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# Short-term water level prediction using neural networks and neuro-fuzzy approach

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**Abstract**

A comparative study on a short-term water level prediction using artificial neural networks (ANN) and neuro-fuzzy system is addressed in this paper. The performance of the traditional approaches applied for such a hydrological task can often be constrained by data availability and simplifying assumptions in the processes description. In this paper, the ANN and neuro-fuzzy approaches are used for handling the situations with scarce data, where the predictions are based on the upstream hydrological conditions only. The models have been tested on two different river reaches in Germany. Moreover, the obtained results are compared to those of linear statistical models. Both ANN and neuro-fuzzy systems have performed comparably well and accurate for the purpose, explicitly outperforming the linear statistical models for a longer prediction horizon. The trained neural networks are partly implemented on-line, as a prototype of a web-based water level predictor.


*Keywords:* Neural networks; Neuro-fuzzy systems; Hydrology; On-line water level prediction

## 1. Introduction

A prediction of flood extent is one of the most essential hydrological tasks and mainly performed by means of different conceptual and deterministic models. Such models may require very specific data in addition to the precipitation depth, which are not always available, such as an evaporation rate, soil type, soil moisture, characteristic and slope of the soil surface, land use and management situations in the catchment area, etc. The precipitation itself has to be predicted as well. Moreover, there are constraints

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on the performance of those models, like simplifying assumptions and a response time. On the contrary, artificial intelligence (AI) or machine learning techniques can be used for a rapid estimation of flood extent at a certain point, taking only a few potential variables. These techniques are less subjected to the constraints of physical description and able to map the logical input/output relations on the basis of the observed data set only. However, this kind of approach cannot provide a spatial distribution of flood.

The AI techniques have already been investigated on and applied to various disciplines of water engineering problems. Using precipitation depth along with the other input parameters, the flow estimation and prediction has been studied extensively, especially by the artificial neural networks (ANN). A large number of publications can be found on the above and other application areas of water engineering (see [1,2,4,14]).

In this study, however, a short-term prediction of water level at certain locations has been considered using its correlation to the hydrological conditions upstream, with no forcing parameters such as a precipitation depth provided. Once the water level is known, the river discharge can easily be derived from a rating curve, a discharge-stage relation. The study was motivated by an intention to develop a cost-effective and rapid-responding on-line tool for a short-term prediction of water level in the areas of interest. A similar study on the prediction of water level change by the ANN, using weighted water level changes at stations upstream has been carried out in [16]. The authors considered predicting daily water level changes, which have a much lower magnitude than the water level itself. The prediction results obtained up to 3 days were considered to be encouraging. A real-time water level predictor, which functions on water level information from one or more gauging stations in a river network, has been developed in [12].

The current paper reports an outcome of a comparative study on water level prediction using the ANN and neuro-fuzzy systems, as well as the linear statistical models, auto-regressive moving average (ARMA) and auto-regressive exogenous (ARX) input models. It was attempted further to implement the prediction model on-line at one of the test locations, as a part of a publicly accessible web-based crisis management system.

## 2. Study area and data

The study has been conducted at two different river reaches in Germany. The first study site is Oder River in the east of Germany, where the test location is city of Frankfurt/Oder, located on the border to Poland (see Fig. 1a). The sixth biggest confluence to the Baltic Sea, Oder is a trans-boundary river. The water level observations at the test location and two other gauging stations, Eisenhuettenstadt and Ratzdorf, 30 and 41 km upstream were available for a hydrological year of 1997 with a sampling interval of 15 min. A data set containing a catastrophic flood with 1000 or more years of estimated return period (a probability of the flood extent to occur), which resulted in maximum water stage of 657 cm (average annual stage 246 cm).

The second study site is the Rhine River reach in the west of Germany, another trans-boundary river and a confluence to the North Sea. Rhine River is much larger


(a) (b)

Fig. 1. Gauging stations at the study sites: (a) Oder River reach; (b) Rhine River reach.

than the Oder, with an average annual water level of around 550 cm and flow discharge of around 4000 $m^3/s$. Available data set consists of hourly water stage observations at three consecutive gauging stations for a period of hydrological years of 1983–1999. The stations Ruhrort and Wesel are located 23 and 57 km upstream of Rees, respectively (see Fig. 1b). The above stations are located in a low-elevated area closer to the border of The Netherlands, where rather frequent floods occur due to excessive rainfall in warm seasons. The locations of the gauging stations at both study sites insure that there are no tidal or backwater effects to the streamflow and no major confluences in between.

