Research Article

Determination of Damage in Reinforced Concrete Frames with Shear Walls Using Self-Organizing Feature Map

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The paper presents the use of a self-organizing feature map (SOFM) for determining damage in reinforced concrete frames with shear walls. For this purpose, a concrete frame with a shear wall was subjected to nonlinear dynamic analysis. The SOFM was optimized using the genetic algorithm (GA) in order to determine the number of layers, number of nodes in the hidden layer, transfer function type, and learning algorithm. The obtained model was compared with linear regression (LR) and nonlinear regression (NonLR) models and also the radial basis function (RBF) of a neural network. It was concluded that the SOFM, when optimized with the GA, has more strength, flexibility, and accuracy.

1. Introduction

Damage to concrete structures mainly occurs because of inadequate management, incorrect maintenance, overloading, exposure to chemical components, climatic factors, and also extra loads such as earthquakes [1]. As mentioned by Nikoo et al. [2], earthquakes are the most devastating of these factors. Their destruction mechanism can cause extraordinary damage to a structure. In the last few years, much attention has been given to the use of artificial neural networks (ANNs) for solving various civil engineering problems [3–8].

In the self-organizing feature map (SOFM), cells are organized in various sensual areas with regular and significant computational maps [6, 9]. As described by Kohonen [9], processor units are placed within the nodes of a one-dimensional (or more) network and are regulated in a competitive learning process [9, 10]. Therefore, the SOFM can be seen as a topographic map for input models, in which the units' locations correspond to the inherent features of the input models. Competitive learning is applied in such

networks, and in each step the units compete in order to be activated. At the end of the initial step of this competition only one unit wins and its weights are changed differently when compared to the weights of other units. This kind of learning is called unsupervised learning [6]. In previous papers, the SOFM was described in more detail [6, 10].

In the genetic algorithm (GA), chromosomes with high competence have a higher chance of repeating in the selected population of the replication process. The basic operators of the GA are reproduction, crossover, and mutation [11]. The GA ends when certain criteria, such as a certain number of generations or the average standard deviation performance of individuals, are fulfilled [12].

The main objective of this study was to evaluate the abilities of the SOFM in determining damage in reinforced concrete frames with shear walls. The SOFM was optimized using the GA in order to determine the number of layers, number of nodes in the hidden layer, transfer function type, and learning algorithm. The obtained model was compared with linear regression (LR), nonlinear regression (NonLR), and the radial basis function (RBF) of a neural network.

TABLE 1: Typical damage range in concrete reinforcement frames [13].

Number	Park & Ang index value	Type of damage
1	$D \leq 0.1$	Without any damage or minor cracking
2	$0.1 \leq D \leq 0.25$	Minor damage/cracking across the structure
3	$0.25 \leq D \leq 0.4$	Moderate damage, severe cracking
4	$0.4 \leq D \leq 1$	Sever damage, crushing of concrete and reinforcement protrusion
5	$D \geq 1$	Structural collapse

FIGURE 1: Structural model of (a) a one-dimensional network [9] and (b) a two-dimensional network [14].

2. A Short Description of the Self-Organizing Feature Map (SOFM)

In the SOFM, the competitive learning method is used for training and is based on specific characteristics of a developed human brain. The cells in the human brain are organized in various sensual areas with regular and significant computational maps [6, 9].

In the SOFM, processor units are placed within the nodes of a one-dimensional or two-dimensional network (Figure 1). These units are regulated in a competitive learning process and compared to the input models [9, 10]. Therefore, the SOFM can be seen as a topographic map for the input models, in which the units' locations correspond to the inherent features of the input models. Competitive learning is applied in such networks, and in each step the units compete in order to be activated. At the end of the initial step of this competition, only one unit wins and its weights are changed differently when compared to the weights of other units. This kind of learning is called unsupervised learning [6].

3. The Park and Ang Damage Index

One of the most useful methods proposed for quantifying the calculation of damage in concrete structures is the Park and Ang model. As mentioned by Valles et al. [13], it is defined as follows [15]:

$$D = \frac{\delta_m}{\delta_u} + \frac{\beta}{\delta_u \cdot P_y} \int dE_h, \quad (1)$$

where

δ_m is the maximum response of deformation under seismic load.

