To contemplate quantitative and qualitative water features by neural networks method

M. Neruda[1], R. Neruda[2]

[1]*Faculty of Environmental Studies, University J.E. Purkyně in Ústí nad Labem, Czech Republic*
[2]*Institute of Computer Science, Academy of Sciences of the Czech Republic, Prague, Czech Republic*

ABSTRACT

An application deals with calibration of neural model and Fourier series model for Ploučnice catchment. This approach has an advantage, that the network choice is independent of other example's parameters. Each networks, and their variants (different units and hidden layer number) can be connected in as a black box and tested independently. A Stuttgart neural simulator SNNS and a multiagent hybrid system Bang2 developed in Institute of Computer Science, AS CR have been used for testing. A perceptron network has been constructed, which was trained by back propagation method improved with a momentum term. The network is capable of an accurate forecast of the next day runoff based on the runoff and rainfall values from previous day.

Keywords: rainfall-runoff models; Ploučnice river catchment; applications of artificial neural networks; water quality

Hydrological models solving rainfall-runoff process can be split to deterministic and stochastic (Fošumpaur 1999). Deterministic models divide to conceptual models, which contain a part of empirical relations and full physical based component models. The main reason of their popularity is a better adaptation to non-stationary catchment conditions. Physical based models can easily react to changes made by catchment urbanization, to changes in agriculture-technical process, to ongoing deforestation and gradual changes in soil composition. Deterministic models are very difficult to design and they have high requirements on data amount and quality.

Stochastic models work with random variable with probability factorization. The best-known stochastic model is the linear autoregression model ARMAX (Autoregressive Moving Average with Exogenous Inputs) introduced by Box and Jenkins (1976). The ARMAX model finds fast binding between previous rainfalls and runoffs and forecasting runoff in outlet catchment profile. Calibrated regressive coefficients have no physical meaning, and it is necessary to calibrate model again with external condition change. To recalibrate model is very easy because a model is simple and not data demanding. Parameter correction in principle of Kalman filter is well known. A characteristic disadvantage of model ARMAX is a real time delay because the model has trend character.

In the article a neural rainfall-runoff model for operative river flows forecasting is introduced. An efficient model's part contains a feed forward neural net which topology and parameters have not a physical meaning, and this arrange a model similar – as ARMAX model – to black box models group. Model weakness is a low possibility of extrapolation out of calibration data set limits. Artificial neural networks represent an advanced technique from the artificial intelligence field, and they enable to approach also very nonlinear relations. The neural model is relatively simple and easy to use for operative forecasting. Drbal and Starý (1998) consider neural networks and statistical models based on robust regression principle as perspective tool for short-time hydrological forecasts.

MATERIAL AND METHODS

Neural networks and their software simulation

A model of multilayer neural network is used to construct a rainfall-runoff neural model. A theory of neural networks is well known at present. A multilayer neural network is very flexible regressive tool for easy identification of difficult relations between inputs and outputs. A studied relation can have a difficult nonlinear character, for which the search for suitable regressive equation by standard statistical approaches is very difficult and often not successful. A multilayer neural network is made of several layers of reciprocally interconnected neurons. Each interneuron connection represents a numerical parameter – weight. Neural network training is a process of all weights calibration. An effective training algorithm called Backpropagation (Rumelhart et al. 1986) discovered in 1986 made big development of multilayer neural networks possible. It is an autocalibrated method based on a gradient method principle for extreme multidimensional function search.

Applications of neural networks in hydrology became very popular. In next overview, we briefly concentrate on known examples of their usage for forecasting hydrological models. Hsu et al. (1995) worked in their research at comparison with conceptual, linear regressive and neural rainfall-runoff model with time discrete one day. Minns's paper (1996) deals with neural model deduction for operative forecasting of river's runoffs for hypothetical catchments constitute different types of real catchment.

Starý (1996, 1998) solves with neural networks forecasts of culminating runoffs and floods volumes above longtime runoff average in the Ostravice catchment with outlet profile Šance. Fošumpaur (1998) in his paper works on neural model application for derivation of a rainfall-runoff relation with a neural networks method for Sušice profile in Otava River.

