Chapter 8
Neuro-fuzzy Techniques and Natural Risk Management. Applications of ANFIS Models in Floods and Comparison with Other Models

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Abstract During the last decades, floods are getting more and more dangerous and they cause a lot of destruction either for human lives and/or for people's properties. Due to different climate conditions, some parts of the world present increased levels of danger from floods. For this reason, the development of a robust tool for the prediction of floods is essential for the protection of people who live in these areas. An adaptive neuro-fuzzy inference system is a hybrid fuzzy system, which is based on Sugeno fuzzy inference along with the use of artificial neural networks for training. In this work, the current literature on adaptive neuro-fuzzy inference system models, which are used for flood prediction, is reviewed. More specifically, the mode of operation of such decision-making systems, along with their major advantages and disadvantages are presented in detail. A comparison with other similar models is also carried out.

Keywords Adaptive neuro-fuzzy inference system · ANFIS · Natural disasters · Floods

Abbreviations

ANFIS	Adaptive neuro-fuzzy inference system
ANGIS	Adaptive neuro genetic algorithms integrated systems
ANN	Artificial neural network
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
BPNN	Back-propagation neural network

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M. Gocić et al. (eds.), *Natural Risk Management and Engineering*, Springer Tracts in Civil Engineering, https://doi.org/10.1007/978-3-030-39391-5_8

CE	Coefficient of efficiency
CGF	Conjugate descent algorithm
CORR	Coefficient of correlation
D	Discrepancy ratio
FIS	Fuzzy inference system
GDX	Gradient descent algorithm
GIS	Geographic information system
GNN	Generalized neural network
HN-FIS	Hybrid neuro-fuzzy inference system
LM	Levenberg–Marquardt algorithm
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MLP	Multi-layer perceptron
Mo-ANFIS	Modified ANFIS
MONF	Metaheuristic optimization neuro-fuzzy
PSO	Particle swarm optimization
R2	Coefficient of determination
RFFA	Regional flood frequency analyses
RMSE	Root mean square error
SAC-SMA	Sacramento technique

8.1 Introduction

Soft computing tools, mainly fuzzy and neural systems, are used in several applications, including natural disaster prediction and management. The correlation of input variables with output (prediction or decision) ones is based on known logical rules, in fuzzy systems, or on blind processing of mass data of examples, in the case of neural systems. Neuro-fuzzy systems represent a combination of these two approaches, where a fuzzy framework representing the basic structure of the inference system is further tuned with the usage of input-output examples and the technique of neural network training.

Fuzzy variables and sets represent an extension of classical quantities with the addition of a membership function which takes values between 0 and 1 and indicates the degree of trueness of the underlying quantity. They are similar in several ways to probability theory and support calculus rules and more complex tasks like optimization of fuzzy systems etc. In terms of prediction and control, the ability of fuzzy inference systems (FIS) to avoid sudden changes of output, for small changes of the inputs, is highly appreciated. Fuzzy systems are used in several fields; e.g. engineering, control, robotics, economics, etc. The core structure of such systems is based on the creation of membership functions, i.e. functions which indicate the degree of fuzziness of a fuzzy set, for inputs and outputs, along with a suitably defined set of verbal rules which are used by the decision-making system. The membership functions can be chosen either by the experience of the designer or even arbitrarily. The rules should be based on the knowledge of an experienced user of the system or process. When such a system is built, the designer cannot always decide the values for its parameters only by considering the available data. In this case, adaptive fuzzy systems can be used instead.

An adaptive neuro-fuzzy inference system (ANFIS) is a very popular technique which uses artificial neural networks (ANNs) and fuzzy theory simultaneously. This type of systems automatically interprets input and output information from experimental or other data in order to create a rule-based decision-making system by using the learning ability of neural network structures. However, in order to achieve adequate accuracy of predictions, an exact and representative set of training data (set of inputs and outputs) is necessary. Information about adaptive fuzzy systems and control can be found in classical monographies (Wang 1994).

The first ANFIS model was developed in the early 1990s (Jang 1993). The predecessor of ANFIS systems was a fuzzy system, modeled using generalized neural networks (GNN) and a Kalman filter in order to achieve minimum squared error (Jang 1991). Neuro-fuzzy modeling refers to the application of learning into fuzzy inference systems. The backpropagation of errors algorithm is the most commonly used technique for supervised learning, i.e. for the identification of the parameters of ANNs, and thus for ANFIS systems as well.

A well-established implementation of ANFIS is presented in the work of Stavroulakis et al. (2011). The first step is the construction of a detailed mechanical model of the total system. Subsequently, the dynamics of the system are calculated and saved. These data are used for training using the ANFIS procedure. The resulting controller can be used for the control of the whole system. Numerical results indicate the efficiency of the proposed control scheme for vibration suppression of smart beam structures under several types of excitation. It is also concluded that the control is not only efficient, but smooth as well.

It is no exaggeration to claim that neuro-fuzzy systems consist one of the more powerful tools either for control as well as for prediction. In fact, such systems can be used in a wide range of real-life applications from the control of smart structures such as beams and plates (Tairidis 2019; Tairidis et al. 2013; Muradova et al. 2017) and structural damage identification (Hakim and Razak 2013), to the trajectory control (Aissa and Fatima 2015) and dynamic morphing (Tairidis et al. 2019), even for stock market predictions (Boyacioglu and Avci 2010) and of course natural disasters predictions, such as forest fires (Ahmed et al. 2017; Bui et al. 2017; Wijayanto et al. 2017), earthquakes (Mirrashid 2014), tropical cyclones (Duong et al. 2013), etc. In the present paper, the capabilities of ANFIS for the prediction of floods will be presented in detail, since such systems have been widely used in water and floods research.

