Available online at www.sciencedirect.com
ScienceDirect
Progress in Nuclear Energy 48 (2006) 655–663
PROGRESS IN NUCLEAR ENERGY
An International Review Journal
www.elsevier.com/locate/pnucene

Adaptive fuzzy system for degradation study in nuclear power plants' passive components ☆

Antônio César Ferreira Guimarães *, Denise Cunha Cabral, Celso Marcelo Franklin Lapa

Instituto de Engenharia Nuclear – CNEN, Divisão de Reatores/Divisão de Rejeitos/Programa de Pós-Graduação, Ilha do Fundão s/n, 21945-970, P.O. Box 68550, Rio de Janeiro, Brazil

Abstract

This paper presents a preliminary study on the use of adaptive neural fuzzy inference system (ANFIS) to determine the fragility curves in degraded nuclear power plant (NPP) passive components. The goal of this approach is to allow the direct association, using a mapping of input/output patterns, between measurable beam deflections and the structure probability of failure for a severe degradation condition. The present study consists of an Artificial Intelligence framework application considering the information obtained from an original Nuclear Regulatory Commission (NRC) research program. The results indicate that the ANFIS modeling is a promising alternative to traditional approach in nuclear studies of structure degradation in passive components.

Keywords: Degradation; Fragility curve; Fuzzy logic; Nuclear power plants

1. Introduction

The U.S. Nuclear Regulatory Commission (NRC) has recently performed an important study to assess the effects of age-related degradation of plant structures, systems, and passive components of nuclear power plants (NPPs) (NUREG/CR-6679, 2000). This study, which has been partitioned on two phases, has been shortly described by Braverman et al. (2004). In Phase I, technical information on aging and specific degradation occurrences were collected and evaluated. This phase also identified structures and components to be analyzed in the next step. In Phase II, a methodology was designed for assessing the effects of degradation in NPP structures and components.

Unfortunately, the classical analytical methods to simulate the degradation phenomena of structures and passive components at nuclear power plants presented complex analysis involving ACI Standards 318, 319, the NRC Standard Review Plan 3.8.4 and a finite element model using ANSYS computer code. Aged or degraded concrete structures are also not well known. Changes in properties, for example, as a result of aging, can produce modifications

☆ Sponsor: Fundação de Amparo à Pesquisa do Estado do Rio de Janeiro – FAPERJ and Conselho Nacional de Desenvolvimento Científico e Tecnológico – CNPq.
* Corresponding author. Tel.: +55 21 2209 8080; fax: +55 21 2590 2692.
E-mail addresses: tony@ien.gov.br (A.C.F. Guimarães), lapa@ien.gov.br (C.M.F. Lapa).

0149-1970/$ - see front matter © 2006 Elsevier Ltd. All rights reserved.
doi:10.1016/j.pnucene.2006.05.002

in resistance/capacity, failure mode, and location of failure initiation. Motivated by the above mentioned reasons and taking into account that Artificial Intelligence (AI) has been successfully applied to many complex nuclear problems (Guimarães, 2003a,b; Guimarães and Lapa, 2004a,b; Mol et al., 2006; Lapa et al., 2004, 2005), a new approach was developed based on adaptive neural fuzzy inference system (ANFIS), which can estimate the passive components' probability of failure, for various beam degradation conditions, as a consequence of analytical beam deflection.

2. Bench mark study

As mentioned, ACI Standard (318–349) and the NRC Standard Review Plan 3.8.4 were used as a reference to design and construct concrete structures. To perform the present study, an important example, about reinforced concrete beams, presented in the original work (Braverman et al., 2004) and based on ACI Standard (318–349) and the NRC Standard Review Plan 3.8.4, was selected: a propped cantilever beam.

The fragility modeling procedures applied to degraded concrete beams were used to assess the effects of degradation on plant risk. During fragility methodology application, degradation effects can be quantified with fragility curves for both under-degraded and degraded components. Fragility analysis is a technique for assessing, in probabilistic terms, the capability of an engineered system to withstand a specified event.

