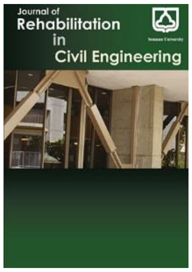
Journal of Rehabilitation in Civil Engineering 8-1 (2020) 75-86



Journal homepage: http://civiljournal.semnan.ac.ir/

Reliability and Sensitivity Analysis of Structures Using Adaptive Neuro-Fuzzy Systems

A. Ghorbani[1] **and M.R. Ghasemi**[2]

1. Assistant Professor, Department of Civil Engineering, Payame Noor University(PNU), 19395-3697 Tehran, I.R. of Iran

2. Professor of Civil Engineering,University of Sistan and Baluchestan,Zahedan, Iran

Corresponding author: *aghorbani@pnu.ac.ir*

ARTICLE INFO

Article history:
Received: 11 July 2017
Accepted: 31 October 2017

Keywords:
Reliability,
Monte Carlo,
Quasi Sensitivity,
Fuzzy Systems.

ABSTRACT

In this study, Adaptive Neuro-Fuzzy Inference System (ANFIS) and Monte Carlo simulation are applied for reliability analysis of structures. The drawback of Monte Carlo Simulation is the amount of computational efforts. ANFIS is capable of approximating structural response for calculating probability of failure, letting the computation burden at much lower cost. In fact, ANFIS derives adaptively an explicit approximation of the implicit limit state functions. To this end, a quasi-sensitivity analysis in consonance with ANFIS was developed for determination of dominant design variables, led to the approximation of the structural failure probability. However, preparation of ANFIS , was preceded using a relaxation-based method developed by which the optimum number of training samples and epochs was obtained. That was introduced to more efficiently reduce the computational time of ANFIS training. The proposed methodology was considered applying some illustrative examples.

1. Introduction

Assessment of structural responses for safe design of structures is inevitable [1,2].

Reliability analysis plays a key role for structural design. The probability of failure (Pf), is usually obtained applying standard reliability analysis methods such as Monte Carlo Simulation (MCS) techniques, the First Order Reliability Methods (FORM) and Second Order Reliability Methods (SORM) [3,4].

Various practical problems can be deliberated involving of any type of probability distribution for the random variables by MCS. It is capable of computing Pf with the desired accuracy [5,6]. However, a great number of structural analyses should be applied letting to rise the computation time excessively. In the case of complicated

DOI: 10.22075/JRCE.2017.11853.1202

structures and their nonlinear behavior, MCS call for enormous structural model [5]. Approximate structural responses could be a noble idea to overcome this drawback of methods in agreement with simulations.

Neural Network (NN) models are proposed for such purposes, recently [7,8]. The combination of NN and MCS can improve the MCS performance [9,10]. On the other hand, both knowledge extraction and knowledge representation are problematic in neural networks. An advanced system, namely, Fuzzy Inference System (FIS) can deal with this type of problem and can model the qualitative characteristics of human data utilizing if-then rules. These systems have to capture the fuzziness of the reasoning process without applying accurate numerical analysis. Consequently, merging these two methodologies constructs Artificial Neural Fuzzy Interference System (ANFIS) [11].

ANFIS has been broadly employed for different purposes such as extrapolation, data discovery and healing [12-15]. In civil engineering, ANFIS has employed to increase the decision-making speed in structural control [16]. ANFIS network was also developed and applied to MCS, improving optimum design of truss structures with probability constraints [17]. Here an attempt is to be performed to merge a modified ANFIS with MCS for sensitivity analysis and structural reliability.

An appropriately trained ANFIS may let the resolve of the structural responses more quickly rather than exact structural analysis. As the number of training samples and epochs for training the ANFIS affects the time and accuracy of the trained network, a relaxation-based method is introduced to reach to the optimum number variables for ANFIS.

Sensitivity analysis is executed to recognize the major parameters affecting safety. The derivative-based approach of sensitivity has the attraction of being very efficient in computer time [18,19]. Derivatives for explicit limit state functions could be easily computed. However, for complex structures, they are not available readily. Applying neural networks, some studies were made to surmount this limitation [20]. However in the present paper, a Quasi Sensitivity Analysis (QSA) in the presence of uncertain inputs using neuro-fuzzy systems is proposed, in order to determine the most influential design variables. Thus, this approach will be employed to estimate Pf with only a certain number of design variables.

