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Estimation of Radon as an Earthquake Precursor: A Neural Network Approach

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Abstract: An artificial neural networks (ANN) approach combined with Fourier Transform based selection of time period in the time series Radon Emission Data has been presented and shown to improve event prediction rates and reduce false alarms in Earthquake Event Identification over the traditional multiple linear regression techniques. The paper presents a neural networks system using radial basis function (RBF) network as an alternative to traditional statistical regression technique in isolating Radon Emission Anomaly caused by seismic activities. The RBF model has been developed to accept and predict earthquakes events based on a known data set of Radon Emanation, Metrological parameters and actual earthquake events. Subsequently, the model was tested and evaluated on a future data set and a prediction rate of 87.8%, if a reduced false alarm was achieved, the results obtained are better than the traditional techniques.

Keywords: Modeling, Prediction, Neural Network, Radon precursor.

INTRODUCTION

In India more than 50% of the land area is seismically active. Any earthquake of M5.5 and above in these areas can cause severe loss of human life and property. It is essential that scientific research based on earthquake precursors be carried out in order to generate earthquake warning sufficiently ahead of the event. There are varieties of parameters like Geo-chemical (Rn and He), Electromagnetic (ULF and VLF) etc., which undergo change at precursory stage of an earthquake. Of these changes, radon emission as a precursory parameter is considered in the paper.

The first evidence of a correlation between radon and earthquake came from Tashkent Basin prior to destructive earthquake in 1966 (Ulamov and Mavashev, 1967). Radon observations revealed many precursory changes in its concentration as far as 1800 km from their respective epicenters (Lomnitz and Lomnitz, 1978; King et al. 1993; Virk and Singh, 1994; Igarashi et al. 1995). The measured radon in soils could be strongly disturbed by meteorological parameters, seasonal factors as well as a deeper phenomenon of seismic activity. Variety of studies which use complex mathematical methods have been done in order to distinguish between the variations of radon caused by the earthquake from those caused by environmental factors (Virk et al. 2000).

The radon precursory data is regarded as being time series, which advances according to time. There are a number of applications of neural network in time series forecasting. The neural network approach provides a good solution to such a problem, because its design is based on training and therefore, no statistical assumptions are required to be made for the source data. They are trained to predict results from examples. They are able to deal with non-linear problems, and once trained can perform prediction at a very high speed.

RADON MEASUREMENT TECHNIQUE

A network of radon recording stations has been established in the highly seismic zone near the Main Boundary Thrust (MBT) in the Himalayas to forecast future earthquakes using radon as a precursor. Recording stations were setup at Guru Nanak Dev University, Amritsar and at Krishi Vishva Vidyalya, Palampur in Kangra Valley of Himachal Pradesh. The fluctuations in near surface and groundwater radon concentration were monitored using both instantaneous and time integrated techniques (Virk, 1986; Virk and Singh, 1992). Track-etch, alpha-logger and emanometry techniques have been exploited for long term, short term and instantaneous data recording respectively.

The present study on radon anomalies has been done in soil-gas at sensitive observation sites in the Kangra and

