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Prediction of acceleration and impact force values of a reinforced concrete slab

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Abstract. Concrete which is a composite material is frequently used in construction works. Properties and behavior of concrete are significant under the effect of different loading cases. Impact loading which is a sudden dynamic one may have destructive effects on structures. Testing apparatuses are designed to investigate the impact effect on test members. Artificial Neural Network (ANN) is a computational model that is inspired by the structure or functional aspects of biological neural networks. It can be defined as an emulation of biological neural system. In this study, impact parameters as acceleration and impact force values of a reinforced concrete slab are obtained by using a testing apparatus and essential test devices. Afterwards, ANN analysis which is used to model different physical dynamic processes depending on several variables is performed in the numerical part of the study. Finally, test and predicted results are compared and it's seen that ANN analysis is an alternative way to predict the results successfully.

Keywords: artificial neural network; concrete; impact effect; testing apparatus

1. Introduction

Concrete is durable against pressure and can be formed easily. It is widely used in construction of structures such as buildings, dams, water tunnels, bridges and roads. Besides, it is used against nuclear radiation in modern structures. Concrete can be used as structural member and decorative material. It is preferred because of noise insulation and resistance against fire properties in construction technology. Besides, it is shapeable, economic and it doesn't need treatment often.

Components of concrete as cement, water, aggregate are easy to access. Concrete is a composite building material whose compression strength is high contrary to tensile strength. Compression strength is a significant property to define the quality of concrete. Reinforcements which are placed in concrete improve the compression strength. Ultimate target of the concrete mixture is the 28-days compression strength which is determined by test press machine.

Concrete and reinforced concrete structural members have been investigated under various loading conditions for several years. Since dynamic loads happen suddenly and cause destructive damages, response of structural members against these loads are more complicated than static ones. Impact loading is the change of stresses developing due to dynamic effects on mechanical

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properties of members at strike moment between objects.

Studies which are performed to investigate the behavior of structural members under impact loading are available in the literature (Zineddin and Krauthammer 2007, Suaris and Shah 1983, Yankelevsky 1997, Tai and Tang 2006, Nataraja *et al.* 1999).

High stress values are observed in structural members under impact effect. Vehicle strikes, explosions especially in military establishments, projectile and missile strikes, crane accidents and rock falls to structures located in roadsides can be counted as examples of impact incidents. Impact effect on members is usually investigated by different testing apparatuses and necessary test devices. There is not an accepted standard about impact test procedures yet. On the other hand, ASTM E 23 presents helpful information about testing devices and limits in impact tests (Siewert and Manahan 2000).

Different solution methods come forward with the development of computing science in the world. ANN analysis is one of these methods and commonly used to model several activities. ANN provides improvement about the accuracy of prediction in common methods. By this way, application of ANN analysis may reduce time and cost amounts. Many studies have been published about ANN by researchers to correct the deficiencies and compare the test results in civil engineering field so far (Guang and Zong 2000, Siddique *et al*. 2011, Słon´ski 2010, Lee 2003, Kim and Kim 2002, Öztaş *et al*. 2006, Yeh, 1998, Kim *et al*. 2004, Caglar and Garip 2013, Erdem *et al*. 2013).

ANN analysis is appropriate to create software about applications. Proven theories of ANN are accepted in our day as well as fuzzy set theories, genetic algorithms and other programming techniques. Success of ANN analysis about input-output relationship of data is accepted for complex theoretical or experimental problems. Therefore, ANN is used by researchers to predict results without any specific equations.

In this study, a reinforced concrete slab test member having 700 × 700 × 100 mm sizes is produced in the first place. This member is tested under impact effect by using testing apparatus and necessary devices. Acceleration and impact force values are measured for each drop movement. After the test member has reached collapse damage level, test results are compared with numerical analysis. ANN analysis is performed according to advanced software to compare both test and predicted results. For this purpose, multi-layer, feed-forward and back propagation ANN algorithm is used. Finally, the relationship between test and numerical results is obtained and presented in figures and tables.

