A Real-Time Stochastic Wave-Type based Model for Prediction of Strong Ground Motion

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SUMMARY:
A wave type based method for real-time prediction of Strong Ground Motion accelerogram is developed. Real-time prediction of SGM is requested in building control systems to trigger and control actuator systems achieving the goal of reduction of the structural deformations. The SGM is a classic example of non-stationary stochastic process with temporal variation in both amplitude and frequency domains. In the suggested real-time predictor the non-stationarity of the process is achieved by dividing the process into the two dominant phases of P and S-Coda. Therefore, an important part of the method is to detect dominant seismic phases. Furthermore, development of the models will be performed separately in amplitude and spectral domains. The parameters of the models will be identified by continuously matching the models to the target accelerograms. The most significance of the proposed model is the wave type based concept which provides physical insight into the models.

Keywords: Real-time, Prediction, Strong Ground Motion, Stochastic, Wave-type Based

1. INTRODUCTION

In spite of the effectiveness of conventional control systems to reduce the structural response in some measures they have a significant drawback. In treating ideal systems, it is assumed that the operations can be performed instantaneously. In reality, however, time has to be consumed in processing measured information, in performing on-line computation, and in executing the control forces as required. Thus, time delay causes unsynchronized application of the control forces and this unsynchronization can not only render the control ineffective, but may also cause instability in system (Pu, 1989).

To eliminate the time delay effect several approaches have been developed. One of the most effective solutions is the predictive control approach (Rodellar et al, 1987). The predictive control approach applied a strong ground motion (SGM) predictor to simulate the signal in the time-windows ahead. Existing methodologies to simulate the SGM excitation used in predictive active control systems can be categorized into the following sub-classes

- Pre-established earthquake models (e.g. Bolotin, 1960)
- Real-time time-series predictors (e.g. Mei et al, 2001)
- Real-time fuzzy logic based predictors (Kawamura et al, 1990)

Mismatching of the prescribed spectral models, lack of the physical background of the process during the modeling and neglecting of non-homogeneity and non-stationarity characteristics of the SGM process are the most considerable drawbacks of the existing methodologies.

In this study we develop a real-time parametric predictor, in which the non-homogeneity of the SGM process is considered by splitting the process in its dominant phases, namely dominant-P, S and coda.

Since separating of the temporal amplitude and spectral content of the SGM process increases the flexibility and ease in modeling and parameter estimation (Rezaeian and Der Kiureghian, 2008), two distinguish models for amplitude envelope and spectral content of the SGM are developed. The real-time predictor model parameters are identified and estimated by continuously matching the model to the target accelerograms.

2. METHODOLOGY

An approach based on the fitting a parameterized stochastic model to real-time recorded ground motion is developed to model the frequency content of the SGM. In addition, to model the amplitude envelope function a model based on the soft-computing approach is developed. It is important to properly model both spectral and temporal non-stationary, particularly for inelastic and degrading structures, which tend to consider the resonant frequencies that also evolve in time. The developed stochastic models consider the non-stationarity of the SGM process by applying an evolutionary time-modulating filtering on Gaussian white-noise, in which according to the spectral characteristics of the current time window the parameters of the filter are estimated continuously. Whereas the time-modulation provides temporal non-stationarity, the variation of filter parameters over time assures the spectral non-stationarity (Figure 1). To map the amplitude and spectral function two separated functions are considered, whose parameters satisfy the requirements and describe the form (shape) of random fluctuations in the stochastic model. The developed approach is built based on the assumption that the spectral content of the non-stationary SGM process can be assumed stationary within the short enough successive time-windows.

