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Publication date:
1996

Document Version
Early version, also known as pre-print

INSTITUTTET FOR BYGNINGSTEKNIK

DEPT. OF BUILDING TECHNOLOGY AND STRUCTURAL ENGINEERING
AALBORG UNIVERSITET • AAU • AALBORG • DANMARK

FRACTURE & DYNAMICS
PAPER NO. 91

To be presented at the 15th International Modal Analysis Conference
Orlando, Florida, USA, February 3-6, 1997

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OCTOBER 1996 **ISSN 1395-7953 R9641**

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Non-Stationary Modelling and Simulation of Near-Source Earthquake Ground Motion: ARMA and Neural Network Methods

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Abstract This paper is concerned with modelling and simulation of near-source earthquake ground motion. Recent studies have revealed that these motions show heavy non-stationary behaviour with very low frequencies dominating parts of the earthquake sequence. Modeling and simulation of this behaviour is of crucial importance in the design of flexible structures and other applications. This paper examines three approaches for the modeling and simulation of non-stationary near-source ground accelerograms: The first one makes use of ARMA models combined with frequency and variance "stabilization". The second is based upon inherently nonstationary Time-dependent ARMA (TARMA) models, the parameters and variance of which are allowed to be explicit functions of time. The third approach is based on Neural Networks. The three approaches are used for the modeling and simulation of an accelerogram characterized by an epicentral distance of 16 km and measured during the 1979 Imperial Valley earthquake in California (U.S.A.). The results of the study indicate that while all three approaches can succesfully predict near-source ground motions, the Neural Network based one gives somewhat poorer simulation results.

Keywords: Earthquake, Near-Source Areas, Non-stationary signals, Stochastic signals.

Nomenclature

σ	Standard deviation.	Z_t	Non-stationary ground motion signal.
ϕ	AR parameter.	θ	MA parameter.
a_t	Innovations (uncorrelated)sequence.	G	Subspace basis function.
$\mathbf{W}$	Weighting matrix.	λ	Exponential weighting factor.
$\mathbf{\Phi}$	Non-linear activation function.	t	Time.
τ	Duration of strong motion.	N	Number of discretized signal samples.
p	TARMA subspace dimensionality.	B	Backshift operator.
$A(\cdot)$	AR polynomial.	$C(\cdot)$	MA polynomial.

1 Introduction

The damage incurred in structures during an earthquake highly depends upon both the nature of the structure and the characteristics of the ground motions. In 1987 Ellis *et al.* [6] studied a large sample of earthquake ground motions recorded in Taiwan, Mexico and California (U.S.A.), and established a method for generating site dependent time histories. Relationships between the considered site, epicenter distance, soil type and other properties, on one hand, and the parameters of the model, on the other, were also established. Nevertheless, this method seems to fail in near-source areas, where very low frequency components have been observed to dominate the recorded accelerograms. This observation contradicts the prevailing impression that the high frequency content of the signals drops with increased source distance.

Since seismic waves are initiated by irregular faulting and then travel through complex ground formations with random properties, resulting in many reflections, refractions and attenuations before reaching the recording station, a stochastic approach has been generally adopted for accelerogram modeling and simulation. The application of AutoRegressive Moving Average (ARMA) models in this respect has proven effective in numerous studies,including those of Jennings *et al.* [10] and Chang *et al.* [5]. The difficulty in modelling accelerograms using ARMA models is in the non-stationarity in the variance and frequency content of the signal. This behaviour is evident in the El Centro near-source accelerogram, characterized by an epicenter distance of 16km and recorded during the 1979 Imperial Valley Earthquake (California, U.S.A.)(Figure 1).

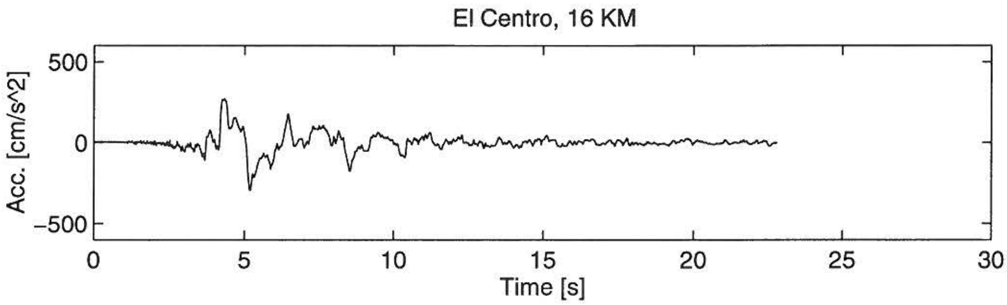

Figure 1: Horizontal component of the acceleration time series measured at El Centro, Imperial Valley, CA (U.S.A.) 1979.

