Structural Safety, 12 (1993) 1–19
Elsevier

Earthquake damage estimation and decision analysis for emergency shut-off of city gas networks using fuzzy set theory *

Laurence Cret, Fumio Yamazaki, Shigeru Nagata and Tsuneo Katayama

Institute of Industrial Science, The University of Tokyo, Roppongi 7-22-1, Minato-ku, Tokyo 106, Japan

Abstract. Earthquake damage estimation for lifelines can be used for many purposes, for example, planning repair works or simulating network recovery. For gas networks, however, the issue is more crucial, as secondary disasters due to leaks are possible. If necessary, the gas supply should be interrupted in heavily-damaged areas. Therefore, emergency shut-off decision is vital and earthquake damage estimation can be effectively used for a more reliable and swift decision-making. The system proposed in this paper uses fuzzy set theory to formalize knowledge acquired from experience and assess earthquake damage from ground conditions and ground motion characteristics. The results are obtained as fuzzy damage indices. Fuzzy decision analysis is then utilized to transform this imprecise information into a clear-cut decision on whether to cut or maintain the gas supply in a given area of the network.

Key words: earthquake damage; gas network; fuzzy reasoning; fuzzy decision analysis.

1. Introduction

When an earthquake occurs in a large city, extensive lifeline networks are especially vulnerable. For gas networks, there is an additional danger since secondary disasters such as fires or explosions may occur if pipelines or customers' houses are damaged. Hence, it may be necessary to interrupt the gas supply in the heavily-damaged areas as soon as possible. However, it should be kept in mind that an untimely shut-off would create confusion as the network recovery might take time.

In the present control system of major gas utilities in Japan, the supply area of the network is monitored by sensors measuring the intensity of ground shaking. However, the actual decision to cut or to maintain the gas supply in a given area is made based on field survey reports. Since a gas network covers a vast area, it takes a long time (up to a few hours) to reach a rough damage figure and to make a decision. To reduce the time of decision-making, the monitored earthquake intensity information should be utilized more effectively. Since the relationship between ground shaking intensity and structural damage contains several kinds of uncertainty, the use of fuzzy inference is considered in this paper to estimate damage. In doing so, the

* Discussion is open until October 1993 (please submit your discussion paper to the Editor, Ross B. Corotis).

estimated damage also becomes a fuzzy set and thence a fuzzy decision analysis is further introduced.

It has been only a decade or so since the fuzzy set theory was first applied to structural engineering problems [1,2]. Since then however, attempts to apply fuzzy set theory to various aspects of structural engineering, including estimation of damage to structures, have been promoted rather quickly. Because damage scales of structures are often linguistic and subjective, they are interpreted as membership functions [3]. Methods to obtain the failure possibility [4] and to calculate the fuzzy probability of failure [5] of a structure have been proposed. Zadeh's extension principle played an important role in introducing fuzzy variables into ordinary arithmetic relationships. A method to estimate earthquake intensity from building damage records, which is the inverse of the problem considered here, was also proposed in this framework [6]. "IF...THEN..." reasoning [7] can also be applied additionally when the relation between some parameters is fuzzy. In this paper, fuzzy reasoning is employed alone because there exists no relevant expression of the damage estimation as a function of the ground motion characteristics measured by the remote sensors. A similar approach is also proposed elsewhere [8].

Techniques to use imprecise information represented by fuzzy set in multiple-attribute decision analysis have been studied by several researchers [9–12]. The decision making strategy can be expressed by a utility function, or rating, depending on the attributes. A fuzzy utility can then be obtained for each possible alternative. The points of view about how to obtain a relevant utility function do not differ so much but the choice of the best fuzzy utility is more difficult. Several studies [10,11] concentrate only on the ranking of the alternatives but the approach proposed by Jain [12] has been used here in order to get an evaluation of each alternative on a scale between 0 and 1.

Although the methodology presented in this paper is still tentative, it may provide damage estimation and decisions more quickly and efficiently than the current methods.

2. Outline of the system

The considered high pressure gas pipeline network is divided into several large blocks in which it is possible to shut off the gas supply independently. These blocks will be referred to as "control blocks" or "blocks", for short, hereafter. A control block typically contains several main pipelines and several hundred thousands customers [13]. This study concentrates on damage assessment and decision analysis for one block.

As soil conditions are known to be a major factor in earthquake damage estimation, each block is divided into zones by considering three soil types. Each zone is further divided into square sub-zones with sides of 300 m (Fig. 1).

Several tens of spectrum intensity (SI) sensors [14] as well as a few accelerometers are laid in each control block. Their measurements are transmitted to the control room by a multiple radio telemeter system. The proposed system uses this information to estimate damage.

Two parameters are chosen to represent the state of the block: damage to buildings (customers' houses) R_b, which is defined as the equivalent percentage of collapsed houses [14], and damage to pipes (buried pipelines of the network) R_p, which is defined as the number of leaks per kilometer of pipeline.

Damage estimation is performed first at a local level and then at the level of the whole block

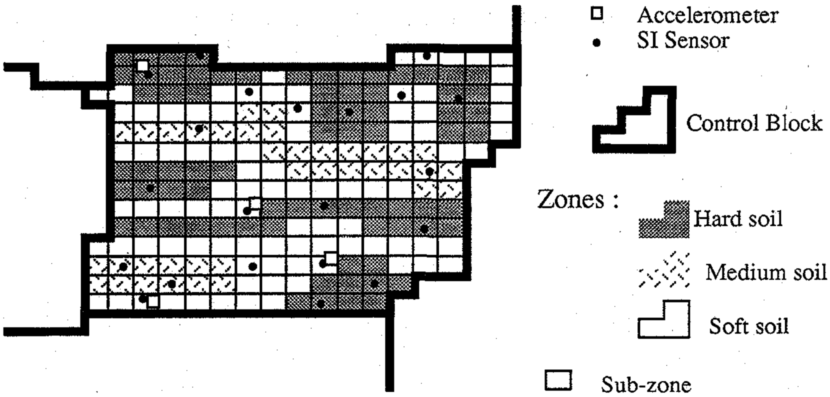

Fig. 1. Layout of one control block.

(see Fig. 2). In each sub-zone, where soil conditions are relatively homogeneous, observed ground motion characteristics (spectrum intensity SI and peak ground acceleration A_{max}) are used to assess building damage while the intensity of ground shaking (represented by SI) and the thickness of the liquefiable sandy soil layer (H_s) are used to predict pipe damage. This information is then converted into the damage state of the whole block by weighted average (phase I damage estimation). The weight of each sub-zone represents its relative importance in some specific sense. If the number of points where SI and A_{max} are observed is small, the obtained phase I damage estimate will be very much biased by the soil conditions at these few points. To remedy this effect, a more primitive but more general damage ratio, calculated by using the magnitude M of the earthquake and the epicentral distance Δ, is used to correct the phase I damage estimate.

