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Application of artificial neural networks in simulating radon levels in soil gas

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ABSTRACT

Anomalies have been observed in radon content in soil gas from three boreholes at the Orlica fault in the Krško basin, Slovenia. To distinguish the anomalies caused by environmental parameters (air and soil temperature, barometric and soil air pressure, rainfall) from those resulting solely from seismic activity, the following approaches have been used. First, the seismic activity data were eliminated from the dataset and then an artificial neural network (ANN) with 5 inputs for environmental parameters and a single output (radon concentration) was trained with the standard backpropagation learning rule. Then the predictions of Rn concentrations (C_p) generated with this ANN for the whole dataset were compared to measurements (C_m) and three types of anomalies (CA — correct anomaly, FA — false anomaly and NA — no anomaly) have been detected in the signal $|C_m/C_p-1|$ by varying five parameters describing an anomaly within predefined intervals. An exhaustive search among results was made to find the best ones and thus identifying the best set of parameters. Finally, an attempt was made to shorten the search procedure by training another ANN with numbers of anomalies of each type in the input and five anomaly detection parameters in the output. With these procedures we were able to correctly predict 10 seismic events out of 13 within the 2-year period.

1. Introduction

Radon is a radioactive noble gas appearing by radioactive decay of radium in the natural radioactive decay chains in the Earth's crust. Only a small fraction of radon (described as the emanation coefficient) enters the space between mineral grains and, thus, has the possibility to travel away from the source, carried either by carrier gases (methane, carbon dioxide) or by water, and eventually reaches the atmosphere (Etiope and Martinelli, 2002). This travel is, in addition to radioactive decay, also subjected to the influence of geochemical and geophysical parameters. Of the three radon isotopes, mostly ^{222}Rn is usually of our interest, as it appears at a measurable level in our environment because of its relatively long half-life compared with half-lives of the other two isotopes. It has been thus for decades known as one of the potential earthquake precursors (Ulomov and Mavashev, 1971; King, 1978; King, 1986; Ui et al., 1988; Ohno and Wakita, 1996; Planinić et al., 2001; Virk et al., 2001; Yang et al., 2005). When radon is recorded in a water source or soil gas, in the time series of radon concentration, significant deviations, called radon anomalies, from its seasonal or annual average value may be observed. These anomalies are possibly related to seismic events and not resulted solely from the influence of environmental parameters. It is often difficult to identify these anomalies by using simple statistics, therefore recently more advanced methods in data mining have been implemented (Di Bello et al., 1998; Cuomo et al., 2000; Biagi et al., 2001; Negarestani et al., 2001; Steinitz et al., 2003; Planinić et al., 2003; Zmazek et al., 2003, 2005).

In our research, radon has been monitored in several thermal springs (Zmazek et al., 2002a, 2006) and in soil gas in boreholes (Zmazek et al., 2002b) at selected, seismically interesting sites in Slovenia. Radon anomalies were first expressed as deviations of radon concentration from the average seasonal value by more than a multiple of the standard deviation, and then identification of anomalies was improved by applying regression/decision trees within the machine learning programs (Džeroski, 2002). In the 2-year time series of radon concentration, an anomaly (or a swarm of anomalies) has been observed for local magnitude scale (M_L). Unfortunately, some 'false' anomalies have been detected also in the periods without any seismic event. By varying criteria in defining the anomalies, we have been able to reduce the number of false anomalies, but not to get rid of them. Therefore, we recently introduced artificial neural networks (ANN) in data evaluation, aimed at further improving identification of radon anomalies caused by seismic events and not resulted from environmental parameters. This paper shows the results obtained for radon in soil gas and compares them with those previously reported based on the decision trees.

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2. Experimental basis

Since April 1999, in 60–90 cm deep boreholes at six locations in the Krško basin (Fig. 1) radon concentration in soil gas, barometric pressure and soil temperature have been measured and recorded once an hour, using barasol probes (MC-450, ALGADE, France). Other meteorological data, such as air temperature and rainfall, have been provided by the Office of Meteorology of the Slovenian Environmental Agency, and seismic data by the Office of Seismology of the same agency. Boreholes 1 and 4 are located in the Orlica fault zone, at a distance about 4000 m from each other, while the other boreholes are at distances from 150 to 2500 m on either side of the fault zone (Fig. 1). Air temperature and rainfall were measured at a meteorological station, approximately 14 km away from the site. This paper deals only with data from the station 1 (Krško-1), because of the longest time scale of measurements (Fig. 2). The experimental procedure is reported elsewhere (Zmazek et al., 2002b). As often experienced, for earthquakes Dobrovolsky's equation (Dobrovolsky et al., 1979) was used to calculate R_D, i.e., $R_D = 10^{0.43M}$, where M is the earthquake magnitude and R_D the radius of the zone within which precursory phenomena may be manifested (so-called Dobrovolsky's radius in km). Earthquakes for which the distance R_E between the epicentre and our measuring site was equal or less than $2R_D$ have been used in the interpretation.