Log-normal distributions for the important beam properties are developed both for the under-degraded and degraded conditions. These properties are then used to evaluate the failure probability for the beam. An analytical model has been used for extensive calculation (as recommended in ACI 318-99) and using finite element model (FEM) to verify these results. Plots of load, to sample beam problem, for both the FEM and the hand calculations can be seen in Fig. 1. In the case of beam design and ACI code analysis the first plastic hinge occurs at the support when the loading equals 105 kN/m (7.22 kip/ft) and the second plastic hinge occurs at 3.81 m (12.5 ft) from the fixed support when the load equals 114 kN/m (7.79 kip/ft). In the case of ANSYS beam model, the first plastic hinge forms at 103 kN/m (7.05 kip/ft) and the second plastic hinge forms at 115 kN/m (7.88 kip/ft). The results are presented in Braverman et al. (2004) and agree well. Based on these results, the ACI 318 was used to generate the beam fragility curves shown in Fig. 2.

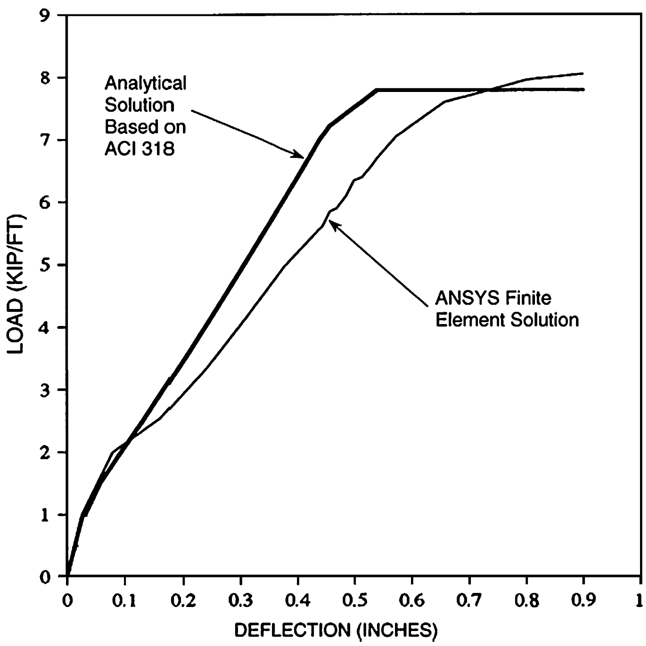

Fig. 1.

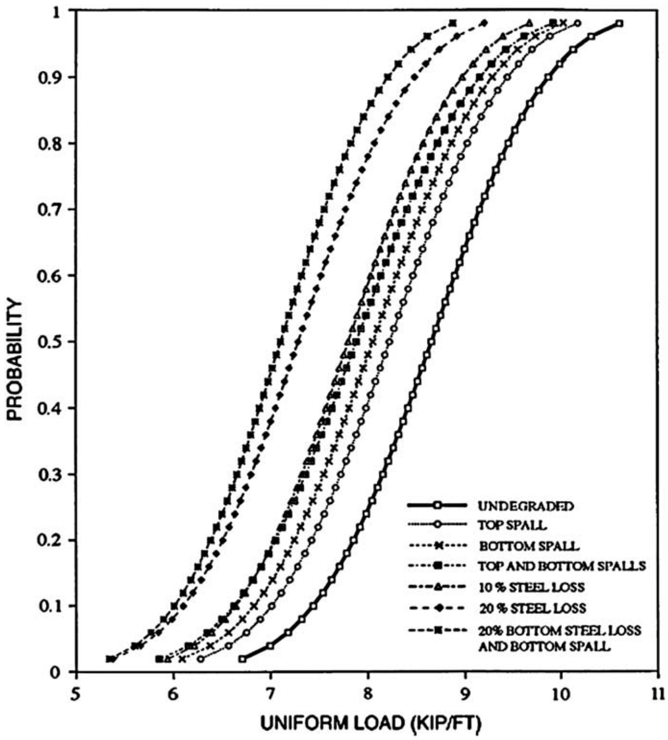

Fig. 2.

Comparative studies were made for different situations. Fragility curves were generated for the under-degraded (benchmark case) and degraded beams (Braverman et al., 2004). Since corrosion can result in loss of steel and concrete spalling (resulting from either freeze–thaw problems or steel corrosion), the combined case of both effects is considered in addition to the individual effects.

