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Machine supported Development of Fuzzy - Flood Forecast Systems

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Abstract. The development of a system for the automated creation of flood forecast models is presented. The system concept is based on building rainfall-runoff models using Fuzzy Logic. Beginning with the discussion of manual discharge forecast of a flood event, the structure of special fuzzy models is pointed out on the basis of an existing rainfall-runoff model. The parallels to the manual forecast calculation are specified and referred to the problems with the generation of complex rainfall-runoff models. It is then shown, how these problems can be solved. The algorithm and it's implementation in a development system is described for an almost completely automated generation for fuzzy rainfall-runoff models. Additionally practical forecast results are demonstrated.

1 Introduction

The emergence of a flood and thus its forecast depend elementarily on the discharge process in the natural catchment area of the river. This process is rather complex and its mapping into a suitable process model for an automated flood forecast is accordingly difficult. Although in many places the number of metering stations (e.g. rainfall, level, etc.) has been increased and the meteorological forecast network becomes more finely strained, some important process variables (e.g. evaporation) cannot be measured explicitly. Thus, describing the flows in a river catchment area must be based on simplifications, which lead to different levels of abstraction and different approaches for modeling.

The increasing number of metering stations, which become more and more on-line accessible, as well as the use of high performance computers, have it made possible to create more complex but also computing-intensive models in the last years. Such models are mainly used in the fields of forecast and simulation and should fulfill various requirements:

- Primarily, the models should provide an optimal correlation of calculated and actual values.
- It should be possible to create models for different forecast periods and catchment areas (e.g. different in morphology, size, climate region). The manual expenditure in creating and adapting a model should be as small as possible.
- Input stems from different types of measured variables and represents different sub areas of the catchment area (e.g. rainfall, seasonal information, …). It should be possible to integrate and combine the different types within the forecast model.
- Modifications of the natural discharge process, as for example dams or weirs should also be considered in connection with changes of the time lags or different wave forms.
- Discharge models have to work on-line with actual measured data and should deliver flood forecast just in time.

In the following we describe the development of a system, which supplies an automated generation of rainfall-runoff models to a large extend. The system is based on a flood forecast model using Fuzzy Logic fulfilling the requirements mentioned above as far as possible. First, a simple example of a flood forecast model is presented to give an insight in the system approach and used Fuzzy Logic concepts. Afterwards an algorithm is presented for an automated generation of forecast models using data from earlier flood events.

2 Fuzzy model for discharge forecasts

2.1 Motivation

In the last years, Fuzzy Logic based procedures have proven to be very efficient for analyzing data and modeling the according processes. Especially they are used, when conventional procedures are getting rather complex and expensive or vague and imprecise information flows directly into the modeling process. With Fuzzy Logic it is possible to describe available knowledge directly in linguistic terms and according rules. Quantitative and qualitative features can be combined directly in a fuzzy model. This leads to a modeling process which is often simpler, more easily manageable and closer to the human way of thinking compared with conventional approaches.

2.2 Discharge forecast for the level Trier

In this section the structure of a fuzzy model is described on the basis of a simple discharge forecast model. For simplification only discharges are used as input variables which are measured at river upward locations and at the level to be predicted. Accordingly no rainfall data or other variables are considered.

Actually, several fuzzy forecast models have been developed and are in practical use. In this example a six hour fuzzy forecast model is described for the level at Trier/Mosel (Germany) [Figure 1]. Inputs are the (river upwards) levels at Perl/Mosel, Fremersdorf/Saar, Bollendorf/Sauer and Prümzurlay/Prüm. Measured data is used from nine previous flood events for the generation of the model. Then the model is tested with four other flood events. Level data is measured and provided regularly in one-hour periods. Figure 2 shows discharge data for the above mentioned levels from flood event in January 1995. The size of the catchment area of level Trier is about 23860 km^2. The arithmetic mean of the discharge is about 277 m^3/s.

