NEURAL NETWORKS AND APPLIED HYDROGEOLOGY

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1 INTRODUCTION TO NEURAL NETWORKS

Neural networks are mathematical black – box models which try to reply functions and form of human brain neurons. Development of neural networks started after the World War II, when first studies on artificial neurons were published (McCulloch, Pitts, 1943). The learning ability, as in the human neurons, was introduced in 1949 (Von Neumann, 1949). The most known form of neural network, the perceptron, was developed at the end of '50s (Rosenblatt, 1958), and its aspect is stayed until nowadays which few changes. Obviously, the development of modern computers allowed to improve and fine the learning techniques and the structure of model, creating the most utilized algorithm, the error backpropagation (Rumelhart, Hilton, Williams, 1986).

A neural network is a non – linear regressor which designs a functional relation between an input vector (or input unit), and one or more output variables (Soncini Sessa, 2007). Each of input variables is linked by an array of neurons, unit elements which operate one simple operation, activating only if the input signal is major than threshold, described by the activation function; each neuron, using a transfert function, transforms the inputs combination, usually linear, in only one output.
The basis structure of a neural network is proposed in Figure 1, where are shown the input vector *I*, the layers *L* which the network is made of: the first *L – 1* are hidden layers, containing each *n* neurons, the last layer *L* is the output one, containing *q* neurons, equal to the output variables *y*. For common applications it is usually necessary only one hidden layer,

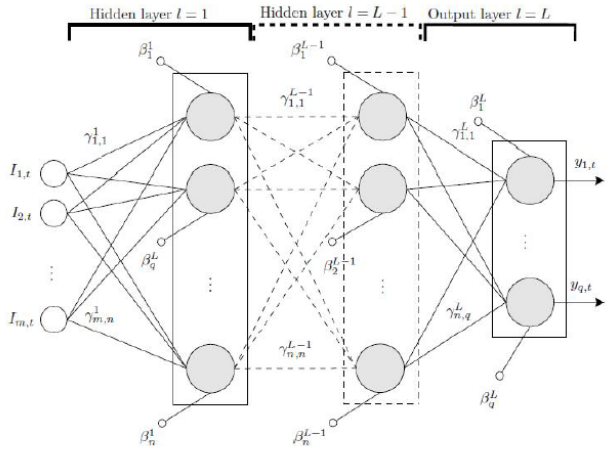


Fig. 1 – Example of generic multi – layered neural network: the input vectors I, internal layers L and output variables y are shown (Soncini Sessa, 2007)

The functioning of neural networks is quite simple: inputs feed the first layer vectors, which feed the vectors of other layers, combining wells and biases, to outputs. This structure, defined "feed – forward", is very simple, general and versatile, and it has been adopted for the most current existing applications.
The biggest advantage of neural networks is about the simplicity of components: each neuron of internal layer is described by a sigmoidal function:

$$P(t) = \frac{1}{1+\exp(-t)} \quad \textbf{(1)}$$

whereas outputs are usually linear functions (Figure 2).