A studied area in the Ploučnice river has an area 267.8 km^2 (Figure 1). Czech hydrometeorological institute carries on measurements of rainfall day sums in four stations: Křižany, Jablonné v Podještědí, Stráž pod Ralskem a Mimoň. From day rainfall sums weight averages of rainfalls have been computed with Thiessen polygons method (1).

$$R = \frac{R_1.A_1 + R_2.A_2 + R_3.A_3 + \ldots + R_n.A_n}{A_1 + A_2 + A_3 + \ldots + A_n} \qquad 1)$$

where: R = 24h rainfall amount (mm/day) in the catchment

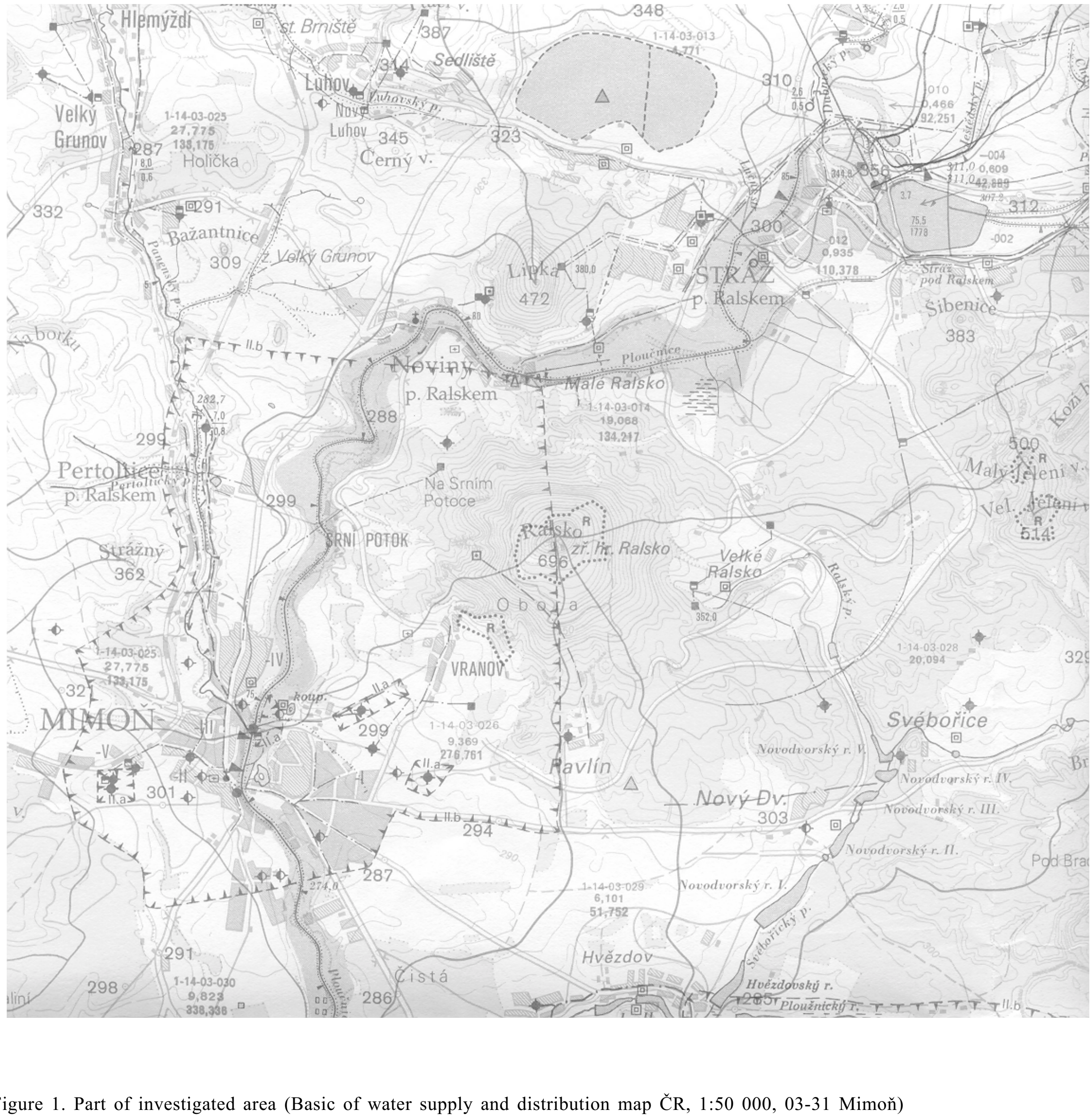

Figure 1. Part of investigated area (Basic of water supply and distribution map ČR, 1:50 000, 03-31 Mimoň)

