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GJCST-D Classification : F.1.1, F.2.1

NEURAL NETWORK ALGORITHMS FOR USING RADON EMANATIONS AS AN EARTHQUAKE PRECURSOR

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Keywords : radon, anomalies, earthquake precursor, neural networks.

I. Introduction

In India more than 50% of the land area is seismically active. Any earthquake in these areas of Magnitude 5.5 Richer Scale and above can cause severe loss of human life and property. The vulnerability of our civilization to earthquakes is rapidly growing, raising earthquakes to the ranks of major threats faced by humankind. About a million earthquakes of Magnitude 2 or more are registered each year worldwide. About a hundred of them cause serious damage and, once or twice in a decade, a catastrophic earthquake occurs. The vulnerability of our world to earthquakes is rapidly growing due to well-known global trends like proliferation of high-risk construction such as nuclear power plants, high dams, radioactive waste disposals, deterioration of the ground and destabilization of engineering infrastructures in megacities, destabilization of the environment, population growth and other factors, including the escalating socioeconomic volatility of the global village.

a) Earthquake Precursory Studies

Earthquakes constitute a source of severe human disasters all around the world that occurs in a relatively short time span of occurrence of an earthquake, and considerable loss of life can be averted if a warning could be issued prior to its occurrence. Consequently, short-term indicators — through the search for precursory signals — have received great attention in the last several decades. As earthquakes are physical phenomena, most techniques used currently with prediction purposes are based on geophysical approaches, including seismology, magnetism, electricity, and geodesy. So, a wide range of methods have been proposed, using the monitoring of parameters such as *b*-values (i.e. the slope of the Gutenberg–Richter law relating the local number of earthquakes and their magnitude), VP/VS-values (ratio of the propagation velocities of P and S seismic waves), coda *Q*, tilt values, self-potential anomalies and electromagnetic data, that allowed to exhibit case by case precursory signals [Varostos and Alexopoulos, 1984]; [Jin and Aki, 1986]; [Molchan and Dmitrieva, 1990]. The most relevant success in this field is probably the successful prediction of the February 4, 1975 magnitude 7.3 earthquake of Haicheng (China), on the basis of multiple precursory phenomena.

In India, earthquake precursor related research was started about three decades back and studies were mostly confined to seismological parameters investigations/observations. Though, the seismic gap hypothesis which proposes that the probability of a large earthquake in an individual fault segment is greater for those segments that have not slipped in a long time, has already been applied to Himalaya on the basis of energy release, micro-earthquake activity and seismicity patterns and three well known seismic gaps have been identified in the Indian Himalayan region namely; (1) Himachal gap in Himachal Pradesh, (2) Central gap in Central Himalaya and (3) Assam gap in Northeast Himalaya [Srivastava,1973]; [Srivastava and Rao, 1991]; [Khattri and Wyss, 1978]. After successful medium term forecast of 1988 M 7.3 earthquake in NE Himalayan region [Gupta and Singh, 1986], there was a lull period for quite some time. The first short term forecast of August 30, 1986 earthquake of M 5.0 was made by [Gupta et. al., 2005]. This forecast was based on the nucleation pattern. Subsequently, several such forecast were made for Koyna region like 13 November 2005 M 4.0, 26 December 2005 M 4.2 and 17 April 2006 M 4.7 based on the nucleation process [Gupta et.al., 2007].

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b) Radon in Soil Gas: Literature Review

The first evidence of a correlation between radon and earthquake came from observation of radon concentration in the mineral water of the Tashkent Basin prior to the destructive earthquake of 1966 [Ulamov and Mavashev, 1967]. Radon observations, both in soil gas and in ground water revealed many precursory changes of radon emission levels [Lomnitz and Lomnitz, 1978[38]; Virk, 1993; Igarashi et al., 1995]. The effect of meteorological parameters was also analyzed by calculation the correlation coefficients and radon anomalies were found using the standard statistical procedures .The differentiation of radon emissions due to earthquakes from those due to effect of meteorological parameters on the measured radon concentrations were studied by [Wattananikorn, 1998].Observations of radon have also been part of the international prediction projects in the Iceland test area. Significant pre-earthquake changes were found and discussed and described in [Stefansson, 2011].