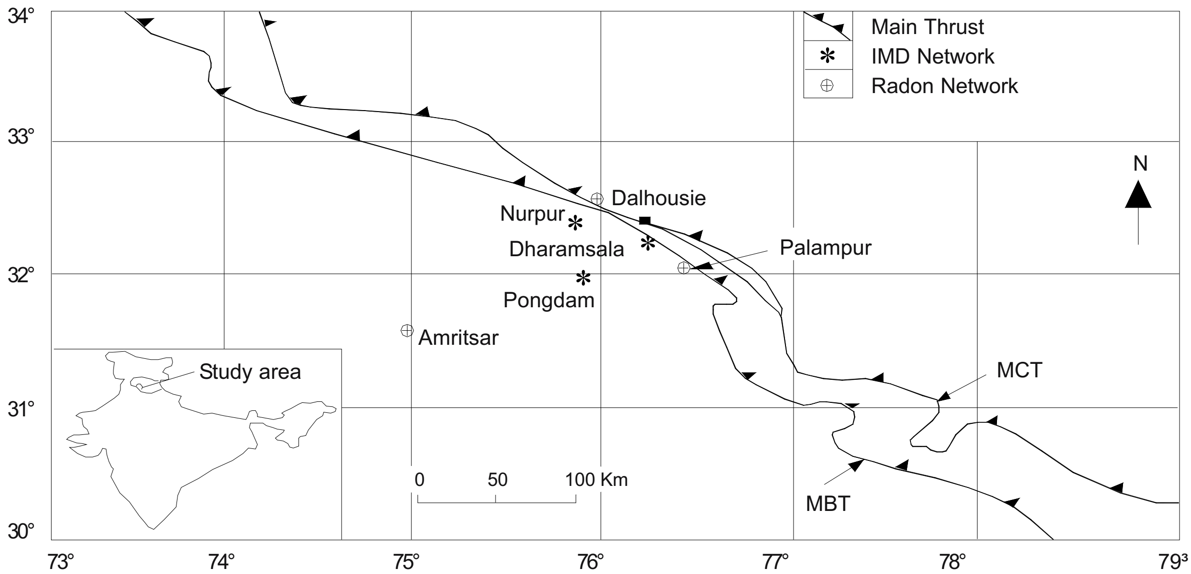

Fig.1. Map showing radon monitoring sites along with IMD network in NW Himalaya (*after* Virk et al. 2000).

Chamba valley, Himachal Pradesh, India (Fig 1). Time series radon concentration data in soil-gas has been monitored and recorded regularly at Palampur and Dalhousie stations since 1992 using radon emanometry. Both Palampur and Dalhousie stations are located in the vicinity of MBT and MCT, the two major thrust faults in the Himalayas. The high micro-seismicity in the Kangra and Chamba valleys in the N-W Himalaya appears to be due to these major thrust faults.

METHODOLOGY

Radon emission is very sensitive to meteorological parameters, seasonal factors as well as a deeper phenomenon of seismic activity. Meteorological and seasonal variations must be isolated for discriminating the seismic induced radon emanation from the overall observed time series.

There are two approaches for the analysis of radon emissions and meteorological parameter effect removal. First is the statistical approach which does regression and correction of radon emissions for the meteorological parameters. The second approach which is presented in this paper is neural network (NN) approach. The results of the both the approaches have been compared in Table 1 and Table 2. The data recorded from June-1994 to May-1996 (Radon Data Source: Department of Science & Technology, New Delhi, Government of India) was used for the network modeling and the data recorded from June-1996 to July-1999 was analyzed by using the created model which takes NN predicted radon and defines the radon anomaly caused by seismic events as the deviation that exceeds the "mean radon level over a pre-defined period" by more than $\pm 1\sigma$, and $\pm 2\sigma$, where σ is the standard deviation for that period.

Regression and Correction of the Measured Radon Approach

In earlier methods event identification was done statistically by the method of regression and correction of radon and the finding the radon anomaly. The approach was based on the well-proved theory that meteorological parameters like temperature, pressure, wind velocity, rainfall and humidity affect the radon emanation from the soil-gas (Virk et al. 2000). The measured radon consisted of the component contributed by the virtue of these parameters. To remove the effect of these meteorological parameters mainly barometric pressure and rainfall were regressed with radon and the effect of these meteorological parameters was removed from the measured "raw" radon data and "corrected" time series was obtained. The mean and standard deviation was computed on a period obtained by applying FFT to the measured ("raw") as well as "corrected" data (Gupta et al. 2007), removing human and subjective factor out of the technique.