2. Experimental study

2.1 Test preparation

In the experimental part of the study, a reinforced concrete slab which has 700 × 700 × 100 mm sizes is produced in the laboratory. There are 7 reinforcements having 8 mm diameters are used in each direction of the slab. Concrete covers are taken as 20 mm. Yield strength of the reinforcements is 420 N/mm^2. Reinforcement configuration of the slab is given in Fig. 1.

CEM I 42.5 Portland cement, sand, gravel, water and chemical admixture are used for concrete production. Concrete mix is prepared in the laboratory. Material ratios for 1 m^3 concrete are given in Table 1.

Concrete mix is produced in the concrete mixing machine and poured to the mold of the slab

Fig. 1 Reinforcement configuration

Table 1 Material ratios

Material	Amount (kg)	Ratio (%)
Cement (42.5 R)	370	15.4
Gravel (5-15 mm)	880	36.7
Sand (0-5 mm)	940	39.3
Water	200	8.4
Chemical admixture	4	0.2

Fig. 2 Slab and cubic members

Fig. 3 Test member in the testing apparatus

and 3 cubic members after lubrication operation. Two slab members are produced in the first place to decide test parameters on one of them. After vibration is performed for a while, top concrete surfaces are straightened with trowels as shown in Fig. 2.

Test members are placed in the curing pool for 28 days. Afterwards, cubic members are tested in the press machine to determine the compression strength value. Average strength value is determined as 38.5 N/mm^2.

Surfaces of the test member are painted by ceiling paint to observe crack patterns better. Places of the accelerometers on the test member are signed. Four accelerometers are placed into the yellow brass devices. These special devices measure and transfer the accelerometer values to the data logger without any loss. Finally, test member is placed in the testing apparatus as shown in Fig. 3.

2.2 Test devices

A testing apparatus is designed for the experimental part of the study. This apparatus has 2500 mm capacity to apply impact loading on test members. Mass of the steel hammer can be changed. The hammer drops to the center of the members to completely reduce eccentricity effects during tests. Base platform of the apparatus whose sizes are 1000 × 1000 × 70 mm is placed on the ground. This platform is produced by using steel plates and weighing almost 500 kg. By this way, effect of the free falling movement is absorbed at impact moment by this platform.

Optic photocells are placed on the left side of the apparatus to measure the drop time in milliseconds. Drop numbers can be seen on the electronic screen as well as drop times. Support conditions of the test member are provided by steel connecting devices which have 50x50x500 mm sizes. These devices restrain the movement of the test members during tests.

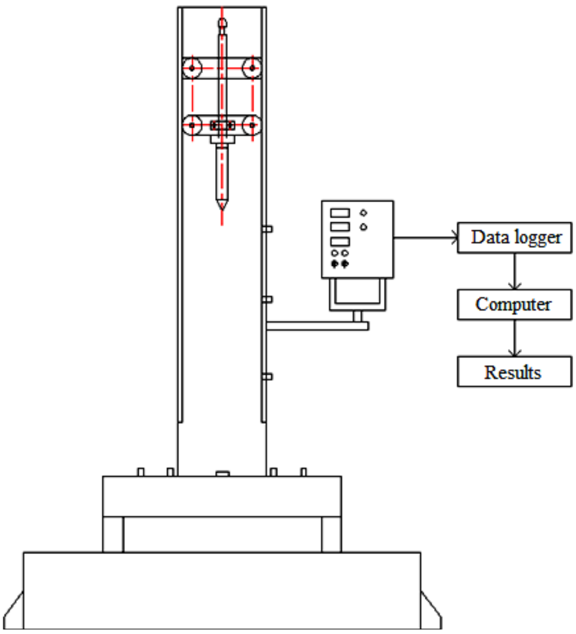


Fig. 4 Working mechanism

A steel plate and a rubber layer are also used in tests. They are placed on the center of the test member to distribute the impact loading uniformly and prevent local crashing on the contact surface during tests. Four accelerometers, a dynamic force sensor that is placed in the edge part of the steel hammer, a camera to observe the free falling movement better, a data logger and special connection cables are used in tests as well.

Accelerations may reach very high values during impact events. In this way, shock accelerometers are placed on the slab member during tests to measure vibrations and acceleration values occurring in a very short time span of time without any data loss. They are specifically designed to measure extreme, high-amplitude, short-duration, transient accelerations during impact tests. These accelerometers has also constant voltage sensitivity and do not lose signal standard even in negative environmental effects.

