Hydrol. Earth Syst. Sci. Discuss., 3, 2735–2756, 2006
www.hydrol-earth-syst-sci-discuss.net/3/2735/2006/

Hydrology and Earth System Sciences Discussions

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A time delay artificial neural network approach for flow routing in a river system

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Received: 6 June 2006 – Accepted: 1 September 2006 – Published: 12 September 2006

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Abstract

River flow routing provides basic information on a wide range of problems related to the design and operation of river systems. In this paper, three layer cascade correlation Time Delay Artificial Neural Network (TDANN) models have been developed to forecast the one day ahead daily flow at Ilarionas station on the Aliakmon river, in Northern Greece. The networks are time lagged feed-formatted with delayed memory processing elements at the input layer. The network topology is using multiple inputs, which include the time lagged daily flow values further up at Siatista station on the Aliakmon river and at Grevena station on the Venetikos river, which is a tributary to the Aliakmon river and a single output, which are the daily flow values at Ilarionas station. The choice of the input variables introduced to the input layer was based on the cross-correlation. The use of cross-correlation between the ith input series and the output provides a short cut to the problem of the delayed memory determination. Kalman's learning rule was used to modify the artificial neural network weights. The networks are designed by putting weights between neurons, by using the hyperbolic-tangent function for training. The number of nodes in the hidden layer was determined based on the maximum value of the correlation coefficient. The results show a good performance of the TDANN approach for forecasting the daily flow values, at Ilarionas station and demonstrate its adequacy and potential for river flow routing. The TDANN approach introduced in this study is sufficiently general and has great potential to be applicable to many hydrological and environmental applications.

1 Introduction

River flow forecasting and specifically river flood forecasting is one of the most important components in many flood control systems. Flood forecasting models are becoming very essential tools to forecast future flood events early enough in order to take appropriate control action to minimize damage. There are different types of flood forecasting models, and they can be classified into three types: empirical (or black box) models, lumped conceptual models and distributed physically based models. Black box models may also be divided into sub groups according to their origin, namely empirical hydrological methods (such as unit hydrograph model), statistically based models (such as ARMA, ARMAX, SARIMA (Hipel and McLeod, 1994; Papamichail and Georgiou, 2001) gauge to gauge correlation models etc.) and artificial intelligence based models (such as artificial neural networks).

In recent years, ANN models have become extremely popular for prediction and forecasting in a number of areas, including finance, power generation, medicine, water resources and environmental science (Maier and Dandy, 2000). A number of researchers have investigated the adaptability of ANN models to the field of hydrology, water resources and hydrologic time series (French et al., 1992; Karunanithi et al., 1994; Lorrai and Sechi, 1995; Raman and Sunilcumar, 1995; Maier and Dandy, 1996; Shamseldin et al., 1997; Zhang and Stanley, 1997; Thirumalasah and Deo, 1998; Zealand et al., 1999; Anmala et al., 2000; Coulibaly et al., 2000; Govindaraju and Rao, 2000; Islam and Kothari, 2000; Tokar and Markus, 2000; Shamseldin and O'Connor, 2001; Dawson et al., 2002; Loukas et al., 2002; Mantoglou and Kourakos, 2002; Agarwal and Singh, 2004; Shrestha et al., 2005; Kumar et al., 2004; Daliakopoulos et al., 2005; Alvisi et al., 2006).

In this paper, three layer cascade correlation Time Delay Artificial Neural Network (TDANN) models were developed to forecast the daily flow at Ilarionas station on the Aliakmon river by using multiple inputs. These inputs include the time lagged daily flow values further up at Siatista station on the Aliakmon river and at Grevena station on the Venetikos river, which is a tributary to the Aliakmon river.

2 Artificial neural networks methodology

Artificial Neural Network is an information processing system that tries to replicate the behavior of a human brain by emulating the operations and connectivity of biological

neurons (Fausett, 1994). The basic structure of an ANN model, usually, consists of three distinctive layers, the input layer, where the data are introduced to the ANN, the hidden layer or layers, where data are processed, and the output layer, where the results of ANN are produced. The structure and operation of ANNs is discussed by a number of authors (Fausett, 1994; Haykin, 1994; Dowla and Rogers, 1995; Patterson, 1996; Gurney, 1999; Diamantopoulou, 2005).