8.2 Adaptive Neuro-fuzzy Inference Systems Modelling

The architecture of ANFIS is based on a fuzzy inference system which is implemented using neural networks for the modification of its parameters. Thus, before proceeding with the ANFIS systems, a small introduction to fuzzy systems is necessary.

8.2.1 Fuzzy Inference Systems

A FIS is a simplified combination of complicated subsystems (see Fig. 8.1). More specifically, such systems consist of the following elements:

(a) A set of membership functions which are introduced through a fuzzification process on the involved parameters. They quantify the characteristics of each value taken by these parameters by defining overlapping fuzzy areas like 'small', 'medium', 'large' etc.
(b) A base of verbal IF-THEN rules, taking values from the previously introduced fuzzy categories.
(c) A decision-making unit, that is, an inference process.
(d) A defuzzification interface for the transformation of the fuzzy output into a classical (crisp) value which can be used further for control or prediction purposes.

The inputs are converted into fuzzy variables through the fuzzification process. Then, a set of rules is drafted, which together with the data, forms the knowledge data base. Subsequently, the decision is made by implication, and the fuzzy output arises. Finally, this value is defuzzified according to the needs of each problem. This whole process is depicted in Fig. 8.1.

The degree of fuzziness of a fuzzy variable (input or output) is defined by its membership functions. In fact, the fuzziness is a term which refers not to the logic itself, but to the vague description of the system variables. For example, we say that someone is tall, instead of telling their actual height. This fuzziness is expressed through the membership functions. The representation of these functions can be done either numerically or graphically. The graphical representations include various

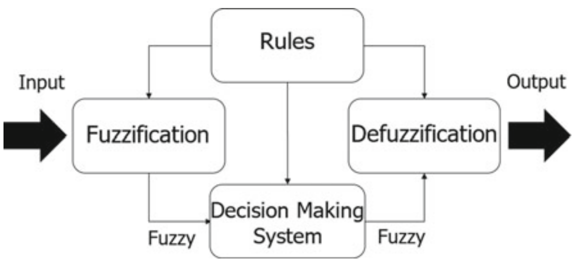

Fig. 8.1 The schematic representation of a fuzzy system

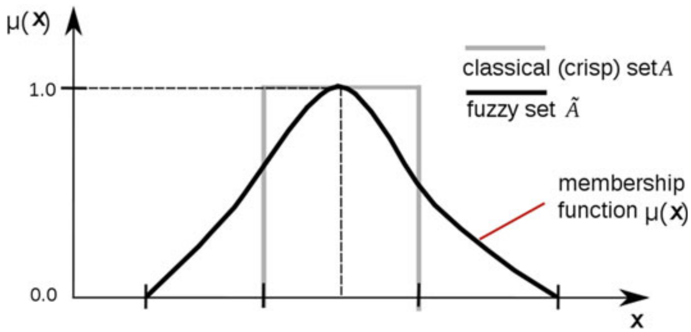

Fig. 8.2 Graphical representation of a membership function in comparison with a crisp set

forms, either symmetric or asymmetric. The most popular options include among others:

(a) Triangular membership functions
(b) Trapezoidal membership functions
(c) Bell membership functions
(d) Gaussian membership functions
(e) Sigmoid membership functions
(f) Polynomial membership functions

A graphical representation of a membership function in comparison with a crisp set is shown in Fig. 8.2.

The verbal rules can be formed by deterministic statements (e.g. velocity = high), condition statements (e.g. IF grade $\geq$ 8.5 THEN excellent) or statements without condition (e.g. GO TO). The properties of the set of rules is the fullness, consistency, continuity and interaction. A fuzzy system is usually described with more than one rules. The process of summarizing the rules for obtaining an overall conclusion is called aggregation. In the case where the rules are associated with the AND operator, the determination of aggregation is done by conjugation of the rule system taking the intersection of the individual rules. If the individual rules are associated with the OR operator, the determination of aggregation is done by the disjunction of the rule system, calculating the union of the individual rules. The methods of conjugation and disjunction are also known as methods of minimum (min) and maximum (max), respectively. An example on the interaction between fuzzy rules and the fuzzified values of two inputs to produce one fuzzy output, along with defuzzification (final crisp value) is depicted in Fig. 8.3.

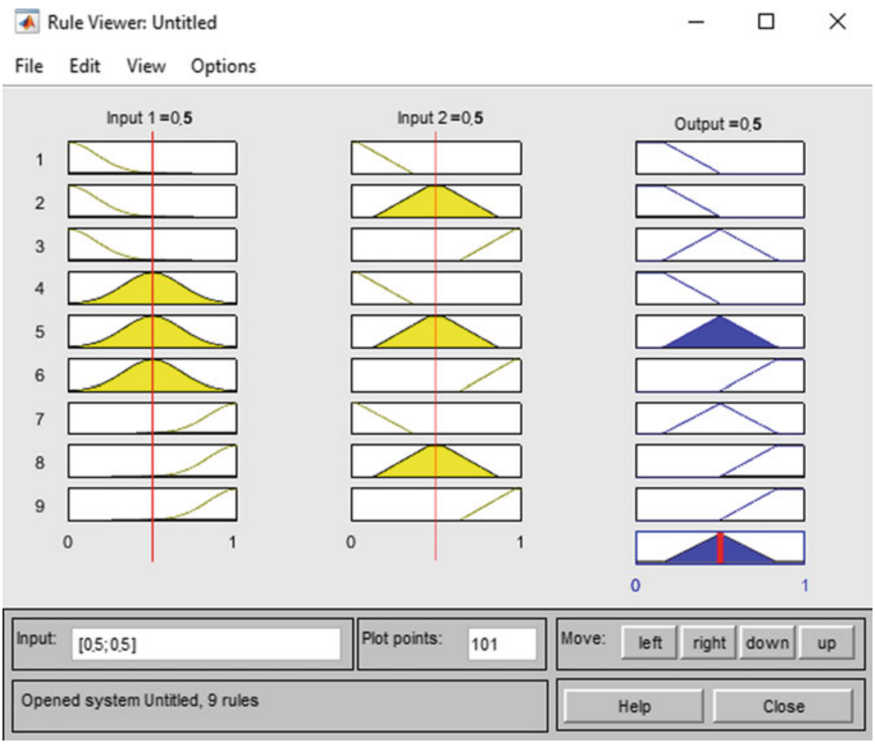

Fig. 8.3 Interaction between fuzzy rules and inputs in the fuzzy toolbox of MATLAB®