A dynamic force sensor which is widely used in impact, shock and crash testing is placed in the edge part of the steel hammer to measure impact force values during tests. This sensor makes the free falling movement with the hammer. By special properties of this device as high linearity and repeatability, correct values are measured during tests.

Connection cables are utilized to connect accelerometers and dynamic force sensor to the data logger. Data logger records acceleration and impact force values by its special sensors on electronic card. In this way, measurement data is collected in data logger. Finally, acceleration and impact force values are transferred to the computer by using special software. Working mechanism of the testing apparatus is presented in Fig. 4.

3. Artificial neural networks

ANN is computing systems simulating the biological neural systems of the human brain. It is an emulation of biological neural networks. Neurons are connected each other with various influence levels to solve problems. Statistical data tools are used to model complex relationships between inputs and outputs in ANN analysis. Therefore, ANN is trained to recognize input patterns and produce proper output responses. ANN can change its structure which is based on the information flowing through the network during learning phase. It also learns and generalizes from training data. So, there is no need for enormous feats of programming. Problems having sufficient data are suitable for ANN analysis. ANN has major advantages such as prediction of complex problems and fast evaluation of new examples.

ANN analysis is an alternative way to solve difficult problems by classic methods. It is widely used in several study areas as classification, modelling and prediction. The common type of ANN is usually formed of three or more layers which are input, output and hidden layers. Neurons are connected to each other with modifiable weighted interconnections in the layers. Input layer is generated from nodes which receive data from independent variables. In other words, number of nodes in input layer equals to the number of input variables of the problem. Hidden layer takes place between input and output layers. It receives information from input layer according to applied weights and pre-specified activation functions. On the other hand, output layer gets theprocessed information from hidden layer and sends the results to an external recreant. It means, number of nodes in output layer equals to the number of output variables of the problem. Architecture of a neural network model is shown in Fig. 5 (Demir 2008).

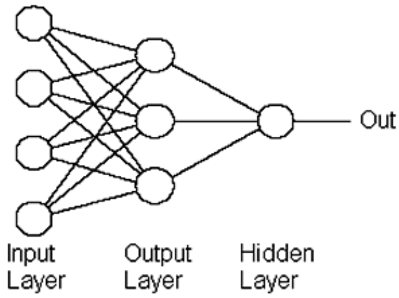


Fig. 5 Architecture of ANN model

ANN is a parallel computational system consisting of several simple processing elements connected together in a specific way in order to perform a particular task. It achieves general characteristics of the problem from numerical data during training and generates significant responses for the whole dataset (Uysal and Tanyildizi 2012). ANN design requires a suitable architecture. Feed-forward, back propagation is the most common learning algorithm of ANN due to its relatively simplicity and universal approximation capacity. Multilayer neural networks are the most popular networks used in applications. Back propagation algorithm defines a systematic way to update the synaptic weights of multi-layer, feed-forward supervised networks composed of input, hidden and output layers. After the data is collected for the problem, it is separated as training and testing datasets. The analysis process starts after deciding the topology of ANN. The correlation coefficient compares the accuracy of the model after analyses. This coefficient approaches to 1 for the perfect fit.

4. Experimental results

After the test member is produced and preparations are completed, support conditions are provided in the testing apparatus. Rubber layer and steel plate take place on the test member. Measurement devices as accelerometers and dynamic force sensor are placed and connected to data logger with particular cables. Strict attention is paid to prevent the test devices and cables from possible damages during tests. Geometrical placement of the necessary devices on the test member is seen in Fig. 6.

While mass of the steel hammer is 10 kg, drop height is taken as 80 cm during tests. Acceleration and impact force values are measured for each drop movement of the hammer.

Experimental part of the study has been continued until the test member reaches collapse damage situation. Bigger values are obtained from the accelerometers which are placed from 150 mm distance of impact point. Rebound movements of the steel hammer are restrained by using the locking mechanism of the testing apparatus. By this way, the hammer hits the test member for once at each drop. Acceleration-time and impact force-time graphs for the first drop movement are presented in Figs. 7(a)-(c).

