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An Approach for Data Analysis and Forecasting with Neuro Fuzzy Systems - demonstrated on Flood Events at River Mosel

M. Stüber and P. Gemmar

Department of Applied Computer Science, Fachhochschule Trier, 54208 Trier

Abstract. The development and usage of soft computing systems for forecasting of water level progress in case of flood events at river Mosel are presented. The practical situation and its requirements are explained and two different system approaches are discussed: a) a neural network for supervised learning of the functional behavior of time series data and its approximation, and b) a fuzzy system for modeling of the system behavior with possibilities to exploit expert information and for systematic optimization. Advantages and disadvantages of both concepts are described and emphasis is laid on the structural development of the fuzzy system. Both systems have been tested and satisfying results are shown with practical data.

1 Introduction

Events of flooded rivers represent a threat for adjoining regions. They can cause tremendous harms depending on their temporal progress. Within 13 months, in December 1993 and January 1995, there have been two extreme events of floods at river Mosel for example, with considerable harms for the surrounding region at middle and lower river section between Trier and Koblenz. In order to plan and timely decide about according measures for protection of people and buildings, it is necessary to have rather accurate and long term forecasting of water level progress. Therefore, e.g. a dense grid of measurement points for water levels, and precipitate has been established in the adjoining regions of river Mosel. Based on this data the progress of water levels has to be estimated during flood events. In practice, precise forecasting of water levels within next 6 hours is required for taking according precautions.

2 Problem and Objectives

Up to now, forecasting is mainly done by experts, whose estimates from actual data are typically carried out manually. They can consider the actual local geological, topological, and meteorological situation to some extend, however estimation is mainly based on their long term experience - and intuition sometimes. A formal description or direct transformation of their approach is hardly possible. On one side, a comprehensive mathematical model of the influencing variables and functional relations is not available till now and can hardly be developed due to the yet unfixed complexity of the hydrological system. On the other side, the lacking of knowledge about quantitative and temporal dependencies of the type and behavior of flood process in the catchment area results in the practical situation that only a small part of available data are being used for level forecasting.

An approach for short term level forecasts is described by the so called pre-level procedure. Here, the available data about levels in up-river sections are used to estimate the passage time and extend of the flood wave in down-river sections. In the following two soft computing approaches are described for a 6 hours forecast of two levels at river Mosel (level at Trier and Cochem, res.) using a neural network and a fuzzy system. For both cases, there are data of 14 previously occurred floods available to be used for building a system model. Up-river levels (at Trier and Perl) and levels of tributary rivers (at Kordel, Platten, Fremersdorf, Bollendorf, Prümzurlay, see Fig. 1) are provided on a one-hour time basis. Fig. 2 shows the progress of flood event in January 1995 with discharge of level Trier to be forecasted.

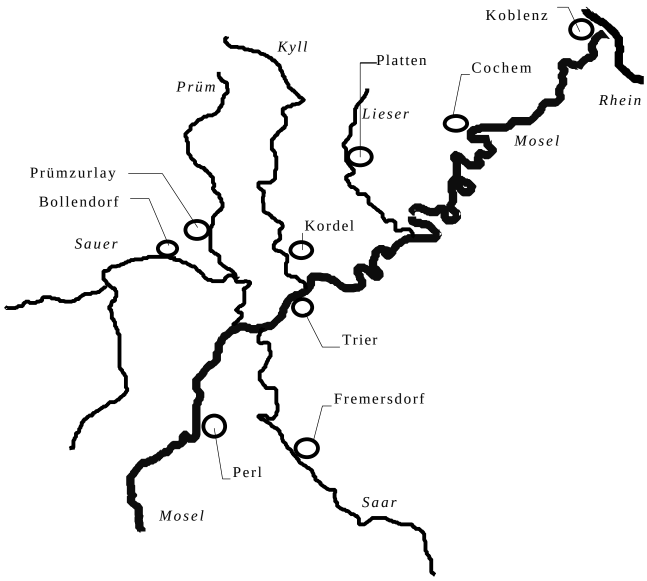

Fig. 1: River Mosel with tributaries

Main goal of the work carried out has been the investigation and development of systems based on Neural Networks and/or Fuzzy Logic for automatic forecasting of the water levels during flood events. Forecasts should estimate the progress of selected levels within next six hours. First, the forecasting problem was investigated using neural networks [sal]. This approach bears the advantage that neither special knowledge from experts nor knowledge about a system model has to be provided or explicitly to be included.

