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DETERMINING RIVER FLOW USING ASPECTS OF SOFT COMPUTING & ARTIFICIAL NEURAL NETWORKS

Samir Mitra[1], Dr. Rashmi Nigam[2]

[1]Research Scholar, Himalayan University, Arunachal Pradesh.
samirmitra58@gmail.com
[2]Research Supervisor, Himalayan University, Arunachal Pradesh.
rashmingm75@gmail.com

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ABSTRACT

Successful forecasting of river flow is the main goal and an important procedure necessary for planning and managing water resources. Depending on the features of hydrological phenomena in the river basin, the flow of rivers varies unevenly. This paper determines the river flow using aspects of soft computing (SC). We have developed a technique to distinguish between the sets of forecast data into subsets before training with a series of neural networks. Genetic algorithm by optimizing fuzzy theoretical models based on rules by recombining these networks this method is demonstrated using historical time-series data from the River OUSE catchment area in northern England. The prediction should be evaluated based on global performance statistics and more specific flood-related indicators, and compared with statistical models and naive forecast benchmarks. The results showed that the development of the best methodology to provide affordable solutions that can be easily connected to an operational and reliable flood warning system.

1. Introduction

Soft Computing (SC) is a set of computational methods inspired by human ambiguity and wisdom, as well as probabilistic problems in real life. Modern data-driven and soft computing knowledge, traditional computing technologies are very time-consuming and inefficient. The use of Soft Computing is the determination of logical algorithms based on current data or problems [1-4]. The main purpose is to solve the problems of surface hydrology, groundwater literature, and water resource engineering problems using fuzzy logic, artificial neural networks (ANN), and genetic algorithms (GA) [5] [6]. All of these methods work with active, nonlinear, and uncompetitive information, at the time of available information is not understand. It is better to use the techniques to use their respective strengths, and to develop this synergistic low-cost hybrid system. Among the various subsets of soft computing, the main players are neural networks, genetic algorithms, and fuzzy logic, which are commonly used to solve problems with real-world applications [7] [8].

Artificial neural networks mean that by using machine learning techniques with the capabilities of the human brain, it is possible to understand the relationship between independent and dependent variables in ways where interactions are unknown, nonlinear, or too difficult to imagine. A genetic algorithm is a probabilistic search and optimization calculation tool that revolves around the theory of the evolution of natural genetics and natural selection. Fuzzy logic always helps to solve real problems that are somehow prone to ambiguity and uncertainty. For hydrological prediction, SC is the new topic, but instead of models, neural networks themselves have already been successfully used [8][9]. Existing models of hydrological forecasting [10] often have very specific data and their effectiveness depends on both the specifications of the model, which is based on existing hydrological knowledge, and the ability of the model to respond to dynamic and rapidly changing events. SC provides independent assumptions that can lead to simulations of inherently complex and dynamic flow processes. The system is also used for modeling in this way. Other benefits include improved performance, faster time and performance models, cost reduction, and the ability to connect computer software components directly to traditional models. The model could also be used to improve the ability of SC components to address the unknown consequences of future climate change and damage from storms.

This paper describes a methodology combining all of the technology into one solution to assess potential performance improvements that can be achieved by forecasting the level of river flooding in real-time using the technology of SC. Historical records of the river OUSE basin in north of England have been used. Performance statistics allows tracking specific compliance levels against statistical, naive, and predictable criteria. These measures are used to determine the overall performance of a hybrid model.

2. BACKGROUND

2.1 Artificial Neural Network (ANN)

Artificial neural networks-this is a kind of computer model, with weak functions in the human brain, but this analogy is misleading: it is more convenient to think about how neural networks perform by displaying inputs and outputs through a series of simple processing of nodes and neurons [11]. The function is dual and it combines data from multiple other sources, through linear functions, and then transmits information through transmitting functions such as sigmoid [12]. The map shows the composition of these neurons by weighing them in order and arranging them as a given layer, as shown in Figure 1, where the first layer and the last layer of neurons have one-to-one communication with I/O values. In input data, a combination of variables is considered important for predicting a data problem. These linked latent layers, which are important for studying the relationships within the data [13] [14].

