Journal of Engineering and Applied Sciences 12 (Special Issue 10): 9001-9005, 2017
ISSN: 1816-949X

Forecasting of Relative Displacement for Building Using Fuzzy Systems

[1]Mohamad Reza Sohrabi, [2]Ehsan Adili and [3]Hamid Mohsenian
[1]Department of Civil Engineering, University of Sistan and Baluchestan, Zahedan, Iran
[2]Department of Civil Engineering, Velayat University, Iranshahr, Iran
[3]Faculty of Engineering, Zahedan Branch, Islamic Azad University, Zahedan, Iran

Abstract: One of the most important parameters in analyzing of one structure is relative displacement of stories which is shown with drift. A lot of design codes for buildings have some limitation and never allow the structure to displace more than the acceptable amount. Actually at the time of any earthquake an extra displacement of the structure may lead to some events such as: destroying the connectors, fear of residents and destroying the whole structure. Sometimes, all structure calculated and finally, the relative displacement of the structure prepared under control. If it is more than the acceptable amount, some changing must take place and also its stiffness should enhance in facing of lateral forces.

Key words: Drift, forecasting, fuzzy system, building skeleton, stiffness, Iran

INTRODUCTION

Structure displacement is one of the most important factors in the process of designing the building skeleton. Researchers tend to have a minimal amount of displacement in structure. In civil engineering, the term Drift is used in order to measure the displacement of floors. All design codes of building limited the amount of drift to a fixed one (Zadeh, 1965). When the amount of displacement is too much at the time of the earthquake, it leads to destroy the skeleton connectors or at least may create some fear for residents or some damages in non-structural items. The amount of drift is calculated by the following equation:

$$\text{Drift} = (D_2\text{-}D_1)/h$$

The process of controlling the relative displacement often occurred after designing the buildings. When the displacement is more than the acceptable amount, the designing engineer must reinforce the amount of acceptable value of structure in order to place the relative displacement. The aim of this study is presenting a fuzzy model which could predict the drift of structure by receiving some primary information such as: number of floors, type of ceiling and lateral stiffness (Fig. 1). It can help the designer to inform about the amount of drift before designing the structure and think about all possible problems tactfully or being assured about the permitted amount of displacement. There are some factors as an input of membership functions such as: number of floors, behavior factor and a unit weight of ceiling. More than 400 buildings were analyzed in this study with different floors, ceilings weight and also different behavior factors (Yazdani-Chamzini and Yakhchali, 2012). Then, the amount of their drift was derived in order to have adequate information for the definition of output membership function. After that, the “if-then” rules adjust and the fuzzy system became completed. After this completion, about 20 structures modulted and analysed randomly their abtained drift comparedwith fuzzy system (Jamshidi *et al.*, 2013).

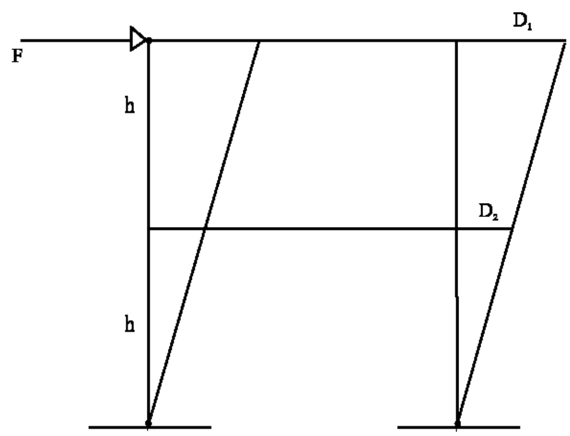

Fig. 1: Displacement of stories during the earthquake

Corresponding Author: Ehsan Adili, Department of Civil Engineering, Velayat University, Iranshahr, Iran

MATERIALS AND METHODS

Fuzzy inference system: Engineers are encountered with a lack of information or deficient data in many practical problems. So, vagueness and uncertainty are separable parts of engineering sciences. Fuzzy logic is presented by Zadeh (1965). It is a powerful tool to solve these kinds of problems. This method uses linguistic terms in the process of modeling complicated problems in order to create an inference structure as well as complicated and advanced modeling. Data are between 0 and 1 in the fuzzy system. So, 1 indicates the whole belonging and 0 illustrates non membership in the collection. While in the classic collection, a member can belong to the collection or cannot. In other words, belonging to this system is defined only with 0 and 1 (Grima *et al*., 2000). A fuzzy inference system is illustrated in Fig. 2. Each FIS include four main parts as the following: fuzzification, knowledge base, fuzzy inference system and defuzification.

