Evaluation of the Environmental Effects on a Medium Rise Building

Ruben Boroschek, Felipe Tamayo, Rafael Aguilar

EVALUATION OF THE ENVIRONMENTAL EFFECTS ON A MEDIUM RISE BUILDING

Ruben Boroschek[1], Felipe Tamayo[2], Rafael Aguilar[3]

[1] *Civil Engineering Department, University of Chile*
[2] *Student, Civil Engineering Department, University of Chile.*
[3] *Civil Engineering Department, Pontifical University of Peru.*

rborosch@ing.uchile.cl

ABSTRACT

This article presents the variation of the dynamics properties due to environmental effects of the Central Tower at the Faculty of Physical and Mathematical Science of the University of Chile. This structure is a nine story, shear wall reinforced concrete building, 30 meters high, which has been monitored automatically and remotely since 2009 with a network of 8 uniaxial accelerometers and 9 environmental sensors. The network registers the ambient conditions, such as wind speed and direction, temperature, radiation, rainfall, ambient and soil humidity. The range of variation on environmental effect and modal properties is presented. Detailed analysis of the temperature effect on the properties is presented. The Principal Component Analysis (PCA) methodology has been utilized to reduce some environmental effects on the vibration frequencies to identify earthquake damage in the structure. The advantages and disadvantages of the method are presented. Typical variations in the range of 4% are observed related to temperature and 6% related to the rain and the surrounding soil humidity. Earthquake damage during the 2010 Mw=8.8 Earthquake is clearly identify from ambient vibration and earthquake records. Damage is considered low, with some visible cracking in structural wall. Variations due to this damage are in the order for 15 to 20% for predominant natural frequencies.

KEYWORDS : *shm, ambient vibrations, temperature, rain, damping, identification*

1 BUILDING DESCRIPTION

The instrumented building called Central Tower was constructed in 1962. It is located at the Engineering Faculty of the University of Chile and is used for office and classroom. It has 9 stories above ground and 2 underground levels. It has a total surface of 4,600 m2, approximately. It has a total height of 30.2 meters and a plan area of 30 x 19 meters, Figure 1. The structural system consists on a reinforced concrete shear and gravity walls. Typical wall thickness is 35 cm and typical slab thickness is 25 cm. The typical ratio between total wall area to plan area is 7.7 %.
The building is instrumented with an array of 8 uniaxial accelerometers that allows the continuous recording of the structural response due to ambient vibrations and seismic events. Furthermore, it has 9 environmental sensors which detect and save the data obtained from ambient conditions, such as speed and direction, temperature, rainfall, etc. [1].

2 AMBIENT CONDITIONS SENSORS DESCRIPTION

Nine environmental sensors register the ambient conditions continuously: wind speed and direction, temperature, radiation, rainfall, ambient and soil humidity, and air pressure. The meteorological conditions are recorded by a meteorological station (Figure 2 (c)) that reports data every 15 minutes (the reported value corresponds to the mean of the data acquired in the previous 15 minutes). The meteorological station is installed on the roof of the Civil Engineering and Geophysics building, which is next to the Central Tower building, and it is maintained by the Meteorology Group of the

Department of Geophysics at the University of Chile. The humidity sensors have been installed in a borehole in the west side of the building (Figure 2 (a) and (b)). The humidity sensors are located at 20, 10 and 5 meters below the surface and they are connected to the accelerometers data acquisition system. The description of the sensors is shown in the Table 1.

Figure 1: Central Tower - General Views.

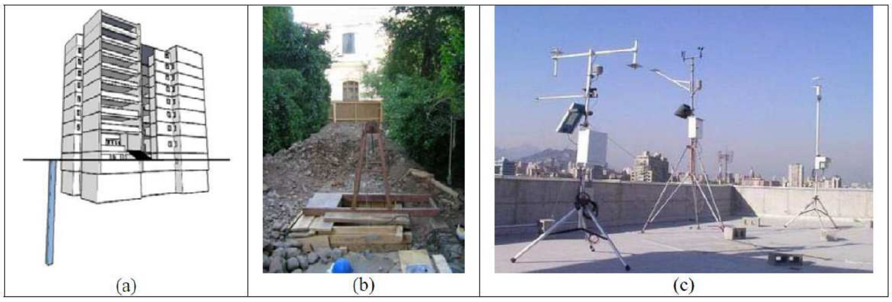


Figure 2 : Sensors: (a) schematic well location, (b) well, humidity sensors and (c) meterological station.