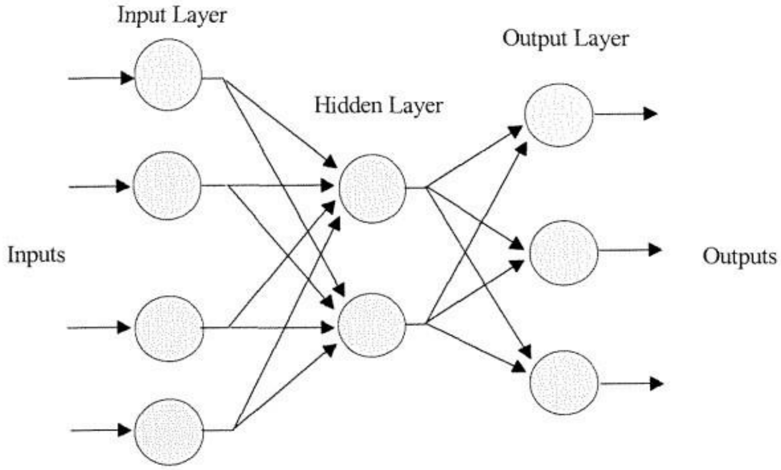

Figure 1: The structure of the MLP model [15]

The back-propagation algorithm is developed for learning the neural network with direct communication. Also called a multi-perceptron (MLP), their original composition remains the most common neurons in the network [16]. Algorithm back propagation-this is an optimization algorithm with a gradient trigger, which is used to reduce errors between predicted and expected outputs. The weight of the neurons adjusts after each motorcycle as long as the criteria for a stop are reached. The training includes all situations representation that may occur with MLPs, and it is important to ensure that the network is not compromised [17][18].

Self-organizing maps (SOM) is an others kind of ANN developed by Kohonen [19] and is more often used for classification than for function matching. From the point of view of the learning algorithm, the structure of a neuron is different from MLP. SOM neurons are placed in a network; all neurons are related to a vector mass associated with an input variable [20]. First, the weight starts randomly. The training consists of selecting an event, identifying the neurons, and notifies the winning neurons and neurons in a specific winner area. This process is repeated several times until the stop condition is reached. The developed hybrid method uses these two types (MLP and SOM) of neural networks [21].

2.2 Fuzzy Logic

Fuzzy logic (FL) will help to solve real tasks that are always, either way, stochastic. This method can solve problems related to the science of water, or because it is complex because water is complex and the study of water carries a dynamic character [22]. Using fuzzy logic, setting information as multiple input variables are essentially quantitative when describing observations as output, although the fuzzy logic tuple method allows accurate results to be generated as output from selected model studies [23] [24]. FL is based on the mathematical theory of fuzzy sets, and the concept of binomial sets is a partial union between 0 and 1. It has fuzzy boundaries, resulting in a gradual transition between certain sets associated with these concepts. After identifying each variable in the model using several sets, the display of I/O is described in the form of the rule If-Then, which can be fully defined by the relevant data. The fuzzy model tends to interpret the rules, so the number of rules enhanced exponentially; making it difficult to define the whole model is only using knowledge

[25].

The surface of the fuzzy solution was obtained as a result of compliance with regulatory requirements for obtaining the output signal of the system [26] [27]. The steps are shown in the figure. 2. Fuzzy IF- then rules can also contain functional consequences, usually in linear or polynomial form, in a formulation called the TSK model [28]. The input of crisp is fuzzy according to the definition of a fuzzy set associated with the inference mechanism, and the result of the function is weighted by the membership obtained as a result of executing the rule. The overall result is this weighted average value of the equation, as some rules actively"release" one path based on the rule. We can extend this type of model with an alternative to traditional models and sequential neural network functions. In terms of hybrid methodology resulting in a weighted average value of various offers MLP, when actively used, there are some rules. See methodology for more information.

