ON THE CONTRADICTORY CHARACTERISTICS OF THE EEP SIGNAL OBSERVED PRIOR TO THE KYTHIRA *M* 6.9 EARTHQUAKE ON JANUARY 2006

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Abstract: - The continuous operation of the telemetric network of seismoelectromagnetic stations at the southern frontal part of the Hellenic Arc, one of the most active geophysical and seismological laboratories of nature in Europe, has enabled the detection and identification of a number of electric, magnetic and electromagnetic phenomena which have been repeatedly reported as forerunners of earthquakes. Aiming to identify the nature of such signals several models have been proposed based upon the characteristics exhibited by the observed anomalies and different possible generation mechanisms. Most of the observed anomalies appear to coincide with the main characteristics featured by seismic electric signals (SES) and electric earthquake precursors (EEP) which are considered to be the main candidates for short-term earthquake precursors. This paper, though, discusses an electric potential anomaly, captured by electric field recordings, accompanying the Kythira *M* 6.9 earthquake on the 8th of January, 2006, which exhibits different characteristics to the existing EEP and SES models, and presents the authors' thesis regarding the nature of this particular signal along with a plausible generation mechanism.

Key-Words: - Electric Earthquake Precursors, Short Term Earthquake Prediction, Neural Fuzzy Models, Hybrid Algorithms, Time-series Prediction, Decision Making

1 Introduction

This research project investigates the nature and the possible generation mechanism of the electric earthquake precursor (EEP) preceding and co-ceding the *M* 6.9 Kythira earthquake on the 8th of January, 2006, located 36.21° North (latitude) and 23.41° East (longitude) in the frontal of the Southern Hellenic arc. The characteristic features of exhibited by the recorded EEP signal support the authors' thesis [1,2,3,4] regarding the nature of EEP signals and their generation mechanism, which is based upon the propagating cracks theory [5,6]. It is the authors' belief that EEP signals are transient electric potential anomalies external to the natural electromagnetic field of the Earth of ionospheric origin, i.e. the result of a different generation mechanism, despite the fact that they are observed upon surface measurements of the Earth's electric field. A strong indication supporting that thesis is the fact that the EEP signal accompanying the Kythira earthquake was only observed upon the surface recordings of the electric field (Figure 1, subplot 'a') whilst there is no indication of the latter upon the simultaneous magnetic field recordings (Figure 1, subplot 'b'). The square on both subplots in Figure 1 indicates the time of occurrence of the main earthquake. This observation contradicts several of the existing models aiming to describe preseismic electromagnetic phenomena [7,8,9]. To enhance our case that EEP signals are external additional distortions to the natural electric field of the Earth due to ionospheric variability and therefore they should not appear upon magnetic field recordings, the authors have employed a pattern recognition application with the incorporation of neuro-fuzzy technology. A neuro-fuzzy model has been developed and trained to predict [3,4] the recorded electric field signal during time-periods of minimal seismic activity. After the successful completion of the training process, the neuro-fuzzy model was activated upon the electric field recordings around the time of the Kythira earthquake, which resulted in the rejection of the observed EEP signal from the surface electric field recordings. The neuro-fuzzy model has 'decided' that the observed variation was not part of the Earth's natural electric field due to ionospheric variability and therefore, it considerably suppressed the variation at its output. The behaviour of the neuro-fuzzy model, plus the fact that the EEP does not appear upon the simultaneous magnetic field recordings, lead us to believe that this EEP signal does not fall within the boundaries of existing models describing preseismic electric phenomena. Instead, the authors present a scientific hypothesis regarding the nature of this particular EEP signal discussing a possible physical generation mechanism producing such a signal based upon the propagating cracks theory.

