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Research Article

Calculate the total Earthquakes Force and Coefficients ARMA

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ABSTRACT

This study discusses the use of ARMA coefficient models. We know that for any random time series, we can write the ARMA(p,q) model detailed by Box and Jenkins. We can implement this using ARMA models, which have proven effective in many procedures, such as earthquakes and acceleration time series generated by random models Within the frequency time limits. provided comprehensive reviews of As a model of acceleration time series in both the frequency and time domains. Several research papers have addressed ARMA models. Box and Jenkins discussed ARMA models in detail .Here, we found the earthquake amplitude in terms of the ARMA(p,q) coefficients, but the ARMA(2,2) model can be considered the most appropriate in this case for the regions of northern Algeria, from which we extracted the Aïn Defla, Casablanca, and Affroun earthquakes. Taking into account the AIC RITERIA criterion, we found that it is in fact ARMA(2,2), which is what we studied. Using mathematical relationships, including some results such as the relationship used in calculating the seismic magnitude, we find that it agrees with the model.ARMA(2.2)

Keywords: Time series, seismic force, spectral density, coefficients ARMA

1. INTRODUCTION

The article by Housner and Jennings is obviously . They adopted a stationary model in amplitude and frequency content where ground motion acceleration was considered as segments which consist of series of impulses distributed randomly in time. This process was described by mean zero and variance σ^2 and a power spectral density

$$G(w) = \frac{\lambda\sigma^2}{\pi} \tag{1}$$

where λ is the average number of impulses per second. Based on the Rosenbluth and Bustamante approximate theory (22) which relates the maximum and for white noise the energy of the oscillator to the density, the spectral density of the process was related to the velocity response spectra for an undamped system. With this relation, Series for earthquake acceleration and intensity spectrum was estimated and used to fit the functional form of the filter developed by Kanai and Tajimi (23). Eight earthquakes were generated, and the response spectra were calculated and compared to the original events. Since the response spectra depends on the nonstationary character of amplitude and frequency of an earthquake, modeling earthquakes based on stationarity assumptions is obviously limited. But in this work, we will try to simulate the equation (1) with coefficients ARMA

2. ARMA PARAMETERS ESTIMATION:

$$L(\zeta, z) = -n\ln(\sigma) - \frac{s(\phi,\theta)}{2\sigma} \tag{2}$$

Where

$$s(\phi,\theta) = \sum a_t^{\,2}$$

For any fixed value of σ_a in the space of $(\emptyset, \theta, \sigma_a)$ contours of L are contours of S. Therefor the maximum likelihood estimates are the same as the least squares estimates. The values of parameters $(\emptyset, \theta, \sigma_a)$ which minimize the residuals some of squares are obtained .As noted in ARMA (p, q) process model could be represented as follows:

$$Z_t - \varphi_1 Z_{t-1} - \cdots - \varphi_p Z_{t-p} = a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \qquad (3)$$

The parameters are: $\varphi_1, \varphi_2, \ldots, \varphi_p, \theta_1, \theta_2, \ldots, \theta_q, \sigma_a$

where (φ_i)) and (θ_i) are constant coefficients, and is the order (p, q) of the model The model contains p+q+1 parameters ($\varphi_1, \varphi_2, \ldots, \varphi_p, \theta_1, \theta_2, \ldots, \theta_q, \sigma_a$) unknown which are usually estimated from data based on maximum likelihood and the order is based on the partial AR functions.

4 .APPLICATION OF ARMA MODELS :

In this study, measured records of acceleration time series are considered, namely Ain Defla (duration 25 seconds), Afroun (duration 80 seconds), and Dar Beida (duration (28 seconds). These acceleration time series are assumed to be a single realization from a nonstationary stochastic process that characterizes the acceleration involved.

One way to prove this hypothesis is to use ten simulated. Time series of acceleration as an inputs for a single degree of freedom system, at the same time the real Time series of acceleration is used as inputs for the same single degree of freedom system and compare the results.

The original acceleration and the mean acceleration time series both are within the mean plus minus one standard deviation (mean $\pm \sigma$).

