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Real-Time Forecasting of Strong Motion Acceleration for Seismic Control of Nuclear Power Plant

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ABSTRACT

The problem of forecasting in general and in real-time of the behaviour of seismic wave is discussed. A hybrid model for real-time forecasting of strong motion acceleration on the bases of general, tectonic, seismic and site parameters is developed. On the base of this forecasting can be made right decision for activating different devices and systems for passive, active or hybrid structural control for protection of high risk structures like power plants, in particular nuclear power plants. The numerical simulation was made with different program package like Fuzzy TECH 5.51, MatLab 6.5 and Simulink**.**

KEY WORDS: seismic wave, structural control system, nuclear power plant, earthquake engineering, stochastic modelling, fuzzy sets theory, probabilistic models, artificial intelligence models, earthquake excitation, accelerograms, resonance frequency, damping ratio, site soil classification, expert systems.

INTRODUCTION

One of the very promising methods in earthquake engineering is the application of structural control. The aim of the structural control is protection the buildings and structures against destructive waves during the earthquake. One of the critical problems there is the problem of forecasting in general and in real-time of the behaviour of seismic wave. This forecast can be made on the bases of general, tectonic, seismic and site parameters, strong motion records.

Forecasting of the behaviour of seismic waves is very actual and attractive for the researchers, especially for the regions with possible seismic activities. On the base of general forecasting of the behaviour of seismic waves can be made different models for determining the main parameters and their relationships. This is useful for studying the earthquake event and for describing this event with different kind of models: stochastic, probabilistic, artificial intelligence models etc. On the base of real-time forecasting can be constructed different devices and systems for structural control. Such devices are developed for very important for protection structures like high-risk structures as nuclear power plants, height buildings, bridges and other important structures. Nowadays in Bulgaria is planning to start building a new nuclear power plant near Belene. For the security of this construction is developing a system for structural control. For this purpose was studied different kind of records for seismic activity in the region which were compared with the others from different region for constructing the model of seismic activity in the region. The models of behaviour of seismic waves can be used in a system for structural control.

Stochastic Models

For describing the process of earthquake event there exists different kind of mathematical models. Most popular are stochastic models. The common stochastic models are dealing with significant simplifications of the ground acceleration process. In non-stationary stochastic models, the phases of the earthquake excitation usually are separately dealt with, resulting in more simple stochastic sub-models [1], [2]. In stochastic models every wave has a transient character because its source is active only for a short time and its energy will be damped and finally absorbed by the body of the earth [3]. Key parameters and quantities of current empirical seismic hazard analyses, as peak ground acceleration, response spectra, power spectra, are very often based on one-dimensional extracts from recorded or simulated three-dimensional seismogram data, which are crisp values.

According to the stochastic model, presented in [4] each wave is dividing into three phases and has different spreading velocity of longitudinal or primary (P- waves) and transversal or secondary (S- waves), causing an S-wave of the same origin to arrive later than the corresponding P-wave. The third phase (C-/G- waves) is connected with converted and guided waves. Waves during an earthquake have more than one origin. While the main source of all is the earthquake fault, emitting so called direct waves, abrupt changes of material density cause reflections as well as P-S, S-P and other wave conversions anywhere along the propagation path. Usually, waves of different type and origin differ in the share of energy and the frequency content, and overlay each other.

The first phase is connected with domination of direct P-waves, which have earliest origin and highest velocity. With increasing the distance from epicenter, the first arrival of S-waves is delayed, and with its arrival, the direct S-wave dominates the principal direction because its share of energy is usually the greatest of all wave types. When the phase of direct P-waves has finished, the characteristics of the S-wave are very clear. As the energy of the direct s-wave

decays, indirect waves converted at discontinuities of layered rock determine the state, alone or together with surface waves.

When the area is not so far from the epicenter of an earthquake, (as the area of Belene and Vrancea source [5]) the share of energy of the direct P-wave could come up to that of the direct S-wave and the offset between their arrivals may be vary small. Surface waves may occur very early even during the direct S-waves endure. A moving rapture process causes a Doppler effect and changing angle of incidence along with the fault at certain sites. At greater distance, where the P-phase should be generally longer because of the increasing runtime difference to the S-wave, PS waves converted in the bedrock could precede the direct S-wave and disturb the P-wave characteristics. These guided waves from the third phase may completely change the spreading of the wave in bedrock over long distances at very high velocity.