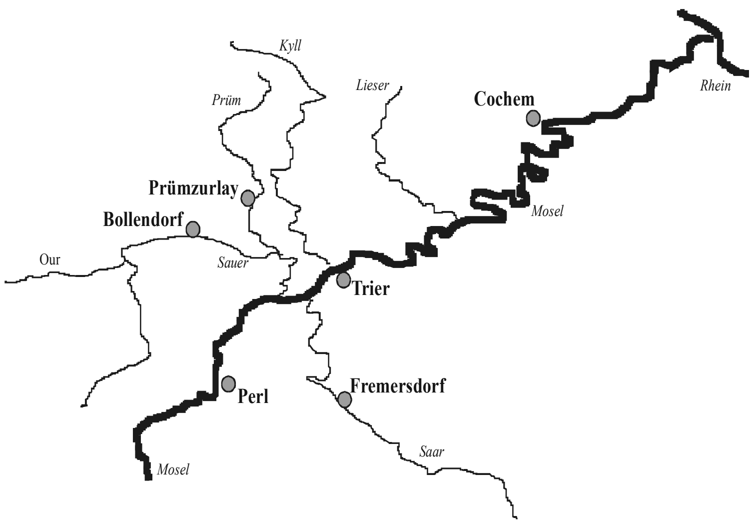

Figure 1: Part of the basin of river Mosel with tributaries

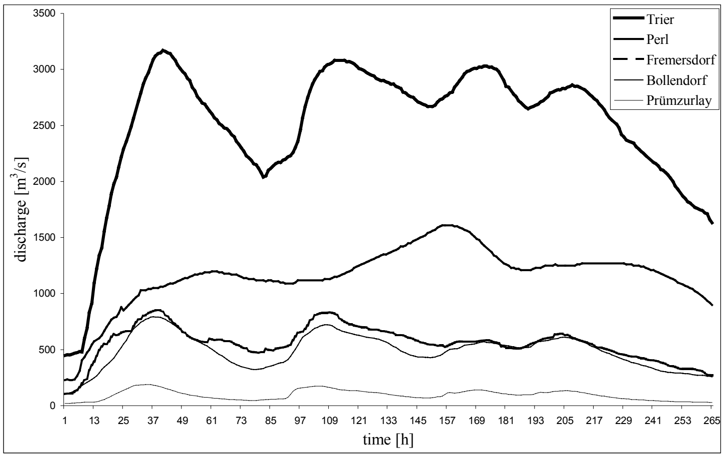

Figure 2: Discharge levels in January 1995

The forecast of the discharge at Trier is known to be difficult, because the two largest tributaries Saar and Sauer meet the Mosel directly in front of Trier. Both the discharges within the upper Mosel area and the discharges of Saar and Sauer alone can influence the flood considerably. The waves arriving at a flood event at Trier at different times can lead to different superpositions and flood cases, which have to be treated differently. The time lags of the waves from the up-river levels to the level Trier amount from approx. six to ten hours. The catchment area between these levels is not considered due to the too short time lags and the limitation on discharge data of the simplified model.

Taking a look at the methods used by experts when manually generating a discharge forecast one can see, that the influence of the various input levels is regarded differently with respect to an intuitive estimation of the discharge situations in the regarded areas. These situations are merging fluently and cannot be expressed by sharp numerical values. On the other hand, the number of input variables (stations) which can be considered by the experts is limited due to the complexity of the process.

The situations can be described typically in following form:

Situation i: Discharge at Perl at time (t_l) is high and ... and
discharge at Fremersdorf at time (t_{k-j}) is very_high ... and ... and
discharge at Perl between (t_{k-2}, t_{k-1}) rises strongly and ...

The calculation of the six hours discharge forecast at level Trier ($Q_{Trier}(t+6)$) could be carried out for the above situation as follows:

Situation i: Q_{Trier} $(t+6)$ =A proportion p_1 of the discharge at Perl (t_k) +
a proportion p_2 of the discharge at Perl (t_{k+1}) +
a proportion p_3 of the discharge at Fremersdorf (t_{k+2}) +... +
a proportion p_n of the discharge at Prümzurlay (t_l).

The description of a situation and the calculation of the according discharge are connected together in an IF... THEN... - Rule. The set of all rules created in this way results in the rule base of the fuzzy model.

The flow times (t_1, ..., t_l) and the proportions (p_1, ..., p_n) of the intermediate catchment area can be estimated by local experts or figured out by comparison with historical flood events. Figure 3 shows the water level forecasts of the experts for the level Trier for the flood event in January 1995. If colloquially formulated knowledge or experience should be used directly for the generation of a forecast model, then fuzzy models can be used in an advantageous way. This has been shown already for different application areas [suka, ne].

Fuzzy models can serve to automate the forecast estimation, to support and relieve the experts at a flood event, and to provide a comprehensible forecast estimation.