8.2.2 Adaptive Neuro-fuzzy Inference Systems

ANFIS was introduced at the University of California by Jang (1993). This type of adaptive systems consists of fuzzy rules, which, in contrast to classical fuzzy systems, are local mappings instead of global ones (Jang and Sun 1995). This feature is really important when on-line learning is considered. The learning procedure could be hybrid, i.e. the proposed model can construct input-output mappings based on both human knowledge and appropriate input/output data. However, even when human knowledge is unavailable, it is still possible to generate the rules using a learning process according to a desired performance criterion. This means that, rather than choosing the parameters of the system (membership functions, rules, etc.) arbitrarily, an automated process based on neural networks (see Fig. 8.4) can provide tailor-made values based on the available system data. Moreover, a set of rules, or other parameters of the system can be also considered in the same way (Tairidis and Stavroulakis 2019).

The modeling of these systems is quite similar to other system identification techniques, that is, a parameterized model is first considered and then a carefully selected set of training data is used for the modification/adjustment of fuzzy parameters. In case of noisy systems or when the collected data are not representative of the system,

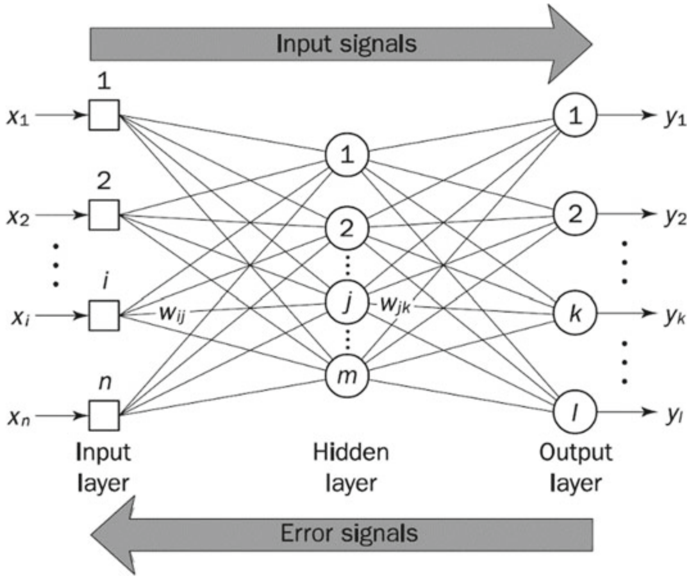

Fig. 8.4 A typical feed-forward back-propagation neural network

model validation is necessary, and can be done using another set of data, the so-called data for testing. In general, model validation is the process by which inputs on which the system was not trained, are presented to the trained model, to check the accuracy of the prediction. This is necessary because after a certain point in the training process, the model may overfit the training data. The testing data also allow the designer to check the generalization capability (robustness) of the resulting system (Tairidis and Stavroulakis 2019).

There are two methods for the generation of the initial system, that is the formation of membership functions, which are also called clusters, and the fuzzy rules. The first one applies grid partitioning on the data, while the second one categorizes the training data by using subtractive clustering.

Grid partition is one of the most common options when designing fuzzy systems, especially if the desired amount and the type of clusters is known. This method usually considers certain of the parameters of the system, such as the input variables. This strategy is affected by the curse of dimensionality; however, it works perfect for a small amount of membership functions for each input (Jang and Sun 1995). On the other hand, the subtractive clustering method is the suitable option if there is lack of knowledge for the examined system (Chiu 1994). It is a fast algorithm which estimates the number of clusters and the cluster centers in a set of data. These estimates can be used for the initialization of identification methods like ANFIS.

After loading the training data and generating the initial FIS structure, the learning process can be proceed in order to train the membership function parameters to emulate the available training data.

The backpropagation method, which is a gradient descent method, can be used for this purpose. A theoretical framework for this method can be found in (le Cun 1988). A hybrid method, that is, a combination of least-squares error method (LSE) and backpropagation can be also used. Least squares method is a standard approach in regression analysis which is used for the computation of an approximate solution in overdetermined systems. The hybrid method is based on backpropagation for the calculation of the parameters associated with the input membership functions, and least squares method for the estimation of the parameters related to the output membership functions. It is shown that the use of least-squares method for the calculation of is of great importance, since the learning time would be ten times longer without it (Jang 1993).

The number of training epochs and the error tolerance are the stopping criteria for training and are both set by the designer. The training process stops whenever one of the criteria is met, i.e. when the maximum epoch number is reached, or the training error goal is achieved. If the impact of the training error to the results is unknown, error tolerance should be set to zero.

The results of each iteration can be used as initial conditions for the next epoch in order to enhance accuracy. The training error, which occurs in the output, decreases, at least locally, throughout the learning process, which means that, the more the initial membership functions approach the optimal ones, the easier it will be for the training algorithm to converge. Human knowledge or expertise about the target system can be of great assistance in setting up these initial parameters of the fuzzy inference system. An example of ANFIS training is given in Fig. 8.5. More details are available in Tairidis (2016).

