Structural Engineering and Mechanics, *Vol. 47, No. 3 (2013) 401-419*
DOI: http://dx.doi.org/10.12989/sem.2013.47.3.401

Effects of infill walls on RC buildings under time history loading using genetic programming and neuro-fuzzy

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(Received August 24, 2012, Revised June 11, 2013, Accepted July 31, 2013)

Abstract. In this study, the efficiency of adaptive neuro-fuzzy inference system (ANFIS) and genetic expression programming (GEP) in predicting the effects of infill walls on base reactions and roof drift of reinforced concrete frames were investigated. Current standards generally consider weight and fundamental period of structures in predicting base reactions and roof drift of structures by neglecting numbers of floors, bays, shear walls and infilled bays. Number of stories, number of bays in *x* and *y* directions, ratio of shear wall areas to the floor area, ratio of bays with infilled walls to total number bays and existence of open story were selected as parameters in GEP and ANFIS modeling. GEP and ANFIS have been widely used as alternative approaches to model complex systems. The effects of these parameters on base reactions and roof drift of RC frames were studied using 3D finite element method on 216 building models. Results obtained from 3D FEM models were used to in training and testing ANFIS and GEP models. In ANFIS and GEP models, number of floors, number of bays, ratio of shear walls and ratio of infilled bays were selected as input parameters, and base reactions and roof drifts were selected as output parameters. Results showed that the ANFIS and GEP models are capable of accurately predicting the base reactions and roof drifts of RC frames used in the training and testing phase of the study. The GEP model results better prediction compared to ANFIS model.

Keywords: infill wall; base reactions; roof drift; time history analysis; ANFIS; GEP

1. Introduction

In structural analysis, the effects of infill walls are usually ignored during the design process. Several studies were investigated the contribution of these elements to building stiffness, strength and damping properties. The building performance and expected level of damage have affected by the distribution and amount of partition walls per unit floor area. So, the strength and deformability of non-structural elements have significant impact on the performance of buildings. Also, under dynamic forces, behavior of buildings depends upon mass and stiffness properties of buildings. So, in design process, any non-structural element should be taken into account (Kose and Karslioglu 2011).

The structural elements and non-structural elements are affected by the lateral deflection and drift. The non-structural elements experience deflections and rotations similar to the structural

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http://www.techno-press.org/?journal=sem&subpage=8 ISSN: 1225-4568 (Print), 1598-6217 (Online)

system although they are generally ignored during the design process. The non-structural elements should be designed in a way that they do not interfere with the expected movement of the structural system in case of any lateral deflection. Otherwise, the non-structural elements lead to create short columns, torsion, or stiffness irregularities in the structural system.

The design base shear is simply calculated by current code equations. However, current code equations do not provide any equation to estimate the vertical force distribution on the base of the structure. Dynamic analysis becomes advantageous but costly and time consuming compared to code equations to obtain the vertical force distribution on the base of the structure.

In modern multistory structures, ground floors are generally designed as open story without infill walls and higher story height compared to upper floors due to the commercial stores or reception lobbies in the entrance. Existence of such an open story in ground floor can cause soft story formation and largely affect behavior of the structure in case of an earthquake.

Neuro-fuzzy inference system and genetic expression programming (GEP) have been widely used to model the complex relationship between the input parameters and output of the engineering problems (Fonseca *et al*. 2003, Darus and Al-Khafaji *et al*. 2012, Zheng *et al*. 2011, Vieira *et al*. 2004, Štemberk *et al*. 2013).

The objective of this study is to investigate the usability of neuro-fuzzy inference system (ANFIS) and genetic expression programming (GEP) in predicting the base ractions and roof drifts of RC frames. Results from a study (Kose and Karslioglu 2011) were used in training and testing phase of ANFIS and GEP approaches. 216 computational results in total were used to investigate the effects of the infill walls to the base shear, normal base reaction and the roof drift of the structures. In this study, number of floors, number of bays, ratio the infilled bays to the total number of bays, ratio of the area of the shear walls to the total area of the floor and the existence of open floor were selected as parameters. Complex relationship between the number of floors, number of bays, ratio of shear walls and ratio of infilled bays and base reactions and roof drifts of RC frames can be easily modeled by use ANFIS and GEP approach unlike statistical models.

2. Selected data

Results obtained from a study (Kose and Karslioglu 2011) were used in training and testing phase of ANFIS and GEP models. In that study, building models were divided in two groups. In the first group of the models, entrance floor was designed as open floor. There are no internal infill walls between the columns in open floor. In the second group of the models, entrance floor was designed as residential floor. The number of bays was selected as 3, 4 and 5 in both directions. The ratio of the number of infilled bays to the total number of bays was selected as 0%, 40-50%, 50-70% and 70-90%. The ratio of the total areas of the shear walls to the floor area was selected as 0%, 0.5% and 1%, and the number of upper floors was selected as 5, 7 and 10. Infill walls were modeled as structural members with mass. Using these combinations, 216 3-dimensional computer models were prepared and analyzed.

In computer models, frame elements were used to model beams and columns. The equivalent diagonal compression strut elements were used to model the effects of infill walls and these strut elements were connected to the structural system by hinge connection. Plate elements were used to model shear walls and slabs. Area mass elements were used to model mass of the infill walls. Window opening of 120x120 cm were assumed in all exterior infill walls and there was no opening in all interior infill walls. All computer models were generated and analyzed in SAP2000

(CSI 2006) using nonlinear time history analysis. Bingol earthquake was used in time history analysis. Since symmetrical floor plans on *x*- and *y*- directions were used, time history loading was applied only on *x*-direction.

3. Current code equations for storey drift and base shear

3.1 Storey drift limitations

In Eurocode 8 (2003), interstorey drift is limited to about 1% of storey height for general structures. UBC (1997) requires that storey drift be limited to 0.025h for short period structures and 0.020h for long period structures. The intent of the code was to limit the interstorey drift to a reasonable value, beyond which it was thought that the structure might experience loss of vertical stability. UBC also allows these limits to be exceeded, provided that the greater drift could be tolerated by both structural elements and nonstructural elements that could affect life safety.

3.2 Base shear equations

In UBC (1997), the static base shear, *V*, equation is given as

$$0.11C_a IW \leq V = \left(\frac{C_v I}{RT}\right) W \leq \left(\frac{2.5C_a I}{R}\right) W \tag{1}$$

where, C_a and C_v are acceleration spectrum coefficient and velocity spectrum coefficient, respectively.
Coefficient *I* is importance factor and varies between 1.0 and 1.25. *W* is the total weight of the building. Coefficient *R* is response modification factor which accounts for building ductility and damping. Coefficient *T* is fundamental period of the structure.

However, in Eurocode 8 (2003), base shear, F_b is given as

$$F_b = S_d(T_1)W \tag{2}$$

where $S_d(T)$ stands for the design spectrum which is normalized by the acceleration of gravity, g. T_1 is fundamental period of the building.