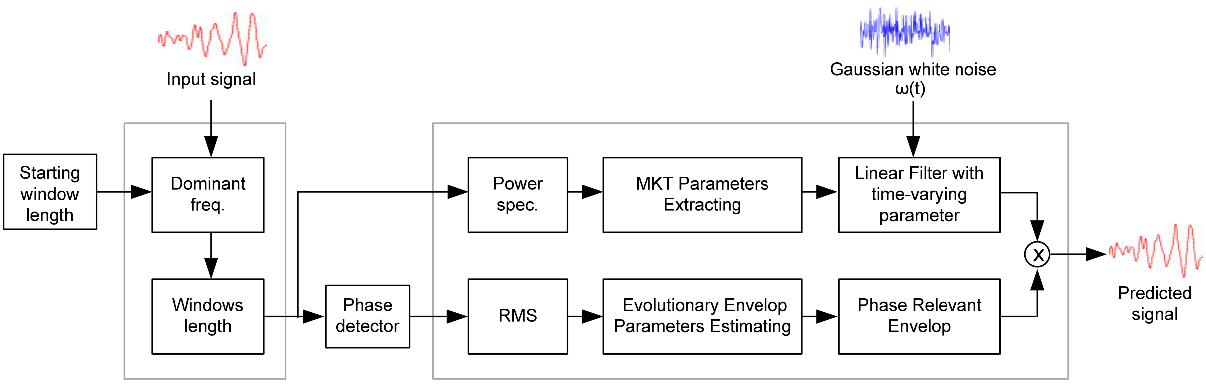


Figure 1. Schematic of the real-time stochastic prediction model

To consider the non-homogeneity of SGM process it is assumed that the process is consisted of a set of the theoretically homogeneous phases. To be able to apply the phase relevant prediction models, discrimination of the dominant seismic phases is required. To distinguish the most significant seismic phases the Time-Dependent Principal Correlation Axes (TPCA) analysis (Scherer and Bretschneider, 2000) is adopted. The physical concept of the TPCA which is based on the propagation path of the wave types makes this method distinguish from the other phase detection methods. The early idea of the TPCA was introduced by Kubo & Penzien (Kubo and Penzien, 1979) and is defined as the Eigenvectors of the covariance matrix of acceleration components, which is correctly defined only if the underlying process is a stochastic stationary process.

2.1. Modeling of Frequency Content of the Strong Ground Motion

The power spectral density (PSD) function is intended to reflect the modulation of the bedrock over a wide frequency range of distributed energy of the wave train by the local underground in the frequency range. The significance of the power spectrum arises from the fact that it illustrates how the variance of the stochastic process is distributed with frequency. Frequency content of the recorded ground acceleration is generally expressed by the PSD proposed by Kanai (1957) and Tajimi (1960). Kanai-Tajimi (KT) power spectral density function may be interpreted as corresponding to a band limited white noise excitation at the bedrock level filtered through the overlying soil deposit at a site. The local soil layer can be seen as an amplifying filter, amplifies only certain frequencies, but others can pass through.

In fact, sites are often consisted of several layers of sediment with several potential resonance frequencies. It is observed that more than one predominant frequency may be present in the data, reflecting effects of topography and soil condition. In general PSD model cannot be able to map resonant frequencies of several layers. Applying the independent KT-PSD for every potentially layer and superposing them to a multi-Kanai-Tajimi (Multi-KT) spectrum, which was proposed by Bretschneider and Scherer (2004), to consider the effect of n layer deposit in spectral modeling (Figure 2)

$$Multi\ S(\omega) = \sum_{i=1,2,\dots,n} S(\omega, S_{0i}, \omega_{gi}, \zeta_{gi}) \tag{2.1}$$

The second significant shortcoming of implantation of KT-PSD in SGM prediction model is the stationarity of KT-PSD. To overcome this limitation it is assumed that there is specific long enough time windows length, in which the SGM process, can be considered as a stationary stochastic process with a zero-mean and can be described by its power spectrum.

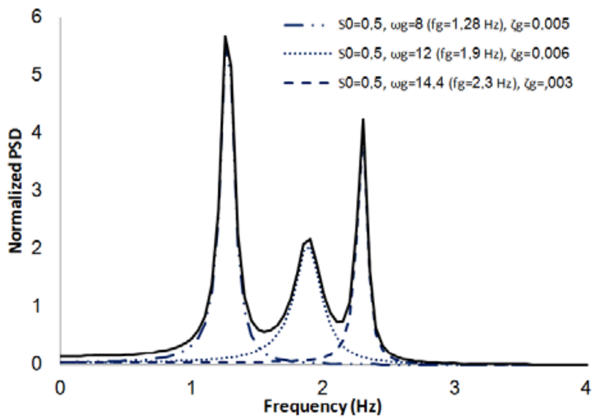


Figure 2. Multi Kanai-Tajimi Power Spectrum for three resonance modes

2.2. Modeling of Amplitude Envelope of the Strong Ground Motion

To consider the temporal non-stationarity generally the SGM simulation models applying the time-varying amplitude (variance) models which called envelope or modulating functions. The form of the envelope function is arrived at through consideration of the manner in which energy is temporally distributed throughout an accelerogram.

