The 2013 World Congress on
Advances in Structural Engineering and Mechanics (ASEM13)
Jeju, Korea, September 8-12, 2013

Seismic regionalization based on an artificial neural network

*Jaime García-Pérez[1)] and René Riaño[2)]

[1), 2)] Instituto de Ingeniería, UNAM, CU, Coyoacán, México D.F., 014510, Mexico
[1)] jgap@pumas.ii.unam.mx

ABSTRACT

Zoning of a region of known seismicity through a neural network is presented. The resulting zones comprising the region are defined by boundaries coinciding with jurisdictional limits and constant design parameters, which are optimum in the sense of minimizing the total expected present value of costs, composed of initial cost of the structure built in the region and costs of damage and failure due to earthquakes. The Kohonen neural network is applied to divide a seismic region into zones considering several structural types built in the region. Input data vectors used in the process of zoning are seismic intensities and expected present values of total costs. Different scenarios of regionalization are presented depending on the number of structures considered. It can be seen that the neural network employed gives a suitable and quick solution to the problem of zoning.

1. INTRODUCTION

It is usual to present seismicity of a region in both, normative documents as well as in those due to support them, as a set of curves of certain relevant parameters (such as peak ground acceleration, maximum effective acceleration, or peak ground velocity) corresponding to fixed return periods, and that it is assumed they govern entirely the design. The alternative is to zone the region. This can be done optimally in two ways. In the first each type of structure can be designed for the worst condition corresponding to the zone, thus we minimize the initial cost. This approach is justified when seismicity is so high that in choosing the design parameters social tolerance rules over damages caused by earthquakes. In the second we minimize the expected present value of the total cost (including initial cost and those caused by earthquakes). Here we use the latter because it takes into account all benefits and costs and it is equivalent to maximize the utility of our decisions (utility in the sense of a rational measure of preference). The results of zoning will provide us with both optimum boundaries and design parameters corresponding to each zone. For practical and legal reasons boundaries will coincide with jurisdictional limits.

[1)] Researcher
[2)] Graduate Student

There are several methods in the literature that can be used for optimization, among them are those based on artificial intelligence, namely genetic algorithms and artificial neural networks (ANNs). Genetic algorithms use a procedure analogous to that developed on the selection of natural species to find the optimum zoning, in this case the chromosome is the seismic region comprised of cells represented by genes associated according to their position in the chromosome. On the other hand ANNs process information in the same way biological nervous systems do for optimum decisions. Pattern classification is a problem in which ANNs give a better solution than linear programming methods.

This paper starts by showing the equations used in computing the expected present value of the total costs comprised of the initial cost and the costs due to earthquakes, which will be used in the process of zoning a region of known seismicity. Equations are developed for both cases, when a single structure is built in the region, and when several structures are considered. Then the self-organized artificial neural network (Kohonen) used in the regionalization process is explained, and finally the application is shown through some examples.

2. COSTS

The expected present value of the total cost takes into account initial costs of the structure, costs of structural damages due to earthquakes and costs for social impact, thus it comprises all damages including direct economic, indirect and non-economics, which earthquakes cause to society.

2.1 Initial cost

The initial cost of a structure is taken as a function of the seismic design coefficient c used in designing the structure. Based on available results García-Pérez (2000) concludes that it is reasonable to adopt the following relationship:

$$
\begin{aligned}
u &= C && if\ c \leq c_0 \\
u &= [1 + \alpha_2 (c - c_0)^{\alpha_3}]C && if\ c > c_0
\end{aligned}
\tag{1}
$$

where C is the initial cost, c_0 the lateral resistance when the structure is not designed to withstand earthquakes, α_2 and α_3 are constants greater than zero. Thus the expected present value of the initial cost per unit area is given by

$$\bar{u}(c) = \varphi u(c) \tag{2}$$

where $\varphi(x, y)$ is the expected present value of the number of structures per unit area that will be built in the region and it is defined by $\varphi(x, y) = \int_0^\infty \psi(x, y, t) e^{-\gamma t} dt$, where $\psi(x, y, t)$ is a function that shows the variation of φ per unit time, and γ is the discount rate.

