Chapter 8
Application of Neuro-Fuzzy Techniques in the Estimation of Extreme Events

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Abstract In hydroclimatic science, a hydrologic or climatic event like a flood or rainfall is said to be extreme if its occurrence is rare or the probability of its occurrence is below 5%. Predicting extreme events is a difficult task, and often conceptual models fail to perform optimally while predicting the time and frequency of extreme events. Due to this drawback, scientists are now opting for nature-based algorithms to make predictions about extreme events. The application of neural networks, along with the categorization ability of fuzzy logic, has been found to perform much better than conceptual models. The present study uses the same concept to develop a model that can predict the occurrence and frequency of extreme events with the help of a data set categorized by the application of fuzzy logic.

Keywords Extreme events • Neuro-fuzzy systems • Combinatorial data matrix

8.1 Introduction

Artificial neural networks (ANNs) are a popular method of prediction and categorization that mimics the signal-transmission mechanism in the human nervous system. In such a network, layers of inputs are connected to layers of output, just as axons are connected to dendrites in a nerve cell. All the inputs are attached to a weight layer that is continually updated to attain the desired level of accuracy in

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obtaining the targeted values of the output; this resembles the signal-transmission process that occurs among interconnected nerve cells. Once an input signal, like a change in temperature on a stove burner, is detected by receptor cells, a signal is transmitted to the brain for a desired response. The brain, based on its experience, communicates its response, which will certainly be to remove the hand from the cause of the change. The neural network also has a third layer besides the input and output layers – the hidden layer, which works as a buffer between the two main layers. The hidden layers are just duplicate connections of the input and output layers, so experience gained from repeated iterations becomes replicated.

Thus, with a larger number of hidden layers, the model will gain more experience in a single iteration. But too many hidden layers can make the iteration procedure lengthy and computationally extensive, which is undesirable, making the selection of the number of hidden layers rather confusing and complex. Various decision-making techniques have been implemented to find a logical solution to this problem, but so far, the trial-and-error method is the most widely followed in the selection of network topologies.

On the other hand, the rarity of extreme events has made predicting them extremely difficult and complex. The accuracy of any model, whether conceptual or statistical, will depend on the commonality of the output variable. Neural networks are popular for their prediction accuracy, even in the case of complex problems, such methods are now widely used to predict rare events.

It also has been found that the accuracy of a model developed from a set of clustered or categorized data is more than a model created with the help of a numerical data set. Fuzzy logic is widely used for categorizing sets of data retaining the inherent characteristics of the data. Thus, in this study, neural networks and fuzzy logic were used to predict extreme events.

8.1.1 Prediction of Extreme Events

"Climate is defined not simply as average temperature and precipitation but also by the *type*, *frequency* and *intensity* of weather events" (USEPA). Climate change induced by global warming has the potential to change the probability and severity of extremes such as heat waves, cold waves, storms, floods, and droughts.

As reported in the Intergovernmental Panel on Climate Change Fourth Assessment Report (IPCC 2007), the number of extreme events, especially in the tropics, has greatly increased in magnitude and frequency. For example, the number of heat waves, the area of regions affected by droughts(due to marginal decreases in precipitation and increases in evaporation), the number of heavy daily precipitation, and the intensity, frequency, and duration of tropical storms have increased substantially since the 1950s (USEPA).

But predicting such events under a changing climate is complex and rather impossible, whereas understanding the intensity, probability, and frequency of the changes can help us estimate and prepare for the threats to human health, society, and the environment.

8.1.2 Objective and Scope

The objective model will have the following variables as input:

1. Intensity of rainfall (P)
2. Probability of rainfall (P_p)
3. Frequency of rainfall (P_f)
4. Previous day's evapotranspiration (ET)
5. Probability of evapotranspiration (ET_p)
6. Frequency of evapotranspiration (ET_f)
7. Previous day's humidity (H)
8. Probability of humidity (H_p)
9. Frequency of humidity (H_f)
10. Previous day's wind speed (W)
11. Probability of wind speed (W_p)
12. Frequency of wind speeds (W_f)
13. Average of last 5 day's rainfall (P_5)
14. Average of last 5 day's evapotranspiration (ET_5)
15. Average of last 5 day's humidity (H_5)
16. Average of last 5 day's wind speed (W_5)
17. Types of cloud cover (C_t)
18. Amount of cloud cover (C)
19. Probability of cloud cover (C_p)
20. Frequency of cloud cover (C_f)

There is one output variable:

1. Probability of rainfall (P_p)

8.1.3 Brief Methodology

The entire data set of variables will be categorized with respect to the concept of maximization and minimization under the fuzzy theory of categorization. All the categorized data will be used in predicting the category of the output variable.