8.3 Adaptive Neuro-fuzzy Inference Systems for the Prediction of Floods

The adaptive neuro-fuzzy inference system had been extensively used for flood forecast, since it is a tool which can systematically and effectively construct forecast models. The complete strategy of building a flood forecast model by using a neuro-fuzzy network is analytically described in the work of Chen et al. (2006). For the purpose of comparison, the commonly used back-propagation neural network (BPNN) is also examined.

Namely, a neuro-fuzzy approach for flood forecasting is presented. The motivation lies primarily in evaluating the feasibility of applying a hybrid scheme to the problem, thereby providing an alternative to fuzzy and neural approaches. It is assumed that stream flow series can be estimated by using a set of if-then rules that relate future stream flows based on antecedent data. This study has assignment to illustrate the practical application of forecasting models on the Choshui River. The inputs are the level of water, rainfall levels, and travel time of the flow.

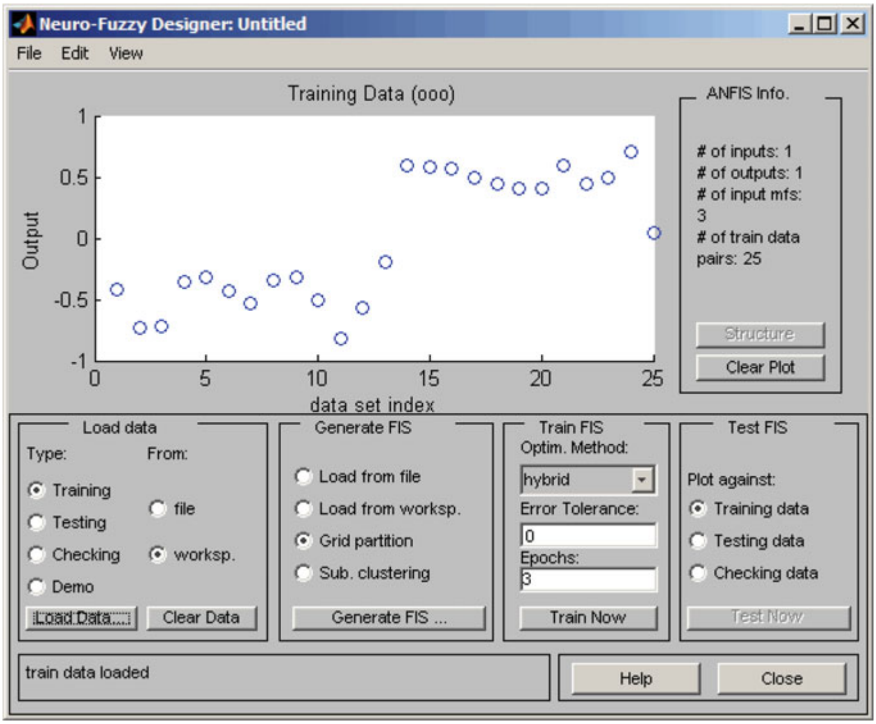

Fig. 8.5 An example of training through ANFIS of MATLAB®

Twenty-three events were used for this study. The data were divided into three independent subsets: the training, validating, and testing subsets. The training subset includes 1554 sets of data, the validating subset has 222 sets, and the testing subset also has 222 sets. First, the training subset is used to build networks and to adjust the connected weights of the constructed networks. Then, the validating subset is used to simulate the performance of the built models to check their suitability for generalization, and the best network is selected for later use. The testing data set is then used for final evaluation of the selected network performance.

The effect of rainfall on the water level varies from time to time in all rain gauging stations and cannot be identified as a solid relation, whereas the watershed's average rainfall provides other useful information for flood forecasting. The comparative results obtained by the BPNN and ANFIS provide evidence that the ANFIS can offer a higher degree of reliability and accuracy than BPNN in flood forecasting.

For further investigation, three ANFIS models, based on different input information, were built to perform one- and two-steps ahead flood forecasting. The results show that:

1. A downstream water level can be suitably estimated by just using several of the previous downstream and upstream water levels as input to the ANFIS model

2. Using the differential values, which could remove the non-stationarity of a time series, could provide better performance than the original values
3. Adding the watershed average rainfall information in addition to water-level information would enhance the forecasting accuracy.

In the work of Nayak et al. (2004), the application of ANFIS to hydrological time series modeling is presented and illustrated by an application of modelling the river flow of Baitarani river in Orissa state, India. This method does not require a priori knowledge of the model, in contrast to most of time series modeling techniques. The objective of the study was to investigate the potential of neuro-fuzzy systems in modeling hydrologic time series and to assess its performance relative to ANN and other traditional time series modeling techniques such as autoregressive moving average (ARMA). The applicability of the method is demonstrated by modeling river flow for an Indian basin.

An ANFIS model has been tested for time series modeling of river flow. The river Baitarani is one of the biggest rivers of Orissa state in India. The drainage area of this river is 14,218 km^2, while the average annual rainfall of the area reads 1187 mm. Monsoons last from June to October and nearly the 80% of the annual precipitation occurs during these months. Heavy flow is created in lower reaches during the monsoon season que to the extreme rainfall.

For the ANFIS model three inputs were used:

- Rainfall
- Evaporation
- Other exogenous variables

The analysis starts with one antecedent flow as the input vector and an ANFIS model is constructed. The input vector is then modified by successively adding flow at one more time lag, and a new ANFIS model is developed each time. The model with the best fit was trained using 6, 12, 18 years of data, for testing during the period from 1990 to 1995. From the results it was shown that all models performed in a similar way, as the root mean square error (RMSE) do not vary significantly. However, it is very important to mention that all models presented poor efficiency during training. Poor efficiency indicates that ANFIS model prediction is far from the mean values. More specifically, the model showed a training efficiency of 81.95% (increase of 27.86%) and a validation efficiency of 81.55% (gain of 11%). The correlation coefficient between the computed and observed flow series was stable during the training, as well as the validation process.

