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Research Article

Simulation of Seismic Motions by Stochastic ARMA Identification Based on ACF, PACF, and AIC Criterion

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Abstract:

This study presents a stochastic approach for simulating earthquake ground motions using time-varying ARMA models with parameters fitted to real accelerograms. The ARMA model identification relies on the autocorrelation function (ACF), partial autocorrelation function (PACF), and the Akaike Information Criterion (AIC) to ensure optimal model order selection. The maximum likelihood technique is applied for parameter estimation. Near-field earthquakes recorded on dense soils in Algeria Boumerdes (2003) are synthesized using a moving time-window technique. Random sets of synthetic earthquakes are generated for each event to establish statistically valid structural response spectra. Key damage predictors, including peak linear displacement, ductility demand, and hysteretic energy, are computed from the mean and variance of response spectral ordinates and compared with spectra based on single earthquake records. Results show that low-order ARMA (2,1) models, excited by Gaussian white noise and amplitude-modulated with a simple envelope function, reliably reproduce both the nonstationary amplitude and frequency content of real earthquake records. This highlights the effectiveness of the proposed methodology for seismic motion simulation and structural damage assessment.

1. Introduction

Time-domain analysis of seismic ground motions requires the availability of multiple ground motion records to ensure an adequate statistical and spectral representation of the seismic phenomenon. However, the limited number of recorded earthquakes available for a given site often constitutes a major constraint for dynamic analyses and structural performance validation. In this context, numerical simulation of seismic signals represents a relevant alternative to enrich the available database and enhance the reliability of seismic studies [7,8,10].

In this study, a seismic simulation methodology is developed based on the identification of real earthquake records from the Boumerdes (2003) events using autoregressive moving average (ARMA) models. This approach relies on the assumption that an observed earthquake can be considered as a particular realization of a family of stochastic processes that can be generated by an ARMA model with similar statistical properties [10]. Once the model is identified, it becomes possible to generate artificial earthquakes exhibiting temporal and frequency characteristics consistent with those of the real records.

The proper identification of ARMA models is primarily based on the analysis of the autocorrelation function (ACF) and the partial autocorrelation function (PACF). The ACF highlights the temporal dependence of the seismic signal and provides an initial indication of the presence of autoregressive or moving average

components. The PACF allows a more accurate determination of the order of the autoregressive term by isolating the direct correlation between observations at different time lags, in accordance with classical time series identification methodology [3–5].
The optimal selection of ARMA model orders is further refined using the Akaike Information Criterion (AIC), ensuring an appropriate balance between model goodness-of-fit and model complexity [1]. The combined use of ACF, PACF, and AIC thus allows the identification of a robust ARMA model, avoiding under- or over-parameterization and ensuring realistic simulation of seismic ground motions.
Ultimately, this methodology provides a rigorous framework for generating artificial seismic motions compatible with the statistical characteristics of real earthquake records and represents an effective tool for nonlinear dynamic analyses and the assessment of seismic structural performance [7,8,10].

2. Stochastic Modeling of Major Earthquakes in Algeria

2.1 Seismotectonic and Stochastic Modeling of Major Earthquakes in Algeria

Earthquakes result from instabilities along lithospheric faults caused by the progressive accumulation of tectonic stresses [2,12]. Faults remain locked for long periods while plates continue to move until a sudden rupture releases the accumulated energy in the form of seismic waves, inducing rapid displacement of the fault blocks.
In Algeria, the major earthquake of Boumerdes (2003) illustrate these mechanisms. The first is associated with the rupture of a local fault, while the second results from the interaction between the African plate and the Iberian block, generating a relative motion of approximately 3–4 mm/year toward the northwest [2]. These events caused significant human and material losses.
In the absence of reliable prediction or control measures, seismic risk reduction relies on statistical analysis and stochastic modeling. This study focuses on the modeling of seismic records associated with these major events using ARMA models [10].

2.2 Seismic Data and Preparation for ARMA Modeling

For modeling purposes, seismic records of the major Boumerdes (2003) earthquakes were collected from local stations and international databases [9,11,14]. The signals were filtered to remove noise, and the ground motion time series were analyzed to extract the statistical and spectral characteristics necessary for ARMA model calibration.

2.2.1 Boumerdes Earthquake (21 May 2003)

The study is based on records from the earthquake that struck the Boumerdes region, provided by the National Center for Seismic Engineering (CGS), Algeria [9]. The region experienced a sequence of shocks, with significant magnitude variations within two consecutive hours [11]. The earthquake was perceptible up to 250 km from the epicenter, with recorded ground accelerations on the order of 0.02 g.

Table 1. *Parameters of the 21 May 2003 earthquake according to various sources [9,11,14].*

Source	Latitude (°N)	Longitude (°E)	Depth (km)	Magnitude
CRAAG	36.91	3.58	—	6.2 (M_I)
USGS	36.90	3.71	10	6.8 (M_w)
CSEM	36.7941	3.9966	10	6.78 (M_w)
Strasbourg	36.94	3.75	10	6.7 (M_sz)
ETH	37.04	3.74	10	6.78 (M_w)

3. ARMA Model Identification

The identification of the ARMA model applied to stationary seismic accelerograms is based on the Box and Jenkins methodology, combining the analysis of the autocorrelation function (ACF), the partial autocorrelation function (PACF), and the Akaike information criterion (AIC) [3–6].
The ACF is used to characterize the temporal dependence of the signal and to identify the order of the moving average component, while the PACF allows the determination of the order of the autoregressive component. A sharp cutoff in the ACF or PACF indicates an MA(q) or AR(p) model, respectively, whereas a gradual decay suggests a mixed ARMA structure [3,6].The candidate models are then compared using the AIC, which penalizes excessive model complexity and enables the selection of the model that provides the best compromise between accuracy and parsimony [1]. The optimal model corresponds to the minimum AIC value.This approach allows the selection of a stationary ARMA model capable of reproducing the essential temporal and spectral properties of seismic accelerograms, providing a reliable basis for the generation of synthetic ground motion records for structural dynamic analyses [7,10,13].

ARMA Modeling of Seismic Acceleration Time Series.

An earthquake represented by an acceleration time series is a time-dependent phenomenon triggered by fault slip, for which it is impossible to establish a deterministic model that allows exact calculation. Therefore, an acceleration time series is considered a sample from the set of all possible time series that could be generated by the underlying stochastic process**.**

Since acceleration records exhibit highly irregular motion and have finite duration, they are modeled as a nonstationary stochastic process. In this framework, the damage potential is characterized by the statistical properties of the population generated by the stochastic model.

A general representation of the ARMA (p, q)process is as follows:

$$Z_t - \varphi_i Z_{t-1}, \dots \dots, \varphi_p Z_{t-p} = a_t - \theta_1 a_{t-1} - \cdots \dots, \theta_q a_{t-q} \quad (1)$$

where Where φ_i and θ_i are constant coefficients, and (p, q) denotes the model order. The model contains p+q unknown parameters, $\varphi_1, \varphi_2, \dots \dots, \varphi_p, \theta_1, \theta_2, \dots \dots, \theta_q, \theta_q, \sigma_a$, which are typically estimated from data using maximum likelihood, while the model order is selected according to the Akaike Information Criterion (AIC).

The left-hand side of Eq. (1) represents the autoregressive (AR) part of order p, where $[Z_t]$] is the sequence of measured data. The right-hand side represents the moving average (MA) part of order q, with $[a_t]$ being a sequence of independent, identically distributed Gaussian random variables.