II. Neural Network Algorithm for Radon Emanations Estimate

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. The statistical algorithm involves regression of meteorological parameters with measured radon. The regression equations thus obtained are used to find corrected radon time series. In case of neural networks the regression step is avoided. Hence a neural network model can be found which can learn the behavior of radon with respect to meteorological parameter in order that changing emission patterns may be adapted to by the model on its own. The output of this neural model is the estimated radon values. This estimated radon value is used to decide whether anomalous behavior of radon has occurred and a valid precursor may be identified.

There are varieties of neural network architectures available, which can model time series like Multi-layer perceptrons, Probabilistic neural networks, and Radial Basis function networks. Initially different neural network architectures were tested. Fig 1(a-b) shows the multi layer or MLP neural network architectures which were tested for the estimation of radon. The nomenclature followed for naming the neural network in the figure is <Type of NN>< Input> : <L1><L2><L3> :< Output>. The Fig. 1(a) indicates MLP s20 5:100-3-1:1 which indicates that the type of neural network is Multi Layer Perceptron with five inputs, three hidden layers with 100, 3 and 1 hidden neuron and one output. Fig. 1(a-b) also indicates the training performance, selection performance and test performance.

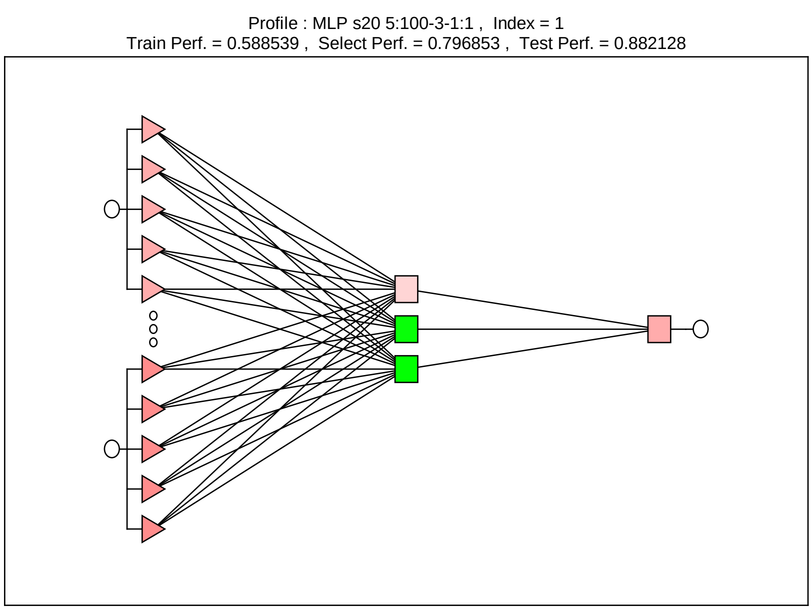

Figure 1 (a)

