

Estimating of analysis results for structures with linear base isolation systems using artificial neural network model

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Abstract: Artificial Intelligence (AI) methods can be used in engineering problem to predict results without the need of long design or optimization processes. In this study, the dynamic analyses of base isolated seismic structures are used in the training of an artificial neural network (ANN) model. The maximum acceleration and displacement of the structure are predicted according to the base isolation period, base isolation damping ratio and pulse period of directivity pulse used in the analyses. The machine learning process was done in three different cases according to number of analysis results used in training. According to the result, the developed ANN model is effective in predicting the behavior of base isolated structures if enough numbers of analyses results were used in machine learning. The ANN model can be used in optimization in future studies.

Key-Words: Artificial neural network, prediction, structural dynamics, base isolators, machine learning.

1 Introduction

In dynamic analyses of structures, numerical integration methods must be used. This process is long because of iterations done according to time interval which effect the precision of the results. Especially when searching an optimum design, the process may be too long.

To skip the long decision process on optimum design, using of artificial intelligence (AI) and machine learning (ML) techniques may be a useful tool. A set of analysis results can be used in machine learning to get information about different analysis results which are not used in machine learning.

One of the AI techniques is multilayer artificial neural networks (ANN). In the documented methods, ANN has been used with metaheuristic algorithms. Examples include the optimum design problems such as determination of optimal lot sizes that can ensure minimum of total cost under demand and price uncertainty [1], optimal temperature and airflow distribution to provide control of energy [2], determination of values of optimal machining parameters [3] and predicting DAX stock prices by using quarterly cycles of eight years [4].

Examples include civil engineering applications such as development of a model for determining the prediction of 14 days previous salinity amount [5], predicting unconfined compressive strength of granite and limestone rock samples [6], evaluation of slope stability [7], estimation of the tender price amounts for bridge construction projects [8], performance-based optimal seismic design [9], predicting self-compacting concrete properties [10]

and determination of structural failure of multistory reinforced concrete buildings [11].

In this study, a set of dynamic analysis results of base isolated structures has been used in machine learning to generate an ANN model for estimating dynamic analysis results of base isolated systems.

The developed model was trained by using impulsive motions seen in near-fault ground motion records. The directivity pulse model of Makris [12] was used. The peak ground velocity of the pulses is taken as 200 cm/s.

Feed-forward networks and back-propagation training algorithm are chosen. The ANN model can predict the analyses results such as maximum displacement and acceleration according to base isolation period, base isolation damping ratio and pulse period. The ANN model is generated for future use in the optimum design of base isolated structures.

2 Seismically Isolated Benchmark Building

In this study, a one-story seismically isolated benchmark building given in Figure 1 is used. The superstructure is a three-dimensional shear building which is supported on a base isolation system. The plan of the building is symmetric which has four 5m bays in each direction [13]. The mass of each floor and the story stiffnesses are assumed to be same, providing a fundamental fixed-base superstructure period of 0.1s. The modal damping ratio of the superstructure has been set at 5% for all modes.