The most important differences for identification of all types of body and surface waves are the characteristics of particle movement. Particles are moved in parallel to the spreading direction by longitudinal waves, but perpendicularly to the transversal waves of either polarization. Surface waves roll particles within a plane parallel or perpendicularly to the surface plane. If the share of energy of one type of wave is significantly larger than the others, it dominates the adjustment of the principal plane or direction of acceleration at this time. When this dominance is strong enough over a certain period, the principal direction should remain at a certain state. If there are strong changes of shares in the present mix of waves there will be significant changes in the accelerograms.

The purpose of stochastic modeling for this investigation is the defining of the three phases of the earthquake wave and identification of the main parameters for each phase, such as resonance frequency, damping ratio, peak value. The next step is forecasting the resonance frequency of S-wave on the base of registrated resonance frequency of P-wave with the help of artificial intelligence methods.

Artificial Intelligence Methods for Describing the Behaviour of Seismic Waves

Nowadays increase implementation of artificial intelligence methods for describing the behaviour of seismic waves [6]. Most of them are based on neural networks for receiving artificial earthquake records on the base of networks, which are trained, with real seismic records [7]. Other models are based on the fact that crisp values as earthquake parameters can be successful described with the help of fuzzy logic models [8]. On the base of fuzzy models can be made classification of different parameters and type of waves for predicting the behaviour of the process [9].

One of the very promising trends is creating models, which combines different approaches like Neuro-Fuzzy models, models combining stochastic and artificial intelligence approach etc. Such hybrid models uses the machine learning capabilities of neural networks and combines it with transparency and representation power of fuzzy logic and stochastic models. The combination of neural networks and fuzzy logic leads to improving the real time performance, robustness and accuracy of certain control system. This approach can be used successful in a system for structural control.

Systems for Structural Control

All systems for structural control are based on one of mentioned above models for their activating. The basic activating methods are mass method, damping method, stiffness method and reduction method [10]. Lately most of the models for different kind of methods of Structural Control Systems are base on Artificial Intelligence Methods [11]. These methods are used in Structural control systems base on fluid dampers, optical fibber sensors, semi-active tune mass dampers, magnetorheological dampers, semi-active friction dampers.

The aim of this research is to forecast in real time further development of the seismic record from the recorded data during a real earthquake for switching the system of structural control.

OBJECTIVES AND SUGGESTED APPROACH

The purpose of investigation is developing from basic seismic information and the recorded parts of the seismic records the parameters of a wave-based non-stationary strong motion model and identification on the bases of the model best fitting records from database of worldwide strong motion records.

The records in database should be classified according to the most important parameters, characterized the earthquake excitation, such as resonance frequency, damping ratio, site soil classification etc. On the base of early registrated signals and stochastic models for the main characteristics the of the earthquake event if there would be a possibility to compare this characteristics with the similar ones from database of selected records for this area, than we can make a decision for giving a signal for activating a Structural control system.

During this investigation was developed an intelligent hybrid model, which can forecast in real-time the behavior of strong motion records on the bases of general, tectonic, seismic and site parameters. This hybrid model is based on seismic wave theory, data analysis, stochastic modeling, classification methods, fuzzy theory and neural networks and will be used for structural control on the base of real-time forecasting of the behavior of seismic wave. This forecasting will help to be made right decision for activating a system for active structural control. This system will be developed for the new nuclear power plant, which will be built in Bulgaria near Belene at the Danube River.

PARAMETRIC LOAD MODEL

Very important task in this investigation is to determine and classify the main parameters, describing seismic waves. The parametric load model is based on the evolutionary spectrum of the main stochastic accelerograms and a reference accelerograms, which incorporates the dominant parts of all wave types occurring in strong motion records.

The time dependent stochastic principal axes method, combined with the moving window technique [12] is used in this research for stochastic modeling of the proposed hybrid wave-based non-stationary strong motion model of the seismic waves. According to this method earthquake accelerograms are delivered as representations of the three-dimensional acceleration vector in a Cartesian co-ordinate system, generally with axes parallel to east -west, north-south and vertical direction. In stochastic non-stationary load model one- and two- dimensional particle movements of body and surface waves, respectively constituted this three-dimensional vector process. The combination of this method with the moving window technique helps for approximation of the non-stationary process like stochastic stationary in wide sense within short time intervals.