2.2 Costs due to earthquakes

The cost of damages due to earthquakes, L_z, can be divided into two groups. In the first we have material damages on the structures, and in the second group the indirect economic damages (damages in non-structural elements, contents of the structure, impact in the regional economy), and the non-economic damages (social impact, loss of human lives). These costs are in terms of the seismic design coefficient. We will use the expression developed in García-Pérez (2000) as: $L_z = u\xi(z/c)[1 + b\xi(z/c)]$ where $\xi(z/c) = \xi(\zeta) = 0.025\zeta^6 - 0.015\zeta^9$ if $\zeta \leq 1$, and $\xi(\zeta) = (0.188 + \zeta^{1.8})/(117.8 + \zeta^{1.8})$ if $\zeta > 1$. Here b is a coefficient greater than one.

Let $\kappa(z) = -d\lambda/dz$ denote the density of occurrence of earthquakes with intensity z, where $\lambda = \lambda(z)$ is the exceedance rate of z. If earthquake arrival times constitute a Poisson process, and if we assume that the original condition is restored to the structure after each earthquake, and if the expected cost of damage and failure per unit time is (Rosenblueth 1976):

$$d_0 = \int_0^\infty -\frac{d\lambda}{dz} L_z dz \quad (3)$$

then the expected present value of all seismic losses for all structures built in the area under study becomes:

$$\nu = \varphi \int_0^\infty d_0 e^{-\gamma t} dt \quad (4)$$

The exceedance rate of intensities in the region, z, $\lambda = \lambda(z)$ is computed as $\lambda(z) = \int_{M_0}^{M_u} (-d\lambda(M)/dM) P[Z > z|M, R] dM$, here M_0 and M_u are upper and lower limits of the magnitudes involved in the seismic process, $\lambda(M)$ is the exceedance rate of magnitudes of earthquakes under study, which fits reasonably to the Gutenberg-Richter law that Cornell and Vanmarcke (1969) have formalized through the following expression $\lambda(M) = \alpha_1(e^{-\beta M} - e^{-\beta M_m})$, where α_1 and β are constants, M_m is the maximum magnitude of M that can be generated in the seismic province.

$P[Z > z|M, R]$ is the probability of occurrence of an earthquake with intensity greater than z, given magnitude M and source to site distance R. It is assumed that this probability is determined by a lognormal distribution with median equal to the attenuation law given by $z = aR^{-2}e^{\beta' M}$, where a and β' are variables depending on both the structure´s natural period of vibration and its location. Therefore by relating random variable Z, with a random variable X defined by a cumulative standard normal distribution we obtain $P[Z > z|M, R] = \Phi(X)$, where $X = [\ln(aR^{-2}) - lnz + \beta' M]/\sigma_{lnz}$. Thus after doing substitutions $\lambda(z)$ and $\kappa(z)$ become: $\lambda(z) = \int_{M_0}^{M_u} \alpha_1 \beta e^{-\beta M} \Phi(X) dM$ and $\kappa(z) = \int_{M_0}^{M_u} (\alpha_5/z) \exp\left[-\beta M - \frac{X^2}{2}\right] dM$. Where $\alpha_5 = \alpha_4/(\sqrt{2\pi}\sigma_{lnz})$, and $\alpha_4 = \alpha_1\beta$. Thus, making substitutions in Eq. (4) we get:

$$\nu = (\varphi u \alpha_5/\gamma) \int_0^{z_m} \int_{M_0}^{M_u} (1/z)\xi(z/c)[1 + b\xi(z/c)] \exp[-\beta M - X^2/2]\, dM dz \quad (5)$$

It is convenient to write $\zeta_m = z_m/c$ and integrate with respect to ζ rather than with respect to z. We then get

$$\nu = (\varphi u \alpha_5/\gamma) \int_0^{\zeta_m} \int_{M_0}^{M_u} (1/\zeta)\xi(\zeta)[1 + b\xi(\zeta)] \exp[-\beta M - Y^2/2]\, dM d\zeta \quad (6)$$

Where, $Y = [\ln(aR^{-2}) - ln\zeta - lnc + \beta' M]/\sigma_{lnz}$. Once the boundaries are known, the total cost W_k related to zone k is calculated as $W_k = u_k[(F_k - F_{k-1}) + (G_k - G_{k-1})]$, where: $F_k = \iint \varphi(x, y) dxdy$ and
$G_k = \iint (\varphi \alpha_5/\gamma \int_0^{\zeta_m} \int_{M_0}^{M_u} [\xi(\zeta)/\zeta][1 + b\xi(\zeta)] \exp[-\beta M - Y^2/2] dM d\zeta dxdy$.