## 3. Methodology

Logically, the driving force to change water level is primarily a change in water level upstream [16]. To predict the water level at both test locations, the observations at two successive gauging stations upstream have been used, taking the approximate travel time into account. This is simply a notion of a propagating flood wave downstream or a principle of a non-hydrograph flood routing, based on a comparison of water level elevations at different location along the river (see [11,15]). This implies that a precipitation depth is not used as a forcing parameter.

The ratios between length of the training and testing data sets were around 3:2 for all models considered. The performance indices used in this paper are root mean square error (RMSE), mean absolute error (MAE) or mean error in percentage and the correlation coefficient ($r$) between the observed and calculated values.

### 3.1. Artificial intelligence methods

A multi-layer perceptron network with one hidden layer has been used throughout the study [5]. The Levenberg–Marquardt learning algorithm is used, for its speed and effectiveness. A structure of the model is determined by a trial and error. The size of the input and hidden layer of the networks has been variable depending on the prediction horizon, whereas the output layer have had a single node throughout. Overtraining of the networks are prevented by a cross validation or the early stopping method.

The adaptive neuro-fuzzy inference system used in the study is a fuzzy inference model of Sugeno type, in which the membership function parameters are tuned to fit a given input/output set by an optimisation algorithm [9]. A number of rules and a shape of the membership function have to be specified beforehand. The adjustment of adequate membership function parameters is facilitated by a gradient vector. After determining a gradient vector, the performance function is minimised by a least-squares estimation, to adjust those parameters. In this study, only a triangular membership function is applied, where the adjustment parameters are breakpoints locations of a triangle.

In order to predict the conditions at successive locations downstream, the inputs to the above two models consisted simply of time-lagged water levels at the gauging stations upstream, taking into account the travel time of several hours. The selections of relevant time lags in the input, which differ with the prediction horizon, were considered carefully.

### *3.2. Linear statistical models*

ARMA model is a linear time series model. It contains as a subset the AR model, which uses the direct dependence of the previous measurements and MA models that depend on the previous innovation of the process in a moving average form. In other words, the time series fits into estimated MA and AR parameter coefficients, plus a white noise term. The ARX input models use the exogenous forcing variables instead of moving average, which are water levels at gauging stations upstream, in this case. For details see [7].

## 4. Off-line prediction results and discussion

### *4.1. Frankfurt (Oder River)*

Water level prediction at Frankfurt (Oder) has been carried out for 15 min–10 h ahead, in order to observe the degradation of prediction accuracy obtained by different models considered. A part of the data containing the extreme flood of the year of 1997 is used for training and the rest for verification. For a prediction of shorter lead time, the performance indices of different models were comparable to each other and resulted in a high accuracy (see summary in Table 1).

Up to the prediction of 5 h ahead, all four models resulted in the MAE $< 0.8\%$ and RMSE $< 2.8$ cm. Partly produced plots of the verification results of 5 h prediction illustrate a very good agreement of observed and predicted values, with no significant over or underestimation (see Fig. 2). However, the prediction accuracies of the models

Table 1
Model performances for different prediction lead time at Frankfurt (Oder River)

| Lead time | 15 min | 2 h | 5 h | 10 h |
|---|---|---|---|---|
| *ANN* | | | | |
| RMSE (cm) | 1.390 | 1.520 | 2.370 | 4.580 |
| MAE(%) | 0.390 | 0.423 | 0.659 | 1.285 |
| $r$ | 0.999 | 0.999 | 0.996 | 0.984 |
| *ANFIS* | | | | |
| RMSE (cm) | 1.610 | 1.746 | 2.660 | 5.089 |
| MAE(%) | 0.460 | 0.495 | 0.767 | 1.431 |
| $r$ | 0.998 | 0.998 | 0.995 | 0.980 |
| *ARMA* | | | | |
| RMSE (cm) | 0.376 | 1.081 | 2.810 | 9.250 |
| MAE(%) | 0.060 | 0.309 | 0.799 | 1.744 |
| $r$ | 0.999 | 0.999 | 0.995 | 0.945 |
| *ARX* | | | | |
| RMSE (cm) | 1.267 | 1.606 | 2.587 | 6.045 |
| MAE(%) | 0.106 | 0.233 | 0.381 | 1.477 |
| $r$ | 0.999 | 0.998 | 0.996 | 0.974 |

differ quite significantly for a longer lead time. Specially, the performance of ARMA model diminishes rapidly for a lead time of more than 5 h.

