A Neurofuzzy System for Safer Gas Supply: An Application to Seismic Emergencies

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Abstract: In order to achieve an efficient real-time system for disaster mitigation, the most extensive high-density seismic motions/flow conditions monitoring in Mexico City is being developed. Known as SISES, the proposed system employs a soft coding for evaluating shaking intensity and for setting in operation district remote regulators (valves), strategically installed in the gas supply area. Micromachining technology is used for measuring ground acceleration, detecting abnormal gas flow conditions, and for fuzzy control of regulators. The SISES configuration is designed for high-precision estimations of damage and failures detection in real time. Dynamic neural networks are used for forecasting the surface distribution of seismic motions and for constructing the premises and conclusions for cutting-off or continuing the gas supply, fuzzy logic is employed. The SISES operation is very precise, simple, and highly reliable. Emerging technologies and methodologies are included in SISES conception as a part of the responsibility of gas suppliers and scientific/technologic community to assure safety particularly during severe earthquakes.

Keywords: seismic emergency systems, safe natural gas supply, PGA prediction, fuzzy logic systems, neural networks, soft data management

1. Introduction

Since earthquakes are unpredictable, they present a challenge to Asia-Pacific Economies to ensure that energy supply systems remain secure during earthquakes. Governments and private investors have worked hand-in-hand to promote earthquake response cooperation to guarantee energy-supply security. In recent decades, developed and developing economies including Australia, China, Japan, Mexico, Chile, Chinese Taipei, the Philippines, Indonesia and USA have experienced severe earthquakes that have resulted in serious damage to energy supply infrastructures and economic development, in addition to the loss of thousands of lives.

During the 1994 Northridge Earthquake Mw6.7, Southern California Gas companies reported 35 breaks in its natural gas transmission lines and 717 breaks in distribution lines. About 74% of the 752 leaks were result of a precarious combination of corrosion with extreme soil deformation levels. As was the case with crude oil pipelines, most other leaks were from cracked or ruptured in pipes assembled before 1932. Two of the larger incidents involved fires. There was a much greater occurrence of fires in mobiles homes than in other structures. In the 2009 Chi-Chi Earthquake, the government-controlled natural gas companies in Taiwan, particularly the five major companies serving Central Taiwan; these installations were seriously affected by the Mw7.7 Chinese earthquake. These top-five companies were among the hardest hit area and as a result, the service provider suffered huge losses and fires. The Japanese experience about the impact of earthquakes on energy supply systems is vast and properly documented. In the 1995 Kobe Earthquake Mw6.8 the gas system sustained at least 1,400 breaks in its underground distribution system, primarily on service lines, with subsequent general curtailment of service by Osaka Gas Company to 834,000 households. Japanese buildings and homes have automatic gas shutoff systems, but many failed to work because of structures collapsed, other minor building damages, and broken pipes. The population in the heavily impacted areas was also notified to expect no gas service for about two months. The gas system in Kobe sustained major damage. Many gas pipelines were destroyed when buildings collapsed and these leaks caused major problems for firefighters, fires lasted dozens of hours in several areas. The shocking Kobe experience showed a natural gas system seriously affected that took 6 to 15 hours till the decisions of supply cutoff were made. To cope with secondary disasters, e.g., fires and explosions, after Kobe earthquake, city gas utilities in Japan promoted several safety structures, primordially increasing seismic resistance of facilities and pipelines, segmentation of gas networks into blocks and earthquake monitoring. Unfortunately, during the 2011 Heisei-Tohoku Earthquake Mw9.1, according to Japan's Fire and Disaster Management Agency, there were at least 300 fires reported after the earthquake and tsunami events occurred. Despite of the after Kobe security modifications, the exhibited during the largest seismic event in the Japanese history (Tohoku earthquake) demonstrated that it was extremely difficult to act immediately because of the astounding ground motions: at least 18 accelerographic stations recorded peak horizontal accelerations of over 980 cm/s^2 (Tohata et al., 2011). There are several ways to explain this tragedy as causes-effects relations but there is no doubt that "unrecognized" factors contributed to the high vulnerability of the area.

The Tohoku experience pointed out the limitations of traditional analysis and design approaches, which relied mainly on "rigid" prediction-based technology-oriented solutions. So, there is an urgent requirement for the actualization of regulations and praxis oriented to develop safer and more reliable distribution systems of hazardous substances in densely populated districts. This is especially recognized in Mexico City, where the high concentration of political, economic, and cultural functions and overpopulation combine on a scale unique in the world. The procedure presented in this paper intend to be a transition from the common "rigid" alarm systems to a more balanced and "flexible" approach, involving comprehensive measures (accelerations and flow conditions), real-time damage estimation (surface distribution of seismic motion that takes into account site amplification factors) and an "intelligent" environment for cutting-off/continuing supply decisions.

The proposed system is called SISES (for its acronym in Spanish *Sistema de Interrupción del Suministro de Gas ante Emergencia Sísmica*) and it is composed by two symbiotic structures: AMIE, soft environment for characterization of geo-seismic-information (*Ambiente de Información Geosísmica*), and MECA, automatic cut-off mechanism (*Mecanismo de Cierre Automático*). In the following the general methodology and operational criteria of SISES will be established. The strategic installation of the soft seismic-shutdown sensors and microcomputer-controlled gas in upstream district governors would serves to prevent secondary disasters such as gas-leakage, fires or explosions. The recent advances in the use of soft technologies (Dynamic Neural Networks NN and Fuzzy Logic FL) for analyzing massive geo-seismic databases and for determining unsafe situations are described. This emergency-operational support system helps to decide on cutting-off gas supplies promptly and it represents an alternative for dealing more adequately with the complex earthquake phenomena.

2. Neurofuzzy systems

Over the last few decades, neural networks and fuzzy systems have established their reputation as alternative approaches to information processing. Both have certain advantages over classical methods, especially when vague data or prior knowledge is involved. However, their applicability suffered from several weaknesses of the individual models. Neural networks combined with fuzzy systems complement each other, thus eliminating some of their particular deficiencies.