Fuzzification: Fuzzification operation is a kind of process which crisp amounts transform to types of membership degrees for linguistic terms. The membership function is used in order to connect the grade into each linguistic term. The first part of FIS is fuzzification. In fact, this is a kind of operation that converts classic values to fuzzy functions in order to utilize them as membership functions for linguistic variables. In other words, entry vector which is alike with some linguistic terms converts as the following: very high, high, medium, low and very low. This process takes place in membership function. There are both linear and non-linear functions. The type of membership function depends on the modulated problem, the ability of expert and the case of the study (Ghasemi and Ataei, 2013).

Knowledge base: "If-then rules" are determined on the basis of some parameters such as: judgment, experiences of experts and engineering science. A conditional rule generally includes a premise and consequent parameter. The relationship between input and output is defined on the basis of conditional functions which called fuzzy "if-then" rules. A conditional rule often consists of one premise and a consequent. As an example, "if x is high then y is low". Here, "y is low" is consequent. The above terms such as "high" and "low" are specified on the basis of MFs (Jang, 1997).

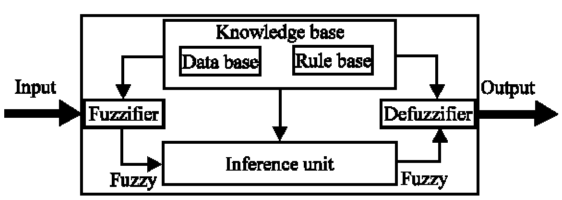

Fig. 2: Fuzzy inference system

Fuzzy inference system: The "if-then" rules are used in this step in order to provide an output by combination of rules. This step is the most important part of the fuzzy expert system. It extracts the findings from the fuzzy operation on the basis of previous rules and completes the modeling process. There are types of FISs which are used in different conditions and also for different practical and engineering problems. One of the most important algorithms is Mamdani Fuzzy Model. Definition of fuzzy systems and fuzzy logic in order to completely transfer of the unstructured system and linguistic heuristics into an algorithm is used in this method. There is a general rule in Mamdani algorithm as the following:

$$\text{If } x_1 \text{ is } A_{i1} \text{ and } x_2 \text{ is } A_{i2} \text{ and } ..., x_r \text{ is } A_{ir}$$
$$\text{then } y \text{ is } B_i \,(\text{for } i = 1, 2, ..., k)$$

Where:

x_i	=	An entry variable
A_{ij} and B_j	=	Linguistic terms
y	=	An output variable
k	=	The number of rules

Different types of methods can be used in Mamdani fuzzy model with a combination of fuzzy rules. The composition of maximum and minimum has been used in this study which is also a common method. From the point of mathematical view, this technique is defined as the following equation:

$$\mu_{C_K}(Z) = \max\left[\min\left[\mu_{A_K}(\text{input}(x)), \mu_{B_K}(\text{input}(y))\right]\right]$$

where, μ_{Ck}, μ_{AK} and μ_{BK} are the membership function of output z for rule k, input x and "y", respectively (Li, 2006).

Defuzzification: Finally, fuzzy collections convert to crisp values in the level of defuzzification. There are a lot of different defuzzification methods and the most common of them is used in this research which is "centroid of area". In the "centroid of area" the following function is used in order to transform fuzzy collections to crisp value:

$$Z^*_{COA} = \frac{\int_z \mu_A(z) z dz}{\int_z \mu_A(z) dz}$$

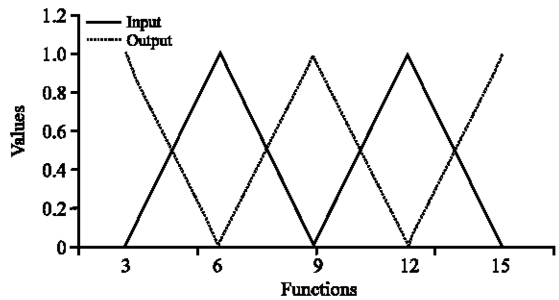

Fig. 3: Height membership function (input)