To analyse the ability to preserve statistical attributes of the target data, the mean and standard deviation of the outcome 5 h ahead prediction, obtained by different models have been compared (see Table 2). Alike the ANN, the neuro-fuzzy system preserved the mean and standard deviation of the target data very well.

### 4.2. Rees (Rhine River)

In case of Rhine River reach, the water stage at Rees gauging station was predicted 1–15 h ahead in time. A number of models were built and tested using data for different periods within 1983–1999. A similar sequence of decaying accuracy of the models with increasing lead time can be observed from a summary of the obtained outcomes (see Table 3). For shorter prediction lead times of up to 5 h, all four models performed comparably well. However, RMSE $> 80$ cm and MAE $> 7\%$ were obtained for prediction of 15 h ahead by ARMA and ARX models, while for the same lead time RMSE $< 8$ cm and MAE $< 1.2\%$ obtained by ANN and neuro-fuzzy models. The oscillated outputs or probably a so called 'edge effect' by both the ARMA and ARX models can be observed in the beginning of the verification period (see Fig. 3).

A comparison of ability to preserve the statistical attributes for a prediction 15 h ahead at Rees illustrate a similar pattern as in the previous case (see Table 4). Although, the difference in values of the mean and standard deviation within four models is rather small, the ANN model could preserve the mean and standard deviations better than the other three.

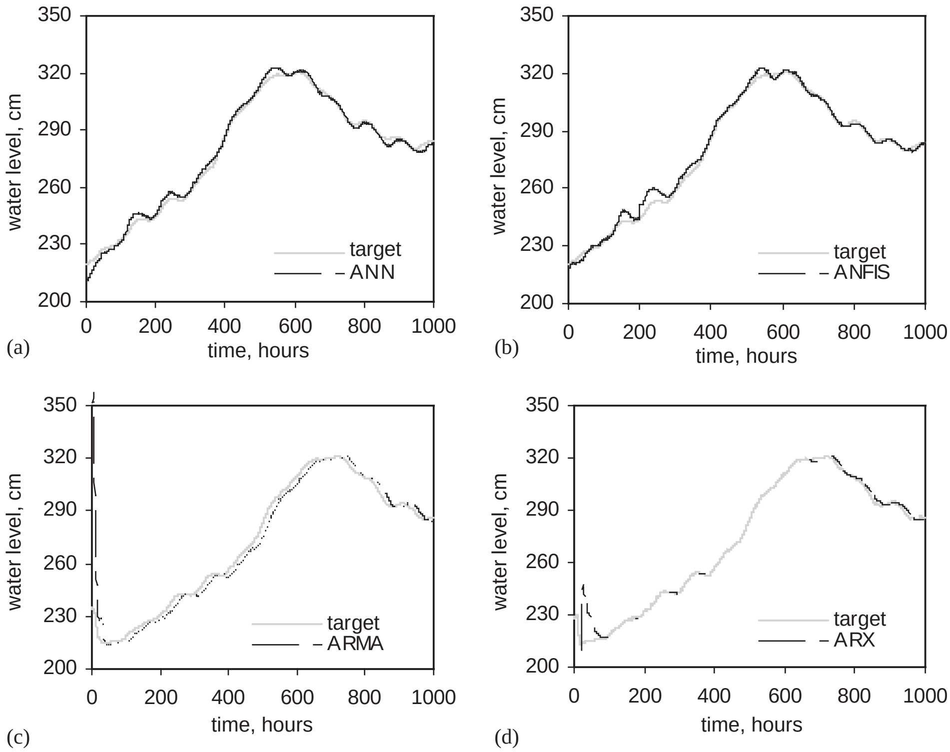



Fig. 2. Prediction result for 5 h ahead at Frankfurt(O) by (a) ANN; (b) ANFIS; (c) ARMA; (d) ARX compared to the target values.