Minimum, maximum accelerations with absolute average values and maximum impact forces which are obtained by accelerometers and dynamic force sensor for all drop movements are given in Table 2.

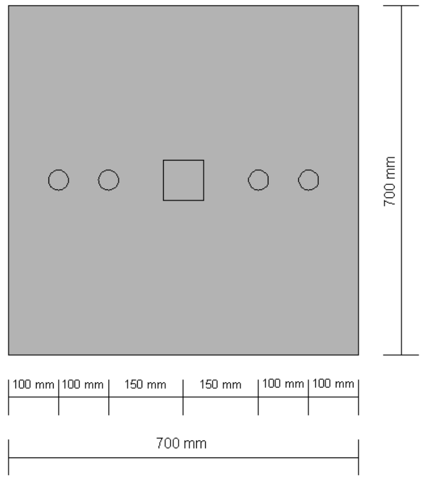
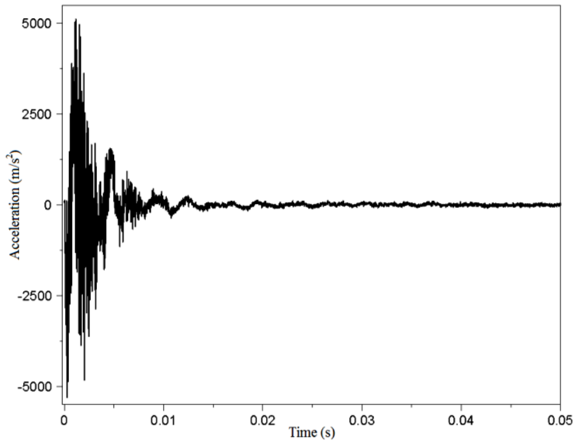
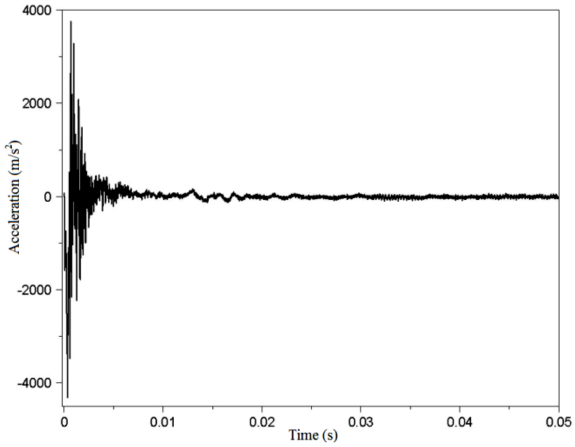