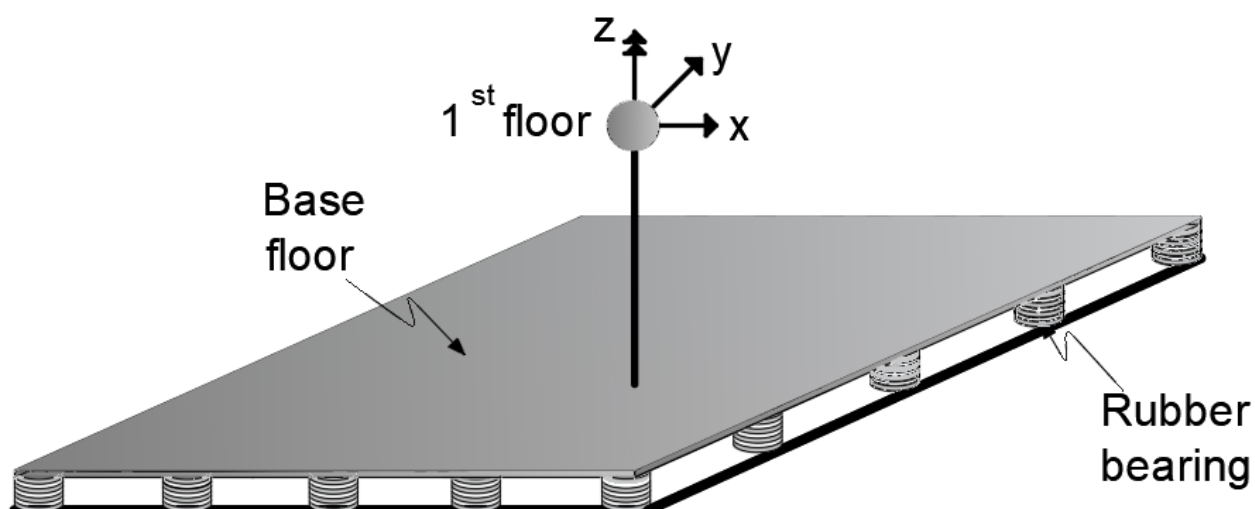


Figure 1 Seismically isolated benchmark building model

Especially in isolation systems where low-damping rubber bearings are used, these supports show linear behavior until they reach 100% shear strains. The low-damping rubber bearings have effective viscous damping ranging from 2-3% and are usually used in conjunction with viscous dampers providing additional damping [14]. The behavior of a linear seismic isolation system is defined by the Kelvin-Voight model consisting of a linear spring in parallel with linear damping.

Considering the isolation system stiffness K_i , isolation system period (T_i) can be calculated by Eq. (1), in which W is the total weight of the seismically isolated building and g is the gravitational acceleration.

$$T_i = 2\pi \sqrt{\frac{W}{K_i g}} \quad (1)$$

By considering the angular frequency ($\omega_i = 2\pi/T_i$), the isolation system damping ratio (ζ_i) can be obtained by using Eq. (2). Here, C_i is the viscous damping coefficient of the isolation system and M is the total mass of the isolation system.

$$\zeta_i = \frac{C_i}{2M\omega_i} \quad (2)$$

3 Generation of ANN model

In numerical applications, 21 different isolator periods have been handled in the dynamic analysis process. Each isolator has periods are ranging with 0.1 s intervals between 2-4 seconds. Different damping ratios are considered and these are increasing from 0.1 to 0.3 in rate of 0.01 and the training has subjected to three different pulse periods such as 2, 3 and 4 s. Displacement and acceleration values were trained with feed-forward neural networks for all combinations.

ANN structure which was used during training, is generated with three input nodes; isolator period (T_{eff}), isolator damping ratio (β_{eff}) and pulse period (TP_s), and two output nodes; displacement and acceleration, which are selected variables from dynamic analyses, and ten hidden nodes.

4 Results and Conclusions

A part of ANN predicts, error values and error metrics, which are obtained for training data are shown in Table 1. Some of the values are presented in the table since 1323 data are used in training. The average error is 2.9096% for the prediction of used in the machine learning. All displacement values are given in meter and all acceleration values are given meter per square second.

TABLE I. PREDICTION RESULTS AND ERROR VALUES FOR TRAINING DATA

ANN		Error Metric Values			ANN		Error Metric Values		
Displacement	Error	Absolute error	Square error	Absolute percentage error (%)	Acceleration	Error	Absolute error	Square error	Absolute percentage error (%)
1.2783	0.0067	0.0067	0.000045	0.5220	12.4821	0.4779	0.4779	0.228410	3.6877
1.2371	-0.0041	0.0041	0.000016	0.3290	12.1454	0.3446	0.3446	0.118782	2.7594
1.1974	-0.0134	0.0134	0.000180	1.1321	11.8166	0.2334	0.2334	0.054489	1.9372
1.1597	-0.0217	0.0217	0.000473	1.9107	11.5022	0.1378	0.1378	0.018986	1.1837
1.1244	-0.0284	0.0284	0.000808	2.5933	11.2081	0.0419	0.0419	0.001758	0.3727
1.0917	-0.0197	0.0197	0.000388	1.8385	10.9389	0.1211	0.1211	0.014654	1.0945
1.0618	-0.0128	0.0128	0.000164	1.2197	10.6983	0.1917	0.1917	0.036748	1.7603
1.0348	-0.0068	0.0068	0.000046	0.6602	10.4881	0.2319	0.2319	0.053788	2.1635
1.0107	-0.0047	0.0047	0.000022	0.4683	10.3085	0.2515	0.2515	0.063232	2.3812
Average		0.0359	0.004016	2.9096			0.1035	0.0040	2.9096
RMSE		0.0634			RMSE		0.2016		