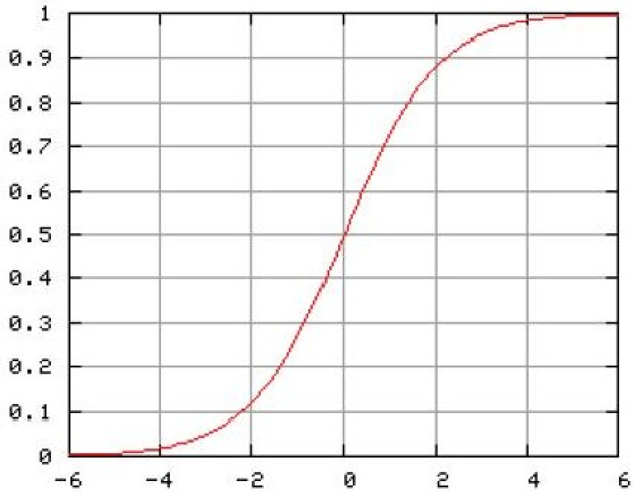


Fig. 2 –Typical aspect of activation function of a neural network

An another advantage of neural network is about their generality: in fact, they are not structure written for a particular computer language (such as Fortran, Basic or C), but they are simple automata which learn by imitation, and they can be built for diverse operations.
The versatility of neural networks is a distinctive elements of these black – box models, which must be made of high number of internal components, in order to allow to each to do a simple and precise action, after a specific training (i. e., weighted means, activation or inhibition capacity over or under a threshold).
The training is a very important element of a neural network: it is done by a recursive procedure, which allows to optimize the values of weights and biases of all neurons of internal layers. To do the training, lots of example data (named "training data"), which inputs and output must be known, are necessary, with a new neural network is fed whom (i.e., daily rain heights, river hydrograph oscillations to implement a model which calculates river levels related to rain events).
Applying the training algorithm (the most known is the error backpropagation algorithm), the neural network automatically activates a weights and biases calibration procedure, in order to best fitting the neuron linking functions (the calibration procedure operates for "imitation": the function is built to calculate, known the input, the closest output to the observed one), to obtain outputs, using different inputs, the most similar to the observed one, if the natural system were realized.
One of the most evident advantages of neural networks is the possibility to use the model to simulate the behaviors of system critically solicited, to analyze outputs without operating physically on system. Also, neural networks are very fexible, because they are capable to simulate different systems and behaviors, if correctly trained, without changing their structure. Finally, neural networks are very simple models, because the internal structure is unknown by the user (these kind of models are called "black . box" models).
One of the negative aspect of the neural networks is that they can be bad simulators, when the structure is not correct (for example, wrong number of neurons or layers), or the training is not efficient, if the training data series are too much short or long, or repeated.

2 APPLICATION OF NEURAL NETWORKS

By their genesis, neural networks have been used in the field of mathematic programming to solve optimization problems of complex water system, such as the African or Asian basins, for which the poor availability of historical data has obliged to build models which lie outside the knowledge of number of data (Onida, 1991; Solomatine, Avila Torres, 1996; Ching-Gung, Chih-Sheng, 1998; Cremonesi, 2010). Study case for Italian systems (Baratti et al., 2003) or to study the water quality (Jan-Tai et al., 2006), are known.

In the hydrogeological field, neural networks have been used to model the response of water basins of specific rainfall situations (Shamseldin, 1996; Sajikumar, Thandaverswara, 1998; Rajurkar at al., 2003), and the obtained results can be considered good. Neural networks have been applied to estimate hydrogeological parameters (Horng, Lee, 2009), or to solve complex problems about groundwater exploitation (Coppola et al., 2003; Shigidi, Garcia, 2003), or to study hydrocarbons reservoirs (Ouenes, 2000), and also to study the susceptibility to landslides (Bartolomei et al., 2006).

Models built to reply natural systems must be calibrated to well describe the specific system which is analyzed. Sometimes environ has a different behavior even if parameters are subject to little changes. The analysis of different answers of a system due to changes in parameters is called sensitivity analysis: it must cover lots of parameters and values, to be exhaustive.

Neural networks have a "black box" structure, so they can not show what is the change in output range when the inputs vary, and it is not simple do a sensitivity analysis, registering outputs due to different inputs. It is possible, instead, to build a neural network trained to simulate a sensitivity analysis: operating in this way, both the hidden structure and the difficulties of a similar model architecture to evaluate the sensitivity, are exceeded.

These are not the unique applications of neural networks; by their generality and diffusion, neural networks are used, even if born in recent years, in lots of fields: OCR softwares to text reconnaissance, financial and social analysis (Di Franco, 1998; Gallo, 2007), frequency spectrum analysis of sound waves (Lang et al., 1998), communication systems (Baglietto et al., 2000).

3 PRACTICAL STUDIES: THE CASE OF THE OLONA RIVER AND THE CASE OF THE NOSSANA SPRING (LOMBARDY, ITALY)

Neural networks, even if are a recent kind of black – box model, have lots of applications, especially in the prevention of hydrogeological risk and to prevent the levels of rivers and lakes, in order to reduce risk of exondation.

For example, a known and well – done case of application of neural networks, is about the prevision of levels of the Olona River (Soncini Sessa et al., 2010).