P_y is the calculated yield strength.

δ_u is the ultimate deformation under uniform loading.

$\int dE$ is the hysteric absorbed energy.

β is the resistance reduction parameter according to hysteric energy.

The Park and Ang index value is between 0 and 1. The damage range is shown in Table 1.

FIGURE 2: Comparison of the Park and Ang damage index and calculated data for (a) training, (b) validation, and (c) testing.

4. Experimental Setup

To determine the distribution function for the Park and Ang damage index, a concrete frame with a shear wall was selected. Lateral loading of the mentioned structure was then applied. In the next step, the structure was designed. The data associated with reinforced concrete frames with shear walls is listed in Table 2.

One of the main parameters influencing the input energy of structures is the earthquake accelerogram applied in seismic analysis. The extent of input energy applied to the structure is more dependent on input mapping than its structural characteristics [2]. In this research, thirty earthquakes were used for nonlinear dynamic analysis, as listed in Table 3.

After the analysis, the overall Park and Ang damage index was extracted using version 4.0 of IDARC 2D software.

The input parameters in this research include the following: peak ground acceleration (PGA); input time of the earthquake to a structure; time; frequency; input acceleration to the building (Acc); and also displacement. The output parameter is the Park and Ang damage index. Table 4 represents the statistical characteristics of the parameters.

5. Experimental Results

5.1. Performance Evaluation of the SOFM. Three Kohonen ANNs (Square, Line, and Diamond) were employed in this

TABLE 2: Data associated with reinforced concrete frames with shear walls [2, 16].

Frame	Special reinforced concrete with a shear wall
Height of each story	3.2 m
Bay of each frame	5 m
Dead load at roof	600 kg/m ²
Live load at roof	175 kg/m ²
Dead load at stories	500 kg/m ²
Live load at stories	200 kg/m ²
Earthquake danger	Areas with a relatively high risk
Ratio of steel (ρ) in building columns	$0.015 \leq \rho \leq 0.035$
Twenty-eight day resistance of the concrete cylindrical sample	$f'_c = 240 \text{ kg/cm}^2$
Flow stress in steel	$f_y = 3000 \text{ kg/cm}^2$
Shear wall	At the middle bay

research for the SOFM. From 412 sets of data, 70% (288 sets) were used for training, 15% (62 sets) were used for validation, and 15% (62 sets) were used for testing of the ANN. Different stimulation functions, including LinearTanhAxon, LinearAxon, and TanhAxon, were used. Table 5 shows the characteristics of the selected SOFM models.

Table 6 presents the optimized structure of the SOFM models for training, validation and testing. Table 7 presents the statistical results of different models in the SOFM. As can be seen from these tables, the SOFM1 model enjoys the highest values of the correlation coefficient R^2 for prediction of the Park and Ang damage index for training, validation, and testing.

Comparison of the Park and Ang damage index and calculated data for training, validation, and testing for each of the laboratory samples is presented in Figure 2.

The obtained values of correlation coefficient R^2 for the Park and Ang damage index for the SOFM1 model were 0.9330, 0.9216, and 0.9221 for training, validation, and testing, respectively. Additionally, the values of mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE) are less than those for the two other models. Considering the above, MSE versus epoch for the SOFM1 model is presented in Figure 3.

Considering the above, the best ANN for adaptation of input data is the SOFM with a 5×5 structure (Figure 4).

In addition, the impact of distances and weights of the neighborhood in a 5×5 structure in the SOFM1 model is presented in Figure 5.

5.2. Comparison of Selected SOFM Models

5.2.1. Linear Regression (LR). First, linear regression (LR) was used [15]. LR models are based on a data oriented technique, where the collected data is directly associated with each other. The process behind this data is not considered. In a specific

FIGURE 3: MSE versus epoch in training and validation of the SOFM1 model.

FIGURE 4: Structure for the adaptation of input data in training and validation of the SOFM1 model.

FIGURE 5: The impact of distances and weights of the neighborhood in a 5×5 structure in the SOFM1 model.

TABLE 3: Seismic characteristics used in the study [2, 16].