Table 1: Meteorological Station Instruments and Soil Saturation Sensors

Variable	**Instrument**	**Model / Brand**
Air Temperature (°C)	Solid state hygro-thermometer	CS-500, Campbell Sci.
Relative Humidity (%)	Solid state hygro-thermometer	CS-500, Campbell Sci.
Solar Radiation (W/m^2)	Silicon pyranometer	LI200X, Campbell Sci.
Air Pressure (hPa)	Solid state barometer	PTA-127, Vaisala.
Rainfall (mm)	Scales pluviometer	TE525mm, Texas Instruments
Wind (magnitude in m/s, direction in degrees)	Anenometer + weather vaine	03001 Wind Sentry Wind Set, Young.
Soil Saturation (%)	Moisture Probe	MP406, ICT International

3 VARIATION OF MODAL PROPERTIES DUE TO ENVIRONMENTAL EFFECT

Natural frequencies are derived from acceleration automatically. The data span a period of 2 years and 6 months, from June 24th of 2009 to December 31th of 2011. The frequencies were obtained through the application of the SSI_COV identification method, which was applied on acceleration data every 15 minutes [2].
The results for the first three frequencies are presented in Figure 3 in terms of time series. Also, the same results are shown in the histograms presented in Figure 4, before and after the 8.8 Mw Earthquake, which produced slight damage.