F_k terms are related to initial costs of the structures, and G_k those related to indirect and social costs due to earthquakes. Summations cover the area in which $c \leq c_k$. Optimum coefficients are calculated numerically such that W_k is minimum.

3. COST MINIMIZATION

Let x, y be the coordinates of a point on the region to be divided, $i = 1, \ldots, I$ the type of structure to be built in the region, $k = 1, \ldots, K$ the zone, $z = z(x, y)$ the seismicity defined by the demand of shear base coefficients (we use here the spectral acceleration ordinates in terms of the acceleration of gravity) and by their exceedance rates. Furthermore, let c represents the vector of the adopted design coefficients, $w = w(c, z)$ the unit expected present value of the total cost, $\varphi = \varphi(x,$ y) the expected present value of the number of structures built in the region, and W the expected present value of the total cost of all structures. Then, $W_{ik} = \iint_k \varphi_i w_i dxdy$, $W_k = \sum_{i=}^{1} W_{ik}$, $W = \sum_{k=1}^{K} W_k$. The problem consists in minimizing W.

3.*1 Several structures*

The method developed above can be extended when two or more structural types are considered. Now we will divide into K zones a region comprised of J cells with I structural types. If each cell were a zone, the initial cost of a structure type i at point x, y inside cell j would be $u_i(c_{ij})$, where c_{ij} would be the vector of the design parameters for type i in this cell. The expected present value of all structures type i per unit area would be:

$$\bar{u}_i(c_{ij}) = \varphi_i(x, y) u_i(c_{ij}) \quad (7)$$

Where $\varphi_i(x, y) = \int_0^{\infty} \psi_i\,(x, y, t) e^{-\gamma t} dt$, here $\psi_i(x, y, t)$ is the expected number of structures type i that will be built at x, y per unit area and per unit time. Following a similar procedure as in the case of a single structure, the expected present value of the losses due to earthquakes is given by

$$\nu_i = (\varphi_i u_i(c_{ij})\, \alpha_5/\gamma) \int_0^{\zeta_m} \int_{M_0}^{M_u} (1/\zeta)\xi(\zeta)[1 + b\xi(\zeta)] \exp[-\beta M - Y^2/2]\, dM d\zeta \qquad (8)$$

The total expected present value of all structural type i that will be built in cell j is obtained by adding Eq. (7) and Eq. (8), therefore

$$W_{ij}(c_{ij}, z_{ij}) = \iint_j \, [\bar{u}_i(c_{ij}) + \nu_i(c_{ij}, z_{ij})] dxdy \qquad (9)$$

In the case when cell j is assigned to zone k, the cost of cell j is given by Eq. (9) replacing c_{ij} by the corresponding c_{ik}. Thus if zone k is comprised of N of the J cells composing the region, then the cost associated to this zone k is given as $W_{ik} = u_{ik}[F_{ik} + G_{ik}]$, with $F_{ik} = \iint_N \, \varphi_{in}(x, y) dxdy$ and
$G_{ik} = \iint_N \, (\varphi_{in}\alpha_5)/\gamma) \int_0^{\zeta_m} \int_{M_0}^{M_u} [\xi(\zeta)/\zeta_{in}][1 + b\xi(\zeta)] \exp[-\beta M - Y^2/2] dM d\zeta dxdy.$

4. ARTIFICIAL NEURAL NETWORKS

An artificial neural network is an information processing system that mimics those characteristics pertaining to a biological neural network. It has been developed as a generalization of the mathematical models of the human cognition or neural biology, based on the following assumptions: The information process takes place in a set of simple elements called neurons, where signals are transmitted by link connections with a weight that multiplies them such that each neuron applies an activation function (usually non-linear) to its net input (the weighted sum of the input signals). Moreover, ANNs are defined by the pattern connections among neurons (architecture) as well as the method to establish weights (training or learning algorithm), and the activation function.