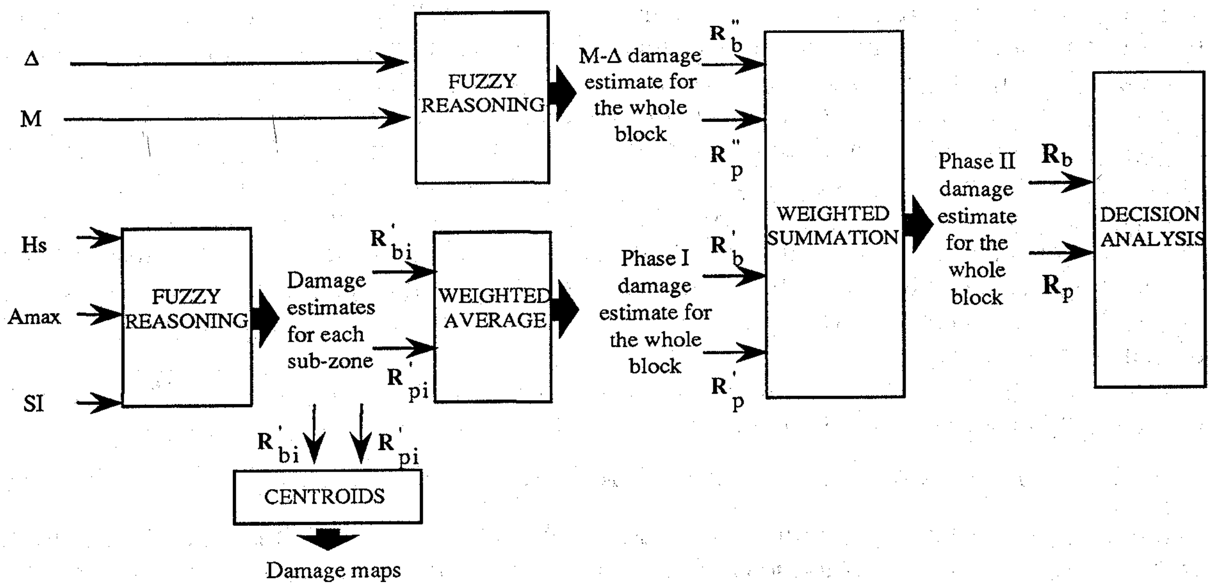

Fig. 2. Flowchart of the study.

The proposed method has been used to develop a computer system for damage estimation during earthquakes. The outputs of this system are maps showing the damage state in all subzones and global damage indices for each control block which can be used in decision analysis.

3. Earthquake damage estimation at a local level

The first step of the proposed method is to assess building and pipe damage at the sub-zone level. For a given sub-zone of the considered block, values of the variables SI, A_{max}, H_s are obtained either by direct observation or by interpolation. From the experience of past earthquakes, it is known that there is a close relationship between these input variables and earthquake damage [15], but it is difficult to quantify it. To mathematically model this imprecise knowledge, fuzzy set theory has been utilized.

Fuzzy set theory has been introduced in structural engineering by several authors by "fuzzifying" the usual reliability analysis which is based on probabilities [5]. This means that the parameters of the probabilistic analysis are considered as fuzzy sets and that a fuzzy probability of failure is obtained by applying the extension principle. In a similar way, the concept of possibility of failure has been introduced [4]. However, in the present case damage estimation is performed in a very wide area and it is practically unthinkable to determine the necessary parameters for each structure, even in a fuzzy manner. In addition, the application of the extension principle induces very heavy computations [16] which is not compatible with online damage estimation. Another tool of fuzzy set theory is fuzzy reasoning, which has been applied either in combination with the above mentioned fuzzified reliability analysis or alone [8]. As only a global damage estimation is needed here, fuzzy reasoning will be used. It is possible to complement the present analysis with a more precise damage assessment for a few sensitive structures in the considered zone.

The idea of fuzzy reasoning [7] is to express the modelling of the system in a simple, natural-language-like form. Instead of ordinary functional relationships, fuzzy inference rules are used. To construct a model for fuzzy reasoning, the range of each variable is divided into k linguistic values, for example, from *Small* to *Large* (italics are used for terms implying fuzziness) as shown in Fig. 3. Each of these linguistic values is represented by a fuzzy set and its membership function $\mu(x)$, which can take values between 0 and 1. For example, if we consider the fuzzy set *Small* and the variable SI, $\mu(\mathrm{SI} = 15\ \mathrm{cm/s}) = 0.5$ means that the value 15 cm/s for SI can be said to be *small* to the extent 0.5. For each of the variables, the shape of the membership functions has been chosen to be very simple, i.e. triangular or trapezoidal as shown in Fig. 3. Table 1 shows the values at which the membership functions cross the axis $\mu = 0$ for the different variables.

In addition to the fuzzy sets, inference rules are also defined. The general form of a fuzzy inference rule is (boldface letters are used to represent fuzzy sets):

$$\text{IF } x_1 \text{ is } \mathbf{A}_{i,1} \text{ and } x_2 \text{ is } \mathbf{A}_{i,2} \text{ and } \dots \text{ and } x_n \text{ is } \mathbf{A}_{i,n} \text{ then } y \text{ is } \mathbf{B}_i, \quad i = 1, \dots, m \tag{1}$$

where n is the number of conditions, m is the number of rules, $\mathbf{A}_{i,j}$ are fuzzy sets (e.g., *Small, Medium*) representing the conditions of the rules, and $\mathbf{B}_i$ are the fuzzy sets representing the consequences of the rules. In this study, $n = 2$ (2 conditions), $m = 25$ (25 rules); $x_1 = \mathrm{SI}$,

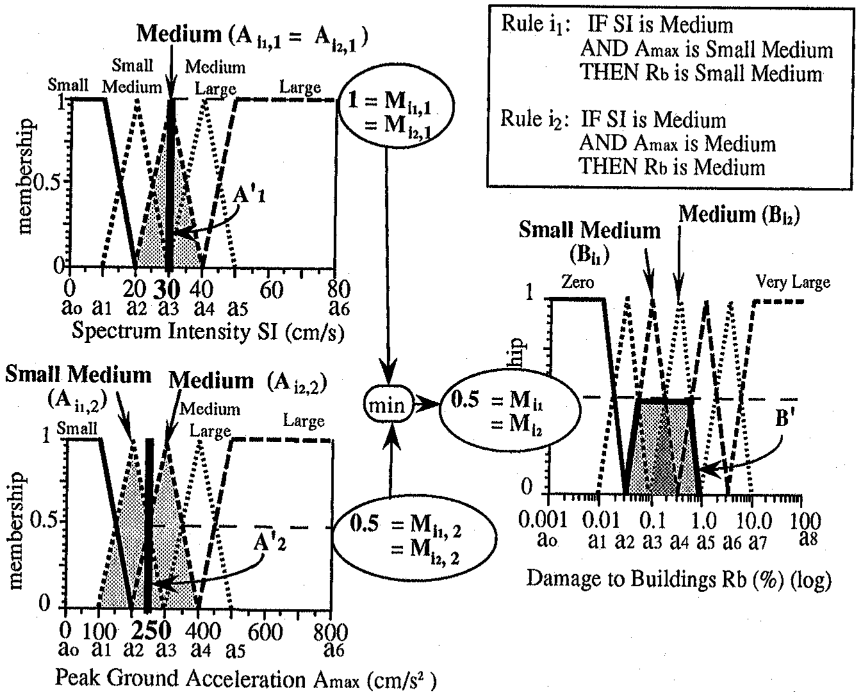

Fig. 3. Procedure for estimating building damage by fuzzy inference (the observed values are SI = 30 cm/s and $A_{\max} = 250$ cm/s^2).

$x_2 = A_{\max}$ and $y = R_b$ for the first set of rules (Table 2); $x_1 = \mathrm{SI}$, $x_2 = H_s$ and $y = R_p$ for the second set of rules (Table 3).

Once this type of set of rules is constructed, actual values for $x_1, x_2, \ldots, x_n$ (which are the measured values in our case) are represented by the fuzzy subsets $\mathbf{A}'_1, \mathbf{A}'_2, \ldots, \mathbf{A}'_n$ (for example, *around 20 cm/s, approcimately 100 cm/s²)*.