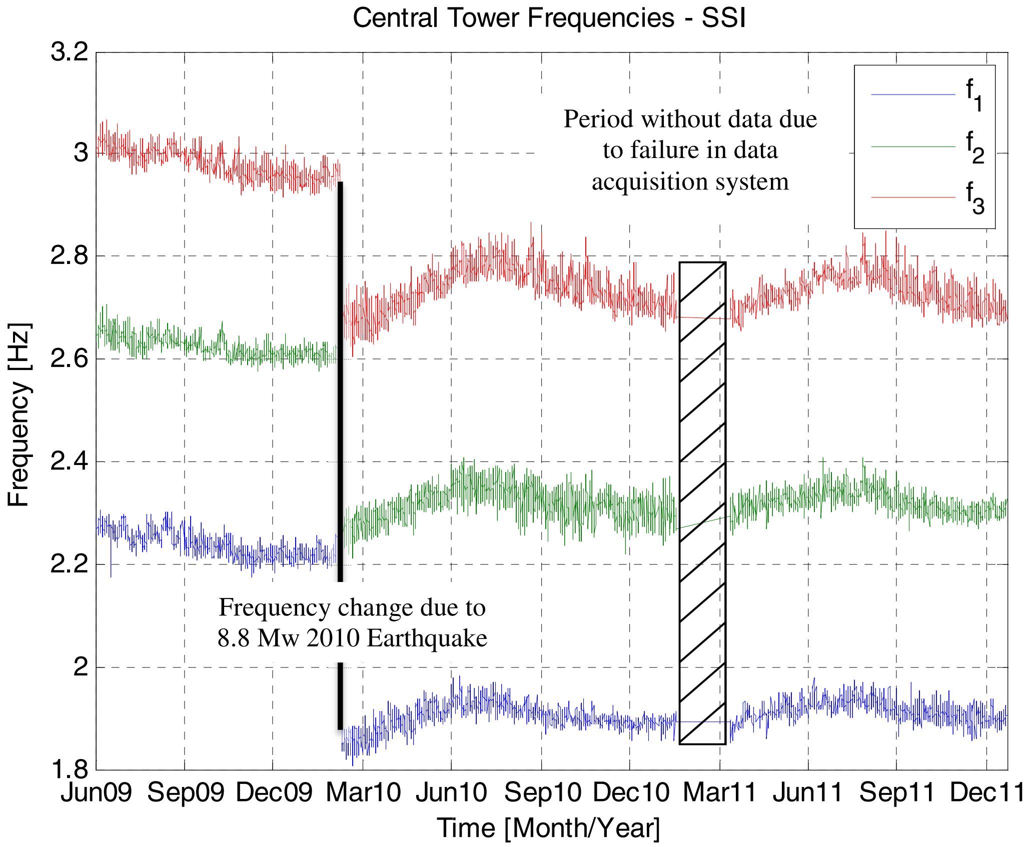


Figure 3: Central Tower Frequencies - SSI

Additionally in Figure 5 histograms show the full range of data after the earthquake, and a set of filtered data. For the filtered data histograms we have removed the effects of the responses of the structure under seismic events (approximately 1700 events), periods of high humidity in the ground and for which we have selected only the natural frequencies when the external temperature is in the range of 20.5°C and 21.5°C. The effect of amplitude of response, temperature and soil humidity can be observed as a change in the median frequency and the standard deviation of the frequency histogram. The mean frequency decreased 0.7%, 0.6% and 0.7% while the standard deviation decreased 23%, 12% and 17% for frequencies 1, 2 and 3 respectively. Also the histogram changes from bimodal to a unimodal shape.

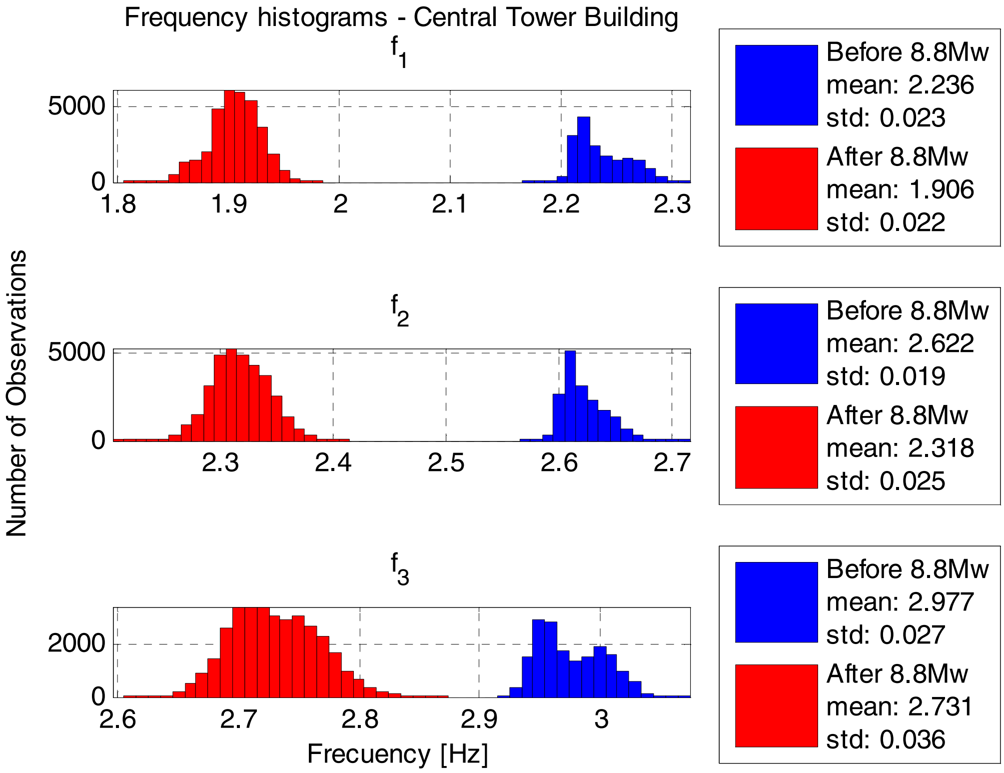


Figure 4: Frequency histograms, before and after 8.8 Mw Earthquake. Central Tower Building.