The ANNs are designed by putting weights between neurons, by using a transfer function that controls the generation of the output in a neuron, and using adjustable laws that define the relative importance of weights for input to a neuron. In the training, the ANN defines the importance of the weights and adjusts them through an iterative procedure.

The training of ANNs suitable for the current application is the cascade correlation algorithm (Fahlman and Lebiere, 1990; Diamantopoulou, 2005), which produces the cascade correlation Time Delay Artificial Neural Network (TDANN) that belongs to the feedforward type, which is a supervised algorithm in the multilayer feed-forward ANNs. The Cascade part refers to the architecture and its mode of construction entails adding hidden units once at a time and always connecting all the previous units to the current unit. The Correlation part refers to the way hidden units were trained by trying to maximize the correlation between output of the hidden unit and the desired output of the network across the training data. The training procedure of TDANNs is composed of a forward pass. The information is processed in the forward direction from the input layer to the hidden layer or layers to the output layer. Kalman's learning rule (Brown and Hwang, 1992; Grewal and Andrews, 1993; Masters, 1993; Demuth and Beale, 2001) was used to modify the TDANN weights. Such, a network has the ability to approximate any continuous function. As it was mentioned the input nodes receive the data values and pass them on to the hidden layer nodes. Each one of them collects the input from all inputs nodes after multiplying each input value by a weight, attaches a bias to this sum and passes on the result through a nonlinear transformation, the hyperbolic transfer function (Fausett, 1994):

$$f(s) = \tanh(s) = \frac{e^{s} - e^{-s}}{e^{s} + e^{-s}} \tag{1}$$

where: $s = \sum_{i=1}^{n} w_i x_i$, in which w_i are weights and x_i are input values, $s \in [-\infty, +\infty]$ and $\tanh(s) \in (-1, +1)$.

Generally, the objective of the training algorithm needed by the network for training, is to reduce the global error e (Eq. 2) (Govindaraju and Rao, 2000) by adjusting the weights and biases.

$$e = \frac{1}{P} \sum_{p=1}^{P} e_p \tag{2}$$

where: P is the total number of training patterns and e_p is the error for the training pattern p defined by:

$$e_p = \frac{1}{2} \sum_{i}^{n} (O_i - d_i)^2 \tag{3}$$

where: n is the total number of the output nodes, O_i is the network output at the ith output node and the d_i is the desired target output at the ith output node.

The cascade correlation algorithm starts the training without any hidden nodes. If the error between the network realized output and the target is not small enough, it adds one hidden node. This node is connected to all other nodes except the output nodes. The optimal number of the hidden nodes is commonly determined by trial and error. The approach is to begin without any hidden nodes and train the network, iteratively repeating the process for an increasing number of nodes till no further improvement in network performance is obtained. Because of its dynamic expansion that continues until the problem is successfully learned the cascade correlation algorithm automatically

consists a suitable algorithm for a given problem (Karunanithi et al., 1994). This procedure goes on until the correlation between the hidden node's output and the residual error of the network, is maximized:

$$S = \sum_{O} \left| \sum_{p} \left(v_p - \bar{v}\right) \cdot \left(e_{p,o} - \bar{e}_o\right) \right| \tag{4}$$

where: o is the oth node, p is the pth train pattern, v_p is the candidate node's value at pth training pattern, $\bar{v}$ is the average of v over all patterns, $e_{p,o}$ is the residual error observed at node o at pth training patern and $\bar{e}_o$ is the average of $e_{p,o}$ over all patterns.

In each training step, a new hidden neuron is added and its weights are adjusted to maximize the magnitude of the correlation. Each hidden neuron is trained just once and then its weights are frozen.

The error between the output of the TDANN and the target value of the output was computed, as well. In order to achieve an estimation of the daily flow at the output station on the river, the time lagged with delayed memory daily flow values further up at a station on the river and at a station on a tributary to the river are introduced as inputs into TDANNs. In this sense, the input layer of TDANNs consists of a number input neurons and one output neuron, which is the daily flow at the output station on the river.

The choice of the input variables introduced to the input layer based on the cross-correlation. The use of cross-correlation between the ith input series and the output provides a short cut to the problem of the delayed memory determination (Papamichail and Papazafiriou, 1992). The cross-correlation coefficient of the ith input series and the output records on a span of N times intervals has been given by Yevjevich (1972). As the output increases after the occurrence of the ith input series and then decreases gradually towards to its original level, the cross-correlation coefficient is expected to decrease gradually with increase of the time lag, k. The first minimum positive value of the correlogram approximately indicates the delayed memory. Therefore, personal judgement must be exercised in interpreting the correlogram.