In order to have a real validation of the potential efficiency of the ANFIS model, its results were compared to traditional time series models. The performance of the ANFIS model has been also compared with an ARMA model. It was shown that the performance of both ANFIS and ANN models was similar during training and validation periods.

Moreover, although the ANFIS model was capable of preserving the statistical properties of the time series, the model might show poor performance if it is not trained carefully. The proposed model showed good performance in terms of validation using statistical indices.

Short-term flood forecasting with a neuro-fuzzy model is presented in the study of Nayak et al. (2005). Namely, the potential of the neuro-fuzzy computing paradigm to model them rainfall-runoff process for forecasting the river flow of Kolar basin in India is explored. A simple FIS and a classical ANN were used for validation. The paper demonstrates the applicability of neuro-fuzzy systems in developing effective nonlinear models of the rainfall-runoff process for short-term flood forecasting. A neuro-fuzzy model, that forecasts hourly flood discharge at a given stream flow gauge station at different lead times, has been developed for the river Kolar (a tributary of Narmada) in India.

Only one input, the rainfall, and one output, the runoff were considered; thus, a single input–single output system was developed. Most papers in the literature accounts for inputs and outputs like rainfall and runoff. Data for rainfall and runoff are also used in Kolar basin in India during the monsoon season for three years (1987–1989) between July to September. The total available data are divided in two sets; a calibration set (1987–1988), and a validation set (during 1989).

Different models for lead times of up to 6 h have been developed in the study. The parameters of the model are identified using the calibration data set, and the model is tested for its performance on the validation data set. It is evident that the slope of the RMSE versus the prediction time horizon is minimum for the ANFIS model during calibration as well as during the validation process. Moreover, it was found that while the ANFIS model forecasted the flows with a RMSE of 77.52% at 6 h, the ANN and FIS models forecasted the flows with an RMSE of 100.38% and 96.48% respectively, which is clearly bigger.

The results suggest that the value of the percent error in peak flow prediction, which is a useful index in simulating events such as floods, is within reasonable limits for the ANFIS model. It is worth mentioning that the ANFIS was able to forecast the peak flows with minimum relative error, irrespective of the magnitude of the peak flow. It is important to know whether the model is predicting higher- or lower-magnitude flows poorly, which may help in further refining the model. The foregoing discussions clearly illustrate that the ANFIS model performs better than the ANN and FIS models in modeling the rainfall-runoff process. The performance of these models was comparable at a 1-h lead time, but only the ANFIS tends to preserve the performance at higher lead times compared to the others. Although the preliminary concepts of the FIS and the ANN were developed on a different basis, they are essentially rooted in the same concepts of data driven modeling.

To sum up, the objective of the paper was twofold; one was to demonstrate the potential of the neuro-fuzzy computing paradigm in modeling the rainfall-runoff process, and second was to evaluate the relative merits and demerits of this paradigm with reference to already popular ANN and fuzzy modeling approaches. ANFIS presents good results, and in the same time it can be easily implemented by any flexible neural network simulator. Hence, its use is very attractive for the development of forecasting models.

A neuro-fuzzy-based adaptive flood warning system for Bangladesh was developed by Hossain et al. (2014). The input data have been collected using wireless sensor network. The proposed model has collected input parameters, such as rainfall, river water level and river water flow, from a specific site and send the data to decentralized node. Based on the inputs, an ANFIS model has determined the flood possibility index. The main objective of this work was to design a neuro-fuzzy-based adaptive flood warning system for Bangladesh which predicts the possibility and persistence of flood in an area. In the proposed system, a rainfall measurement sensor, a river water level measurement sensor and a river water flow measurement sensor will collect data about the condition of rainfall, river water level and river water flow respectively, and send them to a decentralized node via a wired medium.

The system generates a warning in a particular site based on the values of the three inputs and determines the flood persistence index by comparing with last ten years data. Finally, linguistic parameters such as “red”, “yellow” or “green” appear on a geographic information system (GIS) map in order to show the possibility and severity of a potential flood.

A detailed application of ANFIS in river flood forecasting is presented by Ullah (2013). More specifically, the models are used to forecast common downstream flow rates and flow depths in a river system. For this purpose, three different ANFIS modes were considered; a depth–depth model, a depth–discharge model and a discharge–discharge model.

The models were used for the prediction of 1-h downstream flow rate and flow depths in the river. The ANFIS model with selected categories and membership functions are verified by autoregressive integrated moving average (ARIMA). For the validation of the ANFIS model, data from river Barak in India and river Tar in the USA were used.

The inputs of the system are the upstream depth flow, the flow rate in time, the downstream flow depth and the downstream flow rate. The whole dataset of the flood period is segmented into two categories, namely, high flows and low flows; the categories are selected such that peak flow rate has zero membership value in low flow category and minimum flow rate has no or zero membership in the high flow category.

Four statistical criteria were used in the analysis; the mean absolute errors (MAE), the coefficient of correlation (CORR), the RMSE and the coefficient of efficiency (CE). The CE and CORR values for different ANFIS models were found to be more then 0.82–0.86, while CE and CORR values obtained from the ARIMA were more then 0.81–0.83. From the comparison between ANFIS and ARIMA models, the results showed better performance from ANFIS model in forecasting downstream flow depths and discharges in the studied river system. The application of the ANFIS model was further tested with data from the Tar river, where the forecast of downstream discharge has been done using multiple inflows in basin.