Window parameters were used for defining the three phases (P-, S- and C-/G-) of the earthquake wave. Using the time windows we are searching the most dominant and energetic component for every phase. For a certain given time t_0 time delay τ and window length L the covariance matrix, presented in (1) would consist of components, which are statistically independent within those intervals.

$$C_{ij}(t_0,\tau,L) = \int_{t_0-\frac{1}{2}}^{t_0+\frac{1}{2}} a_i(t')\cdot a_j(t'+\tau)dt' \quad \text{for } i, j = x, y, z \qquad (1)$$

The purpose of stochastic modeling for this investigation is the defining of the three phases of the earthquake wave and identification of the main parameters for each phase, such as resonance frequency, damping ratio, peak value etc. There exists nonlinear dependence at the site between these parameters from earthquake to earthquake. One of the most important parameters, which were analyzed, is predominant frequency at the first P-phase of the earthquake excitation and her comparison with the predominant frequency at the second S-phase. The behavior of this parameter is very important for forecasting the behavior of seismic waves.

If on the base of early registrated resonance frequency we can calculate the future resonance frequency for the next destructive phase of earthquake on the base of stochastic models and fuzzy expert systems, than this can be used for switching on a system for Structural control if the earthquake is classified as destructive. A database for strong motion records was created after classifying the main parameters of stochastic seismic waves. The records in database was sorted according to the most important parameters, characterized the earthquake excitation, such as resonance frequency, damping ratio, peak value, site soil classification etc.

INTELLIGENT HYBRID MODEL

For the purposes of investigation were made an attempt to combine this stochastic model with neuro-fuzzy model. This so-called hybrid model combines learning capability of neural networks with possibility of taking decision in fuzzy-logic models. Neuro-adaptive learning techniques were used for the fuzzy modeling procedure to learn information about a data set for P-wave characteristics, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. The membership function of constructed fuzzy inference system was adjusted using either a backpropagation algorithm alone, or in combination with a least squares type of method. That's allows the fuzzy system to learn from the data they are modeling. For interpretation of the input/output map were used a network type structure similar to that of a neural network, which maps inputs through input membership function and associated parameters, and then through output membership functions and associated parameters to outputs. The parameters, associated with membership function were changed through the learning process. Their adjustment was facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters as power spectral density of the bedrock acceleration S_0, the predominant frequency $\overline{\zeta}_g$, the damping ratio of the soil layer $\overline{\omega}_g$. For this investigation were made a model of soil layers under construction of reactor building.

In simulating earthquake excitation, a stationary filtered white noise $\ddot{x}_g(t)$ is often used as a model of the strong stage of the earthquake. The ground acceleration $a(t) = \ddot{x}_g(t)$ can be obtained by the equation (2),

$$\left.\begin{aligned} \ddot{y} + 2\overline{\zeta}_g\omega_g\dot{y} + \overline{\omega}_g^2 y = -\ddot{z}(t) \\ \ddot{x}_g(t) = \ddot{y}(t) + \ddot{z}(t) \end{aligned}\right\} \qquad (2)$$

in which $\ddot{z}(t)$ is the acceleration of the bedrock caused by the earthquake and can be simulated as a white noise with zero mean and power spectral density $S_0, \bar{\zeta}_g$ and ω_g are the damping ratio and predominant frequency of the soil layer respectively. The ground acceleration can be presented as (3).

$$a(t) = \ddot{x}_g(t) = -2\bar{\zeta}_g \bar{\omega}_g \dot{y} - \bar{\omega}_g^2 y \tag{3}$$

When the bedrock acceleration S_0 is expressed by parameters of the ground motion, the model can be related to the 0earthquake intensity. The variance of the ground acceleration can be expressed as (4).

$$\sigma_a^2 = \frac{(1+4\bar{\zeta}_g^2)\pi\bar{\omega}_g}{2\bar{\zeta}_g} S_0 \tag{4}$$

The relation between S_0 and σ_a from (4) can be presented a mapping and extending its inverse mapping to σ_a can be obtained (5).

$$S_0 = \frac{2\bar{\zeta}_g}{(1+4\zeta_g^2)\pi\bar{\omega}_g} \sigma_a^2 \tag{5}$$