The basic idea of merging fuzzy systems and neural networks is to design an architecture that uses a fuzzy system to represent knowledge in an interpretable manner and profits from the learning ability of a neural network to optimize its parameters. This blending can constitute an interpretable model that is capable of learning and can use problem-specific prior knowledge. Neurofuzzy models are specifically suited for applications where user interaction in model design or interpretation is desired. With the purpose of making this document self-contained, some useful neuro and fuzzy logic concepts are briefly reviewed.

2.1 Neural networks

A NN is made up of a large number of highly interconnected processing units (idealized neurons). Each processing unit receives input cells to which it is connected, computes an activation level and transmits it to other units. The connections between these neurons, of which there are many, vary in their efficiency of transmittal of the activation signal. Network computations are highly dependent on how the units are interconnected and the strengths of the connections between them. It is throughout training cases and application of their self-organization (learning) capabilities that a NN derives the knowledge (represented in the connection strengths) of what it is to compute.

In a process to construct NN architecture, networks can include as many layers, nodes and connections between them as it is required. The architecture type establishes the connections among the weights and the learning rules. Most applications in engineering and other fields such as biology, economics, medicine, etc. make use of multilayer forward propagation architecture (MFP). In this case, the connectivity pattern and the number of processing units (neurons or nodes) in each layer can vary arbitrarily, however, processing units in the same layer cannot be interconnected and each neuron in a given layer forwards its input to nodes in upper layers.
NNs trained with a comprehensive data-base, process new information the same way. Training rules are the mechanisms by which neural nets modify individual neurons and weights of their connections in such a way that the behavior of the net reflects the desired one. The NNs developed in this study to evaluate shear modulus (G) and damping ratio (λ) versus shear strain (γ) curves were designed according to the MFP architecture characteristics. The learning rule utilized in this investigation to train the network was Quick Propagation (QP).
This is a lineal second-order algorithm that automatically adjusts the size of the search step and detects the best conditions to speed up the training. The most significant advance in QP is that it uses a lineally second-order process that is more efficient than the purely linearized method like the steepest descent method with smoothed direction proposed in (Fahlman et al, 1980). The dot product (DP) was selected as the input function. Its objective is combining linearly the input vector {x} with the weight vector {w} via the dot (inner) product. The bipolar sigmoid (or logistic) was used as activation function, which is continuously differentiable and has the form

$$f(s) = \frac{1 - \exp(-\propto s)}{1 + \exp(-\propto s)}$$

it squashes the sum that results from the DP into a value either (-1, 1) in a way that tends to push s toward a low or high value to determine the decision halfspace (Fig. 1). Hence, a neuronode performs linear discrimination on the space of feature vectors.

2.2. Fuzzy concepts and modeling methods

2.2.1. Basic concepts

A classical set is characterized by a crisp boundary. This means that there is a clear unambiguous boundary such that when the variable exceeds a given threshold then the variable belongs to the set; otherwise does not belong to the set. Classical sets are suitable for various applications; however, they do not reflect the nature of human concepts

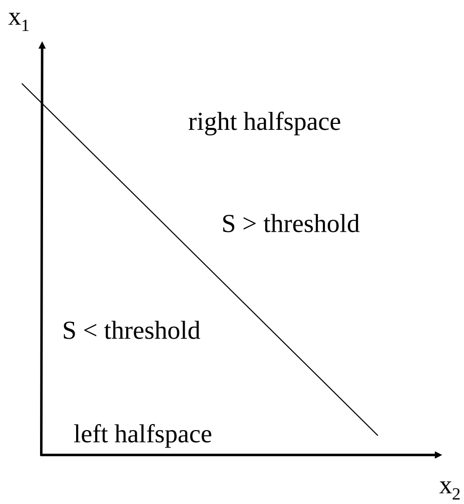


Figure 1. Two half-spaces determined by a single neuronode in twodimensional feature space.

and thoughts, which tend to be abstract and imprecise. Thus, sharp transition between inclusion and exclusion in a set as implied by a classical set is not representative of human reasoning.
On the contrary a fuzzy set has no crisp boundaries. That is the transition from belong to a set to not belong to a set is gradual. This smooth transition is characterized by membership functions (MF) that give fuzzy sets flexibility in modeling commonly used linguistic expressions such as the soil is soft or the compressibility is high.
Zadeh (Zadeh L., 1965), in his seminal paper pointed out that such imprecisely defined sets play an important role in human thinking. It is fundamental to stress the fact that fuzziness does not come from the randomness of the constituent members of the sets, but from the uncertain and imprecise nature of abstract thoughts and concepts. Now, for the sake of completeness some basic definitions concerning fuzzy sets are given below. Interested readers may wish to consult the book by (Dubois D. et al, 1980).
If X is a collection of objects denoted generically by x; then a fuzzy set A in X is defined as a set of ordered pairs

$$A = \{(x, \mu_A(x)) | x \epsilon X\}$$

where $\mu_A(x)$ is called the MF for the fuzzy set A. The MF maps each element of X to a membership grade (or membership value) between 0 and 1. Obviously, if $\mu_A(x)$ is restricted to either 1 or 0, then A is reduced to a classical set and $\mu_A(x)$ is the characteristic function of A.

A fuzzy if–then rule assumes the form if x is A then y is B; where A and B are linguistic values defined by fuzzy sets in the universe of discourse X and Y; respectively. At this point it is necessary to define what a linguistic variable is. A linguistic variable is characterized by a quintuple (x; T(x), X, G, M) in which x is the name of the variable; T(x) is the term set of x (that is, the set of its linguistic values or linguistic terms); X is the universe of discourse (i.e. X=strength); G is a syntactic rule which generates the terms in T(x); and M is a semantic rule which associates its meaning M(A) with each linguistic value A; where M(A) denotes a fuzzy set in X: The expression 'if x is A then y is B',which sometimes is abbreviated as A→B; in essence describes a relation between two variables x and y, and is implemented by a fuzzy relation which has a MF $\mu_{A\rightarrow B}(x,y) \in [0,1]$. Note that $\mu_{A\rightarrow B}(x,y)$ measures the degree of truth of the implication relation between x and y: The if part is called antecedent (or premise), where as the then part is named the consequent. The antecedent part of a fuzzy rule is a conjunction and/or a disfunction of fuzzy propositions.

