A Multi-objective Approach to Design Seismic Networks Using a Genetic Algorithm

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Abstract*-Most of the real world optimization problems are naturally multi-objective problems. In order to simplify the solution, many of them are modelled as mono-objective problems. The purpose of this research is to design a seismic network to maximize the warning time of a particular city; that is, the gap between the time when the alert is launched and the arrival time of the disaster, and minimizing the number of seismic stations in the network. To attack this multi-objective optimization problem, it is proposed to turn it into a mono-objective constrained problem and solve it with a simple genetic algorithm. As a case study, it was considered the region of the State of Guerrero, Mexico, where the seismic network could take place. The main disasters targeted in this paper are earthquakes, but this research can be extended easily to alert systems of tsunamis or volcanic eruptions, for the positioning of telecommunications antennas, etc.

***Keywords*-Design of Seismic Sensor Networks; Optimization; Artificial Intelligence; Genetic Algorithms; Computer Application; Profitability**

I. INTRODUCTION

In the constant effort to understand the behaviour of seismic activity, recently, many studies on geodesy and seismology have been developed around the world. A great variety of them focuses on the magnitude and propagation of seismic waves [1][2]; others use statistical techniques and intelligent computing to predict the event of earthquakes [3][4]. In particular, artificial neural networks (ANN) and evolutionary strategies have kept great attention in recent years [5]. A third group has focused in the measurement and development of methods and instrumentation devices. It is evident that all these researches are of great interest and importance; however, little work has been done about how to design and construct seismic networks [6][7].

Some fundamental scientific questions about the internal structure and dynamics of the Moon, and their implications for the Earth-Moon system, are driving the development of a new broadband seismic network on a large scale, covering a wide geographical area, such as the surface of the moon. An investigation related to this topic can be found in the article "Lunar seismic network sensitivity Depending on network geometry"[8]. The authors try to obtain a geometry optimized for a network from seismic records and present the geometric dependence of the classification the shape of the position, the feasible space, particularly the depth, and resolution seismic networks as a function of the number of available seismometers (seismic sensor network).

In "Optimization of design seismic network: Application to a Lunar geophysical international network"[9], published in January 2011, information on lunar seismicity subsurface seismic modelling, provided by the Apollo missions, is used as a priori information to optimize the geometry of future lunar seismic stations networks, in order to solve the best seismic interior structure of the moon. This article assumes that the seismic sources are the events of deep earthquakes and the simulation of lunar meteorite impact. They assume that the seismic data are synthetic arrivals of P and S waves, calculated in a radial seismic model of the Moon. The linearized estimates of resolution and covariance of the disturbances of radial seismic velocity can be calculated for a particular geometry of the seismic network.

The implementation of several computational techniques, including evolutionary computation, have had good results for the solution of certain problems related to seismology, however, they have not been fully exploited for optimal seismic networks. The disadvantage for the construction of optimal networks is that its design must be based on information and data analysis to answer specific scientific questions.

The aim of this particular research is determine the best position of the stations of a seismic network to maximize the warning time (the gap between the time when the seismic network detects a large magnitude earthquake and launches an alert, and the time at which the seismic wave arrives to a populated city), and at the same time minimize the number of stations in the network. To attack this multi-objective optimization problem, it is proposed to turn it into a mono-objective constrained problem and solve it with a simple genetic algorithm (SGA).

Many Disaster Alert Systems (DAS), such as the Seismic Alert System of Mexico City (SASMEX), or the Deep-ocean Assessment and Reporting of Tsunamis (DART II), are located not based in earthquake or tsunami data, but simply by spacing the sensors more or less evenly around the contour of the Pacific Ocean, far away from the City of interest. In contrast, the SGA proposed uses a reliable database of events of recorded earthquakes in a specific region. This information is also used in the testing phase to validate the efficiency of the SGA.