The power spectral density S of the ground acceleration $\beta(\sigma_a, t)$ corresponding to the fuzzy predictive intensity is presented at (6),

$$S_\beta(\sigma_a, \omega) = \int_{\sup \sigma_a} \mu_{\sigma_a}(\sigma_a) / S_a(\sigma_a, \omega) \tag{6}$$

where $S_a(\sigma_a,\omega)$, presented at (7) is the power spectral density of $a(\sigma_a, t)$ corresponding to a specific σ_a and belongs to $S_\beta(\sigma_a, \omega)$ with membership degree $\mu_{\sigma_a}(\sigma_a)$.

$$S_a(\sigma_a,\omega) = \frac{1+4\bar{\zeta}_g^2 \frac{\omega^2}{\bar{\omega}_g^2}}{4\bar{\zeta}_g^2 \frac{\omega^2}{\bar{\omega}_g^2} + \left(1 - \frac{\omega^2}{\bar{\omega}_g^2}\right)^2} \frac{2\bar{\zeta}_g}{(1+4\bar{\zeta}_g^2)\pi\bar{\omega}_g} \sigma_a \tag{7}$$

Fuzzy stationary process $\beta(\sigma_a, t)$ can be expressed refer to (8) in which $a(\sigma_a, t)$ is a non-fuzzy stationary process with zero mean and power spectral density $S_\beta(\sigma_a, \omega)$ and belongs to $\beta(\sigma_a, t)$ with membership degree $\mu_{\sigma_a}(\sigma_a)$.

$$\beta(\sigma_a, t) = \int_{\sup \sigma_a} \mu_{\sigma_a}(\sigma_a) / a(\sigma_a, t) \tag{8}$$

Equation (8) is simplified fuzzy random model of the earthquake ground acceleration which is established after taking account of the fuzziness of both the site soil classification and the predictive intensity.

The basic model of this investigation is the hybrid wave-based non-stationary strong motion model, which is based on stochastic models for forecasting the wave behaviour, combined with neuro-fuzzy models. The architecture of the model was based on stochastic and intelligent methods.

The basic algorithm of the model was made on fuzzy logic rules. The optimisation of the algorithm and the rules with the help of Neuro – fuzzy approach helped for receiving a proper real-time solution for switching on the system for structural control. Afterwards the model was adjusted to the main characteristics of the object of investigation. In our case these are bedrock and soil layer system under Belene nuclear power plant. For this particular object intelligent models for Structural Control was developed and explored.

SEISMIC CONTROL

For developing an effective active control system, it is necessary to take account of not only uncertainty of future loading but also special features of buildings such as large scale, complexity, many objective judgments of users and experts. Fig. 1 shows a flowchart of the proposed system for intelligent fuzzy optimal active structural control.