4.1 Self-organizing maps

Self-organizing maps provide a way of representing multidimensional data into spaces of lower dimension by establishing a link between input data and a two-dimensional output, such that under data with similar characteristics neurons located in zones next to the output layer are activated. This process of reducing dimension of the vectors is essentially a data compression technique called vector quantization. One of the most important aspects of these maps is that they learn to classify data without supervision. In its most simple presentation self-organizing maps consist of two layers, namely the input data layer containing information to be classified or training data and the output layer that is a neuronal array each one with a vector of weights of the same dimension as the input vector.

4.2 Kohonen network

Teuvo Kohonen presented in 1982 a neural network model able to make maps through a matrix organization of artificial neurons in a similar way as it happens in the brain. This type of ANN uses competitive learning, which is a form of unsupervised learning where nodes compete for the right to respond to a subset of the input data. Competition can be either hard or soft, in the first just one neuron get the resources, and in the second, there is a clear winner but its neighbors share a small percentage of the system resources. A typical competitive neural network consists of a layer of neurons in which all of them get the same input. The neuron presenting the best output (maximum or minimum according to the criterion established) is the winning neuron. A logical criterion to select the winning output neuron in a network of this kind could be proximity, thus the neuron closest to current input data will be the one to win. Kohonen network shows that input data information by itself is enough to make topological maps, assuming that a self-structure and an efficient behavior of the network are provided.

In the Kohonen network, prior to the training process, both data and each neuron's weights must be initialized. In the case of data, initialization is done by normalizing or scaling each one of the attributes of the training set such that its norm is unit, thus preventing any of the attributes to dominate the classification. On the other hand, neuron's weights are initialized beginning with small standardized random values. At this stage the radius of the neighborhood is also initialized with a large value thus covering a great number of neighbor neurons. As long as iterations increase this radius tend to diminish becoming a unit distance. After this, a vector is chosen at random from the set of training data and every neuron is examined to calculate which weights are most like the input vector. The winning neuron is commonly known as the Best Matching Unit (BMU). One way to determine the BMU is to compute the Euclidean distance between each node's weight vector and the current input vector. The neuron with a weight vector closest to the input vector is the BMU. Now it is necessary to adjust the weights of each neighboring neuron in order to make them more like the input vector, and it is seen that the closer a node is to the BMU, the more its weights get modified. Training ends when either the root-mean-square-error of the input vectors is reduced to an acceptable value or the prescribed number of iterations is reached.

5. EXAMPLES

Figure 1 shows a region of approximately 1100 square kilometers with administrative divisions and locations of 751 cells considered in this study. The structures built in these cells are defined by their fundamental vibration periods which in our case are 0.1 and 0.7 sec., and that from now on we will refer as structural type 1 and 2 respectively. Variation of the construction areas and seismic intensities in the region considered for the two different types of structures are shown in figures 2 to 5 respectively.