After training process, according to three different cases, outputs and predict errors are obtained with ANN for new isolator combinations with pulse periods. The results compared with the analysis results are given in tables such as Table 2 for case 1

(all data are trained), Table 3 for case 2 (T_{eff} values equal to 2.1, 2.8, 3.3 and 3.9 s are excluding in training.) and Table 4 for case 3 (T_{eff} values equal to 2.4 and 3.6 s are excluding training.).

TABLE II. PREDICTION RESULTS FOR NEW ISOLATOR COMBINATIONS (CASE I)

T_{eff}	β_{eff}	TP_s	ANN				ANN					
			<i>Displ.</i>	<i>Error</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>	<i>Acc.</i>	<i>Error</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>
2	0.21	2	0.9553	-0.01	0.01	0.98	0.0001	9.9323	0.20	1.95	0.0391	0.20
2.2	0.1	3	1.3167	0.00	0.00	0.10	0.0000	10.6556	0.34	3.13	0.1186	0.34
2.9	0.25	4	1.0950	-0.01	0.01	0.46	0.0000	5.5215	0.06	1.05	0.0034	0.06
3.1	0.3	4	1.1503	-0.04	0.04	3.63	0.0016	5.1141	0.01	0.12	0.0000	0.01
2.5	0.28	2	1.0558	-0.04	0.04	3.91	0.0016	7.5203	0.10	1.31	0.0099	0.10
4	0.15	3	2.0370	-0.04	0.04	1.85	0.0014	5.2976	0.03	0.52	0.0008	0.03
2	0.19	2.5	0.9027	0.02	0.02	2.52	0.0005	9.4782	0.37	3.77	0.1382	0.37
2.8	0.27	3.2	1.0741	0.06	0.06	5.54	0.0040	6.0389	0.32	5.05	0.1031	0.32
2.4	0.16	2.2	1.2130	0.05	0.05	3.73	0.0022	9.0538	0.06	0.62	0.0032	0.06
3.7	0.12	3.8	2.1044	0.10	0.10	4.35	0.0091	6.3499	0.25	3.79	0.0625	0.25
4.3	0.21	2	1.2612	-0.03	0.03	2.54	0.0010	3.4093	0.12	3.63	0.0142	0.12
1.8	0.22	3	0.6338	-0.04	0.04	7.60	0.0020	7.3997	0.14	1.86	0.0197	0.14
2.2	0.05	4	0.9278	0.01	0.01	1.08	0.0001	6.9785	0.70	9.13	0.4920	0.70
3.8	0.4	2	0.9817	0.02	0.02	1.83	0.0003	4.2006	0.27	6.03	0.0726	0.27
3.4	0.18	2.5	1.5338	0.06	0.06	3.53	0.0032	5.8129	0.14	2.30	0.0188	0.14
2.5	0.26	3.2	0.9082	0.07	0.07	6.76	0.0043	6.5724	0.14	2.12	0.0203	0.14
2.1	0.15	2	1.1170	0.01	0.01	0.97	0.0001	10.5583	0.02	0.20	0.0005	0.02
2.8	0.18	3	1.3965	-0.01	0.01	0.47	0.0000	7.2780	0.12	1.69	0.0156	0.12
3.3	0.25	4	1.3655	-0.01	0.01	0.93	0.0002	5.3439	0.01	0.13	0.0000	0.01
3.9	0.28	3	1.5347	0.03	0.03	1.87	0.0009	4.8824	0.02	0.46	0.0005	0.02
			<i>Average</i>		0.03	2.73	0.0016	<i>Average</i>		0.17	2.44	0.0567
			<i>RMSE</i>		0.0404		<i>RMSE</i>		0.2380			