2. Reliability Analysis by Monte Carlo Simulation

A reliability problem is normally expressed applying a failure function which is called a Limit State Function (LSF), $g(X)$ where $X = \{x_1, x_2, ..., x_n\}$ is a random vector of design variables. Violation of the LSF is defined by the condition $g(X) \le 0$. P_f is presented by the following expression [21]:

$$P_f = P[g(X) \le 0] = \int_{g(X) \le 0} \int ... \int f_X(X) \mathrm{d}x_1 \mathrm{d}x_2 ... \mathrm{d}x_n \tag{1}$$

$f_X(X)$ is the joint probability density function.

Estimation of P_f via MCS can be given by:

$$P_f = \frac{1}{N} \sum_{i=1}^{N} I(X) \tag{2}$$

where $I(X)$ is:

$$I(X) = \begin{cases} 1 & \text{if } g(X) \le 0 \\ 0 & \text{if } g(X) > 0 \end{cases} \tag{3}$$

According to Eq. (2), N represents the number of independent sets of random design variables. Therefore, P_f is achieved by:

$$P_f = \frac{N_H}{N} \tag{4}$$

where N_H is the total number of cases where LSF would be negative and failure of the structure has occurred.

3. ANFIS Structure

The ANFIS normally consists of a feed-forward network that uses back-propagation learning algorithms and fuzzy reasoning to map inputs into an output. A typical ANFIS architecture with only two inputs leading to four rules and one output for the first order Sugeno fuzzy model is expressed here. Such architecture can be simply adjusted confirming to problem characteristics.

Each input requires two associated Membership Functions (MFs). The MF of a fuzzy set is a generalization of the indicator function in classical sets. In fuzzy logic, it represents the degree of truth as an extension of valuation [22].

A typical rule set with four fuzzy if–then rules that is to say Sugeno fuzzy model can be expressed as [23,24]:

$$\begin{aligned} &\text{Rule 1: if } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_{11} = p_{11}x + q_{11}y + r_{11} \\ &\text{Rule 2: if } x \text{ is } A_1 \text{ and } y \text{ is } B_2 \text{ then } f_{12} = p_{12}x + q_{12}y + r_{12} \\ &\text{Rule 3: if } x \text{ is } A_2 \text{ and } y \text{ is } B_1 \text{ then } f_{21} = p_{21}x + q_{21}y + r_{21} \\ &\text{Rule 4: if } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_{22} = p_{22}x + q_{22}y + r_{22} \end{aligned} \tag{5}$$

where A_1, A_2 are labels representing MFs for the input x. Similarly, B_1 and B_2 are labels for input y. Also, p_{ij}, q_{ij} and r_{ij} ($i, j = 1, 2$) are parameters of the output MFs.