The categorical data of the input variables, which can be referred to as a decision matrix, will be fed to the neural network model to predict the output variable.

The decision matrix will have all possible situations that can arise in the near future. Whenever the probability of an extreme event must be estimated, the data value of the input variables will be converted into corresponding groups and then may be fed to the neural network model for prediction. The predicted group will show the occurrence of extreme events in the desired time, space, geophysical, and hydroclimatic domains.

8.2 Artificial Neural Networks and Fuzzy Logic

8.2.1 Artificial Neural Network

An ANN is a pattern identification iteration methodology that mimics the procedures of the human nervous system in responding to a stimulus. The model is flexible and can be applied to any type of problem using available data sets of the input and output variables. Neural networks are applied in various techniques and follow different logic in a wide variety of fields in the arts, science, and engineering. It is widely accepted as a simple but efficient model development methodology with a high level of accuracy.

In neural networks the input layers are multiplied by a weight, and the summation of this weighted sum is converted into a function (logistic, sigmoidal, etc.) to estimate the output. The output is compared with the observed data set for accuracy. If the estimation fails to reach the desired accuracy, then the weights are updated according to a logic known as a training algorithm and the entire process is repeated. In this way, until and unless the accuracy reaches the desired level or a certain number of iterations are conducted, the model continues to minimize the error by optimization of the weights.

But the main distinction of neural networks with respect to nonlinear models is the introduction of hidden layers, which enables a model to replicate its estimation. Hidden layers act as a buffer between the input and output layers. When a hidden layer is introduced, the output becomes the hidden layer and moreover, it becomes the input with respect to the output layer. The estimation work is performed two or three times depending on the number of hidden layers. But embedding too many hidden layers will also increase the requirements for computational power, which is undesirable. Thus, selection of the topology is done in steps that are accomplished either by trial and error or with the help of specialized search algorithms. Methods for updating weights and choosing an activation function are also determined by trial and error. The drawbacks of a neural network lie in these trial-and-error methods, and many studies have been conducted on how to overcome these shortcomings.

8.2.2 Fuzzy Logic

Fuzzy logic is one of the most popular technologies for the development of decision support modules. The capability of fuzzy logic resembles human decision making with its ability to generate precision from approximations. It successfully compensates the gap in engineering design methods produced by "purely mathematical approaches and purely logic-based approaches in system design" (Aziz and Parthiban 1996).

While equations are required to model real-world behaviors, fuzzy design can help to include the ambiguities of real-world human language and logic.

The initial applications of fuzzy theory include process control for cement kilns, the first fuzzy-logic-controlled subway of Sendai in northern Japan (1987), elevators to reduce waiting time, etc. After the initial decade of the 1980s, applications of fuzzy logic in different technologies increased at an alarming rate, affecting the things we use every day.

Some of the noticeable applications of fuzzy logic in essential durable goods include the fuzzy washing machine, which uses fuzzy logic to select the best cycle, the identification of the right time at the proper temperature in a fuzzy microwave, and a fuzzy car with automaneuvering technology.

Fuzzy logic was derived from the fact that most modes of human reasoning are approximate in nature.

The theory of fuzzy logic was first developed by Professor Lofti Zadeh at the University of California in 1965. At that time application of fuzzy logic made the following assumptions:

- In fuzzy logic, exact reasoning is viewed as a limiting case of approximate reasoning.
- In fuzzy logic, everything is a matter of degree.
- Any logical system can be fuzzified.
- In fuzzy logic, knowledge is interpreted as a collection of elastic or, equivalently, fuzzy constraints on a collection of variables.
- Inference is viewed as a process of propagating elastic constraints.

8.2.2.1 Application of Fuzzy Logic

Fuzzy logic has been applied in various fields where decision making with the help of linear or nonlinear conceptual or statistical models was found to be erroneous. For example, the control systems of the 165 MWe Fugen advanced thermal reactor in Tokyo, Japan was embedded with fuzzy logic so that proper decisions could be made by the controller without any manual interference but based on system uncertainty (Iijima et al. 1995). The Steam drum water level had been controlled by proportional-integral control systems, but after the development of fuzzy logic, the water level became more effectively regulated.

Fuzzy logic was applied to control the demand for electric water heater power in such a way that the on-peak demands were shifted to the off-peak period. To achieve that objective, Nehrir and La Meres (2000) divided the entire distribution area into multiple blocks, with each block separately regulated by a fuzzy controller. The use of the fuzzy controller was found to be beneficial in achieving the objectives through demand-side management (DSM).