3. Adaptive neuro-fuzzy inference system methodology

3.1. ANFIS basic configuration

An ANFIS is a FIS (Fuzzy Inference System) that can be trained with a back-propagation algorithm to model some collection of input/output data. Allowing the system to adapt provides the fuzzy system with the ability to learn the input/output relationships embedded in the collected data. The ANFIS network structure facilitates the computation of a gradient vector that relates the reduction of an error function to a change in the parameters of the FIS. Once this gradient vector is obtained, a number of optimization routines can be applied to reduce the error between the actual and the desired outputs. In the neural network literature, this process is called learning by example (Uhrig et al., 1997). The ANFIS described here uses the Sugeno-style fuzzy model (also known as the TSK fuzzy model) proposed by Takagi and Sugeno (1985) and Sugeno and Kang (1988). Takagi and Sugeno (1985) proposed to use the following fuzzy IF–THEN rules in a general form:

$$\begin{aligned} &L^{(l)}:\ \text{IF } x_1 \text{ is } F_1^l \text{ and } \ldots \text{ and } x_n \text{ is } F_n^l, \\ &\text{THEN } y^l = c_0^l + c_1^l x_1 + \cdots + c_n^l x_n \end{aligned} \tag{1}$$

where F_i^l are fuzzy sets, c_i are real-valued parameters, y^l is the system output due to rule $L^{(l)}$, and $l = 1,2, \ldots, M$. That is, they considered rules whose IF part is fuzzy but whose THEN part is crisp – the output is a linear combination of input variables. For a real-valued input vector $\underline{x} = (x_1, \ldots, x_n)^T$, the output $y(\underline{x})$ of Takagi and Sugeno's fuzzy system is a weighted average of the y^l's:

$$y(\underline{x}) = \left(\sum_{l=1}^{M} w^l y^l\right) \Bigg/ \left(\sum_{l=1}^{M} w^l\right) \tag{2}$$

where the weight w^l implies the overall truth value of the premise of rule $L^{(l)}$ for the input and is calculated as:

$$w^l = \prod\nolimits_{i=1}^{n} \mu F_{li}(x_i) \tag{3}$$

The configuration of Takagi and Sugeno's fuzzy system is shown in Fig. 3. The description of architecture and learning procedure underlying ANFIS can be found with more details in Jang (1993).

3.2. MatLab ANFIS

The software package and its associated fuzzy logic toolbox were used to create the adaptive neural fuzzy inference system. Matlab's ANFIS support first-order Sugeno systems that have a single output and unitary weights for each rule. For ANFIS architectures for Mandani, Tsukamoto and Sugeno fuzzy models, the reader is referred to Jang (1993). Since September 1993, Jang has been with The MathWorks, Inc., working on the fuzzy logic toolbox used with Matlab.

4. System development and obtained results

In this paper, as an illustration for the proposed approach potential, the "20% BOTTOM STEEL LOSS AND BOTTOM SPALL" problem was used for analysis with ANFIS methodology. This is the most severe case associated with severe cracking of concrete observed during a facility inspection.

4.1. Input and output parameters

We defined 29 patterns of load with an increment of 0.1 kip/ft by intervals. These values are presented in Table 1. The deflection and the probability of failure were used as input/output parameters to propitiate a mapping among their behavior using a fuzzy inference system (FIS).

The analytical beam deflection, input data, is presented in Fig. 4a. The fragility curve is presented in Fig. 4b.

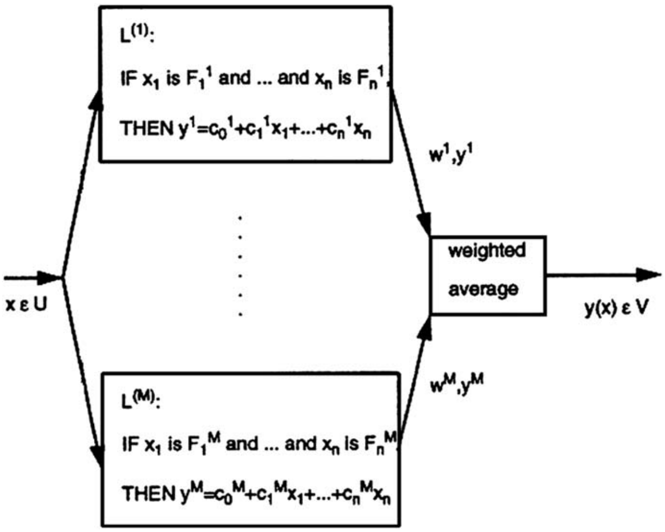

Fig. 3. Basic configuration of Takagi and Sugeno's fuzzy system.