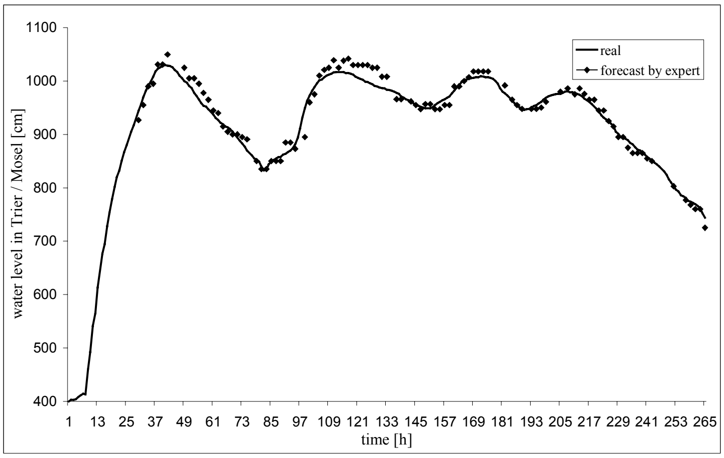

Figure 3: Forecast produced by experts

2.3 Fuzzy concepts and representation of experiences

This section describes the representation of existing experience (e.g. about discharge processes) by a fuzzy model based on Takagi Sugeno [tasu]. In addition the concepts of a fuzzy model are briefly shown and translated into a practical discharge model.

Fuzzy Set

The classical theory of sharp sets can describe only the membership or non-membership of an item to a set. A *fuzzy set A* over X is characterized by a membership function $\mu_A(x)$, which assigns to each item of X a real number of the interval [0,1]. The value of μ_A at x is called *truth value* of x to the set *A*. A sharp set is a special case of a fuzzy set, if the membership function can take only the values 0 and 1.

The range of the model input values, which are judged necessary for the description of the situation, can be partitioned into such fuzzy sets. Figure 4 shows for example, how the range for the discharge at level Perl is partitioned into three overlapping fuzzy sets (low, middle, high).

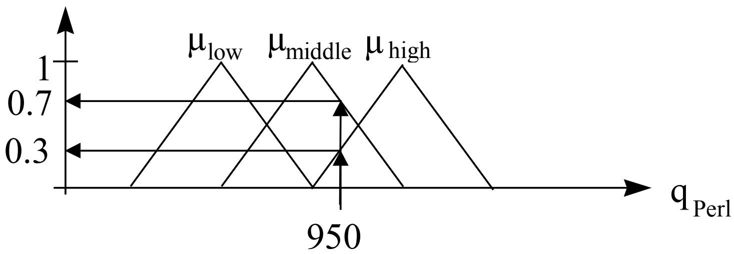

Figure 4: Linguistic variable of discharge in Perl with three fuzzy sets

The premise *"the discharge at Perl is middle*" is fulfilled in this example with a discharge of 950 m^3/s to 0.7. The truth value of the premise *"the discharge at Perl is high"* amounts simultaneously to 0.3.

Inference

If adjectives are assigned to these fuzzy sets, then these fuzzy sets can be combined to colloquially formulated descriptions of situations. These descriptions are formulated in the form of rule premises, whose sub premises are combined through AND-Operators. For the forecast model such rule premises for example, may have the following form:

IF $Q_{Perl}(t_1)$ IS *high* AND $Q_{Fremersdorf}(t_{k-j})$ IS *very_high* AND ...

In a fuzzy system according to Takagi Sugeno the conclusion of each rule consist of the summation of linear weightings of the input variables. If the same inputs are to be used in each conclusion and different wave lag times should be considered at the same time for example depending on a determined situation, then such conclusions can be read as follows:

THEN $Q_{Trier}(t+6) =$
$Q_{Perl}(t_k)*p_1 + Q_{Perl}(t_{k+1})*p_2 +$
$Q_{Fremersdorf}(t_{k+2})*p_3.+ ... +$
$Q_{Prümzurlay}(t_l)*p_n$

The t_1, ..., t_l and p_1, ..., p_n represent model parameters, which have to be optimized to achieve optimal forecast results. The parameters p_1, ..., p_n describe the proportional influence of the respective inputs, and therefore they can be adjusted roughly based on experience. Afterwards the parameters can be fine tuned and further optimized on the basis of filed data from previous events.