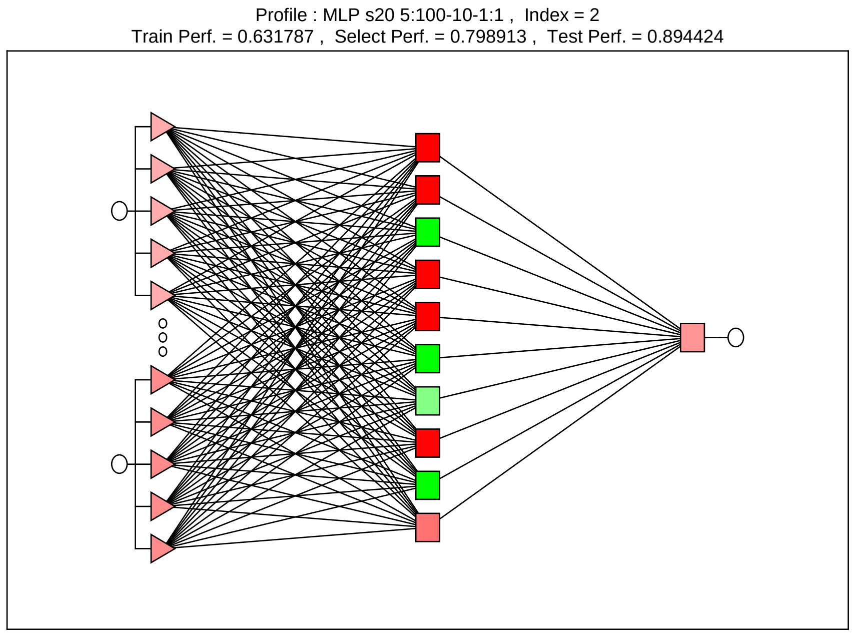

Figure 1 (b)

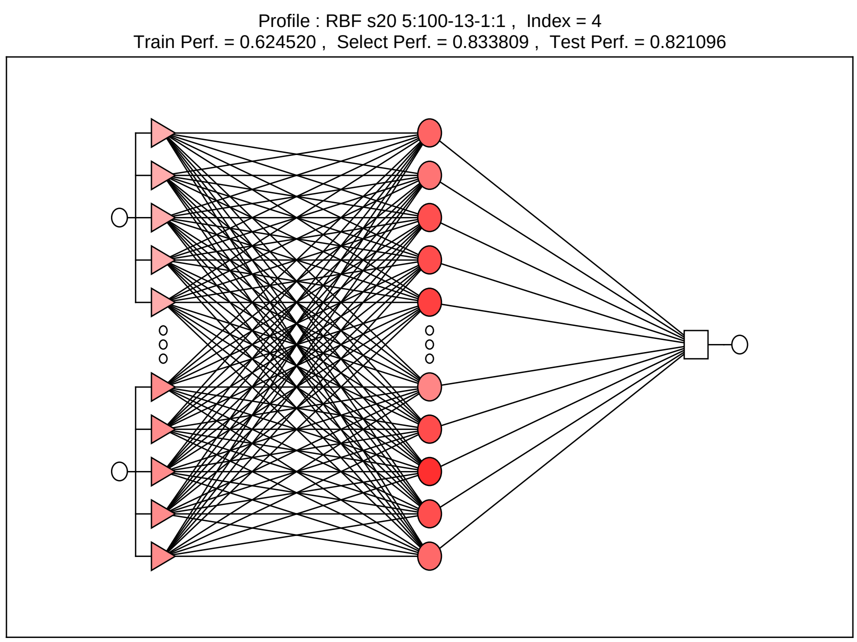

Figure 1 (c)

The inputs to the neural network are Measured Radon, Meteorological parameters Temperature, Rainfall, Relative humidity, and barometric pressure. The selection performance for both the MLP based neural network architectures is not satisfactory. Apart from MLP based neural networks radial basis neural networks are also tried. 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. The comparison summary for different networks is presented in table 1.As shown in the table different training methods are employed for these two chosen architectures. For MLPs based neural networks Back Propagation (BP) and Conjugate Gradient descent (CG) are used. For radial basis neural network K-Means (KM) is used for centre assignment, K-Nearest Neighbor(KN) for deviation assignment and

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Pseudo Invert (PI) is used for linear least squares optimization.