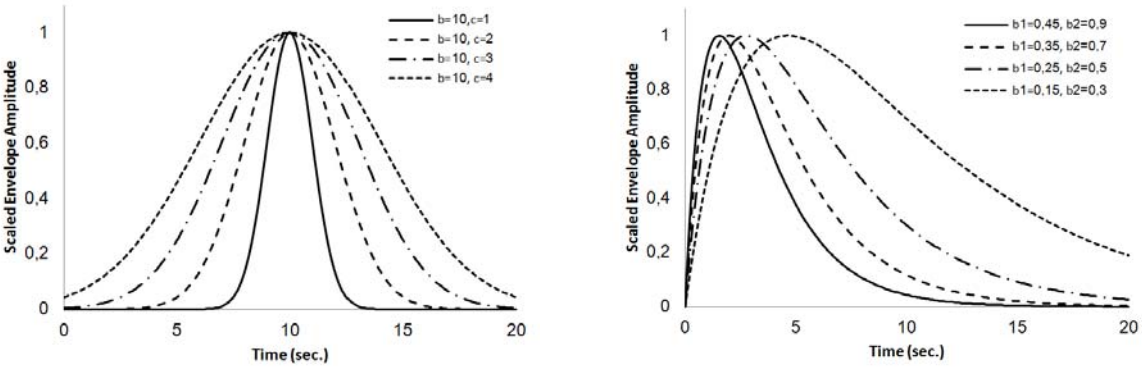
Because of the wave-type related non-homogeneity appears in the amplitude envelope-function it is reasonable to separately model envelope function for the dominant P-wave and S-Coda phases. It was observed that the amplitude envelopes of the dominant P-wave follow well the Gaussian function, hence the corresponding envelope function is defined as

$$A(t) = A_0 e^{-\frac{(x-b)^2}{2c^2}} \quad a_0,\ b,\ c>0 \tag{2.2}$$

Where b is the position of the centre of peak, and c controls the width of the bell shape envelope curve and A_0 is the scaling factor (see Figure 3a). To model the amplitude envelope of dominant S-Coda phase (see Figure 3b) the modulation function proposed by Shinozuka and Sato (1967) have been selected

$$A(t) = A_0\left(e^{-b_1 t} - e^{-b_2 t}\right) \; b_2 > b_1 \tag{2.3}$$

Where b_1 and b_2 are the parameters which control the shape of the modulation function and A_0 is the scaling factor (see Figure 3b). For generation of simulated earthquakes, b_1 has been varied from 0.25 to 0.45 and b_2 has been varied between 0.50 and 0.90.



a   b

Figure 3. a) Gaussian envelope function for b=10 and various c, b) Shinozuka-Sato envelope function for various b_1 and b_2

3. MODELS DEVELOPING

3.1. Developing the Real-Time Power Spectral Model

The resonance parameters of every sub-processes is extracted from the PSD and will be used to filter Gaussian white noise process in order to form the spectral content of the following sub-process(time-window sequences). PSD predictor is fundamentally established based on the assumption that the frequency distribution within a dominant wave phase changes gradually therefore the PSD pattern in a stationary sub-process can be used to build up the PSD function in the following sub-process.