R_1–R_a = 24h rainfall amount measured in the station (mm/day)

A_1–A_a = area size by Thiessen polygons (km^2)

An outlet profile for runoffs measuring is situated in Mimoň town. There are investigated daily runoff's values in the Ploučnice river. The company Diamo, s. p., Stráž pod Ralskem has been doing water quality monitoring and radiological analyses. This company makes water sampling four times a year in six places: Chrastná, Ještědský and Dubnický stream, Noviny pod Ralskem, and in two places behind drain channel for mining water quality measuring. The Povodí Ohře company makes special radiological water sampling in two places: water reservoir Horka and in Mimoň town. We have data for five years period 1994–1999. There were chosen two rainfall rich periods: 8. 5. to 6. 7. 1995 and 31. 5. to 23. 8. 1996.

Neural networks

In the article we work with three different neural networks models, multilayer perceptron, Radial Basis Function (RBF) and Cascade Correlation (Figures 2 and 3). There are all networks' architectures, which realize a function relation between input and output neurons with feedforward binding. Perceptron networks contain neurons, which realize affined transformation of input values, to which a nonlinear stepwise transitional function is applied (Šíma and Neruda 1997).

$$y = \sigma\left(\sum_{i=1}^{n} w_i x_i - w_0\right)$$

$$y = \gamma\left(\|x - c\|\right)$$

Neurons in the perceptron network are arranged to layers, which are reciprocally connected by synapses. Typically, we think about a network with one or two perceptron layers (hidden layers). This network learns typically with Backpropagation algorithm.

A Cascade Correlation network uses same neurons as perceptron network, but its topology is more complicated. In addition to feedforward synapses, neurons are connected also laterally. All lateral links have the same orientation, they do not form any cycles. A richer network's structure is compensated with more complicated learning algorithm, which combines gradient minimization with Correlation maximization.

Radial Basis Function networks represent an alternative architecture of neural networks, which uses different neuron's type – local units. They have different transitional function, which first calculates a distance between input and center determined by unit's parameters and then applies a nonlinear activation function (the most often it is a Gaussian function). RBF networks can be trained with gradient algorithm method or also with genetic algorithm (Neruda 1995).

An advantage of used approach is that network's type choice does not depend on other task parameters. Single networks, or their variants (different number of units, different number of hidden layers), can be connected as black box and tested independently. For testing, we use the Stuttgart neuron simulator SNNS and the multiagent hybrid system Bang2 developed in Institute of Computer Science, ASCR.

RESULTS AND DISCUSSION

In described data, we first identified two important rainfall high periods, which culminate with extreme runoffs. First rainfall period happen between 8. 5. to 6. 7. 1995 and second between 31. 5. to 23. 8. 1996. In these events, we tested if we can construct a realistic neuron model. Because in both periods we have about 60–70 training examples, we can construct and learn quite a compact neural network with five neurons in hidden layer, which accurately models the time series.

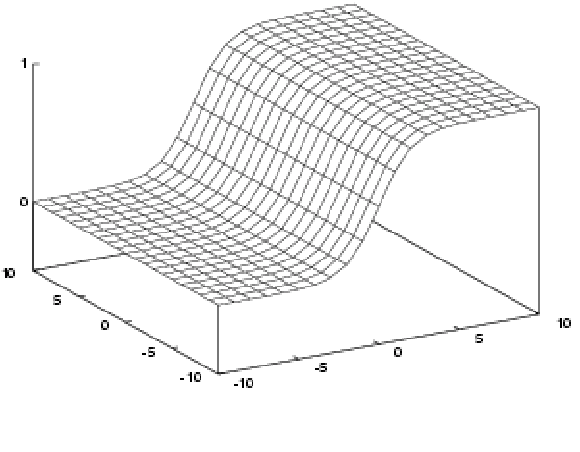

Figure 2a. Transitional perceptron Function (logistic sigmoid)