The "classical" way of handling this difficulty is by applying frequency and variance stabilizing transformations using appropriate envelope functions before proceeding with conventional ARMA modelling (Ellis *et al.* [6] and Ellis and Çakmak [7]). The drawback of this approach is that it is, by conception, an approximate procedure, and that the selection of the appropriate envelope functions may be subjective and difficult.

The goal of this paper is the introduction and assessment of two alternative approaches to near-source earthquake ground motion modelling and simulation. The first approach postulates direct non-stationary modelling via Time-dependent ARMA (TARMA) models, that is ARMA models whose parameters and innovations variance are explicit functions of time. Such representations have been found to be capable of modelling a wide variety of non-stationary phenomena [4, 12]. The second approach postulates Neural Network based modelling [8], where the non-linear behavior of the signal is modelled directly by the network.

The specific *objectives* of the paper may be outlined as follows:

1. Assessment of the capability of TARMA models to model and simulate near-source earthquake ground motion.
2. Assessment of the capability of Neural Networks to model and simulate near-source earthquake ground motion.
3. Comparison of the TARMA and Neural Network approaches with the classical stationary ARMA approach using envelope function based stabilization.

The rest of the paper is organized as follows: The classical stationary ARMA approach using envelope functions is briefly reviewed in Section 2. The non-stationary TARMA approach is presented in Section 3, and the Neural Network based approach in Section 4. Ground-motion modelling and simulation results by all three approaches for the El Centro accelerogram are presented in Section 5. The conclusions of the study are finally summarized in Section 5.

2 Stationary ARMA Modeling Using Envelope Functions

2.1 Stabilization of Earthquake Time Series

In the case where stationary ARMA modelling is employed, the measured signal should be normalized with respect to both frequency content and variance (amplitude). In the following the procedure used by Ellis *et al.* [6] is briefly reviewed.

2.1.1 Estimation of the Standard Deviation Envelope

The empirical standard deviation envelope is calculated from the running average of the squared acceleration. Ellis *et al.* [6] suggested the use of an equally weighted two second time-window. In that case the variance envelope is computed as:

$$\sigma_Z^2(t) = \frac{1}{n} \sum_{i=t-\frac{1}{\Delta t}}^{t+\frac{1}{\Delta t}} Z_i^2 \tag{1}$$

In the above Z_t represents the time series to be modelled, n the number of points within the window, and $2\Delta t$ the window length. $\Delta t = 1$ s has been shown to be the smallest window size to estimate a resonably smooth variance envelope [6]. The standard deviation envelope is then calculated as the square root of the variance. By dividing the shortened accelerogram by the standard deviation envelope, a time series with unity variance is obtained.

In their effort to relate the standard deviation envelope to physical variables, Ellis *et al.* [6] fitted a smooth function $\hat{\sigma}_Z(t)$ of the form:

$$\hat{\sigma}_Z(t) = c_1(\alpha - k_1)\left(\frac{t}{\tau}\right)^3 \exp -(\frac{c_2}{\tau})t + k_1 \tag{2}$$

to the empirically obtained standard deviation envelope. The maximum intensity of the strong shaking is measured by α. The standard deviation of the weak shaking k_1 is estimated as the average of the standard deviation envelope during the final 1/3 of the record. Finally the duration of the strong shaking τ is estimated such that the energy, as measured by the empirical standard deviation function, is equal to the energy of the function fitted to it in Eq. (2).