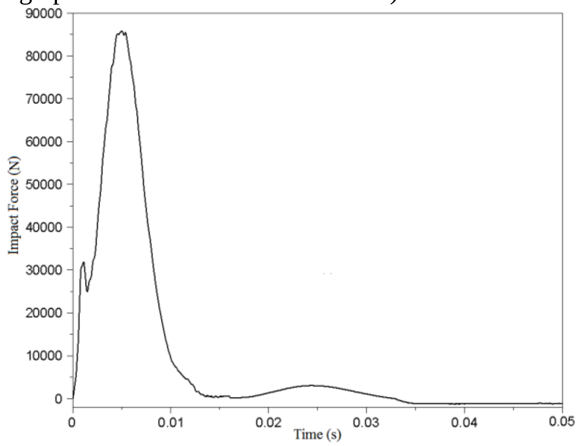
Fig. 6 Test devices on the test member



a) Acceleration-time graph at 150 mm



b) Acceleration-time graph at 250 mm



c) Impact force-time graph

Fig. 7 Graphs for the first drop movement

Table 2 Measured values for each drop

Drop Number	Accelerations at 150 mm (m/s^2)			Accelerations at 250 mm (m/s^2)			Max. Impact forces (N)
	Min.	Max.	Abs. Ave.	Min.	Max.	Abs. Ave.	
1	-5302	5106	5204	-4307	3763	4035	85810
2	-5217	5176	5196.5	-4105	3864	3984.5	85541
3	-5088	5197	5142.5	-4214	3672	3943	85396
4	-5076	4986	5031	-4083	3654	3868.5	84918
5	-5002	5052	5027	-3981	3745	3863	84451
6	-4961	5011	4986	-3661	3798	3729.5	83824
7	-4970	4921	4945.5	-3586	3765	3675.5	83417
8	-4954	4861	4907.5	-3513	3687	3600	82890
9	-4872	4716	4794	-3446	3652	3549	82217
10	-4804	4652	4728	-3237	3581	3409	81544
11	-4712	4561	4636.5	-3281	3574	3427.5	80418
12	-4714	4462	4588	-3305	3523	3414	79247
13	-4587	4428	4507.5	-3358	3361	3359.5	78458
14	-4418	4457	4437.5	-3374	3281	3327,5	78024
15	-4204	4327	4265.5	-3281	3141	3211	77413
16	-4086	4294	4190	-3263	3088	3175.5	76965
17	-3997	4125	4061	-3277	3019	3148	76635
18	-3984	3806	3895	-2977	3084	3030.5	75655
19	-3877	3584	3730.5	-3102	2946	3024	75066
20	-3812	3394	3603	-3047	2912	2979.5	74635
21	-3761	3416	3588.5	-3005	2779	2892	73826
22	-3661	3328	3494.5	-3054	2591	2822.5	71857
23	-3544	3442	3493	-2876	2685	2780.5	71087
24	-3487	3413	3450	-2539	2857	2698	70655
25	-3168	3458	3313	-2479	2776	2627.5	70086
26	-3084	3375	3229.5	-2413	2628	2520.5	69643
27	-3216	3165	3190.5	-2579	2368	2473.5	69126
28	-3123	2968	3045.5	-2486	2298	2392	68626
29	-3094	2768	2931	-2175	2344	2259.5	68045
30	-2954	2685	2819.5	-2018	2283	2150.5	67865
31	-2743	2692	2717.5	-2169	1983	2076	67215
32	-2517	2603	2560	-2077	1893	1985	66910
33	-2364	2487	2425.5	-1806	1877	1841.5	66727
34	-2156	2324	2240	-1673	1802	1737.5	66454
35	-2087	2216	2151.5	-1573	1783	1678	66118
36	-2192	1865	2028.5	-1663	1441	1552	65881
37	-2047	1764	1905.5	-1579	1432	1505.5	65521
38	-1924	1782	1853	-1293	1577	1435	65214
39	-1946	1742	1844	-1347	1502	1424.5	65105
40	-1785	1836	1810.5	-1316	1421	1368.5	65005

5. Numerical results

After experimental part of the study, prediction of absolute average acceleration values from 150 mm and 250 mm distance of impact point and impact force values are performed according to ANN. For this purpose, a multi-layer, feed-forward, back propagation neural network is applied to dataset by using neural network toolbox of Matlab software. In ANN analysis, several Matlab subroutines have been developed and various other commands are used to reach the optimum result.

There are 40 sets for acceleration and impact force values take part in the database. While 30 sets are used for training, 10 sets are used for testing the network. Support conditions, drop height and mass of the steel hammer are the constant inputs. On the other hand, absolute average acceleration and impact force values are the output parameters of the ANN analysis. A single hidden layer also takes place in the network.

Several trials are performed to find out the most suitable architecture of the network. Normalization operation is applied to the datasets. This operation makes non-linearity characteristic of neural networks meaningful. Data normalization shall be performed to restrain problems arising from overvalued cumulative amounts. For this reason, input and output values are normalized between -0.9 and 0.9 in the ANN analysis according to Eq. (1).

$$z_n = 1.8\left[\frac{z_i - z_{min}}{z_{max} - z_{min}}\right] - 0.9 \qquad (1)$$

Neuron numbers in each layer are important characteristics of the network. However, there is no clear theory to give information about choosing the number of neurons in the layers. The common practice is the trial and error method. Neuron numbers of the layers are selected in the first place. Then, the numbers are changed until reaching the desired performance of the network. While four neurons take place in input layer, there are five neurons in hidden layer and two neurons in output layer respectively.