In Patel and Parekh (2014), artificial intelligence techniques, such as ANFIS for the prediction of floods on the Subarmati river, Mehsana district in India, is presented. The technique was in fact a combination of the learning ability of neural networks, along with the transparent linguistic representation of a fuzzy system. Two inputs were considered for the analysis; the past discharge and the rainfall levels. These inputs are essential for ANFIS modelling in this case. Statistical indices, such as

RMSE, R, R^2 and D are presented as well. The ANFIS model was compared with the statistical method Log Pearson III. According to this method 70% of the data were used for training and 30% for testing. The output of the final model is the predicted discharge.

In this study ANFIS has been developed to run real time flood forecasting and the statistical method Log Person III was used for evaluation. From the results it is shown that the coefficient of correlation of the observed peak discharge is 0.99 from prediction and 0.98 from statistical data, which is very close. The coefficient of determination of observed peak discharge is 0.98 from forecasting and 0.97 from statistics. Also, the predicted peak discharge as shown from the coefficient of correlation is 0.89 from ANFIS, and 0.92 from the experimental data. Finally, the coefficient of determination of observed peak discharge is 0.79 from prediction and 0.84 from the values which were used for validation, which again is acceptable.

Another study on the use of hybrid neuro-fuzzy inference systems for flood event vulnerability forecasting has been conducted by Supatmi et al. (2019). More specifically, detailed information and experimental data for flood forecasting in Indonesia are provided in this study. The best access for performance predictions and vulnerabilities is sought. Three different models are considered and tested in this article; a Mandani FIS, a Sugeno FIS and a hybrid neuro-fuzzy inference system (HN-FIS). The data which are used, has been collected from the area of Bandung Indonesia, where the tropical climate is convenient for monsoon. Average rainfall is between 2000 and 3000 mm per year and temperature is from 12 to 24 °C in range, while humidity is about 78% in monsoon season and 70% in dry period.

The inputs of the model, along with their fuzzy categories (in parenthesis) for this study were chosen to be:

- Population density (very low, low, high, over)
- Altitude of the area (low, moderate, high)
- Rainfall data (low, moderate, high, extreme)

As for the outputs, one variable, which indicates how to respond when flood occurs is considered, and that is:

- Vulnerability of flood (safe, alert, danger)

Mamdani FIS is more widely used, particularly for decision support applications, and mostly refers to the intuitive and interpretability nature of the rule base. On the other hand, Sugeno FIS do not have linguistic terms, which means that the model cannot describe in an exact way how it acquires the output from the decision-making platform. The Mamdani fuzzy inference system was combined to form a HN-FIS. The major advantage of the proposed model is its capability of automatically learning and obtaining an output of fuzzy logic decision more clearly, which can exhibit human judgment reasonable.

In the work of Khasiya (2017) the prediction of flood of the river Tapi in India, using ANFIS linguistic representation, is discussed. The data which are used for ANFIS prediction in this case, are the daily rainfall data and the daily peak discharge data.

The objective of the study was to evaluate the ANFIS model with "log Pearson type III", a statistical method which is used in the forecasting of floods. The correct assessment requires accurate data for the amount of precipitation and discharge. ANFIS systems are constructed, used and tested for different models. The results are compared with the ones received by Gumbel's method.

Again, the ANFIS model has been developed to run real time flood forecasting. Three Gaussian models were used for input variables. More specifically, the model is developed using hybrid optimization method and 10 linear trapezoidal membership functions. 70% of the data was used for training, while the remaining 30% was used for testing. The RMSE, the CORR, the coefficient of determination (R2) and the discrepancy ratio (D) for the ANFIS model are 255.10, 0.993, 0.986, and 1.003 respectively for training and 924.15, 0.964, 0.945, and 0.893 respectively for validation. From the results, it can be concluded that the observed discharge is very near to the predicted values.

For Gumbel's Method, the RMSE, CORR, R2 and D are 2576.275, 0.954, 0.910, 0.677 respectively for training and 1252.875, 0.927, 0.859, 0.958 respectively for testing. As per the evaluation of the numerical results, it is shown that this latter model is very efficient, however ANFIS returned better results.

In the work of Pramanik and Panda (2009) ANNs and ANFIS are used in order to estimate the flow at downstream stretch of a river using data for upstream location. A comparison between the performance of neural networks and ANFIS was made by estimating the daily outflow of the dam which is located in the downstream region of Mahanadi river, India. In order to obtain the best input-output correlation, five different models with various input combinations were evaluated using both techniques. Among the five models which were formulated and tested:

- Models 1–4 considers discharging of water from tank without tributary
- Model 5 considers tributary inflows

Three backpropagation algorithms were used for the training process and they are:

- The Levenberg–Marquardt algorithm (LM)
- The gradient descent algorithm (GDX)
- Conjugate descent algorithms (CGF)

The influence of small tributaries on dams was not considered at first. The reason was that, there were not enough available data (e.g. on an hour basis), thus the prediction was based on daily data for the discharge of the water from tank. Later predictions include water from side tributaries and discharge from tank. All data were collected from 1997–2001 and 2002–2003. The model which considers the effect of tributaries, seems to provide the more accurate results using every possible training method. Regarding the two identification techniques, the results showed that ANFIS performs better than the ANN in terms of capturing the input-output relationship, and it could be used successfully in hydrological applications.