3. Genetic Expression Programming (GEP)

GEP which is a new algorithm based on genetic algorithms (GA) and genetic programming (GP) was developed by Ferreira (2001). In this method, a computer program is encoded in linear chromosomes of fixed-length. For the main process, GEP utilizes the most of the genetic operators of GA such as selection, mutation and recombination. Its principal goal is to develop a mathematical function that fits to a set of data presented it (Muñoz 2005, Cevik 2007). The basic algorithm of genetic expression programing which needs five elements such as the function set, terminal set, fitness function, control parameters and stop condition is sketched in Fig. 1. Before a GEP model is configured, the fitness function is designated and then the algorithm encodes the problem by composing randomly an initial population of viable individuals (chromosomes). The

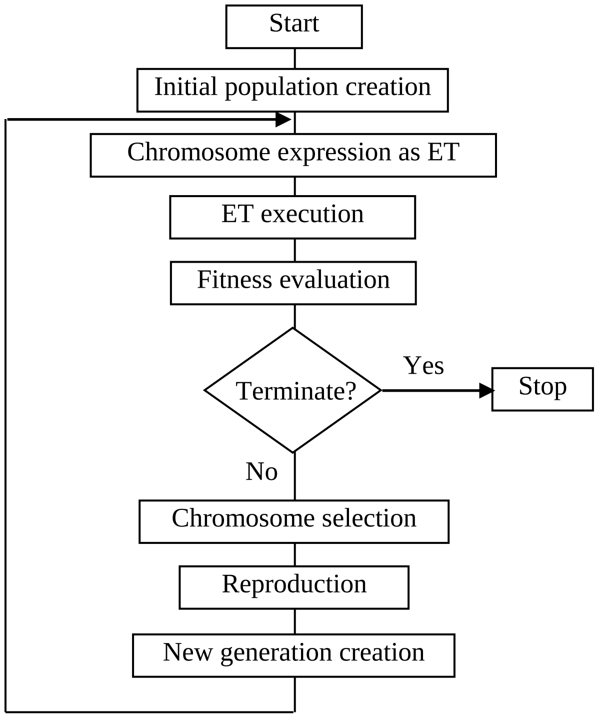
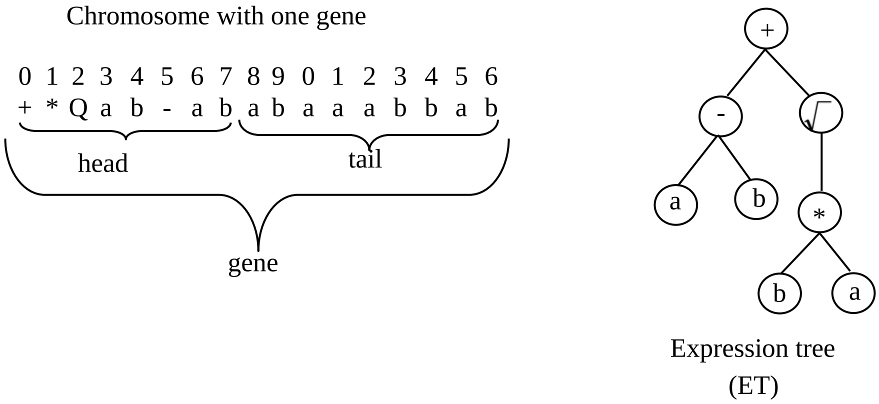


Fig. 1 The algorithm of genetic expression programing (Eurocode 8 2003)



$$(a-b)+\sqrt{(a*b)}$$

Corresponding mathematical equation

Fig. 2 Schematic indication of a chromosome with one gene and its expression tree and corresponding mathematical equation

each chromosome is converted into an expression tree corresponding to a mathematical expression fits to the data presented to it. The last step of the GEP process is that the results obtained from mathematical expression are compared with the actual values according to the fitness score of each chromosome. If the desired error level is not achieved some chromosomes are selected using roulette-wheel sampling and then mutated to obtain the new generations. If the results are satisfactory, the algorithm is stopped and then the knowledge that is encoded in a chromosome is decoded for the best solutions of the problem (Teodorescu and Sherwood 2008, Sherrwood 2008).

The chromosomes and the expression trees are primary elements of GEP structure. The chromosomes can contain one or more genes that correspond to a mathematical expression. For coding of a gene, a special language known as Karva Language which has two types such as the language of the genes and the language of the expression trees (ET) is employed. The genes are separated two parts with the head and the tail. The mathematical operators, variables and constants such as +, -, *, /, $\sqrt{\ }$, sin, cos, 1, a, b, c that are employed for coding a mathematical expression are in the head. In the tail, there are only variables and constants such as 1, a, b, c known as Terminal Symbols which is used when the symbols in the head are deficient. Fig. 2 indicates a simple chromosome as linear string with one gene and its ET and the corresponding mathematical equation. On the other hand, more than one chromosome called multigenic chromosomes may be used for definition of more complex mathematical equations. The genes in the chromosomes are joined by linking function such as addition, subtraction, multiplication, or division.

Several operators are used for the modifications of chromosomes for the next generation. Selection of chromosomes is used to select the chromosome that is mutated by applying the method the roulette-wheel sampling. So, new offspring with higher probability is obtained. Mutation of chromosomes is used to change the any symbols which define the genetic codes of any chromosome. Transposition of chromosomes is used to duplicate and carry the part of chromosome to another location. Finally, Recombination (Cross-over) arranges the changed information of a chromosome.

4. Adaptive Neuro-Fuzzy Inference System (ANFIS)

There is crisp definition in classical set theory for belonging of a variable to a set. It belongs to a set or not. Whereas, there is a softer answer in fuzzy theory introduced by Lotfi Zadeh (Zadeh 1965). According this theory a variable may partially belong to a set with continuous membership functions which vary between 0 and 1 (Zadeh 1965, Topcu and Saridemir 2008). In general, two types of fuzzy approach are employed known as Mamdani and Tagagi-Sugeno (TS) (Takagi and Sugeno 1985). In the Mamdani fuzzy approach, the human expertise and linguistic knowledge's is used to design the membership functions and if-then rules. There some superiorities in TS model, since the model parameters and the membership functions are selected by using optimization and adaptive techniques and also the output membership function is simpler constructed as either linear or constant (Tutmez and Tercan 2007, Shahin *et al*. 2003).

