Nonlinear Analysis by Using Artificial Neural Networks of Radon Gas (^{222}Rn) Time Series in Kozan, Adana and Osmaniye, Turkey

Miraç Kamışlıoğlu[1], Fatih Külahcı[2], Fatih Özkaynak[3], and A. Bedri Özer[4]

[1,2]Department of Physics, Faculty of Science, Nuclear Physics Division, Elazig, 23119, Turkey.
(E-mail: m.kamislioglu@gmail.com;fatihkulahci@gmail.com)
[3]Fırat University, Department of Software Engineering, Faculty of Technology, 23119 Elazig, Turkey.
(E-mail: ozkaynak@firat.edu.tr)
[4]Department of Computer Engineering, Faculty of Enginering, Fırat University, Elazığ, Turkey.
(E-mail:bedriozer@firat.edu.tr)

Abstract. The artificial neural network (ANN) approximation is a non-linear black box model. This approach can use for modelling of time series of radon gas (^{222}Rn). The ANN methodology was used for determining of time series, which have been used for earthquake prediction studies. The traditional model applications can be complexed sometimes for nonlinear systems. Determining of the characteristic behaviours of the time series are very hard. On the other hand, the formation of seismic activity is highly important to record the continuous measurements of the soil radon gas (^{222}Rn). The chaotic time series analyses methods explain to irregular behaviours of ^{222}Rn gas in the dynamic systems, which are not stochastic. Lyapunov exponents' method is used to indicate the existence of chaos time series. Application of methodologies is achieved for Kozan, Adana and Osmaniye Regions in Turkey, where it is seismically very active.

Keywords: Chaos, Nonlinear time series analyse, Radon, Earthquake, Artificial Neural Network.

1 Introduction

Natural and geophysical observations are not regular usually. Earthquake occurrence are considerably complex and it has incomprehensible a structure.
During the seismic formation changes many parameters. One of these parameters is ^{222}Rn gas. It is occurred by natural radioactive decay chains in the Earth's crust. Soil and rocks contain high level ^{238}U as natural source of ^{222}Rn gas. ^{222}Rn gas has 3.82 days half-life and is a noble gas emits alpha particles. Its

Received revised: 12 September 2016 / Accepted: 23 October 2016

ISSN 2241-0503

concentration levels are affected from environmental parameters and geologic conditions [1, 2]. Radon concentrations can arise during earthquake or before earthquake [3]. There are various studies dealing with the measurements of radon in gas emanating from the ground along active faults which may provide useful signals before seismic events [4, 5].

Chaotic analyses are useful tools to describe the natural irregularity. In this study, we have used the chaotic methods and ANN. The non-linear behavior of ^{222}Rn in the Earth layers has been showed. The chaos methodologies are applied to ^{222}Rn data taken from the Kozan, Adana and Osmaniye Regions near the East Anatolian Fault Line in order to show non-linear behavior of ^{222}Rn. The measuring stations are located on the Southern Turkey that is one of the Mediterranean regions. The soil ^{222}Rn gas, which propagates from the fault lines, has a nonlinear characteristic. The nonlinear prediction method with nearest neighbor algorithm is now employed to predict the radon gas concentration for the year 2009. The errors between the observation and the prediction values have been seen clearly.

2 Study Area

The monitoring locations of ^{222}Rn gas are Kozan, Adana and Osmaniye regions between east longitude (35^{0}48', 35^{0}18', 36^{0}14') and northern latitudes (37^{0}26', 37^{0}01', 37^{0}05'), respectively as shown in Figure 1.

Kozan fault starts from the south of Kozan Town and passes to the north of Imamoğlu Town. Sarıkeçili-Karatepe trapping commences as high dips fault, which is Karataş Fault [6]. Osmaniye and Adana region is one of the most active fault zones in Turkey.