2 EEPs as external additional distortions upon the Earth's natural electric field

The propagating cracks theory proposed by Teysseyre and Nagahama [5,6] accommodates the superposition of signals from all the simultaneously propagating cracks in the surrounding seismogenic area. According to this theory EEP signals are the result of a different generation mechanism, independent to the source that causes the natural electric field of the Earth, i.e. ionospheric variability. This could well be the reason why the possible EEP signal accompanying the 2006 Kythira *M* 6.9 earthquake was only recorded by electric field measurements whilst there was no indication of it upon magnetic field recordings. Based on that hypothesis the EEP signal could be the result of a continuous large upward shift of the sea-bed in the seismogenic area captured as an external additional electric potential anomaly upon the recordings of the natural electric field of the Earth.

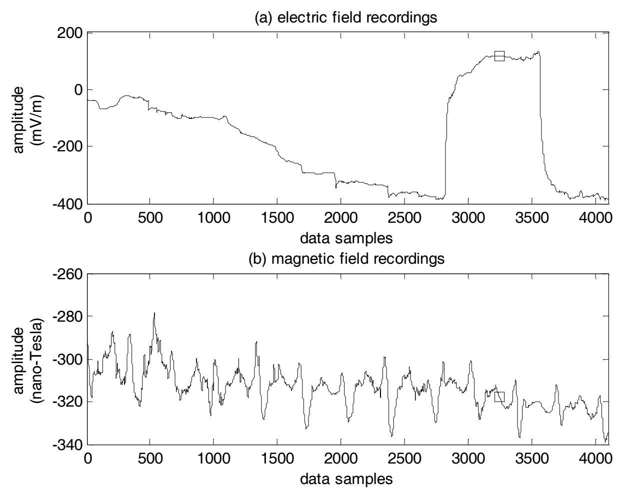

Fig. 1 (a) recorded electric field signal from approximately 9 p.m. on the 29th of December, 2005 till 1 p.m. on the 11th of January, 2006. (b) simultaneous magnetic field recordings. The sampling frequency of the recordings is f_s = 1Hz. The recorded time-series have been decimated by a factor of 256, and filtered by a Chebyshev lowpass filter to prevent aliasing, in order to reduce the workload and the processing time required to sufficiently train the neuro-fuzzy model. The square indicates the time of the occurrence of the Kythira *M* 6.9 earthquake at approximately 11:35 a.m. on the 8th of January, 2006.

In order to identify whether the EEP was the outcome of a different generation mechanism than the Earth's natural and due to ionospheric variability electric field, we have resolved to a pattern recognition experiment with the incorporation of soft computing technology. A neuro-fuzzy model, i.e. a neural network with intrinsic fuzzy logic abilities [10], has been developed and trained to identify the recorded electric field signal using the data recorded before the occurrence of the possible electric earthquake precursor. Then, propagating through the electric field recordings, the neuro-fuzzy model forecasts the next sample of the recorded signal based upon a number of previously recorded data. The purpose of the experiment is to monitor the output of the neuro-fuzzy model and identify whether it follows the detected EEP signal as if it was a part of the natural due to ionospheric variability electric field; or rejects it as an external distortion by considerably suppressing the EEP aiming for the actual value of the natural due to ionospheric variability electric field alone.

3 Neuro-fuzzy model training and operation

To train and evaluate the performance of the neuro-fuzzy model, 4096 data samples of electric field recordings (Figure 1, subplot 'a') have been selected [2], corresponding approximately to the time-period from 9 p.m. on the 29th of December, 2005 to 1 p.m. on January the 11th, 2006, which includes the possible electric earthquake precursor. The original sampling frequency of the recorded data is f_s = 1 Hz but the overall data set has been decimated by a factor of 256 because it is very costly in processing time [11] to train a neural network with such a heavy workload. A sliding window consisting of four previous inputs, at *n*-12, *n*-24, *n*-36 and *n*-48 [12], propagating though the time-series forms the four input vectors of the neuro-fuzzy model. The first 2548 samples in the time-series, are used to train the neuro-fuzzy model to predict the next sample (*n*+1) in the time-series [13], whilst the following part of the time-series remains unseen by the neuro-fuzzy model. The initial 2048 data samples of the training data set were shown to the neuro-fuzzy model during training, whilst the last 500 (2049 to 2548) data samples remained unseen by the network and were used to monitor its performance and prevent overtraining the model.