Table 1
Input and output data for ANFIS methodology

Index	Load (kip/ft)	Deflection (inches)	Probability
1	5.0	0.300	0.0511
2	5.1	0.308	0.0515
3	5.2	0.316	0.0555
4	5.3	0.324	0.0529
5	5.4	0.332	0.0538
6	5.5	0.340	0.0583
7	5.6	0.348	0.0662
8	5.7	0.356	0.0776
9	5.8	0.364	0.0924
10	5.9	0.372	0.1105
11	6.0	0.380	0.1319
12	6.1	0.388	0.1564
13	6.2	0.396	0.1839
14	6.3	0.404	0.2143
15	6.4	0.412	0.2474
16	6.5	0.420	0.2831
17	6.6	0.428	0.3211
18	6.7	0.436	0.3613
19	6.8	0.444	0.4034
20	6.9	0.452	0.4471
21	7.0	0.460	0.4923
22	7.1	0.465	0.5386
23	7.2	0.470	0.5858
24	7.3	0.483	0.6335
25	7.4	0.496	0.6815
26	7.5	0.509	0.7293
27	7.6	0.522	0.7766
28	7.7	0.535	0.8230
29	7.8	0.548	0.8682

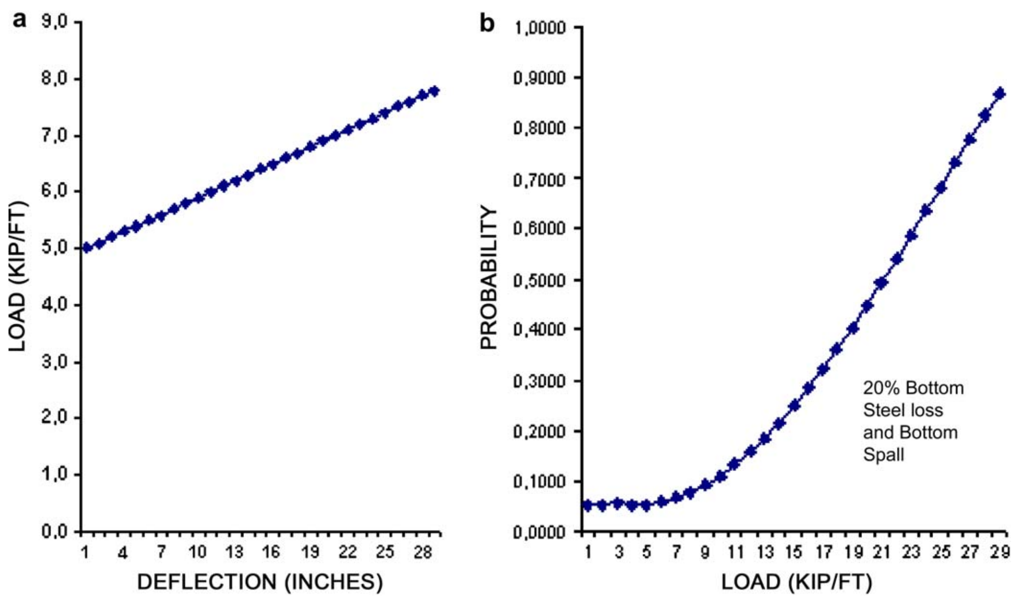

Fig. 4. (a) Analytical beam deflection (1 in. = 25.4 mm; 1 kip/ft = 14.6 kN/m); and (b) fragility curve (probability × load) for only one type of beam degradation condition (1 kip/ft = 14.6 kN/m) − log-normal CDF.