The Olona River has a basin of 190 km^2, a medium flow of 2.5 l/s, and the correlation between rains and outflows is usually low. In the river basin, there are three pluviometers and one hydrometer. A simple neural network, made of only six neurons, can be used to have correct previsions of river level of the following three hours. This neural network uses the six neurons to join and link data of about all the pluviometers: a simple model can manage with no problem all the available information.

Even if the application of neural network in the Olona River levels prevention has given good results, it is not always simple using neural networks.

For example, a complex known hydrogeological system, the basin of the Nossana spring has chosen with the purpose of prevent the hydrogeological risk.

The hydrogeological structure of the Nossana spring is known by previous studies (Jadoul et al., 1985; Gattinoni & Francani, 2009).

The Nossana spring has elevate mean flows, around 3 m^3/s, and its basin is extended around 80 km^2, constituted by carbonatic rocks and interconnected reticulum, formed along the synclinal of Calcare di Esino; the substratum is formed by the marls of Gorno. There are also two rivers, the Nossana and the Fontanone, which provide for the remaining part of inflows,

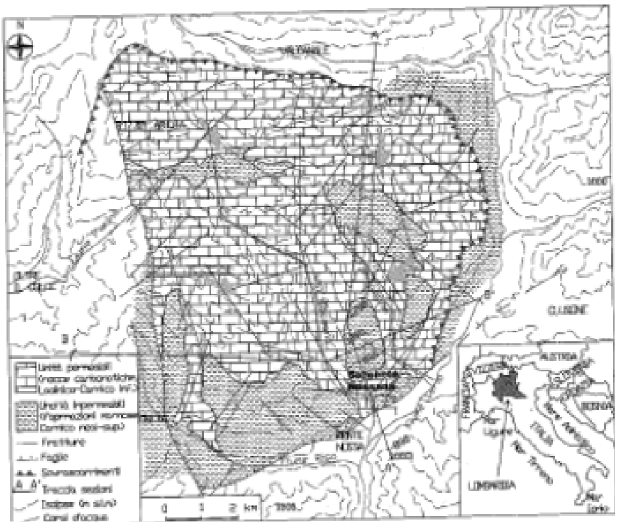


Fig. 3 – The basin of the Nossana spring

Neural networks seem to be the best kind of black - box model to study the basin of the Nossana spring, and how particular rain events can cause a crisis on the outflows from the spring, considering the fact that in last years have observed smaller outflows than in the past (Fig. 4).

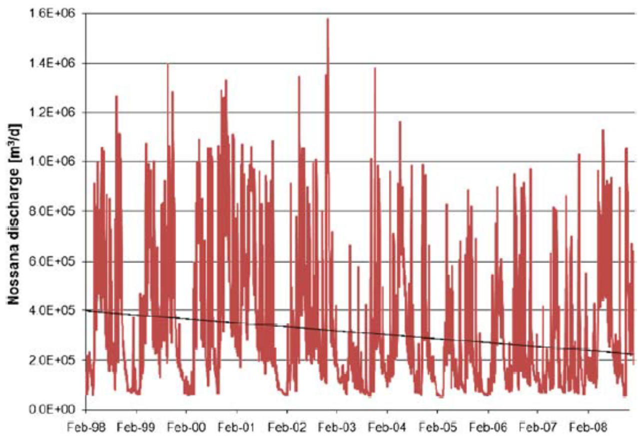


Fig. 4 – Training input data; the red line shows the separation between historical and synthetic series

The most important problem in this stadium has been the choice of the training data, because there are six series, often incomplete, daily rain data from 2003 to 2008 (Fig. 5).

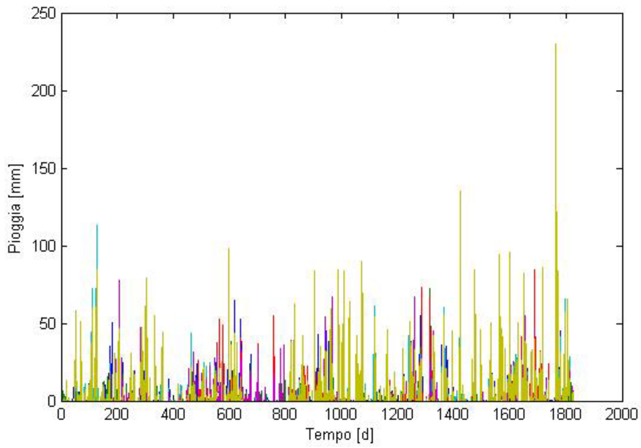


Figura 5 – Complete output data; the red line shows the separation between historical and synthetic serie