Stationarity conditions were explained in section 1. The stationarity depends on the mean, standard deviation, and seasonality. All real acceleration time series used in this study are non-stationary time series, at least these time series don't have a constant standard deviation: Figures 1, 2, and 3. As explained by Box and Jenkins (2) ARMA models could be used only for stationary time series. For this reason, all real acceleration time series (Afroun, Dar El Beida, Ain Defla) are transformed to a stationary time series as explained in Section 2 the stationary time series. Standard deviation of one and mean of zero. When ARMA parameters are obtained, a stationary time series is generated as explained in Section 3 and multiplied by an envelope function S(t) the final time series will be a no-stationary time series. The output of this method is a non-stationary time series.

I was trying to estimate ARMA parameters using MATLAB, but my laptop couldn't handle big data. I am using real acceleration times series data namely Afroun with 16000 data points, Ain Defla with 5000 data point, Dar Beida with 5528 data points, so I used STATGRAPHICS which is a computer software that perform statistical procedures and handles big data. I included in the appendices the use of STATGRAPHICS to estimate ARMA parameters as follows:

The procedure to obtain ARMA(p, q) parameters is summarized by the following steps:

1) Find the adjustment function. f(t) and normalization the original time series data (Afroun, Dar El Beida, Ain Defla)
2) Let it be a simple general analytical form. for f(t) And appreciation the parameters using least square method programed using MATLAB.
3) Calculate the Autocorrelation with partial autocorrelation functions.
4) Select the request "p" for the autoregressive part AR with an order "q" for the moving average part MA.
5) Transaction estimation $\varphi_i, i = 1, 2, \ldots, p$ with $\theta_j, j = 1, 2, \ldots, q$ on Maximum likelihood basis using STATGRAPHICS.
6) Based on the AIC criteria evaluate an alternative set of model orders (p, q) with the choice of course of the model with the minimum AIC (p, q).

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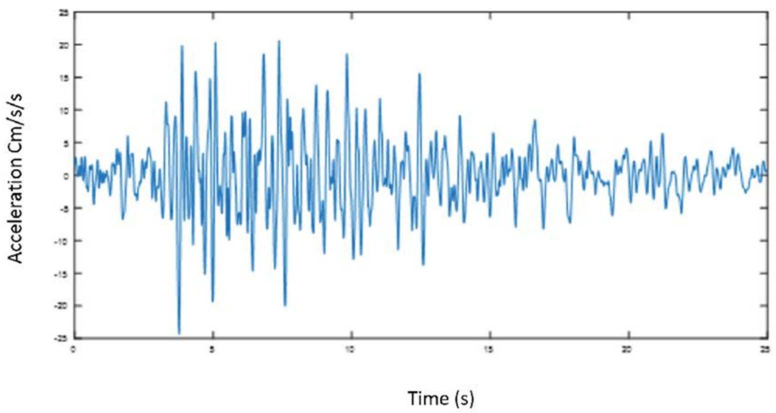

Figure.1 Ain Defla Acceleration time series

Ain Defla

Envelope function

$$Y = \alpha . e^{-(\frac{t-\beta}{\gamma})^2}$$

Parameters

α = 6.081

β = 8.098

γ = 8.991

STAGRAPHICS

Automatic Forecasting - col2

Ain Defla

Number of observations = 5000

Table 1 : **ARMA** Model Summary

Parameter	Estimate	Stnd. Error	t	P-value
AR(1)	1.95609	0.00315201	620.584	0.000000
AR(2)	-0.973781	0.00314767	-309.366	0.000000
MA(1)	-0.357189	0.00840041	-42.5205	0.000000

Backforecasting: yes

Estimated white noise variance = 0.000611619 with 4997 degrees of freedom

Estimated white noise standard deviation = 0.0247309

Number of **iterations**: 8

Table 2 : Estimation the Period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	SBIC
(A)	0.0229678	0.017108		0.000307717		-7.54612	-7.54475	-7.54221

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	0.0229678	***	***	***	OK	***

The **model A** is the Akaike Information Criterion (AIC) that is used to generate predictions..