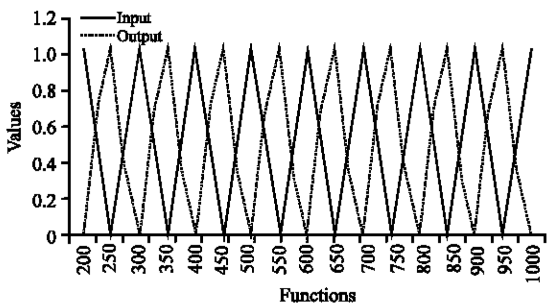

Fig. 4: Weight membership function (input)

Where:

Z^*_{COA} = The Crisp value for the "z" output

$\mu A(z)$ = The aggregated output membership function (Mamdani and Assilian, 1975)

Membership functions: In the forecasting fuzzy system, membership functions must be defined at first. Actually, there are two ways for the definition of MFs. The first one is the definition of linguistic variables by experts and second is the process inference of the functions on the basis of experiment, algebraic equations and mathematical relations. Three input membership functions and one output are used in this study. The output membership function is drift of the structure and the input ones are as the following: height, weight and behavior factor. More than 900 structures were analyzed in Etabs Software in order to define the input membership functions and also the amount of maximum drift was prepared. The effect of different input parameters was determined and also the amount interval of the drift and input and output membership functions were specified. From the viewpoint of height, the height of analyzed structures was between 3 and 15, the amount of their resistance relate to the earthquake was between 6 and 11. Finally, from the standpoint of weight, they had ceilings with 200-1000 kg weight (Ross, 2009). According to the above analysis, input and output membership functions were defined as Fig. 3-6.

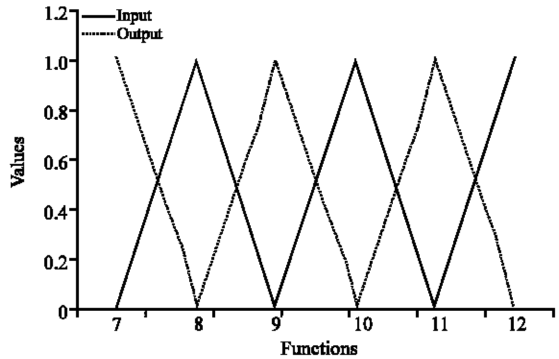

Fig. 5: Behavior factor membership function (input)

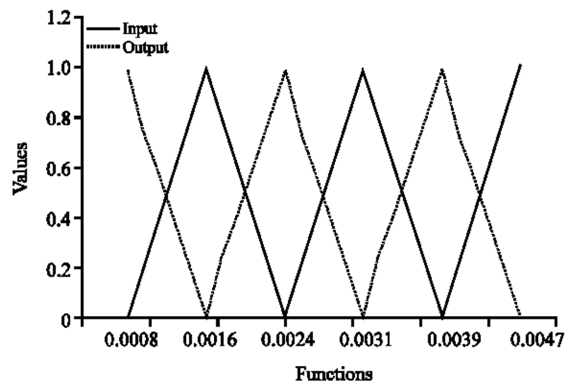

Fig. 6: Drift membership function (output)

The outputs of the fuzzy model were determined on the basis of Mamdani relationship and formation of the fuzzy inference engine. In this level, the fuzzy system is completed and can predict the relative displacement of the structure. This system is able to predict the relative displacement of the structure by receiving just the parameters of input membership functions. Here, there is no need of having a completed building (Monjezi and Rezaei, 2011).

RESULTS AND DISCUSSION

The fuzzy system experimented randomly after the completion. Different combined structures with different loadings and also with varied conditions were determined and the amounts of their relative displacement were computed using building design software (Iphar and Goktan, 2006). The properties of 29 controlling buildings are illustrated in Table 1.

The results of Table 1 and its desirable accordance to the findings of designated structures and fuzzy results are shown in Fig. 7.

