Overview of the artificial neural networks and fuzzy logic applications in operational hydrological forecasting systems

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Abstract

Damage due to flooding has increase in many countries in the last years, and due to the global climate change, which is now recognized as a real threat, an increase in the occurrence of flooding events and especially of flash flooding events is likely to continue into the future.
In those conditions and because building new flood defences structures for defending vulnerable areas has serious financial implications, the timely forecasting of floods is becoming more important for flood defence and in general for water management purposes.
The complexity of natural systems and of hydrological processes that influence river levels evolutions make the traditional modelling approaches, based on mirroring natural processes with physically based equations very difficult. Despite the fact that in the last decades the Operational Hydrological Forecasting Systems were significantly developed, becoming more and more complex systems, ingesting and processing in real time a great amount of data from automated hydrometrical and meteorological stations networks and high resolution grided data from radars and satellites, together with the use of distributed hydrological models, the warning and forecasts improvements are not very significant, in many cases the performance of the new physically based distributed models being comparable with the "older" conceptual lumped models.
The paper presents an overview of some alternative and complementary modelling approaches, artificial neural networks and fuzzy logic systems, possible applications for the improvements of the Operational Hydrological Forecasting Systems, and presenting also some example of rainfall-runoff modelling implementations.
Artificial neural networks are widely used as an effective approach for handling non-linear and noisy data, especially in situations where the physical processes relationships are not fully understood and they are also particularly well suited to modelling complex systems on a real-time basis.
Fuzzy logic is a generalisation of Boolean logic implementing the concept of partial truth or uncertainty, so within the fuzzy set theory an element can have a gradual membership to different sets. To describe system behaviour with fuzzy logic, you need to define fuzzy sets, fuzzy rules or so called IF-THEN rules and apply a fuzzy inference scheme. The generation of a fuzzy forecast model can be based both on experts knowledge and historical data.
In conclusion, both artificial neural networks and fuzzy logic modelling systems offer the potential for a more flexible, less assumption approach to hydrological processes, and they have already been demonstrated as successfully substitutes for the classical rainfall – runoff models, and also as tools for the real time updating of hydrological forecasting models and especially for the multimodel approach.
Keywords: hydrological forecasting model, artificial neural network, fuzzy logic, operational hydrological forecasting systems

Operational hydrological forecasting systems

On a global scale, floods account for over 65% of people affected by natural disasters and they are the most damaging of all natural disasters. Better forecasting floods and with a larger lead time, is the main sustainable way of adapting to and managing such disasters.
Operational hydrological forecasting systems, which link state of the river catchments, river discharges and water levels, recorded precipitations and weather forecasts, can be used to respond to floods as they occur and to reduce their costs in term of lives, property and other damages.
Current flood forecasting and warning systems have several limitations, such as, insufficient lead-time to provide accurate flood warnings, inadequate spatial and temporal resolution of the real-time rainfall observations and forecasts for flood producing storm, little integration of different sources of forecast information. Moreover their ability in considering the uncertainties in estimating and forecasting precipitation and flood discharges is very limited.
The desirable characteristics of a good flood forecasting system are:

- Timeliness: The lead-time is the time between making a forecast of an event and its occurrence, if sufficient lead-time is available and the predictions are accurate then evacuation, even of relatively large numbers of people may be possible. The increase of the lead-time is mainly limited by the availability of reliable quantitative precipitations forecasts, but also can be limited by the hydrological models or forecasting methodologies that are implemented.
- Accuracy: Is usually related to the correctness the forecasts of the magnitude and time of the flood peak and of the resulting levels. In special situations, it may relate to the forecasts of the complete hydrograph of the flood. The more accurate the forecast the better flood control/modification and damage mitigation measures can be implemented.
- Reliability: Can be associated with accuracy, but is related to the overall long-term reliability of the flood forecasting system, and not just to the accuracy of a forecast for a particular flood. Usually the long-term reliability of the system can be assessed by its performance in two respects. It should always forecast a flood when one occurs and it should not forecast floods when one doesn't occur. The reliability, like accuracy, affects the confidence in deciding on response measures, as the public perception of warnings messages may be very important.