Examples of fuzzy if–then rules are widespread in our daily linguistic expressions, such as: if the floor is slippery, then walking is dangerous. Likewise, for a geotechnical problem a linguistic expression could be for example, if the soil is soft, then the foundation will settle.

2.2.2 Fuzzy systems

The fuzzy system is a computer framework based on the concepts of fuzzy set theory, fuzzy if–then rules, and fuzzy reasoning. Its basic structure consists of three components: a rule base, which contains a selection of fuzzy rules; a data base, which defines the MFs used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion. Sometimes it is necessary to have a crisp output, particularly where a fuzzy inference system is used as a controller. Therefore, a defuzzyfication method is needed to extract a crisp value that best represents a fuzzy set. The most common mean of defuzzyfication is called the center of gravity method in which the center of gravity of the fuzzy set is measured and projected to the x-axis to get the crisp result (Fig. 2).

The most commonly used inference method is the Max– Min inference method or Mamdani inference method (Mamdani E., et al, 1975). Another popular fuzzy model structure is called the Takagi–Sugeno model ((Sugeno M. et al, 1998), (Takagi T. et al, 1985)). The Mamdani method is used in this investigation.

Mamdani model. Let us consider the following rule base (where X; Y and Z are linguistic variables)

$$R_i\colon if\ X\ is\ A_i\ and\ Y\ is\ B_i\ then\ Z\ is\ C_i\ i = 1,\dots,n$$

Given the input fact (x_0,y_0), the goal is to determine the output 'Z is C'. The first step is to fuzzify the given input. The fuzzyfier maps the input data $x_0 \in Y_x$ into the fuzzy set A* and $y_0 \in X_y$ into the fuzzy set B*. The next step is to evaluate the true value for the premise of each rule using the fuzzy implication. The MFs defined on the input variables are applied to the actual values to determine the degree of truth for each rule premise. The degree of truth for a rule's premise is computed in our example rule base as follows

$$\propto_i = \mu_{A_i and^{B_i}}(x_0,y_0) = \min\left(\mu_{A_i}(x_0),\mu_{B_i}(y_0)\right)$$

if a rule's premise has nonzero degree of truth then the rule is activated. The next step is to find the output, C'_i, of each of the rules

$$\mu_{C_i}(w) = \mu_{(A_i\ and\ B_i)\rightarrow C_i}(x_0,y_0,w), \qquad \forall\ w\ \in W$$

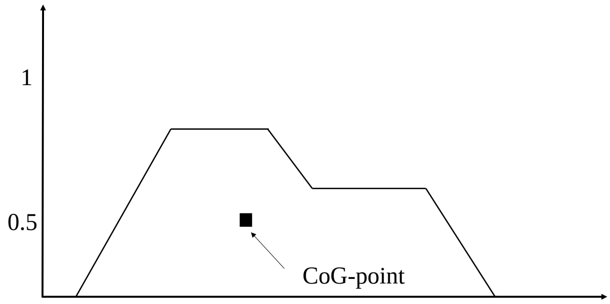


Figure 2. Center of Gravity (CoG) defuzzification

In Min inferencing (or Mamdani implication rule) the implication is interpreted as a fuzzy and operator

$$\begin{aligned}\mu_{C_i}(w) &= \mu_{(A_i\ and\ B_i)\rightarrow C_i}(x_0,y_0,w),\\ &\forall\ w\ \in W\\ &= \mu_{A_{i\,and}{}^{B_i}}(x_0,y_0)\ and\ \mu_{C_i}(w)\\ &= \min(\mu_{A_{i\,and}{}^{B_i}}(x_0,y_0),\mu_{C_i}(w)\end{aligned}$$

In the rule aggregation step, all fuzzy subsets assigned to each output variable are combined together to form a single fuzzy subset for each output variable. The purpose is to aggregate all individual rule outputs to obtain the overall system output. In the Max composition, the combined output fuzzy subset C* is constructed by taking the maximum over all of the fuzzy subsets assigned to the output variable by the inference rule

$$\mu_{C^*}(w) = \max\left(\mu_{C_1}(w), \mu_{C_2}(w), \dots, \mu_{C_n}(w)\right)$$

Normally, the defuzzyfication step is executed as the last step and the most commonly used method is the center of gravity described earlier.

2.2.3 Neurofuzzy model extraction methods

It is generally agreed that fuzzy inference systems (FIS) provide a useful way of representing human knowledge in a fairly readable way in form of fuzzy inference rules. FIS rules are also capable of representing inexact knowledge and to reason with such knowledge in a theoretically sound way. However, the tuning of FIS proves to be challenging, as in a nontrivial FIS there are quite a few parameters to modify (typically the MF parameters). It would be useful to be able to create or tune a FIS based on a training data set of input values and desired target outputs. One of the ideas has been to apply the learning abilities available with the NN architectures to FIS tuning.

In the NN domain, supervised learning task is often solved using a feedforward layered network structure with simple processing units organized in layers. The nodes in each of the layers are typically fully connected with those of the neighboring layers. For each of the nodes are only few adjustable parameters like the weights for each of the neighbors and a bias weight. The network is adjusted to a set of learning data (inputs and outputs) by feeding the inputs into the system, propagating the evidence trough the network and by calculating the difference from the desired target. Then the parameters are adjusted by gradient descent optimization performed by a special error back-propagation algorithm.

Jang (Jang J., 1993) has introduced the ANFIS architecture (Adaptive Network based Fuzzy Inference System). Fig. 3 provides an example of a simple FIS represented in an ANFIS network. In ANFIS architecture, a FIS is described in a layered, feedforward network structure where some of the parameters are represented by adjustable nodes (rectangular entities in the Fig. 3) and the other as fixed nodes (elliptical entities in the Fig. 3). The raw inputs are fed into layer 1 nodes that represent the MFs. The parameters in this layer are called premise parameters and they are adjustable. The second layer represents the T-norm operators that combine the possible input membership grades in order to compute the firing strength of the rule. At least in the basic ANFIS method these parameters are not adjustable, in this investigation the Degree of Support (DoS) value is also introduce with every rule. A DoS value gives a weight for each value to be used in the rule aggregation step of fuzzy inference. The value is between [0…1].