Table 1: The properties of 29 controlling buildings

No. of stories	------------Behavior factors------------			Weight	Real amount	Fuzzy	Percentage of differences
4	S	9	R	320	0.00684	0.00638	0.06766
4	S	10	R	760	0.00303	0.00195	0.35558
4	S	11	R	260	0.00021	0.00031	-0.45540
4	S	11	R	810	0.00027	0.00081	-1.95620
5	S	11	R	820	0.00028	0.00031	-0.12320
5	S	6	R	270	0.00099	0.00200	-1.01410
5	S	11	R	310	0.00025	0.00031	-0.24500
5	S	10	R	760	0.00331	0.00295	0.10957
5	S	7	R	710	0.00461	0.00330	0.28432
7	S	7	R	340	0.00293	0.00469	-0.60290
7	S	10	R	760	0.00325	0.00428	-0.31610
7	S	10	R	520	0.00262	0.00354	-0.35170
7	S	11	R	470	0.00037	0.00047	-0.25270
8	S	11	R	570	0.00049	0.00049	-0.00820
8	S	6	R	890	0.00206	0.00488	-1.36430
8	S	9	R	210	0.00579	0.00515	0.11084
10	S	7	R	280	0.00406	0.00504	-0.24080
10	S	7	R	420	0.00367	0.00504	-0.37180
10	S	6	R	680	0.00544	0.00495	0.08940
11	S	6	R	730	0.00474	0.00440	0.07095
11	S	10	R	930	0.00390	0.00440	-0.12730
11	S	7	R	340	0.00476	0.00443	0.06874
11	S	7	R	460	0.00387	0.00443	-0.14530
13	S	10	R	410	0.00294	0.00195	0.33764
13	S	6	R	470	0.00791	0.00820	-0.03690
13	S	8	R	930	0.00196	0.00191	0.02749
13	S	7	R	310	0.00628	0.00710	-0.13040
14	S	6	R	560	0.00651	0.00497	0.23597
14	S	10	R	260	0.00220	0.00195	0.11162

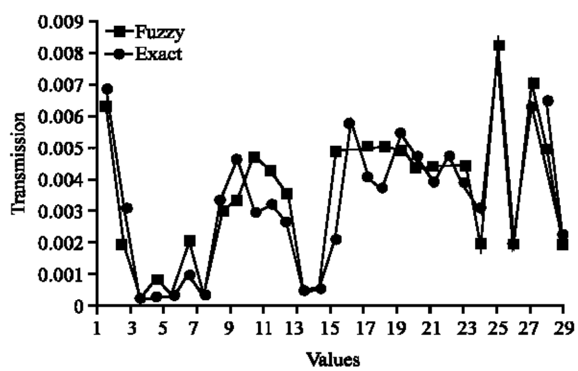

Fig. 7: Comparison of fuzzy results with an exact relative displacement of the structure

CONCLUSION

This study presented a fuzzy model in order to forecast the relative displacement of the the structure. This model can predict the final relative displacement of the the structure by receiving the primary features such as: weight of the structure, lateral stiffness and number of floors. So, at the first step of designing the skeleton of the building, the designer must think about necessary preparation for some possible relative displacement.

REFERENCES

Ghasemi, E. and M. Ataei, 2013. Application of fuzzy logic for predicting roof fall rate in coal mines. Neural Comput. Appl., 22: 311-321.

Grima, M.A., P.A. Bruines and P.N.W. Verhoef, 2000. Modeling tunnel boring machine performance by neuro-fuzzy methods. Tunnelling Underground Space Technol., 15: 259-269.

Iphar, M. and R.M. Goktan, 2006. An application of fuzzy sets to the diggability index rating method for surface mine equipment selection. Intl. J. Rock Mech. Min. Sci., 43: 253-266.

Jamshidi, A., A. Yazdani-Chamzini, S.H. Yakhchali and S. Khaleghi, 2013. Developing a new fuzzy inference system for pipeline risk assessment. J. Loss. Preven. Proc. Indus., 26: 197-208.

Jang, J.S.R., 1997. Neuro-Fuzzy and Soft Computing; A computational Approach to Learning and Machine Intelligence. Prentice-Hall, New Jersey, USA., ISBN:9780132610667, Pages: 614.

Li, Z., 2006. Fuzzy Chaotic Systems: Modeling, Control and Applications. Springer, Berlin, Germany, ISBN:9783540332213, Pages: 300.

Mamdani, E.H. and S. Assilian, 1975. An experiment in linguistic synthesis with a fuzzy logic controller. Int. J. Man-Mach. Stud., 7: 1-13.

Monjezi, M. and M. Rezaei, 2011. Developing a new fuzzy model to predict burden from rock geomechanical properties. Expert Sys. Appl., 38: 9266-9273.

Ross, T.J., 2009. Fuzzy Logic with Engineering Applications. 3rd Edn., John Wiley & Sons, Hoboken, New Jersey, USA., ISBN:978-0-470-74376-8, Pages: 585.

Yazdani-Chamzini, A. and S.H. Yakhchali, 2012. Tunnel Boring Machine (TBM) selection using fuzzy multicriteria decision making methods. Tunnelling Underground Space Technol., 30: 194-204.

Zedeh, L., 1965. Fuzzy sets. Inf. Control, 8: 338-353.