The set of all rules results in a rule base, which reflects the experience of the expert. The analysis of all rules of a rule base is understood as inference and supplies for a certain combination of input values exactly one output value. For the calculation of this output value, the entire truth value of each rule is determined and according to this value the output value of each rule becomes part of the total result. Calculating the entire truth value of a rule is done by combining the truth values of all sub premises of this rule with an AND operator. The AND operator is assigned a mathematical function, i.e. the algebraic product. The structure of such a fuzzy model can be formulated as follows:

The *i*-th rule is of the form

R^i: If x_1 is A_1^i, x_2 is $A_2^i, ..., x_n$ is A_n^i,
then $y^i = p_0^i + p_1^i x_1 + ... + p_n^i x_n$

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

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

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

$$y = \sum_{i=1}^{m} w^i y^i \Bigg/ \sum_{i=1}^{m} w^i$$

2.4 Comparison of manual and fuzzy model based forecasts

A fuzzy model is easy to interpret, because it has colloquially formulated rules and the calculation of the forecast is similar to the expert's methodology. It can serve as a starting point for the integration of further input variables. Thus more input variables could be used than the human expert is able to consider or to handle. Once a fuzzy model is created, it needs only less than 1 min. computing time on a 500 MHz-PC for the calculation of the forecasts and it does not require any calibrating. The forecasts of a fuzzy model which was manually created and optimized are presented in Figure 5 for i.e. the flood event in January 1995. Compared with the forecasts of the experts (see Figure 3) it shows up that at least the same forecast quality is achieved even without the consideration of measured rainfall values and rainfall forecasts.

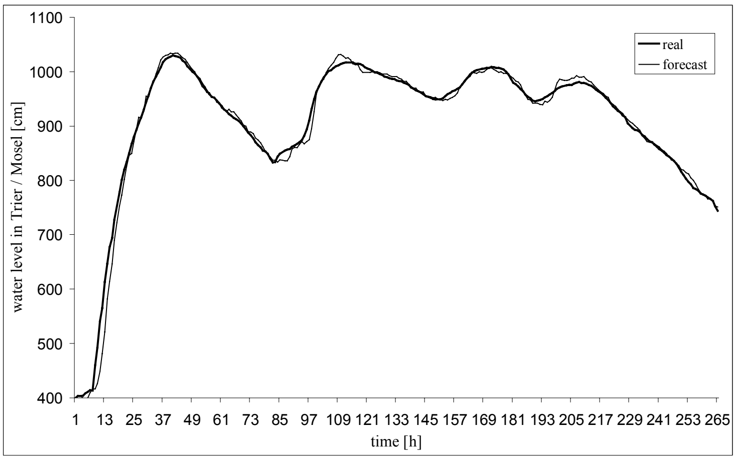

Figure 5: Six hours forecast produced by fuzzy-model

If additional input variables like e.g. rainfall, temperatures, etc. should be used in the model, then the expenditure for the generation and optimization rises significantly with the increased number of decisions to be made during the design process and the increased complexity of the parameter optimization task. In order to reduce the amount of manual tasks during the generation process, one needs procedures for an automated generation of fuzzy models. These automated procedures should partition the input variables into fuzzy sets, produce the rules and optimize the conclusion parameters.

In the last years, a set of different procedures for different applications was suggested [ne, suka, tasu]. In the following a procedure is presented, which has been developed and implemented for a machine supported development and generation of fuzzy forecast models.

3 Automated generation of fuzzy rainfall-runoff models

3.1 Motivation

In the previous chapter the structure of a fuzzy model was presented on the basis of a forecast model for the level of river Mosel at Trier. The model creation process requires design decisions and parameter adjustments, both producing substantial expenditure if accomplished manually. Unfortunately the expenditure rises non-linearly with an increasing number of input variables. In order to create models with larger numbers of input variables but with reduced manual expenditure machine supported procedures could be used. For the automated generation of fuzzy models there exist already some principal approaches for typical application fields [nhi]. In this section a machine supported procedure is presented for the creation of fuzzy rainfall-runoff models.

3.2 Steps for generating a fuzzy model

The steps needed for generating a fuzzy model are illustrated by a simplified flow chart in Figure 6.