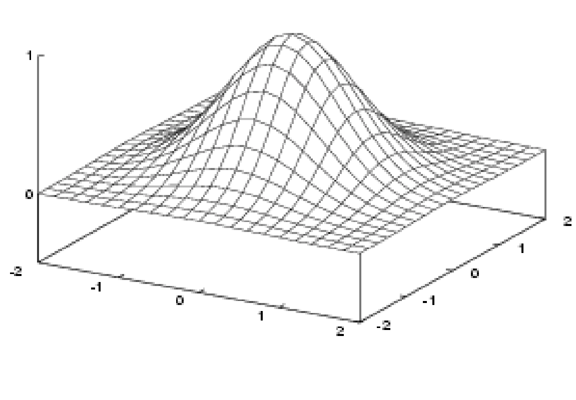

Figure 2b. RBF units (Gauss function) for neuron with two inputs

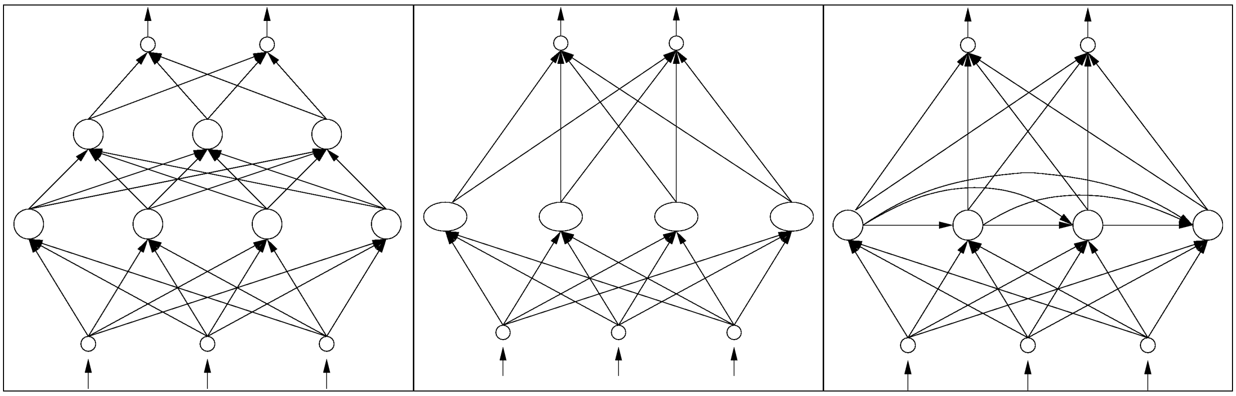

Figure 3. Graphs of connection typical multilayer perceptron network, RBF network and Cascade Correlation network, a) input layer, b) middle layer, c) outputs layer

The main result is a model constructed on the base of neural network trained with data from the whole period. For this example, we constructed a perceptron network with 2-8-1 architecture, which we trained with Back propagation method improved with momentum term. After about 100 000 iteration of learning we reached a satisfiable result (Table 1). A network can accurately forecast runoff next day on the base of runoff and rainfall in the previous day. A network can rightly indicate extreme tendency in runoff values, for example in two chosen rainfall periods. In the forecast of extreme values are the biggest network's mistakes: trend is caught right, but an absolute runoff value is forecasted lower. It is an understandable quality, because data with higher runoff are relatively rare. For next work, we plan to categorize runoff (normal/increased/…), and to increase the presence of extreme data in a training set. Perceptron networks made described experiments results.

Roman Neruda has been partially supported by Grant Agency of the Academy of Sciences of the Czech Republic under grant no. B1030006. Martin Neruda has been supported by internal grant of the Faculty of environmental studies, University of Jan Evangelista Purkyně in Ústí nad Labem.

Table 1. A comparison of real runoff and perceptron network type 2-8-1 forecast for period 4. 6. to 20. 6. 1995