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Automatic Forecasting - col2

Number of observations = 5000

Time indices: col1

Table 3 : Summary Model ARIMA

Parameters	estimate	. error	t	P - values
AR(1)	0.944001	0.00348822	557.397	0.000000
AR(2)	-0.962991	0.00347994	-276.753	0.000000
MA(1)	-0.295011	0.00803535	-58.413	0.000000
MA(2)	-0.294998	0.00726037	-40.6427	0.000000

Yes **Backforecasting**

noise variance the estimated = 0.000440171 with 4996 degrees of freedom

noise standard deviation the estimated = 0.0209803

Iterations of number 8

Model Comparison

Data variable: col2

Observation of number = 5000

Models

(A) ARIMA(2,0,2)

Table 4 : Estimation the Period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	SBIC
(A)	0.019158	0.0139502		0.000198123		-7.91847	-7.90664	-7.90326

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	0.019158	***	***	***	OK	***

Automatic Forecasting - col2

Variable the data : col2

Observation of number = 5000

Time indices: col1

Forecast Summary

Forecast model selected: ARIMA(1,0,1)

Table 5 : Summary Model ARIMA

Parameter	Estimate	Stnd. Error	t	P-value
AR(1)	0.98517	0.00191628	514.105	0.000000
MA(1)	-0.829718	0.00830794	-99.8705	0.000000

Backforecasting: yes

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Whit noise variance the estimated = 0.00781525 with 4998 degrees of freedom

white noise standard deviation estimated = 0.0884039

Number of **iterations**: 6

Model Comparison

Data variable: col2

Number of observations = 5000

Models

(A) ARIMA(1,0,1)

Table 6 : Estimation the Period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	SBIC
(A)	0.0868446	0.0671582		0.000214863		-4.88647	-4.88556	-4.88386

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	0.0868446	***	***	***	OK	***

Automatic Forecasting - col2

Data variable: col2

Number of observations = 5000

Time indices: col1

Table 7 : Summary Model ARIMA

Parameter	**Estimate**	**Stnd. Error**	**t**	**P-value**
AR(1)	0.978276	0.00200187	488.681	0.000000
MA(1)	-1.20824	0.00862181	-140.138	0.000000
MA(2)	-0.690355	0.00857704	-80.4887	0.000000

Backforecasting: yes
white noise variance the estimated = 0.00338131 with 4997 degrees of freedom
white noise standard deviation estimated = 0.058149
Number of **iterations**: 13
Model Comparison
Data variable: col2
Number of observations = 5000
Models
(A) ARIMA(1,0,2)

Table 8 : Estimation the Period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	SBIC
(A)	0.056141	0.0430136		0.0000891853		-5.75858	-5.75721	-5.75467

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	0.056141	***	***	***	OK	***

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(2,1) -7.54612
(1,2) -5.75858
(1,1) -4.88647
(2,2) -7.91847

Automatic Forecasting - col2

Data variable: col2
Number of observations = 5000
Time indices: col1

Forecast Summary

Forecast model selected: ARIMA(4,0,2)

Table 9 : Summary Model ARIMA

Parameters	Estimates	. Error	Time	q - values
AR(1)	3.50314	0.00670632	522.364	0.000000
AR(2)	-4.90208	0.0149132	-328.709	0.000000
AR(3)	3.27198	0.0111689	292.956	0.000000
AR(4)	-0.877829	0.00335142	-261.928	0.000000
MA(1)	-0.808126	0.0115042	-70.2459	0.000000
MA(2)	-0.569172	0.0101836	-55.8911	0.000000

Backforecasting: yes
white noise variance the estimated = 0.0000355552 with 4994 degrees of freedom
white noise standard deviation estimated = 0.00596282
Number of **iterations**: 66

Model Comparison

Data variable: col2
Number of observations = 5000

Models

(A) ARIMA(4,0,2)
(B) ARIMA(3,0,1)

Table 10: Estimation the Period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC
(A)	0.00573953	0.00411782		0.0000454058		-7.90599	-10.3156
(B)	0.0113527	0.00823757		0.0000377377		-7.9055	-8.95317

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	0.00573953	***	***	***	OK	***
(B)	0.0113527	***	***	***	OK	***

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$$Y = \alpha . e^{-(\frac{t-\beta}{\gamma})^2}$$