Forecasts require both data collection and modelling. The amounts of data and the complexity of the modelling necessary to achieve specific targets of lead-time, accuracy and reliability vary from catchment to catchment, and there is a natural conflict between the desire for greater forecast lead-time and greater accuracy and reliability (usually the warning messages are based on model simulations that take into account just the recorded precipitations and not the forecasted precipitations). Generally the longer the lead times the less accurate and reliable are the forecasts of flood magnitude, location and timing.

Operational hydrological forecasting systems have (or could have) the following components:

- Data acquisition systems: Is the basic component for an operational system, and the data type and availability have major implications on the modelling part of the system.
- Rainfall forecasts models: Is the most important part for the forecast lead-time increase. Unfortunately the present results of the numerical meteorological models are not enough accurate for the hydrological forecasts applications. On short term, the solution could be a combination with the short future scan estimations based on radar information.
- Rainfall-runoff forecasts models: The possible approach extend from the extremely simple forecast relations, event type model, through conceptual semi-distributed models, which are still the most used models in operational, to complex physically based models.
- Flood routing and flood plain models: The hydrological routing methods are still extensively used, but the general direction is to use appropriate hydraulic models, which take into account the river geometry, and allow reasonable estimations of flood maps.
- Flood impact analysis component: If flood maps are available, flood impact analysis could be finally obtained by superimposing flood maps with GIS georeferenced spatial data on constructions, traffic, agriculture, etc.

Artificial Neural Networks Models

The field of neural networks has a history of five decades but has found solid application only in the past decade, and the field is still developing rapidly. Neural networks are composed of many simple elements operating in parallel. These elements are inspired by biological nervous systems. The network function is determined largely by the connections between elements.

Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, forecasting, identification, classification, speech, vision and control systems.

Artificial neural networks can be characterised most adequately as computational models with particular properties such as the ability to adapt or learn, to generalise, or to cluster or organise data, and which operation is based on parallel processing.

An artificial network consists of a pool of simple processing units which communicate by sending signals to each other over a large number of weighted connections.

A set of major aspects can be distinguished:

- a set of processing units (neurons);
- a state of activation for every unit, which also determines the output of the unit;
- connections between the units, generally each connection is defined by a weight which determines the effect which the signal of one unit has on other unit;

- a propagation rule, which determines the effective input of a unit from its external inputs;
- an activation function, which determines the new level of activation based on the effective input and the current state;
- an external input or offset for each unit;
- a neural network architecture;
- a training method.

Within neural systems it is useful to distinguish three types of units: input units which may receive data from outside the system, output units which send data out of the system and hidden units whose input and output signals remain within the system itself.
The neuron model and the architectures of a neural network describe how a network transforms its input into an output. Both the neuron model and the network architecture each place limitations on what a particular model can compute. The way a network computes its output must be understood before training methods for the network can be explained.

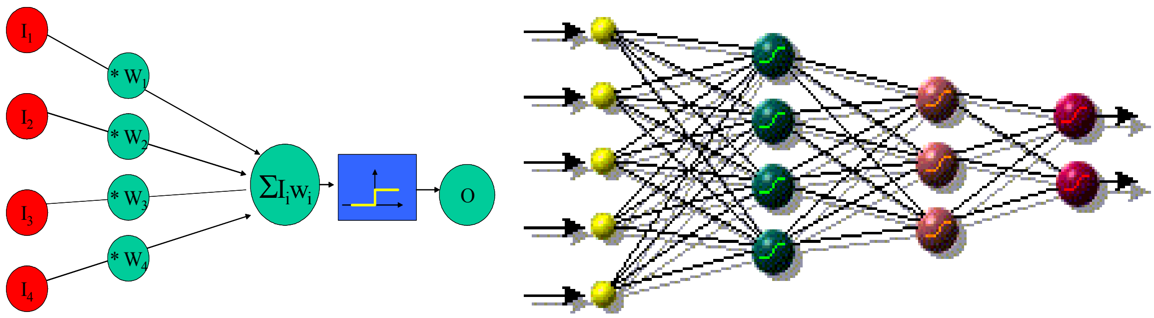

Figure 1. Typical representation of an artificial neuron model and for a full connected feedforward neural network, with two hidden layers

Backpropagation neural networks have been successfully used as a basic tool for the construction of effective forecasting schemes.
Different neural network architectures have been proposed as the basis of forecasting methods. The one hidden layer feedforward network is gaining broad acceptance due to its simplicity and expressiveness power. This net can be thought of as a nonlinear autoregressive (AR) model. The mathematical relationship, established through the sigmoid processing elements of the network, is essentially nonlinear.