The result of fuzzy inference is the predicted value for y (damage in this study), which is represented by the fuzzy set $\mathbf{B}'$ defined by the membership function $\mu'_B(y)$ (Mamdani method):

$$\mu_{\mathbf{B}'}(y) = \operatorname*{Max}_{i} \min\left(M_i, \mu_{\mathbf{B}_i}(y)\right) \tag{2}$$

where

$$M_i = \operatorname*{Min}_{j} M_{i,j}, \quad M_{i,j} = \operatorname*{Max}_{x_j} \min\left(\mu_{\mathbf{A}'j}(x_j), \mu_{\mathbf{A}_{ij}}(x_j)\right) \tag{3}$$

TABLE 1

Parameters of the basic membership functions for each variable

variable	unit	k *	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
SI	cm/s	5	0	10	20	30	40	50	80	–	–
$A_{\max}$	cm/s^2	5	0	100	200	300	400	500	800	–	–
H_s	m (log)	5	0.1	0.316	1	3.16	10	31.6	100	–	–
R_b	% (log)	7	0.001	0.00316	0.01	0.0316	0.1	0.316	1.0	3.16	100
R_p	leaks/km (log)	7	0.001	0.00316	0.01	0.0316	0.1	0.316	1.0	3.16	100

* k is the number of fuzzy sets for a given variable.

TABLE 2

Fuzzy inference rules for building damage estimation using SI and A_{max}

	$\mathbf{B}_i$	IF SI is ... ($\mathbf{A}_{i,1}$)				
		Small	Small Medium	Medium	Medium Large	Large
and	Small	Zero	Small	Small Medium	Medium	Medium Large
A_{max}	Small Medium	Zero	Small	Small Medium	Medium	Medium Large
is	Medium	Small	Small Medium	Medium	Medium Large	Large
...	Medium Large	Small	Small Medium	Medium	Medium Large	Large
($A_{i,2}$)	Large	Small Medium	Medium	Medium Large	Large	Very Large

Mamdani method has been chosen here because it enables to separate variables and to increase the computational speed, which is of concern here. Liu et al. [8] use the Zadeh–Łukasiewicz formula but this method has non-satisfactory properties: if, for a given i in eqn. (1), $\mathbf{A}'_j = \mathbf{A}_{i,j}$ for all j then $\mathbf{B}'$ is not necessarily equal to $\mathbf{B}_i$. Figure 3 illustrates the procedure corresponding to eqns. (2) and (3) when the $\mathbf{A}'_j$ represent crisp values.

Examples of the application of this fuzzy inference model are shown in Section 5.

TABLE 3

Fuzzy inference rules for pipe damage estimation using SI and H_s

	B_i	IF SI is... ($\mathbf{A}_{i,1}$)				
		Small	Small Medium	Medium	Medium Large	Large
and	Small	Zero	Zero	Zero	Small	Small Medium
H_s	Small Medium	Zero	Zero	Small	Small Medium	Medium
is	Medium	Zero	Small	Small Medium	Medium	Medium Large
...	Medium Large	Small	Small Medium	Medium	Medium Large	Large
($\mathbf{A}_{i,2}$)	Large	Small Medium	Medium	Medium Large	Large	Very Large

4. Earthquake damage estimation at a global level

When an earthquake occurs, ground motion characteristics (SI and A_{max}) are measured at discrete points in the supply area and interpolated between points having the same soil type. This gives values of the input variables for each sub-zone of the considered control block. The procedure for local damage estimation explained in the previous section can then be applied and yields the fuzzy damage indices $\mathbf{R}'_{bi}$ and $\mathbf{R}'_{pi}$ for sub-zone i. Global phase I damage estimates $\mathbf{R}'_{\mathrm{b}}$ and $\mathbf{R}'_{\mathrm{p}}$ for the whole block are then calculated by taking the weighted averages:

$$\mathbf{R}'_{\mathrm{b}} = \sum_i \omega_{\mathrm{b}i} \mathbf{R}'_{\mathrm{b}i}, \quad \mathbf{R}'_{\mathrm{p}} = \sum_i \omega_{\mathrm{p}i} \mathbf{R}'_{\mathrm{p}i} \tag{4}$$

The weights $\omega_{\mathrm{b}i}$ and $\omega_{\mathrm{p}i}$ represent the relative importance of sub-zone i, that is, the relative number of buildings in the sub-zone for $\omega_{\mathrm{b}i}$, and the relative pipe length in the sub-zone for $\omega_{\mathrm{p}i}$.

The summation of the fuzzy sets is done by using arithmetics of fuzzy numbers [17]. If **A** and **B** are two fuzzy numbers and α and β are two constants, then the fuzzy set $\alpha\mathbf{A} + \beta\mathbf{B}$ is defined by its membership function as (see Fig. 4):

$$\mu_{\alpha\mathbf{A}+\beta\mathbf{B}}(z) = \underset{(x,y)\,|\,\alpha x+\beta y=z}{\mathrm{Max}} \min(\mu_{\mathbf{A}}(x), \mu_{\mathbf{B}}(y)) \tag{5}$$

The damage estimates obtained from SI and A_{max} use directly-observed values and thence take ground conditions implicitly into account. This can be an advantage if the soil conditions at each measurement point are representative of the soil conditions in the surrounding area where this measurement is used for damage estimation (Figs. 5(a) and 5(e)). However, if the soil conditions at the measurement points are particular or if the number of measurement points is small, the SI–A_{max} method can lead to underestimation (Fig. 5(d)) or overestimation (Fig. 5(b)). Hence, a correction of the phase I damage estimates is performed by using another estimate obtained from the magnitude M of the earthquake and the epicentral distance Δ. This M–Δ estimate is rougher but more general than the SI–A_{max} estimate and is not calculated for each sub-zone, but for the whole control block.

As the relationships between M, Δ and the damage indices are again only qualitatively known, fuzzy reasoning is applied as before. The procedure is, in all respects, similar to the one explained in Section 3. The parameters of the membership functions are given in Table 4 and

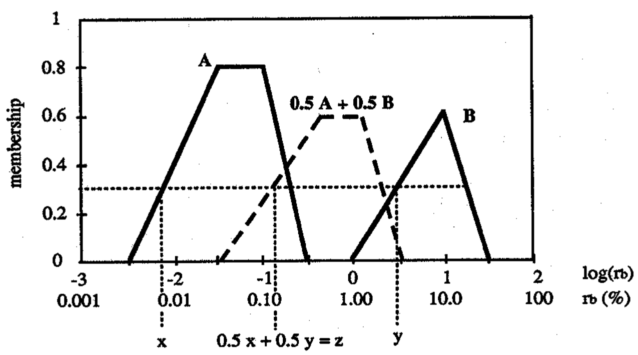

Fig. 4. Weighted average of two fuzzy sets.