Index	Model Summary Report (traindata in nnmodeling.stw)							
	Profile	Train Perf	Select Perf	Test Perf	Train Error	Select Error	Test Error	Training
1	MLP s20 5:100-3-1:1	0.588539	0.796853	0.882128	0.125560	0.213866	0.187257	BP100,CG40
2	MLP s20 5:100-10-1:1	0.631787	0.798913	0.894424	0.141368	0.213025	0.188681	BP71
3	RBF s20 5:100-12-1:1	0.617619	0.843557	0.807473	0.064166	0.113283	0.085103	KM,KN,PI
4	RBF s20 5:100-13-1:1	0.624520	0.833809	0.821096	0.064883	0.113147	0.086312	KM,KN,PI
5	RBF s20 5:100-15-1:1	0.631014	0.812851	0.798642	0.065557	0.110153	0.084371	KM,KN,PI

Table 1

The K-means algorithm assigns radial centers to the first hidden layer in the network if it consists of radial units. K-means assigns each training case to one of K clusters (where K is the number of radial units), such that each cluster is represented by the centroids of its cases, and each case is nearer to the centroids of its cluster than to the centroids of any other cluster. It is the centroids that are copied to the radial units. The intention is to discover a set of cluster centers which best represent the natural distribution of the training cases. The radial basis function is indented to be used 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.

The chosen architecture of Radial Basis Function network is shown in Fig. 1 (c). The architecture is chosen based on the selection performance of different networks. The chosen network has five inputs which are Measured Radon, Meteorological parameters like Temperature, Rainfall, Relative humidity, and corrected barometric pressure. The RBF contained three hidden layers with 100, 13 and 1 hidden neurons and single output which is the estimated radon value. The estimation of radon was done for different time periods starting from 10 days going up to 360 days. The radon was predicted for the subsequent day of period selection. If 20 days data is fed to the network then the estimated radon value is for 21st day. The neural network estimated radon value is compared with the measured value to find out the anomaly.

Four cases are presented for the prediction comparison for the above described algorithm:

In the first case the estimation of radon was done over an annual period and the deviations from “raw” radon of the “neural predicted” radon was used to detect the anomaly. The “raw” refers to the actual measured data.

In the second case the estimation of radon 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 estimation of radon 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.

In the fourth case the estimation of radon was done on all other randomly varying periods. The results of all the above cases were compared with the results of statistically corrected radon results.

a) Results and Comparison of Proposed Neural Network algorithm

The predicted radon using the Radial Basis Function Network is plotted versus the measured radon for the June 96-May 97 in Fig. 2 and for June 97- May 98 in Fig. 3. It may be observed from the Fig. 2 and Fig. 3 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.