Fuzzy Logic Models

The origin of the fuzzy logic approach dates back to 1965 since Lotfi Zadeh's introduction of the fuzzy-set theory and its applications. Since then the fuzzy logic concept has found a very wide range of applications in various domains like: estimation, prediction, control, approximate reasoning, pattern recognition, medical computing, robotics, optimization and industrial engineering, etc.
In the fuzzy logic approach the Boolean logic is extended to handle the concept of partial truth which implies that the truth takes a value between a completely true value and a completely false value. For example, the partial truth can have values in linguistic variables like not very truth, more or less false etc. To accomplish this idea the notion of the fuzzy sets has to be introduced, which is the collection of the objects that might belong to the set to a degree, taking any values between 0 and 1, instead of taking a crisp value (0 or 1).
The fuzzy logic approach is particularly a preferable tool for dealing with problems with uncertainties and imprecise information.
Here is a list of some general observations about fuzzy logic models:

- Fuzzy logic is conceptually easy to understand.
- Fuzzy logic is flexible.
- Fuzzy logic is tolerant of imprecise data.
- Fuzzy logic can model nonlinear functions of arbitrary complexity.
- Fuzzy logic can be built on top of the experience of experts. In direct contrast to neural networks, which take training data and generate Black-Box models, fuzzy logic lets the modelling process rely also on the experience of people.
- Fuzzy logic can be blended with conventional control techniques.
- Fuzzy systems don't necessarily replace conventional control methods. In many cases fuzzy systems augment them and simplify their implementation.

- Fuzzy logic is based on natural language. The basis for fuzzy logic is the basis for human communication.

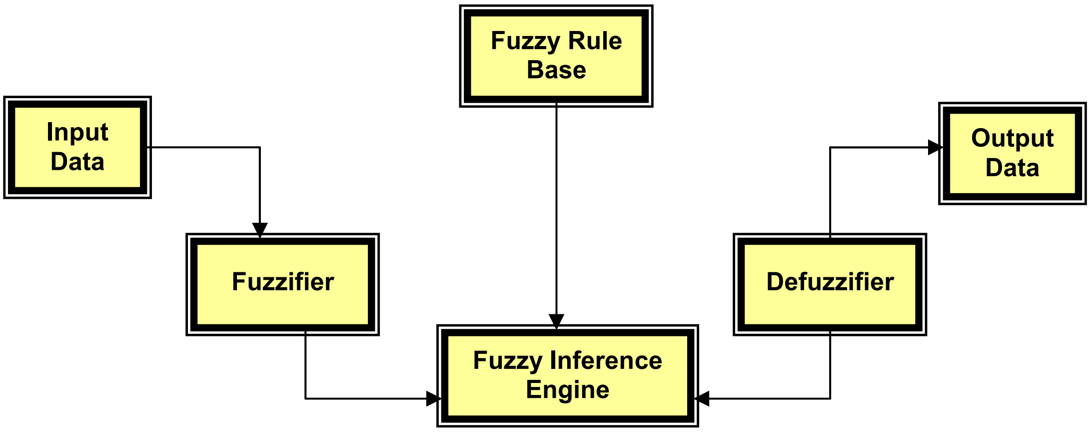

Figure 2. General block diagram of a fuzzy inference system

In general, in a fuzzy model application we find the following steps:

- Fuzzification of the input and output variables by considering convenient linguistic subsets such as very high, high, medium, low, very low, big, small, etc.
- Construction of rules based on the expert knowledge and/or on the available theory. The rules relate the combined linguistic subsets of input variables to the convenient linguistic output subset. Any fuzzy rule includes statement as "IF-THEN" with two part. The first part starts with IF and ends before THEN is referred to as the predicate (premise, antecedent), which combines in a harmonious manner the subsets of input variables. After the THEN comes the consequent part, which includes the convenient fuzzy subset of the output based on the premise part. This implies that there is a set of rules each of which is valid for a specific portion of the inputs variation domain. The input subsets within the premise part are combined most often with the logical "and" conjunction whereas the rules are combined with the logical "or".
- The result appears as a fuzzy subset and therefore, it is necessary to defuzzify the output set for arriving to a crisp value that will be required by the final user. There are two main type of fuzzy inference: Mamdani and Sugeno. Mamdani-type inference, in which the output membership functions are fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification, in which we integrate across the two-dimensional function to find the centroid. Sugeno-type inference can be used to model any inference system in which the output membership functions are either linear or constant. This is sometimes known as a *singleton* output membership function, and it can be thought of as a pre-defuzzified fuzzy set. It enhances the efficiency of the defuzzification process because it greatly simplifies the computation required by the more general Mamdani method, which finds the centroid of a two-dimensional function, we can simply use the weighted average of a few data points.