Table 2
Mean and standard deviation of observed and computed values for Frankfurt (Oder River)

| Observed | | ANN | | ANFIS | | ARMA | | ARX | |
|---|---|---|---|---|---|---|---|---|---|
| Mean | Std.dev | Mean | Std.dev | Mean | Std.dev | Mean | Std.dev | Mean | Std.dev |
| 284.803 | 26.238 | 284.805 | 26.319 | 284.796 | 26.411 | 283.887 | 27.936 | 283.918 | 28.060 |

### 4.3. Summary of the prediction results

Practically, a water level prediction for a half day has to be provided at least, to enable primary prevention measures during high-water situations. In this paper, a longest considered prediction horizon was 15 h. For a prediction of shorter time span of up to 5 h, the ARMA and ARX models outperformed the ANN and neuro-fuzzy models at both test locations. However, as the time span increases further on, the linear models especially the ARMA models tended to provide shifted (late) predictions, whereas the

Table 3
Prediction performances of models for different lead time at Rees (Rhein River)

| Lead time | 1 h | 5 h | 10 h | 15 h |
|---|---|---|---|---|
| *ANN* | | | | |
| RMSE (cm) | 3.398 | 4.303 | 5.821 | 7.845 |
| MAE(%) | 0.520 | 0.664 | 0.892 | 1.189 |
| $r$ | 0.999 | 0.999 | 0.999 | 0.998 |
| *ANFIS* | | | | |
| RMSE (cm) | 3.430 | 4.567 | 5.870 | 7.920 |
| MAE(%) | 0.553 | 0.708 | 0.898 | 1.196 |
| $r$ | 0.999 | 0.999 | 0.999 | 0.998 |
| *ARMA* | | | | |
| RMSE (cm) | 2.410 | 5.090 | 8.788 | 118.76 |
| MAE(%) | 0.689 | 2.014 | 4.142 | 14.427 |
| $r$ | 0.999 | 0.999 | 0.998 | 0.993 |
| *ARX* | | | | |
| RMSE (cm) | 1.940 | 5.402 | 9.441 | 88.567 |
| MAE(%) | 0.685 | 2.000 | 5.590 | 7.140 |
| $r$ | 0.999 | 0.999 | 0.999 | 0.997 |

ANN and neuro-fuzzy models generalised the situation better. Similar results of shifted prediction by ARMA model have been obtained in [14]. The statistical attributes of the target values have also been better preserved by the ANN and neuro-fuzzy model prediction.

Within the linear statistical models, the ARX models outperformed the ARMA models. The ARMA model uses a weighted linear combination of previous values. Thus, the shifted prediction can be explained by auto-regressive parts, in which abrupt changes of water level have not been reflected yet. Opposed to that, the ARX models use water level at gauging stations upstream as forcing parameters in addition to the auto-regression. Unstable outcome of the linear models in the beginning of the verification period, together with the late response for a longer prediction span caused lower performance attributes.

A degradation of prediction accuracy of considered models can be seen from the MAE plotted against the prediction horizon (see Fig. 4). The error of the linear models, especially those of ARMA models, increases exponentially for a longer prediction horizon. Prediction of 15 h at Rees resulted in MAE of 14.4% and RSME of 119 cm, which is not acceptable for a practical use. Therefore, for an on-line implementation, the ANN model is considered to be more suitable.

On the whole, the actual prediction problem was less complicated, since there are no significant confluences between the considered gauging stations, somewhat closely located to each other compared to the size of the rivers under investigation. When available, the use of observation at stations further upstream would enable a longer prediction horizon as in [16].