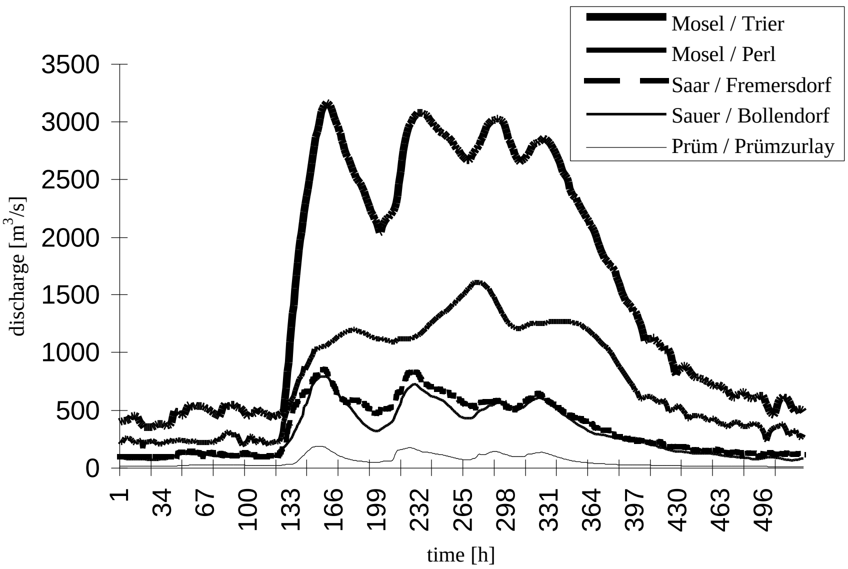

Fig. 2: Flood event January 1995
Discharge level Trier, up-river level Perl, and levels of tributaries Saar, Sauer, Prüm,
critical out-shore level at Trier is arrived at 1230 m^3/s equaling a water level of 6,5m

The system to be modeled can be looked upon as a time series consisting of sequences of patterns whose elements are standing in a temporal relationship. This relationship determines both the pattern and its position in the time series. Using a neural network for processing of such data the output of the network must depend on the actual input and previous inputs too. If one wants to use state-free feedforward neural networks, one has to provide specific input patterns showing the temporal dependencies to the network. In the given task a time window of size W is laid over the data series and shifted along the time axis during the training and recalling phase (see Fig. 3). Different schemes for input vectors were defined using actual discharge values *d(t)* of river levels and derivatives (discrete differences) *Dd(t)* of discharges in order to eliminate dependencies from absolute levels.