ANFIS that is suggested by Jang (1993) uses some properties of artificial neural network (ANN) such as learning and parallelism. It generates adaptively fuzzy rules and membership functions by neuro training process with data that is presented to it. Two methods are used for this aim such as grid partitioning and subtractive clustering. An example of if-then rules of sugeno type fuzzy inference system with Linear function (Padmini *et al*. 22) that is referred as first-order is shown as below.

$$\text{If } x=A_1 \text{ and } y=B_1 \text{ then } f_{1(x,y)}=p_1x+q_1y+k_1 \tag{3}$$

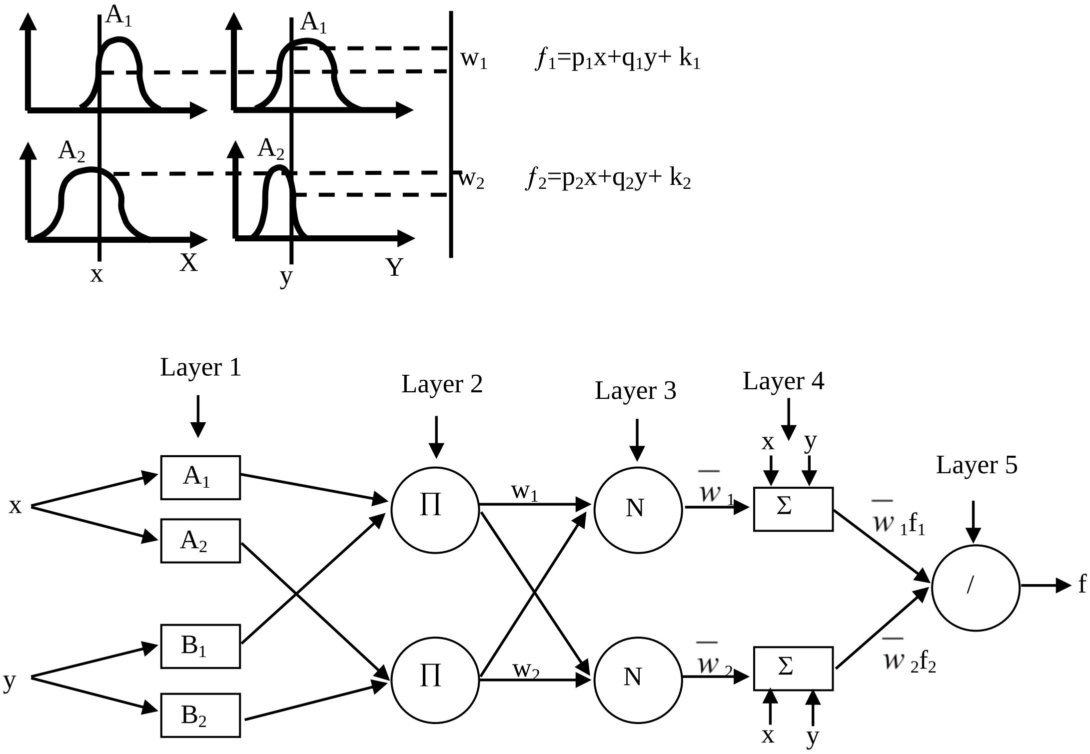


Fig. 3 First order TS model reasoning and ANFIS architecture (Padmini *et al*. 2008)

where x (or y) : the input node, i, p, q and k: the consequence parameters obtained from the training, A: the label of fuzzy set defined suitable membership function.

In order to enhance the membership functions, one of the methods that are a hybrid learning algorithm and backpropagation learning algorithm is employed. They are described in detail in Demuth and Beale (2001). The simple indication and algorithm of first order TS model reasoning is sketched in Fig. 3 in which the mathematical process is performed in five layers. In first stage, the value of the ith node is calculated using the equation below

$$U_{1,i}=\eta A_i(x) \text{ for } i=1,2 \text{ or} \tag{4}$$

$$U_{1,i}=\eta B_{i-2}(x) \text{ for } i=3,4 \tag{5}$$

where η=The membership function

$U_{2,i}$ is defined as product of the incoming signals using following equation in second stage in which the nodes are represented as the fire strength of the rule.

$$U_{2,i}=w_i==\eta A_i(x)\eta B_i(y) \quad i=1,2 \tag{6}$$

In subsequent stage, firing strengths are normalized, this shows the ratio of the ith rule's firing strength versus all rules' firing strength are computed by following equation

$$U_{3,i}=U_{3,i}=\overline{w_i}=\frac{w_i}{w_1+w_2}, \qquad i=1,2 \tag{7}$$

Table 1 Parameters used in GEP Models

	Model-R_d	Model-F_x	Model-F_z	Model-M_y
Generation	3243	99266	262350	620824
Program size	63	37	54	38
Number of the genes	5	4	4	3
Length of the gene head	10	8	10	8
Max. fitness	1000			
Linking function	+			
Function set	+, -, *, /, $\sqrt{}$,exp,log, sin, cos, arctan			
Mutation rate	0.044			
One-point recombination rate	0.3			
Two-point recombination rate	0.3			
Inversion rate	0.1			
Transposition rate	0.1			

The contribution of the *i*th rule to output is calculated by using equation given below in fourth stage

$$U_{4,i} = \overline{w_i}\, f_i = \overline{w_i}\,(p_i x + q_i y + k_i) \tag{8}$$

where $\overline{w}$: the normalized firing strength found from layer, p_i, q_i and k_i: the consequent parameters. As a last calculation, the final output of the ANFIS is calculated by the equation below

$$U_{5,i} = \sum_i \overline{w_i}\, f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{9}$$

5. Model development using GEP and ANFIS

5.1 GEP model development

The fundamental aim of development of GEP models was to generate the mathematical functions for the prediction of the base reactions and roof drift of reinforced concrete frames. The GEP Model has five input parameters; number of stories, number of bays in *x* and *y* directions, ratio of shear wall areas to the floor area, ratio of bays with infilled walls to total number bays and existence of open story. The parameters used in GEP model developments were given in Table 1.

GEP model was prepared and analyzed by DTREG software (Jang 1993). The maximum numbers of generations was 1793 in training of GEP model. The functions obtained for base reactions and roof drift from the GEP model were given in the followings

$$Fx = Cos\left(x1 + \frac{x3}{-x1 + x4 - \frac{x4}{x1}}\right) + Cos\left(Cos\left(\frac{1}{Cos\left(x1 + \frac{x3^2}{x4}\right)}\right)\right) \tag{10}$$

$$+Cos\big(Arctan(x1)*Arctan(x3)+\ln(x1)*Cos(x3)\big)+Sin\big(Sin(x3)\big)$$

$$Fz=e^{\left(\sqrt[3]{(x1-x3)*x5-(x2+x4)}+x5\right)*x1}+Sin\left(x3^3+Cos\big(x4+\sqrt[3]{x3}\big)^6\right)+Cos\left(e^{x1}+Sin\big(\sqrt[3]{x1^2x2+x3^3}\big)\right)+Cos\left(ArcTan\big(x2*(x1+x5-x2)+Cos(x3*x4)\big)\right)^2 \quad (11)$$

$$My=\left(x3+x5+2x1+x3+\frac{x2-x4}{\sqrt[3]{x1}}\right)+ln(x1-ArcTan(x3))*e^{x^2}+(x4(x3-1)-x1)ArcTan\big(Sin(x4)\big)+x1 \quad (12)$$

$$Rd=ArcTan\big(x2^2x3Sin(x4)\big)+ArcTan\big(x3^3+Cos(x2)\big)+Sin(x4)Sin\big(e^{(x2-x3)}-x3+Cos(x4)\big)+\sqrt[3]{ArcTan\left(e^{e^{e^{x3}}+2x1Cos(x4)}\right)^3}+\sqrt{(x4+x3^3)+Cos\big(\sqrt[3]{x5}+x4/x1\big)+\sqrt{x4}+Sin(ArcTan(x2)+x4-x3+x5^2)} \quad (13)$$

where $x1$ = number of bays, $x2$ = existence of open floor (0 or 1), $x3$ = ratio of the area of the shear walls to the total area of the floor, $x4$ = number of floors and $x5$ = ratio the infilled bays to the total number of bays.