Neural Network Approach

An artificial neural network is an information processing system that consists of large number of simple processing elements called neurons. Each neuron is connected to other neuron by means of direct connection with an associated weight, which present information being used by the net to solve a problem. A general neural network is characterized by its pattern connections among the neurons, its method of determining weights and its activation function. The main advantages of the neural network method are learning capability for developing new solutions to problems that are not well defined, an ability to deal with computational complexity, a facility of carrying out quick interpolative reasoning, and finding functional relationship between sets of data. There are varieties of neural network architectures available, which can model time series like Multi-layer perceptrons, Probabilistic neural networks, Radial basis function networks.

In this paper we intend to use the radial basis function as a time series approximation wherein the input data represents data samples of certain past times and the network has only one output, which is the estimated value. RBF networks have a number of advantages over MLPs. First, they can model any nonlinear function using a single hidden layer, which removes some design-decisions about numbers of layers. Second, the simple linear transformation in the output layer can be optimized fully using traditional linear modeling techniques, which are fast and do not suffer from problems such as local minima which plague MLP training techniques. RBF networks can therefore be trained extremely quickly (i.e. orders of magnitude faster than MLPs).

The chosen architecture of Radial Basis Function network is shown in Fig.2. The chosen network has five inputs which are Measured Radon, Meteorological parameters like Temperature, Rainfall, Relative humidity, wind velocity and corrected barometric pressure. Twenty days of data is fed to the network to obtain the estimation of radon on the 21^{st} day. The RBF contained three hidden layers with 100, 13 and 1 hidden neurons and single output which is the estimated radon value.

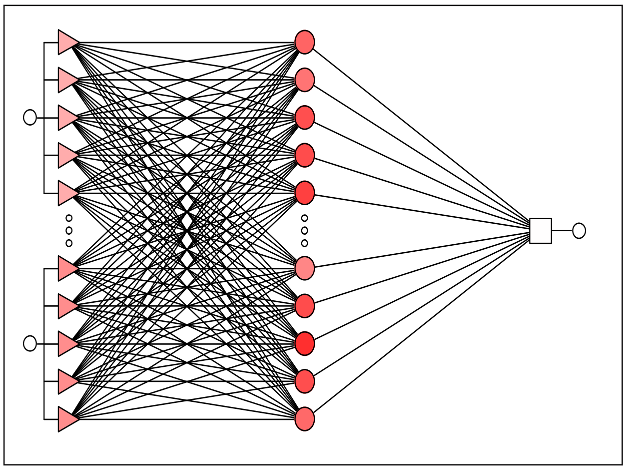

Fig.2. Radial Basis Function network Architecture.

Three cases are presented for the prediction comparison.

In the first case the mean and standard deviations were computed over an annual period and the deviations of "raw", "corrected" and "neural predicted" emission from mean was used to detect the anomaly. The "raw" refers to the actual measured data. The "corrected" data refers to the data in which environmental anomalies are removed using statistical approach.

In the second case the mean and standard deviation calculation period was taken over a period corresponding to the seasons. The seasonal period selected offered better results, but it has a problem that the seasonal periods are manually selected for region, can vary from place to place and not amenable to automation.

In the third case, the mean and standard deviation was computed on a period obtained by applying FFT to the measured "raw", "corrected" data (Gupta et al. 2007), and "neural predicted" data removing human and subjective factor out of the technique. This technique has the advantage that it can be applied automatically to the data of any location and is amenable to computerization and also showed best performance.

RESULTS AND DISCUSSION

Time series Radon concentration data recorded in soil gas at Palampur was analyzed from June- 1996 to July-1999. There were 33 earthquake events reported for this period. The distance between the epicenter and measuring site for all these earthquakes was equal or less than 2D where D being the Dobrovolsky's radius (Dobrovolsky et al. 1979).

In the 33 actual earthquake events, those that were predicted by the algorithm are denoted by TA case: *true anomaly and* others that went undetected are denoted by NA case: *No anomaly.* Anomalies that were not accompanied by seismic event are denoted as FA: *false anomaly*. The duration period for these anomalies was selected to be 10 days before an actual event (Zmazek et al. 2005).