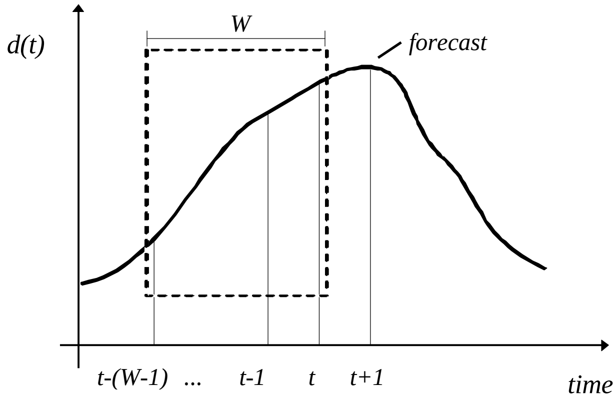

Fig. 3: Times series with input window of size W

Different network structures have be considered for level forecasting. Obviously the input and output layer were fixed according to the specified input *($d_i(t)$,$\Delta d_i(t-1)$,$\Delta d_i(t-2)$,...,$\Delta d_i(t-W+1)$)* and output vectors *($\Delta d_o(t)$)* whereas the hidden layers could be chosen arbitrary. This was done with respect to the variability of the input patterns and the desired plasticity of the approximate network behavior. An appropriate neural network was specified with 20 input neurons, two hidden layers with 10 neurons each, and one output neuron for the forecast of Mosel level at Cochem. The network was trained with data from a set of 11 previous flood events and teaching was achieved by backpropagation algorithm. Training was controlled with test data from the training set and extra validation data. Primary goals have been minimization of RMS error (real - forecast) and avoiding of special network behavior like e.g. overfitting caused by too long training phases. During tests with unknown events from the data set the network showed satisfying results, e.g. compared with manually produced forecast data (see Tab. 3).

However, this approach bears several disadvantages. First, the network requires a comprehensive set of training data. In practice, these data have been available only for some levels. Second, data from elder events were of limited use in the training set because of reconstructions having taken place on the river bed or in the catchment area in the meantime. Third, the black box nature of the neural network doesn't allow to extract acquired model information and therefore cannot be systematically improved with regard to the specific application. This means for example, that the system cannot work correctly in cases of extreme situations that have not be shown in the training data but do not injure the nature of the function approximation.

Alternatively, a Fuzzy Model for the forecasting of water levels (for Trier and Cochem) was investigated and developed [stu]. This approach allows the consideration of knowledge in the system description. In addition, this technique gives the opportunity to analyze directly the used system model and according input data in the development phase and also during system tuning. By this means, practical evaluations and conclusions about the actual problem situation can be achieved.

3 Fuzzy System Approach

Many parameters with essential impact to the process of level discharges are known in general, but their quantitative and temporal influence can only be guessed even by experts. Aside from the type and amount of precipitate, the height and topology of the catchment area as well as the climatic and time of the year situation are of importance. The condition and changes of the soil, subsoil, and river bed have influence to the discharge behavior beside other aspects regarding the natural and artificial environment. Discharge levels considered within the framework of this approach implicitly bear information about precipitate in the up-river area, but rain fallen in the catchment area between up-river locations and the location of the level to be forecasted is not contained. In addition, the controlling of weirs in this intermediate section is not registered.

The following requirements have been considered for the modeling of the fuzzy system. From the investigation of the problem and from interviews with experts it was not possible to derive specific hints for the partitioning of the input and output variables and for the defining of according membership functions. The time delay of waves between Trier and Cochem lies in the range of 11 and 17 hours according to informations from experts. A dependency between varying time delays Δt of flood wave and progress of flood at down-river levels is assumed. However, its effect is not clearly known for river Mosel. The time delay or passage time is dependent from the distance of the according level locations, the height of the discharge level, the shape of the flood waves, and meetings with waves from tributaries a.s.o.

A general description of the dependencies of the forecasted discharge (d_o) and its changes (Δd_o) during the next six hours are given by equation (1).

$$d_o(t) = d_o(t-6) + \Delta d_o(t)_{w=6} \tag{1}$$

The fuzzy description of discharge changes is given by (2):

$$\Delta d_o(t)_{w=6} = f(\Delta d_1(t-\Delta t_1)_{w=3,6,9}, \Delta d_2(t-\Delta t_2)_{w=3,6,9}, \ldots, \Delta d_n(t-\Delta t_n)_{w=3,6,9}) \tag{2}$$

($w \in W$, input window; d_i, $i=1...,n$, input levels).

At this stage of problem analysis it could be stated that expert knowledge gained from many years of experience could only be used to a small extend. For this reason, the rule base will bear little pre-knowledge about the problem. A system model with approximate functional behavior based on previous events leads to limits in the extreme results the system can provide. Future events would be forecasted with increased error values in such cases.