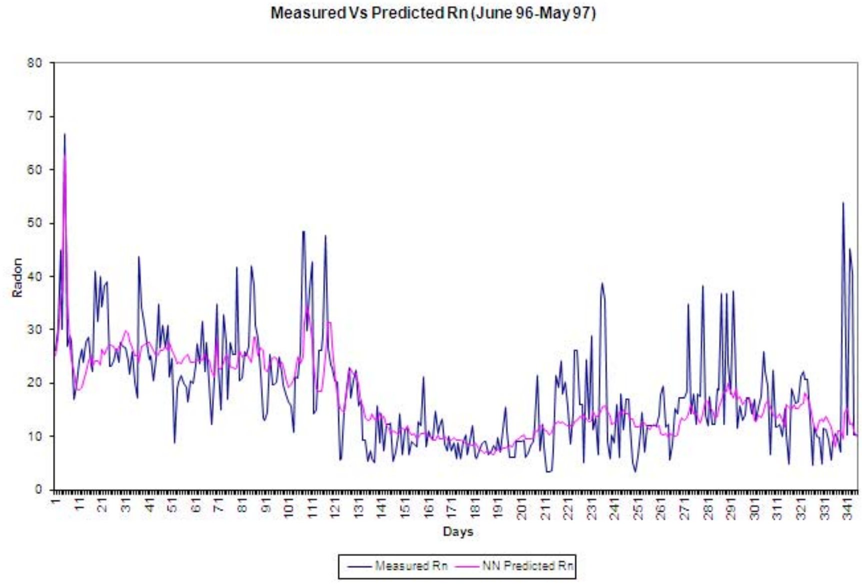

Figure 2

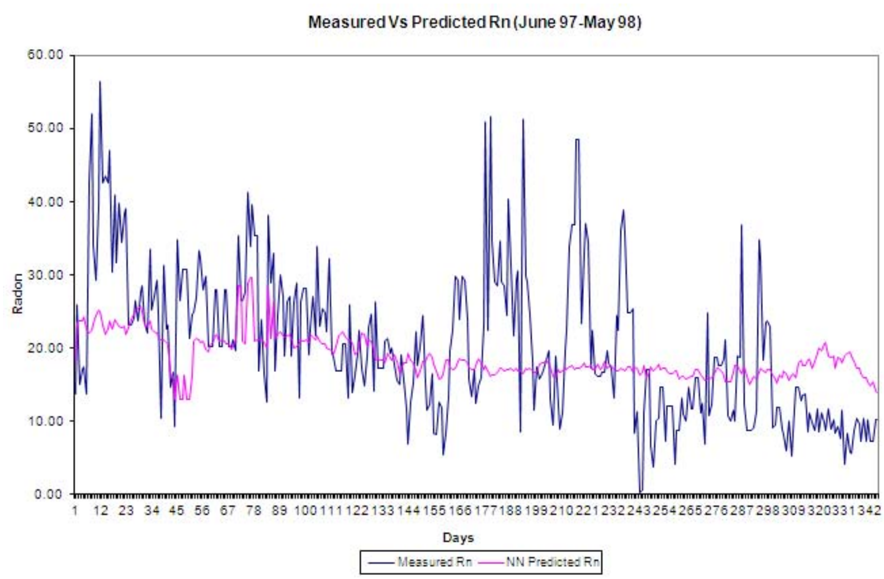

Figure 3

Case 1: In the first case the 360 days of data samples were fed to the neural network. 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 2). The false anomalies were 28, 37 and 30 respectively for the "raw", "corrected" and "neural predicted" Radon respectively. The use of neural network for estimating the radon value has not made a significant impact on the prediction rate (Table 3). It was observed that there was no improvement in the event prediction i.e. true anomalies (TA) rate but there was a reduction in the false anomalies (FA). This analysis proved that the neural network was able to learn the meteorological parameter effect of radon, better than regression method used earlier.

Period	Raw TA/33	Corrected TA/33	NN TA/33
Annual	18	19	19
Seasonal	20	26	25
FFT 47	20	27	28
FFT 32	25	27	29

Table 2

Period	Raw FA	Corrected FA	NN FA
Annual	28	37	30
Seasonal	35	64	48
FFT 47	32	23	18
FFT 32	25	21	17

Table 3

Case 2: 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 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 2). The false anomalies were 35, 64 and 48 respectively for "raw", "corrected" and "neural predicted" radon respectively (Table 3).

Case 3: In this case periodicity was taken corresponding to the periodicity worked out by FFT. The same has been discussed in detail in chapter 3.It was observed in the case of 47 days there was 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 anomalies were 32, 23 and 15 respectively for the "raw", "corrected" and "neural predicted" radon respectively. However for 32-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 anomalies were 25, 21 and 14 respectively for "raw", "corrected" and "neural predicted" radon respectively. **It was observed that there was about 6% improvement in the event prediction rate i.e. true anomalies (TA) as compared to the statistically corrected radon. The false anomalies (FA) were also found to be further reduced** [Gupta et. al., 2011].