4 PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA) is a statistical tool commonly used to reduce the dimension of a data set, replacing a group of related variables by a new smaller group of independent variables, which are designated as principal components.
Consider a matrix $Y \in R^{nxN}$, where each row corresponds to a variable, and each column corresponds to the measurement of that variable at each instant of time t_k. The original variables stored in the matrix Y can be transformed into a set of variables $X \in R^{mxN}$ through the following equation:

$$X = T \cdot Y \tag{1}$$

Where $T \in R^{mxn}$, with $m \leq n$ is an orthogonal matrix (its inverse coincides with its transpose) which applies a rotation to the original coordinate system.
The object of PCA is to find a transformation that leads to a set of variables X (principal components) which are independent of each other, so that the covariance matrix of X is diagonal, and also the variance of X_1 to X_m decreases from X_1 to X_m. Thus, the first principal component, X_1, explains the largest proportion of the variance of the original variables, while the last principal components explains a smaller proportion of the variance.

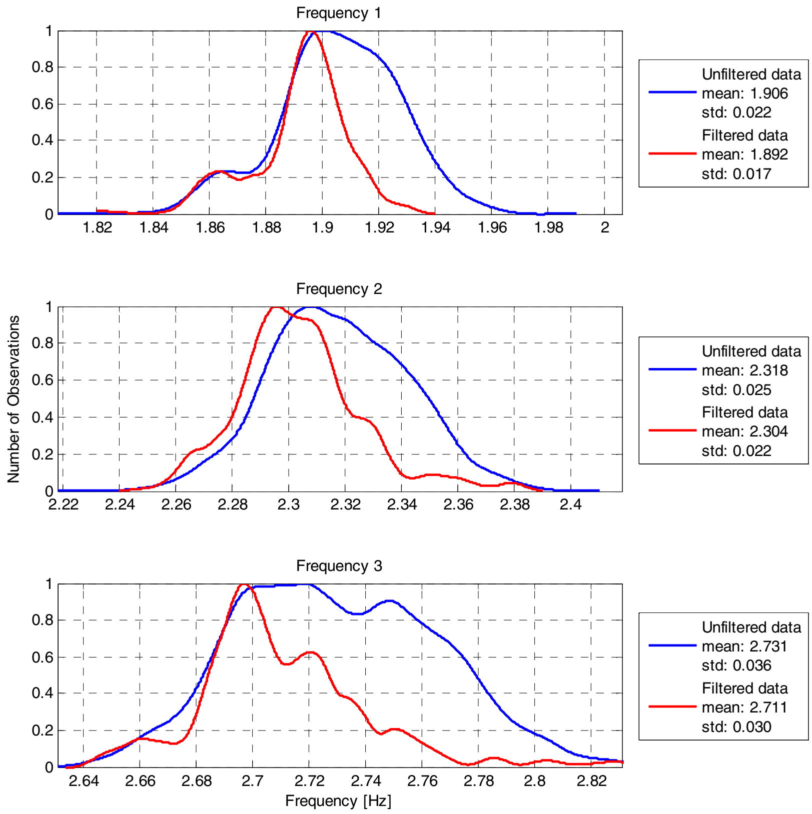


Figure 5: Normalized frequency histograms after 8.8 Mw Earthquake. Blue lines correspond to raw data and red lines corresponds to filtered data in the range 20.5°C and 21.5°C, and removing rain and earthquakes effects.

Considering the relation between X and Y given in equation (1), and taking into account the orthogonality of T, the covariance matrix of Y designated by Σ can be related to the covariance matrix of X designated by Λ through the following expression:

$$\Sigma = E[Y \cdot Y^T] = E[T^T \cdot X \cdot X^T \cdot T] = T^T \cdot \Lambda \cdot T \tag{2}$$

And since the singular value decomposition gives:

$$\Sigma = U \cdot S \cdot U^T \tag{3}$$

The matrices obtained by the SVD decomposition can be used to obtain the transformation matrix $T = U^T$ and the variances of the components of X (diagonal elements of the matrix S).