An initial structure for the neuro-fuzzy model is obtained by applying grid partitioning [1] on the first half of the input data set. This initial model is subjected to training with a hybrid algorithm [10], i.e. a combination of the least squares estimator and the backpropagation algorithm. During a forward pass an input vector is fed to the neuro-fuzzy model and the least squares estimator is used to adapt its consequent parameters, which define the rules and output membership functions (MFs) of the model. A training error is computed by subtracting the output of the neuro-fuzzy model, for the current set of parameters, from the required output, i.e. the actual value of the electric field signal at data sample n+1. The training error is deployed during the backward pass through the neuro-fuzzy model by the backpropagation algorithm in order to adapt its premise parameters, which determine the shape and dimensions of the input MFs. After every training epoch the neuro-fuzzy model is tested against the last 500 samples of the training data set to prevent overtraining [13]. The final neuro-fuzzy model holds the parameters set which produced the minimum checking error. The structure of the developed neuro-fuzzy model is shown in Figure 2. The neuro-fuzzy model has four inputs (layer 1) with two input membership functions per input (layer 2), and it is guided by sixteen rules (layer 3). The contribution of each rule to the output of the neuro-fuzzy model is determined by the output MF (layer 4) allocated to it, whilst the bias neuron (dashed line in Figure 2) sets a weighting factor to each rule. The neuron in layer 5 defuzzifies the normalised weighted outputs of all rules to produce a crisp output (layer 6).

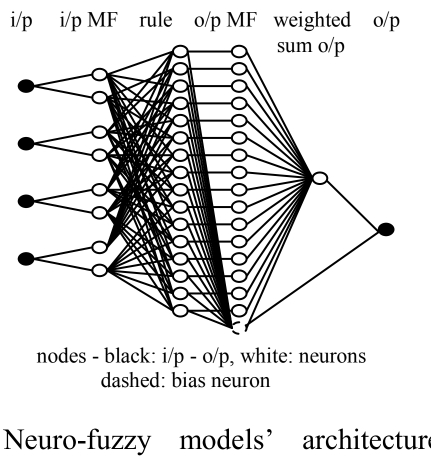

Fig. 2 Neuro-fuzzy models' architecture. Black nodes: inputs to and output from the neuro-fuzzy model. White nodes: neurons. Dashed node: rules' bias neuron.

3.1 Experimental Results

The result of the application of the neuro-fuzzy pattern recognition model upon the full electric field signal after training the neuro-fuzzy model is shown in Figure 3, where the square on subplot 'a' indicates the time occurrence of the main earthquake. Comparing subplots 'a' and 'b' on Figure 3, it is made apparent that there is a significant suppression of the density of the possible recorded EEP signal. The output of neuro-fuzzy model follows closely the recorded electric field signal until the moment of occurrence of the possible EEP, at approximately data-sample 2752. The sudden rise of the magnitude of the recorded signal over the next few samples 'confuses' the neuro-fuzzy model and for a sort time it becomes unstable, hence the overshooting observed at the models output between data-samples 2780 and 2830.