Case 4: The above analysis represents three specific cases in which specific periods were taken which ranged from annual, seasonal and selection based on Fast Fourier transform technique. It was thought to consider all the time periods starting from 10 days to 360 days. The calculated anomalies were then plotted. Fig 4 shows the three kinds of anomalies for period varying from 10 days to 360 days. The values are calculated as a percentage of each anomaly over the total anomalies observed. **It is observed from the graph that the prediction rate of the anomalies is highest in the range of periods defined by FFT also. This proves the using FFT technique to calculate the time period gives most effective results.**

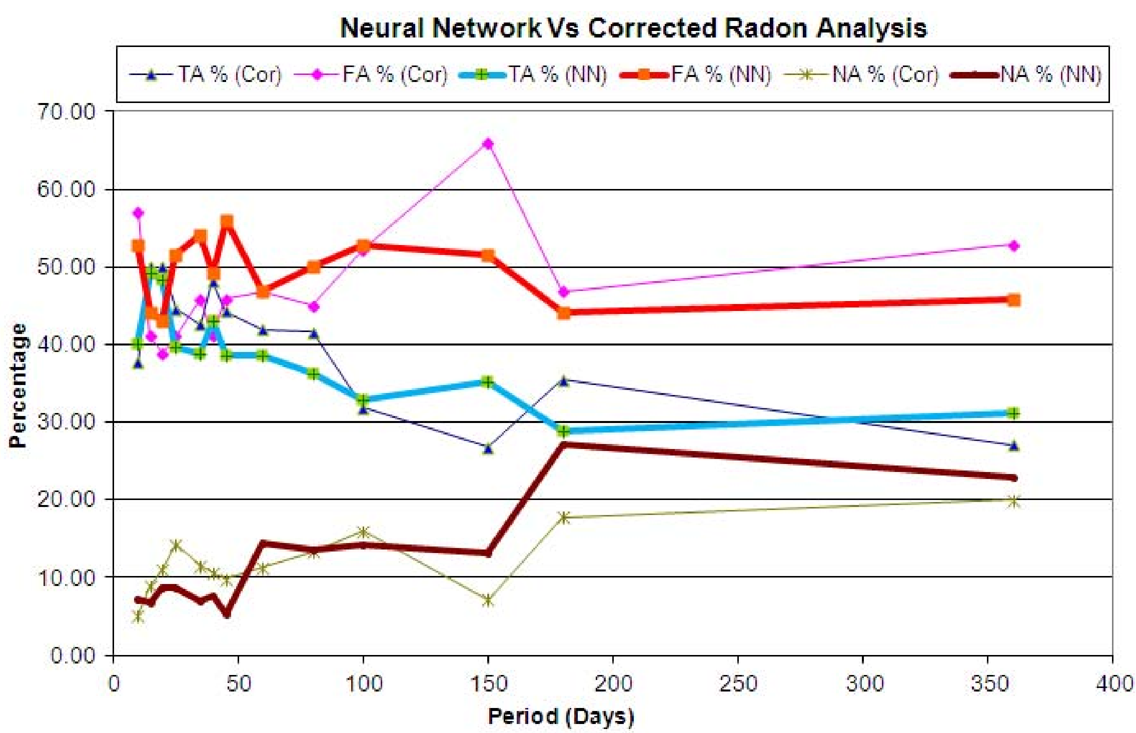

Figure 4

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 anomalies in case of FFT period-defined neural network analysis compared to other methods.

b) Neural Network Algorithm for Probabilistic Event Estimate

The neural network algorithm discussed above gives the radon estimates and further by using these estimates for finding out the anomalies has definitely given better result as compared to statistical algorithm. There are two basic aspects that need to be improved in this algorithm. Firstly, there are huge numbers of false anomalies which are undesirable. Secondly, radon emanations depend on not only earthquake build up but many other geophysical activities. Also as neural networks have the ability to learn complex non linear patterns inside the data which may not be identified by any statistical approach. Hence, another algorithm of probabilistic estimation of earthquake events is experimented upon. In this algorithm probabilistic neural network architecture is chosen. The probabilistic neural network is predominantly a classifier which maps the input pattern to a number of classifications. As the models involve classification the regression of the data is not done. The measured radon values with meteorological parameters are presented a continuous input. The earthquake event was presented to the network as a categorical output. The duration period for these events was selected to be 10 days before an actual event [Zmazek et. al., 2005]. This not only increased the data set which otherwise is very minimalistic, but it also increased the span of probability output by the network. The chosen network is a probabilistic neural network. The chosen network is shown in the Fig. 5.The result for the above chosen network is presented in Fig. 9. It was observed that although there was not much improvement in the event identification i.e. true anomalies (TA) (Table 4) but the probabilistic neural network reduced the false anomalies (FA) to zero (Table 5).