The main feature of the method is the possibility to determine principal components explaining a greater or lesser extent the variability of the measured variables. Since the algorithms that perform the singular value decomposition SVD delivers singular values in decreasing order, the first diagonal element of S matches with the variance of X_1, while the rest of the singular values decrease, as well as the variances of the components of X. Thus, it is possible to divide the matrix S into two parts: $S_1 = diag(s_1, s_2, \ldots, s_p)$ and $S_2 = diag(s_{p+1}, s_{p+2}, \ldots, s_m)$, where S_1 is a diagonal matrix containing the first p singular values, and S_1 a diagonal matrix containing the rest of the singular values, which are not relevant to explain the variability of the components of Y.

A way to determine the value of p is through the determination of the following equation:

$$I = \frac{\sum_{i=1}^{p} s_i}{\sum_{i=1}^{m} s_i} \tag{4}$$

This ratio determines the percentage of variance of observed data that is represented by the p first components of X. In this way, it is possible to determine p defining a minimum value for I, for example 0.95.
Once p is selected, the set of variables X_1 to X_p can be calculated using equation (1), using a matrix $\hat{T}$ constructed from the first p columns of U. After reducing the dimension of the set of original variables through the $\hat{T}$ matrix, it is possible to reallocate the variables to its original space. Thus we have:

$$\hat{Y} = \hat{T}^T \cdot \hat{T} \cdot Y \tag{5}$$

Where $\hat{Y}$ corresponds to the modified original variables, which retain the variation due to factors that produce more variance in the original data, discarding the factors that produce little variability in these, which in the event that the measured variables are , for example, frequencies in a structure, may correspond to measurement errors or structural damage.
Once the modified variables are calculated, the residual error matrix can be obtained as follows:

$$\varepsilon = Y - \hat{Y} \tag{6}$$

From the prediction error vector ε_k obtained at time t_k, the Novelty Index (NI) is defined using the Euclidean norm :

$$NI_k^{\varepsilon} = ||\varepsilon_k|| \tag{7}$$

Defining $\overline{NI}$ and σ as the mean value and the standard deviation of NI obtained in the reference state, a control chart is constructed by drawing a centerline (CL) at $\overline{NI}$ and two additional horizontal lines corresponding to the upper and lower limits (UCL and LCL) :

$$CL = \overline{NI} \tag{8}$$
$$UCL = \overline{NI} + \alpha\sigma \tag{9}$$
$$LCL = \overline{NI} - \alpha\sigma \tag{10}$$

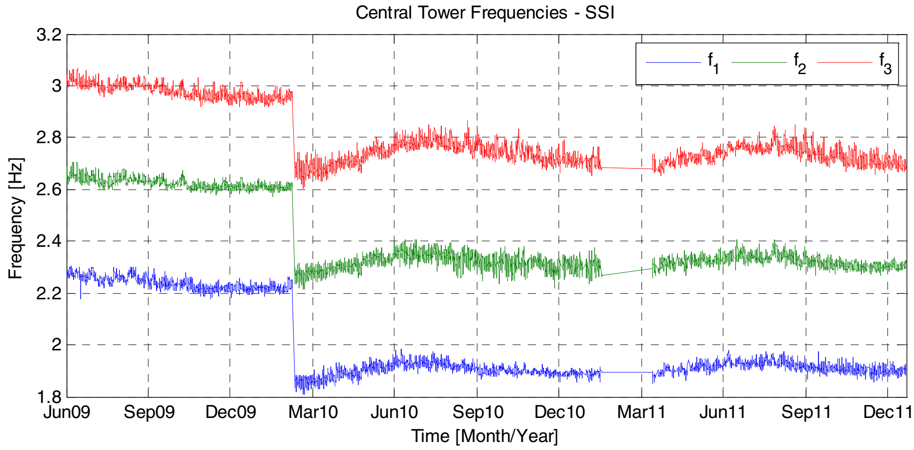
Where coefficient α is taken equal to 3, which corresponds to a confidence interval of 99.7% with the assumption of a normal distribution. In the absence of damage, the Novelty Index should lie between the UCL and LCL limits, and if structural damage occurs the NI value should fall outside the control chart limits [3].