During the training of TDANNs in the calibration period, the simulated daily flow values at the output station are compared with the corresponding observed daily flow values to identify the simulation errors. The geometry of TDANNs, which determines the number of connection weights and how these are arranged, depends on the number of hidden layers and the number of the hidden nodes in these layers. In the developed TDANNs, one hidden layer is used and the number of the hidden nodes is optimized by maximizing the correlation between output of the hidden unit and the desired output of the network across the training data. However, the final network architecture and geometry are tested to avoid over-fitting as suggested by Maier and Dandy (2000).

3 Application and results

The study area is the Alaikmon river basin, Northern Greece (Fig. 1), between 39°30 S to 40°30 N and 20°30 W to 22° E. In this paper, TDANN models were developed to forecast the daily flow values at Ilarionas station on the Aliakmon river by using multiple inputs, which include the time lagged daily flows further up at Siatista station on the Aliakmon river and at Grevena station on the Venetikos river, which is a tributary to the Aliakmon river (Fig. 1). The distance from Siatista to Ilarionas is approximately 100 km. Thus, there are two separate independent input functions of time and a single output function of time.

The TDANN models were developed by using the daily flow data from 1 October 1977 to 30 September 1986 as the calibration period and from 1 October 1986 to 30 September 1987 as the validation period. The daily flow data were obtained from the archives of the Public Power Corporation of Greece. Related information for the three flow stations (Fig. 1) and statistical parameters of their time series of daily flow values for the periods 1977–1986 and 1986–1987, are given in Table 1.

For TDANN models construction, daily flow data from 1 October 1977 to 30 September 1986 randomly partitioned into training (90% of all data) and test (the remaining 10% of all data) data sets, were used. The time lagged daily flows further up at Siatista

station on the Aliakmon river and at Grevena station on the Venetikos river, which is a tributary to the Aliakmon river, were used as inputs. The delayed memory corresponding to the ith input series was determined by using the cross-correlation between the ith input series and the output. This procedure was applied to the Aliakmon river system (Fig. 1), using daily flow data and the correlograms, between daily flow values at Siatista and Ilarionas and between daily flow values at Grevena and Ilarionas during the calibration period (Fig. 2) indicate that the delayed memory of the system corresponding to the ith input series appears to be equal to 10 days.

Numerous TDANN structures tested in order to determine the optimum number of hidden layers and the number of nodes in each. The architecture of the best TDANN model for Aliakmon river flow routing is composed of one input layer with twenty input variables, one hidden layer with three nodes and one output layer with one output variable. The inputs Q_{St}, $Q_{S(t-1)}$, $Q_{S(t-2)}, \ldots$, $Q_{S(t-9)}$ and Q_{Gt}, $Q_{G(t-1)}$, $Q_{G(t-2)}, \ldots$, $Q_{G(t-9)}$ represent the delayed daily flows recorded at Siatista and Grevena, respectively. The output Q_I represents the daily flows forecasted at Ilarionas station.

The best TDANN model, the correlation coefficient (R), the mean absolute error (MAE), the root mean square error (RMSE), the RMSE (%) of the mean, between the output of the hidden unit and the desired output of the TDANN model, for the Aliakmon river daily flow routing, for the calibration, the training, the test and the validation data sets, are given in Table 2. The notation (Q_I / TDANN: 20-3-1/0.9976) (Table 2) means that the best architecture of the specific TDANN model is composed of one input layer with twenty input variables, one hidden layer with three nodes and one output layer with one output variable, with value of correlation coefficient equals to 0.9976.

According to the results of Table 2 we can see that the difference in the R, MAE and RMSE obtained using the test data set is not markedly different than that obtained using the training data, meaning there is no overfitting. Also, the results of Table 2 show a good performance of the selected TDANN model for forecasting the daily flow values at Ilarionas station.

The observed daily flow hydrographs for the three flow stations of the Aliakmon river system and the forecasted by the selected TDANN model daily flow hydrograph at Ilarionas station during the calibration period (1 October 1977 to 30 September 1986) and the validation period (1 October 1986 to 30 September 1987) are shown in Figs. 3 and 4, respectively.