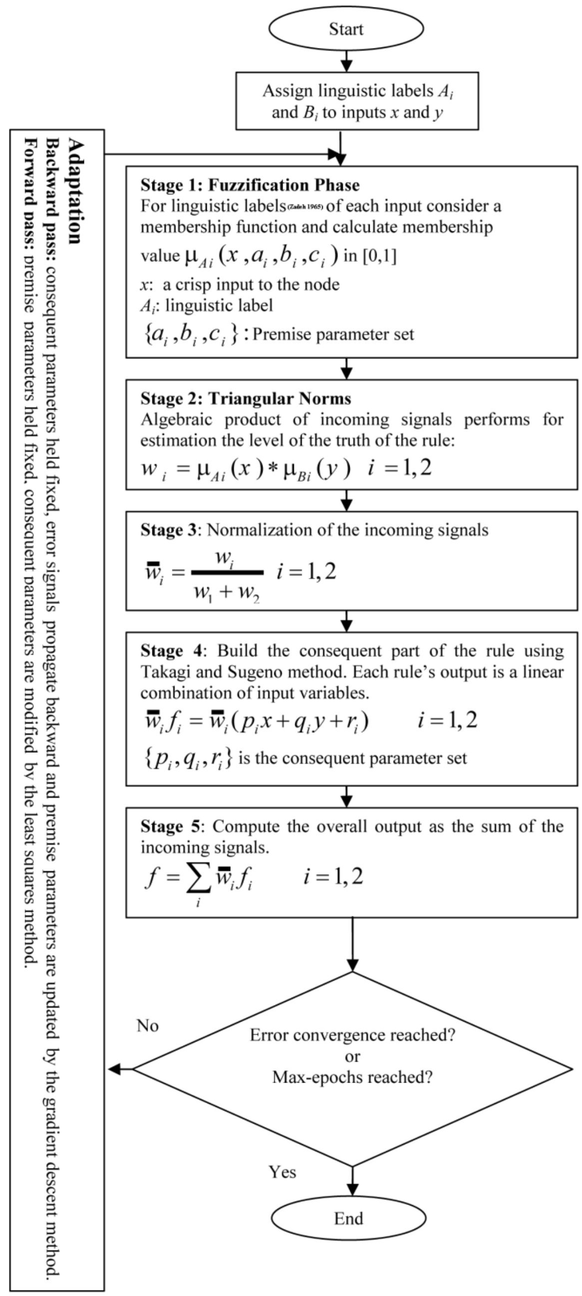


Fig. 1. Flowchart of ANFIS.

An adaptive network is a multi-layer feed forward network in which each node performs a particular function on received signals. Figure 1 illustrates ANFIS architecture as a special configuration of adaptive networks.

Learning process of ANFIS is to adjust all of the modifiable parameters to make the

ANFIS output match the desired output. For this purpose, a two-step process is carried out; the backward pass and the forward pass under a so-called hybrid learning algorithm [25]. In the backward pass, the output MF parameters or consequent parameters (p_i, q_i, r_i) are held fixed, the error signals propagate backward and the input MF parameters or the premise parameters (a_i, b_i, c_i) are updated by the gradient descent method. In the forward pass, premise parameters are held fixed up to stage 4, where the consequent parameters are updated by the least squares method.

4. Quasi Sensitivity Study for Reliability Analysis

Sensitivity analysis may be applying to answer the questions of 'which of the input factors is major in determining the uncertainty in the output of interest?' Or if we could exclude the uncertainty in one of the input elements, which factor should we choose to mostly diminish the change of the output?' [26].

In traditional sensitivity methods, usually the derivatives of the output with respect to the distribution parameters of inputs are deliberated. For most structures, the LSF is an implicit function of design variables. Thus, aiming for reliability analysis of complicated structures in particular; derivatives of the LSFs are not readily available.

One major aim of the present study is, to determine the probability of failure with participation of just some of the input variables. If possible, which inputs are most inflectional in P_f prediction?

To seek those answers, a hybrid ANFIS-MCS methodology, followed then by reliability analysis is innovated. The proposed technique undertakes three main objectives; (1) since the number of training samples and epochs are two essential parameters affecting the accuracy and training time of ANFIS, the first aim is to introduce a relaxation-based scheme through which optimum numbers for training samples and epochs are performed. (2) To focus merely on the most influential design variables, a QSA approach presented here. (3) To allow for the determination of the structural failure probability in a considerable reduction of computational time by merging QSA-based ANFIS with MCS, considering the numerous amounts of analyses encountered the crude MCS.

4.1. Training of the ANFIS

Firstly, the number of epochs is kept fixed to one while the number of training samples is allowed to vary from one to a point where the process may be halt due to some relaxation criteria. Thus, for each training sample, adjustable parameters of ANFIS are modified only once. Using test samples, then the Mean Relative Percentage Error (MRPE) for each set of training samples will be calculated as in Eq. (6):

$$MRPE = \frac{1}{n_t}\sum_{i=1}^{n_t} 100 \times \left(\frac{|p_i - a_i|}{a_i}\right) \quad (6)$$

where a_i and p_i represent actual and predicted values of structural response respectively, and n_t is the number of testing samples.

The variation of MRPE will then relax to a value which indicates a minimum number of training samples required.

As the second stage then, the number of training samples is fixed while the number of epochs is allowed to vary and the corresponding MRPE values are recorded. The convergence history will then be studied through which the minimum number of epochs required will be obtained.