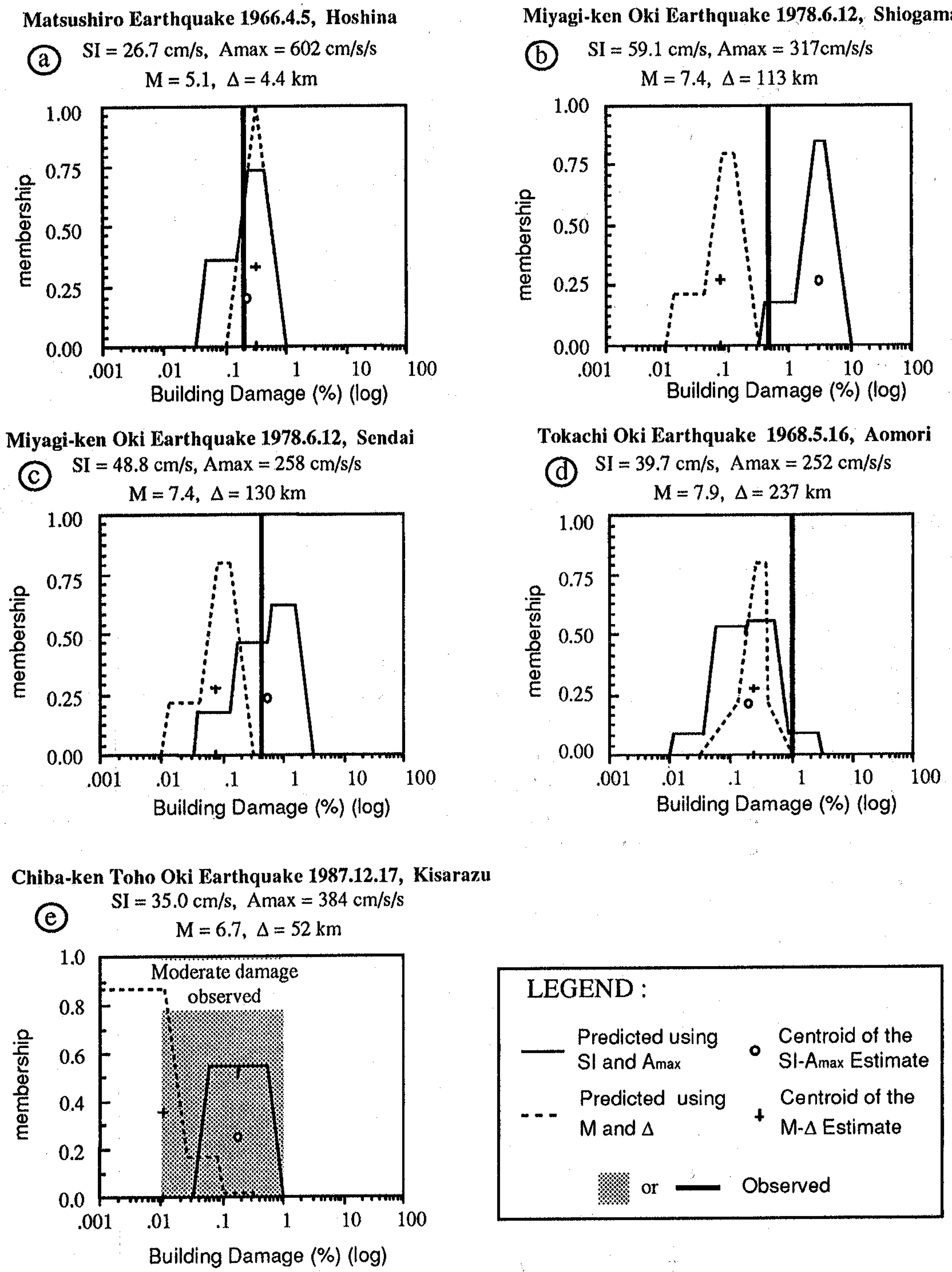

Fig. 5. Application of the proposed damage estimation method to some past earthquakes in Japan.

the rules for fuzzy reasoning are shown in Table 5. As this method gives only an order estimate for earthquake damage, it has not been distinguished between damage to buildings and damage to pipes: the same set of rules (shown in Table 5) has been used for assessing R_b and R_p.

TABLE 4

Parameters of the basic membership functions for variables M and Δ

variable	unit	k	a_0	a_1	a_2	a_3	a_4	a_5	a_6
M	–	5	5	6	6.5	7	7.5	8	9
Δ	km (log)	5	1	10	17.8	31.6	52.6	100	1000

Corresponding values for R_b and R_p are the same as in Table 1.

The final (phase II) damage estimates for the whole control block ($\mathbf{R}_b$, $\mathbf{R}_b$) are obtained after correction of the phase I estimates ($\mathbf{R}'_b$, $\mathbf{R}'_p$) by the M–Δ estimates ($\mathbf{R}''_b$, $\mathbf{R}''_p$) by weighted summation:

$$\mathbf{R}_b = \Omega'_b \mathbf{R}'_b + \Omega''_b \mathbf{R}''_b, \quad \mathbf{R}_p = \Omega'_p \mathbf{R}'_p + \Omega''_p \mathbf{R}''_p \quad \text{with } \Omega'_\beta + \Omega''_\beta = 1, \quad \beta = \text{b, p} \tag{6}$$

The weights Ω'_b, Ω''_b, Ω'_p and Ω''_p are not easy to determine for optimum damage estimation. The larger the number of measurement points is and the better the precision of soil zoning is, the smaller should the weights Ω''_b and Ω''_p of the M–Δ estimates be. The values $\Omega'_b = \Omega'_p = 0.66$ and $\Omega'_b = \Omega''_p = 0.33$ have been chosen for the application in Section 7.

5. Verification of the damage estimation method

To verify the effectiveness of the proposed earthquake damage estimation method, it has been applied to past earthquake data. Unfortunately, the number of earthquakes for which thorough damage survey as well as precise ground motion characteristics are available is small. Most of the time, only one strong motion record is available for a whole city and thence it has only been possible to perform global damage estimation.

TABLE 5

Fuzzy inference rules for building and pipe damage estimation using M and Δ

		IF M is … ($\mathbf{A}_{i,1}$)				
	$\mathbf{B}_i$	Small	Small Medium	Medium	Medium Large	Large
and	Small	Medium	Medium Large	Large	Very Large	Very Large
Δ	Small Medium	Small Medium	Medium	Medium Large	Large	Very Large
is	Medium	Small	Small Medium	Medium	Medium Large	Large
…	Medium Large	Zero	Small	Small Medium	Medium	Medium Large
($\mathbf{A}_{i,2}$)	Large	Zero	Zero	Small	Small Medium	Medium

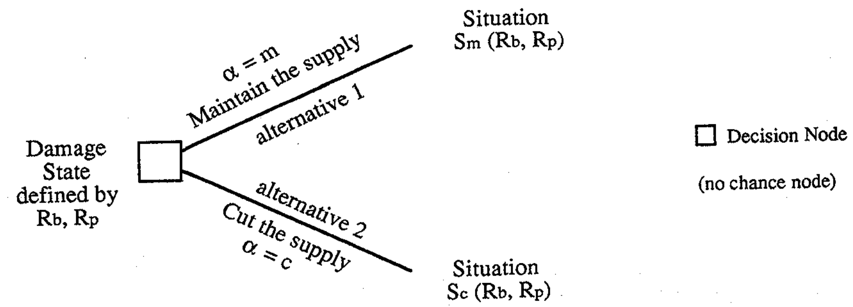

Fig. 6. Decision tree of the problem.

The proposed method has been applied to 14 earthquake events which occurred between 1964 and 1989, most of them in Japan [18]. Figure 5 shows some examples of the results. Predicted and observed values do not always perfectly coincide, but it should be noted that in most cases (11 events out of 14), the observed and predicted values have a non-void intersection. If the lack of data is borne in mind the results can be considered as satisfactory.

6. Decision analysis

Suppose that the damage state of the system (control block of the gas network) is known in terms of the fuzzy sets $\mathbf{R}_b$ and $\mathbf{R}_p$. We would then like to use this information to decide whether to cut or maintain the gas supply in the block. The problem we are facing can be represented by the decision tree in Fig. 6.

6.1. Use of the concept of utility

One general idea to solve a decision problem is to assign a rating or "utility" to each situation at the tip of the decision tree [19]: the "better" the situation, the higher the utility. The procedure is then to make the choice(s) at the decision node(s) that will lead to the situation with the highest possible utility. If the number of possible final situations is discrete (S_i, $i = 1, \ldots, q$), they should be allocated a corresponding number of discrete utility values (u_i, $i = 1, \ldots, q$); if the final situations depend on a continuous parameter $r(s(r), 0\% \leqslant r \leqslant 100\%)$, then thenutility should be defined as a function of this parameter ($u(r)$, $0\% \leqslant r \leqslant 100\%$).

In our case, the problem in Fig. 6 can be considered as being described by one discrete parameter $\alpha = \mathrm{c}, \mathrm{m}$, which represents whether the supply is cut or maintained, and by two continuous parameters, damage to buildings r_b and damage to pipes r_p. Hence a two-variable utility function $u_\alpha(r_b, r_p)$ should be defined for each value of parameter α.