2.1.2 Estimation of the Frequency Envelope

Because of the time lag between the different types of waves in an earthquake, the variance-stabilized series still has a non-stationary frequency content. Most signals recorded more than 50km away from the source normally have an initially high predominant frequency content from P-waves, which quickly decreases with time as the S-waves arrive. One measure of the frequency content of the signal is the number of zero axis crossings per second $F_c(t)$. Like in the variance envelope, the frequency envelope can be calculated using an equally weighted 2 s window as follows:

$$F_c(t) = \frac{\text{No of zero axis crossings in t} \pm \Delta t}{2\Delta t} \tag{3}$$

The following smooth function is then fitted to the zero axis crossings:

$$F_c'(t) = c_0 \exp(-bt) + k_2 \tag{4}$$

in which k_2 is the zero axis crossings of the weak shaking, determined as the average value during the last 1/3 of the record. c_0 and b are found by a least-squares fit.

The variance stabilized series is then frequency stabilized using the smooth function $F_c'(t)$ to change the time increment to:

$$\Delta t'(t) = \Delta t \cdot F_c'(t) \tag{5}$$

where Δt is the original time increment.

The transformed record is reduced to the same duration as the initial record as follows:

$$\Delta t''(t) = \Delta t'(t) \cdot \frac{\text{Duration of the original record}}{\text{Duration of the trans'd record}} \tag{6}$$

and digitized to the original Δt intervals by using linear interpolation.

2.2 Modelling of the Stabilized Series

With the variance and frequency content stabilized, the ground motion time series may be now fitted to a stationary ARMA model. The general form of the stationary ARMA-model of orders (n, m) is:

$$A(B) \cdot Z_t' = C(B) \cdot a_t \tag{7}$$

with t denoting discrete time, Z_t' the stationary signal modeled, and a_t a stationary normalized innovations (uncorrelated) sequence with zero mean and unit variance. B represents the backshift operator $(B \cdot Z_t \triangleq Z_{t-1})$, and $A(B)$, $C(B)$ the time-independent $n - th$ order AutoRegressive (AR) and $m - th$ order Moving Average (MA) polynomials, respectively, which are of the forms:

$$A(B) \triangleq 1 + \phi_1 B + \ldots + \phi_n B^n \tag{8}$$

$$C(B) \triangleq 1 + \theta_1 B + \ldots + \theta_m B^m \tag{9}$$

The autoregressive and moving average parameters ϕ_i and θ_j, respectively, are estimated by minimizing the variance of the model's one-step-ahead prediction error sequence.

2.3 Simulation of the Stabilized Series

Independent realizations of the stabilized series can be simulated by generating stationary normalized innovations sequences with zero mean and unit variance a_t and driving them through the estimated ARMA model. In the simulations, all unknown initial conditions are set to zero. To avoid the effects of this arbitrary choice, the time series is simulated for a period longer than that of the original record and its initial part is then discharged.

In order to introduce the frequency and variance variability, the stabilization procedure from section 2.1 is now reversed. Using the parameters determined in the variance and frequency envelopes [Eqs. (2) and (4)], the ground motion time series can be reconstructed by multiplying the simulated stabilized series by the standard deviation envelope and shifting the time increment as:

$$\Delta t'_s(t) = \frac{(\Delta t)}{F'_c(t)} \tag{10}$$

where Δt is the original time increment (normally $\Delta t = 0.02$ s).

The transformed record is reduced to the same duration as the original by:

$$\Delta t''_s(t) = \Delta t_s(t)' \cdot \frac{\text{Duration of the org. record}}{\text{Duration of the trans. record}} \tag{11}$$

and digitized to the original Δt using linear interpolation.

3 Non-Stationary TARMA Modelling

In this case a class of non-stationary ARMA models, known as *Time-dependent ARMA* (TARMA) models, is used for earthquake ground motion modelling. The TARMA model class is an attractive choice as it is capable of capturing strong non-stationarities through a parsimonious representation and offers a "global" signal description.

TARMA models are conceptually derived from stationary ARMA models by allowing their parameters to be explicit functions of time. Yet, they form a particularly wide class expected to be capable of representing a wide variety of non-stationary phenomena [4, 12].