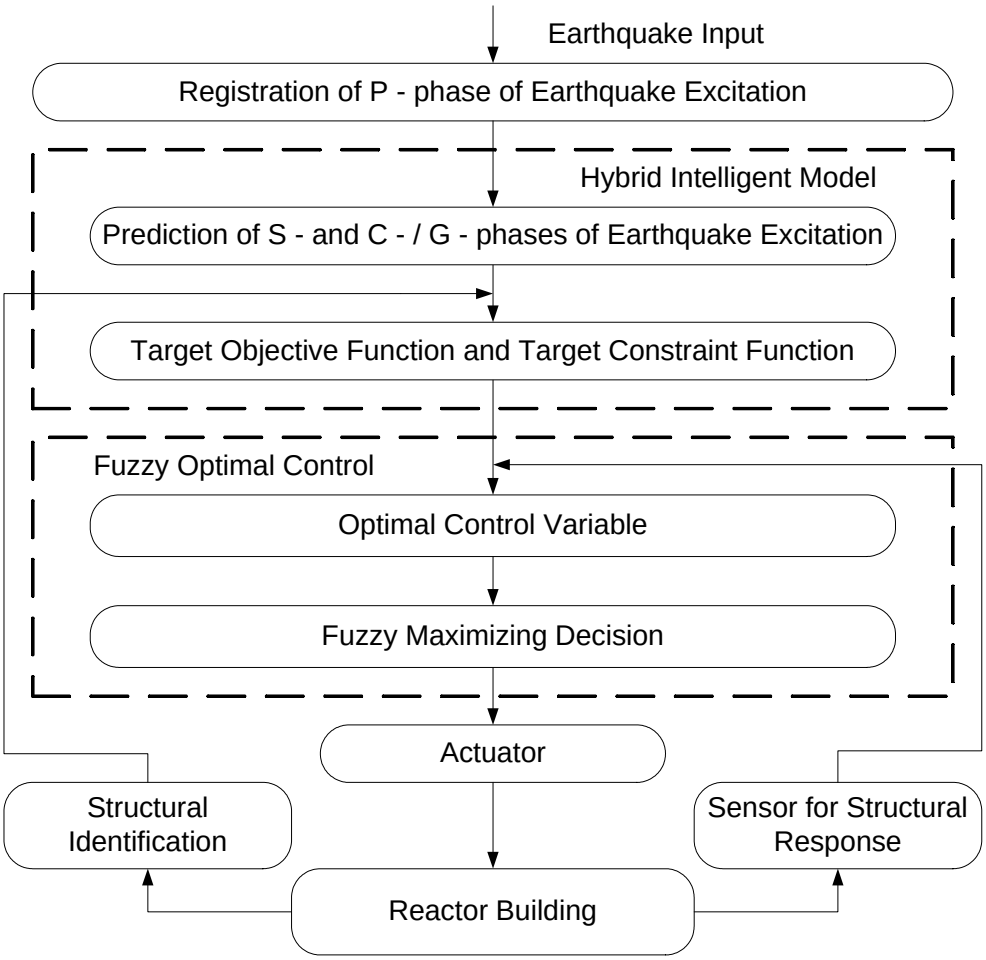

Fig. 1 System for intelligent fuzzy optimal active structural control

The proposed system has following special features:

- Prediction of S – and C-/G- phases and structural responses of the 1000 MW WWER reactor building, which for Belene (Units 1 and 2) and Kozloduy (Units 5 and 6) consists of four distinctive structures. The base substructure starts from the foundation basement, which starts from –7 m below grade is 2.8-m- thick, approximately 74 m by 74 m, concrete slab. It rises up to a second concrete basement, which supports the reactor containment. The three-story building, which houses the main control room and the auxiliary systems, equipment including several large tanks, has a square shape of about 70 m by 70 m with orthogonally distributed walls. The third substructure is the reactor internal structure, which is a massive concrete structure supporting the reactor equipment. The forth substructure is a peripheral auxiliary building called the “outer building”, which houses miscellaneous equipment and the main steam piping going to a turbine building. This building is isolated from the containment shell by a seismic gap.
- Objective and constraint functions of the active control are described with membership functions of fuzzy theory.
- Optimal control variables are determined by fuzzy maximizing decision. Equations of motion are shown in (9) and (10),

$$m\ddot{y} + \overline{\omega}_S \dot{y} - \overline{\omega}_S (\dot{y}_S - \dot{y}) + ky - k_S (y_S - y) + f = -m\ddot{z} \qquad (9)$$

$$m_S \ddot{y}_S + \overline{\omega}_S (\dot{y}_S - \dot{y}) + k_S (y_S - y) - f = -m_S \ddot{z} \qquad (10)$$

where, m is mass, $\overline{\omega}_S$ – damping factor, k – stiffness, y – relative displacement of structure, $\ddot{z}$ - input acceleration of earthquake and subscript S – denotes structural characteristics and responses of an active mass driver or hybrid mass damper, which can be used for seismic control of the reactor building.

Control forces f are calculated by the optimal control variable and assumed activation methods in accordance with proposed system for fuzzy optimal control. The activation of the system for fuzzy optimal control is supposed to be in real time by selected actuator. This force will be calculated for selected method of activation and will be different for Mass Method, Damping Method, Stiffness Method and Input Reduction Method.

The original data for earthquake acceleration are presented on fig 2. Selected S – and C-/G- phases for prognoses is presented on fig. 3.