In the present study, the digitized data are first normalized. For a moving window of 100-time steps centered at time step "t", the root mean square $[S_t]$is computed. A normalized record $[A_t] = \frac{[Z_t]}{[S_t]}$, with zero mean and unit variance, is then constructed and modeled as a second-order stationary process in the form of Eq. (1).

3.1. Methodology for ARMA Modeling of Nonstationary Earthquake Records

The ARMA approach for time series analysis is applicable only to stationary processes [5,17]. However, earthquake ground acceleration records are inherently nonstationary [15,16]. Consequently, prior to applying an ARMA model, the recorded acceleration signal must be transformed into a stationary process.

The first step of the modeling procedure consists in isolating the portion of the record corresponding to significant ground shaking. This is generally achieved by removing the initial 1% and the final 2% of the accelerogram [15].

The modeling of an accelerogram using an ARMA process is then carried out through the following steps:

1. Compute the experimental envelope function $[S_k]$ and normalize the acceleration record [16].
2. Assume a simple analytical expression for S_k and estimate its parameters using a least-squares method [19].
3. Stabilize the original acceleration record by removing the nonstationary characteristics [16,19]..
4. Compute the autocorrelation function (ACF) and the partial autocorrelation function (PACF) [17,18]
5. Select the autoregressive order p and the moving average order q of the ARMA model (Eq. 1).
6. Estimate the AR coefficients $\varphi_i, i = 1,2,3..p$and the MA coefficients, $\theta_j, j = 1,2,3..q$ using a maximum likelihood estimation. The ACF and PACF are recalculated to verify the selected orders and to ensure stationarity of the modeled process.
7. Evaluate alternative ARMA model orders (p, q) using the Akaike Information Criterion (AIC) (and select the model corresponding to the minimum value of AIC(p, q) [18].

3.1.1. Modulating Function

The modulating function of a given time series Zt is estimated using the Pradwarter method [16]. In this approach, the accelerogram is divided into equal-duration segments, whose length is selected to ensure an adequate resolution of the modulation process. In the present study, segments of 0.5 s were adopted, with a discrete time step of 0.02 s, resulting in 25 data points per segment. If N denotes the total number of data points and k the number of segments, then $N = 25k$. Several observation window lengths (25, 50, 100, and 200 samples) were tested, and a window of 50 samples was found to provide the most satisfactory compromise between smoothness and resolution. The ordinates of the modulating function are computed as:

were

$$S_i = \sqrt{\frac{1}{101} \sum_{t=i-50}^{t=i+50} (Z_t)^2} \quad (2)$$

where Z_t, $t = 1, 2, \dots, n$ represents the accelerogram.

3.1.2. Autocorrelation Function

To provide information on the selection of the order (p,q)(p,q)(p,q) of the ARMA process that can be used to represent a seismic acceleration record, it is important to refer to the behavior of the autocorrelation function, given by:

$$\rho_k = \sum_{i=1}^{p} \varphi_i \, \rho_{k-i} \; ; k \geq q+1 \qquad (3)$$

where

φ_i: denotes the autoregressive coefficients, and ρ_{k-i} denotes the autocorrelation coefficients [17].

The autocorrelation coefficients corresponding to the first q lags depend on both the autoregressive and moving average process coefficients, whereas for lags greater than q, they depend solely on the autoregressive parameters.

3.1.3. Partial Autocorrelation Function

The partial autocorrelation function (PACF) is a useful tool for describing the temporal dependence of a time series. When used in conjunction with the autocorrelation function (ACF), it plays a key role in identifying the type and order of ARMA models [18].

Unlike the autocorrelation function, which measures the overall correlation between two observations separated by a given lag, the partial autocorrelation function measures the **direct correlation** between two observations by removing the linear influence of the intermediate observations [17].

The partial autocorrelation function of order k is defined through the **Yule–Walker equations** as follows:

$$\begin{bmatrix} 1 & R(1) & . & . & R(k-1) \\ R(1) & . & . & . & R(k-2) \\ . & . & . & . & . \\ . & . & . & . & . \\ R(k-1) & 1 & . & . & 1 \end{bmatrix} \begin{bmatrix} \emptyset_{k1} \\ \emptyset_{k2} \\ . \\ . \\ \emptyset_{kk} \end{bmatrix} = \begin{bmatrix} R(1) \\ R(2) \\ . \\ . \\ R(k) \end{bmatrix} \qquad (4)$$

where:

- k denotes the order of the process,
- $R(i)$ represents the autocorrelation coefficient at lag iii,
- $\emptyset_{k1}, \emptyset_{k2}, \dots\dots\dots, \emptyset_{kk}$ are the autoregressive coefficients.

Solving this system for $k = 1,2,3,\dots$ yields the values of $\emptyset_{kk}$, which correspond directly to the partial autocorrelation coefficients.

For a stationary and invertible ARMA process, the partial autocorrelation function exhibits an exponential decay, possibly accompanied by damped sinusoidal oscillations. This behavior mainly depends on the moving-average (MA) parameters and appears after the first significant $(p-q)$ lags.

***Table 2**. Summary of autocorrelation and partial autocorrelation function characteristics.*

. Process	Autocorrelation Function (ACF)	Partial Autocorrelation Function (PACF)
$\mathbf{AR}(\boldsymbol{p})$	Infinite; exponentially decaying behavior and/or damped oscillations $\rho_k = \sum_{j=1}^{p} \varphi_j \, \rho_{k-j}$	Finite; significant spikes from lag 1 to lag p, followed by a sharp cutoff
$\mathbf{MA}(\boldsymbol{q})$	Finite; significant spikes from lag 1 to lag q, followed by a sharp cutoff	Infinite; exponential decay and/or damped oscillations
$\mathbf{ARMA}(\boldsymbol{p},\boldsymbol{q})$	Infinite; first $(q-p)$ lags are irregular, followed by exponentially decaying behavior and/or damped oscillations $\rho_k = \sum_{i=1}^{p} \varphi_i \, \rho_{k-i}$	Infinite; first (q−p) lags are irregular, followed by exponentially decaying behavior and/or damped oscillations

4. Adopted ARMA Modeling Framework for Seismic Acceleration Analysis

In the analysis of acceleration time series, the selection of an appropriate model depends primarily on the objectives of the application. For engineering design purposes, it is desirable to represent ground motion using a minimal number of parameters while preserving the essential characteristics of the signal.

Accordingly, this study adopts an autoregressive moving average (ARMA) model combined with a parametric envelope function. As established in previous sections, earthquake acceleration records are inherently non-stationary. Therefore, the first step in the modeling procedure consists of transforming the original record into a stationary process. This is achieved by dividing the acceleration time series by a suitable modulating function.

The extracted modulating function is subsequently approximated by a smoothed parametric envelope, which captures the temporal variation of the signal amplitude. For seismic events characterized by a single dominant peak, a simple and effective analytical expression of the envelope function [19]. is given by:

$$s(t) = \alpha e^{-\left(\frac{t-\beta}{\gamma}\right)t} \qquad (5)$$

where α, β, and γ are positive parameters controlling the amplitude, shape, and decay rate of the envelope, respectively.

4.1. Seismic Acceleration Records Analyzed.

For this study, three distinct acceleration time series were systematically analyzed. These include:

- Afroun, comprising 16000 data points with a digitization interval of 0.005 seconds,
- Ain Defla, comprising 5000 data points with a 0.005-second interval, and
- Dar Beida, comprising 5528 data points, also at 0.005-second increments.