A TARMA model is of the form:

$$A(B,t) \cdot Z_t = C(B,t) \cdot w_t \qquad t \geq t_0 \tag{12}$$

$$w_t = \sigma_w(t) \cdot a_t \tag{13}$$

with t_0 denoting the initial time, Z_t the non-stationary signal modelled, w_t a non-stationary innovations (uncorrelated) sequence with zero mean and variance $\sigma_w^2(t)$, and a_t a stationary normalized innovations sequence with zero mean and unit variance. B represents the backshift operator, and $A(B,t)$, $C(B,t)$ the time-dependent $n-th$ order AutoRegressive (AR) and $m-th$ order Moving Average (MA) polynomials, respectively, which are of the forms:

$$A(B,t) \triangleq 1 + \phi_1(t)B + \ldots + \phi_n(t)B^n$$
$$\phi_n(t) \neq 0 \quad \text{for some} \quad t \geq t_0$$

$$C(B,t) \triangleq 1 + \theta_1(t)B + \ldots + \theta_m(t)B^m$$
$$\theta_m(t) \neq 0 \quad \text{for some} \quad t \geq t_0$$

The class of TARMA models considered in this work constitutes a generalization of that of Ben Mrad [2] and Ben Mrad *et al.* [3], as the innovations sequence w_t is, in the present case, allowed to be non-stationary in the variance [Eq.(13)].

In the TARMA model form the time-dependent AR/MA parameters are assumed to belong to a subspace, of dimensionality p, spanned by a set of orthogonal functions, $\{G_1(t),\ G_2(t),\ \ldots\ G_p(t)\}$ *(subspace basis functions)*, that is:

$$\phi_i(t) \triangleq \sum_{j=1}^{p} \alpha_{i,j} \cdot G_j(t) \quad (1 \leq i \leq n) \quad t \geq t_0 \tag{13a}$$

$$\theta_i(t) \triangleq \sum_{j=1}^{p} c_{i,j} \cdot G_j(t) \quad (1 \leq i \leq m) \quad t \geq t_0 \tag{13b}$$

with $\alpha_{i,j}$ and $c_{i,j}$ denoting the AR and MA, respectively, coefficients of projection.

TARMA modelling is based upon the modelling framework of Ben Mrad *et al.* [4], which accounts for projection subspace dimensionality, basis function, and model order selection. TARMA parameter estimation is accomplished through the Polynomial-Algebraic (P-A) approach [3]. Once the model parameters are estimated, the variance $\sigma_w^2(t)$ of the non-stationary innovation sequence is obtained using the model's residual (one-step-ahead prediction error) sequence $e_t = \hat{w}_t$ and a sliding window of length $2K+1$, that is:

$$\hat{\sigma}_w^2(t) = \frac{1}{\sum_{i=-K}^{K} \lambda^{|i|}} \cdot \sum_{i=-K}^{K} \lambda^{|i|} \cdot e_{t-i}^2 \tag{14}$$

where λ represents an exponential weighting factor.

Model validation is based upon verification of the uncorrelatedness hypothesis for the obtained model residuals. Model-based earthquake ground motion simulation is performed via Eqs.(12)-(13) using computer-generated *i.i.d.* $\mathcal{N}(0,1)$ realizations of normalized innovations (a_t) sequences.

4 Neural Network Modelling

Artificial neural networks are computational models inspired by the neuron architecture and the operation of the human brain. The pioneering work in this field is usually attributed to McCulloch and Pitts [11], who developed the simplified model of a neuron. The brain is composed of neurons of many different types. For a more detailed description of neural networks see Hertz *et al.* [8] and Hush and Horne [9].

Since McCulloch and Pitts [11], many studies of mathematical models of neural networks have been undertaken, and many different types of neural networks have been proposed. These are based on various network topologies, node characteristics, as well as learning procedures. The most frequently used network is based on the Multi Layer Perceptron (MLP) structure.

An MLP is made up of one or more hidden layers placed between the input and output layers. Each layer consists of a number of nodes connected in the structure of a layered network. The typical architecture is fully interconnected, that is each node in a lower level is connected to every node in the higher level. Output units cannot receive signals directly from the input layer. During the training phase, activation flows are only allowed in one direction, a feed-forward process from the input layer to the output layer through the hidden layers. The input vector feeds each one of the first layer nodes, the outputs of this layer feed into each one of the second layer nodes, and so on. Associated with each connection between node i in the preceding layer and node j in the following layer is a numerical value which is the strength or the weight of the connection. At the start of the training process these weights are initialized by small random values. For the MLP network with n layers the signal is passed through the network and the input vector $\mathbf{u}$ is linked to the output vector Z_t by means of the equation:

$$Z_t = \Phi_n(\mathbf{W}_n\Phi_{n-1}(\mathbf{W}_{n-1}...\Phi_1(\mathbf{W}_1\mathbf{u}+b_1)+...b_{n-1})+b_n) \tag{15}$$

where $\mathbf{W}_i$ is the weight matrix associated with the i-th layer,the b_i's indicate threshold or bias values associated with each node in the ith layer, and Φ_i is a non-linear operator or activation function associated with the i-th layer. The function Φ_i is assumed to be differentiable and to have a strictly positive first derivative. For the nodes in the hidden layers, the activation function is often chosen to be a so-called sigmoidal function:

$$\Phi_i(\lambda) = \frac{1}{1+e^{-\lambda}} \tag{16}$$

The activation function for the nodes in the input and output layers is often chosen as linear. It is, however, by no means necessary for the number of inputs to be equal to the number of outputs. In fact, this is usually not the case. Also, it is more usual for the number of nodes in the hidden layer to be greater than that of the either the input or output layers. In the present paper an MLP neural network is used to model the earthquake ground motion by a model of the form:

$$\hat{Z}_t = g(\hat{Z}_{t-1}...\hat{Z}_{t-n_a}...a_{t-1}...a_{t-n_b}) \tag{17}$$

where Z_t is the non-stationary signal to be modelled, a_t a stationary sequence with zero mean and unit variance, and $g(\cdot)$ a non-linear function.

5 Ground Motion Modelling and Simulation

In this section the classical ARMA, the non-stationary TARMA, and Neural Network approaches are used for the modeling and simulation of near-source earthquake ground motion. For this purpose the El Centro accelerogram of Figure 1 is used. Signal estimation is, in all cases, based upon the complete data record [$N = 1139$ samples, sampling period $\Delta t = 0.02$ s].

5.1 Stationary ARMA Models

Using the methods described in Section 2, the signal variance and frequency envelopes are computed (Figures 2 and 3, respectively), and used for accelerogram stabilization. The stabilized accelerogram is shown in Figure 4.

In accordance with previous studies [6], a stationary ARMA(3,1) model is fitted to the signal. Model-based one-step ahead predictions are contrasted to the actual accelerogram in Figure 5. An example of model-based ground motion simulation is depicted in Figure 6.

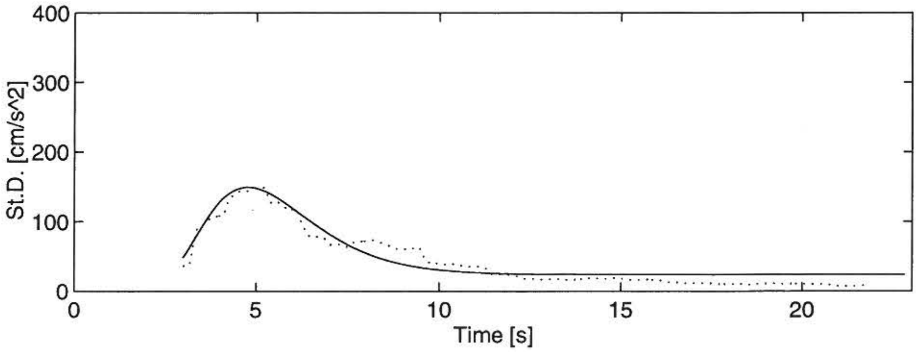

Figure 2: Estimated variance envelope.

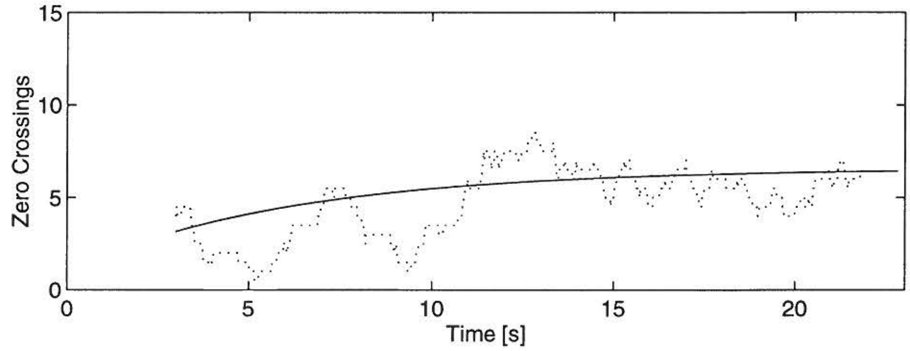

Figure 3: Estimated frequency envelope.