5.2 ANFIS model development

ANFIS model was developed using the same input parameters used in GEP model. In ANFIS modeling, the grid partition and subtractive clustering methods were employed for generation of the membership functions associated with each input parameter. The Gaussian membership function was assigned. The hybrid learning algorithm, which allows a fast identification of parameters and reduces the time to reach convergence, was used for optimizing the parameters. As the stopping criterion, the minimum validation error is used to avoid over fitting. The ANFIS Model has 64 linear parameters, 48 nonlinear parameters, 161 nodes and 64 fuzzy rules. The fuzzy toolbox of MATLAB software (Demuth and Beale 2001) was used for ANFIS model development.

6. Results and discussions

Although several previous studies (Cavaleri and Papia 2003, Villaverde 2006) investigated the contribution of infill walls to overall building behavior, in code equations, structures are designed to remain elastic, and the effects of infill walls are ignored. The range of distributions of partition walls per unit floor area may have a significant impact on building behavior and level of damage during an earthquake (Anil and Altin 2007). Building behavior under dynamic forces depends upon the dynamic characteristics of buildings, which are controlled by both their mass and stiffness properties. So, any element with mass and/or stiffness (infill walls and shear walls) and structural system (number of floor, number of bays and presence of open floor) must be taken into account in calculation any parameter related to building behavior.

Table 2 MSE and MAE of GEP and ANFIS models in training process

Quantity	MSE		MAE	
	GEP	ANFIS	GEP	ANFIS
Base Shear F_x	0.0154	0.0002	0.0959	0.0039
Base Normal F_z	0.3480	0.0016	0.4456	0.0159
Overturning Moment M_y	2.5797	0.1505	1.2546	0.2744
Roof Displacement R_d	0.1968	0.0069	0.3477	0.0789

Current code specifications (Eurocode 8 and UBC) are over simplified and don't take the all relevant parameters into the account. These equations usually take into account only weight and natural period of buildings when estimating the story drift and base shear reactions. Other base reactions such as base overturning moment and base normal force are not predicted by any code equations as shown in Eqs. (1) and (2). However, all the relevant parameters were included in GEP and ANFIS models to have better estimate of story drift and base reactions of RC frames.

The acceptance of GEP and ANFIS models for predicting story drift and base reactions is based on their predictions to a new set of inputs, which are not included in training process. The training process must be completed successfully, before the performance of GEP and ANFIS models are tested for new set of inputs.

6.1 Training process

The GEP and ANFIS models were trained to predict the story drift and base reactions of RC frames. 195 roof drift and base reactions were selected from computer models (Kose and Karslioglu 2011) for training process. As mentioned previously, each training pattern contains five parameters, which are the number of floor, number of bays, presence of open floor, ratio of shear wall areas to floor area and ratio of bays infilled with masonry walls to total number of bays, and corresponding targets, which are the story drift, base shear reaction, base normal reaction and base overturning moment. The training of GEP and ANFIS models were completed when the GEP and ANFIS models correctly predicted the story drift and the base reactions of RC frames. Training results of base shear force *Fx*, base normal force F_z, overturning moment M_y and roof drift R_d by GEP and ANFIS models were shown in from Fig. 4 to Fig. 11. The predicted roof drift and base reactions and the computed roof drift and base reactions were compared by drawing a 45-degree equity line.

Also, mean squared error (MSE) and mean absolute error (MAE) for the predictions obtained by GEP and ANFIS models were shown in Table 2 to determine trend capture and the degree of scatter. The MSE values of ANFIS modeling much less than that of GEP modeling. Base shear response have the minimum value of error value whereas overturning moment have the maximum value of error in both MSE and MAE calculations. So, best trend capture (minimum value of error) was obtained for base shear forces. GEP and ANFIS modeling of base shear response have the error value of 0.0154 and 0.0002 in MSE calculations, respectively and also have the error value of 0.0959 and 0.0039 in MAE calculations, respectively. However, GEP and ANFIS modeling of overturning moment response have the error value of 2.5797 and 0.1505 in MSE calculations, respectively and also have the error value of 1.2546 and 0.2744 in MAE calculations, respectively Although both models have small values of MSE and MAE, the ANFIS models have the minimum degree of scatter and maximum ability of trend capture for base reactions and roof displacement.

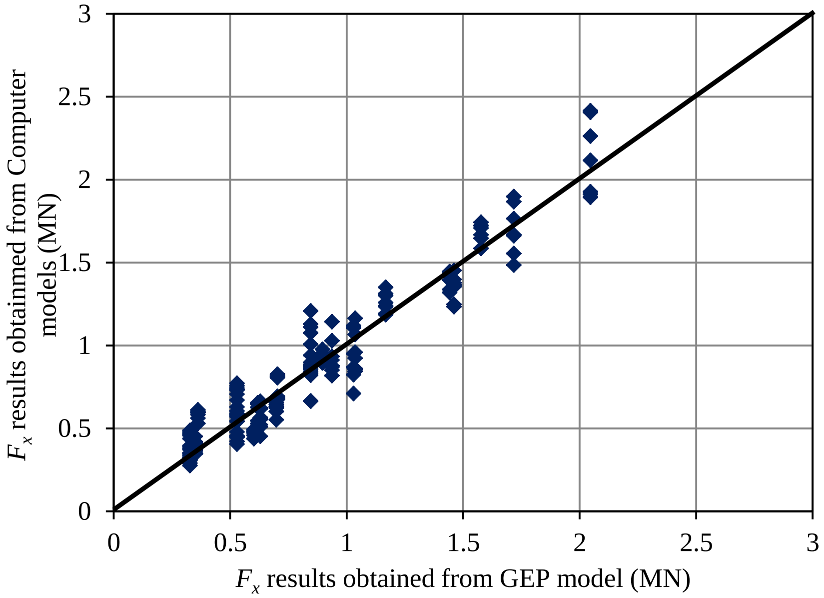


Fig. 4 Predicted Base Shear Force F_x by GEP model versus computed Base Shear Force F_x after training process