In general, PSD is computed by applying Fourier transformation. Since ground consists not just of horizontal, homogeneous and isotropic layers, but is much more complex structure, so that the estimated spectrum may contain a great number of local peaks and valleys and is quite irregular hence it requires smoothing techniques to improve the spectrum estimator and reduce the variance, which may introduce bias or distortion to the data. Accordingly the PSD is smoothed sing the moving average technique with the span of 0.1 Hz (see Figure 4). The moving average treats as a low-pass filter with filter coefficients equal to the reciprocal of the moving average span. Soil damping and resonant frequency are two primary dynamic factors of soil layer(s) near the ground surface. The resonant parameters can greatly influence seismic wave responses at soil site, which plays a key role in design of geotechnical and structural engineering systems on soils (e.g. NEHRP). Typically, identification of these two factors in linear and non-linear soil sites is performed by examining the frequency-dependent site-amplification factor that is normally calculated as the Fourier spectral ratio of seismic wave recordings at soil versus referenced rock sites (e.g. Safak, 1997). In absence of the SGM record on the rock site (reference record) the resonance parameters of the multi Kanai-Tajimi PSD are estimated by fitting the power spectrum of every sub-process. Curve fitting is strictly limited to every dominant resonance modes.

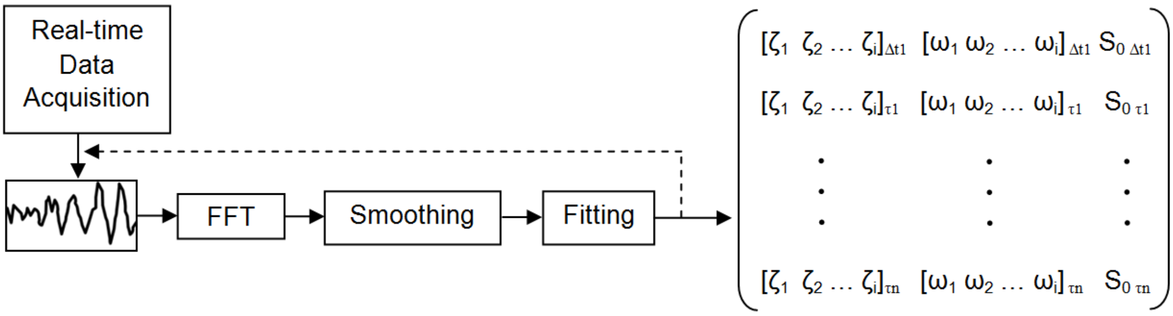


Figure 4. Real-time power spectral model

3.2. Developing the Real-Time Evolutionary Amplitude Model

According to the amplitude envelope functions relevant to the dominant seismic waves which were introduced in previous section, the three envelope parameters for consequent time-windows for every seismic phase should be estimated. A model contains the Artificial Neural Networks in combination with curve-fitting technique has been developed to form evolutionary the amplitude envelope functions. The model parameters are identified for a large number of recorded accelerograms with known earthquake and site characteristics. The resulting observational data are used to construct predictive relations for the model parameters in terms of earthquake and site characteristics by the means of ANNs.

3.2.1. Artificial Neural Networks

The Artificial Neural Networks (ANNs) belong to the more recent machine learning and automated tools which the wide spread use of computers has spawned. ANNs inspired methods have found a wide range of applications in different fields of engineering during the last decades. Specifically, the ability of ANNs to map the nonlinear phenomena as well as learning capability and approximation property make them very powerful tool to solve several complicated engineering problems.

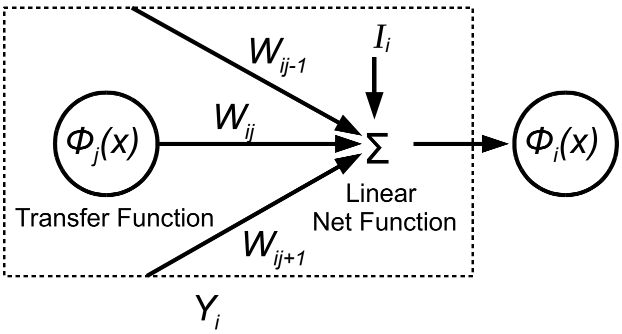


Figure 5. Artificial neural network model

In Figure 5, each neuron consists of two parts: the net function and the transfer function. The net function determines how the network inputs are combined inside the neuron. Set of connections between the artificial neurons create a complex structure which projects a multivariable function. The variables (weights) of the ANNs have to be weighted such that the desired target vector can be produced by the input vector. Based on the transfer function, the form of connectivity between the artificial neurons and the learning strategy which is used the architecture of ANNs system can be identified.