As a case study, the seismic network is located in the State of Guerrero, Mexico, where it is recorded 25% of the seismic activity of the country, and it is of particular interest for the population of Mexico City. Currently, the SASMEX has 12 stations located along the coast of Guerrero. The main function of SASMEX is to issue a public alert to warn Mexico City, when it detects an earthquake of magnitude greater than5.0° on the Richter scale. This system is capable of warn the population up to 60 seconds before the seismic wave reaches Mexico City[10].

The seismic network solutions created by the SGA are compared against the current SASMEX to validate the efficiency in terms of warning time and the number of stations.

It is worth mentioning that this research does not pretend to discredit the labour of "Centro de Instrumentación y RegistroSísmico (CIRES)" [10], but to have a real parameter to compare and demonstrate that this work is feasible.

II. MULTI-OBJECTIVE EVOLUTIONARY OPTIMIZATION

Most of the real world optimization problems are naturally multi-objective; this is, they usually have two or more objective functions which must be satisfied at the same time and possibly are in conflict each other.

The most accepted notion of an optimal in the environment of the multi-objective problems is that originally proposed by Francis Ysidro Edgeworth in 1881 and later generalized by Vilfredo Pareto in 1896.

We say that a point$\vec{x}^* \in \Omega$ is an optimal of Pareto if, for all $\vec{x} \in \Omega$ and$I = \{1,2,\dots,k\}$ either,

$$\forall i \in I\big(f_i(\vec{x}) = f_i(\vec{x}^*)\big) \tag{1}$$

or, there is at least one $i \in I$ such that:

$$f_i(\vec{x}) > f_i(\vec{x}^*) \tag{2}$$

Then the general multi-objective evolutionary optimization problem (MOEP) [11], can be formulated as:

Finding thevector$\vec{x}^* = [x_1^*, x_2^*, \dots, x_n^*]^T$, that satisfies the m inequality constraints:

$$g_i(\vec{x}) \geq 0 \quad i = 1,2,\dots,m \tag{3}$$

the equality constraints

$$h_i(\vec{x}) = 0 \quad i = 1,2,\dots,p \tag{4}$$

and optimizes

$$\vec{f}(\vec{x}) = [f_i(\vec{x}), f_2(\vec{x}), \dots, f_k(\vec{x})]^T \tag{5}$$

In order to simplify the solution, many of these multi-objective problems tend to be modelled as mono-objective problems, using only one of the original functions and managing the additional as constraints.

III. GENETIC ALGORITHM

The Genetic Algorithm (GA) leads to the search for an optimalsolution to a problem, inspired by inheritance mechanismsobserved in nature. This heuristic process keeps theset of solutions (individuals or chromosomes) called populationin genetic terms. During each iteration (generation) of the algorithm, the performance (fitness) of all solutions of the population is measured by the objective function that evaluates a particular problem. Then, some solutions are selected from the population (parents) to create the next generation of solutions. This selection depends on the values of f and can follow several schemes such as the elitistor roulette selection among the most popular [12][13]. The selected solutions undergo a series of combinations, usually consisting of the random exchange of certain parts of the parents. In this process, the useful features of parent solutions are preserved. Thereafter, children were randomly chosen to undergo a mutation. The sequence of evaluation, selection and recombination is repeated until an individual has a satisfactory value for f or until a predefined numberof generations are reached. A simple genetic algorithm, Algorithm 1, is presented in its algorithmic form.

Algorithm 1 Simple genetic algorithm
t:=0;
initialize $P(0) \coloneqq \{\vec{a}_i(0), \dots, \vec{a}_\mu(0)\} \in I^\mu$;
evaluate $P(0) \coloneqq \{\Phi(\vec{a}_i(0)), \dots, \Phi(\vec{a}_\mu(0))\}$;
while $(\iota(P(t)) \neq true)$ do
recombine: $P'(t) \coloneqq r_{\Theta_r}(P(t))$;
mutate: $P''(t) \coloneqq m_{\Theta_m}(P'(t))$;
evaluate $P''(t)$: $\{\Phi(\vec{a}_1''(t)), \dots, \Phi(\vec{a}_\lambda''(t))\}$;
select: $P(t+1) \coloneqq s_{\Theta_s}(P''(t) \cup Q)$;
$T \coloneqq T + 1$;
end while