TABLE III. PREDICTION RESULTS FOR NEW ISOLATOR COMBINATIONS (CASE II)

T_{eff}	β_{eff}	TP_s	ANN				ANN					
			<i>Displ.</i>	<i>Error</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>	<i>Acc.</i>	<i>Error</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>
2	0.21	2	0.9553	-0.04	0.04	4.05	0.0015	9.9323	-0.10	0.10	0.98	0.0098
2.2	0.1	3	1.3167	0.03	0.03	2.11	0.0008	10.6556	0.09	0.09	0.80	0.0077
2.9	0.25	4	1.0950	-0.02	0.02	1.95	0.0005	5.5215	-0.02	0.02	0.42	0.0005
3.1	0.3	4	1.1503	-0.04	0.04	4.01	0.0020	5.1141	0.02	0.02	0.44	0.0005
2.5	0.28	2	1.0558	-0.03	0.03	2.98	0.0009	7.5203	-0.07	0.07	0.89	0.0046
4	0.15	3	2.0370	0.02	0.02	0.85	0.0003	5.2976	0.05	0.05	0.88	0.0022
2	0.19	2.5	0.9027	-0.10	0.10	10.39	0.0093	9.4782	-0.73	0.73	7.41	0.5331
2.8	0.27	3.2	1.0741	-0.07	0.07	5.82	0.0044	6.0389	-0.44	0.44	6.96	0.1960
2.4	0.16	2.2	1.2130	0.01	0.01	0.48	0.0000	9.0538	0.16	0.16	1.74	0.0252
3.7	0.12	3.8	2.1044	0.02	0.02	0.95	0.0004	6.3499	0.31	0.31	4.73	0.0974
4.3	0.21	2	1.2612	0.39	0.39	32.06	0.1555	3.4093	2.35	2.35	71.34	5.5083
1.8	0.22	3	0.6338	0.16	0.16	26.99	0.0253	7.3997	0.36	0.36	4.74	0.1277
2.2	0.05	4	0.9278	-0.40	0.40	42.34	0.1577	6.9785	0.10	0.10	1.34	0.0106
3.8	0.4	2	0.9817	-0.10	0.10	10.15	0.0103	4.2006	-0.04	0.04	0.82	0.0013
3.4	0.18	2.5	1.5338	-0.05	0.05	2.88	0.0021	5.8129	-0.37	0.37	6.15	0.1337
2.5	0.26	3.2	0.9082	0.00	0.00	0.37	0.0000	6.5724	0.10	0.10	1.44	0.0093
2.1	0.15	2	1.1170	-0.03	0.03	2.24	0.0006	10.5583	-0.08	0.08	0.78	0.0067
2.8	0.18	3	1.3965	0.06	0.06	4.22	0.0034	7.2780	0.50	0.50	6.79	0.2529
3.3	0.25	4	1.3655	0.02	0.02	1.59	0.0005	5.3439	0.13	0.13	2.52	0.0181
3.9	0.28	3	1.5347	-0.04	0.04	2.40	0.0014	4.8824	-0.08	0.08	1.63	0.0062
			<i>Average</i>		0.08	7.94	0.0188	<i>Average</i>		0.30	6.14	0.3476
			<i>RMSE</i>		0.1373		<i>RMSE</i>		0.5896			

The results include the predicted results for displacement and acceleration and error values with error metrics; mean absolute error (MAE), mean absolute percentage error (MAPE), mean squared error (MSE) and root mean squared error (RMSE) comparing to dynamic analyses results. Some of

these combinations are not used in the training process of ANN model.