In the case of a water treatment mechanism, fuzzy logical operators were used to model the time-variant specific fluxes during crossflow microfiltration of several feed suspensions. According to the model output, it was found that fuzzy logic controllers could become an efficient regulator in programmable control systems for improved onsite operation of membrane-based liquid–solid separation (Altunkaynaka and Chellam 2010).

In 1998 fuzzy logic was used to model the advective flux of Atrazine in unsaturated calcareous soil (Freissineta et al. 1998) for dealing with the imprecise estimates that are normally present in water and solute movement in soils. Fuzzy logic was also applied in the development of a strategy to shift the average power demand of residential electric water heaters by selecting a minimum temperature as the control variable (LaMeres et al. 1999); in estimating "environ-metrics," i.e., the interrelations of air, water, and land ecosystems (Astel 2006); in the development of a new water quality index based on fuzzy logic; in a literature review and hydrographic survey for the Ribeira de Iguape River in the southwestern part of São Paulo State, Brazil (Lermontova et al. 2009); in the creation of an index to evaluate surface water quality by converting the traditional, discontinuous classes into continuous forms, where the summed values of the available data (with respect to the latter method of classification) were defuzzified to estimate the actual value of the index (Lcaga 2006). Benlarbi et al. (2004) developed an online fuzzy optimization algorithm that was used to maximize the drive speed and water discharge rate of the coupled centrifugal pump of a photovoltaic water pumping system driven by a separately excited DC motor (DCM), a permanent magnet synchronous motor (PMSM), or an induction motor (IM) coupled to a centrifugal pump. Monthly water consumption was estimated successfully by Yurduseva and Firat (2008) with the help of fuzzy logic with an adaptive neural network [Adaptive Neuro-Fuzzy Inference System (ANFIS)].

Table 8.1 presents more applications of fuzzy logic for solving problems in the field of water research.

8.3 Methodology

The present study will try to highlight a methodology for estimating the probability and frequency of extreme events. As discussed earlier, due to the uncertainty involved in the occurrence of extreme events, it is rather complex to define the exact amount or occurrence of such events. But their zone of certainty can be predicted if the required amount of data is available.

8.3.1 Data Set Preparation

At first the parameters related to the occurrence of extreme events were identified based on the available studies, governmental reports, and expert opinion. In the selection of the input variables the latter was given the maximum weighting due to the experts vast field experience. The variables were then encoded into nine groups representing the different levels of quantity and quality. Figure 8.1 represents the groups in which the variables were distributed.

Table 8.1 Some applications of fuzzy logic to different water-related problems

Authors	Field of water research	Model objective	Success rate
Schulz and Huwe (1998)	One-dimensional, steady-state water flow in unsaturated zone of homogeneous soils	Describe soil water pressures with depth and calculate evapotranspiration rates under steady-state conditions	Impact of different shapes of membership functions of input parameters on resulting membership functions
Ocampo-Duquea et al. (2006)	Water quality	Assess water quality by developing an index	Successful
en and Altunkaynak, (2009)	Water consumption rate (important for planning requirements of drinking water)	Predict water consumption rate using body weight, activity, and temperature of consumers	Classification based on crisp numbers was avoided by introducing fuzzy sets
Saruwatari and Yomota (2000)	Irrigation water management	Predict irrigation water requirements using categorized data generated in consultation with various experts and knowledge base	Successful
Karabogaa et al. (2007)	Reservoir operation	Control operation dynamics of spillway gates	Successful
Khalid (2003)	Operation management	Temperature control of water bath using neuro-fuzzy compensator and back-propagation neural network	Successful

Once the data set was categorized, all possible combinations between the input variables and output were generated and used to prepare a combinatorial data set representing all the possible scenarios that could arise for the present interrelationships between input and output variables. The categorization of any data set must be performed in such a way that the lower categories like L (Low), SL (Semi Low), VL (Very Low), and EL (Extremely Low) will have values that are small but not rare and the higher categories must represent data possessing opposite characteristics.