3. Methodology of data analysis

3.1. Artificial neural networks

An ANN is a well known computational structure inspired by the operation of the biological neural system (Jain et al., 1996). It consists of a set of units (neurons, nodes), and a set of weighted interconnections among them (links). ANN units are simple analog computing devices. They take a weighted sum of input links, decreased by a threshold value, and feed it as an argument to a linear or more often non-linear activation (transfer, squashing) function, which produces a neuron output value.

The organization of neurons and interconnections defines the net topology. In our case, the neurons accept real values (as opposed to those that accept only binary inputs) and are arranged in layers, and the structure is referred to as multilayer perceptron (MLP) which can be regarded as a black box. The inputs are grouped in an input layer, outputs in an output layer and all the other units in so-called hidden layers that "cannot be seen". All links are made among units in different layers from the input side toward the output side of a network. Connections within a layer or from a layer closer to output to layers farther to output are forbidden.

The term backpropagation refers to a training method that uses backpropagation of a network error to compute the gradient of an error function with respect to the network weights. The algorithm repeatedly adjusts the weights to minimize the mean square error between the actual output vector and the desired network output vector. Since the desired (target) output vector is known, this method belongs to a family of supervised learning rules (with a "teacher"). The traditional backpropagation implies a deterministic optimization algorithm called *direct gradient descent*, but can be replaced with other, more advanced methods (Masters, 1995). The weights are changed by an amount proportional to the error gradient. The proportional factor is denoted as a *learning rate*. Usually, the weight changes are corrected by a *momentum* (decay) factor, used to control the velocity of the point in the weight space. Using this, the local minima in the error minimization procedure are more successfully avoided (Rumelhart et al., 1986). Although there exists a relationship between the gain of the activation function, learning rate and initial weights (Thimm et al., 1996), these factors and the net topology are usually chosen either experimentally or using some existing thumb rules. Recently, the genetic algorithm has gotten much attention in the determination of the optimal network parameters.

The ANNs are well established tools for different forecasting problems in different areas, like weather, econometrics, financial, stock prices, material science, with over 40 years of tradition (Zhang et al., 1998). Because of their universal approximator functional form, ANNs also seemed to be a good choice for modelling non-linear dependency of radon concentrations on multiple variables. There exist enormous number of various topologies, training algorithms and architectures, applicable to a class of modelling problems. It is difficult to tell in advance which training rule is the most suitable for a certain problem or which topology would produce the best results. After extensive

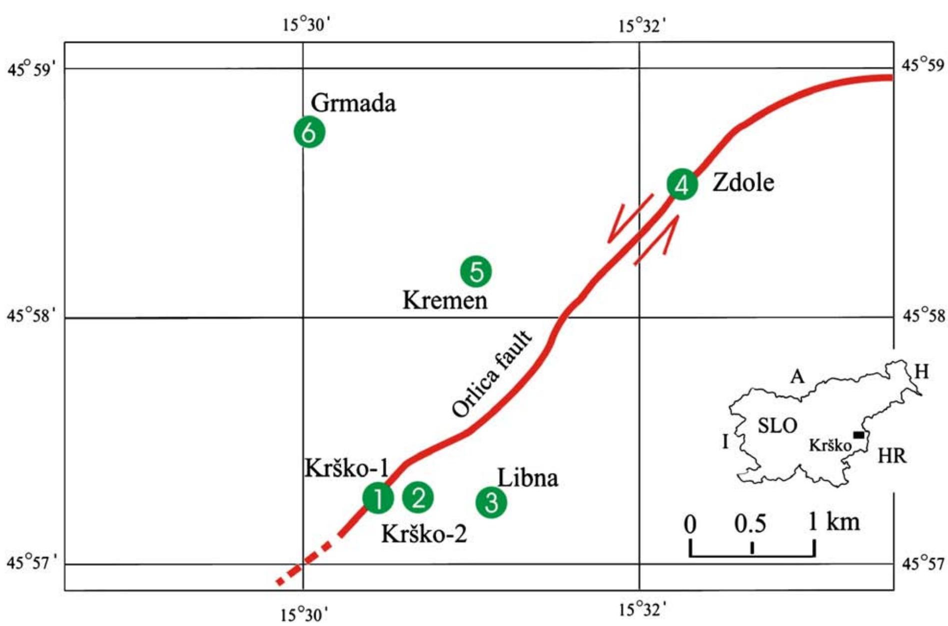

Fig. 1. Map of the Krško basin with locations of radon monitoring stations at the Orlica fault with strike–slip displacement. The insert shows the position of Krško (SLO — Slovenia, I — Italy, A — Austria, H — Hungary, HR — Croatia).