In this algorithm, t is the generation counter, $P(t) = \{\vec{a}_1(t), \dots, \vec{a}_\mu(t)\}$ is the population at generation t, with $\vec{a}_i \in I$ individuals, and μ is the parent population size. $Q \in \{\emptyset, P(t)\}$is an additional set of individuals to be considered by a selection mechanism. Symbols *m* and *r*, are used to denote a high level mutation and recombination description respectively, while m' and r' denote their sexual, asexual or panmictic form.

IV. METHODOLOGY

A. Problem Representation

The first step to define an evolutionary algorithm is to build a bridge between the original problem context and the solution space of the problem where the evolutionary process takes place. In this research a candidate solution (named individual or chromosome in biological terms), is a vector $\vec{x} \in \mathbb{R}^D$, where the dimensionality D of the problem represents the number of stations of the seismic network. Each, *j* dimension of $\vec{x}$is the geographical coordinate of a station in terms of its longitude and its latitude respectively, see Fig. 1.

The value (phenotype) of each gene is the real representation of a string of bits (alleles). This value is computed applying Equation 6, which encodes binary values to real values.

$$V = \frac{(v_{max} - V_{\min})}{(2^n - 1)} v_{bin} + v_{min} \tag{6}$$

(where v_{max} and v_{min} are the maximum and minimum value of the gene, *n* is the number of bits (alleles) and v_{bin} is the real representation in binary code (phenotype).

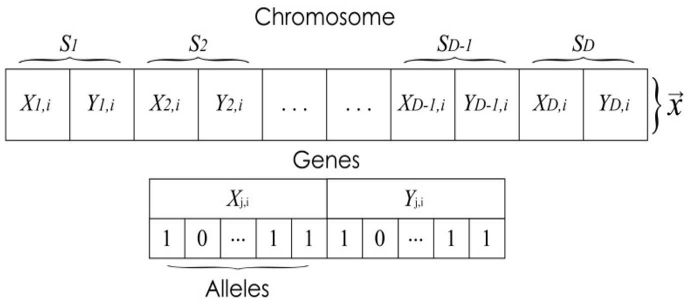

Fig. 1 A graphical representation of a chromosome

The search space of the genes and therefore the candidate solution are located within the boundaries of a specific region.

B. Objective Function

As we mention before, in this research the authors propose a multi-objective optimization problem, where the first objective function is maximizing the warning time, *i.e.* the gap between the time when the seismic network detects an earthquake and issues an alert, and the time in which the seismic wave arrives to a populated city. The second objective function is minimizing the number of the stations of the seismic network; this function will be managed as a constraint. Then, the multi-objective problem is turned into a mono-objective constrained problem. But, the labour to solve this problem is not simple, since each candidate solution has to be evaluated in a process that simulates the event of recorded earthquakes in a specific region. As case study, this region is the State of Guerrero, Mexico, where it is recorded the 25% of the seismic activity of the country, and it is of particular interest for the population of Mexico City.

In many evolutionary algorithms, the objective function is considered as the fitness function which helps to evaluate how close a given solution is from the set aims. In this research, the fitness value of each candidate solution is the average of the warning time achieved when it is simulated every recorded earthquake. It is important to remain that, the candidate solution is a set of seismic stations, so to obtain the warning time T_w it is necessary to compute the difference between the time that a seismic wave arrives the city to alert T_c, and the time a station detects the event of an earthquake T_s, and issues the alert.

$$T_w = T_c - T_s \tag{17}$$

(7This model is subjected to the following considerations during the simulation process:

1) Use reliable databases with recorded earthquakes of the region of interest.