8.3.2 Development of Scoring Mechanism by Fuzzy Logic

The scoring of the categories to rate the data was performed with the help of fuzzy logic's theory of minimization. In this theory, a fuzzy matrix was prepared by

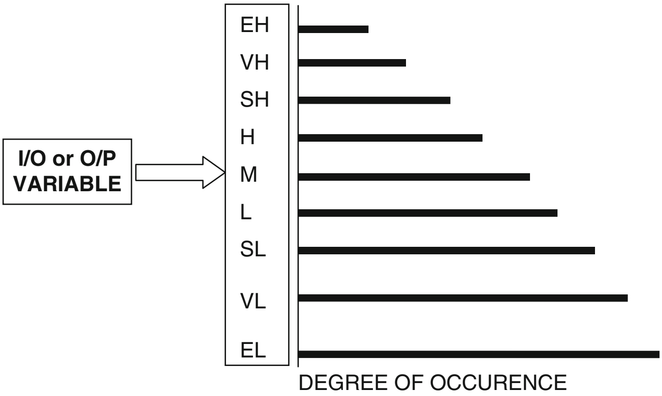

Fig. 8.1 Groups in which the data set must be encoded (*EH* highest degree of quantity or quality, *EL* lowest level of quantity and quality)

comparing each input variable with the others according to the degree of importance with respect to each other. The degree of importance was represented by the following classes:

1. Very Important (VI)
2. Important (I)
3. Neither Important nor Unimportant (NIUI)
4. Unimportant (UI)
5. Completely Unimportant (CUI)

After the input variables were rated, they were all ranked according to their importance in ascending order, i.e., a variable with a VI rating was ranked 1, whereas a variable with a CUI rating was assigned a rank of 5.

After ranking the variables with respect to their importance, the rankings were divided by the worst rank achieved by a given variable. The minimum value of the result from the division represents the highest importance achieved by the variable compared with the other variables. This minimum value was taken as the scale to rate the present variable.

All the variables were assigned a rank with respect to their individual categories such that a higher rank implies a higher probability and frequency of an extreme event and vice versa.

The objective function used to represent the probability of extreme events was developed by summing all the scales and the respective scores based on the scale of the input variables and deducing the percentage of the input variable with respect to the total value of the scale. The percentage will be directly proportional to the probability of the extreme events. After the percentage value of the objective function was derived, it was again categorized, where EH indicates the maximum probability and EL represents the opposite.

With the input and output variables a combinatorial data matrix was used to develop a neural network model with Levenberg-Marquardt as the training algorithm, a logistic activation function, and an exhaustive trial-and-error method for identifying the optimal network topology where all the input variables were used to predict the category of the output.

The results show the probability of extreme events with respect to the given scenarios as represented by the categories of the input variables. The methodology can be replicated in any study area to determine the probability of occurrence of an extreme event.

8.4 Results and Discussion

Table 8.2 shows the fuzzy matrix developed for scoring the input variables with respect to their importance compared to the other input variables. Table 8.3 represents the neural network parameters, and Table 8.4 shows the sensitivity, specificity, and precision of the neural network output.

According to the performance metrics (like sensitivity, specificity, and precision), the model had values of 99.02, 99.98, and 99.51%, respectively, for precision, sensitivity, and specificity, which shows the model's level of accuracy.

8.5 Conclusion

The present study represents an attempt to predict the probability of occurrence of extreme events with the help of 20 selected variables. The variables are encoded into nine categories and rated using fuzzy logic. The rated input variables were used to develop an objective function representing the likelihood of the extreme events. The function was then encoded into nine categories that were similar to the input categories. The categorized input and output variable was used to generate all the possible combinations of the variables and a combinatorial data matrix was produced. This data matrix was used to create a neural network model to predict the outcome of the combinations of the input variables. Once the model is trained to predict the chance of occurrence of extreme events for all possible scenarios, it can be used to predict extreme events based on the input variables in any given study area. Due to a lack of time, the model was not tested for real-time situations, but the authors would be interested in receiving results in real-time settings from the research community that might help to further improve the model's efficiency.

Table 8.2 Fuzzy ratings of each criteria with respect to each other based on the five point fuzzy scale