Number	Peak ground acceleration (PGA)	Earthquake name	Station
1	0.254	Imperial Valley 1979	Chihuahua
2	0.27	Imperial Valley 1979	Chihuahua
3	0.231	Northridge 1994	Hollywood Storage
4	0.145	San Fernando 1971	Lake Hughes #1
5	0.210	San Fernando 1971	Hollywood Stor Lot
6	0.134	Superstition Hills 1987	Wildlife Liquefaction Arrey
7	0.134	Superstition Hills 1987	Wildlife iquefaction Arrey
8	0.119	Superstition Hills 1987	Salton Sea Wildlife Refuge
9	0.186	Superstition Hills 1987	Plaster City
10	0.247	Superstition Hills 1987	Calipatria Fire Station
11	0.135	Landers 1992	Barstow
12	0.385	Cape Mendocino 1992	Rio Dell Overpass
13	0.549	Cape Mendocino 1992	Rio Dell Overpass
14	0.164	Coalinga 1983	Parkfield-Fault Zone 3
15	0.126	Whittier Narrows 1987	Beverly Hills
16	0.239	Northridge, 1994	LA, Baldwin Hills
17	0.143	Imperial Valley, 1979	El Centro Array #12
18	0.240	Loma Prieta, 1989	Anderson Dam Downstream
19	0.247	Loma Prieta, 1989	Anderson Dam Downstream
20	0.159	Loma Prieta, 1989	Agnews State Hospital
21	0.244	Loma Prieta, 1989	Anderson Dam Downstream
22	0.179	Loma Prieta, 1989	Coyote Lake Dam Downstream
23	0.309	Imperial Valley, 1979	Cucapah
24	0.207	Loma Prieta, 1989	Sunnyvale Colton Ave
25	0.117	Imperial Valley, 1979	El Centro Array #13
26	0.074	Imperial Valley, 1979	Westmoreland Fire Station
27	0.209	Loma Prieta, 1989	Sunnyvale Colton Ave
28	0.139	Imperial Valley, 1979	El Centro Array #13
29	0.110	Imperial Valley, 1979	Westmoreland Fire Station
30	0.269	Loma Prieta, 1989	Hollister Diff. Array

TABLE 4: Selected statistical characteristics of the parameters.

Row	Parameter name	Unit	Parameter type	Minimum	Maximum	Average	Standard deviation
1	Peak ground acceleration (PGA)	m/s ²	Input	0.074	0.549	0.207	0.095
2	Input time of the earthquake to a structure	s	Input	0.005	0.020	0.011	0.004
3	Time	s	Input	21.880	39.990	36.187	5.896
4	Frequency	Hz	Input	0.025	0.046	0.029	0.006
5	Input acceleration to the building (Acc)	m/s ²	Input	0.100	1.500	0.795	0.406
6	Displacement	mm	Input	11.025	1023.293	222.576	208.891
7	Park & Ang damage index	—	Output	0.008	0.823	0.153	0.138

TABLE 5: The characteristics of the selected SOFM models.

Row	Model name	Number of inputs	Number of outputs	Number of hidden layers	Number of nodes in the hidden layer	Column and Row in the network	Training algorithm	Transfer function	Neighborhood shape
1	SOFM 1	6	1	1	6	5 * 5	TanhAxon	Momentum	Square
2	SOFM 2			2	8_4	6 * 6	LinearTanhAxon	Step	Line
3	SOFM 3			3	4_4_4	7 * 7	LinearAxon	QuickProp	Diamond

TABLE 6: The optimized structure of SOFM models in training, validation, and testing.

Number	Model	R^2	Training	R^2	Validation	R^2	Testing
			Equation		Equation		Equation
1	SOFM1	0.9216	$y = 0.9229x + 0.0128$	0.9330	$y = 0.9102x + 0.0133$	0.9213	$y = 0.9353x + 0.0118$
2	SOFM2	0.7590	$y = 0.7178x + 0.0483$	0.6703	$y = 0.7542x + 0.049$	0.8250	$y = 0.9174x + 0.0232$
3	SOFM3	0.6321	$y = 0.6561x + 0.0579$	0.5323	$y = 0.7059x + 0.0713$	0.6864	$y = 0.8166x + 0.0435$

TABLE 7: Statistical results of different SOFM models.