Parameters

α = 126.2

β = 8.132

γ = 3.287

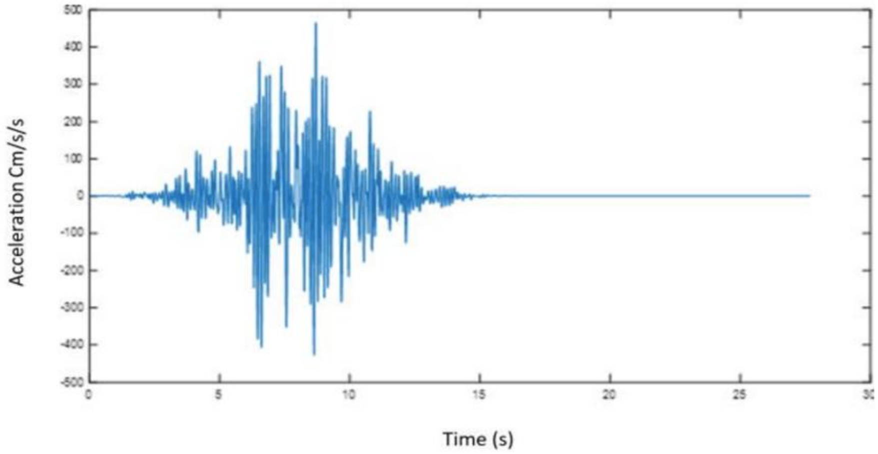

Figure.2 Dar El-Beida Acceleration time series

Automatic Forecasting - col2

Data variable: col2

observations of number = 5536

Time indices: col1

Forecast Summary

Forecast model selected: ARIMA(2,0,2)

Table 11 : Summary Model ARIMA

Parameters	Estimate	Error	Time	P - values
AR(1)	1.90798	0.00567934	335.952	0.000000
AR(2)	-0.959485	0.00559577	-171.466	0.000000
MA(1)	-1.15027	0.00523337	-219.795	0.000000
MA(2)	-0.888074	0.005873	-151.213	0.000000

Backforecasting: yes

white noise variance the estimated = 0.00112679 with 5532 degrees of freedom

white noise standard deviation estimated = 0.0335677

Number of **iterations**: 14

Model Comparison

variable of data: col2

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observations of number = 5536

Models

(A) ARIMA(2,0,2)

(B) ARIMA(2,0,1)

Table 12: Estimation the Period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC
(A)	0.0333601	0.0222345		-0.000435097		-6.79935	-6.79768
(B)	0.0477349	0.0315594		-0.000502236		-6.0831	-6.08185

Model Comparison

Data variable: col2

Number of observations = 5536

Models

(A) ARIMA(1,0,2)

Table 13 : Estimation the Period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC
(A)	0.0702707	0.0484233		-0.000121641		-5.30972	-5.30846

(A) ARIMA(1,0,1)

Table 14 : Estimation the Period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC
(A)	0.119527	0.0829379		-0.0000871306		-4.24771	-4.24687

(A) ARIMA(4,0,2)

(B) ARIMA(4,0,1)

Table 15: Estimation the Period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC
(A)	0.00894965	0.00596582		-0.0000537856		-4.43011	-9.42761
(B)	0.0108839	0.0076673		-0.000137169		-4.03914	-9.03706

Afroun

Envelope function

$$Y = \alpha . e^{-(\frac{t-\beta}{\gamma})^2}$$

Parameters

α = 27.36

β = 18.26

γ = 3.522

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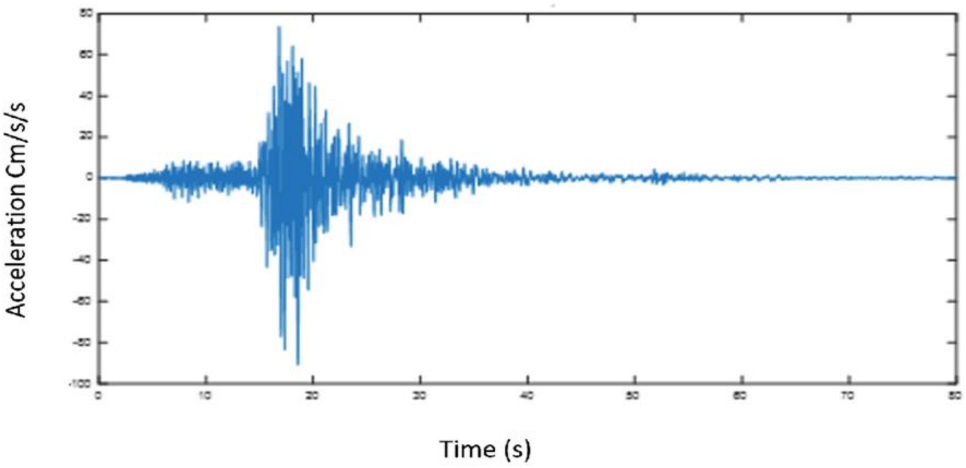