Different types of neural networks have been trained with these data, but, even if model architectures were very complex (more than 20 neurons), the results have not been satisfying. To improve the fitting of the training, simple AR(0) or AR(1) models have been used to create artificial input and output training data (Figs. 6 and 7 shows the original data series integrated with the artificial ones).

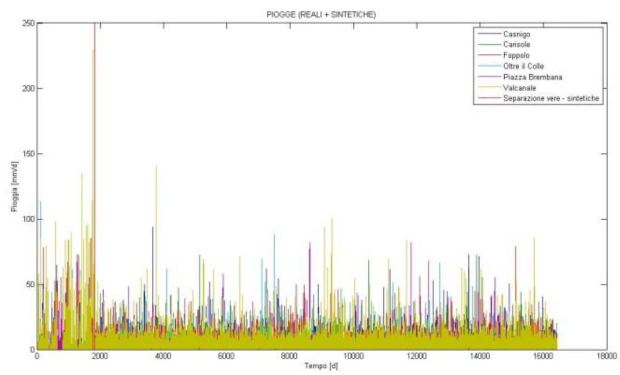


Fig. 6 - Training input data; the red line shows the separation between historical and synthetic series

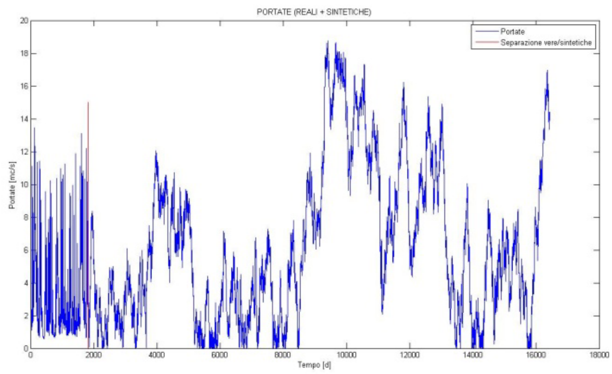
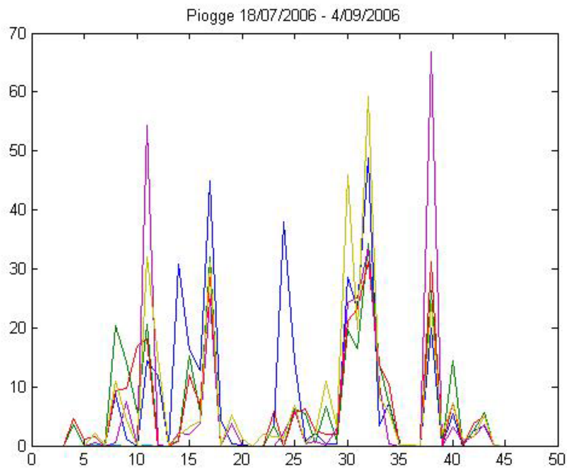


Fig.7 – Complete output data; the red line shows the separation between historical and synthetic series

The synthetic data series have been epurated by values of winter period (from 15/11 to 15/3) in order to simplify the problem, excluding the snowfall and the relation between snow and water equivalent height. Also, a correlation time coefficient between data has been considered.

In this case, using a simple neural network formed has obtained a good training.

In fact, the regression coefficient R is equal to 0.72, indicating that more than 2/3 of observed data are correctly modeled by neural network.