4.2. Determination of Most Influential Design Variables of Structure

The step by step summery of the algorithm to determine the n_i influential design variables from n_d candidates in predicting the LSF, leading thus to the prediction of P_f , is as follows:

a) AInitial parameters of structure are established and n_i is set to 1.
b) Some structures are randomly generated.
c) The structural responses for all members are evaluated using conventional finite element analysis.
d) Structural samples are split into training and testing samples.
e) For each combination of n_i variables from n_d candidates one ANFIS model is built and trains. This leads to a number of n_a ANFIS models where:

$$n_a = \binom{n_d}{n_i} = \frac{(n_d)!}{(n_i)!(n_d - n_i)!} \tag{7}$$

f) Using test samples, MRPE for each model is computed. The variable with relatively minimum MRPE possesses the most influence among all the individual variables. It will then be recorded.
g) The outcome of step (f) will then be combined with a second variable from the list one by one, the minimum MRPE of which will be recorded and thus the corresponding two most influential variables.
h) Step (g) will be repeated adding more variables, until no further considerable reduction of MRPE is observed. Therein, we say a relaxation of the global minimum MRPE is taken place.
i) End of algorithm.

5. Examples

In this section, two high nonlinear examples as explicit and implicit LS functions are presented.

5.1. Example 1

A bumpy multidimensional LSF [27,28] is attempted in the first example, where:

$$g(X) = x_1 + 2x_2 + 2x_3 + x_4 - 5x_5 - 5x_6 + 0.001\sum_{i=1}^{6}\sin(1000.x_i) \tag{8}$$

The statistics of the related six random variables are listed in Table 1.

Table 1. random variables - Example 1.

Variable	Mean	Standard deviation	Distribution
x_1	120	12	Lognormal
x_2	120	12	Lognormal
x_3	120	12	Lognormal
x_4	120	12	Lognormal
x_5	50	15	Lognormal
x_6	40	12	Lognormal

5.1.1. Determination of Relaxed Number of Training Samples and Epochs – Example 1

In this example, the design variable vector $X = \{x_1, x_2, x_3, x_4, x_5, x_6\}$ is selected as input of the ANFIS. LSF value is also taken as the output of the ANFIS. A generalized bell type MF as in Eq. (9) is contemplated for calculating the membership value of the linguistic labels.

$$\mu_{Li}(x) = \frac{1}{1+(\frac{x-c_i}{a_i})^{2b_i}} \tag{9}$$

where μ_{Li} and $\{a_i, b_i, c_i\}$ are the membership function for i^{th} linguistic label and premise parameters set, respectively. Two rules for each MF are considered.

Confirming to the expressions in section 4.1, training of ANFIS was attempted using different number of samples. The reason was to study relaxation of MRPE for a certain number of test samples. In other words, although the ANFIS could be trained applying any number of training samples as small as 50; however, the test samples may not be satisfied as far as the MRPE is concerned. Therefore, a thorough investigation was made to obtain the least amount of training samples for which any number of test samples could result satisfactorily. As a result, two figures are produced. In Fig. 2, relaxation for number of training samples using different number of test samples is presented. It is found that MRPE variations are converged to a relax number of 400 training samples with the corresponding MRPE of 0.061%. By fixing the training samples to 400, number of epochs was allowed to vary. Figure 3 portrays that by increasing the number of epochs from 1 to 100, MRPE does not change considerably and only drops off from 0.061% to 0.059%. Therefore, number of training samples and epochs were fixed to relaxed values of 400 and 1, respectively, for ANFIS model.