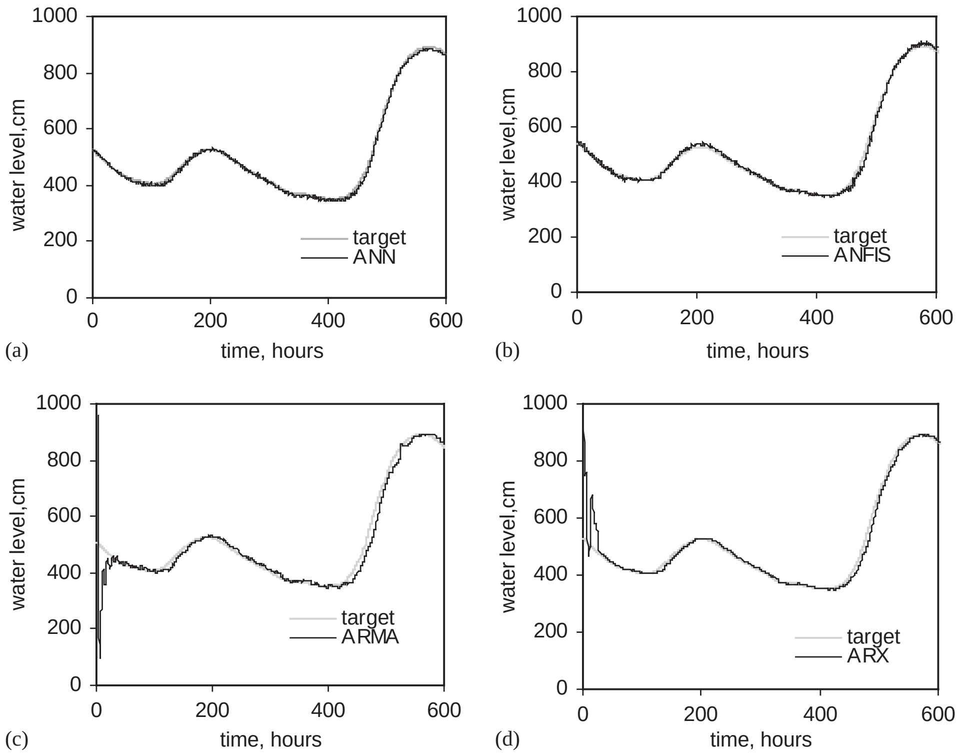



Fig. 3. Prediction result for 15 h ahead at Rees (Rhine) by: (a) ANN; (b) ANFIS; (c) ARMA; (d) ARX compared to the target values.

Table 4
Mean and standard deviation of observed and computed values for Rees (Rhein River)

| Observed | | ANN | | ANFIS | | ARMA | | ARX | |
|---|---|---|---|---|---|---|---|---|---|
| Mean | Std.dev | Mean | Std.dev | Mean | Std.dev | Mean | Std.dev | Mean | Std.dev |
| 539.35 | 119.6 | 538.87 | 119.679 | 538.334 | 120.522 | 538.703 | 120.956 | 539:628 | 120.726 |

## 5. Implementation of an on-line water level predictor

On the basis of the above study, an on-line water level predictor by the ANN has been implemented and integrated into a real-time web service for water level data collection, processing and presentation at the city of Frankfurt (Oder) [6], which is being developed within the framework of the European Commission funded project on a flood crisis management, OSIRIS. The ANN models have been chosen due to their superior prediction ability above the other models considered.

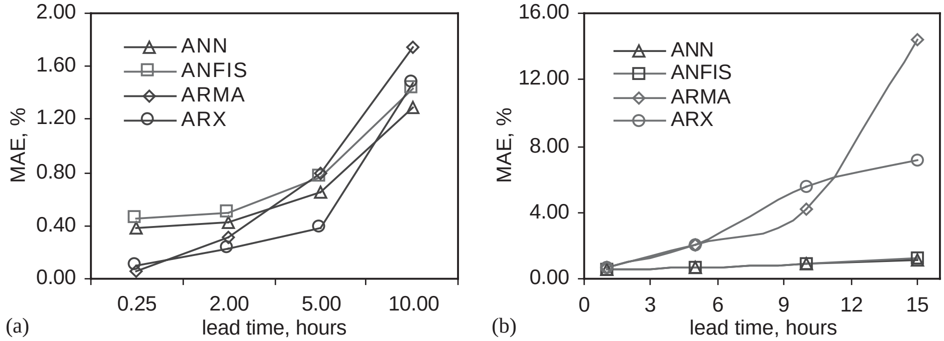
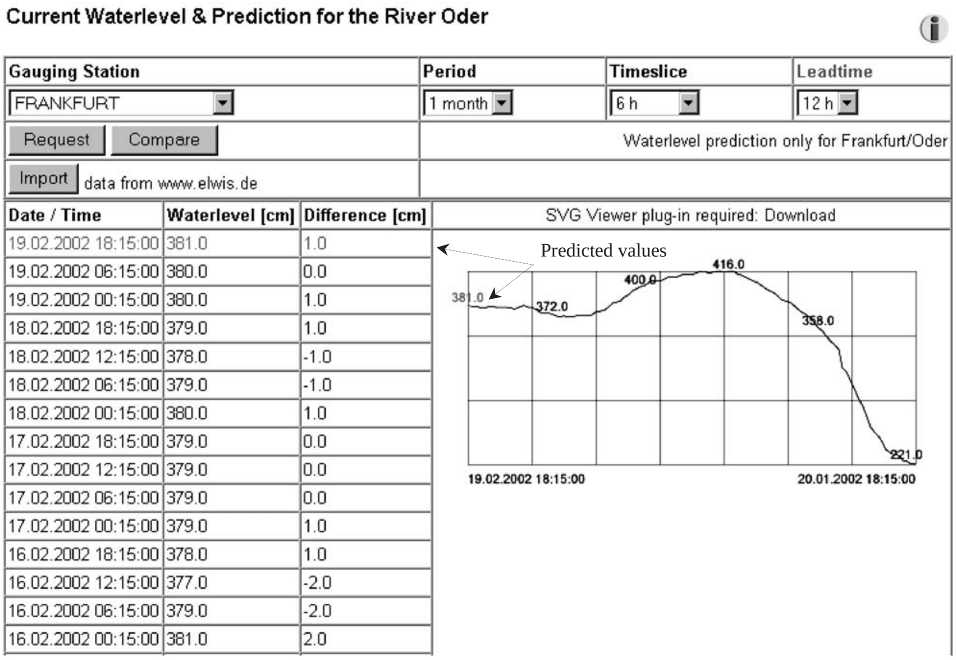