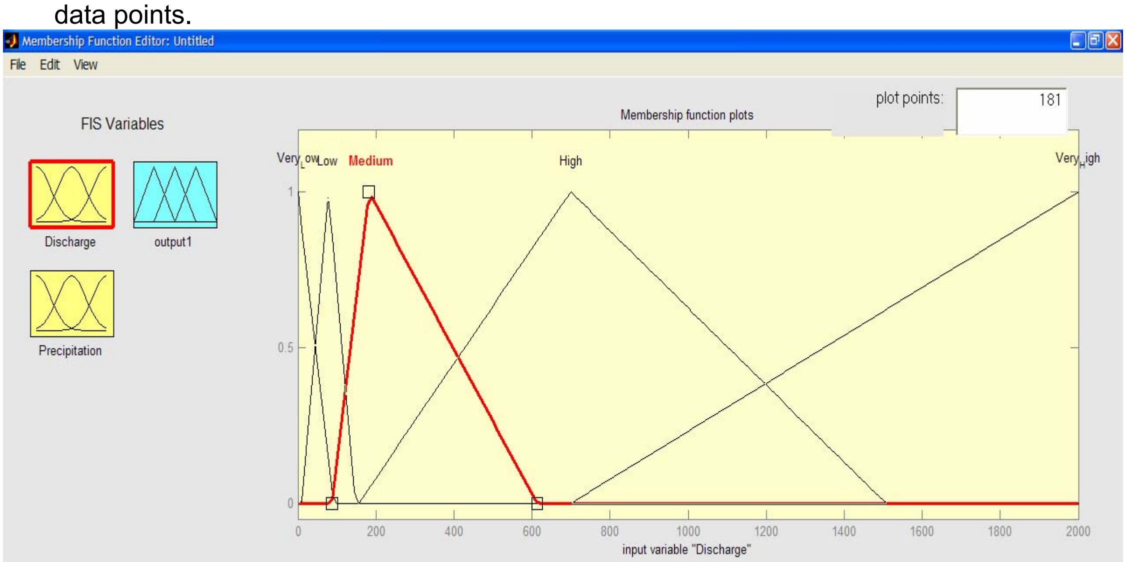

Figure 3. Example of membership functions for discharges fuzzy set

Review of artificial neural networks and fuzzy logic applications in hydrological forecasting

Especially over the last decade, neural network-based flood forecast models have been increasingly used in hydrology. Usually, the input data of the network are composed by past measurements of flows and rainfalls, and eventually the basin state could be assessed analyzing the rainfall occurred on a certain time window before the flood event. The most used neural networks type is the feedforward network trained with backpropagation family algorithms. In some applications are implemented neural network that uses recurrence, i.e. outputs at some level are fed back in as inputs. This allows the net to better train on time dependent data. Examples of this are Jordan, Elman, Real-Time Recurrent Learning (RTRL) networks, or Time Delay Neural Network (TDNN), which uses not only the current input data values (time t) but also the previous several input sets (t-1, t-2. etc.).

In general, the fuzzy models used for hydrological forecasting are based on a fuzzy rule base describing the hydrological behaviour of the river basin. Expert knowledge about specific discharge situations combined with precipitation information and soil moisture conditions can be transformed directly in IF ... THEN ... rules, using linguistic entities like discharge=low AND precipitation=high AND soil moisture=high and thus building up an initial rule base. Optimization procedures are then used to adapt the rule base on the basis of data from former flood events in order to achieve an optimal forecast model.

Such kind of modelling systems has already successfully been used for operational hydrological forecasts elaboration in river basin with different sizes and with different lead times. The computational effort of forecasts with different time horizons requires only few seconds on a standard PC.