Secondly, the output of the neural network is event estimation. The inputs presented to the neural network are measured radon and all the meteorological parameters. The primary advantage of this network is that raw measured radon may be presented to the network without any corrections. The neural network takes care of the met corrections on the radon.

Period	Raw TA/33	Corrected TA/33	NN TA/33	PNN TA/33
Annual	18	19	19	19
Seasonal	20	26	25	26
FFT 47	20	27	28	28
FFT 32	25	27	29	29

Table 4

Period	Raw FA	Corrected FA	NN FA	PNN FA
Annual	28	37	30	0
Seasonal	35	64	48	0
FFT 47	32	23	18	0
FFT 32	25	21	17	0

Table 5

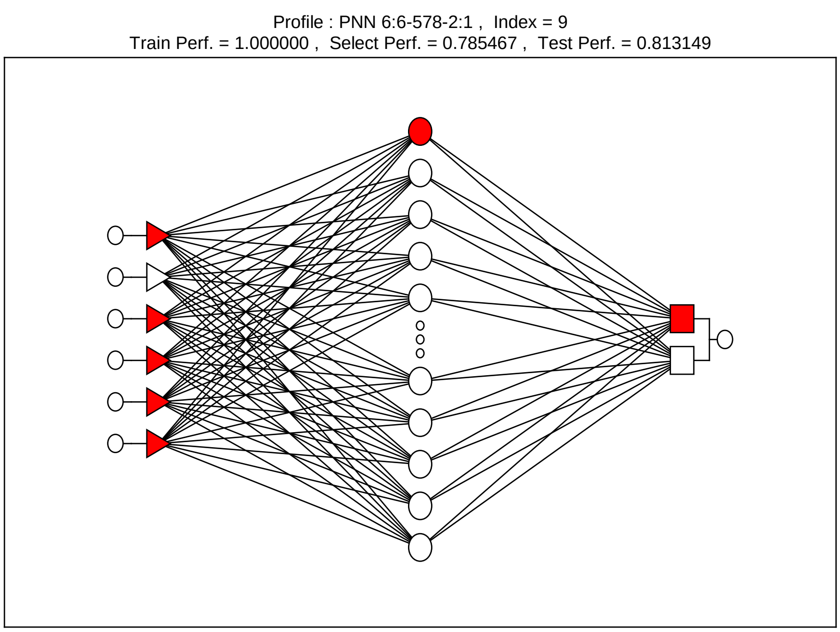

Figure 5

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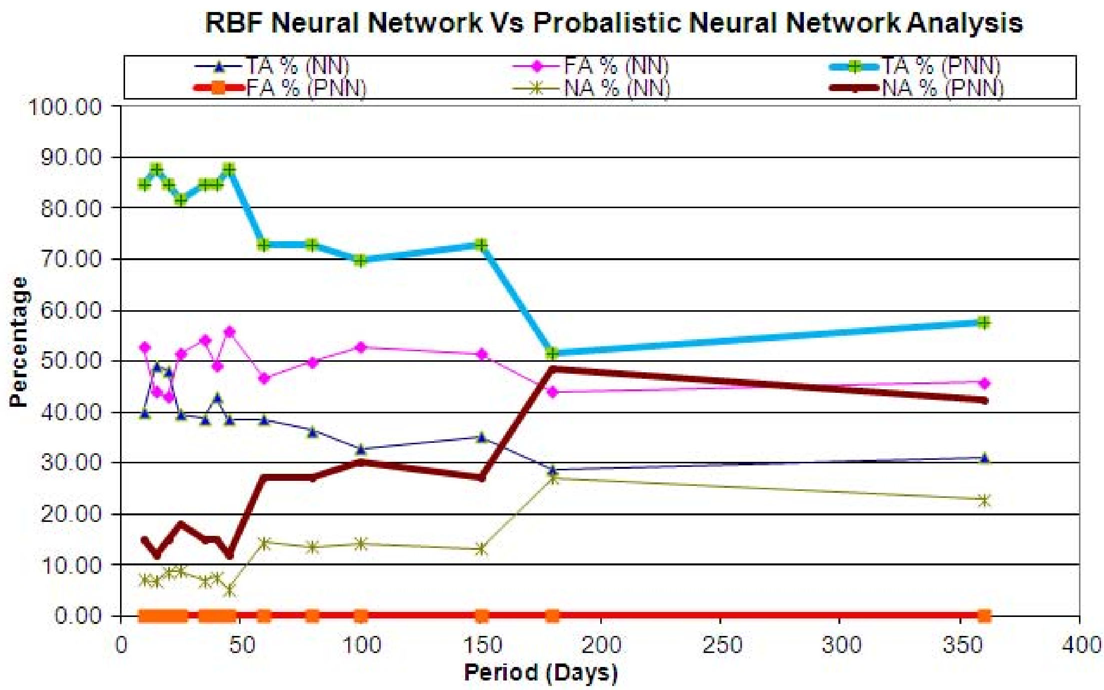

Figure 6

III. Conclusion

Emission of Radon is strongly influenced by day to day meteorological conditions as well as seasonal. Different authors have sought to tackle seasonal variations by normalizing the raw emission values over a local "time period" of observation (varying from days to may be few months or a season) as a way of tackling the periodic variations in the mean emitted value. The day to day meteorological influences on emitted radon have been tackled by some form of regression / corrections on raw data of emission based on measured meteorological parameters like humidity, temperature, pressure etc. There is no uniformity in the methods reported in literature to tackle daily and seasonal influences and no specific method of comparing efficacy of prediction is available.

Neural Network algorithm have been worked out by incorporation of FFT based time period and methods of regression. Additionally, Probabilistic Neural Networks that take all possible measured data (like emitted radon, meteorological conditions) as inputs and focus on event (earthquake) as final output, is also used wherein nonspecific time period or regression is required. The two algorithms are compared by using TA (True anomaly) and FA (False anomaly) on the same basic radon data and the improvement in prediction between the algorithms is clearly brought out.