Effectively the DoS value may be used as a way for structural learning of the fuzzy model. Using the value the size of the rule base can be limited.

The third layer implements a normalization function to the firing strengths producing normalized firing strengths. The fourth layer represents the consequent parameters that are adjustable. The fifth layer displays the aggregation of the outputs performed by weighted summation. It is not adjustable.

Jang (Jang J., 1993) introduces a two-pass algorithm for adjusting the parameters using a modified error-backpropagation optimization algorithm. In the forward pass the premise parameters are held fixed and the consequent parameters are adjusted by least squares estimation (LSE). In the backward pass the network error is back-propagated through the network and the premise parameters are adjusted by gradient descent while the consequent parameters are held fixed.

In (Jang J., 1993) multiple examples of the ANFIS were provided ranging from nonlinear regression on a few inputs to time series prediction of a chaotic time series.

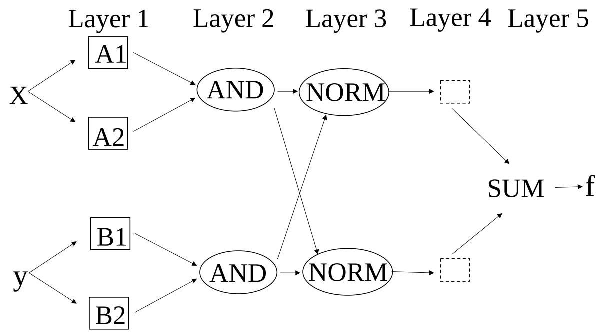


Figure 3. An ANFIS network structure for a simple FIS

3. Emergency gas supply system

3.1 General description

As shown in Figure 4, gas natural is supplied to vast sections of the Mexican capital and a large fraction of its neighboring states. The gas natural delivering is broad classified according its work pressure as high (19 Bar), medium (7 Bar), and low (3 Bar). High pressure gas delivered directly from the plant is supplied to the medium pressure gas pipelines after pressure reduction, from high to medium, at the governor stations. Gas is supplied at the medium pressure level to industrial users and to customers who use gas at lower pressures.

The high pressure pipelines conform an edge ring; it held a seismic information gathering and network alert system for monitoring the activity and sending data to the general commands outside Mexico City. In the event of a major earthquake where pipelines, installations and transmissions are severely damaged, ultimate measures could be taken to cut-off the gas supply at plants or high-pressure governor stations (based on human decisions).

This is done by remote control from the headquarters, employing the emergency shutoff valve installed in a “global” device (remotely from the command room).

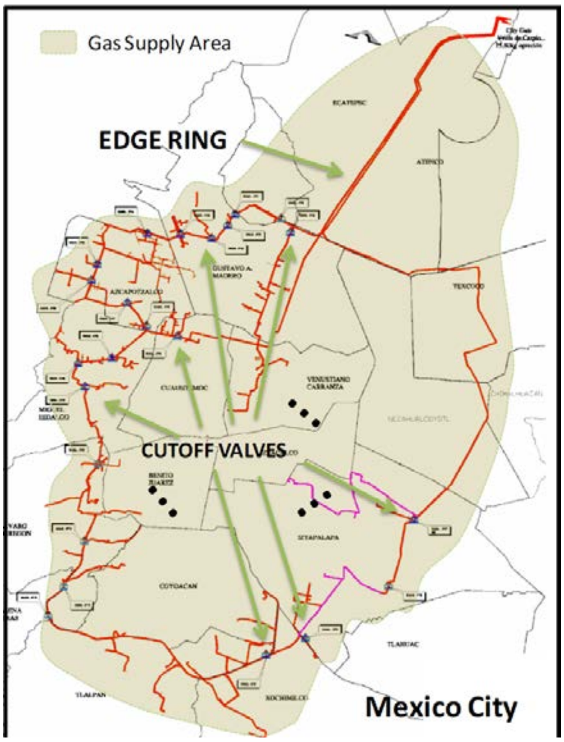


Figure 4. Gas supply zone in Mexico City (medium pressure pipelines where the cutoff valves are installed)

Low-pressure pipeline blocks, which supplies gas directly to the regular customers is made of less robust material and has a smaller diameter, it is more susceptible to damage for large soils-strain than medium-pressure pipes. The low-pressure pipe network is composed of many blocks, which are separately shut-off. Each block contains from thousands of customers. Safe gas supply, in the three pressure levels, must observe general antiseismic principles: i) gas-induced secondary disaster prevention with principal equipment and facilities robust enough (high seismic resistance), ii) timely service shutoff by isolated areas (blocks) and iii) uninterrupted gas supply for unaffected areas. Where service blocks are damaged in varying severity, the system must isolate badly damaged blocks and cuts service tactically. What is presented in this investigation is a procedure for incorporating automatic controls in medium/low-pressure districts.

3.2 SISES components

SISES criteria operation is simple and direct: when a seismic intensity exceeds the level that could cause damage to pipes or buildings, valves on the regulators are shutoff and stop gas supply to the blocked zone. Because of the vast and complex area that covered this service, this instruction cannot be implemented straightforwardly *in situ.* Seismic damage would concentrate in local areas having inferior soil characteristics. The spatial variability of geotechnical and seismic behaviors must be taken into account when designing the better disposition of safety controls (valves) and their programming. This “flexible” cutting-off/continuing valves scheme must be especially concerning to each sectioned sector. Such a response would eliminate disturbance to the entire gas supply system and would help to maintain stable service.

As it has been recognized, a key dangerous situation is the broken pipelines due to excessive (or differential) soil deformations, crushing installations, buildings collapses, and situations related to the anthropomorphic activity inside the blocked areas. SISES introduces a second premise for cutting/continuing service: flow conditions.

In order to better explain how SISES work, firstly it is necessary to describe the components installed *in situ*. MECA, the automatic cut-off mechanism, uses ultra-small acceleration pickups (micromachining technology) and flow conditions monitors as well as central processing units and information transmission apparatus. This arrangement is capable of i) measuring/storing seismic intensity (recording three earthquake wave-form acceleration trends on XYZ axes), ii) recognizing abnormal gas flow conditions, and iii) relating accelerations and flow conditions for determining the premises→conclusions that have to be in operation,

iv) containing the protocol for sending information, and/or for automatically acting on the cutoff gas delivering.