	1. Intensity of rainfall (*P*)	2. Probability of the rainfall (P_p)	3. Frequency of the rainfall (P_f)	4. Previous day evapo-transpiration (ET)	5. Probability of the evapo-transpiration (ET_p)	6. Frequency of the evapo-transpiration (ET_f)	7. Previous day humidity (*H*)	8. Probability of the humidity (H_p)	9. Frequency of the humidity (H_f)
1. Intensity of rainfall (P)	0	I	I	I	I	I	VI	I	I
2. Probability of the rainfall (P_p)	UI	0	NINU	NINU	NINU	NINU	I	NINU	NINU
3. Frequency of the rainfall (P_f)	UI	UI	0	NINU	NINU	NINU	I	NINU	NINU
4. Previous day evapo-transpiration (ET)	UI	NINU	NINU	0	I	I	NINU	NINU	NINU
5. Probability of the evapo-transpiration (ET_p)	UI	NINU	NINU	UI	0	I	I	I	I
6. Frequency of the evapo-transpiration (ET_f)	CUI	UI	UI	NINU	UI	0	I	I	I
7. Previous day humidity (*H*)	CUI	UI	UI	NINU	UI	UI	0	I	I
8. Probability of the humidity (H_p)	UI	NINU	NINU	NINU	UI	UI	UI	0	I
9. Frequency of the humidity (H_f)	UI	NINU	NINU	NINU	UI	UI	UI	UI	0
10. Previous day wind speed (*W*)	UI	NINU	NINU	UI	UI	UI	UI	UI	UI
11. Probability of the wind speed (W_p)	UI	NINU	NINU	UI	UI	UI	UI	UI	UI
12. Frequency of the wind speed (W_f)	UI	NINU	NINU	UI	UI	UI	UI	UI	UI
13. Average of last five days rainfall (P_5)	UI	NINU	NINU	UI	UI	UI	UI	UI	UI
14. Average of last five days evapo-transpiration (ET_5)	NINU	I	I	UI	UI	UI	UI	UI	UI
15. Average of last five days humidity (H_5)	NINU	I	I	UI	UI	UI	UI	UI	UI
16. Average of last five days wind-speed (W_5)	NINU	I	I	UI	UI	UI	UI	UI	UI
17. Types of cloud cover (C_t)	NINU	I	I	I	I	NINU	NINU	NINU	NINU
18. Amount of cloud cover(*C*)	CUI	UI	UI	I	I	NINU	NINU	NINU	NINU
19. Probability of the cloud cover (C_p)	UI	NINU	NINU	I	I	NINU	NINU	NINU	NINU
20. Frequency of the cloud cover (C_f)		UI	NINU	NINU	I	I	NINU	NINU	NINU

10. Previous day wind speed (*W*)	11. Probability of the wind speed (W_p)	12. Frequency of the wind speed (W_f)	13. Average of last five days rainfall (P_5)	14. Average of last five days evapo-transpiration (ET_5)	15. Average of last five days humidity (H_5)	16. Average of last five days wind-speed (W_5)	17. Types of cloud cover (C_t)	18. Amount of cloud cover(*C*)	19. Probability of the cloud cover (C_p)	20. Frequency of the cloud cover (C_f)
I	I	I	I	NINU	NINU	NINU	NINU	VI	I	I
NINU	NINU	NINU	NINU	UI	UI	UI	UI	I	NINU	NINU
NINU	NINU	NINU	NINU	UI	UI	UI	UI	I	NINU	NINU
I	I	I	I	I	I	I	UI	UI	UI	UI
I	I	I	I	I	I	I	UI	UI	UI	UI
I	I	I	I	I	I	I	NINU	NINU	NINU	NINU
I	I	I	I	I	I	I	NINU	NINU	NINU	NINU
I	I	I	I	I	I	I	NINU	NINU	NINU	NINU
I	I	I	I	I	I	I	NINU	NINU	NINU	NINU
0	I	I	I	I	I	I	NINU	NINU	NINU	NINU
UI	0	I	I	I	I	I	NINU	NINU	NINU	NINU
UI	UI	0	I	I	I	I	NINU	NINU	NINU	NINU
UI	UI	UI	0	I	I	I	UI	UI	UI	UI
UI	UI	UI	UI	0	I	I	UI	UI	UI	UI
UI	UI	UI	UI	UI	0	UI	UI	UI	UI	UI
UI	UI	UI	UI	UI	UI	0	UI	UI	UI	UI
NINU	NINU	NINU	I	I	I	I	0	NINU	NINU	NINU
NINU	NINU	NINU	I	I	I	I	NINU	0	I	I
NINU	NINU	NINU	I	I	I	I	NINU	UI	0	I
NINU	NINU	NINU	I	I	I	I	NINU	UI	UI	0

Table 8.3 Neural network parameters of the model

Neural network parameters	Model result
Topology search method	Exhaustive nonlinear
Activation function	Logistic
Training algorithm	Levenberg-Marquardt
Network topology	20-6-1
Network weight	126
Training data set	12157665459056928000 data rows
Stop training condition: correct classification rate (CCR)	97%
Stop training condition: minimum improvement in error	0.0000001 during last 10 iterations
Stop training condition: allowed number of iterations	1,000,000
Training correct classification rate (CCR)	98.55%
Testing correct classification rate (CCR)	99.98%

Table 8.4 Performance metrics of neural network model

Performance metric	Model result (%)
Precision	99.02
Sensitivity	99.98
Specificity	99.51

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