In a one-variable case, it seems rather simple to construct a utility function, for example, by asking some experts' advice. However, it is much more difficult to assess situations that depend on two variables. To tackle this problem, it has been proposed to determine the value of u for several values of the pair (r_b, r_p) and then interpolate between these points by a polynomial function [9]. However, it might be easier for the decision maker to treat each variable separately. Several authors (e.g., [10]) have been using a weighted average rating to represent a situation depending on the rating of each of its attributes. Using the vocabulary of utility theory

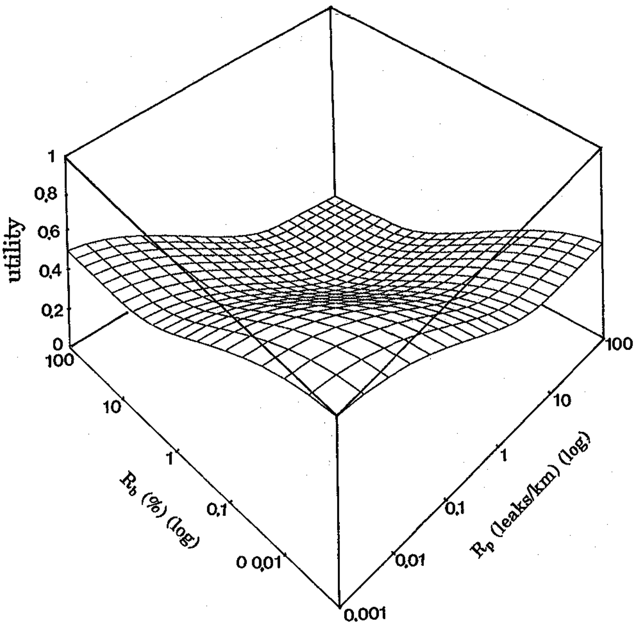

Fig. 7(a). Example of two-variable utility functions: α = m (alternative "maintain the supply").

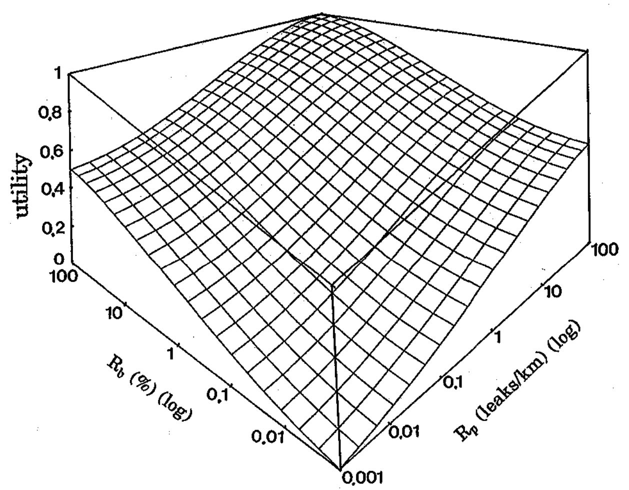

Fig. 7(b). Example of two-variable utility functions: α = c (alternative "cut the supply").

[20], this amount to suppose that the preference structure of the decision maker is additive so that the variables can be separated in the expression of the utility function:

$$u_\alpha(r_b, r_p) = \lambda_\alpha^b \hat{u}_\alpha^b(r_b) + \lambda_\alpha^p \hat{u}_\alpha^p(r_p), \quad \lambda_\alpha^b + \lambda_\alpha^p = 1, \quad \alpha = c, m \tag{7}$$

where λ_α^b and λ_α^p represent the relative importance of the two parameters. It should be noticed that if $\hat{u}_\alpha^b(r_b)$ and $\hat{u}_\alpha^p(r_p)$ are polynomial functions, the obtained mathematical expression of $u_\alpha(r_b, r_p)$ is similar to the one used by Gunaratne et al. [9]. Figure 7 gives an example of such two-variable utility functions when $\lambda_\alpha^\beta = 1/2$ and $\hat{u}_\alpha^\beta(r_\beta)$ ($\alpha = c$, m; $\beta = b$, p) are third order polynomials with one degree of freedom such that $\hat{u}_m^\beta(r_\beta = 100) = 0$ and $\hat{u}_c^\beta(r_\beta = 0) = 1$.

It is possible to use a fuzzy value of utility $\mathbf{U}_\alpha(r_b, r_p)$ for each crisp value of the pair (r_b, r_p) as has been done by the above mentioned authors [9,10]. In our case, this could be done by using fuzzy values for the coefficients λ_α^β ($\alpha = c$, m; $\beta = b$, p) and using Zadeh's extension principle to obtain the membership function $\mu_{\mathbf{U}_\alpha(r_b,r_p)}(u)$ for each value of (r_b, r_p) similarly to what has been done in [10]. However, for the sake of simplicity, crisp utility functions $u_\alpha(r_b, r_p)$ are used hereafter.

The definition of the utility function $u_\alpha(r_b, r_p)$ represents the mathematical modelling of the problem. If the damage state of the system is known as (R_b^0, R_p^0), solving the decision problem is equivalent to choosing $\alpha = c$ or $\alpha = m$ so that $u_\alpha(R_b^0, R_p^0)$ is maximized.

In the present case, there is an additional difficulty due to the fact that the damage state of the system is not known through crisp values (R_b^0, R_p^0) but through fuzzy sets $\mathbf{R}_b$ and $\mathbf{R}_p$. How to use this imprecise information and reach a final decision is explained below.

6.2. Choice of the best alternative

As the information about the system is fuzzy, instead of a utility value $u_\alpha(R_b^0, R_p^0)$ for each alternative, there will be a fuzzy utility $\mathbf{U}_\alpha$ for each alternative ($\alpha = c$, m). The membership function of this fuzzy utility is defined by Jain [12] in the one-variable case and can easily be extended to the two-variable case as follows:

$$\mu_{\mathbf{U}_\alpha}(u) = \operatorname*{Max}_{(r_b,r_p)\in u_\alpha^{-1}(u)} \min\left(\mu_{\mathbf{R}_b}(r_b), \mu_{\mathbf{R}_p}(r_p)\right) \tag{8}$$

where $\mathbf{u}_\alpha^{-1}(u) = \{(r_b, r_p) \mid u_\alpha(r_b, r_p) = u\}$ is the indifference curve of the damage space corresponding to the value u of the utility. The meaning of eqn. (8) is represented in Fig. 8.

Equation (8) enables to obtain two fuzzy utilities $\mathbf{U}_c$ and $\mathbf{U}_m$ corresponding to the two alternatives. It is now necessary to determine which is higher of these two fuzzy utilities and therefore which alternative is better. Several methods have been proposed in order to do so. Dubois and Prade [11] define the maximum of two fuzzy sets $\mathbf{U}_c$ and $\mathbf{U}_m$ by using Zadeh's extension principle. However, this maximum is another fuzzy set which can be different from both $\mathbf{U}_c$ and $\mathbf{U}_m$, so that this concept can be of little use here. The same authors define the truth value $v(\mathbf{U}_m > \mathbf{U}_c)$ of the proposition "$\mathbf{U}_m$ is greater than $\mathbf{U}_c$". If the average value of $\mathbf{U}_m$ is greater than the average value of $\mathbf{U}_c$, $v(\mathbf{U}_m > \mathbf{U}_c)$ is the highest value of the membership of $\mathbf{U}_m$ and $v(\mathbf{U}_c > \mathbf{U}_m)$ is the height of the crossing point between the two memberships (Fig. 9). Baas and Kwakernaak [10] propose a generalization of this approach that can be applied to more than two alternatives and yields a value between 0 and 1 for each alternative. The best alternative is the one yielding the value 1. The drawback of these approaches is that only a ranking of the alternatives is obtained: we can determine which alternative is best, but we do not know how much better it is than the other ones. To solve this problem, Baas and Kwakernaak [10] propose to use $\mathbf{U}_m - \mathbf{U}_c$ and $\mathbf{U}_c - \mathbf{U}_m$ (which they call the fuzzy preferability) to characterize each alternative respectively but that still leaves us with a fuzzy set for each alternative. A more practical (if less elegant mathematically) method which has been introduced by Jain [12] and used by Gunaratne et al. [9] will be applied here.