Figure.3 A froun Acceleration time series

Automatic Forecasting - col2

Variable of data : col2

observations of number = 16001

Time indices: col1

Forecast Summary

Forecast model selected: ARIMA(2,0,2)

Table 16 : Summary Model ARIMA

Parameters	Estimate	Error	Time	P - values
AR(1)	1.8635	0.00341588	545.541	0.000000
AR(2)	-0.922845	0.0032451	-284.381	0.000000
MA(1)	-1.28836	0.00156128	-825.19	0.000000
MA(2)	-0.954263	0.0013227	-721.452	0.000000

Backforecasting: yes

white noise variance the estimated = 0.00166336 with 15997 degrees of freedom

white noise standard deviation estimated = 0.0407843

iterations of number : 12

(A) ARIMA(2,0,2)

(B) ARIMA(2,0,1)

Table 17: Estimation the Period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC
(A)	0.0407723	0.0291291		-0.000103566		-6.39901	-6.39837
(B)	0.0713687	0.0510709		-0.000143314		-5.27942	-5.27894

Models

(A) ARIMA(1,0,2)

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Table 18 : Estimation the Period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	SBIC
(A)	0.0852195	0.0611601		-0.000081499		-4.92468	-4.9242	-4.92324

(A) ARIMA(1,0,1)

Table 19 : Estimation the Period

Model	RMSE	MAE	MAPE	ME	MPE	AIC	HQC	SBIC
(A)	0.151196	0.110331		-0.000101147		-3.7781	-3.77779	-3.77714

Through a careful empirical study of three acceleration time series, it appears that the model adopted in the region is ARMA(2.2)

5 . Calculation of total earthquakes force :

The total earthquakes force V, applied to the base For the building structure, we calculate respectively in two horizontal perpendicular directions according to the formula:

(4)

$$V = \frac{ADQ}{R}W$$

A : The area acceleration coefficient, according to buildings for the seismic zone, is shown in Table 20 usage group

Table 20 : Area acceleration coefficient A

Group	**I**	**II**	**III**
1A	0,120	0,251	0,350
1B	0,101	0,200	0,301
2	0,080	0,151	0,250
3	0,050	0,100	0,150

(5)

$$D = \begin{cases} 2,5\eta & 0 \le T \le T_2 \\ 2,5\eta\left(T_2/T\right)^{\frac{2}{3}} & T_2 \le T \le 3s \\ 2,5\eta\left(T_2/3\right)^{\frac{2}{3}}\left(3/T\right)^{\frac{5}{3}} & T \ge 3s \end{cases}$$

D : We have the average dynamic amplification factor, the damping correction factor (η) the location class function, and the fundamental period of the structure (T).

T2 It is the special period that is associated with with the site category and given by Table 22

D the factor is also given in graphical form in Figure (41), for depreciation η = 5%

depreciation correction factor given by the formula where (%) is the percentage of critical damping depending on the constituent material,the importance of the fillings and the type of structure

$$as\ to \quad \xi = 5\%, \quad we\ have \quad \eta = 1$$

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Table 21 : Values of ξ (%)

filling	Porticos		walls or Sails
	Reinforced concrete	Steels	Reinforced concrete /masonry
Light	6,00	4,01	10,00
Dense	7,01	5,00	

Table 22 : Value of T_1 and T_2

Site	St_1	St_2	St_3	St_4
T_1(sec)	0,151	0,151	0,151	0,151
T_2(sec)	0,300	0,400	0,500	0,700

R: Overall structural behavior coefficient

Its unique value is given in Table 22 depending on the bracing system as defined in 3.4.

If different bracing systems are used in the two directions considered, the smallest value for coefficient R should be adopted

- **Q**: Quality of Factor

- of the structure depends on quality factor

- the geometry of its constituent elements

- the regularity in plan and elevation

- the quality of constructn control 5

The value of Q is determined by the formula : $Q = \dfrac{1}{\sum_{1}^{5} p_i}$ (6)

Pq is the penalty that will be applied depending on whether the quality is criterion q "is satisfied or not."

