PREDICTION OF IMPACT RESULTS ON CEMENT BASED MORTAR SLABS

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Grout mortars are non-permeable, non-shrink and flowing cement based construction materials. Due to reaching high strength values in a short time, grout mortars are used in construction works. However, behavior of cement mortars under sudden impact loading is complex. Because, loading duration is very short in impact scenarios, effect of strain rates is much higher than static loading. So, dynamic responses and failure modes of the materials are different. In this study, it is aimed to investigate the dynamic behavior of slabs that are produced by cement based grout mortars under impact loading. A drop test setup is developed for this purpose and several measurement devices utilized in the impact experiments. Acceleration, displacement and impact load values are obtained as well as drop durations and drop numbers. After completing the experimental part of the study, artificial neural networks (ANN) analysis which is used to model different physical dynamic processes depending on the experimental variables is performed to predict the impact results. So, ANN analysis is used in the verification of experimental study. Due to the comparison of experimental and analysis results, it is considered that proposed ANN model can be used for the evaluation of the dynamic responses of test specimens.

Keywords: *ANN; drop test setup; grout mortars; impact; slabs*

1. Introduction

Recent improvements in materials science offer some advantages in the construction technology. Grout mortars can be defined as cement based and self-consolidating materials. In addition, grout mortars can reach high strength values. They are used to cover areas due to their fluid, non-permeable and non-shrink properties. Short setting periods are provided owing to additive substances in the structure of mortars. Thus, grout mortars can be easily utilized in the applications in which rapid usage is needed.

Impact loading is a sudden dynamic loading whose effect may be bigger than other types of loads in a short span of time. Structural materials or members may be exposed to sudden impact effects in their service lives [1-4]. Main cases of impact loads can be given as the falling rock, sudden explosions, vehicle strikes, crane accidents, ship crashes on offshore structures and aircraft landing to airport runway platforms [5].

Because impact loading is the least known loading type, researchers develop drop test setups to investigate the behavior of different materials or test specimens under sudden impact effects [6-9]. The test mechanism is usually provided by dropping masses from various drop heights. Due to the regulations in American Society for Testing and Materials E23 that present information about impact test limits, performances of the test setups have been improved recently [10].

It is not easy to experimentally study impact resistances of test specimens. Main difficulties of experimental studies are providing test conditions and high costs and calibration difficulties of the measurement devices. Due to these reasons, numerical studies have been carried out by researchers in recent years [11-14].

ANN analysis is a computing system which is inspired by the biological neural networks of the human brain that process information. ANN analysis is an artificial intelligence application and has become popular in recent years because of its success about modeling a number of human activities in many areas in science and engineering [15].

Neural networks are capable of learning and correlating data sets which are obtained from simulations or experimental studies. In ANN analysis, it is important to constitute the relationship of input-output data to establish the proper results in complex problems. Proven theories of ANN are accepted in our day as well as fuzzy set theories, genetic algorithms and other programming techniques. So, the good comparison of ANN results with the experimental or theoretical proves to reliability of ANN analysis in predicting results [16-19].

The literature review reveals that impact effect usually investigated on test specimens that are manufactured by reinforced concrete or steel. In this study, it is aimed to determine the behavior of test specimens under sudden impact loading. For this purpose, 9 slabs have been manufactured by cement based grout mortars. Acceleration, displacement and impact load values are obtained under impact loading. Besides, damage crack patterns are observed during experimental study.

In the numerical analysis part of the study, ANN analysis is performed by the advanced software to predict experimental values according to a numerical algorithm. Predicted results are compared by experimental values and it is seen that proposed ANN model can be useful when evaluating the dynamic behavior of cement based mortar slabs.

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Table 1

Characteristics of mortar types

Property	Type 1	Type 2	Type 3
Chemical content	Cement	Cement	Cement
Shape/colour	Dust/grey	Dust/grey	Dust/grey
Water Amount (lt) (for 25 kg bag)	2.27 - 3.50	2.75 - 3.25	2.5
Application temperature (ºC)	0 - 25	5 - 30	2 - 35
Modulus of elasticity (N/mm^2)	≥ 26000	≥ 28000	≥ 40000
Compression strength (N/mm^2)	30 - 35 (1 day) 60 - 70 (28 days)	30 - 50 (1 day) 60 - 90 (28 days)	≥ 60 (1 day) ≥ 90 (28 days)

2. Experimental study

2.1. Test specimens and materials

A total of 9 test specimens having 500x500x50 mm dimensions are manufactured in the experimental program. 3 different types of cement based grout mortars are used in the manufacture of test specimens [20]. While first type of the grout mortar is used to manufacture Specimens 1-3, second type is used for Specimens 4-6 and third type is used for Specimens 7-9. Aggregates with specific granulometry are in the composition of each ready-mix grout mortar type. As the third mortar type contains metallic aggregates, it provides high strength and impact resistance. Impact loading is applied on the specimens to investigate the impact resistances. Mass of the hammer and drop height are taken constant during impact experiments. Characteristics of mortar types are presented in Table 1.