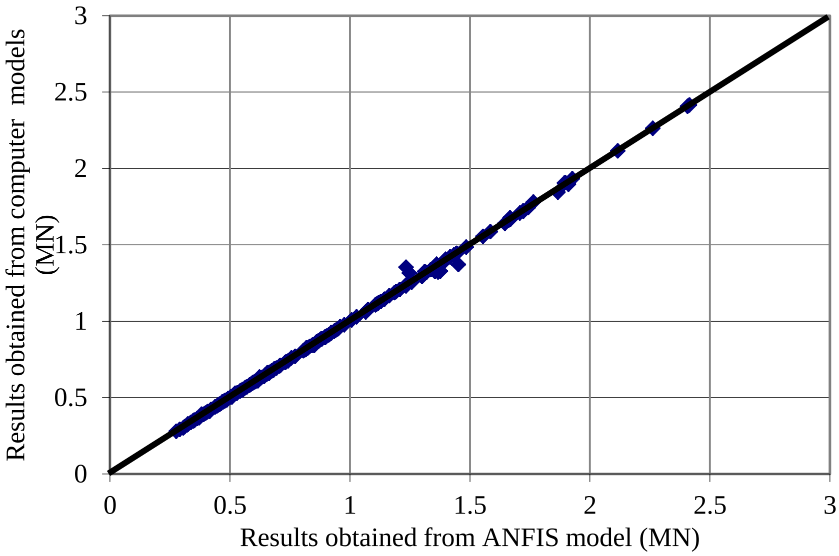


Fig. 5 Predicted Base Shear Force F_x by ANFIS model versus computed Base Shear Force F_x after training process

6.2 Testing process

The acceptability of a trained GEP and ANFIS models depend on the generalization and performance of their predictions when the GEP and ANFIS models are tested with new set of data

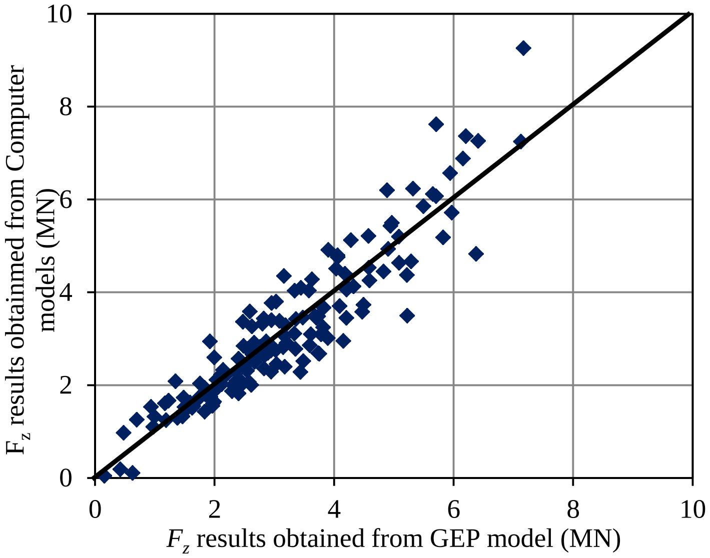


Fig. 6 Predicted Base Normal Force F_z by GEP model versus computed Base Normal Force F_z after training process

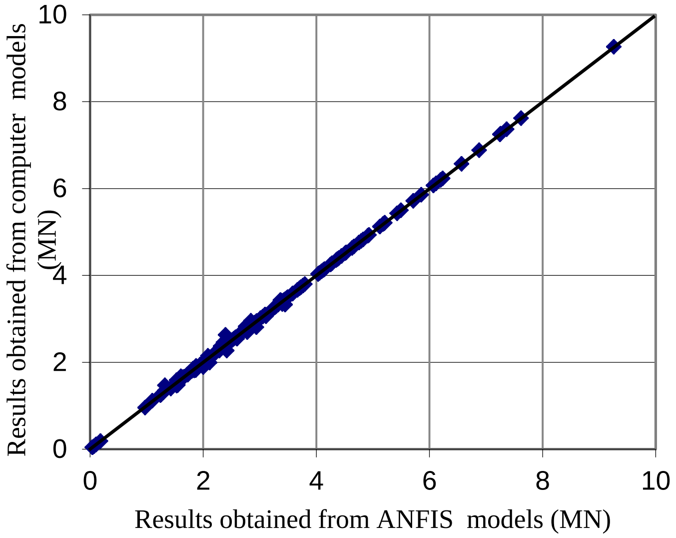


Fig. 7 Predicted Base Normal Force F_z by ANFIS model versus computed Base Normal Force F_z after training process

different from the input variables used in training process. So, performance of the GEP and ANFIS models to predict the story drift and the base reactions for the data excluded in the training process must be validated. The GEP and ANFIS models were tested with a total 21 new input parameters randomly selected from computer models (Kose and Karslioglu 2011) and required to predict the story drift and the base reactions.

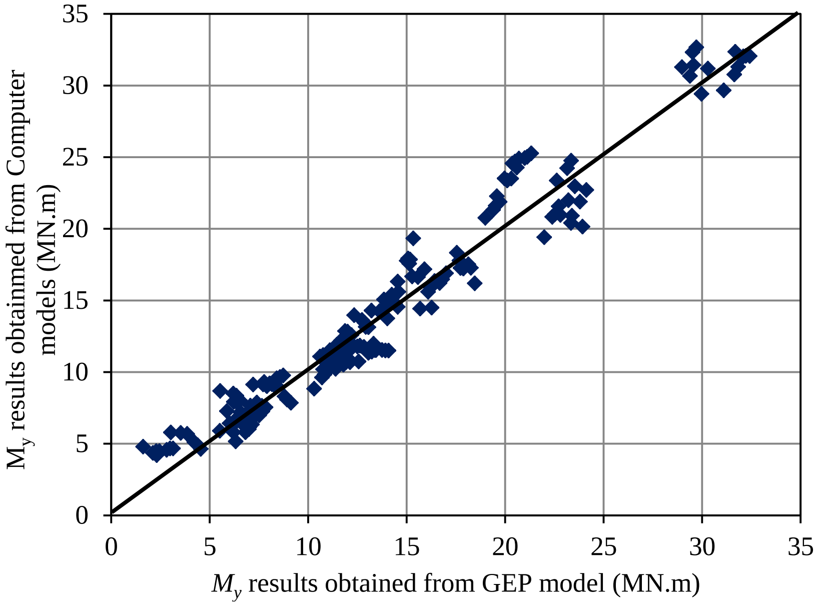


Fig. 8 Predicted Overturning Moment M_y by GEP model versus computed Overturning Moment M_y after training process