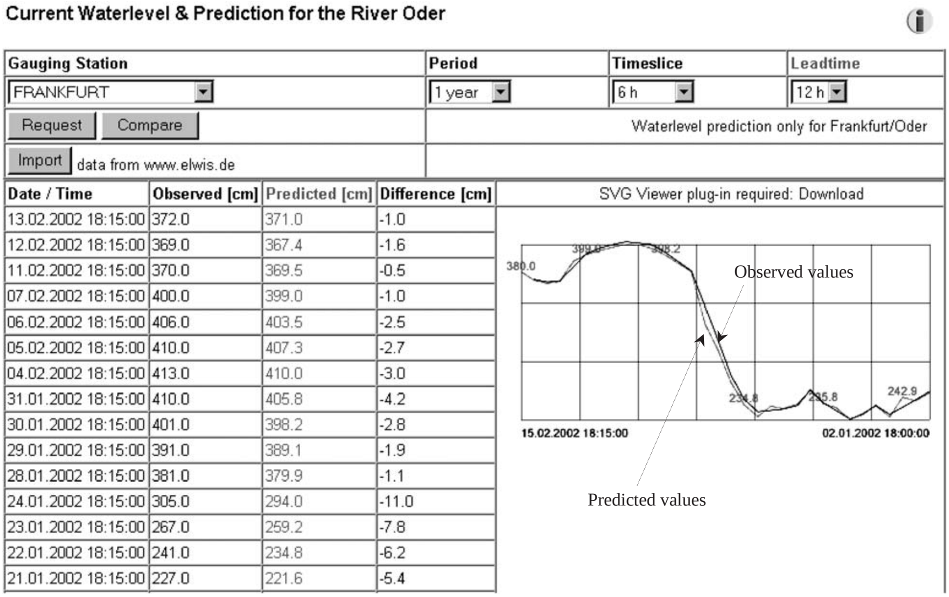

Fig. 4. MAE vs. prediction horizon: (a) Frankfurt (Oder); (b) Rees (Rhine).




| Date / Time | Waterlevel [cm] | Difference [cm] |
|---|---|---|
| 19.02.2002 18:15:00 | 381.0 | 1.0 |
| 19.02.2002 06:15:00 | 380.0 | 0.0 |
| 19.02.2002 00:15:00 | 380.0 | 1.0 |
| 18.02.2002 18:15:00 | 379.0 | 1.0 |
| 18.02.2002 12:15:00 | 378.0 | -1.0 |
| 18.02.2002 06:15:00 | 379.0 | -1.0 |
| 18.02.2002 00:15:00 | 380.0 | 1.0 |
| 17.02.2002 18:15:00 | 379.0 | 0.0 |
| 17.02.2002 12:15:00 | 379.0 | 0.0 |
| 17.02.2002 06:15:00 | 379.0 | 0.0 |
| 17.02.2002 00:15:00 | 379.0 | 1.0 |
| 16.02.2002 18:15:00 | 378.0 | 1.0 |
| 16.02.2002 12:15:00 | 377.0 | -2.0 |
| 16.02.2002 06:15:00 | 379.0 | -2.0 |
| 16.02.2002 00:15:00 | 381.0 | 2.0 |

Fig. 5. Screenshot of the on-line water level predictor (the prediction made for 12 h).