The primary distinction among these records lies in the total number of data points available for estimation. The corresponding measured acceleration time series are presented in Figures1, 2, and.3, illustrating the temporal variations of ground motion for each site.

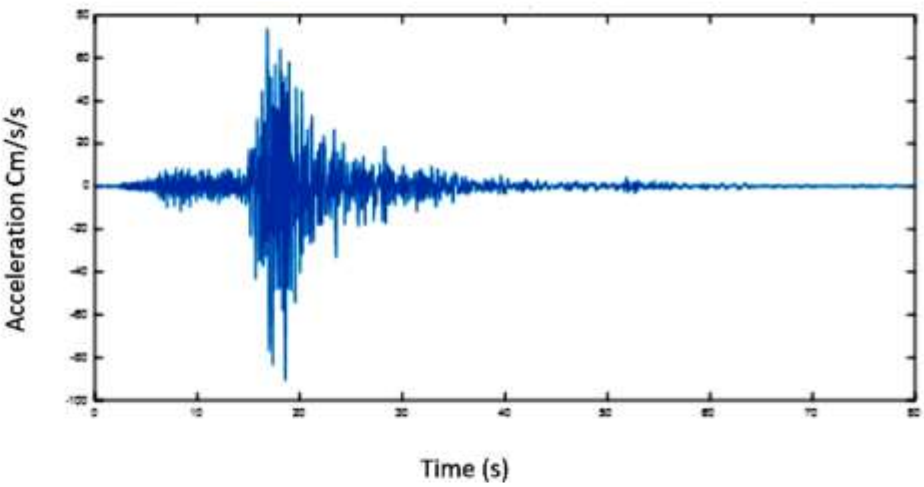

Figure 1. *Recorded Acceleration Time History at Afroun*

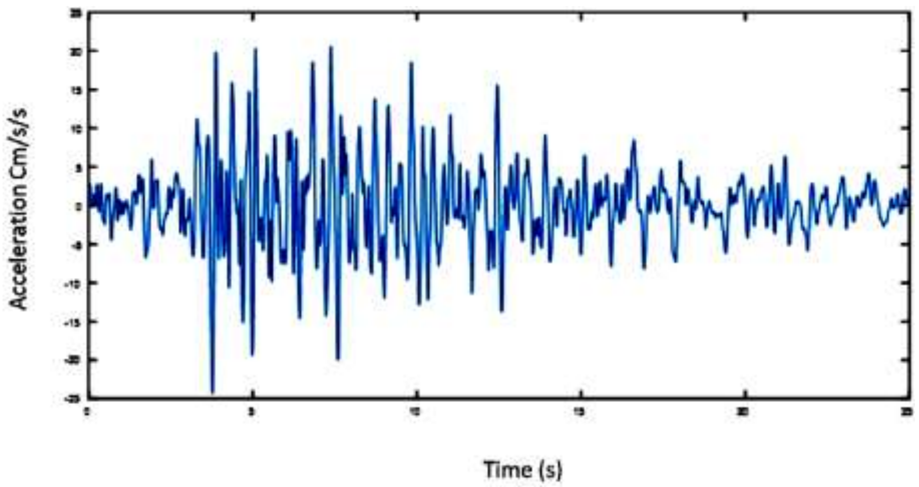

Figure 2. *Recorded Acceleration Time History at Ain Defla.*

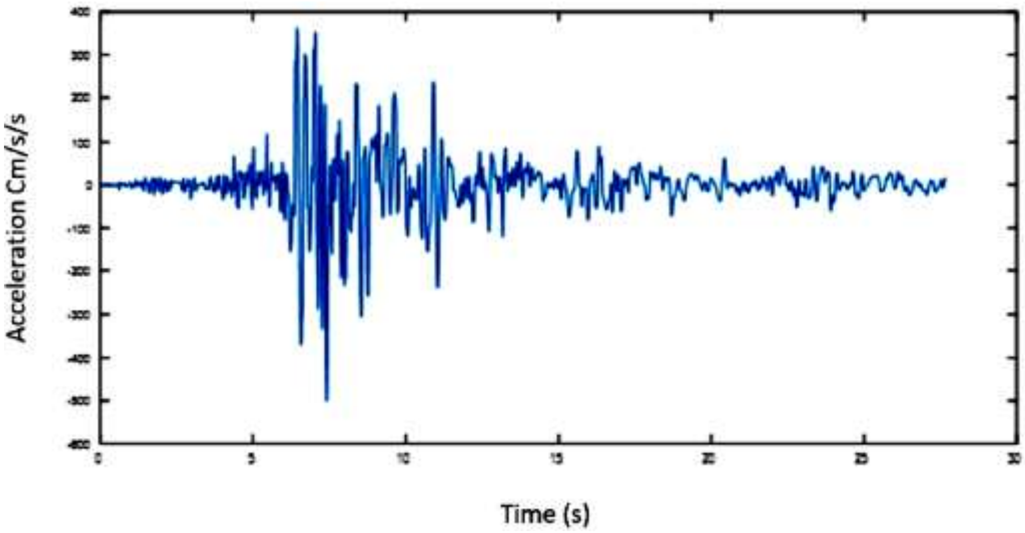

Figure 3. *Recorded Acceleration Time History at Dar El Beida*

As the initial step in model identification, the modulating function f(t)f(t)f(t) was computed for each recorded acceleration time series. The resulting modulating functions are presented in Figures .4, .5, and.6. The analysis clearly demonstrates that non-stationarity is pronounced in all events, highlighting the need for appropriate preprocessing before ARMA modeling.