For Case 1, the maximum error for the displacement is only 0.06 m. The average of all predicted values is 0.03 m. The maximum error for the accelerations is 0.7 m/s² and the average error is 0.17 m/s². As

expected, the error amount is generally low for the predicted values which are also used in the training. The ANN model generated according to Case 1 is effective in predicting the maximum structural responses.

In case 2, 4 of the isolation periods are not used. This case is done in order to see the effectiveness of

the ANN model for less machine learning. For Case 2, the average errors increase to 0.08 m and 0.3 m/s² for displacement and acceleration, respectively. For Case 3, more increases of average values are seen. These average values are acceptable, but some of the predicted results have big error.

TABLE IV. PREDICTION RESULTS FOR NEW ISOLATOR COMBINATIONS (CASE III)

T _{eff}	β _{eff}	TP _s	ANN					ANN				
			Displ.	Error	MAE	MAPE	MSE	Acc.	Error	MAE	MAPE	MSE
2	0.21	2	0.9553	0.01	0.01	1.56	0.0002	9.9323	-0.06	0.06	0.59	0.0036
2.2	0.1	3	1.3167	0.00	0.00	0.01	0.0000	10.6556	0.03	0.03	0.26	0.0008
2.9	0.25	4	1.0950	0.05	0.05	4.54	0.0025	5.5215	-0.03	0.03	0.45	0.0006
3.1	0.3	4	1.1503	-0.03	0.03	2.74	0.0009	5.1141	0.16	0.16	3.11	0.0253
2.5	0.28	2	1.0558	-0.02	0.02	2.13	0.0005	7.5203	-0.01	0.01	0.13	0.0001
4	0.15	3	2.0370	0.01	0.01	0.29	0.0000	5.2976	0.03	0.03	0.65	0.0012
2	0.19	2.5	0.9027	-0.38	0.38	41.49	0.1476	9.4782	-0.73	0.73	7.40	0.5317
2.8	0.27	3.2	1.0741	0.21	0.21	18.48	0.0441	6.0389	0.46	0.46	7.27	0.2137
2.4	0.16	2.2	1.2130	-0.28	0.28	21.86	0.0758	9.0538	-0.79	0.79	8.65	0.6216
3.7	0.12	3.8	2.1044	-0.58	0.58	26.42	0.3378	6.3499	-1.40	1.40	21.25	1.9663
4.3	0.21	2	1.2612	-0.11	0.11	9.28	0.0130	3.4093	-0.12	0.12	3.67	0.0146
1.8	0.22	3	0.6338	0.00	0.00	0.06	0.0000	7.3997	0.14	0.14	1.87	0.0198
2.2	0.05	4	0.9278	0.05	0.05	5.54	0.0027	6.9785	-0.08	0.08	1.09	0.0070
3.8	0.4	2	0.9817	0.06	0.06	5.82	0.0034	4.2006	0.16	0.16	3.60	0.0259
3.4	0.18	2.5	1.5338	-0.15	0.15	9.64	0.0235	5.8129	-0.35	0.35	5.88	0.1225
2.5	0.26	3.2	0.9082	0.18	0.18	18.84	0.0337	6.5724	0.26	0.26	3.88	0.0679
2.1	0.15	2	1.1170	0.06	0.06	5.11	0.0033	10.5583	0.05	0.05	0.43	0.0021
2.8	0.18	3	1.3965	0.04	0.04	2.61	0.0013	7.2780	0.32	0.32	4.37	0.1046
3.3	0.25	4	1.3655	-0.02	0.02	1.36	0.0003	5.3439	0.03	0.03	0.63	0.0011
3.9	0.28	3	1.5347	-0.03	0.03	2.21	0.0012	4.8824	-0.08	0.08	1.69	0.0068
			Average		0.11	9.00	0.0346	Average		0.27	3.84	0.1869
			RMSE		0.1860		RMSE		0.4323			

As a conclusion, the ANN model generated for the problem can be used, but the required number of training must be done as Case 1. The predicted results are not precise, but these results may be useful to know the behavior of structural responses for the change of the base isolator parameters. In future, the ANN model can be used in optimum design. Adding the analysis results for more pulse periods may increase the efficiency of the ANN model.

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