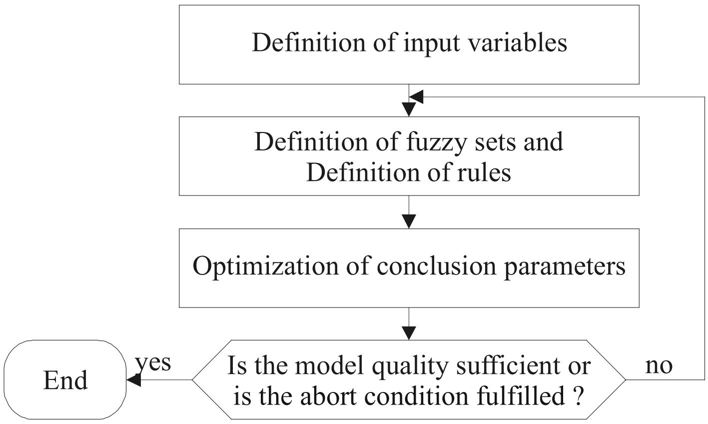

Figure 6: Steps for generating a fuzzy model

Within the procedure for generating a fuzzy model the definition of input and output variables describes the first step. In case of a rainfall-runoff model the output variable is defined as the level to be predicted. Input variables are the measured and on-line available values of the given catchment area, for example there are runoff, rainfall and temperature. In the next step the input variables have to be partitioned into suitable fuzzy sets. Thereby the total number, shape and position of the fuzzy sets have to be specified. Then suitable rules have to be determined on basis of meaningful combinations of the fuzzy sets covering the input space of the application.

For the partitioning of the input space for example cluster algorithms can be used. Because clusters expressed by the fuzzy sets can overlap, fuzzy cluster algorithms are useful [cla, hkk, stu]. Heuristic algorithms could also be used [ne, nhi, suka, tasu]. There exist different strategies for the optimization of the conclusion parameters. The optimization may be seen as a typical least-square problem, because the conclusion of each rule consists of a linear equation. In this case the process for generating the rules has to fulfill some preconditions which can be easily ensured [he]. Gradient procedures are also used for optimization of the conclusion parameters, but they need often more computation time [bre].

3.3 Development system for fuzzy rainfall-runoff models (R-R models)

We have developed an algorithm and implemented an according system for the automated generation of fuzzy rainfall-runoff models. The system supports all development steps for building practical fuzzy forecast models as mentioned in the previous section.

At the beginning of the execution of this algorithm the user has to specify the following items:

- the input variables of the model, the modeling and test data (i.e. filed events),
- the optimization criterion,
- a criterion, when to stop the generation process (abort condition).

Based on these information the implemented algorithm creates a rainfall-runoff model in the following steps:

1) partition each potential premise variable in two fuzzy sets,
2) generate all possible rules,

3) optimize conclusion parameters,
4) calculate model quality over all modeling data on the basis the optimization criterion,
5) for all potential premise variables: Determine, adding a further fuzzy set to which variable provides the highest quality,
6) as long as the abort condition is not fulfilled go to 2).

The algorithm works as follows: In step 1) each input variable specified by the user is partitioned into two fuzzy sets; next in step 2) these are added to the rule premises. Thus it is guaranteed that each input is considered for the description of situation. In addition, the user can accomplish a preselection of variables which should be taken into account. In step 3) the conclusion parameters are optimized, which describe the quantitative influence of all input variables. During this step the modeling data for example from previously filed events is used. For that purpose the conclusions of the rules are treated as a linear set of equations and the parameters are identified with the least square method. In step 4) the quality of the model is determined using the specified optimization criterion. This criterion may be for example a prediction which is as close as possible to the measured data in the area of the rising branch, at the peak flow or over the complete range. In step 5) new fuzzy sets are inserted in most promising premise variables. This is achieved by an iterative insertion and deletion of fuzzy sets in all possible premise variables and the subsequent creation of rules and optimization of parameters. If there is a variable with a new fuzzy set found, which results in the best improvement of the model, then this fuzzy set is transferred to the new model. Steps 2) to 5) are repeated until the abort condition specified by the user is not fulfilled. Further heuristics can be added to this algorithm. For example, selected data areas of the process range can be considered separately or preconditions can be inserted in order to reduce the number of fuzzy sets and to further simplify the model.

The algorithm described above has been implemented in a development system for the generation of fuzzy rainfall-runoff models. With this algorithm generated models are easily interpretable, e.g. considering the influence of input variables and the relations between them.