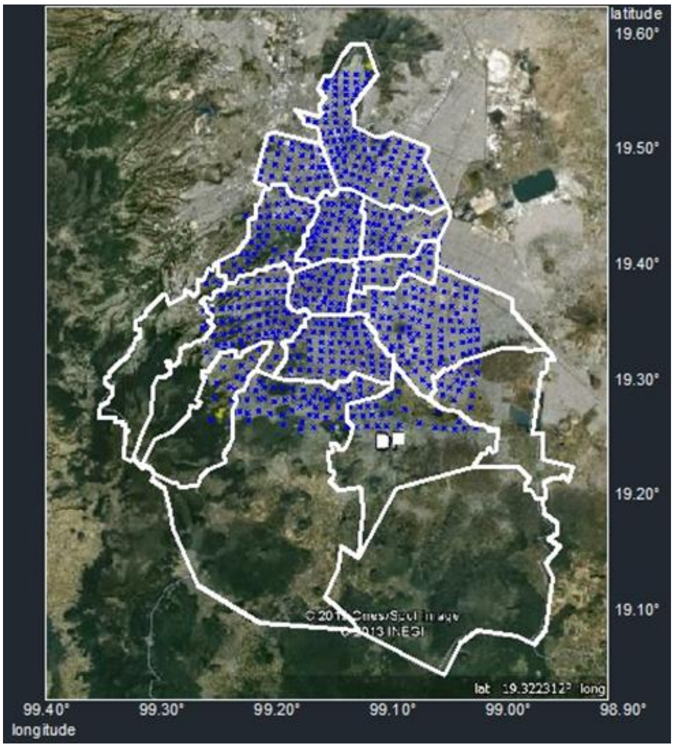

Fig. 1 Seismic region with locations of the 751 cells used in the study

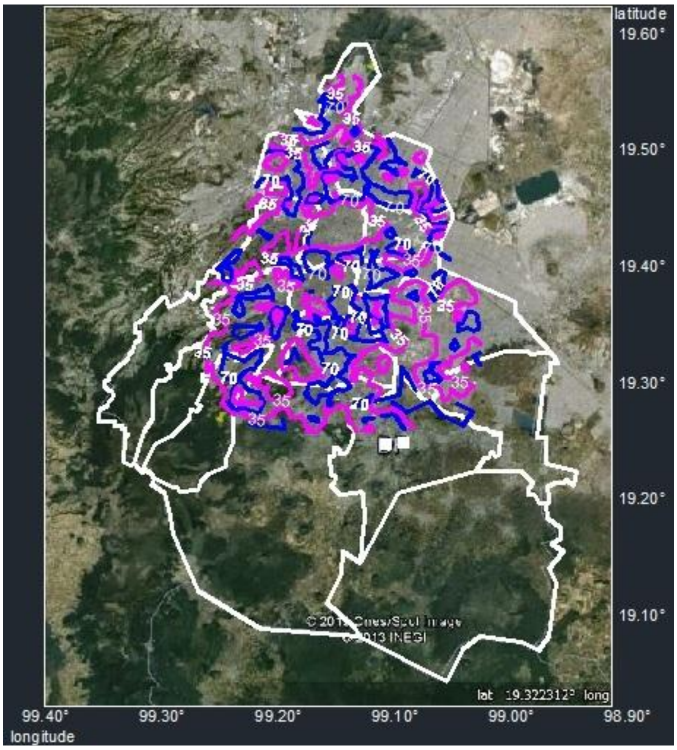

Fig. 2 Isoseismals for construction areas (x$10^{-2}km^2$). Structural type 1

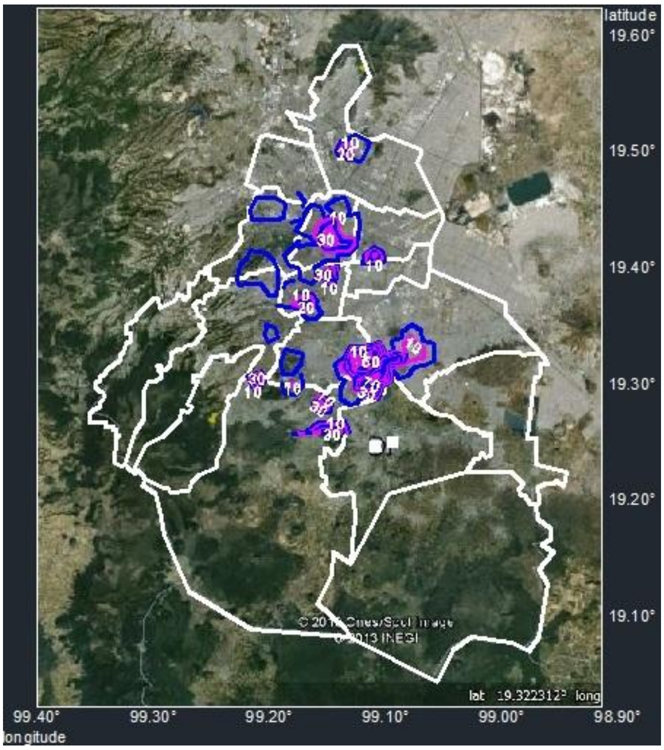

Fig. 3 Isoseismals for construction areas (x$10^{-2}km^2$). Structural type 2

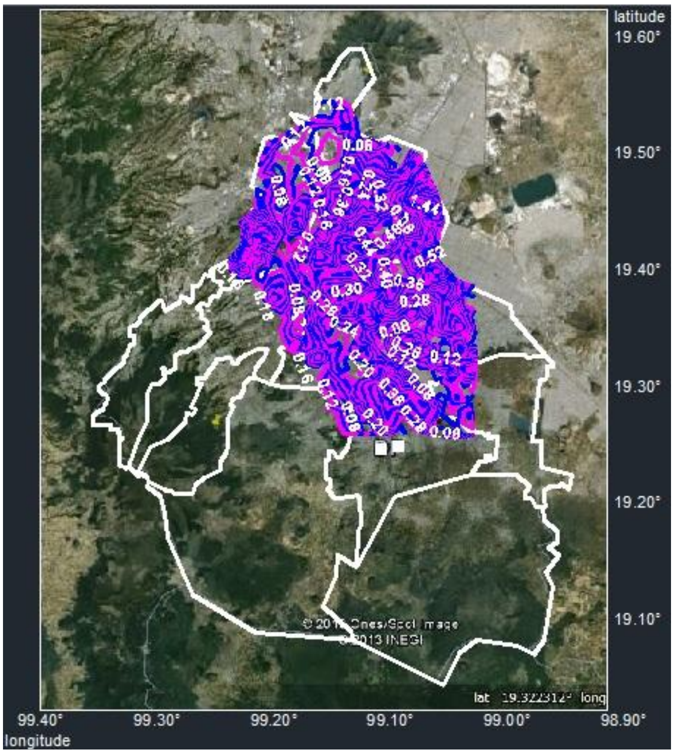

Fig. 4 Isoseismals for intensities (Sa/g). Structural type 1 (curves @0.02)

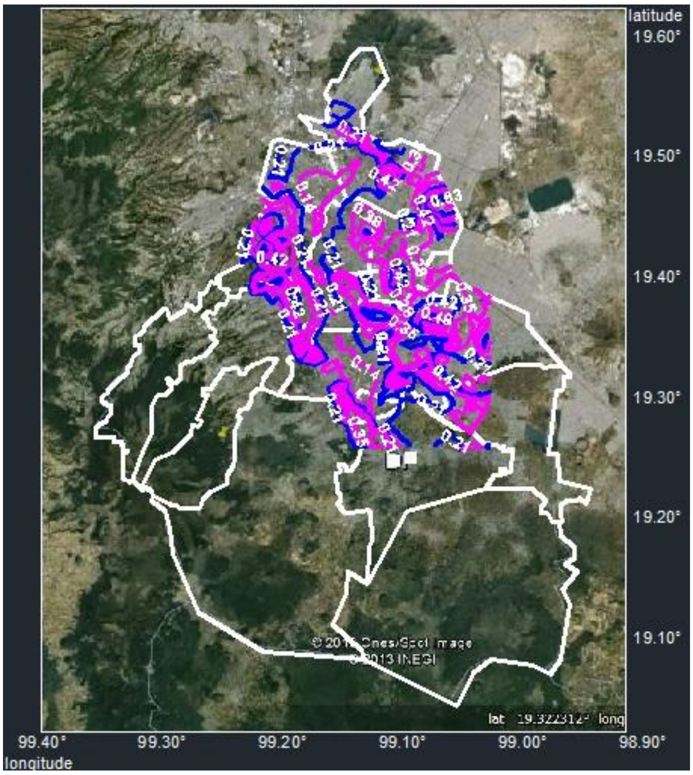

Fig. 5 Isoseismals for intensities (Sa/g). Structural type 2 (curves @0.07)

From figures 2 and 3 we can see that the different types of structures considered are not present in all of the 751 cells shown in figure 1, therefore to find the optimum zoning empty cells were neglected. Total expected costs for the regions were computed from the intensities shown in figures 4 and 5. It is assumed that the intensities correspond to ordinates of the acceleration spectra obtained from considering a possible seismic scenario in the region due to earthquakes generated in seismic sources affecting the site under study.