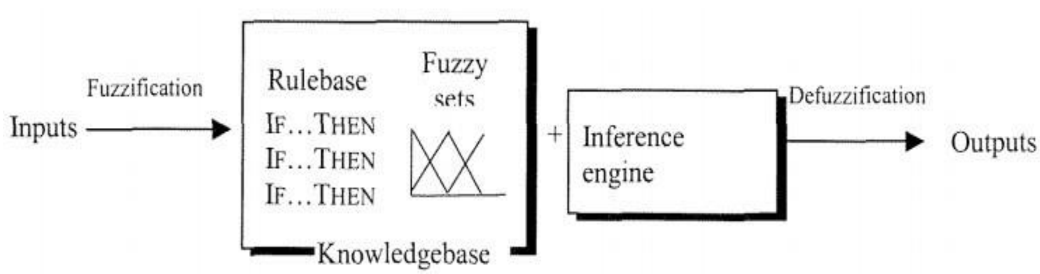

Figure 2: Rule-based fuzzy logic model components [29]

2.3 Genetic Algorithm

Genetic algorithms (GA) - this is the search and optimization of nonlinear methods, based on the natural selection and survival of the most suitable biological processes. GA is manifested by an indirect hit that immediately takes into account many points to look for, thus reducing the likelihood of local optimal similarities [30]. GA also uses probability rules of finding phase, and they are usually better than traditional methods of optimization for harder, broken, and multimodal functions. There is no guarantee that GA will find a solution, but in many cases, it will find an acceptable solution [31] [32]. The basic unit of GA is the gene, which biologically, therefore, possesses certain personality traits, such as eye color. GA genes form optimized parameters. Individual or chromosome-it's just to bring together all the genes; it has all the parameters necessary for the receipt of the decision. A population is randomly generated by these individuals or lines to start a search [33]. A mandatory or target task is for each line to be evaluated according to multiple performance indicators. It's a decision of success and the same way we can get from a population of individual people to survive [34]. To develop an effective solution, the most adapted-out population is selected from a set of genetic operators who will have offspring in the next generation, while the least adapted to the solution will die as a result of natural selection as it is replaced by new species.

GA can be a very useful tool to solve complex tasks with which conventional technology. For example, a model based on fuzzy logic can be completely optimized via a fully inductive approach to GA or using unknown parts of rules or a model using knowledge. For more explanation about optimizing Fuzzy logic models using GA.

3. STUDY AREA AND DATA

The survey data was taken from basins in the north of England, including a mix of urban and rural land use. The area of the pool makes 3286 km2 and is susceptible to regular flood, mainly in winter. The survey station is divided into three sections: Rivers Nid, Swale, and Ole, which flow to merge with River OUSE towards York. Skeleton measurement station located north of York and long from its source and chosen as forecast location. The skeleton has a relatively stable mode to gain input from each tributary. All data was originally recorded at 15-minute intervals, but it was changed to an average time to reduce the load on the data. A forecast period of 6 hours is selected, while a long period is needed for practical implementation for protection (for example, police warning, warning of surrounding industries and households, protection of property, etc.). However, with real-time operational flood forecasts, catchments are constantly monitored by the environment.

4. METHODOLOGY

The hybrid methodology used two types of neural networks. SOM is used to pre-classification input levels in five groups before training a set of five separate MLP. Then, using genetic algorithms, a model based on the rules of fuzzy logic is developed, and individual MLPs are combined into a single forecasting system. Figure 3 shows a flowchart describing the hybrid methodology.