2) The speed propagation of the seismic waves varies from 4 *km/s* to 8 *km/s*[8]. Fortunately, the waves with the greatest magnitude are propagated slower than those with lower magnitude. Considering this, it is proposed that:

a. For an earthquake with magnitude greater than 5.0° in the Richter scale, the seismic wave is propagated at 4 *km/s*.

b. Then, for earthquakes with magnitude between 4.0° and 5.0° Richter, the seismic wave is propagated at 6 *km/s*.

c. Finally, for earthquakes lower than 4.0° Richter, the speed propagation of the seismic is *8 km/s*.

Thus, the speed propagation of the seismic wave is represented by Relation 8.

$$S_p = \begin{cases} 4\ km/s,\ m \geq 5.0° \\ 6\ km/s,\ 4.0° \leq m \leq 5.0° \\ 8\ km/s,\ m < 4.0° \end{cases} \quad (8)$$

(Where *m* is the magnitude of the earthquake.

3) To determine the number of stations that detect the event of an earthquake, the next rules are proposed:

a. For earthquakes with magnitude lower than 4.0° Richter, at least three stations must detect the earthquake. This is to reduce the probability that the sensor of a station is activated by other reasons not related with seismic activity, *e.g.*, the vibrations caused by the pass of heavy vehicles. This means that when the seismic wave reaches the third nearest station from the epicentre, it is time to issue an alert.

b. Following the same criteria, when it is simulated the event of an earthquake with magnitude between 4.0° and 5.0° Richter; at least two stations must detect the earthquake. This is, when the seismic wave reaches the second nearest station from the epicentre, the seismic network must issue a public alarm.

c. Finally, if the magnitude of an earthquake is greater than 5.0 Richter, which it is considered highly risky, it is enough that the nearest station from the epicentre detects the earthquake and issues the alarm immediately. In this case, the probability that a sensor is triggered for other reasons to those caused by an earthquake has a low rate.

To obtain all of these times, the speed formula is applied

$$S_p = \frac{g_d(p,p')}{T} \Longrightarrow T = \frac{g_d(p,p')}{S_p} \quad (9)$$

(9Where T is the time, S_p is the speed propagation of the seismic wave, taken from relation (3). $g_d(p,p')$ represents the geographical distance between two points, in this case p is the geographical coordinate of the epicentre of a recorded earthquake and p' is the geographical coordinate of a station to obtain T_s, or may represent the geographical coordinate of the city to alert to obtain T_c. Then the average of warning time is:

$$T_p = \frac{\sum_{i=1}^{n}(T_{s_i} - T_c)}{n} \quad (10)$$

(For *i=1, 2,…, n* where *n* is the number of recorded earthquakes to simulate. Thus, the objective function is $f(x) = T_p$

C. Constraints

In most optimization problems, the objective function is subject to constraints. These constraints affect directly the individual fitness Φ. The idea is to extend the domain of the objective function, according to Equation 11.

$$\Phi = f(x) \prod_{i=1}^{n} c_i(x)\ (11)$$

For *i=1, 2,…, n-1, n*, where *n* is the number of constraints and $c_i(x)$ is a constraint.

In this research, the given problem is subjected to tree constraints: the first is related to the overlap between stations, the second forces the stations to be located in a region of acceptance, and the third is the use of the second objective function as a constraint. Then, in this particular case equation 11 is turned into Equation 12.

$$\Phi = f(x) \cdot \beta(x) \cdot \gamma(x) \cdot \delta(x) (12)$$

Where $f(x)$ is the objective function subjected to $\beta(x)$, $\gamma(x)$ and $\delta(x)$ constraints or penalty functions.

1) Overlapped stations

One of the goals is to maximize the covered area of the stations. This means that the geographical distance between two or more stations must be maximized. If the geographical distance between two or more stations is lower than their coverage area radius, then they would be covered the same region, which does not help to maximize the individual fitness.

To cover the largest region and to prevent that more than one station is located in the same area, it is necessary that the geographical distance between two or more stations should be at least the double of their coverage area; this is formalized in Equation 13.

$$g_d(p_i, p_j) > 2\rho \quad (13)$$

for *i,j=1,2,…,n-1,n*, where *n* is the number of the station, i ≠ j, and ρ is the radius of the stations coverage area.