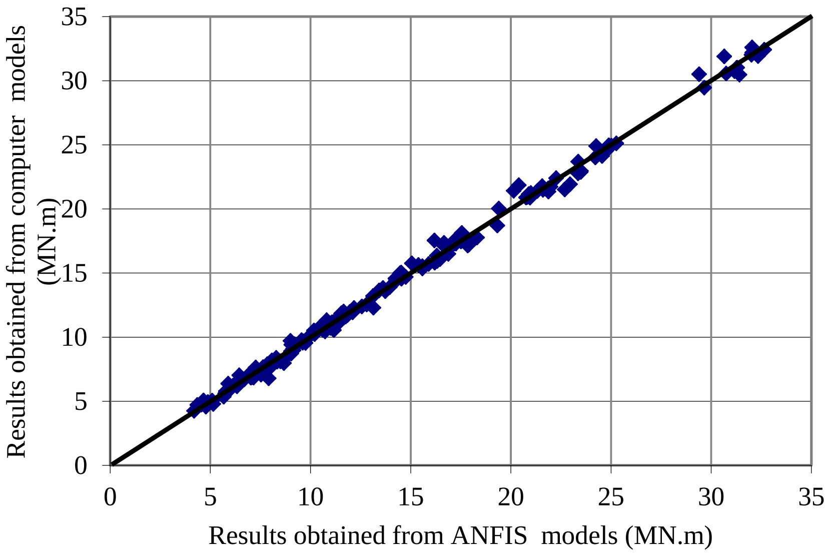


Fig. 9 Predicted Overturning Moment M_y by ANFIS model versus computed Overturning Moment M_y after training process

The predicted roof drift and base reactions and the computed story drift and base reactions were compared by drawing a 45-degree equity line as shown in Fig. 12 to Fig. 19. The GEP and ANFIS models successfully predict the story drift and the base reactions of RC frames for given input

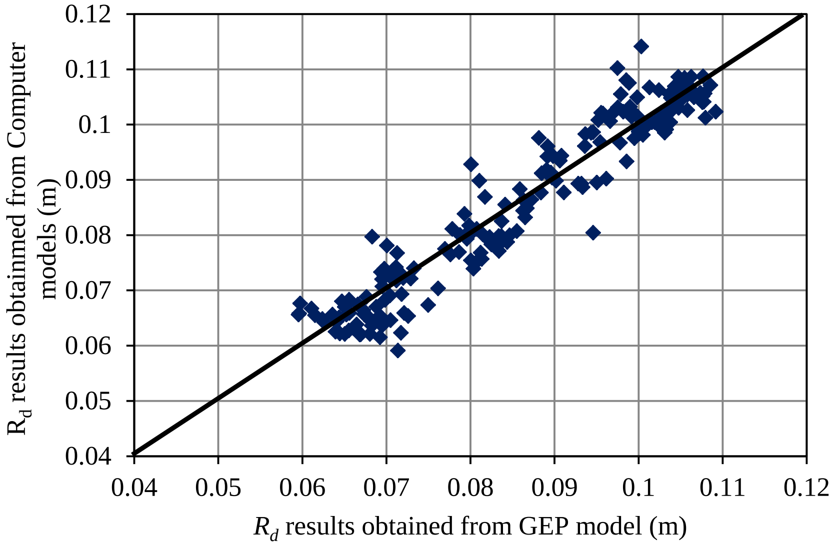


Fig. 10 Predicted Roof Displacement R_d by GEP model versus computed Roof Displacement R_d after training process

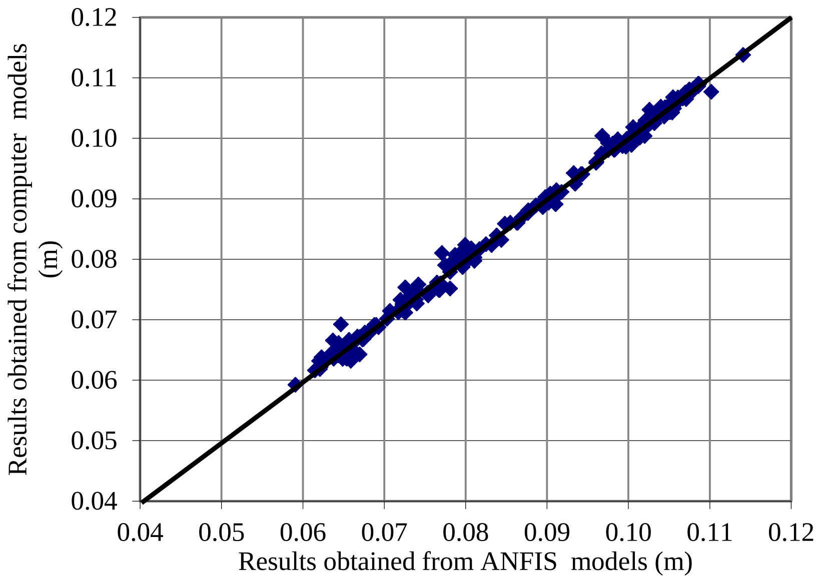


Fig. 11 Predicted Roof Displacement R_d by ANFIS model versus computed Roof Displacement R_d after training process

data. Also, mean squared error (MSE) and mean absolute error (MAE) for the predictions obtained by GEP and ANFIS models were shown in Table 3 to determine trend capture and the degree of scatter. Base shear response have the minimum value of error whereas overturning moment have the maximum value of error in both MSE calculations. However, roof displacement have the

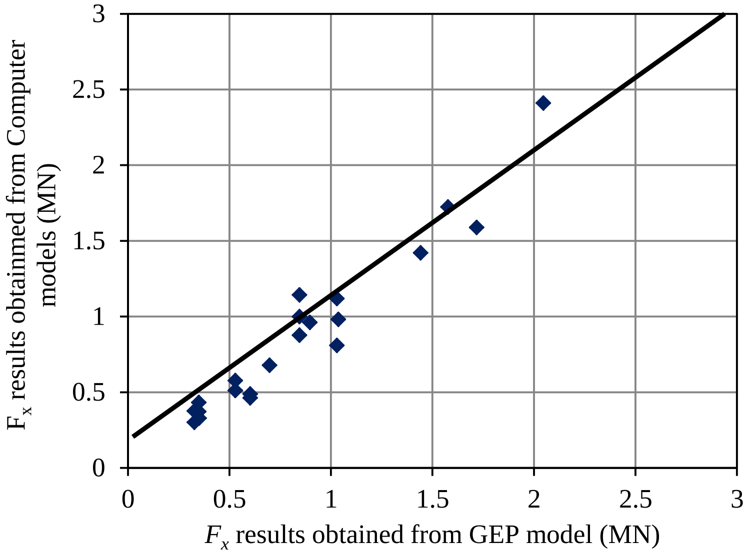


Fig. 12 Predicted Base Shear Force F_x by GEP model versus computed Base Shear Force F_x after testing process