6. RESULTS:

1.Through a careful empirical study of three acceleration time series, it appears that the model adopted in the region is ARMA(2.2)

2. We mention the following relationships:

$$w^2 = 2\pi T \quad (7)$$

$$\log E = c_1 + c_2 \log T \quad (8)$$

We use the two previous relationships and find:

$$\log E = k_1 + k_2 \log w \quad (9)$$

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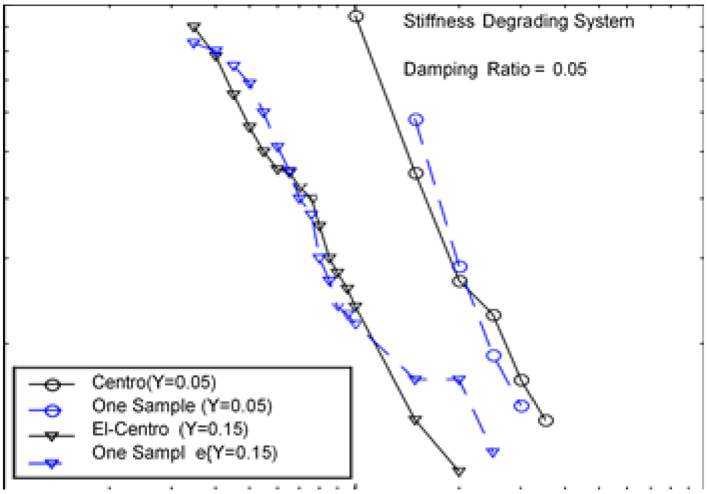

Figure.4 Ain Defla Simulation of the relationship (9)

The curve is a direct result (Ain Defla) of a simulation of the relationship(5 .3) found in the result.

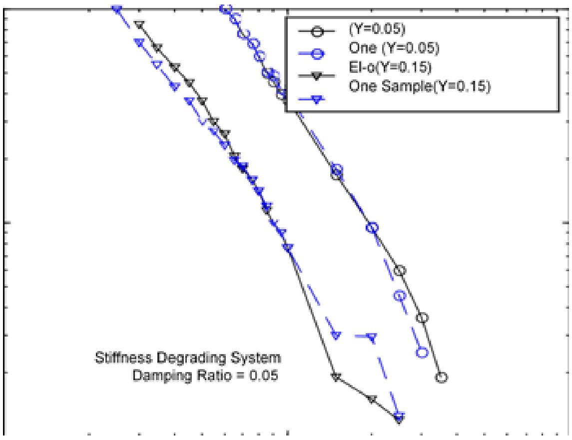

Figure.5 Dar El Beida Simulation of the relationship (9)

The curve is a direct result (Dar El Beida) of a simulation of the relationship (9) found in the result.

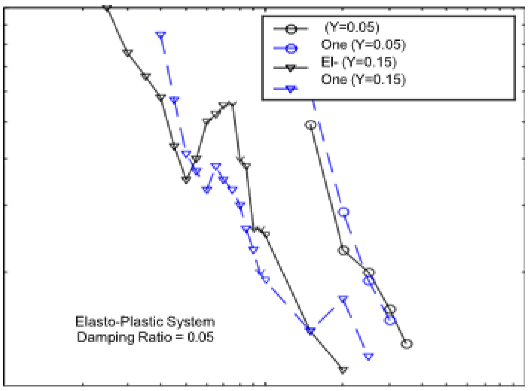

Figure.6 Afroun Simulation of the relationship (9)

The curve is a direct result (Afroun) of a simulation of the relationship(9) found in the result.

Multiple ARMA models were successfully used to analyze the three acceleration time series. The experimental data were recorded for further processing, providing information about the predicted ARMA parameters for ease of visualization

$$V = MZ'' \quad (10)$$

CONCLUSIONS :

(1) This approach provides a time domain using a limited number of parameters.

(2) The coupled relationship is also widely used in practice.

(3) Assuming that the acceleration (earthquake) time series corresponds to the main event, this allows for an accurate description of the response spectra.

(4) The response (acceleration) spectra are roughly related to the envelope coefficients for the system period.

(5) The result is more reliable in determining the constructor's built-up area. ARMA

(6) Next, we will simulate relationships (5.4) and (3.2), which represent the earthquake magnitude and its coefficients. ARMA

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