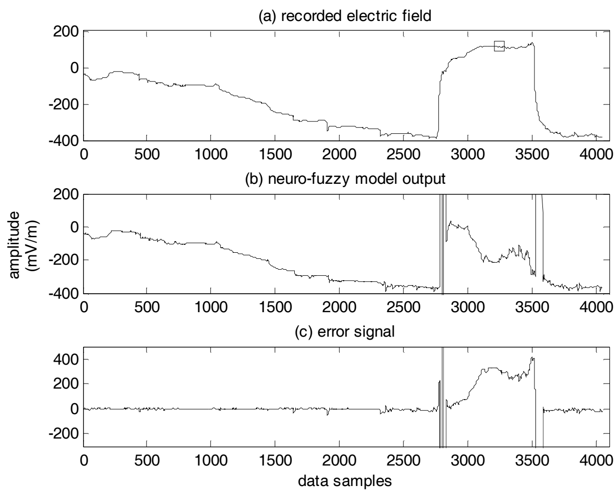

Fig. 3 (a) recorded electric field signal - the square indicates the time of the occurrence of the Kythira M 6.9 earthquake at approximately 11:35 a.m. on the 8th of January, 2006; (b) neuro-fuzzy model output indicating rejection of the possible EEP signal as an external addition upon the electric field recordings; (c) error signal – the difference between the recorded electric field signal the output signal from the neuro-fuzzy model. The error signal highlights the close proximity of the neuro-fuzzy model's output signal to the recorded electric field before and after the occurrence of the possible recorded EEP signal as well as the continuous incremental rejection of the latter at the time of its occurrence.

Because of the adaptive nature [14] of neural networks after a sort time of approximately fifty samples the neuro-fuzzy model adapts accordingly to compensate for the new information received at its input and becomes stable once-more. Following data-sample 2830 the neuro-fuzzy model 'decides' not to follow the information received at its input, i.e. the signal shown by subplot 'a' on Figure 3, while predicting the next sample of the time-series at its output. Instead it tries to approximate the magnitude of the natural electric field alone, thereby considerably suppressing the possible recorded EEP signal. Around data sample 3510 the neuro-fuzzy is affected by a sudden drop in the magnitude data received at its input (the end of the possible EEP signal). Once-more the neuro-fuzzy model temporarily becomes unstable and thus the overshooting observed between data-samples 3530 and 3585. The remarkable observation in this case is that once the model becomes stable again, which is almost immediately after the end of the observed EEP signal around data sample 3595, its output approximates closely again the recorded electric field signal.

The fact that the neuro-fuzzy model follows closely the recorded electric field signal before (signal to difference ratio of 30.45 dB) and after (signal to difference ratio of 28.39 dB) the occurrence of the EEP signal, and the rejection of the latter (signal to difference ratio of -39.68 dB) at the time of its occurrence (Figure 3 – subplot 'c') makes us believe that the neuro-fuzzy model treats the EEP signal as an external additional distortion upon the natural and due to ionospheric variability electric field of the Earth.

4 Conclusions

Existing models describe electric earthquake precursors as signals preceding large seismic events obtained upon recordings of the Earth's electric and magnetic fields. The possible electric earthquake precursor, though, accompanying the Kythira *M* 6.9 earthquake exhibits some 'weird' characteristics. Firstly, the possible EEP signal was only captured by electric field recordings whilst there was no indication of it upon the simultaneous magnetic field recordings. Secondly, the duration of the EEP signal is enormous in comparison to other detected EEP candidate signals, lasting for a couple of days rather than a couple of hours. Finally, EEP signals were believed to precede earthquakes. This is partly true in this case as indeed the possible EEP signal attributed to the Kythira earthquake does precede the main seismic event which occurred at 11:34' a.m. on the 8th of January, 2006. The rising edge of the EEP signal occurred almost 36 hours prior the main seismic event around 1 a.m. on January the 7th, 2006. The EEP, though, outlasted the main seismic event with its falling edge occurring approximately 25 hours later, around 1 p.m. on the 9th of January, 2006.

Therefore, it is the authors' belief that this particular EEP signal was the result of a continuous large upward shift of the sea-bed in the seismogenic area which lasted approximately three days from the 7th to the 9th of January, 2006. This could justify the long duration of the possible EEP signal and the fact that it bounds the main earthquake. Furthermore, the nature of the signal produced by this generation mechanism provides a possible explanation why the EEP signal was only observed upon electric field recordings. This theory, supported also by the outcome of the neuro-fuzzy pattern recognition experiment, suggests that this particular EEP signal is an external transient electric potential anomaly from a different source (propagating cracks) to the natural and of ionospheric origin electric field of the Earth. This results to the detection of the possible EEP signal as an external additional distortion upon electric field recordings, and not as a genuine part of the natural electric field of the Earth due to ionospheric variability, which also justifies why there is no indication of the latter upon the simultaneous magnetic field recordings.

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