The predicted radon using the Radial Basis Function Network is plotted versus the measured radon for the June 96-May 97 in Fig.3a and for June 97- May 98 in Fig.3b. It may be observed from the Fig.3a and b that predicted radon using the neural network algorithm is following the trend of measured radon. This is not observed in case of sudden peaks which signify the precursor for an earthquake. The Neural network approach is compared with the statistical approach with different time periods of standard deviation.

Case 1: Deviations from Raw, Corrected and neural predicted Radon with the predefined period for mean and

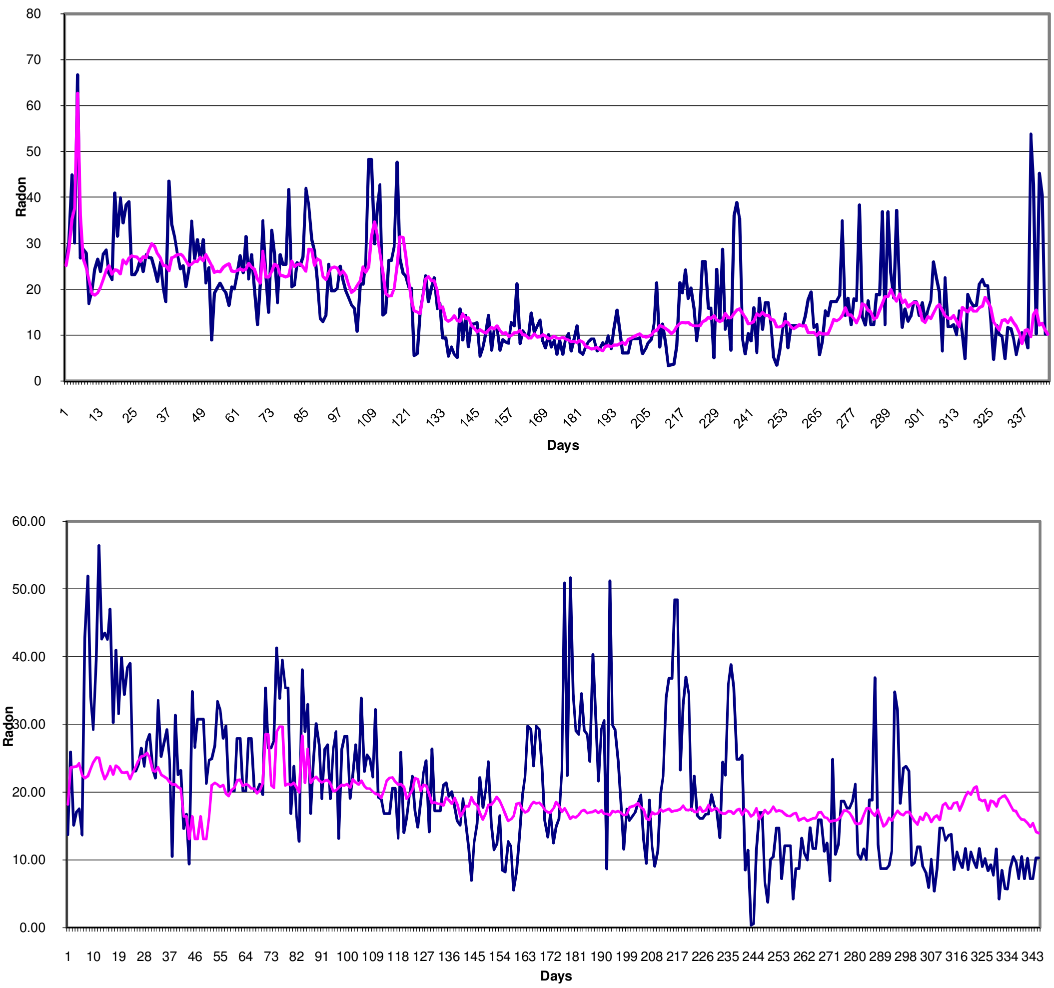

Fig.3. Measured Radon versus the predicted radon for the period **(a)** June 96-May-97. **(b)** June 97-May-98.

standard deviation estimation taken as annual: The annual average value of Radon concentration and standard deviation was calculated for all the three years. It was observed in this case there were 18, 19 and 19 true event predictions in the span of three years for the "raw", "corrected" and "neural predicted" radon out of the total 33 events (Table 1). The false alarms were 28, 37 and 30 respectively for the "raw", "corrected" and "neural predicted" radon respectively. The corrections applied to radon have not made a significant impact on the prediction rate (Table 2).

