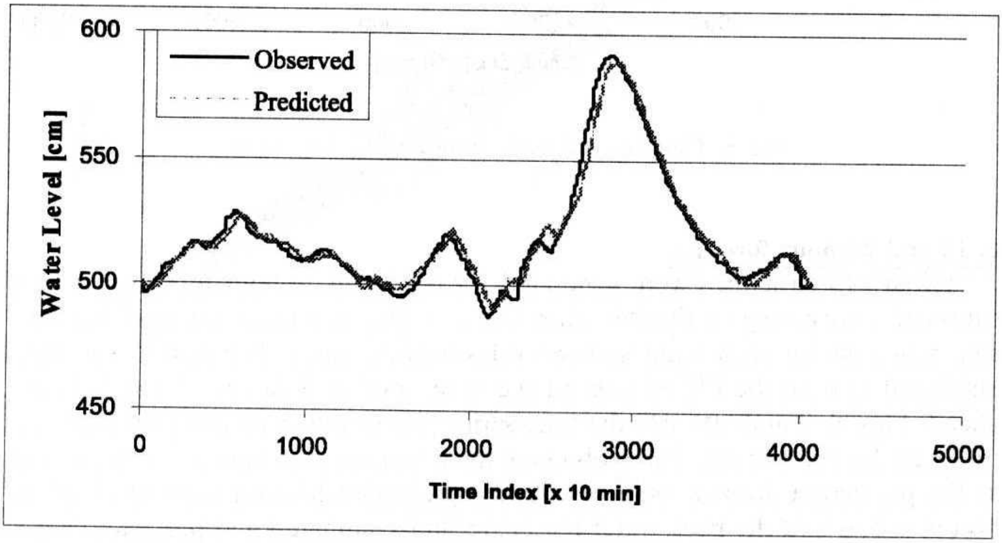

Fig. 8. Observed and 6-hour ahead predicted hydrograph for test set

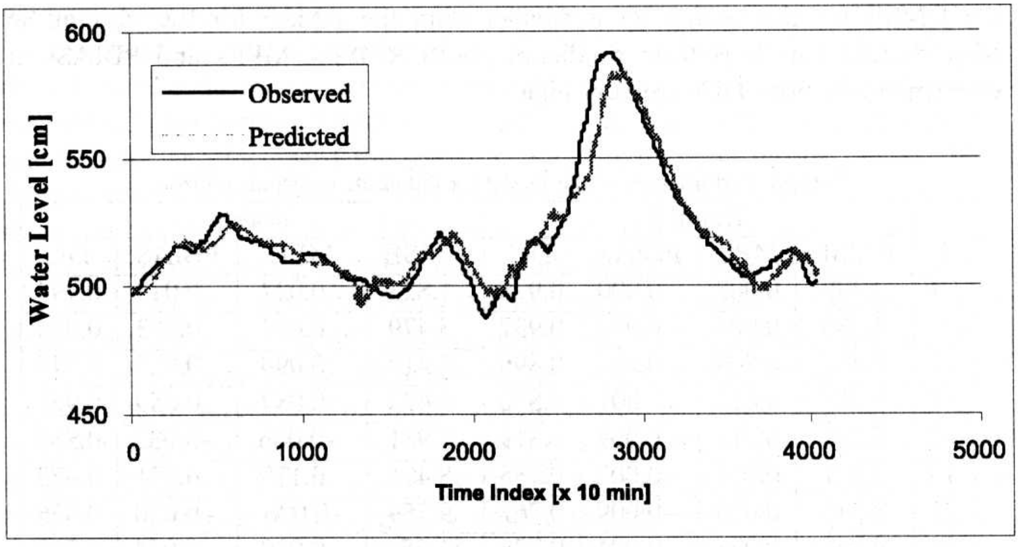

Fig. 9. Observed and 12-hour ahead predicted hydrograph for test set

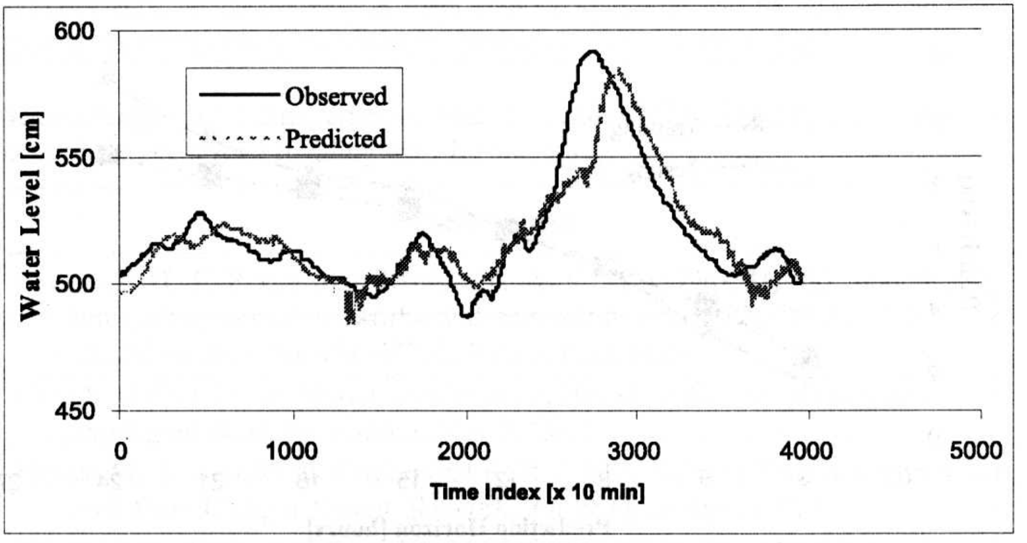

Fig. 10. Observed and 24-hour ahead predicted hydrograph for test set

training and testing. It is quite unusual to observe the phenomenon that the DC for testing set is higher than DC for training set and for small prediction horizon, the RMSE for the testing set is smaller than the RMSE for the training set. Nevertheless, for short term prediction, both RMSEs, MPEs and PBIASs are very small and both DCs are very high.

Table 3. Performance of the model for different prediction horizon.

	Training				Testing			
k	RMSE	MPE	PBIAS	DC	RMSE	MPE	PBIAS	DC
3	2.498	0.002	0.000	0.978	1.823	0.022	0.019	0.994
6	4.288	0.007	0.000	0.937	3.479	0.074	0.063	0.978
9	5.487	0.009	−0.004	0.896	5.419	0.099	0.086	0.947
12	6.568	0.018	0.001	0.852	6.639	0.087	0.059	0.921
15	7.273	0.013	−0.009	0.819	7.981	−0.006	−0.032	0.885
18	7.921	0.024	−0.002	0.785	8.401	0.175	0.131	0.873
21	8.341	0.020	−0.009	0.762	9.559	−0.026	−0.070	0.836
24	8.966	0.031	−0.001	0.726	11.352	0.010	−0.034	0.769

Figure 11 shows the plot of RMSE against prediction horizon for both training and test set. The RMSE increases as the prediction horizon increases both during training and testing, this increase being higher for the test set than for the training set.

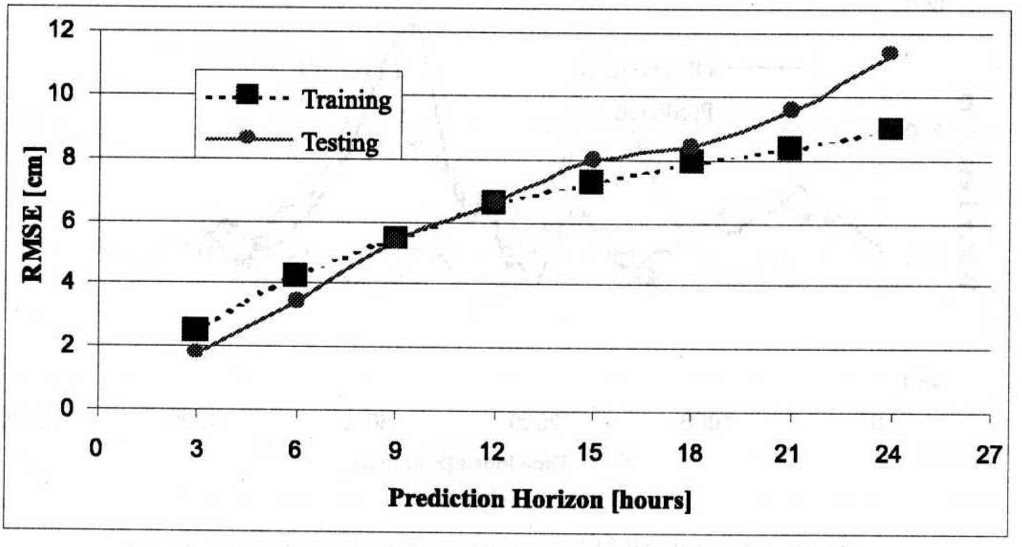

Fig. 11. RMSE plot for different prediction horizons

5. Conclusions