The observed daily flow values used as output for the calibration and validation periods were compared with the corresponding values estimated by the selected TDANN model (Table 2). The daily flow forecasts, at Ilarionas station, by the selected TDANN model versus the observed daily flow values, at Ilarionas station on the Aliakmon river, are shown in Figs. 5a and b, for the calibration and validation periods, respectively.

Figures 3, 4, 5a and b show that the observed and forecasted by the TDANN model daily flows, during the calibration and validation periods, match well and the effectiveness of the selected TDANN model is clear.

Table 3 depicts the percentage error in annual peak flow forecasts for the TDANN model during the calibration and validation hydrologic years. The low percentage error in annual peak flow forecasts simply that the TDANN model is able to forecast the peak flows with reasonable accuracy. Also, the times to peak are well forecasted.

An analysis to assess the potential of the selected TDANN model to preserve the statistical properties of the historic flow series reveals that the flow series computed by the TDANN model reproduces the first three statistical moments (i.e. mean, standard deviation and skewness) for the calibration and validation hydrologic years.

The comparisons were also made by using the paired t-test with the two-sided tabular value (a=0.05) and the 45–degree line test. The computed t-values and the slopes of the selected TDANN model, for the daily flow values, at Ilarionas station on the Aliakmon river, for the calibration, the training, the test and the validation data sets, are given in Table 4.

The computed t-values of the selected TDANN model were less than two-sided tabular t-values, for the calibration, the training, the test and the validation data sets (Table 4). These imply that there were no significant differences between the observed and the forecasted values. Also, the observed values and the forecasted values yielded

slopes close to 45 degrees, for the calibration, the training, the test and the validation data sets (Table 4). It can be observed that the TDANN model tended to make an angle of 45 degrees with the axes, meaning there is no significant difference between the observed and the computed values. Since the data in the test and validation data sets were never seen by the selected TDANN model, the good forecasting on these data sets (Tables 2, 3 and 4 and Figs. 4 and 5) demonstrated the adequacy and the potential of the selected TDANN model for river daily flow routing.

Tables 2, 3 and 4 and Figs. 3, 4 and 5 clearly demonstrate the ability of the selected TDANN model to forecast very well daily flow values, at Ilarionas station on the Aliakmon river. Consequently, the TDANN models introduced in this study is sufficiently general and seem promising to be applicable for any river flow routing.

4 Conclusions

In this paper, Time Delay Artificial Neural Network (TDANN) models were developed for forecasting the daily flow values at Ilarionas station on the Aliakmon river. The training of the TDANNs was achieved by the cascade correlation algorithm which is a feedforward and supervised algorithm with dynamic expansion. Kalman's learning rule was used to modify the artificial neural network weights. The networks are designed by putting weights between neurons, by using the hyperbolic-tangent function for training. The number of nodes in the hidden layer was determined based on the maximum value of the coefficient of correlation. In the training process, the test data were not used with no way neither using them as part of the training procedure or as part of the decision when to stop training. No fixed number of iterations used as the stopping criterion of the procedure. The choice of the input variables introduced to the input layer based on the cross-correlation. The use of cross-correlation between the ith input series and the output during the calibration period provides a short cut to the problem of the delayed memory determination. The results, for the training, the test, the calibration and the validation data sets clearly demonstrate the ability of the TDANN models for river daily flow routing. The TDANN models introduced in this study have the ability to forecast the peak flows with reasonable accuracy, to develop a generalised solution as there is no overfitting and to overcome the problems in data of daily flows in rivers such as outliers and noise in the data. Since the proposed methodology is based on the information contained in the data series itself, the TDANN approach becomes more explicit and can be adopted for any river flow routing. The TDANN approach introduced in this study is sufficiently general and has great potential to be applicable to many hydrological and environmental applications.

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Table 1. Related information for the three flow stations and statistical parameters of their time series of daily flow values for the calibration period 1977–1986 and the validation period 1986–1987.