Another recently developed computing technique is the neurofuzzy approach, which is a combination of a fuzzy computing approach and an artificial neural network technique.

This approach is becoming one of the major areas of interest because it gets the benefits of neural networks as well as of fuzzy logic systems and it removes the individual disadvantages by combining them on the common features. Neural networks and Fuzzy logic have some common features such as distributed representation of knowledge, model-free estimation, ability to handle data with uncertainty and imprecision etc. Fuzzy logic has tolerance for imprecision of data, while neural networks have tolerance for noisy data. A neural network's learning capability provides a good way to adjust expert's knowledge and it automatically generates additional fuzzy rules and membership functions to meet certain specifications. This reduces the design time and cost. On the other hand, the fuzzy logic approach possibly enhances the generalization capability of a neural network by providing more reliable output when extrapolation is needed beyond the limits of the training data.

The neuro-fuzzy system consists of the components of a conventional fuzzy system except that computations at each stage is performed by a layer of hidden neurons and the neural network's learning capacity is provided to enhance the system knowledge.

The system contains at least the following three different layers:

- Fuzzification layer: In a fuzzification layer each neuron represents an input membership function of the antecedent of a fuzzy rule.
- Fuzzy rule layer: In a fuzzy inference layer fuzzy rules are fired and the value at the end of each rule represents the initial weight of the rule, and will be adjusted to its appropriate level at the end of training.

Defuzzification layer: In the defuzzification layer each neuron represents a consequent proposition and its membership function can be implemented by combining one or two sigmoid functions and linear functions. The weight of each output link here represents the centre of gravity of each output membership function of the consequent and is trainable. After getting the corresponding output the adjustment is made in the connection weights and the membership functions in order to compensate the error and produce a new control signal.

Different successfully applications, of those different computing techniques, have been reported by a large number of researchers, especially in the last decade.

Between the applications that are related to the hydrological forecasting activity we can mention:

- Rainfall-runoff modelling;
- Flood routing;
- Directly forecasts of water levels;
- Link different individual forecasting models into a single forecasting system (multimodel / consensus / combination river flow forecasting);
- Forecasting river ice jams break-up;
- Modelling of the flood forecasting uncertainty;

- Quantitative precipitations forecasts;
- River flow forecasts updating technique;
- Control and optimization of reservoir operations;
- Replicating complex hydraulics or rainfall-runoff models;
- Non-linear, non-unique stage-discharge relationship.

Neural Networks models experimentation

For preliminary experimentations of using neural networks models in the hydrological forecasts elaboration, where implemented two types of event forecasting models using feedforward neural networks with modular structure.
The models implementation was done using JOONE software framework (http://www.joone.org/), which is a Open Source Java framework (LGPL licence) that can be used to build and run applications based on neural networks. JOONE applications can be built on a local machine, be trained on a distributed environment and run on whatever device or from external Java applications using the provided classes library, being so a good choice for real-time implementations of neural networks models.
The first model can be used to estimate the peak discharge and the associated momment of occurrence using as input data the rainfall amount and duration, initial discharge and the daily rainfall values for the last 10 days. The rainfall amount and duration can be taken from the meteorological forecasts, providing so a maximum lead time value. One module, within the network, is using the last 10 day rainfall information and the initial discharge in order to estimate an internal index for the soil moisture state, which is used in the main network module, for the flood characteristics estimations.
The second model implementation is a continuous event model, than use as input data the hourly time series values of rainfall and discharges, recorded in the last 3 hours, in order to simulate, one hour ahead, the discharge value.
The two different models were applied for Moneasa River Basin, with an area of 76.2 km^2 and a mean altitude of 586 m, which is situated in the western part of Romania, in the Crisul Alb River basin.
In the figures 4 and 5 are presented some of the results obtained with the two models.