Nowadays, the current SASMEX identifies the earthquakes along the coast of the State of Guerrero, with a linear array of 12 stations spaced approximately every 25*kms.* [14].Due to this, it was chosen a distance of 12.5 *kms*. radius for the coverage area of each station. If the distance between any of the stations does not meet this condition, the constraint will have a value of cero; therefore, the fitness of the individual will be cero too. Thus, the individual will be declared as a not feasible solution. In the other and, if the condition is satisfied, the value of the constraint will be one. Equation 14 formalizes the constraint.

$$\beta(x) = \begin{cases} 0, & G_d(p_i, p_j) < 2\rho \\ 1, & in\ other\ case \end{cases} \tag{14}$$

2) Acceptance Region

The second constraint is applied to prevent that any station is located in a rejection region where its construction is not feasible. For example, when a station is located in the Ocean, or located out of the boundaries of the region of interest.

To define an acceptance region, the authors chose *n* geographical points to establish approximately the limits of the region where the stations must be located. These points form a complex polygon in which the locations of all stations are evaluated to determine whether a station is inside of the polygon.

The solution is to compare each side of the polygon to the Y (vertical) coordinate of a station, and compile a list of nodes, where each node is a point where one side crosses the Y threshold of the station. At the end, if there is an odd number of nodes on each side of the station, then it is inside the polygon; if there is an even number of nodes on each side of the station, then it is outside the polygon [15]. Fig. 2 demonstrates a typical case of a severely concave polygon with 14 sides.

Finally, the individual is penalized according to:

$$\gamma(x) = \frac{m}{n} \tag{15}$$

Where *m* is the number of stations in the rejection region and *n* the total number of stations to evaluate

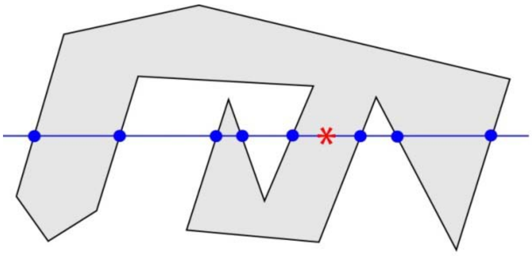

Fig. 2 The red star is the point which needs to be tested, whether it lies inside the polygon

The sample inFig. 3 shows that four of the twelve stations of the seismic network are in a rejection region. Applying equation 15, the value of the constraint $\gamma(x)$is $\frac{4}{12} = 0.33$. Then, if the original value of the fitness function $f(x)$ is 100, then the individual fitness will be 33.33.

Fig. 3 Sample of a seismic network with four stations (in red) in the rejection region

3) Minimizing the Number of Stations

In previous sections of this paper, it was mentioned that the second objective function, which minimizes the number of seismic stations in the network, will be part of the set of constraints, turning the multi-objective optimization problem into a mono-objective optimization problem.

In this way, minimizing the number of stations involves working with individuals of different species; i.e., with a varied number of genes. However, the SGA does not provide a crossover method between individuals of diverse features, so that the algorithm must be adapted to deal with this trouble.

To solve this constraint, it is proposed to create a random vector of bits $\vec{m} \epsilon \mathbb{R}^{\lambda}$ named "the mask", where λ is the maximum number of stations. This mask allows evaluating only those pairs of the individual's genes that correspond with the elements marked with the number one of the vector $\vec{m}$. The number of bits with a value of one is determined by a random integer number between a minimum and maximum number of stations.

Then, the fitness of the individual is affected by equation 16,

$$\delta(x) = 1 + \frac{1}{q} \tag{16}$$

Where q is the number of evaluated stations. This improves proportionally the fitness value of the individuals when the number of stations decreases. A graphical representation of the mask is shown in Fig. 4.