Table 2
Patterns used for ANFIS

Index	Deflection (T)	Probability (T)	Deflection (C)	Probability (C)
1	0.300	0.0511	0.308	0.0515
2	0.316	0.0555	0.324	0.0529
3	0.332	0.0538	0.340	0.0583
4	0.348	0.0662	0.356	0.0776
5	0.364	0.0924	0.372	0.1105
6	0.380	0.1319	0.388	0.1564
7	0.396	0.1839	0.404	0.2143
8	0.412	0.2474	0.420	0.2831
9	0.428	0.3211	0.436	0.3613
10	0.444	0.4034	0.452	0.4471
11	0.460	0.4923	0.465	0.5386
12	0.470	0.5858	0.483	0.6335
13	0.496	0.6815	0.509	0.7293
14	0.522	0.7766	0.535	0.8230
15	0.548	0.8682		

4.2. Training (T), checking (C) and testing data

To train the ANFIS, we used the odd index patterns of the entire data set, which resulted in 15 patterns, while for the checking data set, the even index patterns were used, which yielded a total of 14 validation patterns. The checking set monitors the fuzzy systems' ability to generalize during training (the same principle as cross-validation training in neural network). Basically, each data set contains the maximum and minimum data value for each data pattern in the entire data set. It is important to cover the possible entire span of deflection actuation range so that values will be covered in the membership functions' domain.

The testing of the system was performed with the entire data set, which consisted of 29 patterns. In Table 2, the training (T) and checking (C) data for this application are presented. In Fig. 5a,b graphically the training and the checking data outputs are presented.

The software package and its associated fuzzy logic toolbox were used to create the ANFIS based on the data set defined before. The ANFIS used here supports first-order Sugeno systems that have a single output and unitary

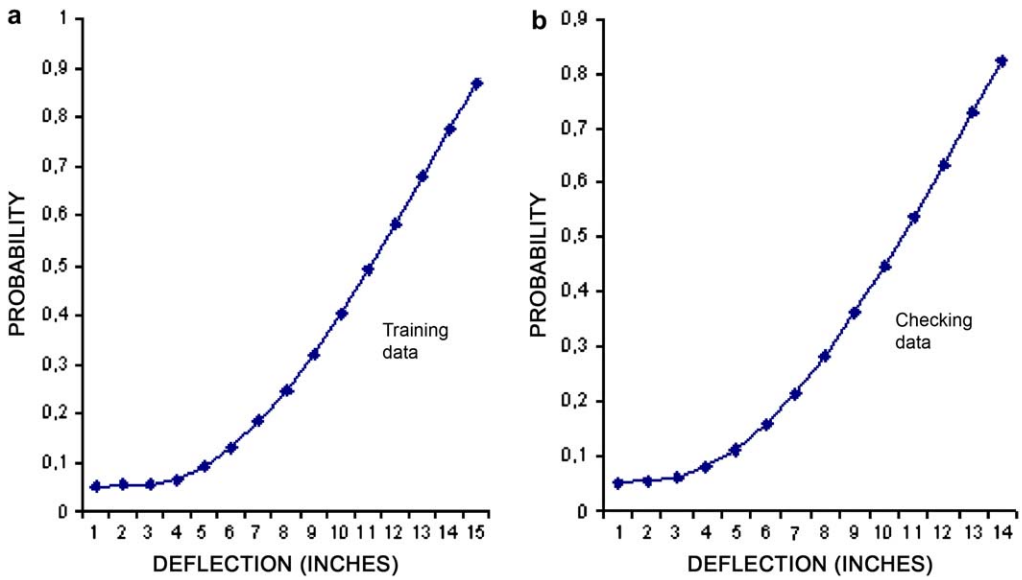

Fig. 5. (a) Training data set for ANFIS obtained of log-normal; and (b) checking data set for ANFIS obtained of log-normal.

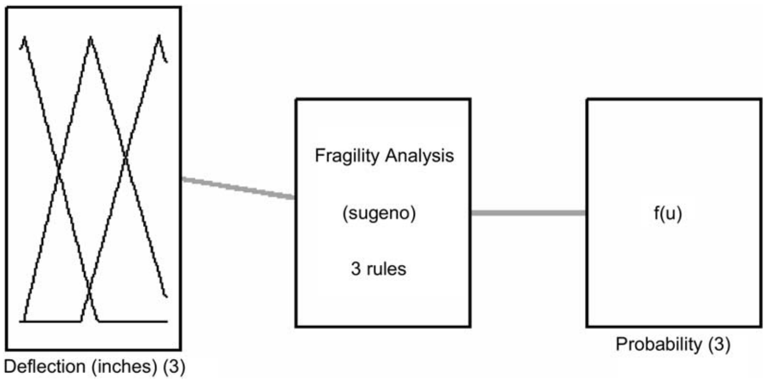

Fig. 6. Sugeno fuzzy inference system.

weights for each rule. A training data set, that contains the desired input/output data pairs of the system, is used to build the system. Another checking data set was used to check the generalization capability of the FIS. The FIS parameters with minimum validation set error are chosen as optimal. The Sugeno FIS is schematically presented in Fig. 6. After some tests with the software simulator, three triangular membership functions were found to be optimal. In Fig. 7, these three membership functions are plotted.