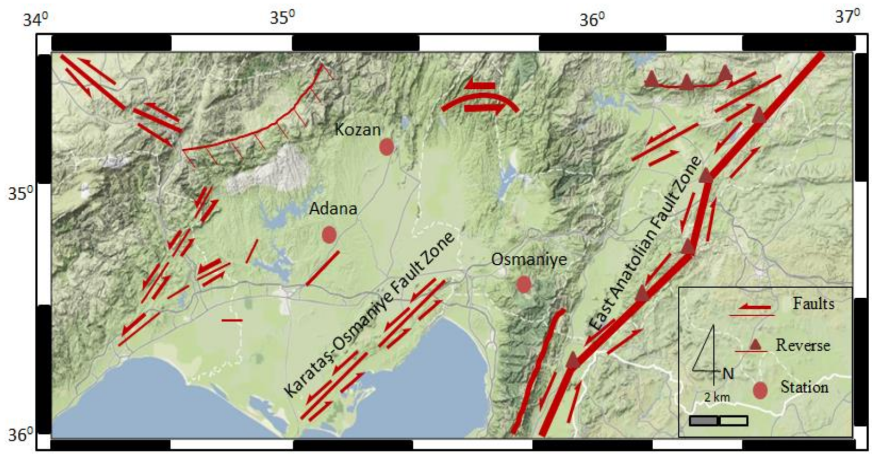


Fig. 1: Research area and soil radon gas monitoring stations.

3 Methodology and Results

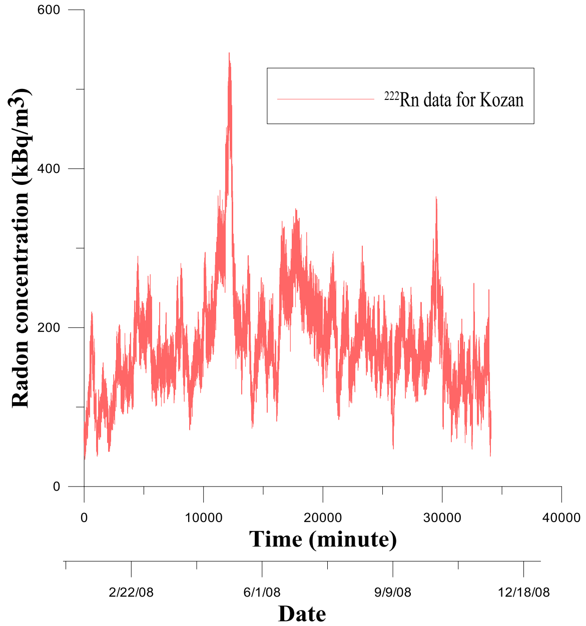
Earthquakes are the complex problems. The formation mechanism of the earthquake shows nonlinear variations. Determination of the chaotic behavior in the natural events' is very difficult; therefore, chaos theory is a suitable tool to show the characteristics of the dynamical system. The chaos methodologies are applied to data recorded at Kozan, Adana and Osmaniye Regions located on the near East Anatolian Fault Zone (EAFZ), which is one of the world's most active zones. ^{222}Rn data for the research are recorded from 01/01/2009 to 31/12/2009 dates. It is continuously measured from the soil at 15 min intervals for a month. Application of methodologies is achieved for Kozan, Adana and Osmaniye Region, Turkey, where it is seismically very active.

3.1 Chaos Methodologies

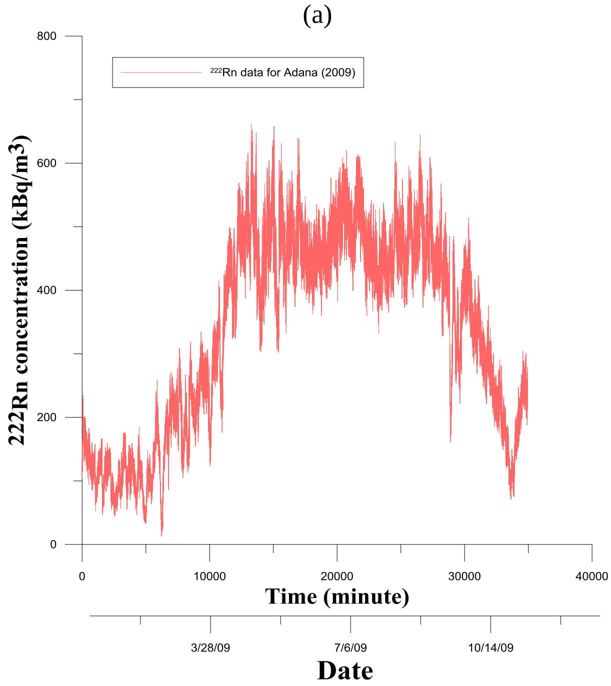
Chaos can define as extreme sensitive initial conditions [9]. In order to detect a chaotic system behavior can be used various methodologies. In this study, the tracing of the orbit is detected by qualitative but logical interpretations and quantitative methods are used such as the Lyapunov exponents.