Since the artificial neural networks are designed to generalize the problem like other nonlinear estimation methods such as kernel regression and smoothing *splines*, they can suffer from either under-fitting or over-fitting. A network that is not sufficiently complex can fail to detect completely the signal in a complicated dataset, leading to under-fitting unlike a network that is too complex may fit the noise, not just the signal, leading to over-fitting. Early stopping approach is widely used to avoid over-fitting. Validation can be used to detect when over-fitting starts during supervised training of a neural network; training is then stopped before convergence to avoid the over-fitting.

To perform the early stopping process the validation data set has been used in the following order. The training data is split to a training set and validation set. The training process is stopped as soon as the error on the validation set reaches the minimum value. As the result of the training processes the weights which has the network before reaching the minimum value by the validation error is selected as the training weights. This approach uses the validation set to anticipate the behavior in real use (or on a test set), assuming that the error on both will be similar: The validation error is used as an estimate of the generalization error.

3.2.2. Establishing of the Evolutionary Amplitude Envelope Model

Using the learning capability of ANNs an evolutionary model has been developed which is trained to estimate the parameters of envelope function during a seismic event. A large SGM free-field accelerogram database of Northridge 1994 records has been collected to train and validate the models. The amplitude evolutionary (AE) ANNs was trained for every dominant seismic phase separately. Every SGM accelerogram is split down into frequency relevant time-windows. Therefore the input vector for AE-ANNs is built up of the consequent time-windows in cumulative manner (see Figure 6). Except the length of the starting time window (Δ_{t1}) which is adjusted manually, lengths of the consequent time-windows are determined by the use of the adaptive windowing algorithm. Accordingly, the fitted signal is split in frequency adaptive time-windows which are used to train the AE-ANNs.

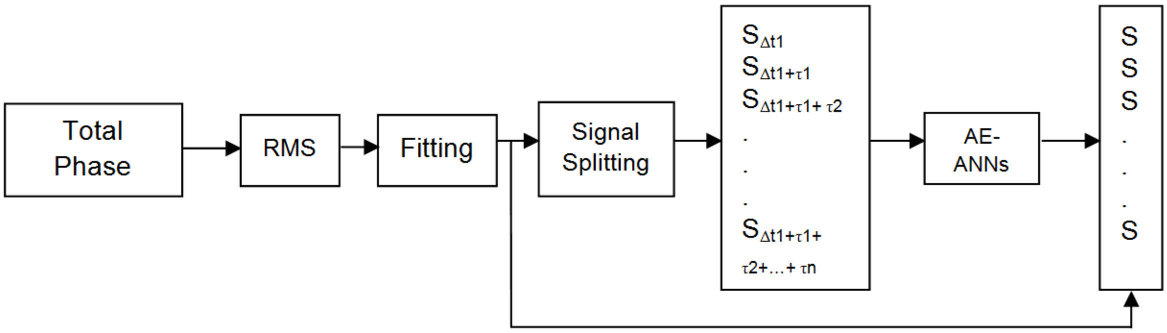


Figure 6. Training process of the evolutionary envelope model

A two layers radial-basis network (RBF) contains a hidden radial-basis and an output linear layer has been designed to form the Evolutionary Amplitude Envelope model. As it is illustrated in Figure 7 the input vector contains 128 points for dominant seismic phase P and 512 points for seismic phase S-Coda. During the training of the AE-ANNs, the networks learn to establish a relationship between the trends (rising angle) of amplitude envelope in every time-window (a part of dominant phase amplitude envelope) and whole of the dominant phase amplitude envelope. In other words the evolutionary models are trained to find the most proper envelope curves corresponding to the vector of the curve segments which is completed gradually during the time. The results shows that the model can estimate the better fitted curve after the passing some time steps.

3.2.3. Applying the Evolutionary Amplitude Model

The real-time amplitude envelope predictor employs the trained AE-ANNs to estimate the parameters of envelope function in every time-windows step. According to the calculated envelope of the measured signal from the beginning of a SGM process the amplitude envelope is predicted by the use of AE-ANNs. The predicted curve will be fitted to the phase relevant envelope functions and the curve parameters are collected in parameters matrices.