The fuzzy sets $\mathbf{U}_c$ and $\mathbf{U}_m$ can be interpreted as the possibility distributions of the utility u when the supply is cut or maintained respectively. We should then consider that a "good"

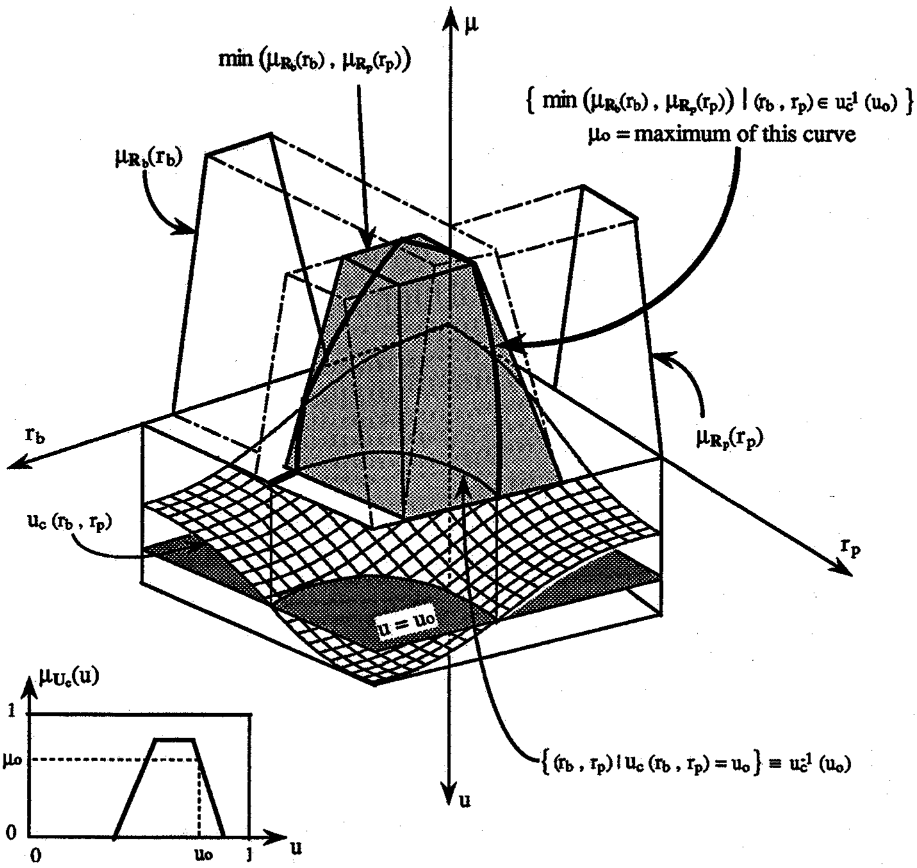

Fig. 8. Obtaining the fuzzy utility of an alternative.

alternative gives a high possibility (or membership) to high values of u. To express this mathematically, the membership function of each fuzzy utility is compared with the fuzzy set **M** for which the higher u, the higher the membership. The "value" v_α ($\alpha = \text{c, m}$) of each alternative is computed as follows:

$$v_\alpha = \underset{u}{\text{Max}} \min\left(\mu_{U_\alpha}(u), \mu_M(u)\right) \tag{9}$$

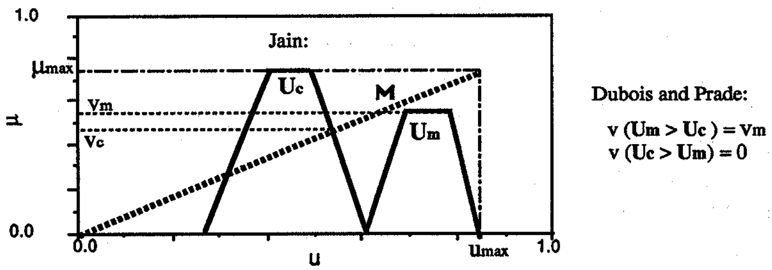

Fig. 9. Choice between two fuzzy utilities.

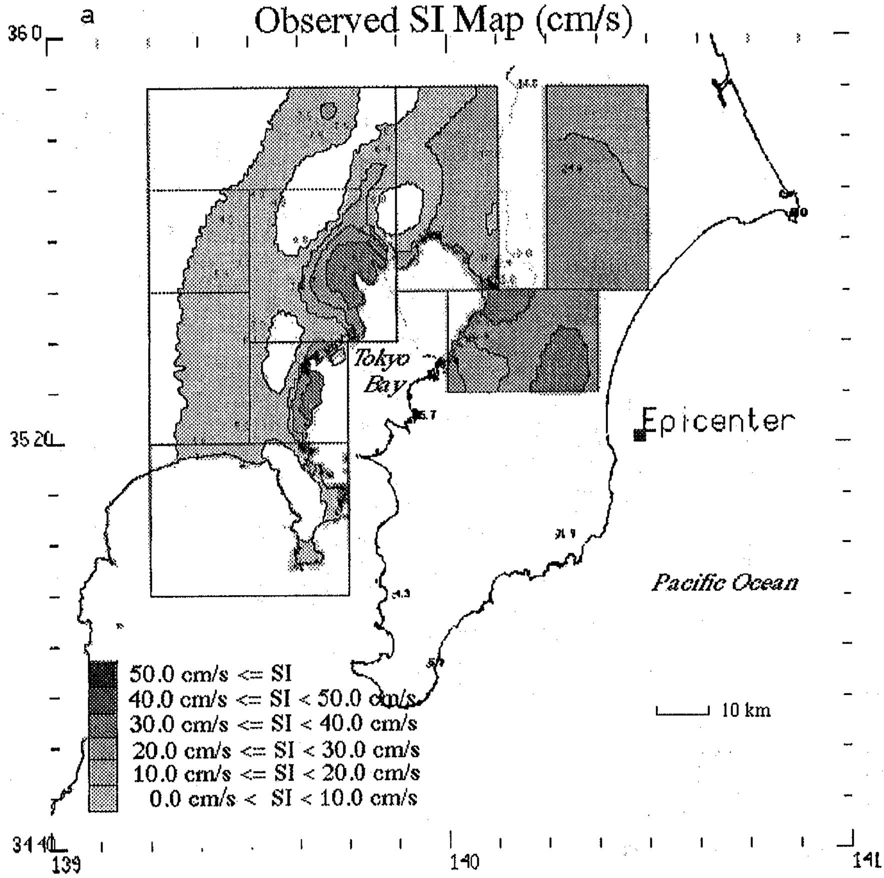

Fig. 10(a). Observed ground motion characteristics during the 1987 Chibaken-Toho-Oki earthquake in Tokyo area: Observed SI values.

where $\mu_M(u) = \mu_{max}(u/u_{max})$, μ_{max} is the highest value for μ_{Um} and μ_{Uc}, and u_{max} is the highest possible utility, i.e. $u_{max} = \max\{u \mid \mu_{Um}(u) \neq 0 \text{ or } \mu_{Uc}(u) \neq 0\}$. Equation (9) is the normalized version of the formula proposed by Jain [12].

The best alternative corresponds to the highest value v_α as illustrated in Fig. 9.