Scaled Conjugate Gradient (SCG) is used as the training function in the network and 4000 iterations are performed to reach the optimum results. Denormalization operation is applied to

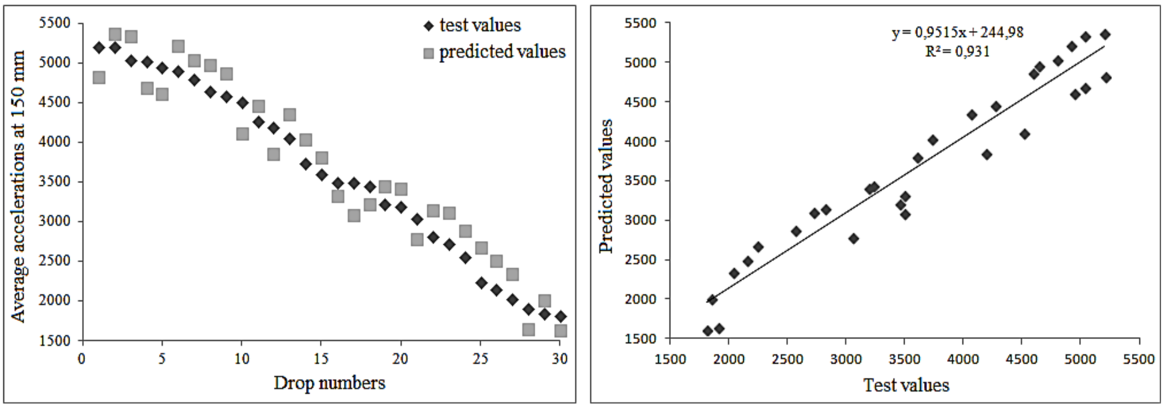


Fig. 8 Dispersion and performance of training set (accelerations at 150 mm)

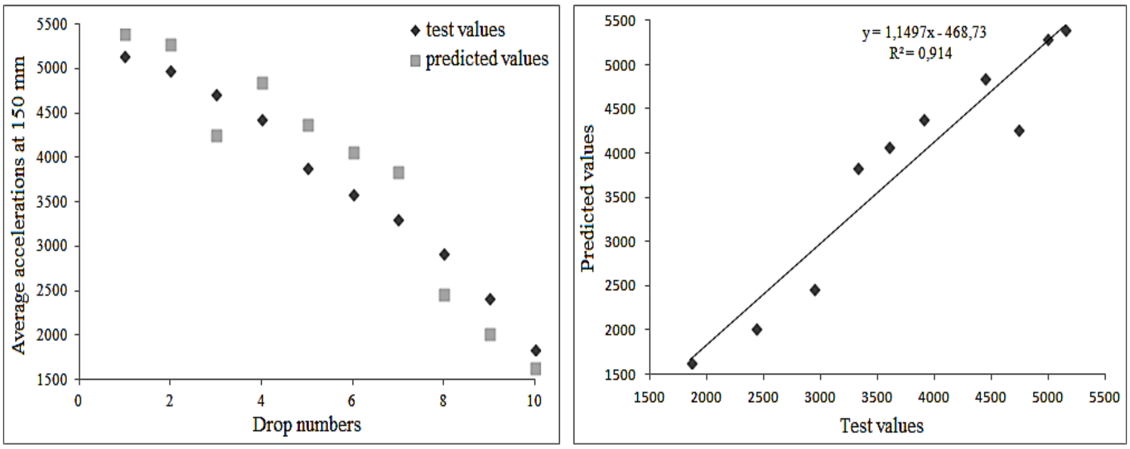


Fig. 9 Dispersion and performance of testing set (accelerations at 150 mm)