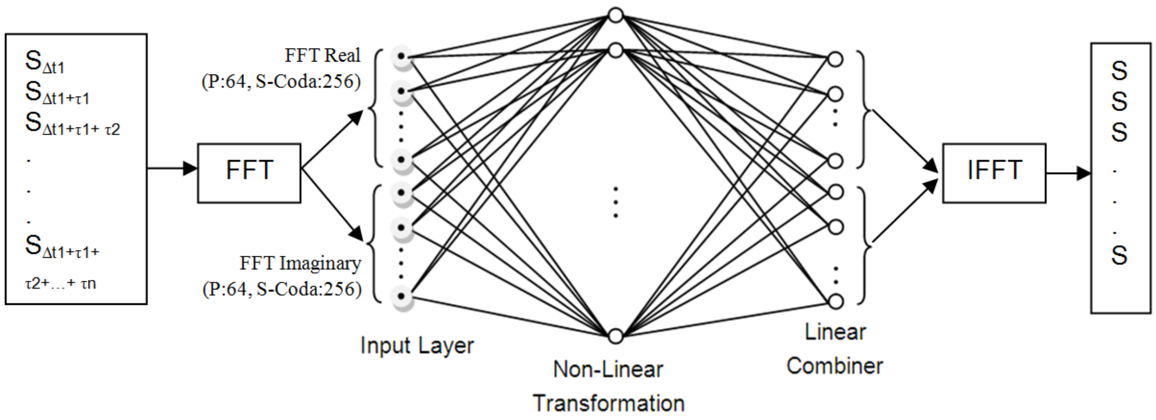


Figure 7. Architecture of amplitude evolutionary Artificial Neural Networks (AE-ANNs)

The resulted SGM signals can catch only the form of the amplitude modulation but their energy content remains still lower than the energy content of the original signals. Therefore the energy content should be corrected by the use of a relevant scaling factor. To perform the energy content correction the arias (Arias, 1970) intensity index is applied, which calculates the energy content by the use of integral of the acceleration square. The energy correction factor is calculated and applied for every time-window.

4. MODELS APPLICATION

4.1. Database

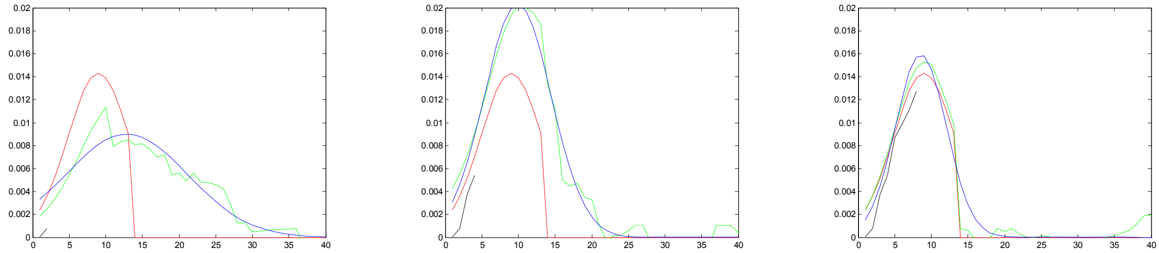
To apply the stochastic real-time prediction models the local SGM records of the main-shock of Northridge 1994 have been used. 109 well recorded SGM free-field records from PEER NGA database are collected. The PGA values of the collected SGM database are ranging from 0.05 g to 1.66 g while the maximum value is recorded in epicentral distance of 5.41 km. The shear wave velocities of the local recording stations are ranging from 160.58 m/s in Corson-Waterst. Station and 996 m/s in Vasquez Rocks Park station (the database covers all EC8 soil conditions). All the accelerograms were resampled at 0.02 sec in order to synchronize the SGM records having different sample rates to be used by training of the amplitude evolutionary model.