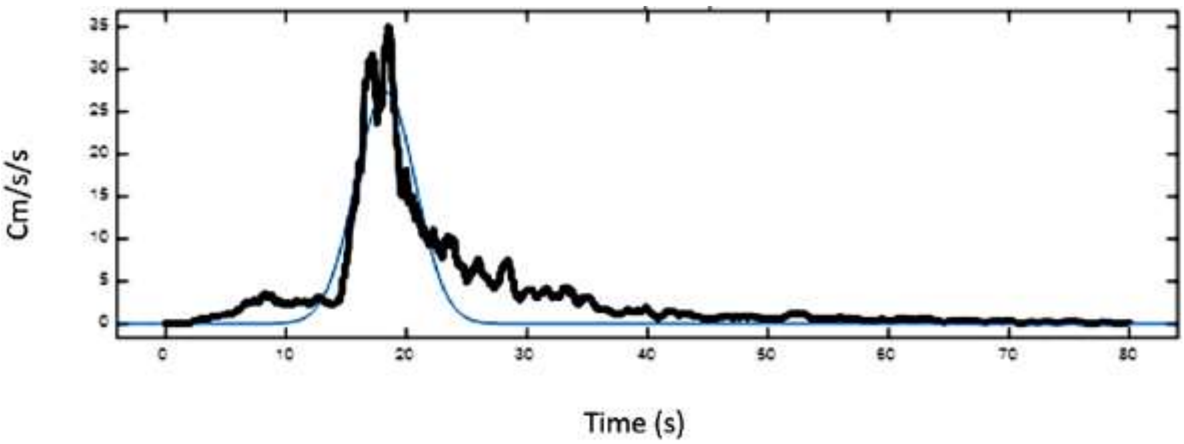

Figure 4. *Measured Acceleration and Envelope Function at Afroun.*

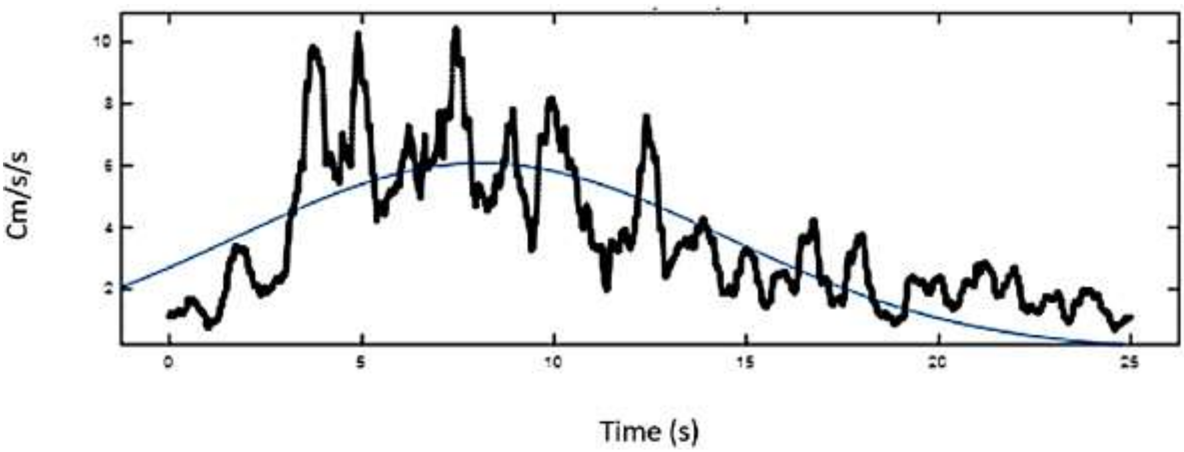

Figure 5: *Measured Acceleration and Envelope Function at Ain Defla*

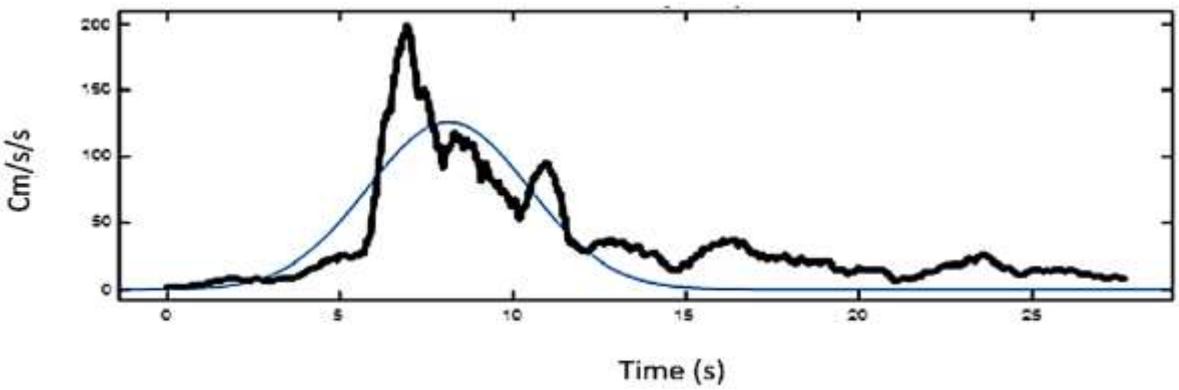

Figure 6. *Measured Acceleration and Envelope Function at Dar Beida*

The single-peak envelope function (Eq. 5) was fitted to each measured modulating function via least squares (Figs. 3.4–3.6). Using the original acceleration records and their modulating functions, stabilized (broad-sense stationary) acceleration time series were derived for the three events (Figs.7,8,.9), exhibiting zero mean and unit variance. The frequency content of each series is incorporated into the ARMA model parameters.