3.1 Fuzzy System Design

A fuzzy model based on *Sugeno* approach [sug, tag] was chosen as an appropriate solution for the given problem. The selected approach allows a piece-wise approximation of non-linear functions. In a first step the input space can be partitioned into coarse intervals. Subspaces which yield insufficient results with respect to predefined quality measures can be subdivided further. The optimization of single subspaces by different weighting of input variables leads to distinct rule sets. This can be equated with an acquisition and adaptation of expert information.

The function approximation can be improved by choosing the available functional degree of freedom to a large extend. The forecast can be evaluated from a linear combination of input variables. Partitioning of the output space with membership functions can be omitted. The influence of input variables on the result can be extracted directly from the rule base and therefore alleviates considerably the optimization of parameters. Optimization can so be performed manually or automatically during the modeling phase. Input variables can be used in output terms without being contained in the premise. This leeds to a smaller rule base for the given problem space. Weighting of input variables in the conclusions allows direct formulation of their influences with respect to the output. This is advantageous compared e.g. with a system approach of *Mamdani* type.

The i-th control rule is of the form

$$R^i: \quad \text{If } x_1 \text{ is } A_1^i, \; x_2 \text{ is } A_2^i, \ldots, x_n \text{ is } A_n^i, \quad \text{then } y^i = p_0^i + p_1^i x_1 + \ldots + p_n^i x_n \tag{3}$$

where the A_j^i are fuzzy variables and y^i is the output of the *i*-th control rule determined by a linear equation with coefficients p_j^i. The membership function of a fuzzy set A is simply written $A(x)$ and is composed of triangle functions. If the inputs $x_1, \ldots, x_n$ are given, the truth value w^i of the premise of the *i*-th rule is calculated as

$$w^i = \prod_{j=1}^{n} A_j^i(x_j) \tag{4}$$

and the output y is inferred from *m* rules by taking the weighted average of the y^i:

$$y = \sum_{i=1}^{m} w^i y^i \Big/ \sum_{i=1}^{m} w^i \tag{5}$$

3.2 Structural Identification

The structural identification and optimization of the fuzzy system can become rather demanding following the approach after *Tagaki*. In practical applications at least a semi-automatic optimization process is required. For this reason a slightly changed strategy was chosen for the given task. This strategy is characterized mainly by the following steps.

1. Discharge values (*d(t)*) serve as input and output variables for the fuzzy system. They can be calculated from flood (or water) levels via transformation tables.

2. The set of available flood data (events) is devided into two sets: one for system modeling - selected regarding characteristic features - and one for system testing.
3. Input variables which probably can influence passing times *Dt* of waves are subdivided in membership functions. Since there was no support by expert knowledge a clustering algorithm was used. For this, the summit of waves of input levels and the output level can be used in the feature vector.
4. Independent models are then generated for all input variables determined according to 1. For each model a rule base is defined containing as much rules as the input variable possesses membership functions. The premises contain one membership function. The conclusions describe the changes of the discharge value *Dd(t)* within 6 hours in advance to the estimated passage time of the wave.
5. The passage times *Dt* and the parameters p_r^s contained within the conclusions are optimized according to criteria (6) so that the total error between forecasted (*Dd*$_{fore}$) and real discharge change (*Dd*$_{real}$) yields a minimum.

$$E = \min\left\{ \left(E_{abs} \right)_q \right\}; \qquad q = 1,..,N;\; N \in \mathrm{N} \tag{6}$$

N: number of parameter sets (*Dt*, p_r^s)

$$E_{abs} = \sum_{j=1}^{k} \sum_{i=1}^{n} \left| \Delta d_{real} - \Delta d_{fore} \right| \tag{7}$$

with *k* elements of modeling set and each with *n* hourly data.

6. Input variables showing dependencies of the discharge value from passing time are collected in premises and then the maximum number of rules is built. The conclusion then contains all discharge changes of all input levels. The parameters than are optimized.
7. If there are discharge changes of several levels (river locations) in a conclusion the passing times are changed until a minimum error value is achieved. After every changing of a passing time an optimization of parameters is performed. These steps are repeated until the required forecasting accuracy is reached or changes don’t result in essential improvements.
8. Further improvements of forecasting results can solely be achieved if new rules are inserted for regions with maximum error values. Again this step is repeated together with optimization steps as mentioned above until there is no further improvement.
9. The influence of the input variables to the passing times can be recognized within the rule base. Assumptions can be made, that these dependencies exist also for other (higher) discharge values. Based on this additional rules are built for discharge levels that are not available or yet displayed in the training set.
10. The discharge values are transformed to (flood or water) level data.