4.3. Final results

The probability of failure as function of the deflection presented by structures is shown in Fig. 8. This relation was constructed using the ANFIS methodology. Based on several postulated states of degradation considered the fragilities curves are nearly parallel to one another (Braverman et al., 2004). The strength of the beam is reduced by less than 18% for the worst cases. The other fragility curves for states of degradation may be obtained promptly using the ANFIS methodology.

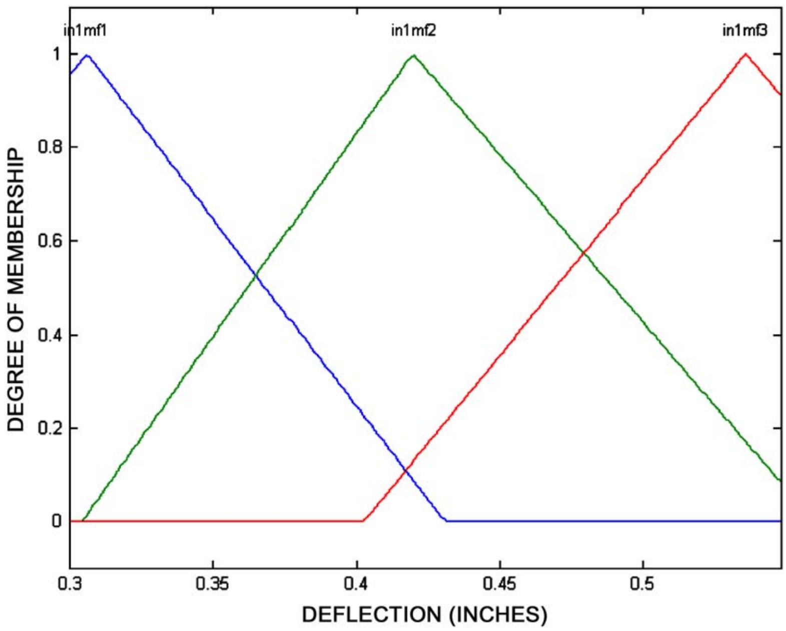

Fig. 7. Membership function of input.

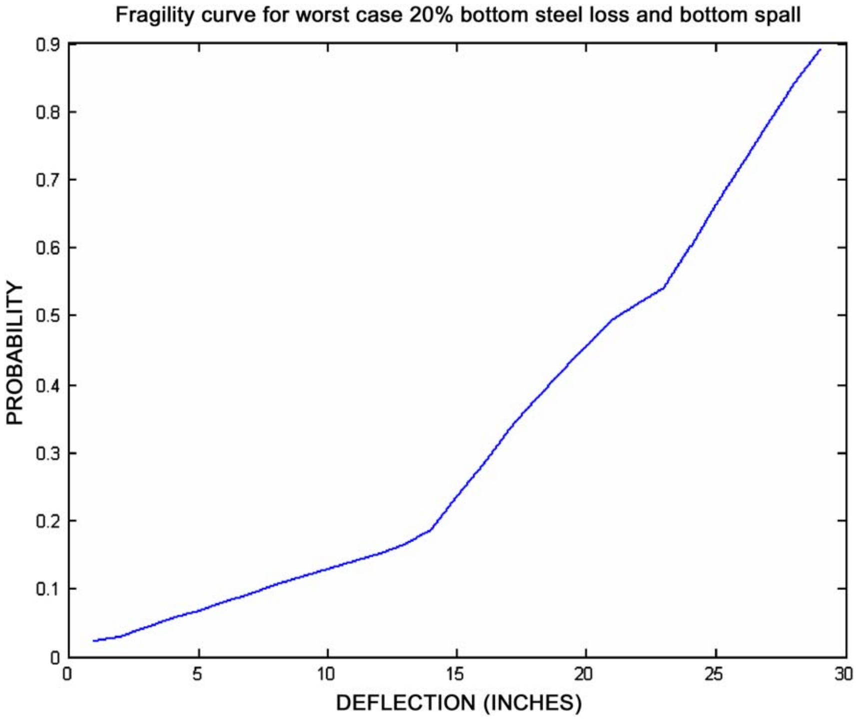

Fig. 8. Predicted fragility curve for worst case of beam degradation.