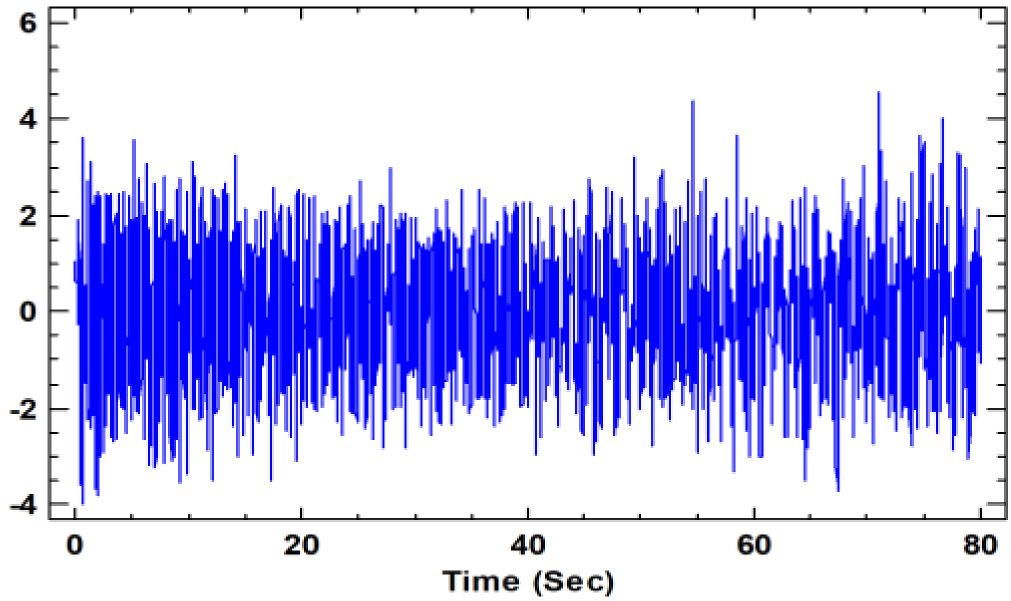

Figure 7. *Stationarized Acceleration Time Series Recorded at Afroun*

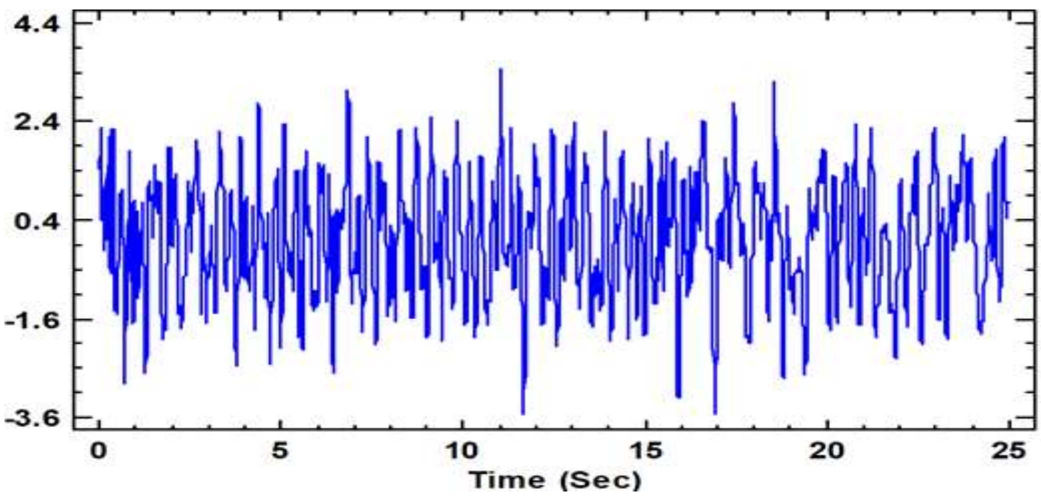

Figure 8. *Stationarized Acceleration Time Series Recorded at Ain Defla*

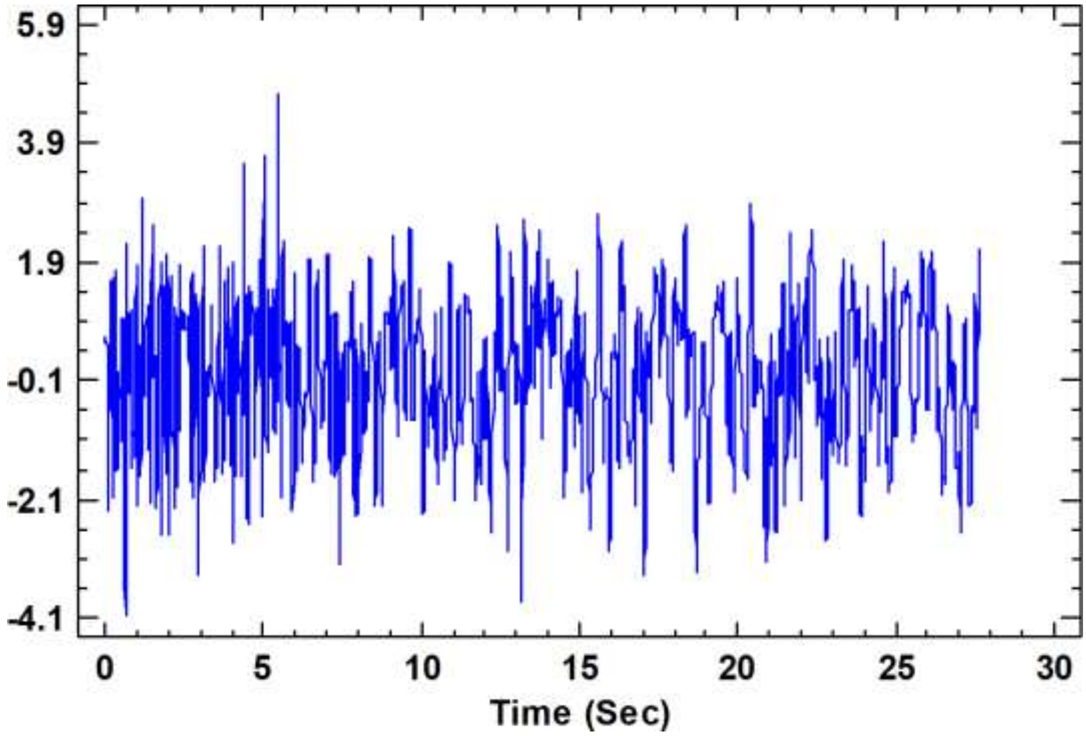

Figure 9. *Stationarized Acceleration Time Series Recorded at Dar El Beida*

4. 2Autocorrelation Analysis of Stabilized Acceleration Series:

The autocorrelation functions of the three stabilized acceleration time series were computed using Eq. 2.10. For clarity, the resulting autocorrelations are presented in Figs.10, 11, and 12. The rapid decay of the autocorrelation functions indicates that none of the characteristic equation roots approach the unit circle boundary, confirming the stationarity of the processed time series.