In this paper it is shown that a period arrived at by applying FFT to annual radon emission data gives improved results. Further the day to day influences of meteorological conditions have been sought to be removed via neural network techniques.

1. It can be concluded that the use of neural networks for characterization and evaluation of radon anomalies gives improved results on account of their known ability to model more complex dependency. The paper has contributed by showing that better dependency modeling reduces FA. It not only shows the extent or scope that is there in improving physical models but also provides better prediction in the interim period as compared to statistical algorithm. The algorithm used automatically models meteorological parameter effects. The event prediction i.e. true anomalies (TA) in this case showed an improvement of 6% as compared to statistical technique and it further reduces the false anomalies (FA).
2. It can be concluded that probabilistic neural network (PNN) algorithm which directly gives event as an output from raw data on radon emission gives no false anomalies and event prediction is also at par with earlier neural network technique. Use of probabilistic neural network also shows that the threshold levels used in precursors also have a dependency that is not clearly understood, and hence the PNN by bypassing the simpler regression and threshold models gives lowest FA of all the three algorithms.
3. It can be concluded that algorithms proposed in this paper for earthquake predictive modeling has several advantages namely:

   i. The algorithms are also highly amenable to computerized implementation.

ii. They algorithms offer options of low to nil manual selection and/or specialized perception of the phenomenon.
iii. Due to (b) above they have better potential of being applied at newer locations.
iv. They automatically take into account regional average of the emitted radon and its day to day variations caused by non-tectonic phenomenon.

Acknowledgements

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