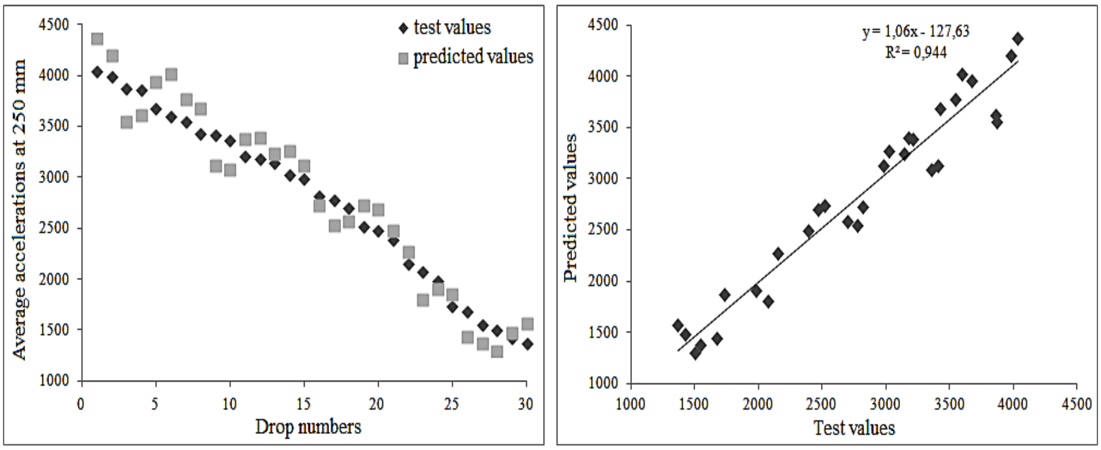


Fig. 10 Dispersion and performance of training set (accelerations at 250 mm)

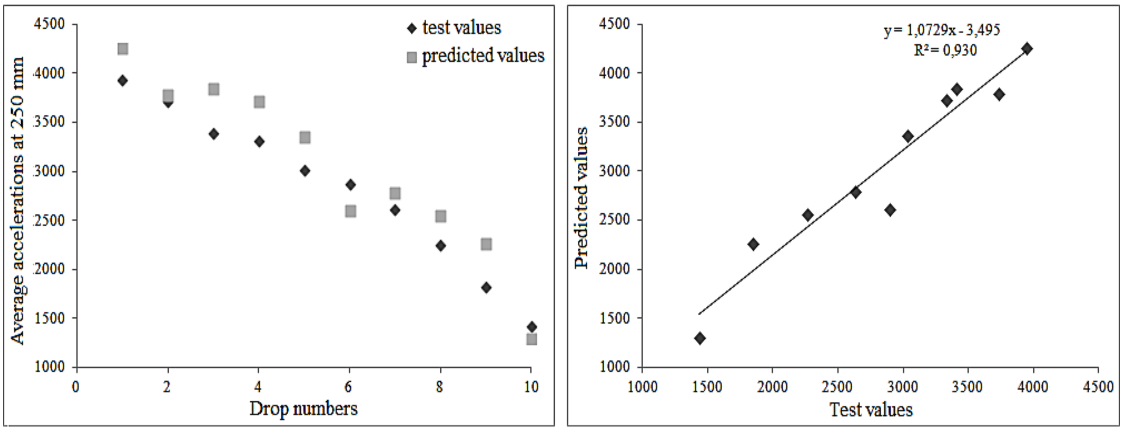


Fig. 11 Dispersion and performance of testing set (accelerations at 250 mm)

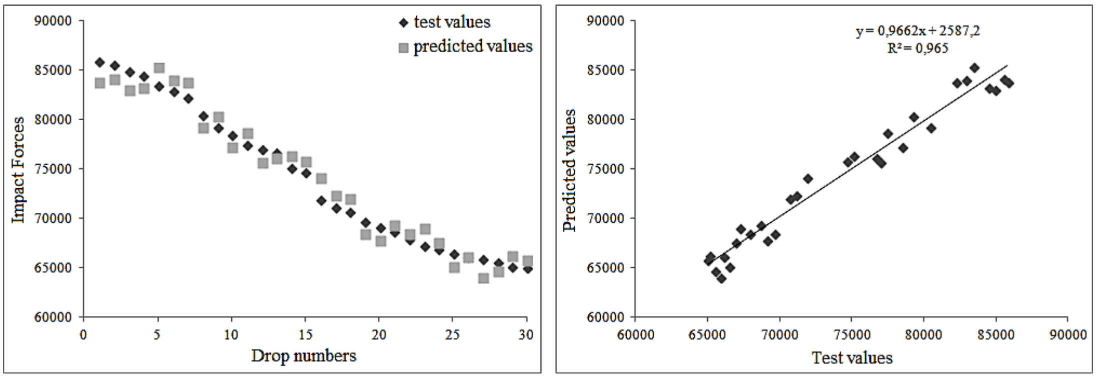


Fig. 12 Dispersion and performance of training set (impact forces)