4.1 PCA analysis on frequency series of the Central Tower Building

To evaluate the effect of PCA on a real structure, two analyses have been made that demonstrate its benefit in certain scenarios.

The first analysis is shown in Figure 6, in which PCA is applied before the 8.8 Mw earthquake, with a training time of 7 months. This is all the data before the damaging earthquake. It can be seen that the slight damage due to the earthquake is clearly identified with the drop of the novelty index below the LCL limit.
The second analysis is shown in Figure 7, in which PCA is applied after the earthquake, with a training time of 12 months. After the period of training it can be seen that despite the fact that there

was not strong shaking in the subsequent period or an event that may suppose that have been damage on the structure, there is some data in the control chart that overpass the upper and lower limits. The number of data in the control chart that overpass the limits is 30, and if we apply PCA to the frequency record but extracting from the frequency series, the data influenced by earthquakes occurred on that period, we find out that the number of data that overpass the limit is 24, meaning that the effect of low intensity earthquakes in the false positives on PCA is relatively small. Other effects that may influence the effectiveness of PCA is the quality of the identification process, which could be responsible for a negative result in the control charts and the duration of the training phase.



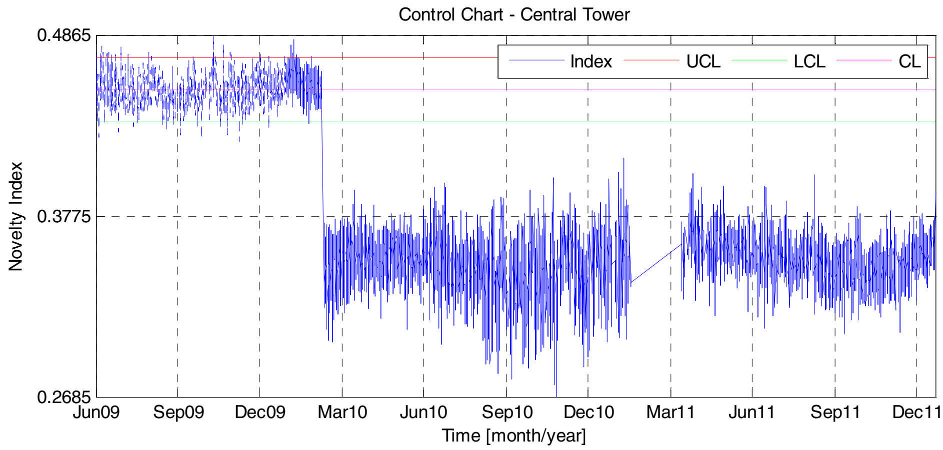


Figure 6: PCA analysis before 8.8 Mw Earthquake. Dotted line on control chart corresponds to the training time

CONCLUSION

The variations of the dynamics properties due to environmental effects of the Central Tower at the Faculty of Physical and Mathematical Science of the University of Chile have been studied. Over 90,000 ambient vibrations records and over 1,700 seismic records have been analyzed, combined with the environmental records obtained from a meteorological station.
Significant reduction of the variance of the frequencies has been obtained when removing data affected by rain, earthquakes and filtering by temperature in the range 20.5°C - 21.5°C.