3.2 Nonlinear Time Series Analysis

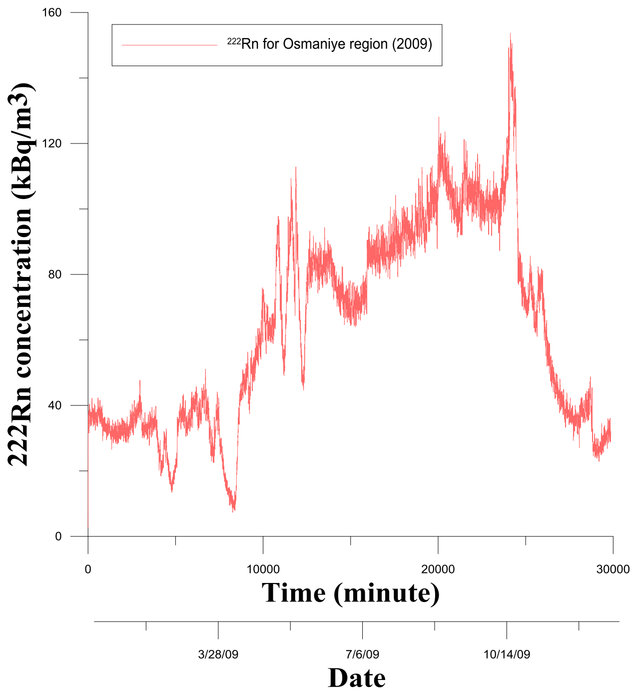
Chaotic time series analyses are not foreseeable systems. These systems have so much complexity. Prediction of non-linear time series is an available method to interpret characteristics of dynamical systems [7, 8]. Dynamical systems can represent a single record of observed variables as $x_1(t), x_2(t), \cdots, x_n(t)$ generated by using the phase-space. A scalar measurement shows $x_n(t) = x(t_0 + n\tau)$ equation. Where, t_0 is beginning time and τ is sampling time of experiment [9].


600
400
200
0
0
10000
20000
30000
40000
Radon concentration (kBq/m3)
222Rn data for Kozan
Time (minute)
2/22/08
6/1/08
9/9/08
12/18/08
Date

(a)


800
600
400
200
0
0
10000
20000
30000
40000
222Rn concentration (kBq/m3)
222Rn data for Adana (2009)
Time (minute)
3/28/09
7/6/09
10/14/09
Date

(b)



(c)

Fig. 2 (a),(b),(c): Time series state variable for chaotic behavior for Kozan, Adana and Osmaniye regions.

Scatterplots of observed and predicted radon concentration are given in Fig. 2 (a), (b), (c). It can be seen these scatterplots that the results give accurate predictions if it is compared with raw data. Figure 2 (a), (b), (c) show 12 monthly data series for three different regions.

3.3 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 [11, 12]. Sano and Sawada algorithms, which determine Lyapunov exponents, have very advantage. In this study, Sano and Sawada's algorithm is used for calculation of Lyapunov Exponential. Detecting of chaos in a dynamical system is an important issue in order to figure out the largest Lyapunov exponent. The algorithm bases on the definition of the largest Lyapunov exponent. We have demonstrated that the algorithm is fast, easy to do, and robust to change in the following quantities; embedding dimension, size of the data set, reconstruction delay, and noise level. Lyapunov exponents provide a useful characterization of chaotic systems. For time series produced by dynamical systems, the presence of a positive characteristic exponent indicates chaos [13].

Sano and Sawada's algorithm works on recorded time-series, where the system formulas may not be available. It begins by reconstructing an approximation of the system dynamics by embedding the time-series in a phase space where each point is a vector of the previous *m* points in time and separated by a lag of *j* time units. Given this embedding of the time-series, for each point find its nearest neighbor (in the Euclidean sense) whose temporal distance is greater than the mean period of the system, corresponding to the next approximate cycle in the system's attractor [14]. This constraint positions the neighbors as a pair of slightly separated initial conditions for different trajectories. The mean period was calculated as the reciprocal of the mean frequency of the power spectrum of the time-series calculated in the FFT [15, 16]. Largest Lyapunov exponent is calculated according to the following expression.

$$\lambda_i = \lim_{n\to\infty} \frac{1}{n\tau} \sum_{j=1}^{n} \left\| A_j e_i^j \right\| \qquad (1)$$

Artificial Neural Networks (ANNs) were used in calculation of maximum Lyapunov exponent with Sano and Sawada Algorithm. ANNs are a parallel method technique that derives new information, explore with learning. These capabilities do not achieve another conventional programming, so ANNs have been extensively used complex real-world problems [10].