Basin area (km^2)	Time periods	Mean (m^3/s)	Min (m^3/s)	Max (m^3/s)	St. dev. (m^3/s)
Aliakmon river at Ilarionas station					
5005	01 Oct 1977–30 Sept 1986 (Calibration)	49.21	2.11	1145.0	62.73
	01 Oct 1986–30 Sept 1987 (Validation)	46.82	3.05	793.0	76.91
Aliakmon river at Siatista station					
2724.6	01 Oct 1977–30 Sept 1986 (Calibration)	22.78	0.28	410.60	27.12
	01 Oct 1986–30 Sept 1987 (Validation)	20.97	1.35	330.00	33.96
Venetikos tributary river at Grevena station					
817.7	01 Oct 1977–30 Sept 1986 (Calibration)	18.84	0.75	353.20	27.27
	01 Oct 1986–30 Sept 1987 (Validation)	18.91	0.83	206.00	27.89

Table 2. TDANN model, Correlation coefficient (R), Mean absolute error (MAE), Root mean square error (RMSE) and the (%) of the mean of the TDANN model, at Ilarionas station, for the Aliakmon river daily flow routing, for the calibration, the training, the test and the validation data sets.

Q_I/ TDANN: 20-3-1/0.9976			
Data	R	MAE	RMSE
Calibration (3287) (01 Oct 1977–30 Sept 86)	0.9976	2.23	3.68 (7.48%)
Train (2958)	0.9979	2.15	3.38 (6.85%)
Test (329)	0.9960	2.92	4.79 (9.73%)
Validation (365) (01 Oct 1986–30 Sept 87)	0.9903	1.38	6.76 (14.4%)

Table 3. Percentage error in annual peak forecasting for the TDANN model during the calibration and validation hydrologic years.

Calibration Period			
Year	Peak flow (m^3/sec)		Error (%)
	Historical	TDANN	
1977–78	463.0	486.3	5.04
1978–79	727.0	689.0	–5.23
1979–80	1145.0	1120.0	–2.18
1980–81	305.0	303.0	–0.65
1981–82	522.0	570.3	9.24
1982–83	427.0	430.3	0.76
1983–84	358.0	360.5	0.69
1984–85	697.0	640.2	–8.14
1985–86	515.0	550.2	6.84
Validation Period			
1986–87	793.0	740.0	–6.68

Table 4. t-value, two-sided tabular value (a=0.05) and slope of the TDANN model, for the daily flow values at Ilarionas station, for the calibration, training, test and validation data sets.

Q_I/ TDANN: 20-3-1/0.9976			
Sample size	t-value	Two-sided tabular value (a=0.05)	Slope (°)
Calibration (3287) (01 Oct 1977–30 Sept 1986)	1.548	1.961	44.54
Train (2958)	1.025	1.961	44.34
Test (329)	1.127	1.967	45.93
Validation (365) (01 Oct 1986–30 Sept 1987)	1.692	1.966	46.02

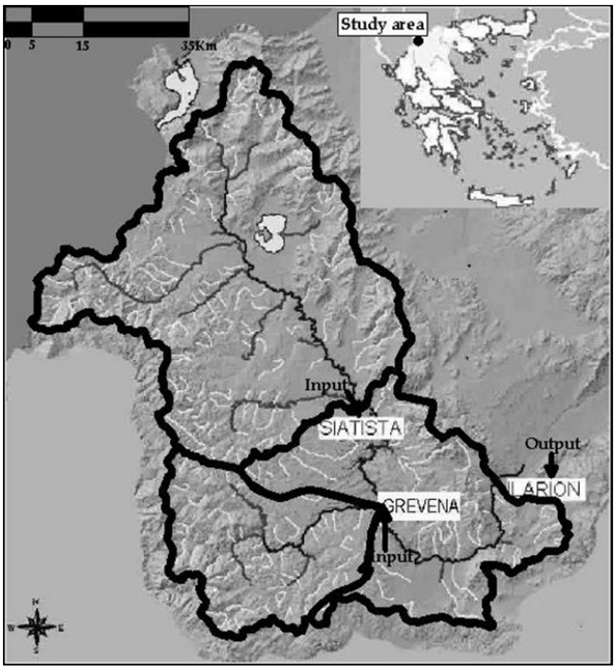

Fig. 1. Map showing the Aliakmon river system.