PCA has been used to identify damage on the structure before and after the 8.8 Mw Earthquake. The results show that the damage due to the 8.8 Mw Earthquake has been clearly identified.
False positives have been obtained when applying PCA after the earthquake, which are slightly reduced if the effects of seismic events are eliminated. This negative result may be influenced by the quality of the identification process or by events of rain due to the limitations of the method or training period to capture its effects. This situation is part of an ongoing research

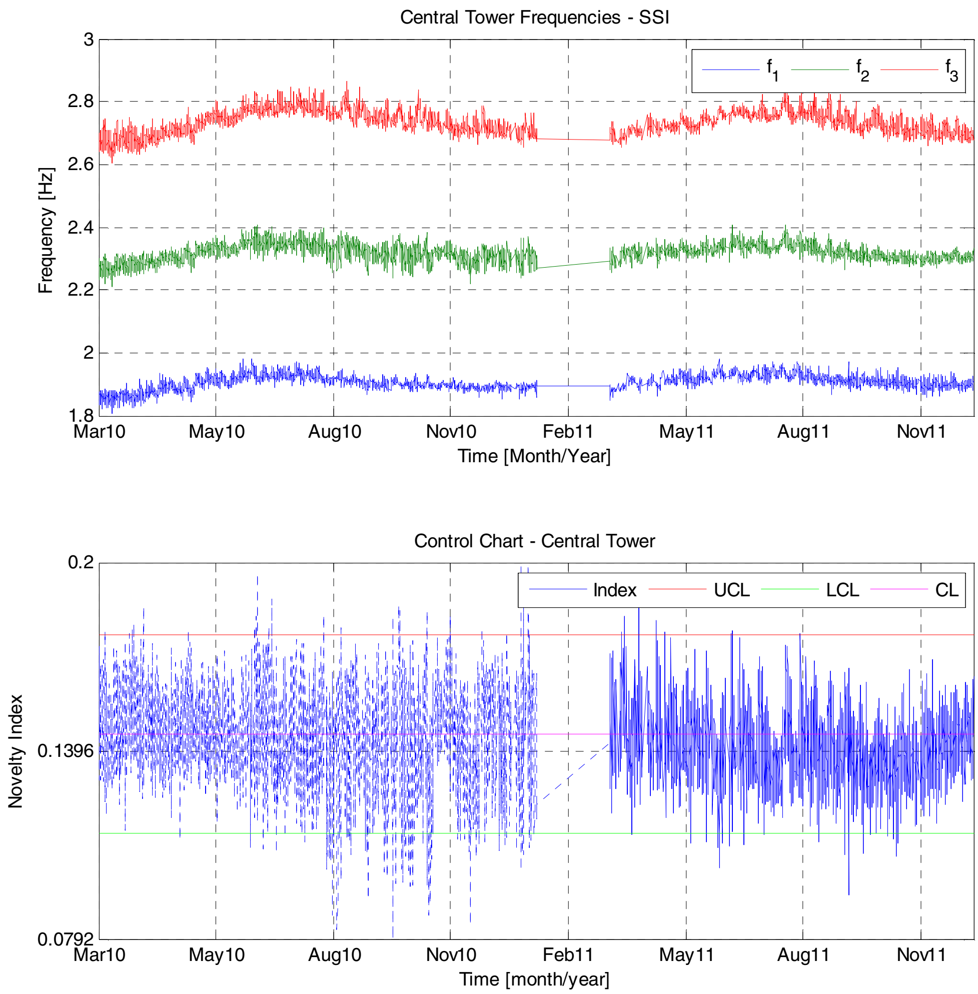


Figure 7: PCA analysis after 8.8 Mw Earthquake. Dotted line on control chart corresponds to the training time

REFERENCES

[1] Boroschek R., Aguilar A., Basoalto J., León P. (2013) "Structural Health Monitoring of a Mid Height Building in Chile", 5th International Operational Modal Analysis Conference, Guimarães, Portugal.

[2] Basoalto J. (2013) "Análisis del efecto de las condiciones ambientales en las propiedades modales de un edificio de hormigón armado", Thesis in fulfillment of the requirements for the degree of Civil Engineer, Universidad de Chile.

[3] Yan, A. -M., Kerschen, G., De Boe, P. and Golinval, J. -C. [2005] "Structural damage diagnosis under varying environmental conditions-Part I: A linear analysis". Mechanical Systems and Signal Processing, 19 (2005) 847-864.