ANNs can learn with using examples that carry out by people and can determine response. Similarly, they can successfully perform learning, identify, classification, generalization and optimization. Artificial cell models have been shown in Fig. 3.

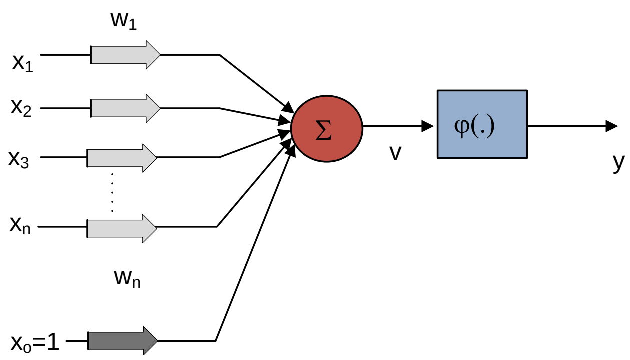
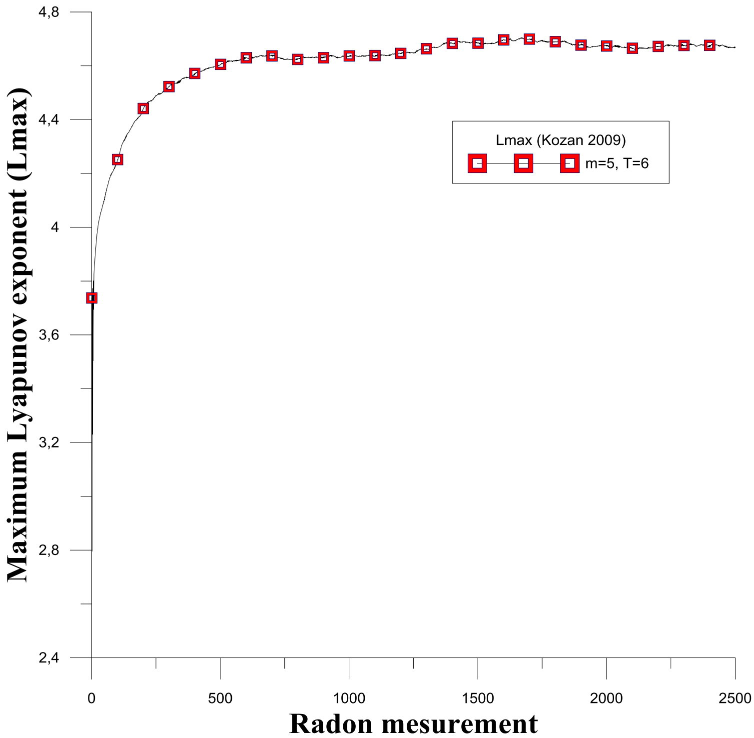


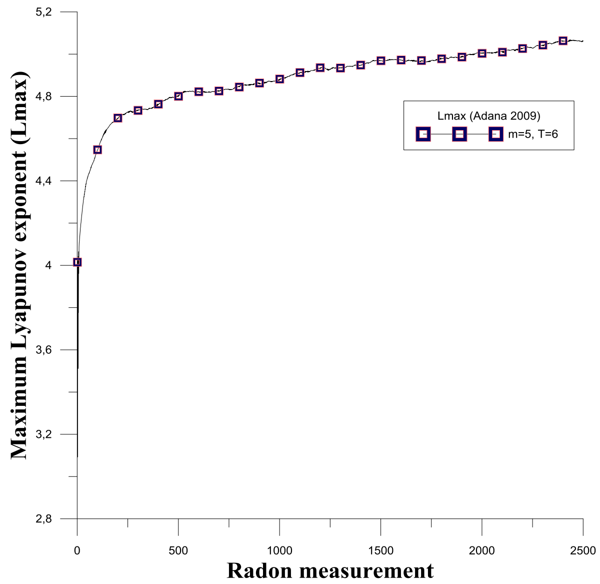
Fig. 3 : Artificial cell models.

ANNs learn by using weights rates. If we take correct weights values, the network can generate correct outputs. This operation is called network training [7]. In this study, Levenberg-Marquardt (LM) method is widely common used for training of the ANNs. The primary objective of using activation function is to change depending on the time. The main advantage of ANN is faster than other numeric methods and is not necessarily mathematical relationships between variables. Therefore, we have used ANN modeling in Sano and Sawada's algorithm which use for calculation of Lyapunov exponents [8].