4.2. Application of the Stochastic Real-Time Prediction Model

4.2.1. Real-time evolutionary amplitude envelope model

Evolutionary prediction of amplitude envelope functions during consecutive prediction steps for dominant seismic waves P are illustrated in figure 8. As it was described previously the evolutionary amplitude envelope predictor performs the form estimation by the use of real-time measured signal in cumulative order. The results obtained from the predictor are fitted to the wave-type based envelope functions to extract the curve parameters (the blue curves in figure 8). During the pre- and post-processing of the input and outputs signals, which is performed by the use of fast Fourier transformation, it is seen that the ending part of the target signal (red curves in figure 8) was manipulated through transformation. Despite the manipulation, since the predicted curve (the green curves in figure 8) will be fitted to the predefined envelope functions, the results will not be affected (the blue curves in figure 8).

The resulted curves obtained from the dominant P-wave envelope predictor show that the model has underestimated the envelope during the first trails. From the fourth step (0.0-1.1 sec.) the obtaining results seem very close to the real signal. It is also notable that the developed prediction models are able to find correctly the position of the peak value.

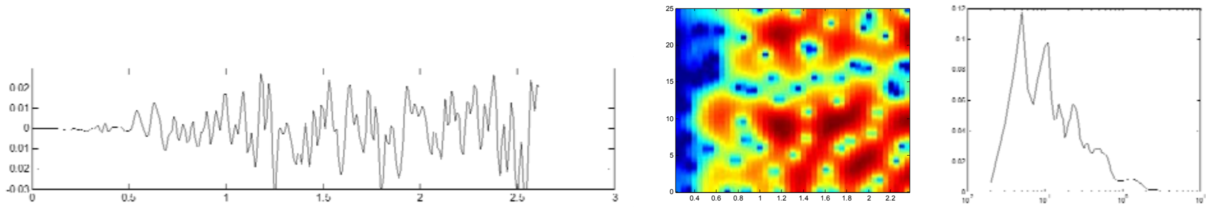


Step 1 (0-0.5 sec.) Step 3 (0-0.9 sec.) Step 4 (0-1.1 sec.)

Figure 8. Evolutionary envelope function for dominant P wave. The red, green, blue and black curves represent the target, the predicted, the fitted predicted and the real-time measured envelope functions, respectively

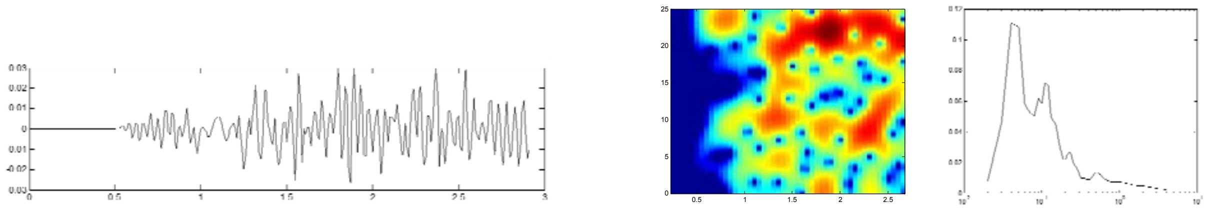
4.2.2. The frequency content of the predicted strong ground motions

In order to evaluate the prediction precision of the developed stochastic real-time prediction model in frequency domain, the results obtained by the use of model for Northridge 1994, LA- Chalon Rd are presented. It is noteworthy that the SGM accelerogram is recorded at the station 14.92 km far away from the epicenter of the main shock and above the soil type B according to Eurocode 8.



Accelerogram (Acc.[g]- Time[sec.]) Spectrogram (Frequency[Hz.]-Time[sec.]) Response Spectrum (Acc.[g]- Period[sec.])

Figure 9. Observed strong ground motion accelerogram, spectrogram and response spectrum of dominant P-wave of Northridge 1994 recorded at LA - Chalon Rd



Accelerogram (Acc.[g]- Time[sec.]) Spectrogram (Frequency[Hz.]-Time[sec.]) Response Spectrum (Acc.[g]- Period[sec.])