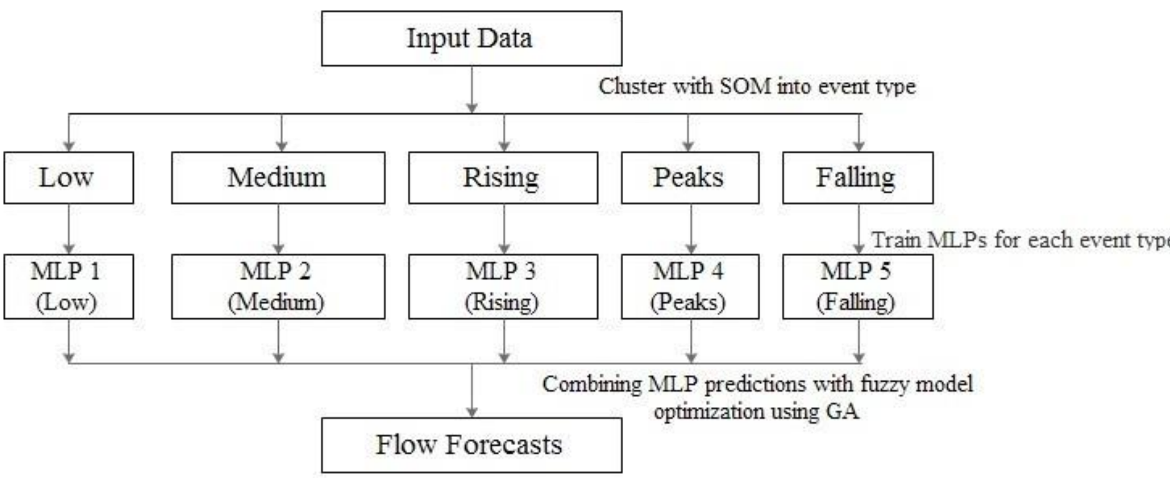

Figure 3: Methodology of river flow using aspects of Soft Computing

4.1 Preliminary classification of input data using SOM

The motive for pre-classifying data before training is the basis of a series of initial experiments using global MLPs to predict Skelton-flow data [35]. As a result, the global standards productivity innovation Agency focuses on a large number of low-level training initiatives and consists of 95% of the database. These indicators deteriorated significantly at the highest level of concern in the context of operational flow forecasts. In this previous study, the Skelton backup alarm was used as a clear boundary to separate the data set into low and high levels. They then trained MLP on a dataset that contained only high-level data and improved the overall performance of ANN.

The current river flow between t was entered into the SOM where x varies between 5, 11, and 23 hours, with prior flow data from t-x to t-x. This classification provides a set of characteristic river flow profiles, which we call hydrographic behavior or event types. The classification used hourly historical data for skeletons and five other catchments, which individually covered most or all of the 2012-2018 periods. Using three different level measurement lengths, a data set is created. An experiment is conducted using each data set. The best result seems to be generated by 75-87% using the current plus last 11 hours of flow data in the event profile, i.e. x=11. 16 cluster creations belong to com, and the model has many behavioral models. To reduce the individual characteristic profiles obtained from SOM, five main types of events were manually identified: fall, rise, peak, low and medium level flow basis on the profile similarity. Many members in the group's sites are ready to support reclassification. An example of a real flow of river classified for each event type is shown in the figure. 4. Small SOM are not given a wider range of events, and larger SOM only made a larger derivative in the same spectrum, and using a 12-hour window also seemed to capture most of the hydrographic changes over time.

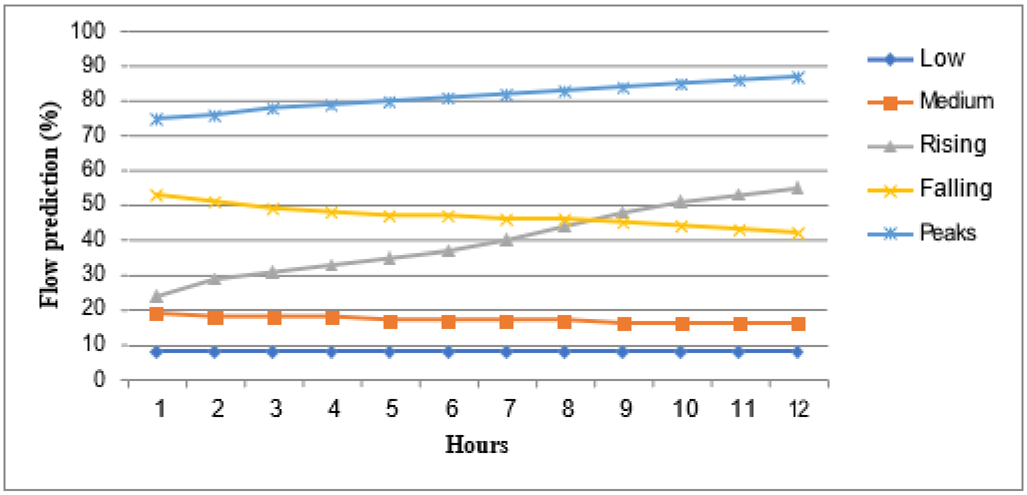

Figure 4: Sample input data showing all five characteristic event types.

4.2 Implements MLPs for each event type

We then divided the database into a series of training and validation files by event type and trained individual MLPs using the Stuttgart Neural Network Simulator (SNNS) software package [36]. The 37 inputs data for each MLP follows:

- Present and past 11 hours of skeleton flow data;
- Average daily precipitation from nearby stations for the last 7 days;
- 6 hours of old flow data at three upstream stations in each section (a total of 18 values) were delayed to correctly account for the average travel time between stations.