5.2 Non-Stationary TARMA Models

5.2.1 TARMA modeling

In this case pure TAR models of various orders, with functional subspaces of various types (spanned by Chebychev II polynomials, cosine, sine, and Haar functions [1]) and dimensions ranging from $p = 2$ up to $p = 14$, are examined.

Model selection is based upon minimization of the model's Residual Sum of Squares (RSS), expressing one-step-ahead predictive ability, and the Akaike Information Criterion (AIC), expressing a compromise between one-step-ahead predictive ability and parametric complexity. In the search for an appropriate model a $TAR(10)_p$ model structure characterized by various functional subspace types and dimensionalities p, is investigated. It is found that a number of these models are close to optimality, with the $TAR(10)_{p=14}$ model, with subspace spanned by Haar functions,

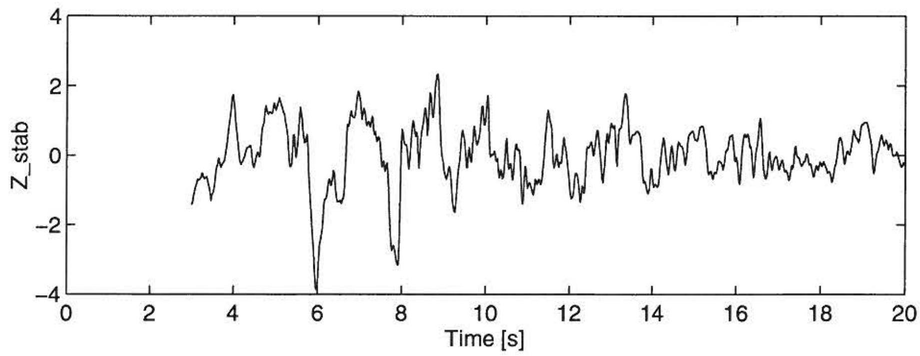

Figure 4: Stabilized accelerogram.

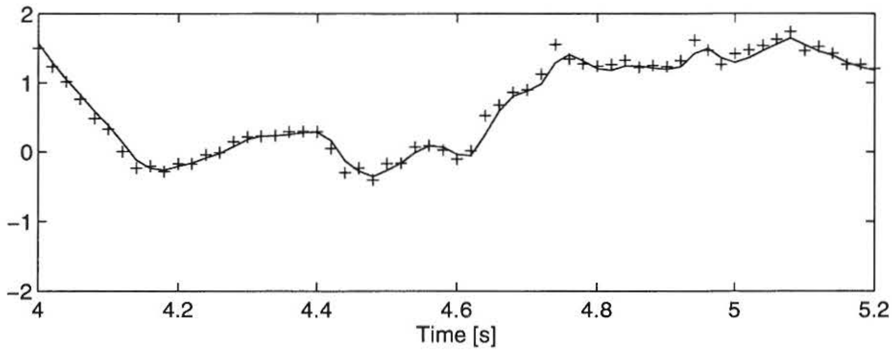

Figure 5: Stationary ARMA(3,1) one-step-ahead predictions versus the stabilized accelerogram (+: one-step-ahead predictions; —: actual accelerogram; part of the El Centro ground motion).

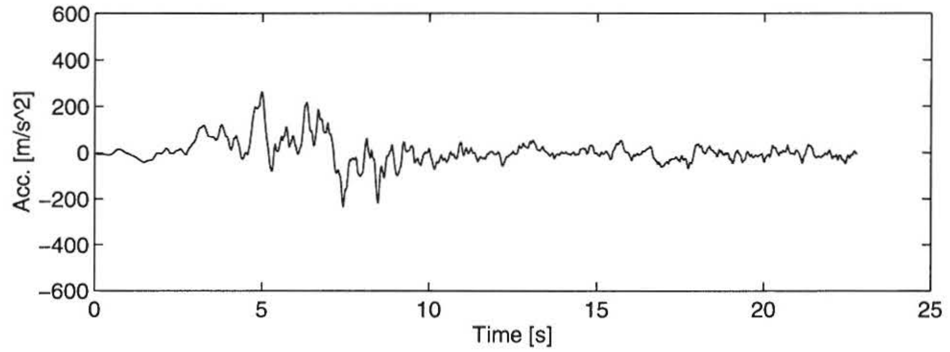

Figure 6: Stationary ARMA(3,1) simulated accelerogram using envelope functions.