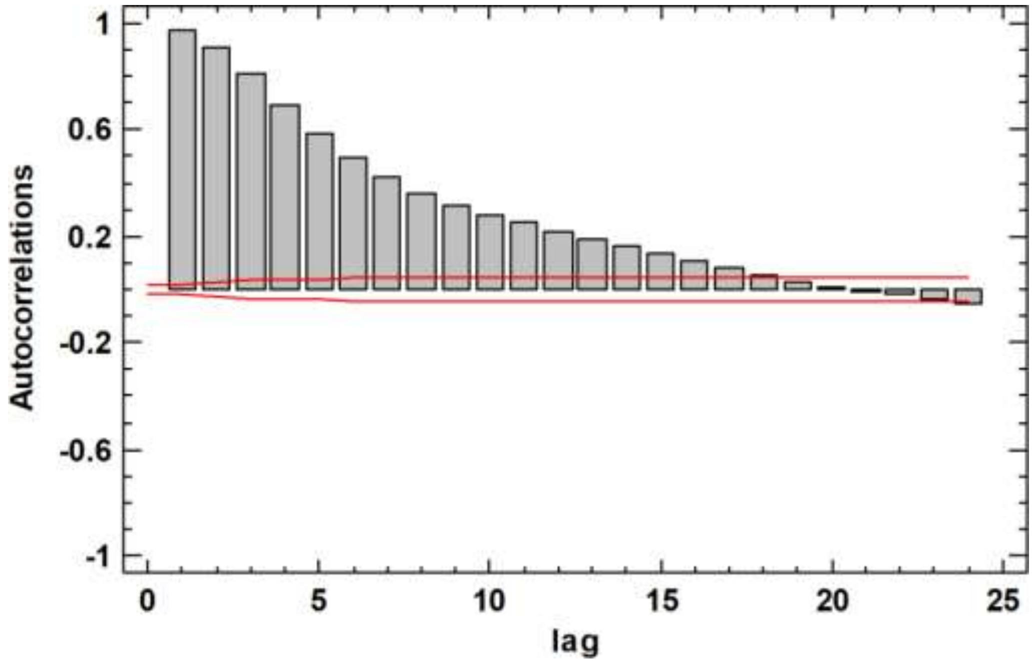

***Figure 10**.* *Autocorrelation Function of Stabilized Acceleration at Afroun*

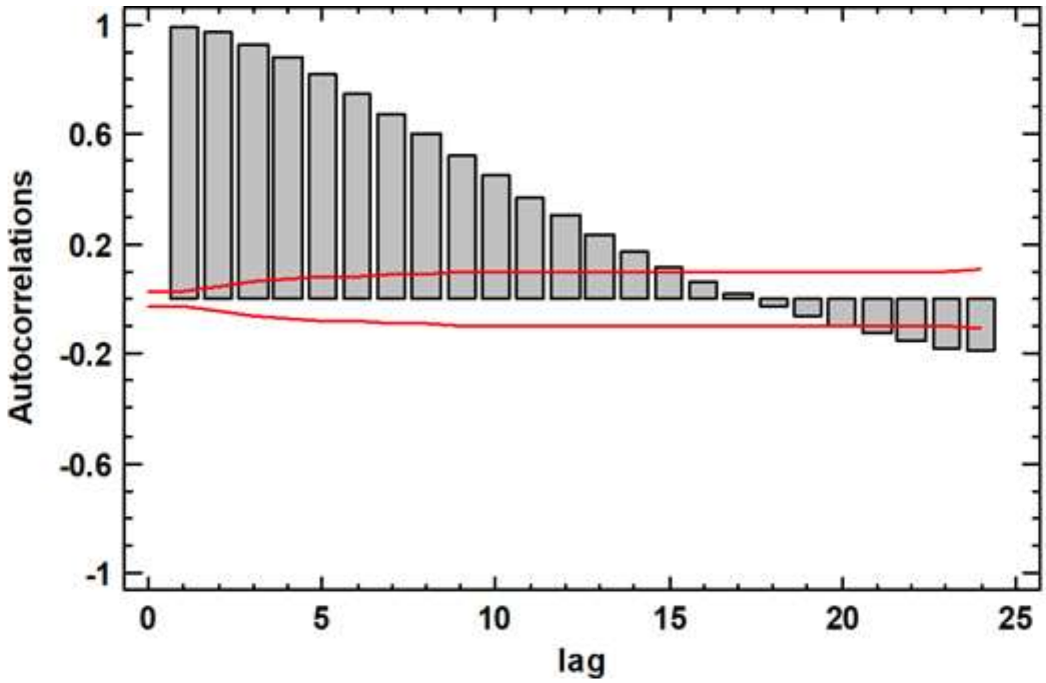

***Figure 11**. Autocorrelation Function of Stabilized Acceleration at Ain Defla*

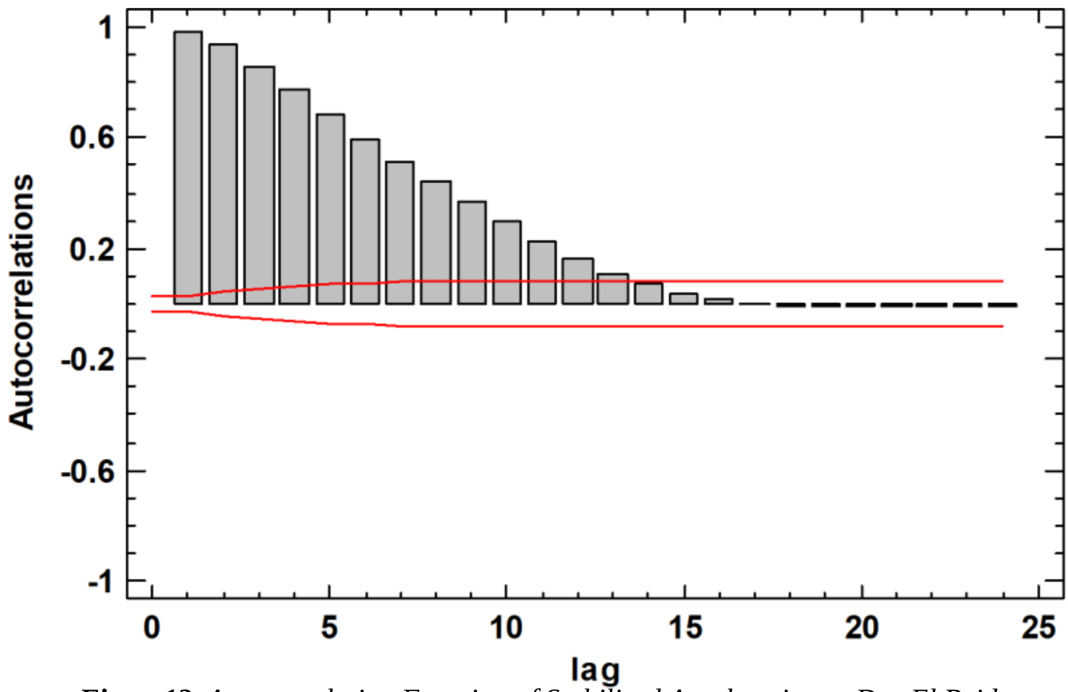

***Figure12**. Autocorrelation Function of Stabilized Acceleration at Dar El Beida*

As described above, the partial autocorrelation functions (PACF) for each seismic record were computed by fitting successive autoregressive (AR) models of increasing order k in MATLAB. The resulting PACFs are shown in Figs. 3.13–3.15. For the Afroun, Ain Defla, and Dar El Beida series, the PACFs exhibit a sharp decay beyond lags k=2, or3 indicating that ARMA models with p-q=2 or 3 appropriate.

Candidate ARMA (p,q) models were systematically evaluated for each event. Parameter estimation was performed via maximum likelihood, approximated by the least squares method, ensuring robust model fitting. The Akaike Information Criterion (AIC) was employed to select the optimal model order. Multiple ARMA simulations including one or two moving average (MA) terms were tested, and the model yielding the minimum AICvalue was adopted as the final representation of the stabilized acceleration series. The selected models and their AIC values are summarized in Table 4. As explained previously, the partial autocorrelation functions (PACF) of the acceleration records were estimated by fitting successive autoregressive (AR) processes of increasing order k using MATLAB. The resulting PACFs are presented in Figs.13, 14, and 15. Examination of the PACFs for the Afroun, Ain Defla, and Dar El Beida time series shows that the correlations decay rapidly after lag k=2 or k=3. This behavior suggests the suitability of ARMA models with orders (p,q) such that p-q=2 or 3. Consequently, ARMA models with p-q in the range of 2,3 were considered as potential candidates.

The combined analysis of the autocorrelation (ACF) and partial autocorrelation (PACF) functions provided preliminary guidance on the structure of the stochastic models to be investigated. To obtain reliable parameter estimates, all candidate models suggested by the ACF and PACF analyses were applied to the three earthquake events under consideration.

A range of ARMA models was fitted to the experimental acceleration time series using maximum likelihood estimation, which was approximated by the least-squares method.

Model selection was performed using the Akaike Information Criterion (AIC). During the computational process, several ARMA models incorporating one or two moving-average (MA) terms were identified as viable candidates. The AIC-based comparison clearly indicated that the optimal simulation model corresponds to the minimum AIC value. The AIC values obtained for the various ARMA(p,q) models for each event are summarized in Table 4.

The results show that the acceleration time series of Afroun, Ain Defla, and Dar El Beida are best represented by ARMA(2,2) processes. Table 3 presents the estimated autoregressive parameters φ_1,φ_2 , the moving-average parameters θ_1,θ_2 as well as the envelope function parameters α,β, and γ corresponding to the maximum likelihood estimates for each seismic event.

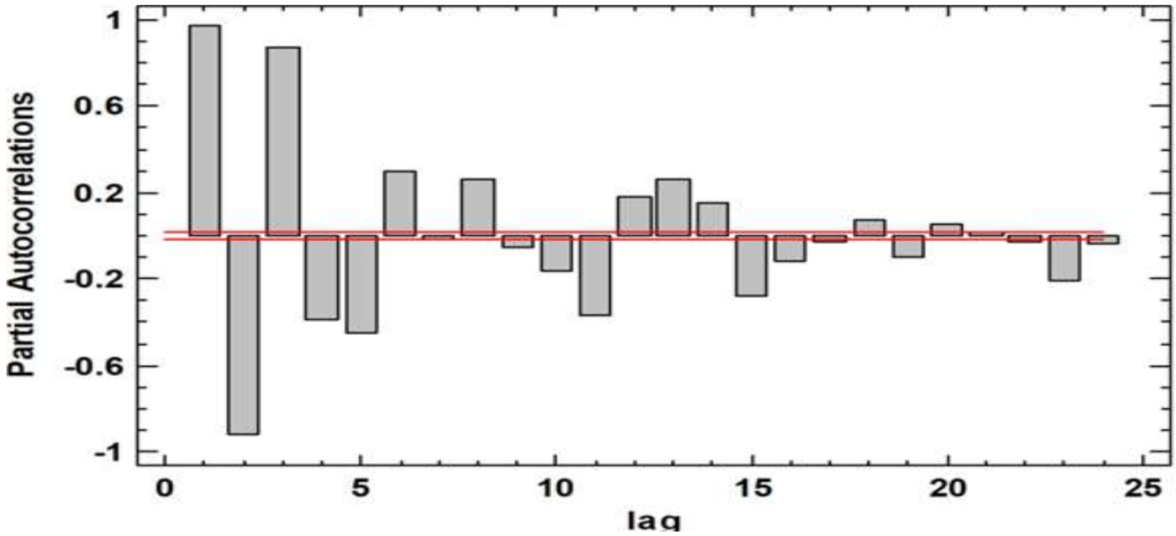

Figure 13. *Partial autocorrelation function (PACF) of the Afroun ground acceleration time series, estimated from successive autoregressive models, and used to identify the appropriate ARMA model order.*