Figure 10. Predicted strong ground motion accelerogram, spectrogram and response spectrum of dominant P-wave of Northridge 1994 recorded at LA - Chalon Rd

The observed SGM time history, the corresponding spectrogram and the response spectrum for dominant seismic wave P are illustrated in figure 9. The prediction time history is shown in figure 10, which reveals that the predicted accelerogram could follow very well the amplitude envelope of the sample data as well as the peak values (The zero values in the beginning of the predicted signal denotes that no prediction is conducted in the first 0.5 sec of the signal). Evaluation of the spectrogram, which represents the distribution of the frequency content along the time, shows a rather well prediction for the higher dominant frequency. Response spectrum of the predicted accelerogram (damping ratio: 5%) shows that spectral response of the predicted signal in lower period is modeled very well.

5. CONCLUSIONS

The proposed stochastic real-time prediction model contains two separated spectral and temporal sub-models to form the non-stationary strong ground motion accelerogram. The results obtained by applying the dominant P-wave envelope predictor show that the model can estimate the target envelope function properly except the early trails in which the model shows instability in prediction of the envelope curve. It is also notable that the developed prediction models are able to find correctly the position of the peak value. The frequency content of the predicted SGM accelerograms shows in some cases a mismatch to the observed data. Despite of it, the dominant frequency distribution along the time could be predicted well. Scaling of the predicted SGM accelerograms by the use of the energy correction factor leads to very well energy distribution in the resulted accelerograms during the time.

It can be concluded that the wave type based modeling concept which has the advantage of a conceptual physical modeling of the different seismic phases will lead to the most proper modeling of the process. An important outcome of the performance studies of the developed models is that the temporal non-stationarity can be considered very well by the use of evolutionary envelope predictor.

REFERENCES

Arias, A. (1970). A Measure of Earthquake Intensity. *In Seismic design for nuclear power plants, (R.J. Hansen, ed.) MIT Press, Cambridge MA*. 438-483.

Bretschneider, J. and Scherer, R. J. (2004). Multi-wave, non-stationary,parametric load model for seismic hazard assessment and prediction. *13th World Conference on Earthquake Engineering*. **2587**.

Bolotin, V.V. (1960). Statistical theory of the aseismic design of structures. *2nd World Conference on Earthquake Engineering*. **II**, 1365–1374.

Kanai, K. (1957). Some empirical formulas for the seismic characteristics of the ground. *Bulletin of the earthquake research institute*. **35**, 309-325.

Kawamura, H., Tani, A., Yamada, M. and Tsunoda, K. (1990). Real Time Prediction of Earthquake Ground Motions and Structural Response by Statistic and Fuzzy Logic. *First International Symposium on Uncertainty Modeling and Analysis*. 534-538.

Kubo, T., and Penzien, J. (1979). Analysis of Three-dimensional Strong Ground Motions along Principal Axes, San Fernando Earthquake. *Earthquake Engineering and Structural Dynamics*. **7**, 265-278.

Mei, G., Kareem, A., and Kantor, J. C. (2001). Real-time model predictive control of structures under earthquake. *Earthquake Engineering and Structural Dynamics*. **30**, 995-1019.

Pu, J.P.(1989). Frequency Response Design of Controlled Structure. *Computer Utilization in Structural Engineering ASCE*. 131-141.

Rezaeian, S. and Der Kiureghian, A. (2008). A stochastic ground motion model with separable temporal and spectral nonstationarities. *Earthquake Engineering and Structural Dynamics*. **37**, 1565-1584.

Rodellar, J., Barbat, A. H. and Matin-Sanchez, J. M. (1987). Predictive control of structures. *Journal of Engineering Mechanics Division ASCE*. **113:6**, 797–812.

Safak, E. (1997). Models and methods to characterize site amplification from a pair of records. *Earthquake Spectra*. **13**, 97–129.

Scherer, R.J., and Bretschneider, J. (2000). Stochastic Identification of Earthquake wave entities. *12th World Conference on Earthquake Engineering*. **2436/4/A**.

Shinozuka, M. and Sato, Y. (1967). Simulation of non-stationary random process. *Journal of Engineering Mechanic ASCE*. **93**, 11-40.

Tajimi, H. (1960). A statistical method of determining the maximum response of a building structure during an earthquake. *2nd world conference on earthquake engineering.* **II**, 781-797.