One data release is an indication of the comparison with the current level and the estimated cost of 6 hours, which gives a serial forecast of 6 hours ahead. Five sets of data corresponding to a personal MLP, divided into five 60% study and 40% verification sets of data with random mixing during studies. The last MLP was a hidden layer with 12 neurons. Some of the experiments performed in MLP architecture were recently conducted in the field of river water flow prediction using benchmarking to realize the effect of studying the performance of the neural network architecture, showing that it is less likely to change the hidden layer itself if there is a problem with neurons.

4.3 The fuzzy logic model optimized with a genetic algorithm

A fuzzy logic model for determining which MLP to use, taking into account the current in t and changes in water flow over the past 5 hours, for binding individual MLPs, the rules, and member functions are presented as binary strings, as shown in Figure 5. The rule base, which has three member functions for each input of the fuzzy model, has nine rules. Since a 3-bit number was used to represent one of the rules, GA creates other possible values, i.e., 5-8, we're programmed to use MLPs corresponding to the original SOM classification, when these "no model" rules were generated by GA to represent rules that do not recommend MLP. For the fuzzy set to be rational and not too duplicate, it must first be sorted after converting the parameters to real numbers. Next, the parameters of the fuzzy set are determined by the values of the variables out of the sorted array. A total of 21 parameters were optimized, each of which was combined to provide an individual chromosome for optimization. The population size of 32 rows is initialized. The degree of compliance is determined by decoding each string into a separate model parameter and giving this fuzzy objective function. The fitness scale is the root mean square error (RMSE) of the entire training dataset, which is the first 60% of the total record for 4 years.

011 + 010 + ...+ 001 + 0100010 + 1000010 + 0001001 + 0110010 + ...

rule 1 rule 2 rule 9 Fuzzy set 1 Fuzzy set 2

Figure 5: Converts a fuzzy model into a binary string for optimization with GA.

5. MODELS BENCHMARK

Auto Regressive Moving Average (ARMA) [37] [38], uses a balanced linear alliance of past values and to obtain forecasts that are designed to forecast the difference between the current value and the expected value of 6 hours. The model was installed in the first 60% of the dataset and tested in the remaining 40%. Then, an attempt was made to compare the multidimensional ARMA model [39] with data obtained from three ascending stations and daily rainfall. However, if we used all the data, i.e., weights between -1 and 1, we would not be able to find a stable model, and using individual bottom- up information would only slightly improve overall performance. Therefore, only the results of one- dimensional ARMA are presented for comparison. Naive predictions replace the past observation in the present forecast; have also been added as a bottom-line benchmark.

6. EXPERIMENTAL RESULTS AND DISCUSSION

The hybrid prediction system is evaluated using the standard global q-factor matching statistic: RMSE. The model's performance was then divided into 5, 10, and 25% forecast percentages for both over (O)- and under (U)-forecasts. These performance indicators were compared with statistical and naïve results. The results for general statistics are presented in Table 1 and the breakdown over both over- and under-forecasts in Table 2.

Table 1: Calculates RMSE for ARMA, Naïve and hybrid predictions.

Model	Training (T)	Validation (V)
Hybrid	0.049	0.054
ARMA	0.083	0.097
Naive	0.157	0.0149

Table 2: Prediction percentage with 5, 10, and 25% of observations in the training (T) and validation (V) the data sets

Model	Type	5 % (T)	5% (V)	10% (T)	10 %(V)	25% (T)	25%(V)
Hybrid	U	47.2	44.0	3.6	3.7	1.5	1.6
	O	40.2	41.3	4.8	4.9	0.8	0.9
ARMA	U	14.3	15.6	4.0	3.5	2.5	2.6
	O	70.2	70.5	3.8	3.8	6.1	5.2
Naïve	U	18.7	19.5	4.7	4.8	5.2	4.2
	O	47.4	49.6	9.8	8.7	5.4	5.8

The hybrid model of general statistical table 1 was very good. Table 2 shows that the hybrid model has a fairly uniform distribution of predicted and predicted values and that the ARMA and naive models are always overestimated, while the hybrid and ARMA models have the same percentage observed at a rate of 5%. These calculations not only provide data on high-level work but are particularly important for flood forecasting. The river flow prediction percentage is calculated in table 3.