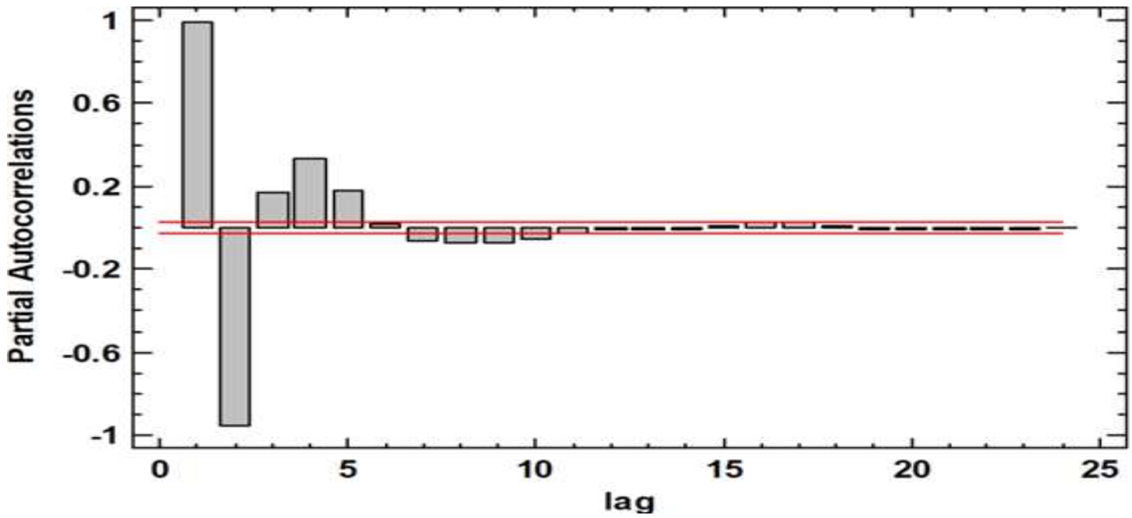

Figure 14. *Partial autocorrelation function (PACF) of the Ain Defla ground acceleration time series, estimated from successive autoregressive models, and used to identify the appropriate ARMA model order.*

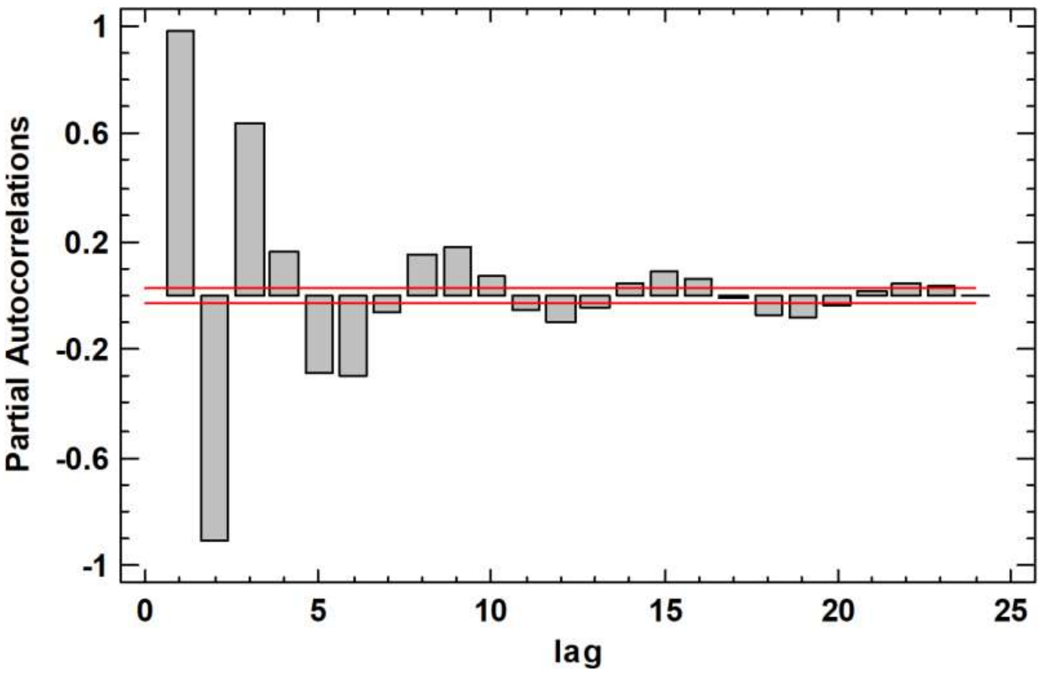

Figure15. *Partial autocorrelation function (PACF) of the Dar E Beida ground acceleration time series, estimated from successive autoregressive models, and used to identify the appropriate ARMA model order*

5. Stochastic Simulation of Earthquake Acceleration Time Series.

As previously discussed, the use of simulated ARMA processes within a time-domain framework allows an accurate representation of seismic acceleration records using a limited number of parameters. In order to generate a synthetic population that adequately reproduces the observed ground acceleration and can be employed for response-spectrum evaluation and damage assessment, acceleration time-series simulation is required.

The experimental procedure adopted in this study is summarized as follows. First, stationary acceleration time series were generated using the identified ARMA models. Subsequently, each stationary series was multiplied by an envelope function $S(t)$ in order to reproduce the non-stationary characteristics of real earthquake ground motions.

Furthermore, the ARMA process was assumed to be a linear combination of Gaussian random variables a(t) and previously generated values Z_t.Under this assumption, the acceleration time series can be simulated recursively in the time domain.

Figures 16, 17, and 18 present representative simulations of the acceleration time series obtained for the three seismic events considered in this study.

