Nonlinear reply of radon and deterministic chaos

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Abstract: Many studies have been achieved in applied sciences on the earthquake prediction by researchers. The chaotic non-linear structural behaviour of earthquakes is well known. In order to understand the formation of seismic activity it is extremely important to record the continuous measurements of the soil radon gas (^{222}Rn). In this study, 2976 data of ^{222}Rn are used and the chaotic time series analysis is applied to ^{222}Rn data from the soil. Chaos theory provides a structured explanation for irregular behavior of ^{222}Rn and gas anomalies in systems that are not stochastic. Lyapunov exponents and correlation dimension method are used to show the existence of chaos time series. Chaotic behavior of ^{222}Rn has been showed. Application of methodologies is achieved for Gölcük Region, İzmit, Turkey, where it is seismically very active.

Keywords: Chaotic time series analysis; Chaotic modeling; Radon measurement; Chaos analysis.

1. Introduction

^{222}Rn exists from the layers of Earth and is created by the uranium deposits source in nature. Certain soils and rocks especially contain high levels of uranium, which is natural deposit of radon. The uranium is rich in structures like granite, phosphate, shale and pitchblende. Relations between ^{222}Rn-earthquake and movement of ^{222}Rn in the Earth layers and in the atmosphere have been searched serious [1, 2, 3, 4 and 5]. ^{222}Rn has a half-life of 3.82 days and it is an α-emitting noble gas, which is produced in the radioactive decay series of ^{238}U. ^{222}Rn tends to migrate from Earth layers to the surface of the Earth. The migration rate of ^{222}Rn, which is non-linear, depends on many factors such as the dispersal of the uranium in the soil and bed rock, porosity of soil, humidity, micro cracks, granulation, and such [6].

Okabe [1956] has indicated radon as an earthquake precursor and radon changes in atmospheric near surface and showed a favorable correlation with seismic activities. On the other hand, anomalously high radon concentrations of ground

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water have been associated with fault lines [7]. Radon is easily soluble in water and it diffuses into the groundwater and spring waters.

High concentration of radon is often found in soils overlying highly fractured rocks such as fault lines. Radon emanation increases during an earthquake [8, 9]. Radon levels, which are correlated with meteorological and hydrological data, and they are used successfully in the earthquake forecasting researches [10, 11].

In this study, 2976 data of the soil ^{222}Rn gas are used and the chaotic time series analysis by considerations of Lyapunov exponents and correlation dimension methods. The chaotic behavior of the ^{222}Rn concentration levels is determined. Finally, the results of the methodologies are achieved for Gölcük Region (Turkey).

2. Methodology and Research Area

The methodologies which are used in this study are based on the chaos theory. It is aperiodic long-term behavior in a deterministic system that exhibits sensitive dependence on initial condition and disorder behaves in an unexpected way [12]. Likewise, it depends on structure of the system as well as by certain parameters and is usually unstable, complex and non-linear systems are emerging [13].

Determination of the chaotic behavior in the natural events' behaviors is very difficult; therefore, chaos theory is a suitable tool to show the characteristic of the dynamical system.

The chaos methodologies are applied to data recorded at Gölcük Region located on the North Anatolian Fault Zone (NAFZ). ^{222}Rn data are recorded between from 01/05/2006 to 31/05/2006 dates. It is continuously measured from the soil at 15 min intervals for a month.

3. Results and Discussions

3.1. Chaotic Time Series Analysis

Chaotic time series are unpredictable systems. These systems contain large complexity. Prediction of non-linear time series is an available method to appraise characteristic of dynamical systems [14].

Chaotic time series analysis methods are most enforceable in cases where the data include nonlinearity. The first of these analysis methods is obtained as the degree of non-linear positive Lyapunov exponents [15].

If these methods display irregular or unpredictable behavior, then it is called chaotic. On the contrary, it is called non-chaotic. Fig. 1 shows the time series of chaotic behavior of ^{222}Rn data taken from Gölcük Region on NAFZ. Non-linear time series analysis starts from measured experimental time series of $x_1(t), x_2(t), \Lambda, x_n(t)$, at n points. The same analysis provides various tools to determine the temporal structures embedded in the time series.