found to be best from both the RSS and AIC points of view. The model residuals are confirmed to be strongly non-stationary, and their variance is non-parametrically estimated according to the procedure of Section 3 ($K = 35$; $\lambda = 0.980$).

5.2.2 TARMA Prediction and Simulation

Figure 7 presents, for part of the data record, the Haar-based $TAR(10)_{p=14}$ one-step-ahead predictions contrasted to the actual El Centro accelerogram. The achieved prediction accuracy is judged as quite good.

A simulated realization of a $TAR(10)_{p=14}$ model-based accelerogram is presented in Figure 8. The realized time series characteristics resemble those of the actual El Centro accelerogram.

5.3 Neural Networks

Important points in the selection of a suitable network topology are: (a) The number of layers of neurons/nodes, and (b) the number of neurons/nodes per layer. These issues are related directly to the model structure selection problem in system identification, the aim being to choose the "best" structure in order to obtain a high degree of accuracy. By trial and error it is found that a network with 72 input nodes (n_a =36, n_b=36), 5 nodes in a hidden layer, and one output node, is giving the best representation when the RSS is considered. The residual autocorrelation function is also indicating whiteness, implying that a proper model is selected.

Figure 9 presents, for part of the data record, the Neural Network based one-step ahead predictions. The predictions correspond to the actual El Centro accelerogram fairly well. A Neural Network

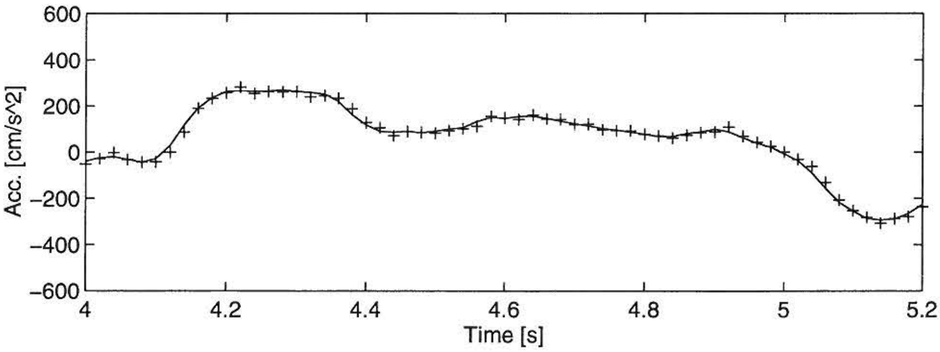

Figure 7: Haar-based $TAR(10)_{p=14}$ one-step-ahead predictions versus the actual accelerogram (+: one-step-ahead predictions; —: actual accelerogram; part of the El Centro ground motion).

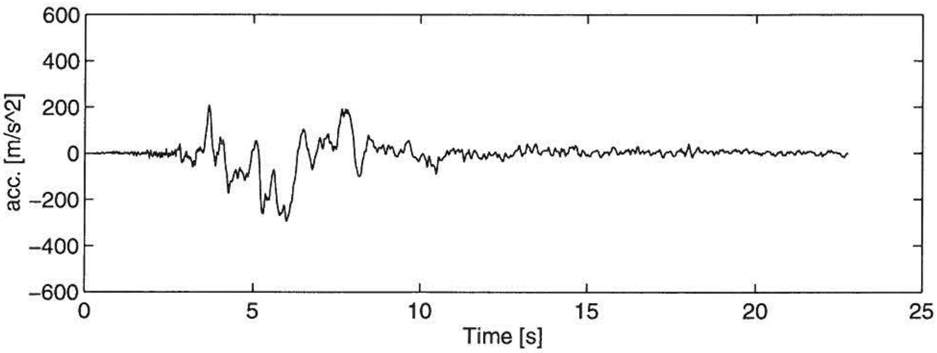

Figure 8: Haar-based $TAR(10)_{p=14}$ simulated accelerogram.

based simulated realization is shown in Figure 10. It is evident that the considered type of Neural Network does not simulate the earthquake ground motion as well as the ARMA and TARMA models. This does not, however, mean that a different type of Neural Network is not capable of achieving better simulation performance.