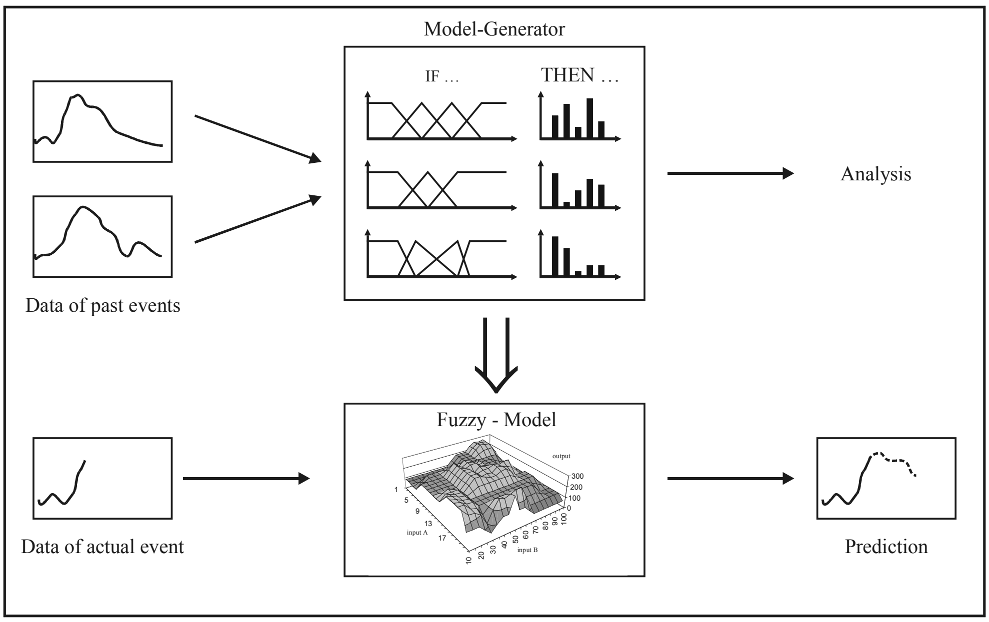

Figure 7: Scheme of the development system for an automated generation of R-R models

Figure 7 shows schematically the use of the development system. The model generator uses the data of past events and the information provided by the user as stated above (optimization criterion, etc.). The generation of a model takes few hours on a commercial PC (e.g. 500 MHz-PC). A model generated with this system for example is presented in Figure 7 as a characteristic diagram of two input variables. It may be used for forecasts without further optimization or calibration. Additionally the determined rules of the fuzzy model can be interpreted. This can be used to analyze or explain the relations and influences of the used input variables as for example discharge values, rainfall values, temperature levels and data for direct or indirect description of the vegetation.

Taking into account the system concept and the application requirements now modular forecast models can be developed by starting for example with a model for an one hour forecast. Forecasts for longer time periods can be achieved by an iterative arrangement and execution of the one hour model; the forecast period is only limited by the available data of rainfall forecasts. Models can be connected and forecasts of one model can be used as input for a following model. In this way large catchment areas can be partitioned into smaller areas and local models can be developed and combined to a complete model.

At present, first forecast models for rivers Mosel and Sieg are developed. Figure 8 shows the results of the Trier/Mosel model for a six hour forecast from flood event in January 1995. This model was developed with the procedure described above and additional rainfall data.

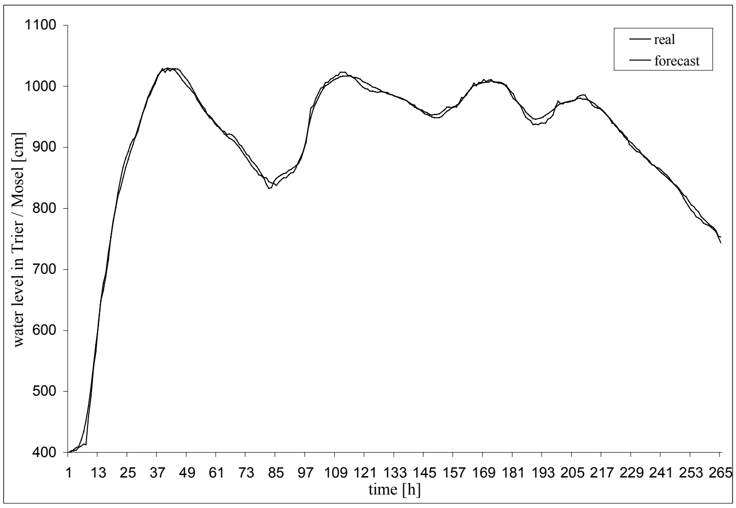

Figure 8: Six hours forecast produced by fuzzy-model with rainfall data

4 Conclusion and Acknowledgement

The presented development system enables and supports the creation and execution of fuzzy rainfall-runoff models. Practical forecast models can be built with little manual and temporal expenditure. Available system data are analyzed automatically and the relationships are presented as fuzzy rules. Dependencies between the input and output variables and their influence within the discharge process can be detected. The created models can be used for forecast or simulation purposes. Practical application of a model takes only seconds for execution. Models can be developed in modular form and local models for example can be combined to a model for the complete catchment area.

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