Number	Model	MAE			MSE			RMSE		
		Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing
1	SOFM1	0.024	0.020	0.024	0.002	0.001	0.001	0.041	0.028	0.033
2	SOFM2	0.048	0.054	0.042	0.005	0.004	0.003	0.072	0.065	0.052
3	SOFM3	0.061	0.063	0.056	0.008	0.007	0.005	0.089	0.085	0.070

form of LR, data is modeled using linear predictor functions. Unknown model parameters are then estimated from the data [16]. In LR, two or more independent variables have a major effect on the dependent variable shown in equation

$$y = f(x_1, x_2, \dots) \rightarrow$$

$$y = a_0 + a_1x_1 + a_2x_2 + \dots, \quad (2)$$

where y is the dependent variable; x_1, x_2 , etc. are the independent variables; and a_1, a_2, a_3 , etc. are the equation regression coefficients. In this research, various models of LR are investigated using MINITAB software. The best LR model, which was more coordinated with damage data, was obtained using

$$Y = \begin{cases} -0.206 - 0.0246X_1 + 0.449X_2 + 0.00350X_3 + 2.08X_4 + 0.7635X_5 + 0.000500X_6 & \text{LR 1} \\ 0.174 - 0.0894X_1 + 0.74X_2 - 0.00278X_3 - 4.71X_4 + 0.28218X_5 & \text{LR 2} \\ 0.572 - 0.1014X_1 + 1.63X_2 - 0.00589X_3 - 7.12X_4 & \text{LR 3.} \end{cases} \quad (3)$$

In the above equation, Y is the damage to the entire frame, X_1 is the PGA variable, X_2 is the input time variable, X_3 is the time variable, X_4 is the frequency variable, X_5 is the acceleration variable, and X_6 is the displacement variable. The analysis results of the three LR models are presented in Table 8 and the results obtained from the statistical indices are presented in Table 9. Figure 6 shows the results arising from different LR models.

In the LR1 model, the values of R^2 are equal to 0.8925, 0.9098, and 0.8924 for training, validation, and testing, respectively. The values of MAE, MSE, and RMSE for the LR1 model are lower than those in the other two LR models.

5.2.2. Nonlinear Regression (NonLR). In nonlinear regression (NonLR), the PARK_ANG parameter (y) is a dependent value and displacement (x) is an independent value. The best NonLR model, which was more coordinated with damage data, was obtained via

$$Y = \begin{cases} 0.5404 * \exp\left(-\left(\frac{(x - 922.9)}{598}\right)^2\right) & \text{NonLR 1} \\ 0.977 * \sin(0.0006597 * x + 0.01211) & \text{NonLR 2.} \end{cases} \quad (4)$$

The analysis results of the selected NonLR models are presented in Table 10 and the results obtained from the statistical

FIGURE 6: Comparison of the Park and Ang damage index obtained using LR and calculated data for (a) training, (b) validation, and (c) testing.

TABLE 8: The structure of LR models in training, validation, and testing.

Number	Model	Type	Training		Validation		Testing	
			R^2	Equation	R^2	Equation	R^2	Equation
1	LR 1	Linear regression (LR)	0.8924	$y = 0.8847x + 0.017$	0.9098	$y = 0.9715x + 0.0053$	0.8925	$y = 0.9319x + 0.0123$
2	LR 2		0.6883	$y = 0.6627x + 0.0486$	0.6693	$y = 0.826x + 0.035$	0.7946	$y = 0.845x + 0.032$
3	LR 3		0.0096	$y = 0.0098x + 0.1509$	0.0062	$y = 0.0131x + 0.1494$	0.0241	$y = 0.0182x + 0.1515$

TABLE 9: Statistical results of different LR models.

Number	Model	MAE			MSE			RMSE		
		Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing
1	LR 1	0.027	0.023	0.026	0.002	0.001	0.002	0.048	0.033	0.039
2	LR 2	0.050	0.048	0.040	0.007	0.004	0.003	0.082	0.066	0.054
3	LR 3	0.114	0.089	0.099	0.021	0.012	0.014	0.145	0.111	0.118

FIGURE 7: Comparison of the Park and Ang damage index obtained by NonLR and calculated data for (a) training, (b) validation, and (c) testing.

indices are presented in Table 11. Figure 7 shows the results arising from different NonLR models.