The trained neural networks, as well as the water level processor are implemented in Java Servlet technology [8,10], which provides web developers a simple, consistent mechanism for extending the functionality of their web server. Primarily, the water level data for a number of gauging stations along the Oder River are collected real-time on 15 min sampling interval from a data server in the Internet, provided by a relevant authority [3]. The input variables are then extracted from the actualised database and passed to the trained neural network. Upon the users request on the prediction horizon




| Date / Time | Observed [cm] | Predicted [cm] | Difference [cm] |
|---|---|---|---|
| 13.02.2002 18:15:00 | 372.0 | 371.0 | -1.0 |
| 12.02.2002 18:15:00 | 369.0 | 367.4 | -1.6 |
| 11.02.2002 18:15:00 | 370.0 | 369.5 | -0.5 |
| 07.02.2002 18:15:00 | 400.0 | 399.0 | -1.0 |
| 06.02.2002 18:15:00 | 406.0 | 403.5 | -2.5 |
| 05.02.2002 18:15:00 | 410.0 | 407.3 | -2.7 |
| 04.02.2002 18:15:00 | 413.0 | 410.0 | -3.0 |
| 31.01.2002 18:15:00 | 410.0 | 405.8 | -4.2 |
| 30.01.2002 18:15:00 | 401.0 | 398.2 | -2.8 |
| 29.01.2002 18:15:00 | 391.0 | 389.1 | -1.9 |
| 28.01.2002 18:15:00 | 381.0 | 379.9 | -1.1 |
| 24.01.2002 18:15:00 | 305.0 | 294.0 | -11.0 |
| 23.01.2002 18:15:00 | 267.0 | 259.2 | -7.8 |
| 22.01.2002 18:15:00 | 241.0 | 234.8 | -6.2 |
| 21.01.2002 18:15:00 | 227.0 | 221.6 | -5.4 |

Fig. 6. Screenshot of the on-line water level predictor (comparison of the prediction produced for 12 h lead time).

and time interval for presentation, the Java Servlet generates simultaneously a HTML page with JavaScript embedded, which produces a tabular and graphical view of the observed and predicted values (see the screen shot in Fig. 5). The graphical view is implemented in scalable vector graphics (SVG) [13].

The neural network predictions can be done for different lead times, ranging from 1 to 12 h. It is also possible to compare the neural network predictions in the past to the observed (target) values (see the screen shot in Fig. 6). Since, the implementation was not aimed the neural networks to be trained on-line, the networks have to be trained over, whenever new extreme values are observed.

The on-line neural network predictor and the overall flood management system should eventually enable a general public with an Internet access to monitor the inundation risks in their area of interest and access the information on the prevention measures suggested by the appropriate authorities. The above on-line predictor prototype is under a continuous development and enhancement.

## 6. Conclusions

The outcome of the study highlights a possibility to predict water level at a certain location for a short time span with an adequate accuracy, simply using relations of water levels at consecutive gauging stations and approximate travel times between the considered locations. The ANN and neuro-fuzzy models have proven their better generalising ability above the ARMA and ARX models for a prediction of longer lead time of up to 15 h, whereas the latter two tended to perform shifted (late) predictions. The ANN and neuro-fuzzy models were comparable with their performance on every aspect of prediction, in spite of a slightly higher accuracy of the ANN. The considered models have performed well, compared to their simplicity and size. This kind of short-term prediction can be applied in case of scarce data, when forcing parameter such as a precipitation depth is not available.

Furthermore, the ANN models trained for one of the test points have been implemented as a prototype of an on-line water level predictor, which eventually should constitute a part of a web-based flood disaster management system. Regardless of the adequate performances of the models, the study ought to be extended to use information from locations further upstream and to include other confluence parts of the river, in order to make the considered approach more practically useful.

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