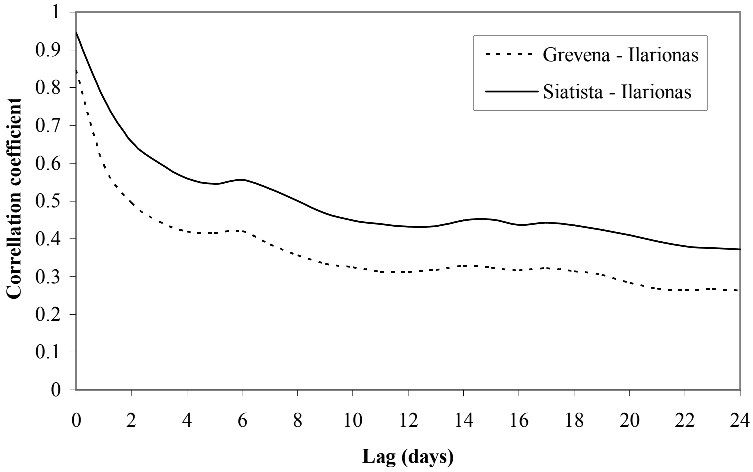

Fig. 2. Correlograms for the daily flow data in the calibration period.

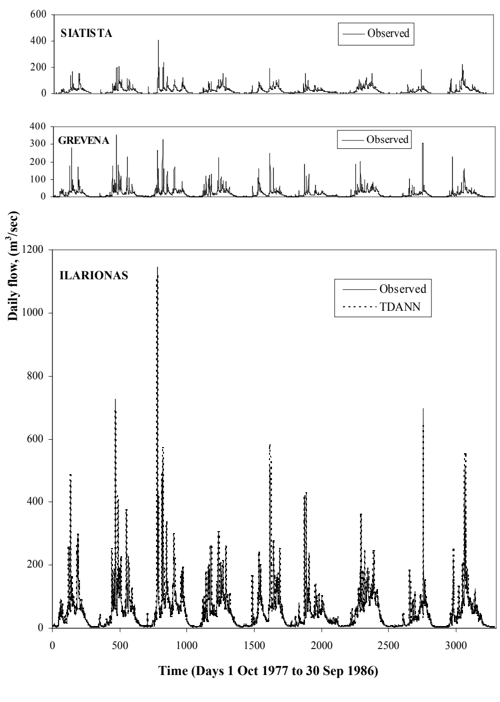

Fig. 3. Observed and estimated by the TDANN model daily flow hydrographs of the Aliakmon river system during the calibration period.

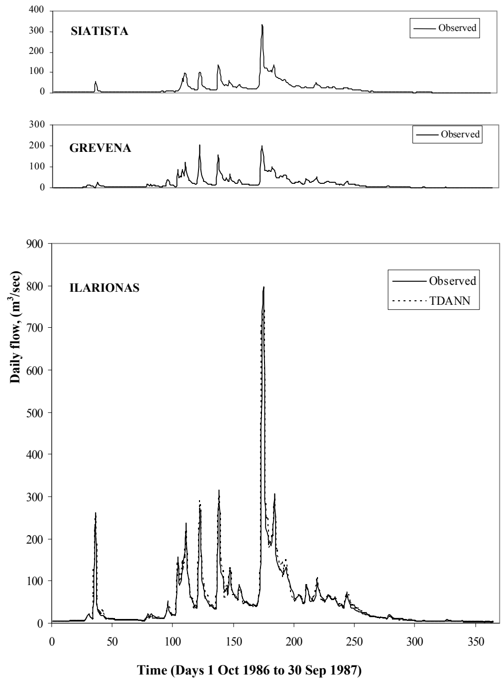

Fig. 4. Observed and forecasted by the TDANN model daily flow hydrographs of the Aliakmon river system during the validation period.

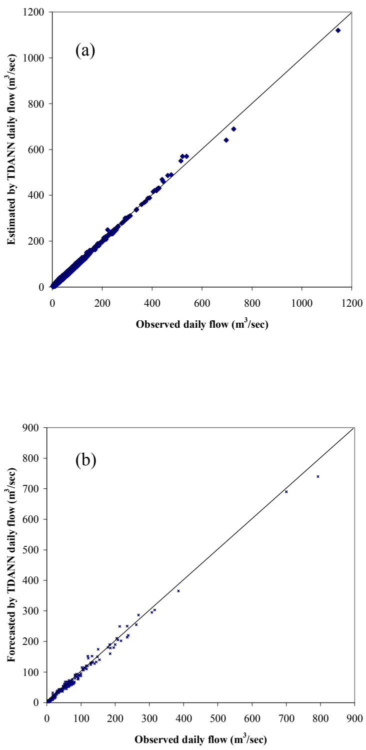

Fig. 5. Daily flow forecasts by the TDANN model versus the corresponding observed daily flow values, at Ilarionas station on the Aliakmon river, for the calibration data set **(a)** and for the validation data set **(b)**.