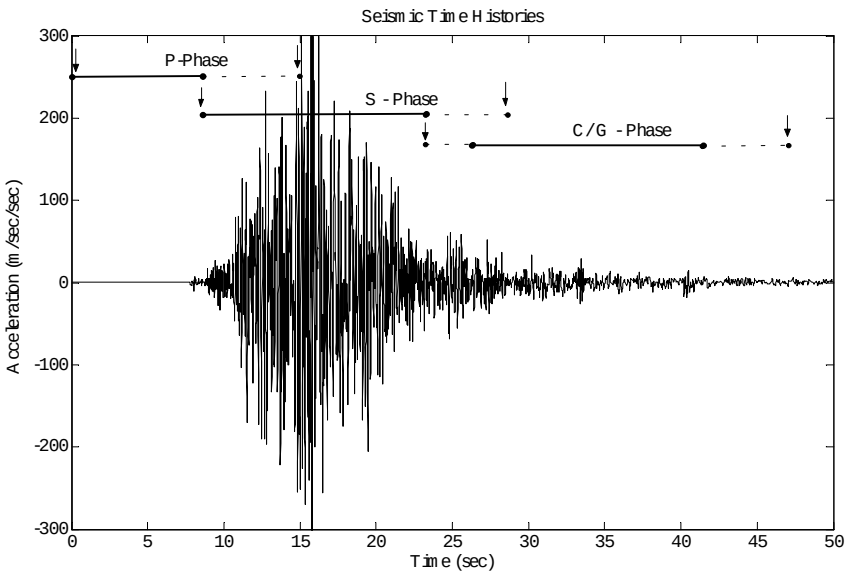

Fig. 2. The data of original P - phase, S – phase and C-/G- phase.

Objective function and constraint conditions are described with fuzzy membership function, which were constructed on the base of 4 inputs and 16 fuzzy rules. The number of fitting parameters is 108, including 24 nonlinear and 84 linear parameters. The response displacements are employed as the objective function of control. The limitations of device for active control (active mass driver, hybrid or tuned mass damper and so on), such as maximal strokes and forces are employed as the constraint functions of control.

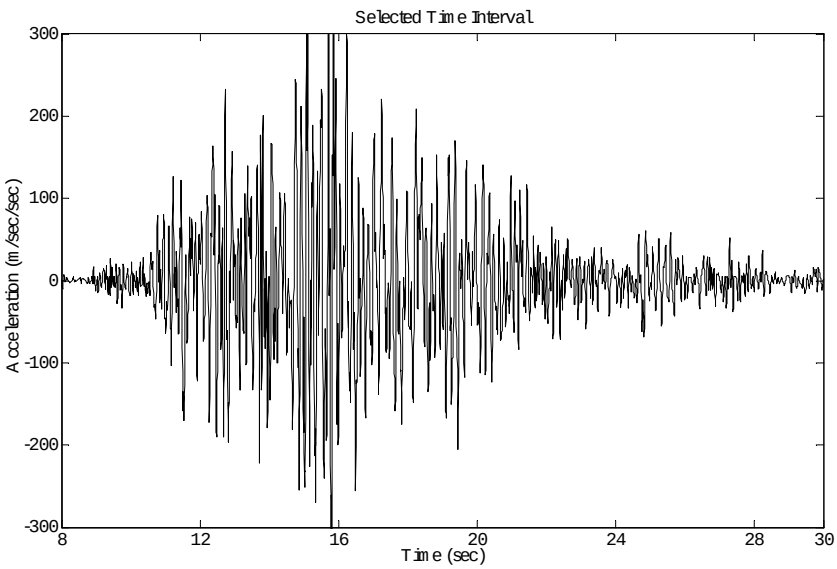

Fig.3. Selected time interval for S – and C-/G- phases prognoses.

The optimal control variable is determined by fuzzy maximizing decision. For reaching this condition proposed Intelligent Neuro-fuzzy Model was trained with data from real and simulated earthquakes. The shapes of trained membership functions for all inputs are presented on fig. 4.