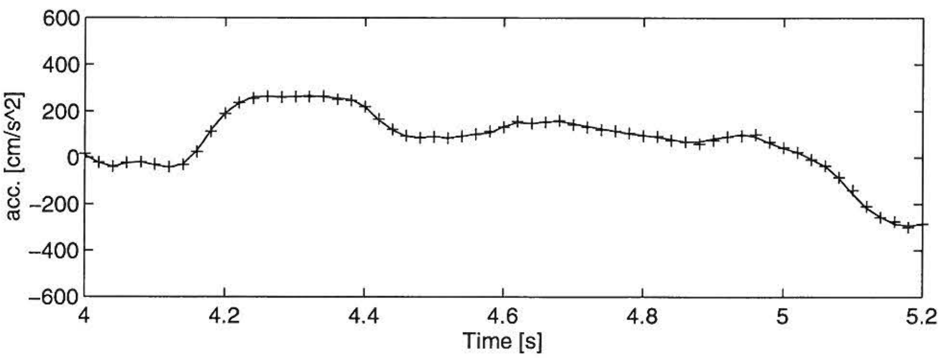

Figure 9: Neural Network one-step-ahead predictions versus the actual accelerogram (+: one-step-ahead predictions; —: actual accelerogram; part of the El Centro ground motion).

5.4 Remarks

The Residual Sum of Squares (RSS) of the considered approaches, computed based upon samples 100 to 1,139 of the accelerogram, are: $\text{RSS}_{ARMA} = 16.4$, $\text{RSS}_{TARMA}=7.55 \times 10^3$ and $\text{RSS}_{NN} = 12.4 \times 10^3$. From these figures the superiority of the TARMA model over the considered Neural Network is also evident. Note that the RSS of the ARMA model is not directly comparable to the

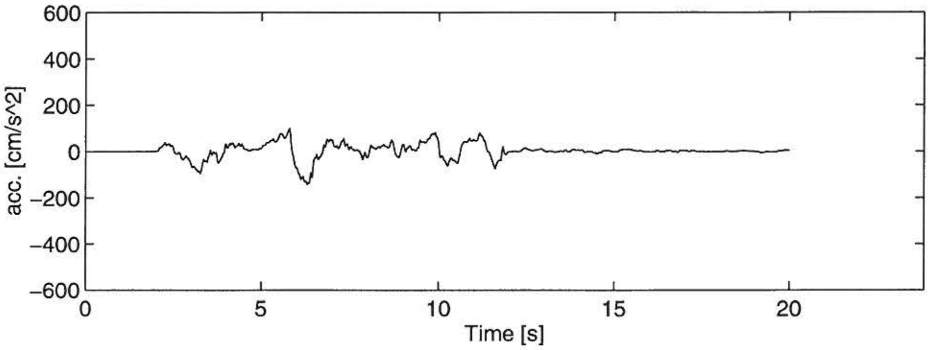

Figure 10: Neural Network simulated accelerogram.

other two, as it, like its one-step-ahead predictions, refers to the stabilized signal with normalized variance.

6 Conclusions

In this paper two approaches for the non-stationary modelling and simulation of near-source earthquake ground motion were presented: The first one is based upon inherently non-stationary Time-dependent ARMA (TARMA) models and the second on Neural Networks.

The modeling and simulation effectiveness of each approach was examined, and comparisons with the classical approach which combines stationary ARMA modeling with signal variance and frequency stabilization were performed. The results of the study suggest that the TARMA approach is capable of modelling and simulating such highly non-stationary signals as the near-source earthquake accelerograms. The stationary ARMA approach with variance and frequency stabilization seems to be also suitable for both modelling and simulation. The Neural Network approach was, however, found to give somewhat poorer simulations, although it worked reasonably well in modelling the earthquake ground motions. Future research should be devoted to the investigation of the relationships between the considered location (soil type, epicenter distance, fault geometry and so on) and the TARMA model parameters.

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