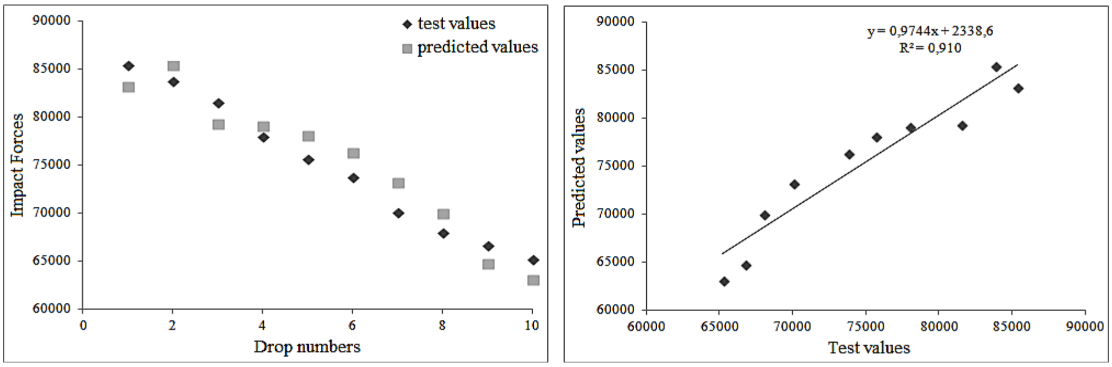


Fig. 13 Dispersion and performance of testing set (impact forces)

Table 3 Correlation coefficients

Accelerations at 150 mm		Accelerations at 250 mm		Impact Forces	
R^2 (training)	R^2 (test)	R^2 (training)	R^2 (test)	R^2 (training)	R^2 (test)
0.931	0.914	0.944	0.930	0.965	0.910

normalized values to compare the results together. The performance of the network is obtained by evaluating the test and predicted absolute average acceleration and impact force values of the dataset. The results of training and testing sets are respectively shown between Figs. 8 and 13.

Correlation coefficients (R^2) are accepted as performance standards. They determine the suitability level of the values. These coefficients which give information about the relationship between experimental and predicted results are calculated according to Eq. (2).

$$R^2 = \left[\frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \right] \tag{2}$$

Calculated correlation coefficient values are seen in Table 3 for both training and testing sets. Since the calculated values are close to each other, a strong relationship is established between results.

6. Conclusions

Developments in science and engineering depend on the variety of materials. Concrete is a widely used composite material in construction of structural members. Determination of the property and behavior of these members under different loading conditions which gives information about the advantages and deficiencies to researchers has been a big area of interest in civil engineering field.

In this paper, a reinforced concrete slab which has 700 × 700 × 100 mm sizes is produced in the laboratory. After the 28 days curing period, test preparations of the slab member are completed. Afterwards, support conditions are provided in the testing apparatus. Accelerometers which are placed on the member and dynamic force sensor that is placed in the edge part of the steel hammer are connected to data logger with particular cables. The reinforced concrete slab member is tested under impact effect. Ultimately, acceleration and impact force values are obtained for all drop movements of the steel hammer.

This study is primarily concerned with the prediction of acceleration and impact force values according to ANN analysis which is a complex system to solve specific problems where neurons are connecting to each other with different influence level. Since it takes time to perform tests in laboratory conditions, ANN analysis is an alternative way to predict the test data successfully by reducing work force. Complex relationships of inputs and outputs are rapidly modeled by ANN statistical data modeling tools. Because of this specialty, ANN is being used in many scientific fields.

A computer program is created to compare the acceleration and impact force values between test and ANN analysis. The correlation coefficients are determined as $R^2 = 0.931$ and $R^2 = 0.914$ for accelerations from 150 mm, $R^2 = 0.944$ and $R^2 = 0.930$ for accelerations from 250 mm distance of impact point and R^2=0.965 and R^2=0.910 for impact forces according to training and test processes respectively. These results reveal that a significant model and a strong relationship have been established between test and predicted values. Consequently, ANN analysis may be used as an alternative way to predict the results successfully.

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