Case 2 Deviations from Raw, Corrected and neural predicted Radon with the predefined period for mean and standard deviation estimation taken as seasonal: The Radon emanation is enhanced in summer months and is somewhat suppressed during winter. The seasons were divided as June-Sep, Oct-Jan, Feb-May, This selection was based on the assumption that June to September is the main rainy season in the area, October to January being the winter season and February to May being the mild summer season in that area. Thus, the selected period was 120 days corresponding to

Table 1. Summary of TA (True Anomalies) for different techniques

Period	Raw TA/33	Corrected TA/33	NN TA/33
Annual	18	19	19
Seasonal	20	26	25
FFT 40	20	**27**	**28**
FFT 20	25	**27**	**29**

Table 2. Summary of FA (False Anomalies) for different techniques

Period	Raw FA	Corrected FA	NN FA
Annual	28	37	30
Seasonal	35	64	48
FFT 40	32	**23**	**18**
FFT 20	25	**21**	**17**

the seasons starting from June-1996. It was observed in this case there were 20, 26 and 25 true event predictions in the span of three years for the "raw", "corrected" and "neural predicted" radon out of the total 33 events (Table 1). The false alarms were 35, 64 and 48 respectively for "raw", "corrected" and "neural predicted" radon respectively (Table 2).

Case 3: Deviations from Raw, Corrected and neural predicted Radon with the predefined period for mean and standard deviation estimation taken as that calculated using Fast Fourier Transform: The measured value of radon was subjected to Fast Fourier Transform (FFT) and periodicity was worked out by a well-defined algorithm [Gupta et al. 2007]. It was observed that there were two prominent periods of approximately 20 days and 40 days. Average of radon concentration corresponding to the periodicity worked out by FFT was calculated and deviations from the average value were considered as radon anomalies. It was observed in the case of 40 days there were 20, 27 and 28 true event predictions in the span of three years for the "raw", "corrected" and "neural predicted" radon respectively and the false alarms were 32, 23 and 15 respectively for the "raw", "corrected" and "neural predicted" radon respectively.

However, for 20-day period it was observed there were 25, 27 and 29 true event predictions in the span of three years for the "raw", "corrected" and "neural predicted" radon and the false alarms were 25, 21 and 14 respectively for "raw", "corrected" and "neural predicted" radon respectively.

It is observed True Anomaly (TA) is best observed in the case of neural predicted radon as compared with meteorologically "corrected" radon and "raw" measured radon in all cases. Secondly computation of the mean and standard deviation over period given by FFT gives the best result both in high TA and low FA, as compared to the seasonal and annual periods. There is a significant improvement in false alarms in case of FFT period-defined neural network analysis compared to other methods.

CONCLUSION

It can be concluded from the above observations that meteorological parameters such as barometric pressure and rainfall contribute significantly to the radon emissions. For improved event prediction the contribution of these factors has to be removed from measured (raw) data and the corresponding neural network has to be trained to get the estimated value of the radon. The best results are obtained when the mean and standard deviation (used as thresholds in anomaly detection) are computed over a time period obtained by FFT processing of time series of "NN predicted" data. The above-proposed algorithm gives better results than the methods proposed earlier based on radon anomaly.

Algorithm proposed in this paper for Radon emission as precursor has several advantages namely

(i) it has potential of application to any region
(ii) analysis can be computerized, not needing expert perspective.
(iii) has extremely significant improvement in quality of prediction, having low failure rates as compared to existing techniques.

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