Figure 6 and 7 show the optimum zoning with the corresponding seismic design coefficients considering structural type 1 and 2 respectively. The resulting regionalization shows a trend of association of cells with similar intensities and whose distributions tend to follow isoseismals of those intensities, as it can be seen in figures 5 and 7 for structural type 2.

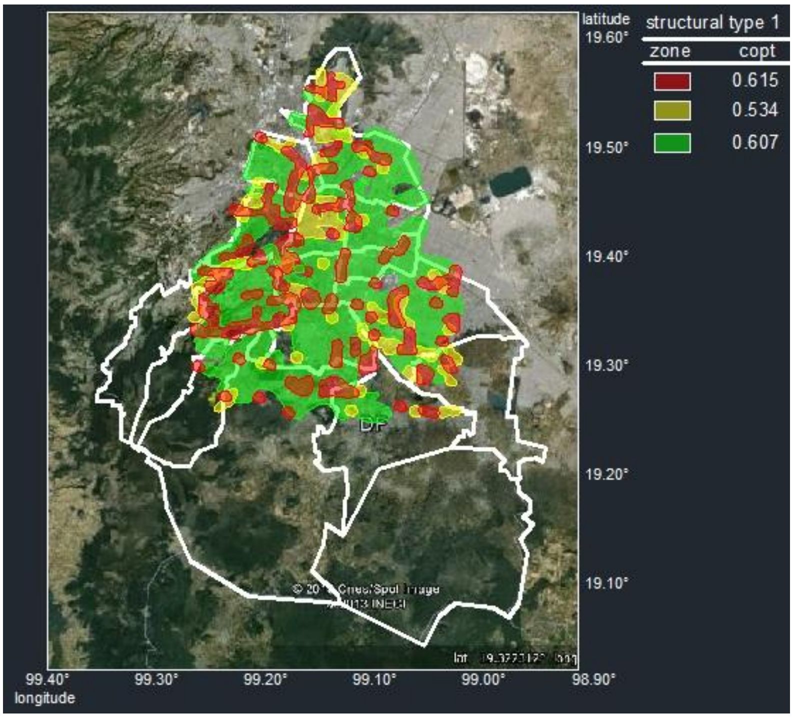

Fig. 6 Zoning considering structural type 1

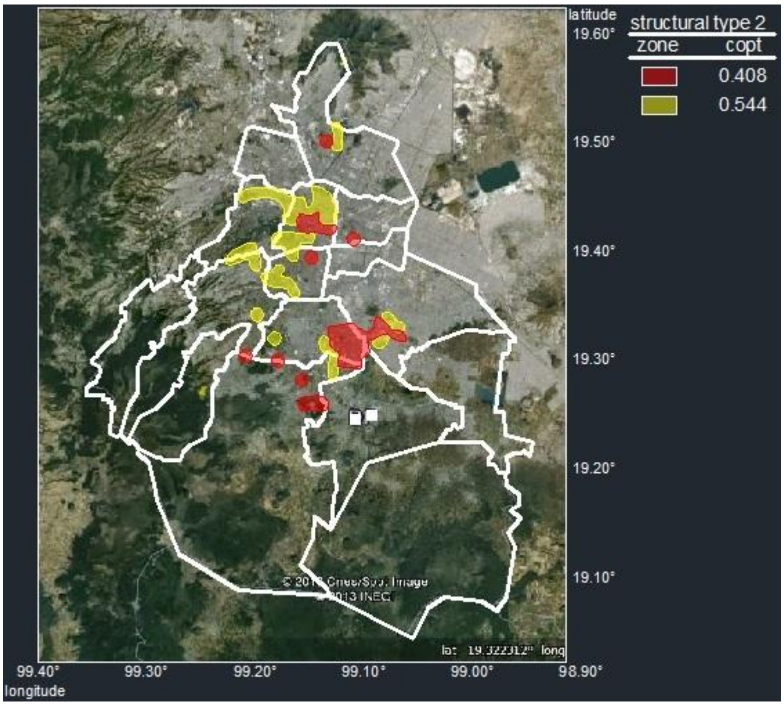

Fig. 7 Zoning considering structural type 2

Zoning resulting from considering structural type 1 and 2 for this study and its corresponding seismic design coefficients is shown in figure 8. This comes from a combination of the zoning taking just a single structural type, usually prevailing the zoning providing more to the total cost. In this case is difficult to distinguish the trend observed as in the case of zoning for a single structural type due to the big number of cells used.

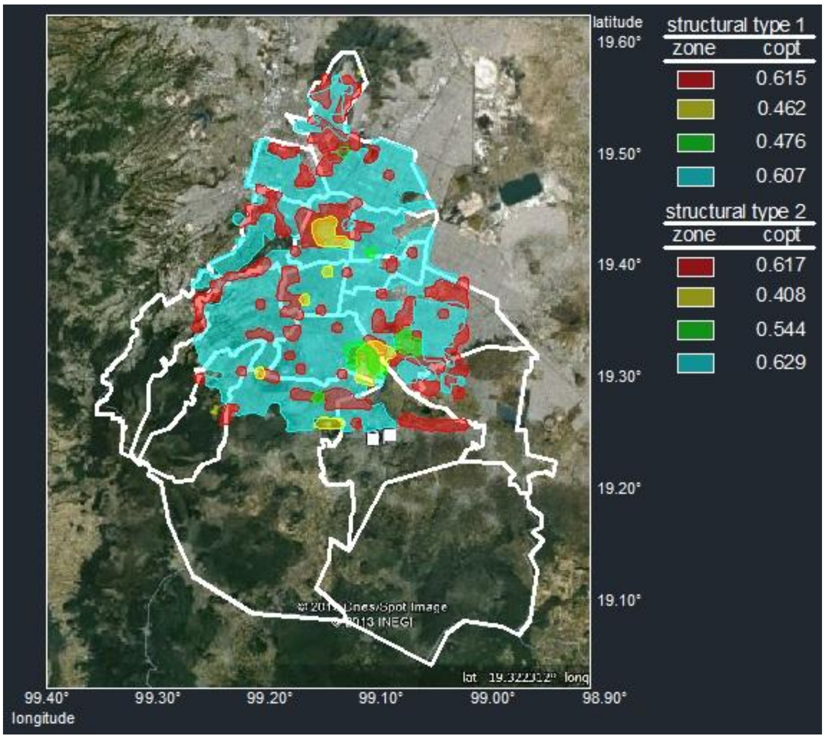

Fig. 8 Zoning considering structural types 1 and 2

3. CONCLUSIONS

Expressions for the expected present value of the total cost used to compute optimum values in a zone are presented. These costs are employed to find the optimum zoning of a seismic region by using a self-organizing neural network called the Kohonen network. This artificial neural network processes information inspired by biological neural networks, and it is trained using unsupervised learning to produce a two-dimensional representation of the input space called a map. The Kohonen network is applied to divide a seismic region into zones defined by jurisdictional boundaries and their corresponding coefficients. Examples with one and two different types of structures are presented using as data the number of structures built in the region and the seismic intensity. The self-organizing method used is flexible, efficient and general in solving the regionalization problem.

REFERENCES

Cornell, CA., Vanmarcke, E. (1969), "The major influence on seismic risk", Proceedings of the IV world congress in earthquake engineering, 169-183.

García-Pérez, J. (2000), "Seismic zoning for initial- and total-cost minimization", Earthquake Engineering & Structural Dynamics, **29**, 847-865.

Kohonen, T. (1982), "Self-organized formation of topologically correct feature maps", Biological Cybernetics, **43**, 59-69.

Rosenblueth, E. (1976), "Optimum design for infrequent disturbances", Proceedings of ASCE, Journal of the Structural Division, 102(ST9),1807-1825.