The seismic sensors installed in district regulators are new sensors, ultra-compact high-performance seismometers that have been developed under nano-techniques. The sensors incorporate the following features and functions: ultra-compact acceleration detection unit, CPU and RAM (incorporated or excluded), low cost, carries out real-time high-precision measurement of maximum acceleration values, and self-diagnostic (carries out self-diagnostic and warns of malfunctions in acceleration pickups, electrical circuits, etc.). Additional to seismic sensors are the flow measurements. The annubars (similar to a pitot tube) are installed to monitoring the gas flow taking multiple samples across the section of the pipes or ducts. In this way, the annubar averages the differential pressures encountered accounting for variations in flow across the section and also registers gas temperature.

These two sensors plus a scheme for operating pneumatic valves and for sending and requesting data from external control-organisms conform the main features of MECA (Figure 5). During or immediately after an earthquake has occurred (depending on the severity), MECA computes intensity values and flow alerts and it transmits them added to topographical/geographical data, permitting a precise estimation of the damage incurred. Furthermore, by checking the operation of all automatic shutoff valves, quick emergency response can be realized. Design, construction, collocation and operation of MECA (*in situ*) can be consulted in Garcia et al., (2013).

In the following the brain component of SISES, AMIE, will be explained.

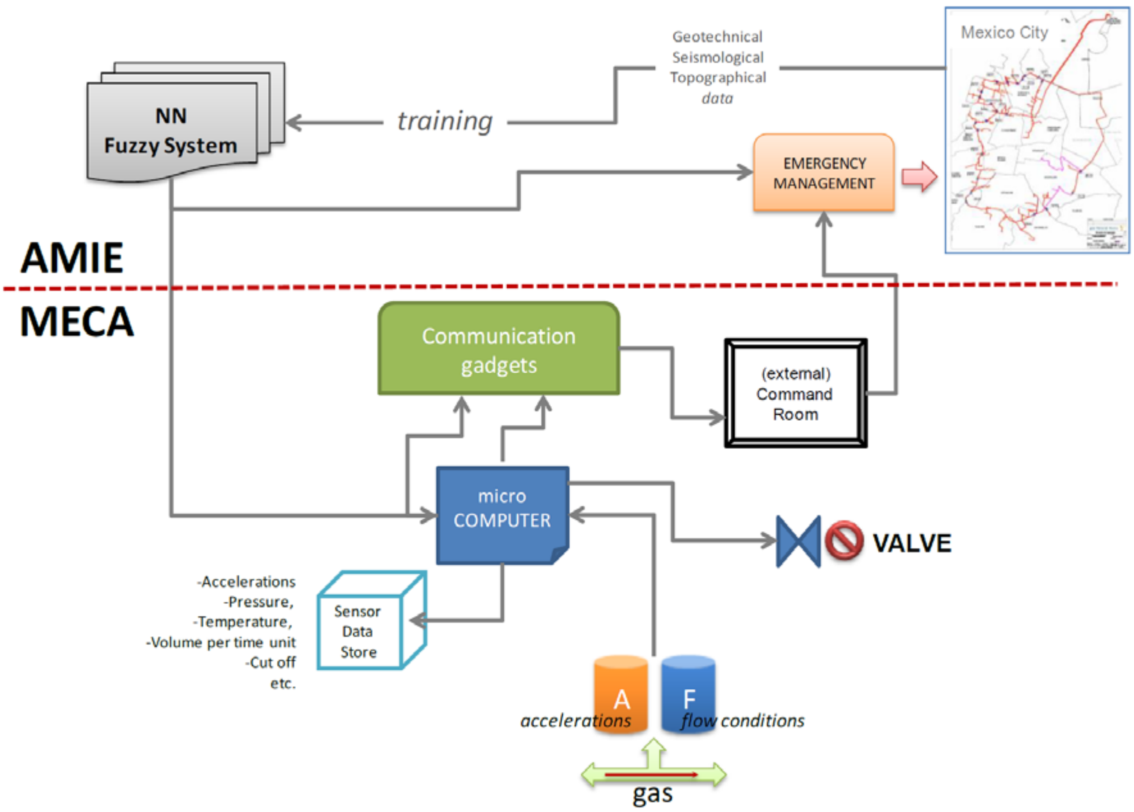


Figure 5. SISES components

3.2.1 Soft environment for the management of geoseismic information

Forecasting the ground movements resulting from static or dynamic forces acting upon a composite system is one of the most pervasive and difficult problems in geotechnical engineering. The manifestation of the earthquakes, soil displacements, are mainly controlled by: (a) reductions in shear strength and stiffness; (b) the continuity and boundary conditions; (c) the characteristics of the dynamic and static forces; (d) the time interval for which these forces exceed the soil strength; and (e) the residual strength of the soil layer, which depends chiefly on the relative density and confining stress (Garcia et al, 2007). For automatic controls that must act immediately and efficiently during a short-period contingence, take into consideration all these aspects, besides being extremely complicated, it is inadequate for practical uses.

Given the unsuccessful using of semi-empirical, traditional, hard computing methods and considering the advantages of soft procedures, they will be commented herein the operation criteria of AMIE, the environment in which the information from the monitors in situ is analyzed and the fuzzy rules that responds better to the emergency situation is determined. Through the exploitation of the implicit knowledge and numerical relations in the recorded seismic experience, the soft methodology represents an appealing alternative for acquiring the anticipation and strategic cut-off responses task.

3.2.2 Spatial Definition of Peak Ground Accelerations

The focal parameter for assessing the earthquake effects in SISES, at a given location, is the prediction of Peak Ground Acceleration PGA (Figure 6). The importance of this parameter is revealed in the development of seismic zoning maps and the construction of design response spectra used in earthquake-resistant construction rules. The strategic situation of the cutoff valves introduces important questions i) how to estimate responses at a site where no accelerometric recording station is installed and ii) how to describe accurately the spatial ground motions in blocked areas (interrelated with the behavior of neighboring sectors). In order to predict PGA at a site, one usually relies on empirical formulations; these equations relate PGA to earthquake and site parameters. The development of such equations requires large database of recorded PGAs and associated metadata on earthquakes and sites (Ambraseys & Douglas, 2003; Takahashi *et al.*, 2000). These Ground Motion Prediction Equations reflect the combination of three effects (source, path and site) using a physical model. Douglas (2003) conducted an analysis on the equations developed in the last 30 years and found that each equation used for this purpose was very dependent on available data. It was also shown that the functional forms vary very much as well and the confidence in the "extreme" events forecasting was very low.