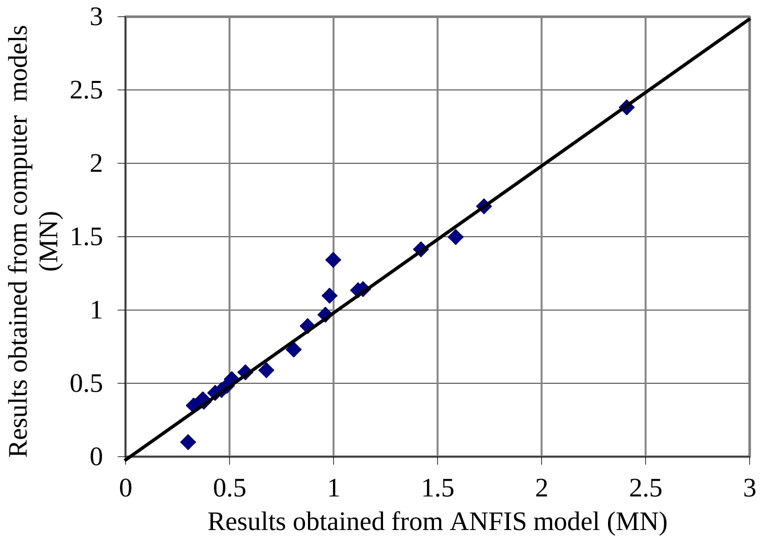


Fig. 13 Predicted Base Shear Force F_x by ANFIS model versus computed Base Shear Force F_x after testing process

minimum value of error whereas overturning moment have the maximum value of error in both MAE calculations. So, best trend capture (minimum value of error) was obtained for base shear forces in GEP modeling and for roof displacement in ANFIS modeling. GEP modeling of base shear have the error value of 0.0187 and 0.0094 in MSE calculations and ANFIS modeling of roof

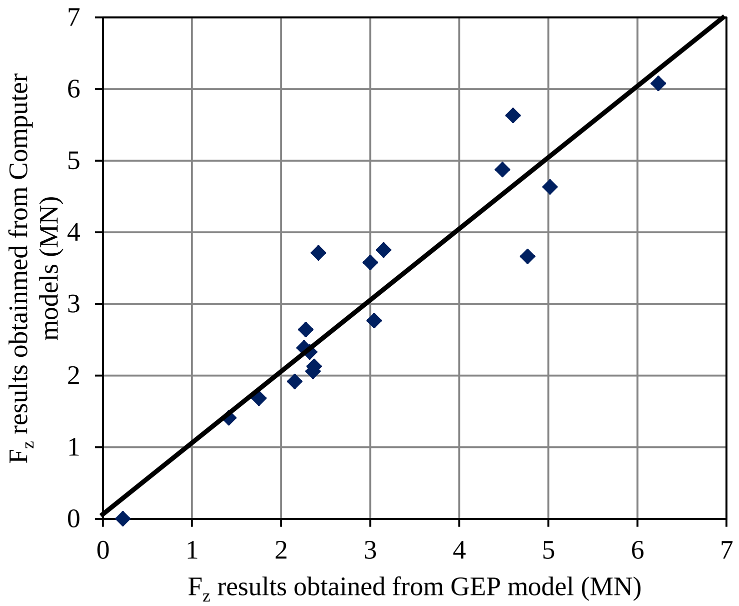


Fig. 14 Predicted Base Normal Force F_z by GEP model versus computed Base Normal Force F_z after testing process

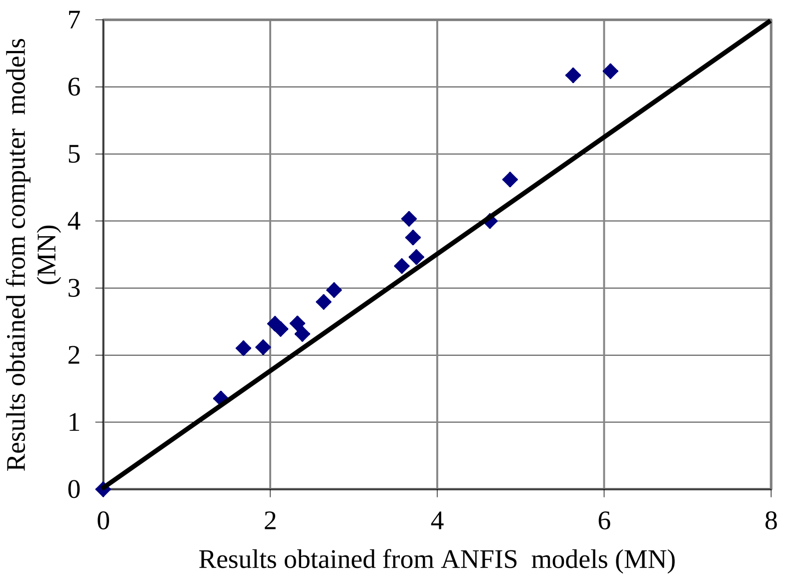


Fig. 15 Predicted Base Normal Force F_z by ANFIS model versus computed Base Normal Force F_z after testing process

displacement have zero error and 0.0020 in MAE calculations. However, GEP and ANFIS modeling of overturning moment response have the error value of 2.3984 and 1.3163 in MSE calculations and have the error value of 0.5400 and 0.5047 in MAE calculations, respectively.

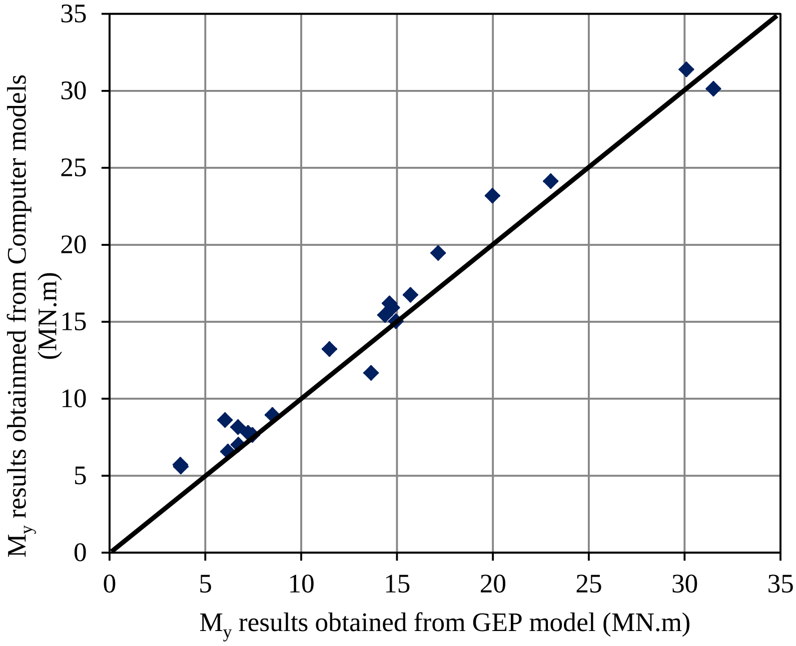


Fig. 16 Predicted Overturning Moment M_y by GEP model versus computed Overturning Moment M_y after testing process