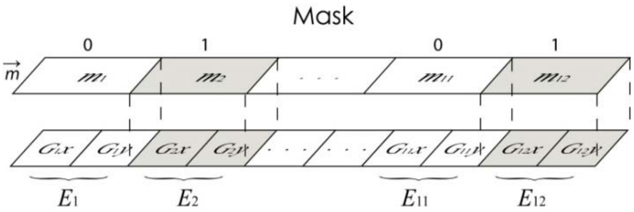

Fig. 4 Only genes shaded by the mask are evaluated

V. EXPERIMENTAL RESULTS

To perform all the experiments and to obtain all the figures of this section, it was developed an application named "Seismic Network Designer v1.0", which is registered with the Mexico's National Copyright.

A. Data Selection

It is noteworthy that, different from what is called training in the field of Artificial Neural Networks (ANN); in this research, training is the process by which the SGA produces solutions with a given percentage of information.

1) Earthquakes Selection

As it was mentioned in the model considerations, to perform the simulation process it is necessary to have information about the events of earthquakes. This information was obtained from the database of the National Seismological Service, and it consists in all the recorded earthquakes from January 1st, 1998 to December 31, 2006. Since the case study is the State of Guerrero, 2180 records of earthquakes were selected whose coordinates are within the boundaries of this State (from 16.19° to 18.53° latitude and from -102.11° to -98.0° longitude). Subsequently, earthquakes with magnitude greater than 4.5° Richter were selected, because they are considered highly risky and trigger the seismic alert system. Fig. 5 shows these large magnitude earthquakes.

Fig. 5 Large magnitude earthquakes

Once the information was extracted, the experiments were performed with the 10%, 50% and 90% of this information. This is, if the total sample space of the database is about 1000 records and the training is performed with the 10% of the information, then the training is conducted with 100 records randomly chosen and the proof is done with the 900 remaining records. For each configuration of the SGA, 30 experiments were performed. This criterion allows validating whether the SGA is an efficient tool for the construction of seismic networks.

2) Acceptance Region

To solve the constraint of the acceptance region, it is applied the point in polygon algorithm. For this algorithm, the authors define 54 geographical points that form a complex polygon and establish the boundaries of the State of Guerrero. Fig. 6 shows these boundaries.

Fig.6 Limits of the state of Guerrero.

After this selection process, each station of the candidate solution is evaluated and identified whether it belongs or not to the region of interest. In Fig. 7 it can be seen a station (in red) located in a rejection region.

Fig. 7 A station located in a rejection region

Finally, the city to alert is Mexico City which geographical coordinates are 19.5° latitude and -99.2° longitude.

B. Configuration of the "Multi-Objective" Algorithm

An important thing that must be defined is the search space where the SGA takes place. This search space is determined by the genes of the chromosome (candidate solution) and all the constraints of the objective function, including the constraint to minimize the number of stations. As it was mention before, the threshold values of the genes are within the boundaries of the State of Guerrero. These values have a real representation in binary encoding; *i.e.*, each gene of the chromosome is a string of bits. The length of the string depends on the precision we want for the search space. For this particular research, it was proposed a length of 12 bits for each gene, this give us a precision of 4096 geographical points between the thresholds of the coordinates.

It is proposed an initial population size of 100 individuals. This population size is maintained to the end of the evolutionary process. This means that during the evolutionary process, the less fit individuals will disappear and the fittest will evolve. In this regard, another thing to consider is the selection for reproduction of the individuals. To avoid a genetic drift of the algorithm, it was selected a uniform selection method, this means that each individual of the population has the chance to reproduce and generate offspring for the next generation.

Because genes have a binary encoding, the authors chose the one-point crossover method and the bit-flip mutation method. A crossover mechanism is applied to explore the search space and mutation to generate solutions that crossover cannot produce. According to the results obtained in [16] to achieve a warning time of 90 *secs.*, the settings of the SGA proposed were a crossover probability of 90% with a mutation probability of 1% and the training phase was performed with 10% of the recorded earthquakes in the State of Guerrero.