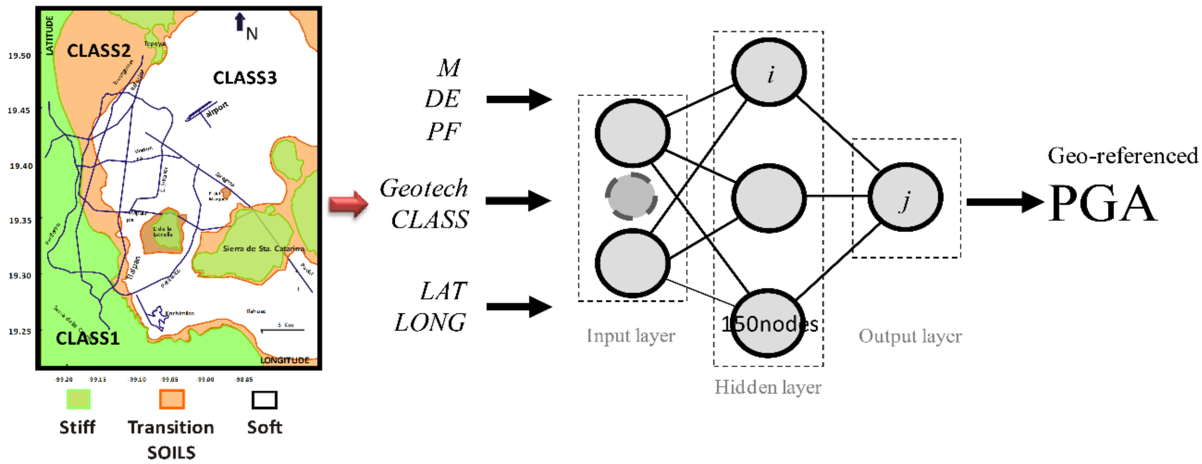


Figure 6. Individual NN for estimating PGA

To develop the knowledge-based NN modeling, information about cause and effect is needed in the form of input vectors and corresponding outputs and also, a clear understanding of the phenomenon to make adequate selections of the variables that should be included as inputs. In AMIE, a dynamic NN is used to obtain a relationship Ground Motion Prediction Equation for PGA in a simple and easy way using the sets of available seismic data in the neighborhood of valves. NNs do not require *a priori* functional form. The input parameters used for generating the PGA in X,Y,Z (two horizontal components and one vertical component) in the free-field, are the magnitude M, the focal depth FD (km) and the epicentral distance ED (km). Each accelerogram can be described as the convolution of the source effect and two filters, the path effect and the site effect. The source is described by its magnitude which reflects the energy release during the earthquake. The seismic waves attenuate while propagating through the crust and the amplitude decrease is related to the source-to-site distance.

Site effects influencing PGA is taken into account by the introduction of the thickness of the sedimentary layers not as a crisp value but as a classification node. This class is based on geotechnical, topographical, seismological and stratigraphical descriptions (Figure 7). Instead to develop a large-scale model, the dynamic NN is valid for blocked-districts and the superficial properties of the soil considered within.

To start the neural training the accelerations information is compiled from recording stations in Mexico City. The inputs M, ED, FD added to LAT,LONG variables transforms the seismic database, not explicit enough for driving the spatial nonlinear connections, as one competent for site-effects mapping task.

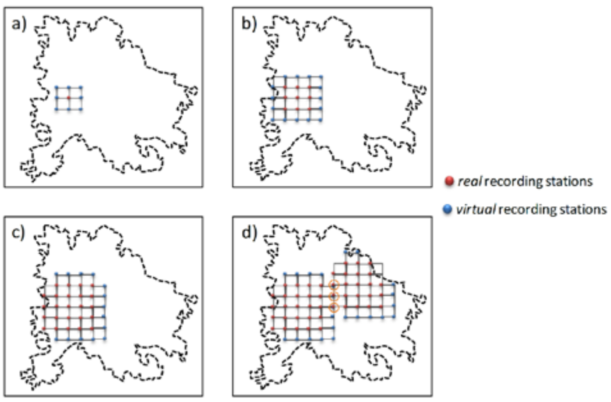


Figure 7. Recurrent feeding for Individual-NN

Once the assembled database is geo-referenced, the input→output vectors are used to train a multilayer feedforward NN using the back-propagation algorithm. After the desired levels of error between measured and calculated PGAs have been reached, the best architecture is used for *re*-training following an iterative process that attempts to exploit the database growing *in situ* information, as it is described schematically in Figure 8. The *re*-training through feeding the NN with *virtual* information consists of two stages i) expanding the information contained in the original training database of PGAs recorded in *real* stations asking to the best NN architecture for accelerations in new situations LAT,LONG close enough to a *real* recording station that the Tobler's law is fulfilled and the confidence in these calculated values is sufficiently high, the new situations are *virtual* stations, and ii) *re*-feeding and *re*-train the NN, with the *real*+*virtual* PGAs, until reach a virtual or the boundaries analysis.

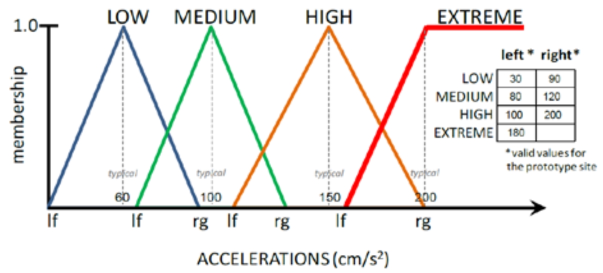


Figure 8. Membership functions for PGA (one horizontal direction, h1), prototype site

Inspired by the recurrent neural networks methodology (Hopfield, 1982), the dynamic NN proposed in this investigation is transient in nature. It is basically a feed forward network with feedback capabilities which are achieved by connecting the neurons' outputs to their inputs. The essence of closing the feedback loop is to enable control of the ith output through the jth (j=1,2,…,n) outputs. This is especially meaningful if the present output controls the output at the following instant; as is the case in the *virtual* stations that samples under monotonically increasing separation the next response.