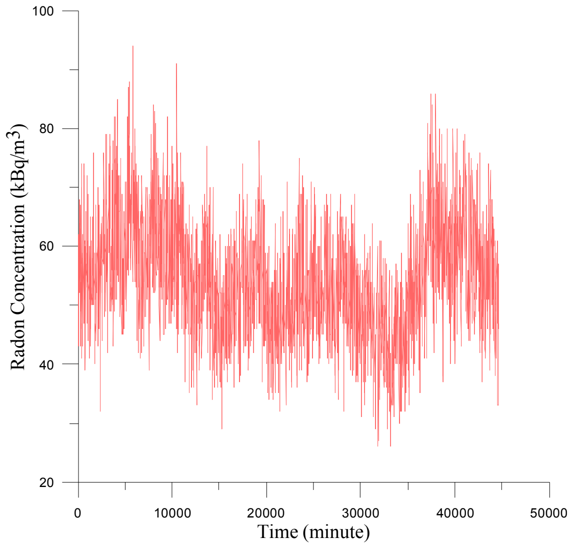

Fig. 1. Time series state variable for chaotic behavior

3.2. Lyapunov Exponent

Lyapunov exponents can be defined as the exponential increase or decrease of minor perturbations on an attractor. Largest Lyapunov exponent is one of the most practical methods to define chaotic behavior in a system [16]. The basis of Lyapunov exponent is very close to each other to monitor both the starting point, which is based on very different trajectories. Its sign gives information about the system dynamics. When exponential value is positive, system indicates chaotic behaviours. This condition, on initial conditions of the system, shows sensitive dependence [17]. The largest Lyapunov exponent can be anticipated in accordance with the algorithm Wolf et al. [18]. These applications are valid between neighboring points in the reconstructed phase space algorithm. In the following, the results have been shown concerning the maximum Lyapunov exponents (L_{max}), where $t \to \infty$, $d(0) \to \infty$ and $d(t)$, and hence, show the difference between two measurements. Largest Lyapunov exponent is calculated according to the following expression. The result is given for the ^{222}Rn data in Fig. 2.

$$L_{max} = \lim \left[\ln \left[\frac{d(t)}{d(0)} \right] \right], \quad (1)$$

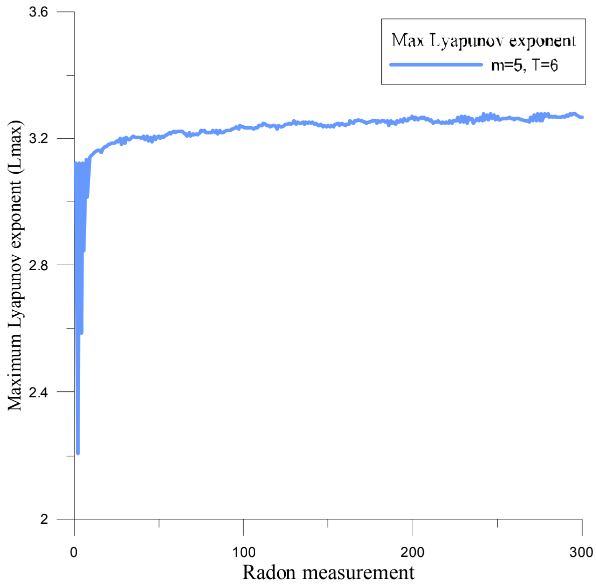

Fig. 2. Lyapunov exponent for ^{222}Rn (m: embedding dimension; τ: delay time)

3.3. Hurst Exponent

Hurst exponent is used to predict from time series [19]. Hurst exponent coefficient is an additional statistical measure necessary for the classification of time series. Hurst exponent calculation is explained also through the Rescaled range, R/S analysis, where R is the range of the accumulated data and S is the standard deviation. This exponent, H, can change between 0 and 1. Its calculation is possible from the discrete time series data set $\{x_t\}$ of dimension N by computing the mean, $\bar{x}(N)$ and standard deviation, $S(N)$ leading to,

$$\bar{x} = \frac{1}{N}\sum_{t=1}^{N} x_t \tag{2}$$

and

$$S(N) = \left[\frac{1}{N}\sum_{t=1}^{N}(x_t - \bar{x}(N))^2\right]^{1/2} \tag{3}$$

respectively. Range of cumulative departures of the data is given by $R(N) = \max\{X(n,N)\} - \min\{X(n,N)\}$

Finally, the Hurst exponent can be calculated as follows,

$$\langle R/S \rangle \cong (n)^H \tag{4}$$

If Hurst exponent is equal to 0.5, then it shows a random walk. A Hurst exponent between 0.5 and 1 proves the presence of chaos in the system. With the data at hand, it is computed as 0.56 for ^{222}Rn data from Eq. 4 and the results are given in Fig. 3.