Neuro-fuzzy techniques such as the ANFIS can be used also for flood forecasting in urban environment. For example, in the work of Choi et al. (2012), such a technique is used to minimize the amount of uncertainties which are included in a conventional flood forecasting model with final objective, the formulation of a more accurate forecasting model of floods. The adaptive neuro-fuzzy interference system, which is a data driven model that combines a neural network and the fuzzy techniques, can decrease the amount of physical data required for constructing a convectional model. This system can predict the water level and creates a model using only observed rainfall and water levels of rivers. The inputs of the system for this study were rainfall data and the level of the water of the Tancheon basin for 7 flood events, where the level of water exceeded five meters in the period 2007–2011.

More specifically, the annual rainfall amount of Tancheon basin is approximately 1238.3 and 959 mm from June to September. The basin has a total area of 302 km^2 and total length of 35.6 km. Seven selected flood events have been included in different combinations for building the ANFIS model, and the necessary training and testing data. All these parameters are compared with RMSE. Some of the models seem to perform well; however, more data are necessary in order to achieve better accuracy.

Two different models; one based on a multilayer perceptron neural network trained with LM algorithm and radial basis, and an adaptive neuro-fuzzy inference system were considered for the modelling of flood discharge in the paper of Seckin (2011). These models were used to capture the non-linear relationship between discharge and four independent variables:

1. Drainage area
2. Evaluation
3. Latitude, longitude, return period
4. Maximum discharge

These four independent variables are also used as input variables. The input data were obtained from the Hand-book of flood frequency Analysis for peak discharges observed through river basins in Turkey.

Regional flood frequency analyses (RFFA) usually involves the identification of homogeneous regions, selection of suitable regional frequency distributions and estimation of flood quintiles. One of the most important procedures in RFFA is the delineation of the homogenous regions. RFFA method is really detailed and it usually requests a lot of data. An ANFIS model which uses Gaussian and triangular membership functions was considered. The model was trained by using a set of 380 events (training sets), while the testing was facilitated using 163 sets (gauge stations). Adaptive rates of learning were used for each network. The sigmoid and linear activation functions were used to hidden and output nodes of the neural network. A multi-layer perceptron (MLP), which used sigmoid activation function for hidden and output layers was also used.

From the results it is shown that the MLP method is more accurate compared to the ANFIS prediction model; however, further studies for the same region recommend that a greater amount of independent data should be included in the modeling set up.

A comparison between Sacramento (SAC-SMA) technique and ANFIS for real-time flood forecasting in small urban catchments is carried out in the paper of Roodsari et al. (2018). Both models are used for flood prediction in nine small urban catchments located near New York City. The models were used for reforecast stream flow for hurricane Irene and storms.

Two key decisions for flood forecasting are:

- How to treat and represent precipitation forecasts and uncertainty in these forecasts
- How to select appropriate model for best stream flow response simulation

In order to compare the capabilities of these two models for flood forecasting, both models were used to reforecast the flood hydrograph of disaster extreme historical events, hurricane Irene and another smaller storm. Namely, the prediction had been focused on the application of the models on two different events:

- Hurricane Irene (160 mm—last 36 h)
- Storm of September 23–25 (35 mm)

As for a validation period, which is associated with hurricane Irene and the studied storm, data simulation approach was used in order to account for current discharge observations. It was shown that SAC-SMA models with input parameters were allowed to vary between 10% below and above their calibration. On the other hand, ANFIS used less inputs, and the consequence was less time of calibration. The ANFIS model is proved to work better when a lot of historical data is available. However, in this research there was lack of data, thus SAC-SMA presented better performance when tested on the data of hurricane Irene. For the smaller event of the storm, ANFIS managed to do better prediction of flood forecasting.

8.4 Hybrid Adaptive Neuro-fuzzy Systems for Flood Prediction

Forecast models based on modern deep-learning techniques such as, ANNs, ANFIS and Adaptive neuro-genetic algorithms integrated systems (ANGIS) are discussed in (Mukerji et al. 2009). All models are compared with each other. First, a suitably defined ANN is developed. Then, the network is integrated into a fuzzy-logic-based inference system in order to form an ANFIS model. The development of the ANGIS model is also based on ANNs. In fact, it is an ANFIS systems, which is optimized by using genetic algorithms. All these models are used for the analysis of river Ajay.

For the development of ANN, ANFIS and ANGIS models, twenty flood events were available. Fifteen of them were selected for training, while the remaining five events were used for testing. For this paper, rainfall levels are used as inputs, while peak discharge is used for output. The annual average rainfall differs, as rainfall levels varies from 1280 to 1380 mm, while it is worth noting that 75–85% of the total rainfall is observed during the monsoon months.

One first conclusion is that all three models take similar values. However, the obtained results suggest that the ANGIS model is more efficient than the simple ANFIS or the ANN model, even if all models perform well in some cases. An important thing here is that these models cannot predict the value of discharge. This is a drawback which is common for all the discussed models.

The prediction of flood abnormalities for improved public safety using a modified ANFIS is studied in Aqil et al. (2006). More specifically, an adaptive approach is proposed to modify the traditional neuro-fuzzy model. This method uses a rule correction to replace the error of back propagation algorithm. The authors show techniques through simulation about study and flood series on the Citarum river in Indonesia. Total drainage area of Citarum river is 11,000 km^2 and the length of the river is 270 km. The average annual rainfall is between 2000 and 5000 mm per year. The temperature range varies from 18 to 24 °C. The so-called modified ANFIS (Mo-ANFIS), is a modification adopted from traditional ANFIS. The suggested Mo-ANFIS model contains sixteen rules and five layers. Mo-ANFIS is useful due to its interactive nature, flexibility approach, and evolving graphical features and it can also be adopted for any similar situation, that is to predict stream flow. The main data processing includes gauging station selection, input generation, lead time selection/generation, and length of prediction.