Table 3: The river flow prediction in percent of hybrid, ARMA, and Naïve for the training and validation data sets

Model	Training (T)	Validation (V)
Hybrid	50	80
ARMA	22	36
Naive	16	27

The naïve model flow determination time is less; also, the ARMA model prediction ability is lower than the hybrid model entirely in the validation dataset. The hybrid model shows much better results at these levels of forecasting, with accurate predictions of data checked accounting for more than 50%. Figure 6 represents the flow prediction taken from validation datasets. In figure 6, the naïve and ARMA model performance is better but not more than the proposed hybrid model. The hybrid model performance is best, predicting the river flow very correctly than ARMA and naïve model. However, the actual hybrid prediction shows more unstable behavior due to the source partition that splits the data into event types. It indicates the neural network model, which was chosen as a more event-driven type, is growing particularly high. Upstream MLP events are too common and can be involved in upstream behavior at all water levels.

Performance models are an important factor because design and calculation are also an important factor when comparing approaches. The hybrid model is more computationally exhaustive than the ARMA model, but it does not compare to the River Flow Prediction System (RFFS), a true model that requires improvement and refinement. After training, hybrid activity moves significantly faster than a single predicted RFFS, and development time can be measured in days rather than months or years. However, the hybrid methodology does not replace either the existing system or the RFFS. The development of a hybrid model directly linked to the existing operating system provides additional support for river flow forecasting.

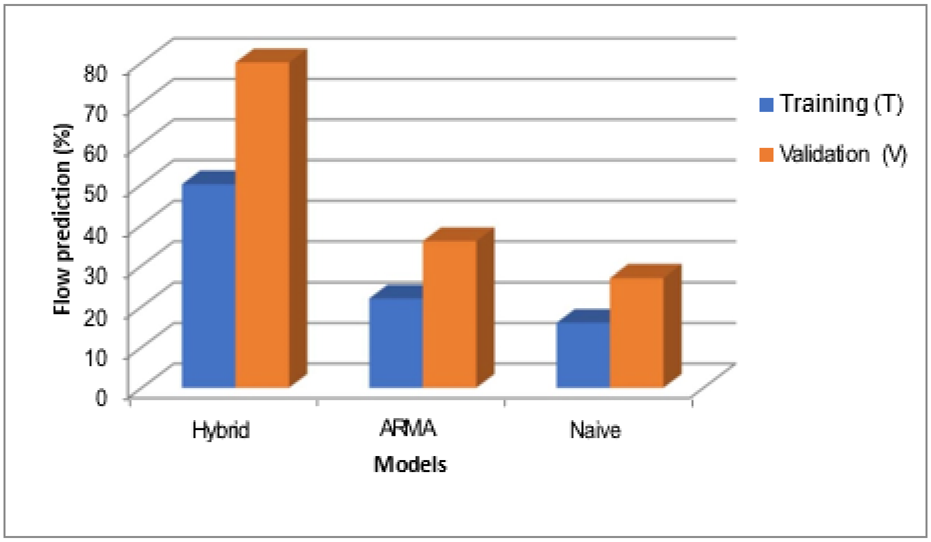

Figure 6: River flow prediction taken from validation datasets.

7. CONCLUSION

The paper determines river flow using aspects of soft computing, In general, the hybrid model is useful for predicting the flow used for global statistics, and more specifically, operational forecasts, statistics, and naive monitoring benchmark. Using SOM to pre-classify the data provides a unique way to separate data into types of events, typically reducing the number of low-level events. The advantage of the SOM classification was that data from several stations were used to create the profile, so it could be applied more often to other stations in the catchment area. Thus, advantages for building a larger, spatially integrated prediction system, where the development of individual MLPs for each type of event can be focused on learning specific behaviors, including a better performance at higher flow. This suggests that the development is separate from the potential benefits of predicting the flow. The model fuzzy Logic gives way to the integration of a separate MLP based on the current flow of river water and the changing flow, but the optimization of the model is possible less favorable than originally thought. The Fuzzy approach is designed to suggest a pair of MLP and ensure the weighted average value of the model's predictions if the initial classification of SOM is incorrect or if the input data is immediately characterized by several types of profiles. Whenever, the fuzzy model cannot provide a recommendation, the solution of the SOM classification is not sufficient in place and further demonstration experiments are required. Overall, we have shown that this kind of methodology can provide useful tools to improve the effectiveness of existing river flow forecasting systems.

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