We have described the application of an adaptive neuro-fuzzy system for real-time forecasting of water levels. The structure of ANFIS was identified by implementing the subtractive clustering method to partition the input-space and determine the number of membership functions on each input. This approach decreased the rule number and increased the speed in both training and testing phases. Then the parameters were identified by ANFIS using hybrid learning rule. The case study has clearly demonstrated that an adaptive neuro-fuzzy system can be used for real-time forecasting of water level variations due to storm surges.

The degree of accuracy of forecast varies with the prediction horizon. As prediction horizon increases, the accuracy of forecast decreases and the performance of the model becomes bias. However, a high degree of accuracy can be obtained for short term forecasts. For short term forecasts, the model has been able to predict reliably the extreme high water levels of test set which were not present in the training set. This was possible thanks to the application of adaptive rule assessment methods which regularly update the rule system by assimilating the recent observations to account for possible changes in the system.

An alternate approach to such real-time forecasting problems will be the application of neural networks. In particular, the neural network based system identification approach which provides the variety of nonlinear dynamic models such as the neural network ARX (NNARX) model, neural network ARMAX (NNARMAX) model, neural network output-error (NNOE) model and neural network state-space innovation form (NNSSIF) model will be very valuable for such applications (See, for example, Nørgaard 1996, Gautam 2000).

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