Continuing with the phases of the SGA, it was chosen an elitist selection method to ensure that the fittest individuals continue in the evolutionary process and improve the candidate solution. In this case, only 40% of the fittest individuals will move to the next generation.

Finally, two stop criteria were chosen. The first criterion is until all the individuals of the current population has the same fitness value, *i.e.*, until the algorithm converges. If this first condition is not met, then a second stop criterion is applied. This condition is until the algorithm reaches at most 10,000 generations.

It is worth mention, that all these settings were used to design a network between 6 and 12 seismic stations. Therefore, the number of elements of the mask marked with the number one is a random number between 6 and 12. These elements are also selected randomly.

C. Settings for Simulation

To determine the efficiency of the SGA in terms of warning time to the Mexico City, current SASMEX and the solutions provided by the SGA were underwent to the simulation process with the lineal model proposed. The data for simulation correspond to the complement of the data used in the training phase. If the SGA is trained with 10% of the earthquakes, then this simulation process must be tested with the remaining 90% of the data.

At least 30 experiments were performed to have sufficiently large sample size of experiments and ensuring a normal distribution of the results.

D. Results

As part of the analysis of the results, the warning time of the solutions given by the SGA are compared against the warning time of SASMEX after simulating with the proposed model. Fig. 8 shows the location of the seismic stations of SASMEX.

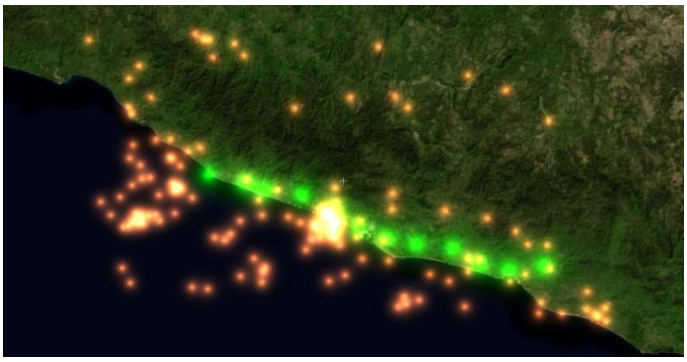

Fig. 8 Seismic Alert System of Mexico City (SASMEX)

The proposed SGA generated a design of a network with ten seismic stations. After the simulation process, the maximum time achieved to alert Mexico City was 89 *secs*. This is just one second less than the seismic networks with 12 stations proposed in [14]. Fig. 9 shows ten blue coloured stations of the seismic network.

Fig. 9 A solution with ten seismic stations

Other design that results more efficient is shown in Fig. 10. Here the seismic network has only six stations and it can issue an alert to Mexico City with almost 87 *secs*., which means tree second less than the seismic networks proposed in [14].

Fig. 10 A solution with six seismic stations

A summary of the results is shown in TABLE I , it includes the maximum warning time of the current SASMEX, the best result of the genetic algorithm GA proposed in [14], and the results obtained with the SGA with a multi-objective approach (MO SGA).

TABLE I SUMMARY RESULTS

Algorithm	Stations	Maximum warning time
SASMEX	12	81
SGA	12	90
MO SGA	10	89
MO SGA	6	87

It can be seen that the difference between the maximum warning times achieved with the MO SGA proposed and the maximum warning times of SASMEX or SGA is not too much; however, the MO SGA significantly reduces the number of stations of the seismic network.

VI. CONCLUSIONS

The SGA with a multi-objective approach demonstrates to be a very competitive and efficient algorithm to solve the problem of designing seismic networks maximizing the warning time and minimizing the number of stations.

This research along with the application developed can be considered as useful tools in planning, prior the construction of seismic networks. In fact, they could help to optimize the resources without compromising the efficiency of the network.

This work may be used to extend the current SASMEX to other States of Mexico, *e.g.*, Michoacán, Veracruz, Tabasco, etc., where seismic activity could affect Mexico City.