By this means, an interpretation of acquired knowledge is made possible relative simply. From the interpretation of the rule base new rules can be derived, which can describe extreme situations beyond events hitherto and can forecast such situations with higher accuracy.

4 Practical Results

Two systems have been investigated for flood level forecasting at river Mosel. A neural network was teached with training data from 11 flood events. A fuzzy system was modeled based on hourly recorded data of two different flood events. A forecast of the level at time *t + 6* hours (so called 6-hours forecast) was defined as central task. The quality measure was defined by the sum of the absolute forecast error (compared to known level progress) beyond a critical level (so called out-shore-threshold). As minor requirement a measure was considered, which provides a better forecast than that produced manually or with the neural network.

Tab. 1 and Tab. 2 show result data of the fuzzy system and Tab. 3 lists according data for the neural network. One recognizes, that quality of forecasting is quite as good for the validation data as for the test data (shaded lines). The fuzzy system forecasted summit levels for flood in 1993 nearly accurately in spite of the fact, that extreme values (see max. flood levels) were not available in the modeling set (Fig. 4). A system comparison (level Cochem) shows, that the fuzzy system approach already was able to produce satisfying results only with two flood events in the modeling set. This system also has better behavior at critical phases of increasing flood levels. Fig. 5 shows manually produced forecasts and Fig. 6 show result of the fuzzy system for the same event.

Legend for Tables: *AAEO*: averaged absolute error between forecasted and real flood level above out-shore threshold, *MES*: maximum error between forecasted and real flood level at summit point, *MAEO*: maximum absolute error between forecasted and real flood level above out-shore threshold; flood events used in modeling data set are in shaded lines

Flood event	*AAEO*	*MES*	*MAEO*	max. flood level
January 1995	8	11	52	1033
December 1993	6	3	61	1128
January 1991	6	8	31	840

Tab. 1: Result flood level forecast using fuzzy model (level Trier, all values in cm)

Flood event	*AAEO*	*MES*	*MAEO*	max. flood level
January 1995	7	-6	45	947
December 1993	6	-24	34	1034
January 1993	6	-14	36	840
January 1991	7	-4	39	750
February 1990	6	-8	31	802

Tab. 2: Result flood level forecast using fuzzy model (level Cochem, all values in cm)

Flood event	*AAEO*	*MES*	*MAEO*	max. flood level
January1993	10	-18	35	840
February 1990	10	-3	67	802

Tab. 3: Result flood level forecast using neural network (level Cochem, all values in cm)

5 Conclusion

The two systems designed for flood level forecasting at river Mosel proved their capabilities for modeling complex system environments. The neural network delivered acceptable results for the approximation of times series functions without the need of specific knowledge about the problem. It is dependent on and also limited to sufficient training data. In comparison the fuzzy system displayed very promising features. The system achieved better results even with only few data sets for system modeling. Without pre-knowledge about e.g. hydrological dependencies a rule base was established by structural system optimization. The rule base was subsequently confirmed by interpretation through experts. A special forecast problem could be modeled and transformed into a simple mathematical description. From the rule base dependencies for extreme situations could be derived and described by which yet unknown situations could be forecasted. The analysis of the system structure delivered detailed information about influences of system variables which have been assumed but could not be verified by the experts before.