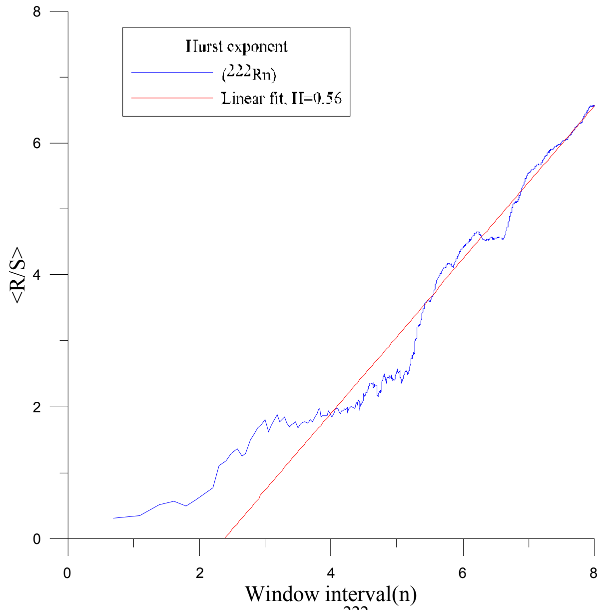

Fig.3. Plot of <R/S> for ^{222}Rn time series

3.4. Correlation Dimension

Correlation dimension is used to determine the degree of chaotic behaviour in a signal or time series. That is, correlation dimension, D_2, aids to determine whether a signal behaves like a random or chaotic distribution. The algorithm, measure of D_2 has presented by Grassberger- Procaccia [20]. These dimensions need to compute the correlation integral. Correlation integral function $C(r)$ can be defined as follows,

$$C(r) \approx \lim_{N\to\infty} \frac{1}{N^2} \left\{ \left| x_i - x_j \right| \leq r \text{ the number of pairs } (i,j) \text{ which statement} \right\} \tag{5}$$

$$C(r) = \lim_{N\to\infty} \frac{1}{N^2} \times \sum_{i=1}^{N} \sum_{j=i+1}^{N} H(\left| x_i - x_j \right| \leq r) \tag{6}$$

The distance between two units with (such as, x_i and x_j) Euclidean definition can be computed as,

$$\left| x_i - x_j \right| = \sqrt{\sum_{k=1}^{m} (x_i(k) - x_j(k))^2} \tag{7}$$

H is the Heaviside step function, which can be expressed as follows.

$$H(x) = \begin{cases} 1, & x \geq 0, \\ 0, & x \leq 0, \end{cases} \quad (8)$$

If the system is chaotic, then D_2 will be the largest value. Kaplan and Yorke study showed correlation of Lyapunov exponents of information dimension [21]. D_2 can also be calculated as follows.

$$D_2 = \lim_{r \to 0} \frac{\log C(r)}{\log(r)} \quad (9)$$

In this study, one can draw $\log C(r)$ as a function of $\log(r)$ and compute D_2 from the slope of a linear fit. Embedding dimensions corresponding to the correlation dimensions for a period of chaotic deterministic process are shown in Figure 4. Also, for ^{222}Rn correlation dimension, D_2, is given in Fig. 4. Time scale of dynamical system is similar to the D_2 values' mutual predictions. Values of the embedding dimension are given resource about the change of $C(r)$.

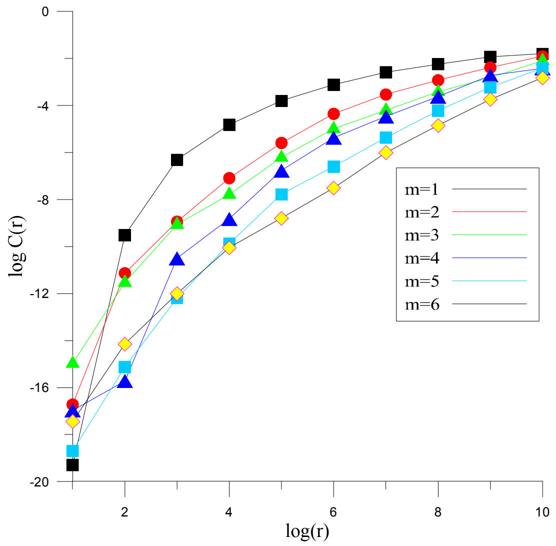

Fig. 4. The estimate of correlation dimension for ^{222}Rn time series

4. Conclusions

Natural and geophysical observations are not regular usually. Chaotic analyses are useful tools to describe the natural irregularity. In this study, they are used as chaotic methods. The non-linear behaviour of ^{222}Rn in the Earth layers is showed. The chaos methodologies in order to show non-linear behaviour of

^{222}Rn are applied to ^{222}Rn data taken from the Gölcük Region on the North Anatolian Fault Line. The soil ^{222}Rn gas, which propagates from the fault lines, has a nonlinear characteristic.

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