The inputs are: the average temperature and the average rainfall data. The data which were used for training are measured from the period 1987–1990, while the data for testing are from years 1991–2002. The forecast results show that the mean absolute percentage error (MAPE) and RMSE vary during validation. For MAPE from 2.632 to 5.650, and for RMSE from 6.957 to 11.826. The results indicate that the neuro-fuzzy model is able to identify the events for which it has been designed. This model can also serve as a tool for real time flood monitoring and process control.

Another hybrid ANFIS system for flood susceptibility is proposed by Bui et al. (2016). Namely, a new artificial intelligence approach based on neural fuzzy inference system and metaheuristic optimization (MONF) for flood susceptibility modeling in a high-frequency tropical cyclone area using GIS is developed and tested. According to this new approach, the neural fuzzy system was used to create an initial flood susceptibility model and then the model was optimized using two metaheuristic algorithms; an evolutionary genetic and a particle swarm optimization (PSO) scheme. The study covered the area of the tropical cyclone in central Vietnam.

Due to the severity of the flood problem in this area, statistical and data driven approaches have been proposed in flood studies, such as analytic hierarchy process, frequency ratio, logistic regression, weights-of-evidence, and fuzzy logic. Application of neural fuzzy models encounter some problems due to their inability to find the best values for critical weight parameters which heavily influence the prediction performance of these models. In addition, neural fuzzy models present slow training speed and sensitivity to noise in hydrological modeling. In this particular study, the inputs are:

- Rainfall
- Elevation
- Slope
- Distance of river
- Stream density

- Lithology
- Curvature

As for the output, one parameter is considered, and that is:

- Flood susceptibility

The annual rainfall of the study area varies from 1679 to 3259 mm. The rainfall is mainly concentrated in the rainy season from April to October which accounts for 88.6–93.3% of the total rainfall in yearly basis.

The results show that both MONF and ANFIS models perform very well with the training data. An important remark is that although the flood influencing factors have been selected based on analysis of flood occurrence and characteristics, however, it is logical to say that the degree of impact of these factors is different, and in some cases, there are factors which may have no influencing to the flood occurrence. Therefore, the predictive power of the influencing factors should be analyzed, and factors with no predictive capability should be eliminated.

The integration of advantages of neural fuzzy systems to a model optimized with the above-mentioned methods yields to higher efficiency of the proposed technique for flood susceptibility mapping for the tropical cyclone area of Vietnam. The result may be accommodating for planners and decision makers for sustainable management of flood-prone areas in the study area. The results show that the proposed MONF model performs above benchmark models, thus it can be concluded that the MONF model consist a new alternative tool, which can and should be used in flood susceptibility mapping.

8.5 Conclusions

From the published papers in literature (see Table 8.1), it can be concluded that ANFIS is a very powerful flood forecasting tool, as it can make predictions with high precision if trained properly, i.e. if a sufficient and representative amount of observation data is available. However, even though the accuracy is high, the predictions of the smart system still do not fully match the later measured and observed data from future events. Compared to other models, ANFIS presents better performance when large amounts of data are present and works better at shorter time intervals (e.g. up to 6 h), above which significant errors may appear. Among the several hybrid ANFIS models, MONF seems to perform better, thus it can be used as a good alternative tool in flood susceptibility mapping. ANGIS present smooth behavior as well. To conclude, ANFIS systems and its variations are widely used for flood risk prediction, however, such models do not appear worldwide. A possible reason for that could be the fact that a large amount of data, as well as long-term research are required for the full implementation of such systems, which, in most cases are hard to collect.

Table 8.1 Flood prediction using neuro-fuzzy techniques such as ANFIS and variations

Models for prediction	Reference	Inputs	Outputs
ANFIS versus Log Pearson type III	Khasiya (2017)	Daily rainfall	Daily peak discharge
ANN versus ANFIS versus ANGIS	Mukerji et al. (2009)	Rainfall	Peak discharge
ANFIS versus Log Pearson type III	Patel and Parekh (2014)	Rainfall and past discharge	Peak discharge
ANN versus ANFIS	Pramanik and Panda (2009)	Discharging water from tank with or without tributary inflows	Downstream flow
ANFIS	Choi et al. (2012)	Rainfall data Level of water	Prediction of water level
RFFA versus MLP versus ANFIS	Seckin (2011)	Drainage area Evaluation Latitude, longitude and return period Maximum discharge	Discharge
Mo-ANFIS	Aqil et al. (2006)	Average temperature Average rainfall	Stream flow prediction
ANFIS versus ARIMA	Ullah (2013)	Upstream depth flow Flow rate in time Downstream flow depth Downstream flow rate	1-h downstream flow rate Flow depths
ANFIS versus SAC-SMA	Roodsari et al. (2018)	Hourly precipitation Temperature	Flood discharge
Mamdani FIS versus Sugeno FIS versus HN-FIS	Supatmi et al. (2019)	Population density Altitude of the area Rainfall data	Vulnerability of flood
ANN versus ANFIS	Nayak et al. (2004)	Rainfall Evaporation Other exogenous variables	Peak flow estimation
ANFIS versus ANN	Nayak et al. (2005)	Rainfall	Runoff
ANFIS	Hossain et al. (2014)	Rainfall River water level River water flow	Flood warning
ANFIS versus MONF	Bui et al. (2016)	Rainfall Elevation Slope Distance of river Stream density Lithology Curvature values	Flood susceptibility
ANFIS	Chen et al. (2006)	Level of water Rainfall Travel time of the flow	Flood forecast

Acknowledgements Nikola Stojanovic and Dusan Stamenkovic gratefully acknowledge the financial support for their visit at the Technical University of Crete, through the Special Mobility Strand action of the "Development of Master Curricula for Natural Disasters Risk Management in Western Balkan Countries/NatRisk" Erasmus+ Capacity Building program.

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