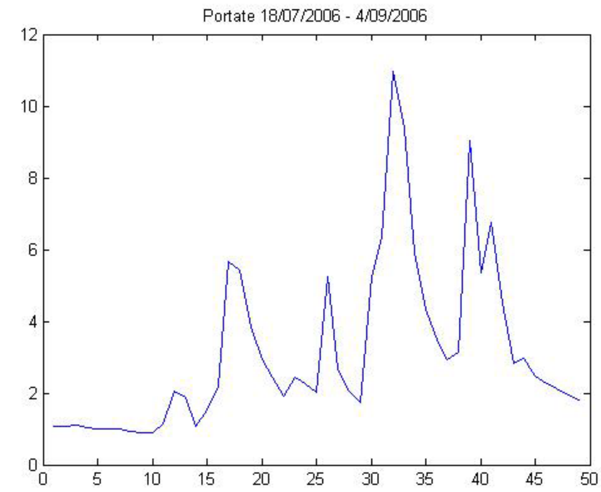


Fig. 8 – Complex rain event (left) and observed outflows (right)

In this case two different simulations have been run, using a neural network trained at first without only the depletion data (Fig. 8) and then without nor the winter snowfall and the depletion data (Fig. 9).

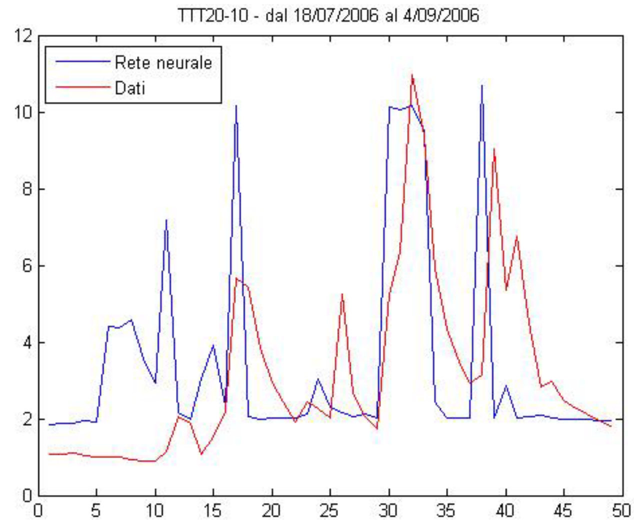


Fig. 9 –Outflows from the Nossana spring calculated by the neural network (blu line) trained without the depletion phase data versus observed outflows (red line)

In this case the depletion initial phase is not correctly described by the neural network, whereas the peaks, especially in the end part of the serie, are better fitted.

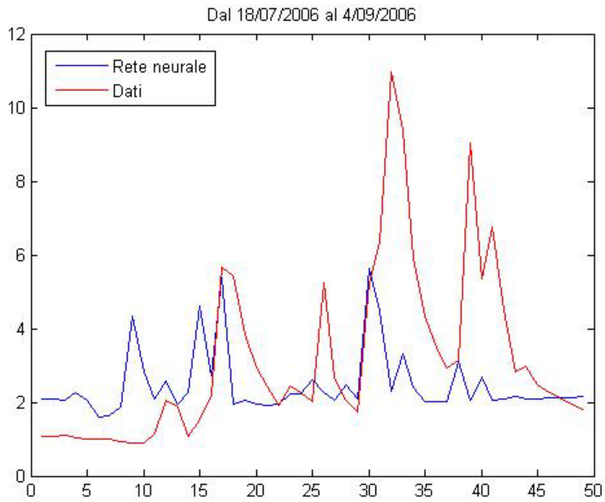


Fig. 10 –Observed outflows (red line) versus calculated (blu lines)

Even if the good training, simulation tests have not given completely satisfying results. The best simulation has proposed in Figg. 8 and 9.

4 CONCLUSIONS

By the fact that neural networks are a recent class of models, they have a good diffusion and their applications are growing up, thanks to their generality and efficacy and simplicity of use. Their validity grows up with experiments and verifying of the obtained results, operations which increase their affidability.

Even if lots of applications of neural networks have good results (e.g. the prevision of the Olona River levels), in other cases there are difficulties (e.g. the case of the Nossana spring), especially when the described hydrogeological system is complex.

In fact, using as input data only the rainfall series, it is difficult to train a neural network which produces the correct output data.

By the quite good obtained results, the training procedure can improved, considering other hydrogeological parameters, such as snowfall data, temperature, sun radiation, meteo – climatic data, the altitude of measurement stations, and the hydrogeological parameters of the spring basin, which are not included in this phase of the study, in order to evaluate its impact factor in the prosecution of the research project.

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