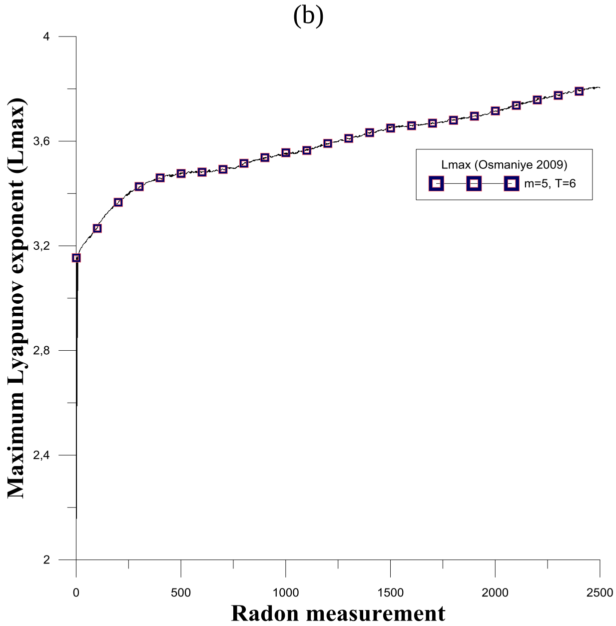
The results are given for the ^{222}Rn data in Fig. 3 (a), (b), (c). If Largest Lyapunov exponents are reached saturation value, then dynamical system behavior can be said that is chaotic.



(a)



(b)



(c)

Fig. 3 (a), (b), (c): Lyapunov exponent for ^{222}Rn step by step for Kozan, Adana, Osmaniye regions (*m*: embedding dimension; *τ*: delay time)

Conclusions

Determination of the chaotic behavior of the natural events is considerably a difficult task. The chaos theory is a suitable methodology to determine characteristics of dynamical systems. The chaos methodologies in order to show non-linear behavior of ^{222}Rn are applied to Kozan, Adana and Osmaniye regions near Osmaniye-Karataş Fault Line and East Anatolian Fault Zone. The soil ^{222}Rn gas, which propagates from the fault lines, has a nonlinear characteristic. In this study has obtained a solution by using jointly chaos methodology (Lyapunov exponent) and ANNs. A chaotic vehicle offers an opportunity to measure these irregularities. Chaotic structure of the system was demonstrated by creating one-dimensional time series with associated data.

Acknowledgements

This work was supported by TUBITAK, Project number and name: 2211-C Priority Areas Related to Domestic Doctoral Scholarship Program and also by Republic of Turkey Prime Ministry Disaster & Emergency Management Presidency.

References

1. H. Friedmann, K. Aric, R. Gutdeutsch, C.Y. King, C. Altay, H. Sav, Tectonophysics. 152, 209-214 1988. 2. J. Janssen and R. Manca. Semi-Markov risk models for finance, insurance and reliability, Springer, New York, 2007.
2. C.Y. King, J. Geophys. Res. 91-B12, 12269-12281 1986.
3. JR.L. Fleischer, Mogro-Campero, A, Geophys. Res. Lett. 6, 361-364 1978.
4. D. Ghash, A. Deb, R. Sengupta, K.K. Patra, S. Bera, Radiat. Measure. 42, 46-471, 2007.
5. H. Kozlu, 1996 Tectono developed in East Anatolian.
6. Baker, G.L., Gollup, J.P., 1990. Chaotic Dynamic, Cambridge University Press, 052138897.
7. Williams, G.P., Chaos Theory, Taylor & Francis Publisher, London 1997.
8. Das, N.K., Sen, P., Bhandari, R.K., Sinha, B., 2009. Appl Radiat Isotop, 67, 313-318.
9. F. Külahcı, M. İnceöz, M. Doğru, E. Aksoy, O Baykara. Appl Radiat Isotop 67, 212-219, 2009.
10. Strogatz, S.H., 1994. Nonlinear dynamics and chaos Persues Books Publishing, New york, 498.
11. Alligood, K.T., Sauer, T.D. and Yorke, J.A., 1997. Chaos, Springer-Verlag, New York, 603.
12. Wolfe A., Swift J.B., Swinney H.L., and Vastano J. A., Physica D 16, 285-317 1985.
13. Sano, M. and Y. Sawada (1985). Measurement of the Lyapunov spectrum from a chaotic time series. Phys. Rev. Lett. 55, 1082-1085.
14. Grassberger, P., ve Procaccia, I., Physica D, 9, 189-208, 1983.
15. Özer, A.B., Akın, E., İstanbul 2006. Chaos theory informatic encyclopedia.