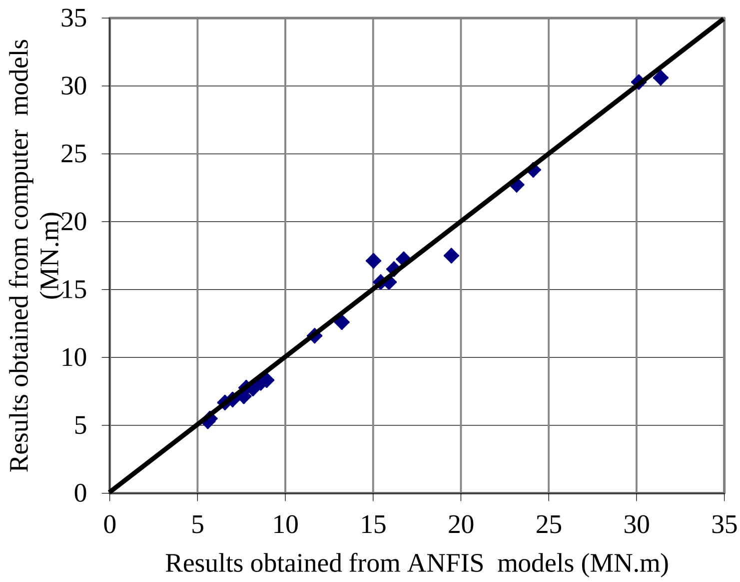


Fig. 17 Predicted Overturning Moment M_y by ANFIS model versus computed Overturning Moment M_y after testing process

Although both models have small values of MSE and MAE, the ANFIS models have the minimum degree of scatter and maximum ability of trend capture for base reactions and roof displacement.

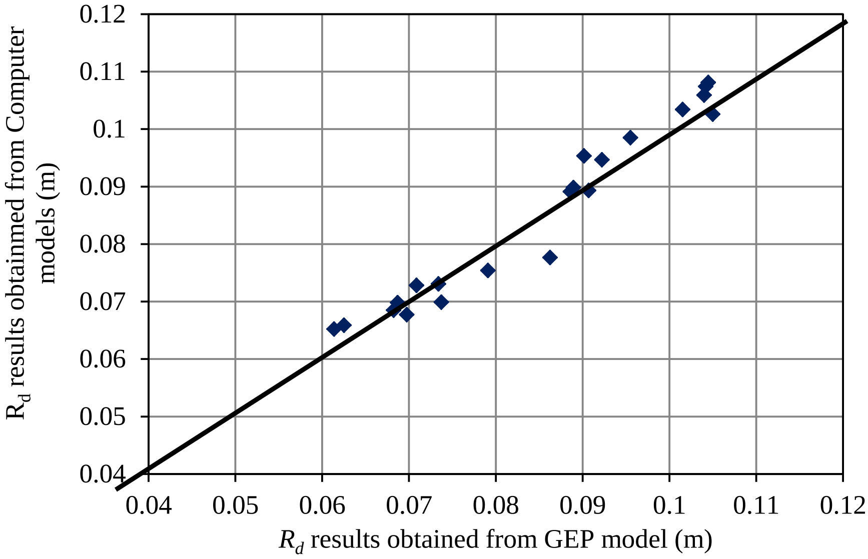


Fig. 18 Predicted Roof Displacement R_d by GEP model versus computed Roof Displacement R_d after training process

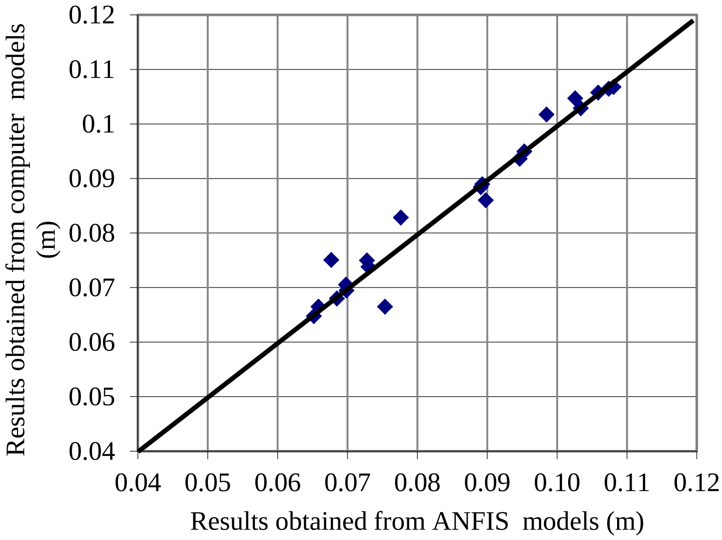


Fig. 19 Predicted Roof Displacement R_d by ANFIS model versus computed Roof Displacement R_d after testing process

7. Conclusions

The following conclusions may be drawn based on the obtained results:

1. This study demonstrates the efficiency of GEP and ANFIS models to predict the story drift and the base shear reaction, base normal reaction and base overturning moment of RC frames under dynamic loading. The developed models were able to predict the story drift and the base shear reaction, base normal reaction and base overturning moment of RC frames for both input data used in training and testing processes.

2. Predicting of the story drift and the base shear reaction, base normal reaction and base overturning moment of RC frames as a function of the number of floor, number of bays, presence of open floor, ratio of shear wall areas to floor area and ratio of bays infilled with masonry walls to total number of bays is a difficult task to achieve. However, a successfully trained GEP and ANFIS models can predict the story drift and the base shear reaction, base normal reaction and base overturning moment of RC frames easily and accurately. So, the GEP and ANFIS models can be a powerful alternative approach to current methods used in developing the relationship between the story drift, the base reactions of RC frames and the parameters affecting them.

3. Although the performance of the developed GEP and ANFIS models is limited to the range of input data used in training process, the model can easily be extended by providing additional new set of data.

4. It was seen that unused parameters in current code specifications and proposed equations have an effect on the story drift and the base shear reaction, base normal reaction and base overturning moment of RC frames.

5. Current codes equations are limited to only the weight and the fundamental period to predict the story drift and the base shear reaction. Also, the current code equations usually overestimate the story drift and the base shear reaction to be on the safe side. The base normal reaction and base overturning moment of RC frames are not estimated by a code equation at all. However, the developed GEP and ANFIS models can incorporate the five parameters mentioned above to predict the story drift and the base shear reaction, base normal reaction and base overturning moment of RC frames more accurately.

6. In training process, among the base reactions and roof displacement, base shear response have the minimum value of error and overturning moment response have the maximum value of error in GEP and ANFIS modeling. Although both models have small values of MSE and MAE, the ANFIS models have the minimum degree of scatter and maximum ability of trend capture for base reactions and roof displacement.

7. In testing process, among the base reactions and roof displacement, overturning moment response have the maximum value of error in GEP and ANFIS modeling. Base shear force have the minimum value of error in GEP modeling and roof displacement have the minimum value of error in ANFIS modeling.

8. It was also seen that ANFIS models generally have the minimum degree of scatter and maximum ability of trend capture compared to GEP models and current code equations.

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