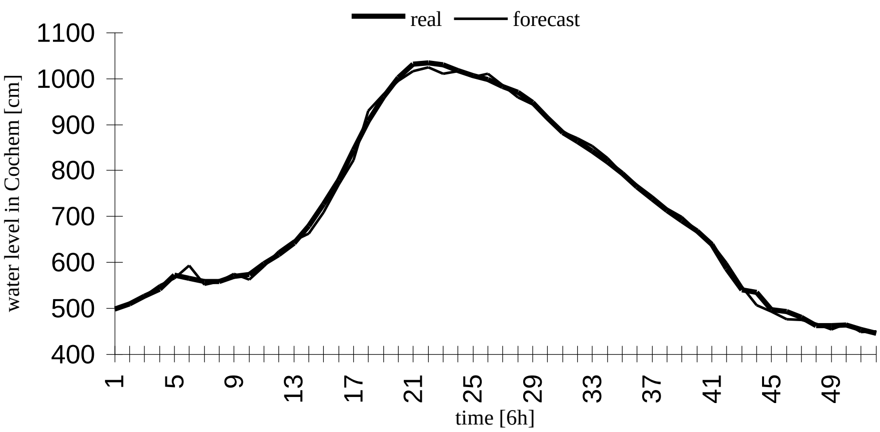

Fig. 4: Flood event Dec. 93 with summit level exceeding modeling data set

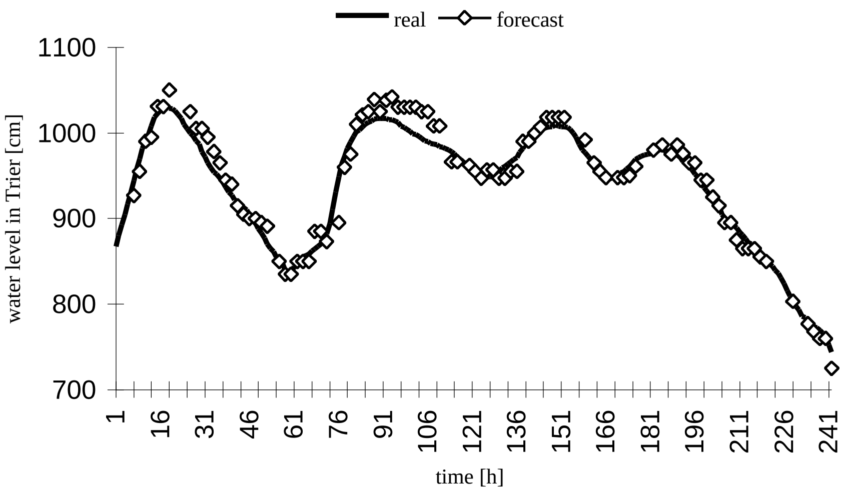

Fig. 5: Forecast produced by experts for flood event Jan. 95[sti]

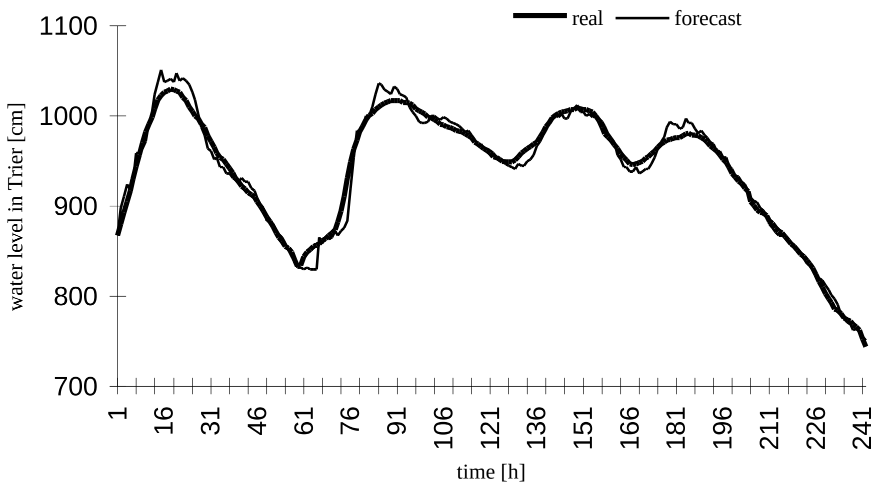

Fig. 6: Forecast produced by fuzzy model for flood event Jan. 95

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