5. Conclusions

A fuzzy inference system using ANFIS was presented in this paper, as an alternative approach to predict the fragility curve (probability of failure) as a function of the deflection caused by loads on aging structures. This is a preliminary application of this methodology involving degradation of structures and passive components at nuclear power plants.

Usually, to estimate the probability of failure as a function of loads or to construct the relationship between loads and structure deflections extensive calculations are necessary. The obtained result indicates that the degraded structure probability of failure can be estimated from deflection experimental data in a structure. However, this is an initial result and the approach validation needs to be done by realistic experimental case study.

Artificial Intelligence or Probability-based methods, frequently used to determine if levels of degradation have a significant effect on plant risk, normally cannot be used for NRC licensing activities. However, efforts like this (additional methodologies) are important to the engineering team with an independent approach in order to contribute to develop non-official degradation acceptance criteria that could be used as a guide.

References

ACI 349, 2001. Code Requirements for Nuclear Safety Related Concrete Structures. American Concrete Institute, Farmington Hills, MI.

ACI 318-99, 1999. Building Code Requirements for Reinforced Concrete. American Concrete Institute, Farmington Hills, MI.

ANSYS, Finite Element Computer Code, ANSYS Ver. 5.4. ANSYS, Inc., Canonsburg, PA.

Braverman, J.I., Miller, C.A., Hofmayer, C.H., Ellingwood, B.R., Naus, D.J., Chang, T.Y., 2004. Degradation assessment of structures and passive components at nuclear power plants. Nuclear Engineering and Design 228, 283−304.

Braverman, J.I., Hofmayer, C.H., Morante, R.J., Shteyngart, S., Bezler, P., 2000. Assessment of age-related degradation of structures and passive components for U.S. nuclear power plants. Brookhaven National Laboratory, Upton, NY, NUREG/CR-6679.

Guimarães, A.C.F., 2003a. The use of fuzzy logic methodology to establish in-service inspection priorities for nuclear components. Progress in Nuclear Energy 42 (3), 311−322.

Guimarães, A.C.F., 2003b. A new methodology for the study of FAC phenomenon based on fuzzy rule system. Annals of Nuclear Energy 30 (7), 853−864.

Guimarães, A.C.F., Lapa, C.M.F., 2004a. Effects analysis fuzzy inference system in nuclear problems using approximate reasoning. Annals of Nuclear Energy 31 (1), 107−115.

Guimarães, A.C.F., Lapa, C.M.F., 2004b. Fuzzy inference system for evaluating and improving nuclear power plant operating performance. Annals of Nuclear Energy 31 (3), 311−322.

Jang, Jyh-Shing Roger, 1993. ANFIS: adaptive-network-based fuzzy inference system. IEEE Transactions on Systems, Man and Cybernetics 23 (3), 665−685.

Lapa, C.M.F., Sampaio, P.A.B., Pereira, C.M.N.A., 2004. A new approach to designing reduced scale thermal-hydraulic experiments. Nuclear Engineering and Design 229 (2−3), 205−212.

Lapa, C.M.F., Sampaio, C.M.N.A.A., Barros, M.P., 2005. A model for preventive maintenance planning by genetic algorithms based in cost and reliability. Reliability Engineering and Safety System 91 (2), 233−240.

Mol, C.A.A., Almeida, J.C.S., Pereira, C.M.N.A., Marins, E.R., Lapa, C.M.F., 2006. Neural and genetic-based approaches to nuclear transient identification including 'don't know' response. Progress Nuclear Energy 48 (3).

Sugeno, M., Kang, G.T., 1988. Structure identification of fuzzy models. Fuzzy Sets and Systems 28.

Takagi, T., Sugeno, M., 1985. Fuzzy identification of systems and its applications to modeling and control. IEEE Transactions on Systems, Man and Cybernetics SMC-15 (1), 116−132.

Uhrig, R.E., Wrest, D.J., Hines, J.W., 1997. Signal validation using an adaptive neural fuzzy inference system. Nuclear Technology 119, 181−193.