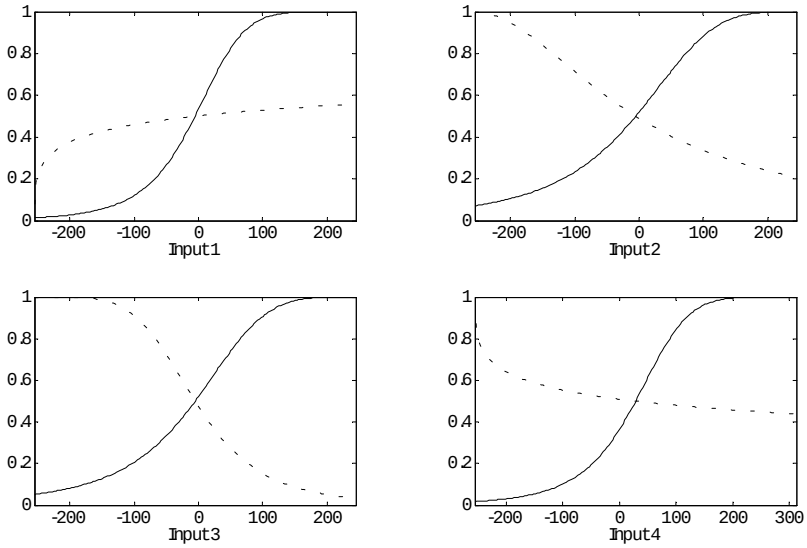

Fig.4 Shapes of trained membership functions

Real-time prediction of S – and C-/G- phases on the base of first P- phase with duration between 8 and 15 sec is presented on fig. 5.

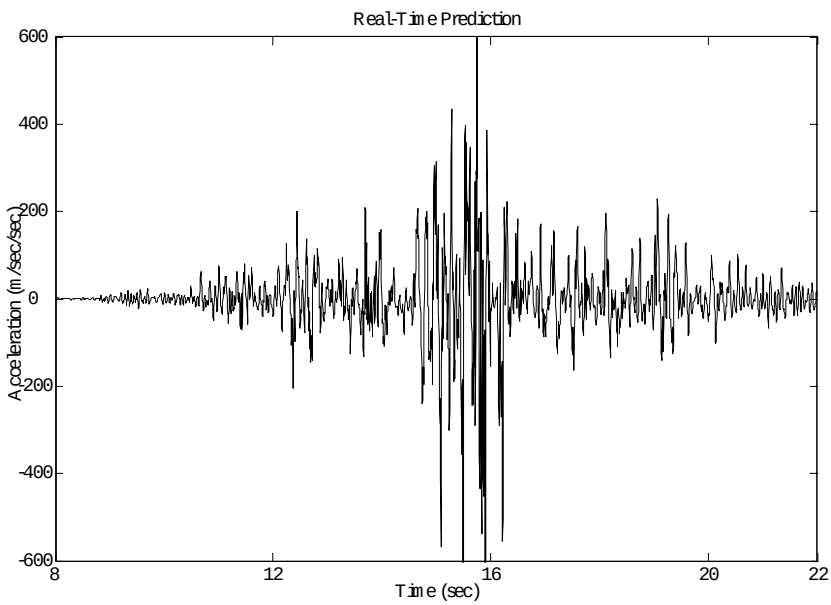

Fig.5 Predicted S – and C-/G- phases on the base of first P- phase (between 8 and 15 sec).

CONCLUSION

The seismic analysis of earthquake waves and their modeling were used for real time forecasting of strong motion acceleration. A hybrid model, based on seismic wave theory, data analysis, stochastic modelling, classification methods, fuzzy theory and neural networks was developed for real time forecast during a real earthquake. The numerical simulation leads to some conclusions:

1. Proposed approach of forecasting further development of the seismic record with a continuous updating of forecasting can be used for developing an effective active control system.

2. From basic seismic information and the recorded parts of the seismic records the parameters of a wave-based non-stationary strong motion model combined with neuro-fuzzy approach describes enough good the process.
3. On the base of developing of seismic wave in first P- phase of earthquake excitation was made a real time prognoses for further development of the wave, which were compared with different kind best fitting records from worldwide strong motion waves.
4. A Hybrid Intelligent Neuro-fuzzy model is proposed for prediction of destructive S – and C-/G- phases of earthquake excitation. These prognoses are supposed to be used for switching on the different kind of systems for active structural control.
5. The minimal duration of P- phase is about 10 –15 sec and after this period if the wave were classified as destructive can be activated the active control system.
6. The proposed system for Fuzzy Optimal Control can be used for activating different system for structural control based on active mass drivers, fluid dampers, optical fibber sensors, semi-active tune mass dampers, magnetorheological dampers, semi-active friction dampers.
7. Numerical simulations with different program package like Fuzzy TECH 5.51, MatLab 6.5 and Simulink were made for the 1000 MW WWER reactor building for Belene (Units 1 and 2) and Kozloduy (Units 5 and 6). On the base of this forecasting can be made right decision for activating different devices and systems for passive, active or hybrid structural control for protection of high-risk structures.

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