This paper can be extended not only for the construction of seismic stations, but also to build other DAS such as tsunamis or volcanic eruptions alert systems. Even it can be used to maximize the coverage area of telecommunications antennas.

Currently, the authors are testing with other evolutionary computation techniques such as Differential Evolution to decrease the complexity and the time to generate new and better solutions.

Further work might focus on adding other characteristics to the simulation process like variations and reflections of seismic waves over strata in earth. Georeferenced data like soil properties could be analysed to show more real and maybe better results.

REFERENCES

[1] S. S. A. Iglesias, «Comportamiento sistemático de bajas aceleraciones provocadas por sismos de trinchera en México,» Reunión Anual 2002 de la Unión Geofíisica Mexicana, p. 386, 2002.

[2] M. C.-S. a. F. C.-G. H. Ferrer-Toledo, «Regional Path Effects on Seismic Wave Propagation in Central Mexico,» Bulletin of the Seismological Society of America, pp. 973-985, 2003.

[3] F. Nava Pichardo, «Fourier spectral analysis for unevenly spaced, average value, data,» Computers & Geosciences, 2010.

[4] S. K. S. O. S. Miguel Ángel Santoyo, «Evidencia estadística de interacción entre grandes sismos de subducción en la región sismogénica del Pacífico Mexicano,» de Reunión Anual 2002 de la Unión Geofísica Mexicana, Jalisco, 2002.

[5] C. W. Qiuwen Zhang, «Using Genetic Algorithm to Optimize Artificial Neural Network: A Case Study on Earthquake Prediction,» de Second International Conference on Genetic and Evolutionary Computing, Hong Kong, China, 2008.

[6] F. A. N. P. J. G. A. C. Jose D. Frez Cardenas, «Source rupture plane determination from directivity doppler effect for small earthquakes recorded by local networks,» Bulletin of the Seismological Society of America, pp. 289-297, 2010.

[7] K. B. M. Chávez, «Modeling of strong ground motions observed for the 09/10/95, MW=8, Colima-Jalisco (México) earthquake,» de 3rd

ACES Workshop Proceedings, 2002.

[8] M. K. a. J. O. Stefanie Hempel, «Lunar seismic network sensitivity depending on network geometry,» Geophysical Research Abstracts, vol. 42, May 2010.

[9] R. a. G. R. F. a. L. P. a. F. M. L. a. C. M. a. G.-B. J. Yamada, «Optimisation of seismic network design: Application to a geophysical international lunar network,» Planetary and Space Science, 19 Jan 2011.

[10] Centro de Instrumentación y Registro Síismico A. C., «Sistema de Alerta Sísmica de la Ciudad de México,» [En línea]. Available: www.cires.org.mx. [Último acceso: 1 Mayo 2011].

[11] C. A. Coello Coello, G. B. Lamont y D. A. Van Veldhuizen, «Evolutionary Algorithms for Solving Multi-Objective Problems (Genetic and Evolutionary Computation),» Springer-Verlag, 2006.

[12] D. E. Goldberg, «Genetic algorithms in search, optimization and machine learning,» Reading, Massachusetts, 1989.

[13] M. Mitchell, «An introduction to genetic algorithms» Cambridge, Massachusetts, 1996.

[14] J. M. Espinosa-Aranda, A. Cuellar, F. H. Rodríguez, B. Frontana, G. Ibarrola, R. Islas y A. García, «The seismic alert system of mexico (SASMEX): Progress and its current applications,» Soil Dynamics and Earthquake Engineering, 2010.

[15] D. R. Finley, «Point in polygon algorithm: Determining whether a point is inside a complex polygon,» [En línea]. Available: http://www.alienryderflex.com/polygon/

[16] J. I. Espinosa Ramos y R. A. Vazquez Espinoza de los Monteros, «Locating seismic-sense stations through genetic algorithm,» de Genetic and Evolutionary Computation Conference GECCO'11, Dublin, Ireland, 2011.

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