7. Application to a real case

The damage estimation procedure described above is used for a gas supply network as part of a computer system aimed at assisting decision-making in an emergency. The system uses the values of the parameters observed in the supply area to estimate damage and displays the results as maps in which the centroids of the obtained fuzzy damage indices are plotted.

As an example, the system was tested for the Chibaken-Toho-Oki earthquake (December 17, 1987, JMA magnitude 6.7) in the Tokyo area. Figures 10(a) and 10(b) show recorded SI and A_{max} values during the quake: maximum values in the block near the epicenter were 34.6 cm/s for SI and 549 cm/s^2 for A_{max}.

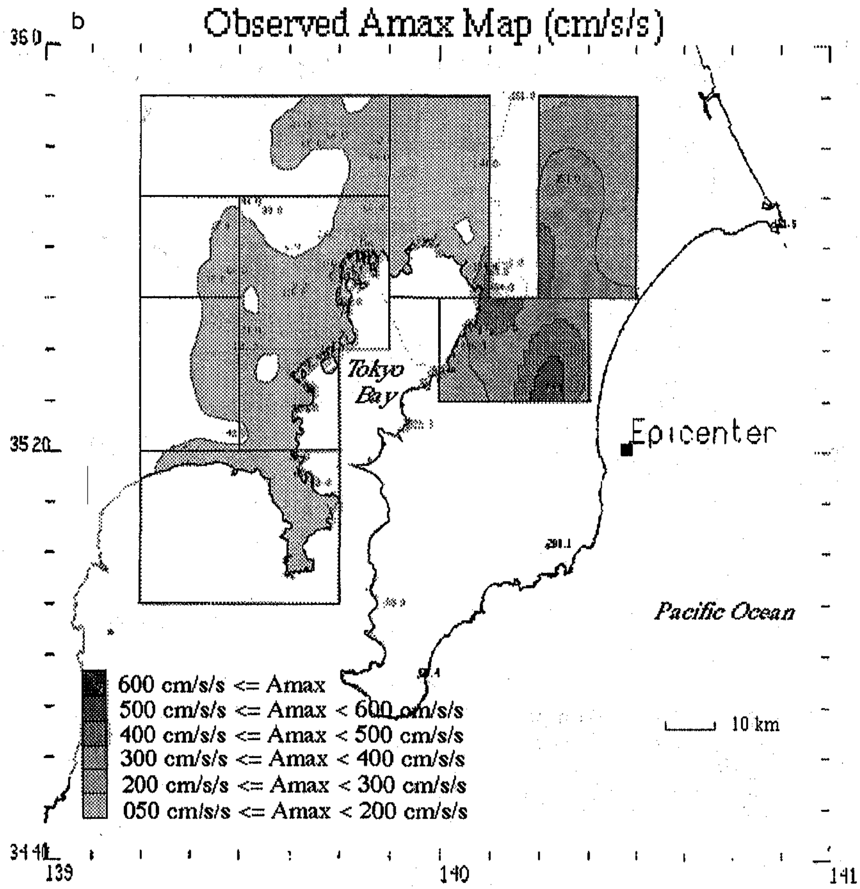

Fig. 10(b). Observed ground motion characteristics during the 1987 Chibaken-Toho-Oki earthquake in Tokyo area: Observed A_{max} values.

Figure 11(a) shows predicted phase I building damage. In the most affected block, maximum values are between 0.1 and 1%. According to the definition of R_b, this means that between 1 and 10 houses out of 1000 collapsed, or equivalently, that between 1 and 10 houses out of 100 were slightly damaged. These figures are rather low but still far from negligible, which is consistent with what was observed in reality. Several houses reportedly completely collapsed in the corresponding area and several tens of thousands of houses were partly damaged [21].

Figure 11(b)) shows phase I and phase II building damage estimates for Block B_0 in Fig. 11(a). The obtained fuzzy damage indices can be interpreted as possibility distributions and show that damage is between 0.01 and 1.0% with a greater possibility around 0.1%.

Figures similar to Figs. 11(a) and 11(b) can be obtained for damage to pipes. Figure 11(c)) shows the obtained building and pipe damage indices for Block B_0. These two fuzzy damage indices are then combined with the utility functions shown in Fig. 7 to yield the two fuzzy utilities shown in Fig. 11(d). The fuzzy utilities of the two alternatives are clearly apart but their intersection is non-void. The difficulty in making the decision is represented by the relative difference of the values v_c and v_m of the two alternatives. In the case of Block B_0, this

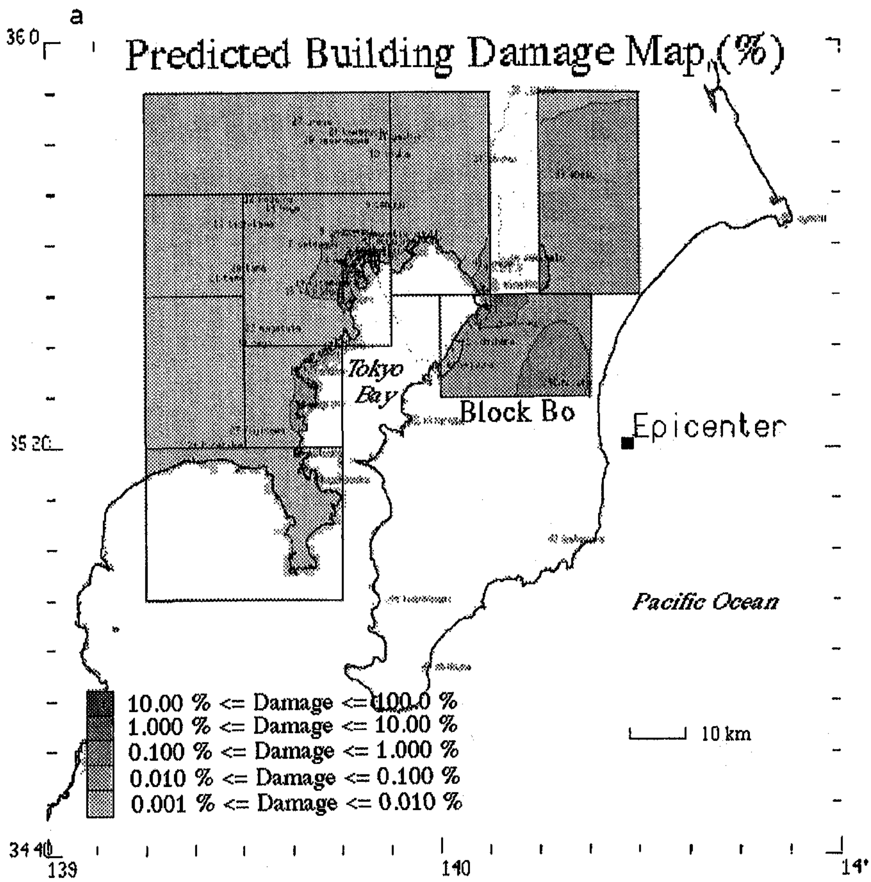

Fig. 11(a). Results of damage estimation and fuzzy decision analysis for the 1987 Chibaken-Toho-Oki earthquake in Tokyo area: Predicted building damage.

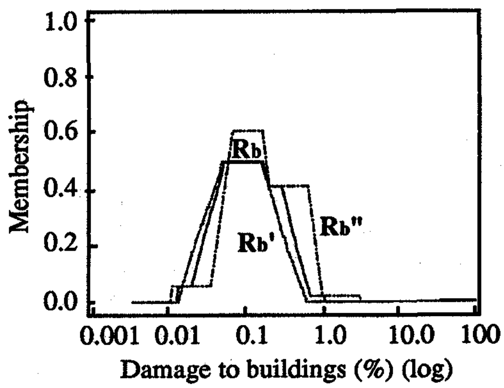

Fig. 11(b). Results of damage estimation and fuzzy decision analysis for the 1987 Chibaken-Toho-Oki earthquake in Tokyo area: Predicted fuzzy building damage for Block B_0 in (a).