3.2.3 Fuzzy Rules for Cutting-off/Continuing Supply

After PGA is neuro-estimated the modeling process continues with the definition of membership functions and fuzzy rules that better describe the relations between site conditions (ground motions), flow conditions and consumers requirements. In real-world applications there is no sharp boundary between safe/unsafe situations; therefore one has to resort to fuzzy labeled instead of the crisp value for deciding cutting-off supply. In AMIE approach membership degrees from zero to one are used; the PGA value is associated with membership functions (here the popular triangles and trapezes were considered).

The geotechnical experience showed that the imprecision that is inherent to most soil properties and seismic measurements makes essential the consideration of subjective categories to evaluate concepts and derive conclusions according to the phenomena behavior. The fuzzy logic system in AMIE resulted of a neurotraining process (ANFIS architecture, see for details Jang (1993)). Three steps were followed to develop this fuzzy system: (i) the variables (inputs/output) were chosen, (ii) the fuzzy sets, membership functions MFs, to represent these variables were defined, and (iii) the fuzzy rules that relate the inputs to the output were designed. The fuzzy rules and MFs are created, they were modified by a neuro process.

The general approach used for seismic/flow conditions→ cutting-off/continuing mapping was to assume that the behavior variations could be classified according to their geo-location, then, in the construction of the initial fuzzy system two input linguistic variables were booked: 'PGA' and 'flow-conditions'. The output linguistic variable is obviously 'cut-off/continue'. Each of these variables was mapped into the fuzzy sets that are used to convert the real values into linguistic variables (fuzzification). Having transformed all input variables into linguistic variables, the fuzzy inference step identifies the rules that apply to the event situation and computes the output.

Horizontal (mutually orthogonal PGAh1, N-S component, and PGAh2, E-W component) and vertical components (PGAv) are the outputs for neural mapping. The PGAs induced by the 1985 Michoacán event, the most severe earthquake registered in the recent history of Mexican metropolis (PGAh2) are shown in Figure 9.

The PGAs predicted for a M9.5 subduction event, in the same blocked zone, is shown in Figure 10. These two 3D configurations and the PGA spatial variation for M<7.5 are used to define the typical of each membership functions. To illustrate the procedure to define the membership degree (fuzzification), assume that PGA is 120 cm/s^2 thus its values are: EXTREME 0.0 HIGH 0.72, MEDIUM 0.28, and LOW 0.0 (Figure 11). The fuzzification process is carried out every Δt = 0.01 s value once an earthquakes starts.

The fuzzy rules (If-Then) that complete the AMIE scheme are those about flow conditions, the flow rules are defined according to the values of pressure, temperature and volume per time unit during the "normal" conditions of gas supply.

Immediately after an earthquake is detected, MECA operates on the pre-programmed fuzzy rules and decides on continuing, cutting-off the gas supply or simply sending information status (Figure 12).