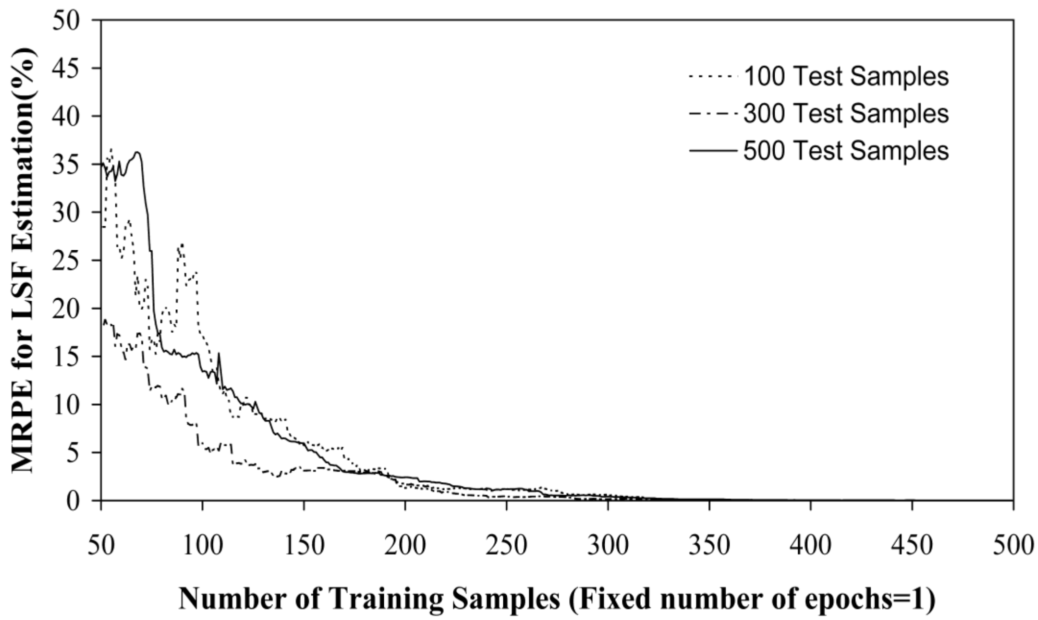


Fig. 2. MRPE versus number of training samples - Example 1.

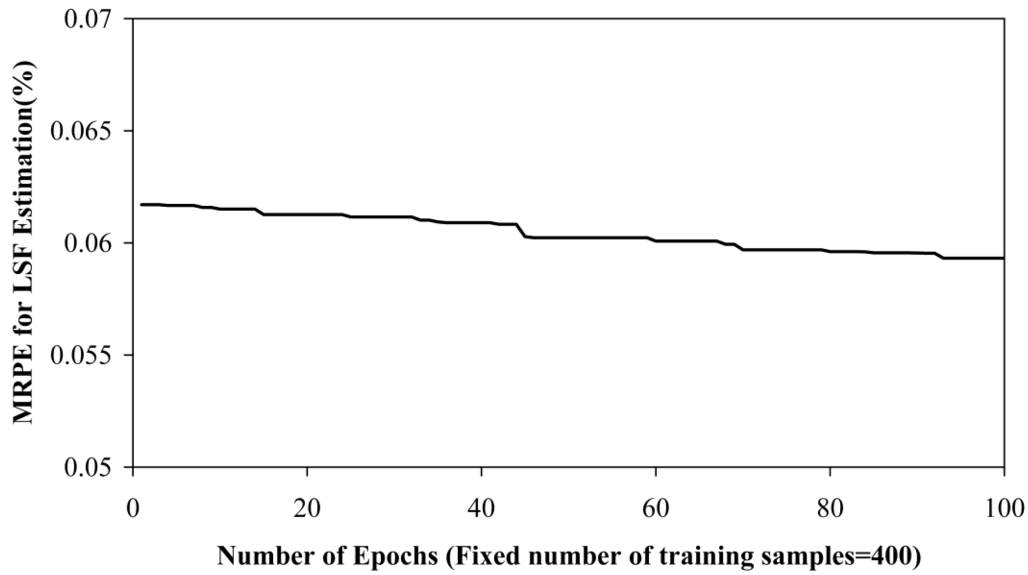


Fig. 3. MRPE versus epochs - Example 1.

5.1.2. Determination of Most Influential Design Variables - Example 1

Here, the idea is to investigate whether it is possible to eliminate the least important design variables. Therefore a QSA technique, described in section 4.3 is implemented. To this end, from the total of 6 candidates, various combinations of design variables from 1 to a maximum of 6 were attempted.

It was observed that among 6 variables, x_5 is mostly influences the LSF. This is clearly demonstrated in Table 2 where the corresponding QSA has the least MRPE. The verification of what accomplished was made applying the sigma-normalized derivatives based on Eq. (10) where:

$$S_{x_i}^{\sigma} = \frac{\sigma_{x_i}}{\sigma_g} \cdot \frac{\partial g}{\partial x_i} \qquad (10)$$

As listed in Table 2, the results obtained reveal that x_5 is most dominant, considering that a cosine function alters between -1 and 1.

Furthermore, by studying the MRPE in Table 2, it can be deduced that the order of importance of the design variables is $x_5 > x_6 > x_3 \geq x_2 > x_1 \geq x_4$ which is in agreement with the traditional sensitivity analysis results using Eq. (10).

Table 2. Results for QSA - Example 1.