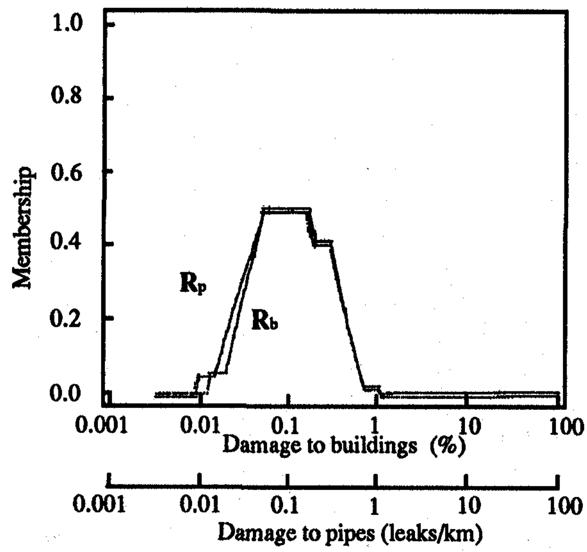

Fig. 11(c). Results of damage estimation and fuzzy decision analysis for the 1987 Chibaken-Toho-Oki earthquake in Tokyo area: Fuzzy damage indices obtained for Block B_0 used in decision analysis.

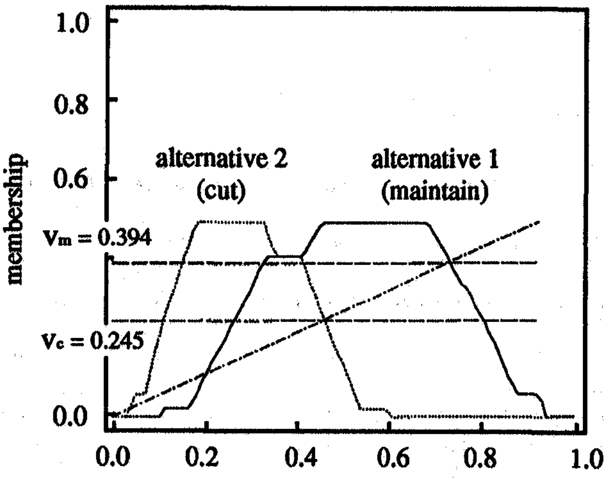

Fig. 11(d). Results of damage estimation and fuzzy decision analysis for the 1987 Chibaken-Toho-Oki earthquake in Tokyo area: Fuzzy utilities and value of each alternative.

difference is still large enough

$$\left(\frac{v_m - v_c}{(v_m + v_c)/2} = 45\%\right)$$

to give a clear advantage to Alternative "maintain the supply". This was the decision which was made in reality.

8. Conclusions

This paper proposes a method for earthquake damage assessment in buried pipeline networks that can be used for assisting emergency shuf-off decision in the case of gas networks.

As the importance of soil conditions in earthquake damage assessment is recognized, damage estimation is first performed at the sub-zone level where soil conditions are supposed to be reasonably homogeneous and then global damage estimates are calculated by weighted average. The parameters taken into account for damage estimation are soil conditions and ground motion characteristics. The magnitude of the earthquake and epicentral distance are also used for correcting the bias due to the limited number of points where the input parameters are known. As the knowledge of the relationship between the different variables is more qualitative than quantitative, fuzzy set theory has been used for modelling. The proposed method for damage assessment has been tested on some past earthquakes and although the amount of available data is small, the results were satisfactory.

The results of earthquake damage assessment are displayed as maps to help the decision-maker have a global understanding of the situation. The obtained fuzzy damage indices are also used in fuzzy decision analysis which will yield clear advice on whether it is preferable to cut or maintain the supply in each block of the gas network.

As an example, the computer system developed on the basis of the proposed methods has been applied to a real case which occurred in the Tokyo area. The results are fully compatible with observations.

References

1 J.T.P. Yao, Damage assessment of existing structures, *J. Engineering Mechanics Division*, 106 (EM4) (1980) 785–799.

2 C.B. Brown and J.T.P. Yao, Fuzzy sets and structural engineering, *J. Structural Engineering*, 109 (5) (1983) 1211–1225.

3 J.T.P. Yao and H. Furuta, Probabilistic treatment of fuzzy events in civil engineering, *Probabilistic Engineering Mechanics*, 1 (1) (1986) 58–64.

4 W. Dong, W.L. Chiang, H.C. Shah and F.S. Wong, Failure possibility of existing buildings, *Civil Engineering Systems*, 6 (1989) 170–179.

5 N. Shiraishi and H. Furuta, System reliability analysis of existing structures, *Structural Safety*, 7 (1990) 291–294.

6 C.H. Juang and D.J. Elton, Fuzzy logic for estimation of earthquake intensity based on building damage records, *Civil Engineering Systems* (1986) 187–191.

7 M. Mizumoto, Fuzzy controls under various fuzzy reasoning methods, *Information Sciences*, 45 (1988) 129–151.

8 X. Liu, M. Wang, J. Dong and J. Liu, A tentative application of fuzzy set theory to damage prediction, *Proc. of the 8th World Conference on Earthquake Engineering*, 1984, pp. 329–336.

9 M. Gunaratne, J.L. Chameau and A.G. Altshaeff, Fuzzy multi-attribute decision making in pavement management, *Civil Engineering Systems*, 2 (1985) 201–208.

10 S.M. Baas and H. Kwakernaat, Rating and ranking of multiple-aspect alternatives using fuzzy sets, *Automatica*, 12 (1977) 47–58.

11 D. Dubois and H. Prade, Decision-making under fuzziness, in *Advances in Fuzzy Set Theory and Applications*, M.M. Gupta, R.K. Ragade and R.R. Yager, Eds., North-Holland, Amsterdam, 1979.

12 R. Jain, Decision-making in the presence of fuzzy variables, *IEEE Trans. on Systems, Man, and Cybernetics*, SMC-6 (1976) 698–703.

13 T. Iwata, Restoration planning system for earthquake damaged gas pipeline network, *Proc. Trilateral Seminar-Workshop on Lifeline Earthquake Engineering*, A.H-S. Ang, T. Katayama and R. Tan, Eds., National Taiwan University, Taipei, 1985.

14 T. Katayama, T. Sato and K. Saito, SI-Sensor for the identification of destructive earthquake ground motion, *Proc. 9th World Conference on Earthquake Engineering*, 1988, Vol. VII, pp. 667–672.
15 Y. Ando, F. Yamazaki and T. Katayama, Damage estimation of structures based on indices of earthquake ground motion, *Proc. 8th Japan Earthquake Engineering Symposium*, 1990, Vol. 1, pp. 715–720 (in Japanese).
16 W. Dong, H.C. Shah and F.S. Wong, Fuzzy computations in risk and decision analysis, *Civil Engineering Systems*, 2 (1985) 201–208.
17 A. Kaufmann and M.M. Gupta, *Introduction to Fuzzy Arithmetic—Theory and Applications*, Van Nostrand Reinhold, New York, 1985.
18 L. Cret, F. Yamazaki, S. Nagata and T. Katayama, Earthquake damage estimation for lifeline systems using fuzzy reasoning, *Proc. Int. Symposium on Natural Disaster Reduction and Civil Engineering*, Sept. 1991, Osaka, Japan.
19 H. Raiffa, *Decision Analysis—Introductory Lectures on Choices under Uncertainty*, Addison-Wesley, Reading, Massachusetts, 1970.
20 R. Keeney and H. Raiffa, *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*, Wiley, New York, 1976.
21 Chiba Prefecture, *Damage report of the Chibaken-Toho-Oki earthquake of 1987* (1989) 42–49 (in Japanese).