Date	Runoff (mm/day)	Rainfall (mm/day)	Measured runoff (mm/day)	Forecasted runoff (mm/day)	Absolute error
4. 6. 1995	1.97	1.41224	1.89	2.10904	0.21904
5. 6.	1.89	1.75976	1.92	2.06712	0.14712
6. 6.	1.92	7.51859	2.01	2.23184	0.22184
7. 6.	2.01	0.03718	2.11	2.00568	0.10432
8. 6.	2.11	5.45176	2.15	2.16936	0.01936
6. 6.	2.15	4.33788	2.46	2.26008	0.19992
10. 6.	2.46	4.34894	2.43	2.56376	0.13376
11.6.	2.43	0.92494	2.38	2.46984	0.08984
12. 6.	2.38	34.91929	7.72	7.72552	0.00552
13. 6.	7.72	4.63341	5.39	5.43552	0.04552
14. 6.	5.39	6.72753	3.68	3.89544	0.21544
15. 6.	3.68	6.51435	3.73	3.88256	0.15256
16. 6.	3.73	3.92447	3.64	3.82136	0.18136
17. 6.	3.64	6.50847	3.59	3.86856	0.27856
18. 6.	3.59	0.29153	3.51	3.19528	0.31472
19. 6.	3.51	0.01859	3.12	3.14656	0.02656
20. 6.	3.12	0	2.82	2.92672	0.10672

REFERENCES

Box G.E., Jenkins G.M. (1976): Time series analysis: forecasting and control. Holden-Day, Oakland, California.

Drbal K., Starý M. (1998): Předpovědní modely a řízení manipulací při povodních. In: Sbor. Ref. 7. Symp. Systém povodňové ochrany ČR, Olomouc: 59–67.

Fošumpaur P. (1998): Application of artificial neural networks (ANNs) to rainfall-runoff process. In: Sbor. Ref. Workshop'98, Part III. ČVUT, Praha: 985–986.

Fošumpaur P. (1999): Použití umělých neuronových sítí pro operativní předpovědi říčních průtoků. Vod. Hospod., *6*: 121–123.

Hsu K., Gupta H.V., Sorooshian S. (1995): Artificial neural network modeling of the rainfall-runoff process. Wat. Resour. Res., *31*: 2517–2530.

Minns A.W. (1996): Extended rainfall-runoff modelling using artificial neural networks. In: Muller (ed.): Hydroinformatics '96. Balkerna, Rotterdam: 207–213.

Neruda R. (1995): Functional equivalence and genetic learning of RBF networks. In: Pearson D.W., Steele N.C., Albrecht R.F. (eds.): Artificial neural nets and genetic algorithms. Proc. Int. Conf. Wien, Springer-Verlag: 53–56.

Rumelhart D., Hinton E.G., Williams R.J. (1986): Learning internal representations by error propagation. MIT Press, Cambridge, Mass.

Starý M. (1996): Modelování hydrogramů povodňových vln v systému stanic s využitím neuronových sítí. In: Sbor. Ref. Konf. Přehradní dny, Hradec nad Moravicí, Povodí Odry, a. s., Český přehradní výbor: 248–252.

Starý M. (1998): Neuronové sítě a předpověď kulminačních průtoků a objemů povodní v povodí řeky Ostravice – uzávěrový profil Šance. Vodohosp. Čas., *46*: 45–61.

Šíma J., Neruda R. (1997): Teoretické otázky neuronových sítí. MatfyzPress, MFF UK Praha.

Základní vodohospodářská mapa (1999): 1:50 000, 03-31 Mimoň. ČÚZK, Praha.

Received on November 28, 2002

ABSTRAKT

Sledování kvantitativních a kvalitativních vlastností vody metodou neuronových sítí

Aplikace spočívá v kalibraci neuronového modelu a modelu Fourierových řad na povodí Ploučnice. Výhodou použitého přístupu je, že volba typu sítě není závislá na dalších parametrech úlohy. Jednotlivé sítě, případně jejich varianty (různý počet jednotek, různé počty skrytých vrstev) lze připojit jako black-box a testovat nezávisle. Při testování se použijí Stuttgartský neuronový simulátor SNNS a multiagentní hybridní systém Bang2 vyvíjený v Ústavu informatiky AV ČR. Byla vytvořena perceptronová síť, která byla učena metodou back propagation, vylepšenou o tzv. momentový člen. Síť je schopna věrné předpovědi hodnot průtoku následujícího dne na základě hodnot průtoku a srážek v den předchozí.

Klíčová slova: srážko-odtokové modely; povodí Ploučnice; aplikace neuronových sítí; kvalita vody

Corresponding author:

Ing. Martin Neruda, Fakulta životního prostředí, Univerzita J. E. Purkyně, Králova výšina 7/3132, 400 96 Ústí nad Labem, Česká republika, tel.: + 420 47 530 97 39, fax: + 420 47 530 97 58, e-mail: neruda@fzp.ujep.cz