Design variable	MRPE (QSA)	$S_{x_i}^{\sigma}$
x_1	72.45%	$S_{x1} = \frac{12}{\sigma_g}[1+\cos(1000x_1)]$
x_2	70.81%	$S_{x2} = \frac{12}{\sigma_g}[2+\cos(1000x_2)]$
x_3	70.79%	$S_{x3} = \frac{12}{\sigma_g}[2+\cos(1000x_3)]$
x_4	72.98%	$S_{x4} = \frac{12}{\sigma_g}[1+\cos(1000x_4)]$
x_5	46.45%	$S_{x5} = \frac{15}{\sigma_g}[-5+\cos(1000x_5)]$
x_6	50.64%	$S_{x6} = \frac{12}{\sigma_g}[-5+\cos(1000x_6)]$

The QSA depended MRPE results for different combinations of Design Variables (D.V.) are listed in Table 3, where a smooth convergence history was detected while removing the least important D.V. of 1.

Final results for calculating the probability of failure has been summarized in Table 4. It is displayed that the number of LSF evaluation is reduced drastically in comparison with crude MCS. On the other hand, reduction in input space of ANFIS to only 5 variables, decreased the computing time to a relative reduction of 15.8%. As listed, the P_f drifts are negligible in proposed methods highlighted in rows 4 and 5 of Table 4, compared to the crude MCS of row 1. Additionally, a comparison between results of the proposed method and those by Cheng (2007)[28] were made and documented in that table. As it is evident, ANFIS based methods applying less training samples matched more closely the MCS results listed as Reference values.

Table 3. Results for predicting most influential variables - Example 1.

Number of variables from 6 candidates	Optimal combination	MRPE
1	5	46.45%
2	5,6	16.65%
3	5,6,3	13.73%
4	5,6,3,2	8.58%
5	5,6,3,2,4	4.19%
6	5,6,3,2,4,1	0.30%

Table 4. Final results for reliability analysis - Example 1.

Method	Number of LSF evaluation	p_f	Error
Crude MCS[27]	100000	0.0121	–
GA–ANN [28]	2600	0.00845	– 30.2%
GA–ANN–MCSIS [28]	1050	0.0124	2.5%
MCS–ANFIS - all variables	400	0.0123	1.65%
MCS–ANFIS - 5 influential variables	400	0.0126	4.13%

5.2. Example 2

A two-dimensional frame as shown in Fig. 4 is considered [28]. This example as an implicit LSF is selected in order to show the efficiency of the proposed approach to apply for a wide range of the actual structures.

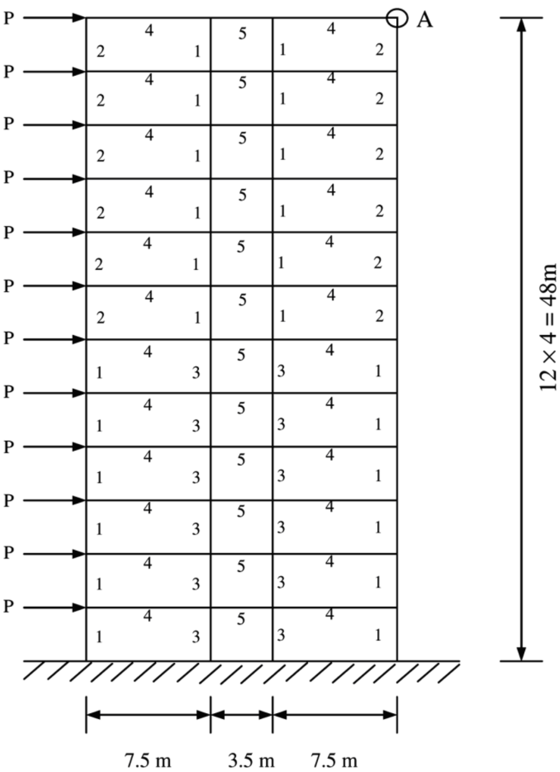


Fig. 4. Linear portal frame - Example 2.

Different cross sectional areas A_i and horizontal load P are treated as independent random variables. The probabilistic distribution of their design variables are listed in Table 5. The sectional moments of inertia are expressed as $I_i = \alpha_i A_i^2$ ($\alpha_1 = \alpha_2 = \alpha_3 = 0.08333,\ \alpha_4 = 0.26670,\ \alpha_5 = 0.2000$). The Young's modulus E is treated as deterministic being equal to $2.0 \times 10^7 \, KN/m^2$.