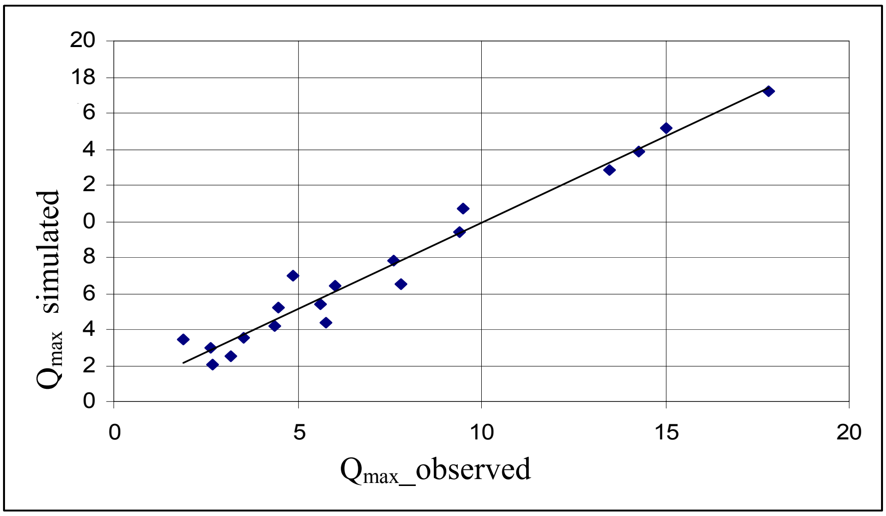

Figure 4: Comparison between the observed and simulated maximum discharges (cm/s), simulated with the first NN model

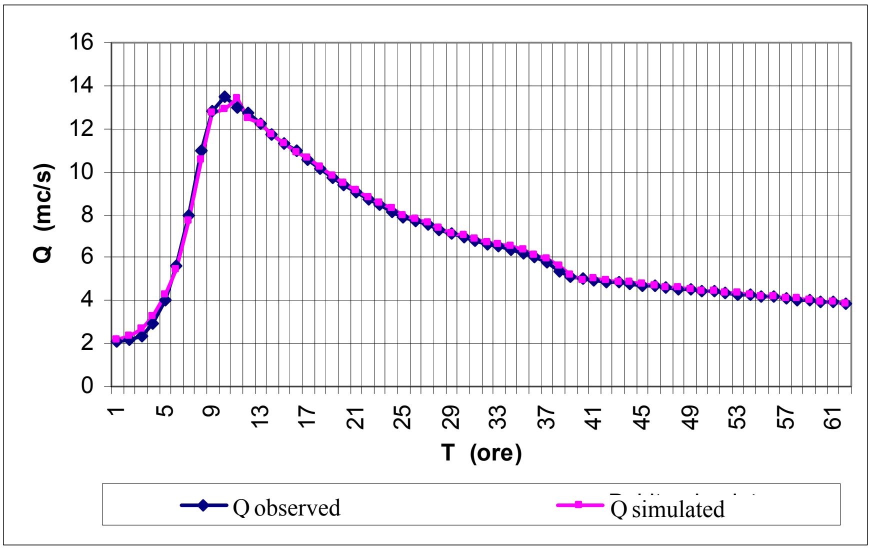

Figure 5: Observed and second neural network event model simulated discharges, for a validation flood event

Conclusions and future work

After the general review of neural networks and fuzzy logic modelling approaches characteristics and applications we can summarizes the following conclusions:

- Both neural networks and fuzzy logic models are a convenient way to map an n-dimensional input space to an m-dimensional output space, being especially useful when the relation between input and output space variables is not well-known, except the fact that is a nonlinear relation.
- Artificial neural networks are widely used as an effective approach for handling non-linear and noisy data, especially in situations where the physical processes relationships are not fully understood and they are also particularly well suited to modelling complex systems on a real-time basis.
- Fuzzy logic is a very powerful tool for dealing quickly and efficiently with imprecision and nonlinearity.
- The generation of a fuzzy forecast model can be based both on experts knowledge and historical data.
- Both artificial neural networks and fuzzy logic modelling systems offer the potential for a more flexible, less assumption approach to hydrological processes, and they have already been demonstrated as successfully substitutes for the classical rainfall – runoff models, and also as tools for the real time updating of hydrological forecasting models and especially for the multimodel approach.

In the next 3 years, the national DESWAT decisional and informational integrated national system for management in case of disasters project will be implemented. The hydrological modelling and forecasting system of this project will implement the following modelling component:

- National Weather Service River Forecasting System (NWSRFS - USA);
- NOAH – LIS distributed modelling component;
- TOPLATS distributed model, for some specific catchments;
- FLASH FLOOD GUIDANCE component.

After the first year modelling system implementation, we intend to investigate the possibility of adding into the system of modelling component using the neural network and fuzzy logic approaches.

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