5.2.3. Summary of the Comparison. To determine the optimized structure of the radial basis function (RBF) neural

network, version 5.0 of NeuroSolutions Software was used. The RBF with a structure of 6-1-4, the TanhAxon training algorithm, and the QuickProp transfer function were selected.

To evaluate the performance of the optimized SOFMI model in assessing the Park and Ang damage, the obtained

FIGURE 8: Comparison of the obtained results for (a) validation and (b) testing.

TABLE 10: Statistical results of different NonLR models.

	Model	MAE	MSE	RMSE
Training	NonLR1	2.792	10.840	3.292
	NonLR2	0.030	0.003	0.051
Validation	NonLR1	3.182	12.835	3.583
	NonLR2	0.021	0.001	0.031
Testing	NonLR1	2.375	8.372	2.894
	NonLR2	0.031	0.002	0.050

TABLE 11: The structure of NonLR models in training, validation, and testing.

Number	Model	Type	R^2	Training Equation	R^2	Validation Equation	R^2	Testing Equation
1	NonLR 1	Nonlinear regression (NonLR)	0.7351	$y = -9.5762x + 4.4271$	0.8014	$y = -13.122x + 4.85$	0.7925	$y = -11.403x + 4.5353$
2	NonLR 2		0.8781	$y = 0.8708x + 0.0203$	0.9174	$y = 0.9506x + 0.0083$	0.8272	$y = 0.878x + 0.0191$

TABLE 12: Structure of different models for assessing the Park & Ang damage.

Number	Model	R^2	Training Equation	R^2	Validation Equation	R^2	Testing Equation
1	SOFM1	0.9216	$y = 0.9229x + 0.0128$	0.933	$y = 0.9102x + 0.0133$	0.9213	$y = 0.9353x + 0.0118$
2	LR1	0.8924	$y = 0.8847x + 0.017$	0.9098	$y = 0.9715x + 0.0053$	0.8925	$y = 0.9319x + 0.0123$
3	RBF	0.8054	$y = 0.8151x + 0.0238$	0.8304	$y = 0.9509x + 0.0187$	0.8789	$y = 0.9784x + 0.0122$
4	NonLR2	0.8781	$y = 0.8708x + 0.0203$	0.9174	$y = 0.9506x + 0.0083$	0.8272	$y = 0.878x + 0.0191$

results were compared with the results derived from the SOFM, LR models, RBF network, and NonLR. This comparison was conducted in three steps of training, testing, and validation. The obtained results are shown in Table 12. Statistical results of different models are presented in Table 13. In Figure 8, a comparison of the obtained results for validation and testing is presented.

When considering R^2 coefficient, the slope of the straight line and statistical indices in each of the three models, it can be concluded that the accuracy of the SOFM1 model is higher than the accuracy of the other two LR models and also the RBF network in the case of training, validation, and test steps.

6. Conclusion

In this paper, the self-organizing feature map (SOFM) was used to evaluate damage in reinforced concrete frames with shear walls. For this purpose, a concrete frame with a shear wall was subjected to nonlinear dynamic analysis. The extent of damage to the frame was calculated using the Park and Ang index.

The SOFM was optimized using the genetic algorithm (GA) in order to determine the number of layers, number of nodes in the hidden layer, transfer function type, and learning algorithm. The obtained model was compared with linear

TABLE 13: Statistical results of different models.

Number	Model	MAE			MSE			RMSE		
		Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing
1	SOFM1	0.024	0.020	0.024	0.002	0.001	0.001	0.041	0.028	0.033
2	LR1	0.027	0.023	0.026	0.002	0.001	0.002	0.048	0.033	0.039
3	RBF	0.043	0.039	0.036	0.004	0.002	0.002	0.064	0.048	0.044
4	NonLR2	0.030	0.021	0.031	0.003	0.001	0.002	0.051	0.031	0.050

regression (LR) and nonlinear regression (NonLR) models and also the radial basis function (RBF) neural network. It can be concluded that the SOFM that is optimized with GA enjoys more strength, flexibility, and accuracy.

Conflicts of Interest

The authors declare that there are no conflicts of interests regarding the publication of this paper.

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