The five element types of the structure are illustrates in Figure 4. The frame is recorded as a failure whenever its horizontal displacement u_A at node A, exceeds 0.096 m. Therefore, one could express the LSF as:

$$g(A_1, A_2, A_3, A_4, A_5, P) = 0.096 - u_A(A_1, A_2, A_3, A_4, A_5, P) \tag{11}$$

Table 5. random variables - Example 2.

Random Variable	Mean	Standard deviation	Distribution
A_1 (m^2)	0.25	0.025	Lognormal
A_2 (m^2)	0.16	0.016	Lognormal
A_3 (m^2)	0.36	0.036	Lognormal
A_4 (m^2)	0.20	0.020	Lognormal
A_5 (m^2)	0.15	0.015	Lognormal
P (KN)	30.0	7.5	Type I largest

5.2.1. Determination of Relaxed Number of Training Samples and Epochs – Example 2

In this example, the design variable vector for the frame structure $X = \{A_1, A_2, A_3, A_4, A_5, P\}$ is selected as the input for the ANFIS. Displacement of node *A* is considered as the output. Like Example 1, bell type MF is applied in ANFIS models.

In Figure 5, the MRPE variation versus the increment of number of training samples is recorded, while keeping number of epochs equal to one. As illustrated in the figure, one realizes that after 300 training samples, the MRPE is independent of the number of test samples. This indicates a relaxation on the least number of training samples after which the exceeded number of training samples is just ineffective as far as the accuracy of LSF estimation is concerned.

Having fixed the number of training samples to 300 then, the variation of number of epochs was studied aiming for minimum sufficiency. The history of convergence of MRPE for LSF prediction against number of epochs is shown in Figure 6, where the epoch number is relaxed to 80, after which no reduction of MRPE is recorded.

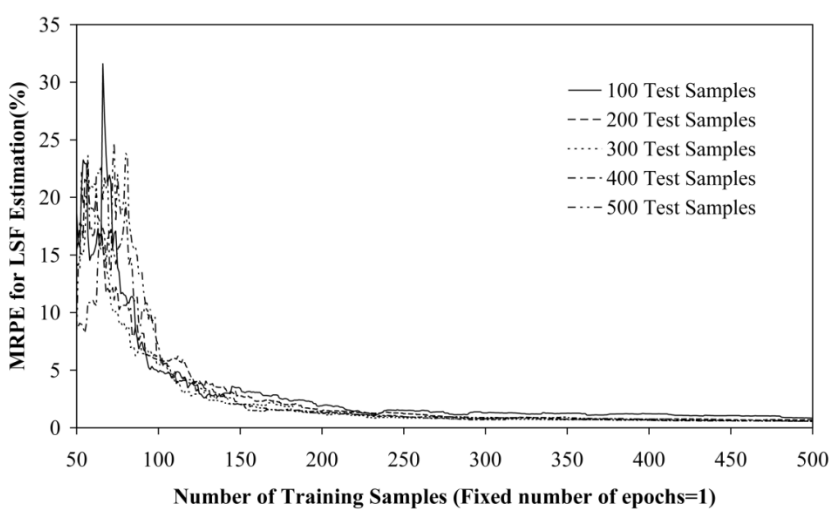


Fig. 5. MRPE versus training samples - Example 2.