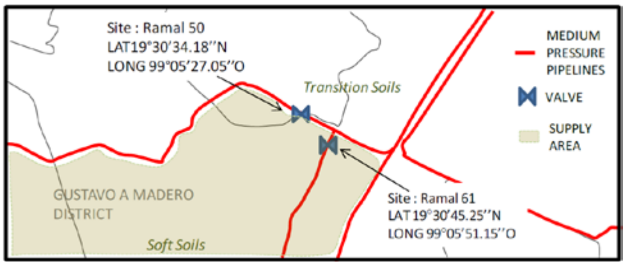


Figure 9. Prototype site, Ramal 50&Ramal 61 valves

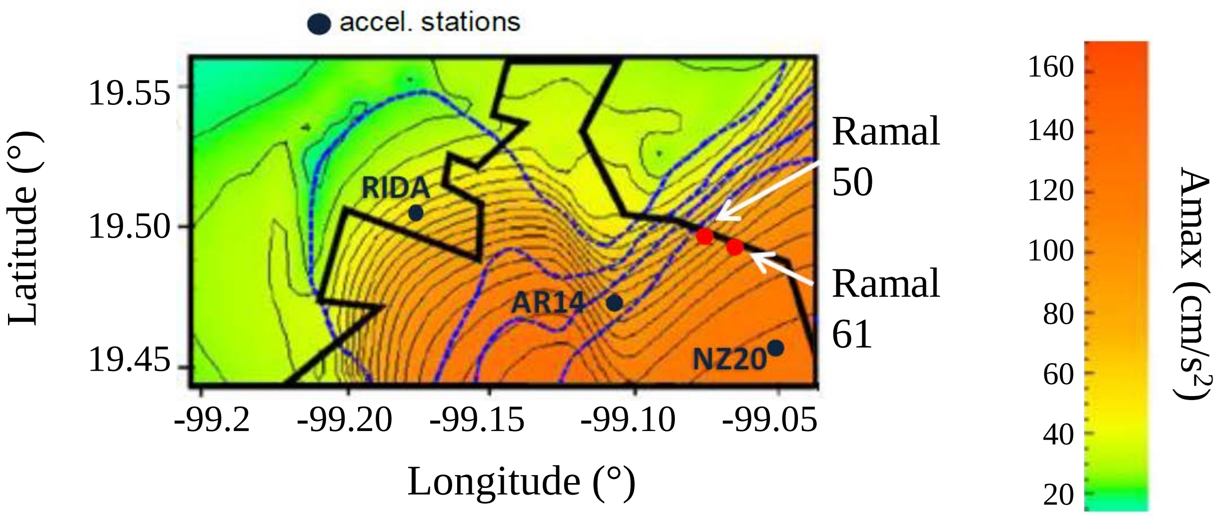


Figure 10. Estimated PGA for the Michoacán 1985 earthquake, M=8.1

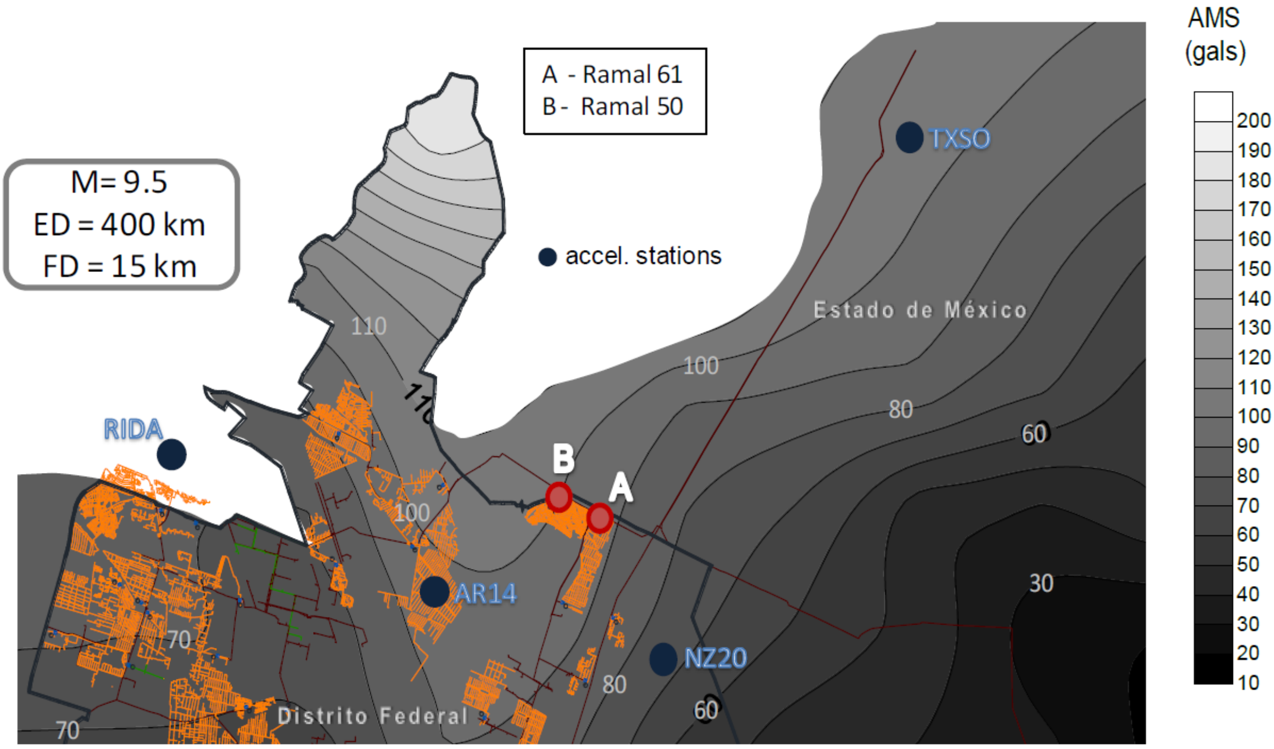
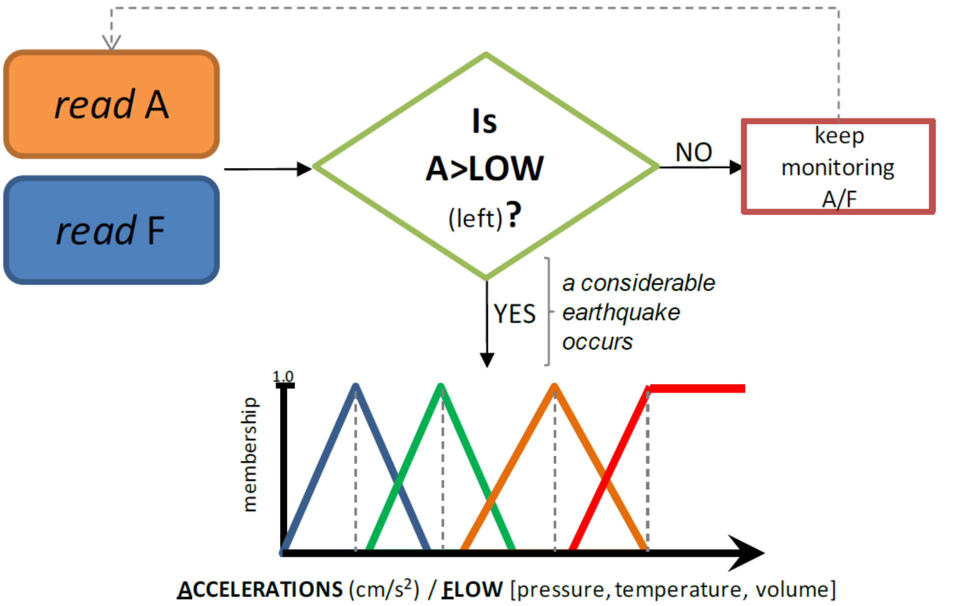


Figure 11. Estimated PGA for the EXTREME event



IF	A is		THEN
		LOW	SEND INFO
		MEDIUM	SEND INFO
		HIGH	ASK F
		EXTREME	CUT OFF

IF	F 's are		THEN
		NORMAL	SEND INFO
		ABNORMAL	SEND INFO
		EXTRAORDINAIRE	CUT OFF

*conditions obtained for domestic customers, PROTOYPE SITE

Figure 12. Actions structure for Ramal50

4. Conclusions

This completes the introduction of SISES, the new real-time disaster mitigation system for gas supply in Mexico City. Advantageous soft tools, a neural network for the extreme accelerations forecasting and a fuzzy system to evaluate the combined premises that could generate an unsafe situation, are behind the promptness and flexibility of SISES. Sensors installed in the challenging Mexican soils (pneumatic valves, micro-machine accelerometers, annubars, microcomputers and transmission gadgets) are used to develop a self-diagnosis environment with a real-time evaluation algorithm that functions to identify extreme ground movements and to decide about cutting/continuing the gas supply. These features are advantageously combined to produce an "intelligent"-safer environment, unparalleled around the world.

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