Table 3. *ARMA and Envelope Function Parameters*

ARMA Envelope Function	Afroun	Ain Defla	Dar Beida
φ_1	1.8635	0.944	1.9080
φ_2	-0.955845	-0.963	-0.9590
θ_1	-1.28836	-0.469	-1.1503
θ_2	-0.954263	-0.295	-0.8881
σ_w	0.0407843	-0.0210	0.03357
α	27.36	6.081	126.2
β	18.26	8.098	8.130
γ	3.29	8.991	3.290

Table 4. *AIC Values for ARMA (p, q) Models*

Acceleration Time Series	**Model**	**AIC (p, q)**
Afroun	ARMA (1, 1)	-3.77779
	ARMA (1, 2)	-5.24942
	ARMA (2, 1)	-5.2794
	ARMA (2, 2)	-6.39901
	ARMA (3, 1)	-6.38901
	ARMA (3, 2)	-6.39902
Ain Defla	ARMA (1, 1)	-4.88647
	ARMA (1, 2)	-5.75858
	ARMA (2, 1)	-7.5461
	ARMA (2, 2)	7.91847*
	ARMA (3, 1)	-7.90599
	ARMA (3, 2)	-7.90799
Dar El Beida	ARMA (1, 1)	-5.-00972
	ARMA (1, 2)	5.3097
	ARMA (2, 1)	-6.0831
	ARMA (2, 2)	-6.79935*
	ARMA (3, 1)	6.69935
	ARMA (3, 2)	6.59935

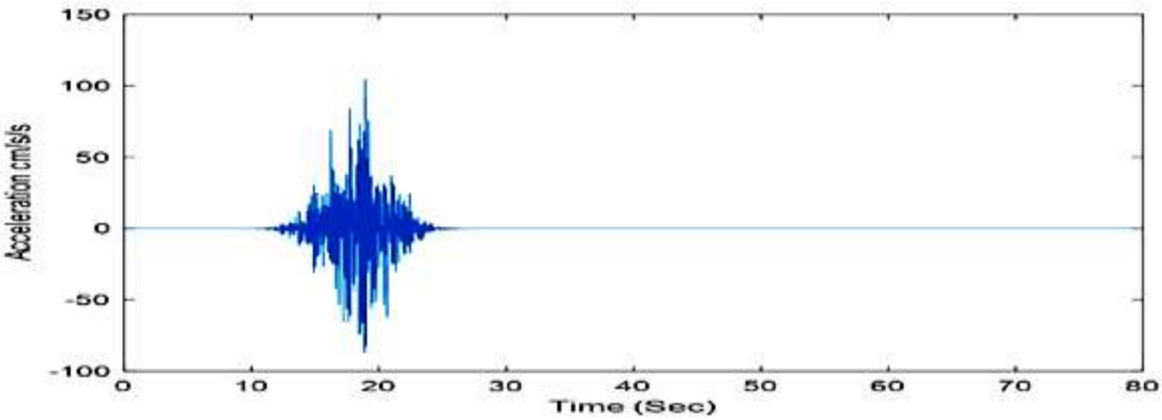

Figure 16. *Afroun Simulated Acceleration Time Series*

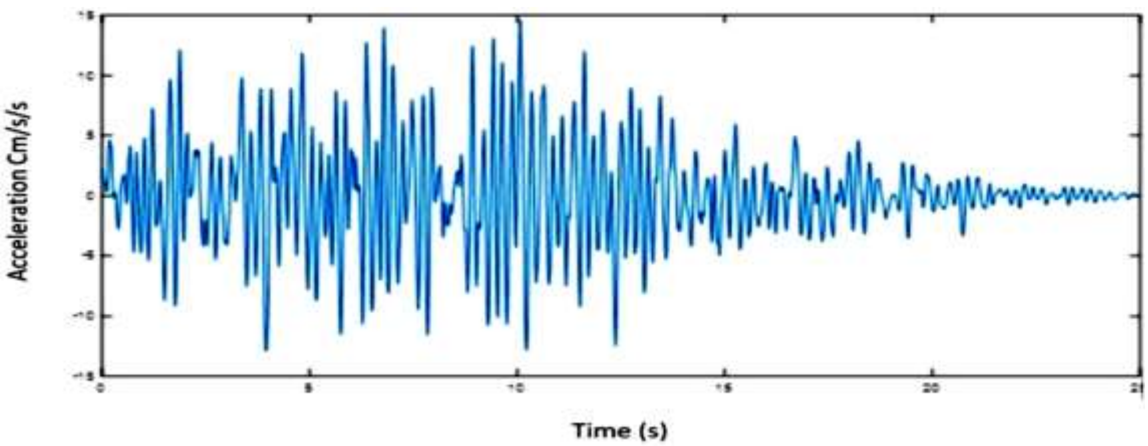

Figure17. *Ain Defla Simulated Acceleration Time Series*

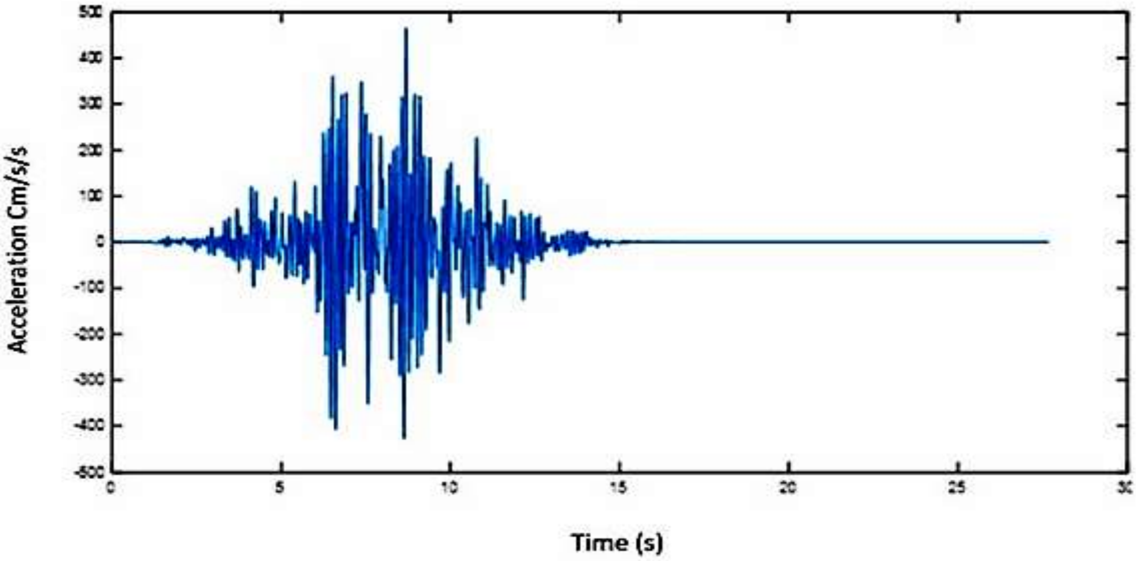

Figure 18. *Dar El Beida Simulated Acceleration Time Series*

6. Conclusions

Earthquake ground motions can be modeled as stochastic time series characterized by white-noise variance and autoregressive and moving-average coefficients. In this study, a time-domain framework for the analysis and simulation of earthquake accelerograms is proposed, with particular emphasis on applications in earthquake engineering and soil–structure interaction analysis. The methodology consists of three main steps: (i) modeling the non-stationary nature of recorded ground motions through a time-varying representation, (ii) estimating the model parameters using the least-squares method, and (iii) generating synthetic earthquake records via recursive simulation formulas.

The identification of the ARMA model structure is based on the combined use of the autocorrelation function (ACF), the partial autocorrelation function (PACF), and the Akaike Information Criterion (AIC). The ACF and PACF provide insight into the temporal dependence of the seismic signal and guide the selection of appropriate autoregressive and moving-average orders, while the AIC ensures an optimal balance between model accuracy and parsimony. This systematic procedure leads to the adoption of a low-order ARMA (2,1) model.

The proposed ARMA-based modeling approach requires a limited number of parameters and proves effective for seismic engineering applications. The response spectra of the simulated accelerograms show good agreement with those of the recorded earthquakes, except at long periods, likely due to residual low-frequency components after filtering. The selected envelope function accurately reproduces the amplitude modulation and duration of strong ground motion. The results indicate that the adopted stochastic model plays a key role in evaluating soil seismic response and provides reliable input motions for dynamic analyses of geotechnical and structural systems.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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