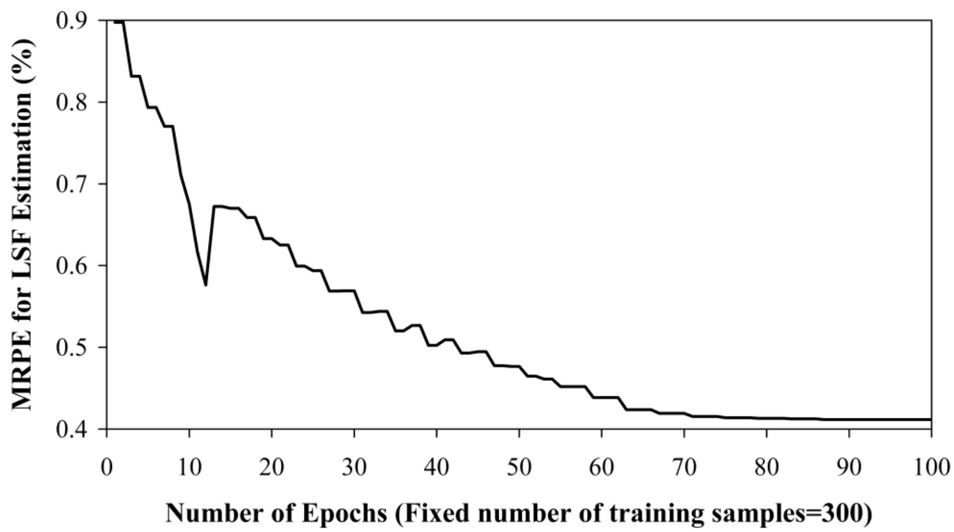


Fig. 6. MRPE versus epochs - Example 2.

Training of ANFIS model for reliability and sensitivity analysis was therefore processed applying 300 training samples with 80 epochs.

5.2.2. Determination of Most Influential Design Variables - Example 2

The study results of combined most influential variables are given in Table 6.

Using QSA, valued statistics about the status of the design variables is in hand. It was found that the lateral load *P* is the most influential variable in this example. Bottom corner columns are the next important parameters which is meaningful in practice. This could be as a result to their key role in lateral resistance in a flexural frame. Moreover, beams with A_4 cross sectional areas covering most of the elements in the frame are in the third level of importance.

As exhibited in Table 6, the 3th combination has been relaxed to a 3.69% MRPE value, after which a negligible reduction on its value is observed. So reliability analysis applying MCS-ANFIS method was performed using only the 3 most important design variables being P, A_1 and A_4.

The structural failure probability was then obtained through the ANFIS. The results were then compared with those of crude MCS and GA-ANN [28] as listed in Table 7. The normalized CPU time illustrated in Table 7 indicates a numerous computational time reduction using the proposed method. It is inferred that ANFIS-MCS method can derive a well-intentioned estimate of the implicit LSF through only few training samples. Through applying ANFIS, the approximation function written in an explicit form, once found, will be directly used instead of conducting deterministic Finite Element Analysis (FEA). The calculation of an explicit function requires only a fraction of a second compared to FEA requiring relatively extensive computational time.

Table 6. Results for predicting most influential variables - Example 2.

Number of variables from 6 candidates	Optimal combination of design Variables	*MRPE*
1	P	8.29%
2	P, A_1	5.54%
3	P, A_1, A_4	3.69%
4	P, A_1, A_4, A_3	3.67%

Table 7. Final results for reliability analysis - Example 2.

Method	Number of FEA	p_f	Error	Normalized CPU time
Crude MCS	100000	0.0751	-	1
GA–ANN [3]	5210	0.0718	–4.3%	Not available
MCS–ANFIS - all variables	300	0.0744	–0.9%	0.0096
MCS–ANFIS - 3 influential variables)	300	0.0776	3.2%	0.0078

6. Conclusion

An effective methodology is accessible for reliability analysis of structures employing MCS and ANFIS. The approximate concepts that are innate in reliability analysis motivated the use of ANFIS.

The computational efforts involved in the crude MCS come to be too much in large scale problems because of the massive sample size and the computing time required for each MCS run. The use of ANFIS can practically diminish any constraint on the scale of the problem. Moreover, the sample size used for MCS provided that the predicted LSF, corresponding to different simulations, fall within acceptable tolerances. It was also inferred that, contrary to neural network applications in other field of computational structural mechanics, the present application demonstrated a considerable robustness with regard to selection of training samples and epochs in estimating the probability of failure. The selection criterion involved a relaxation method to be introduced to extract the operational number of samples and epochs for training ANFIS. The proposed method confirmed to be independent on the type of structure or the type of the required analysis.

A sensitivity method in consonance with ANFIS called quasi sensitivity analysis was developed and validated to discover most influential variables and compute probability of failure using a reduced vector of input variables. The power behind this method was found to be in ANFIS abilities for nonlinear function estimation.

The numerical examples illustrated the application and the effectiveness of the proposed method. Comparisons were made possible with an analytic method based on derivatives of the LSF. It was demonstrated through some examples that the performed method provided accurate results and was computationally efficient for estimating the failure probability of structures.

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