Test specimens are manufactured for 3 sets. Different types of grout mortars are used for each set. After preparing the homogenous mixture, grout mortars are placed into the molds as shown in Figure 1.

Fig. 1 – Manufacture of the specimens.

Steel molds with 40x40x120 mm dimensions are used to determine the compression strength of test specimens. With this object, the samples are taken from each test specimen as presented in Figure 2. Test specimens and samples are kept in laboratory conditions to complete the essential curing period.

Fig. 2 - Test samples.

27 test samples which are taken from 9 test specimens have been tested in the press machine under axial load. By this way, compression strengths of the test specimens are obtained. Afterwards, the average compression strength values are calculated. These values for each specimen are given in Table 2. The values for modulus of elasticity are mentioned in Table 1 due to technical specifications of each mortar type.

Table 2

Average compression strength values

Test specimen	Test sample	Compression strengths of test samples (N/mm^2)			Average compression strengths (N/mm^2)
S1	1, 2, 3	33.06	30.56	31.73	31.78
S2	4, 5, 6	30.45	29.70	31.69	30.61
S3	7, 8, 9	29.28	31.54	30.16	30.33
S4	10, 11, 12	66.59	64.18	65.91	65.56
S5	13, 14, 15	63.41	64.95	66.39	64.92
S6	16, 17, 18	66.74	65.19	67.98	66.64
S7	19, 20, 21	91.14	93.65	94.68	93.16
S8	22, 23, 24	93.41	91.55	92.62	92.53
S9	25, 26, 27	94.13	92.29	95.63	94.02

2.2. Test equipment

A drop test setup is used to investigate the dynamic response of test specimens under impact effect. This test setup has widely used for impact experiments in several studies where impact loading is applied to test specimens. In the test setup, impact loading is applied by a vertical striker named as hammer which is manufactured from steel. To apply different level of impact energies on the test specimens, mass and drop height of the hammer can be changed.

Friction effects may occur during the movement of the hammer. Because of this reason, wheel shaped members that are manufactured from castermid material are used to provide the connection between the hammer and drop test setup. By this way, friction effects during the experimental study are minimized.

A thick base platform is designed in the test setup. Weight of the platform that is produced by high strength steel plates is almost 500 kg. Base platform whose dimensions are 1000 x 1000 x 200mm is placed on the ground. Support devices which are also produced from steel are utilized to restrain horizontal and vertical movement in the across sides of test specimens in the experimental study. Dimensions of these devices are 50 x 50 x 500 mm.

Measurement devices such as accelerometer, linear variable differential transformer (lvdt), dynamic load cell, data-logger and optic photocells are used to obtain measurements during the experimental study. Positions of these devices in the test setup are shown in Figure 3.

Impact loading is applied on the center of all test specimens. A high strength steel plate having 10 mm thickness and neoprene rubber layer with 5 mm thickness are located at impact point. Thus, local crushing on the contact surface is prevented and impact loading on test specimens is uniformly distributed.

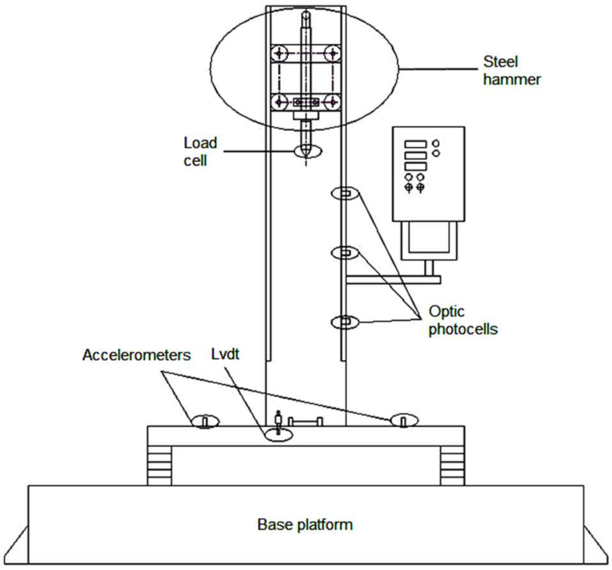

Fig. 3 - Test setup.

ICP typed piezoelectric accelerometers are symmetrically fixed on the specimens from 125 mm distance of impact point. These accelerometers are capable of measuring acceleration values with vibrations in a short period without any loss.

Furthermore, the accelerometers have constant voltage sensitivity and their signal quality is not affected even in negative environmental conditions. While measurement range of the accelerometers is ±4905 m/s², working temperature is between -18 and +66 °C.

Linear variable differential transformer (lvdt) is used to measure the displacement values. It changes the mechanical movement of an object into electrical signals. Lvdt is placed under test specimens around impact point. Measurement range of lvdt is 50 mm with a working temperature between -18 and +66 °C.

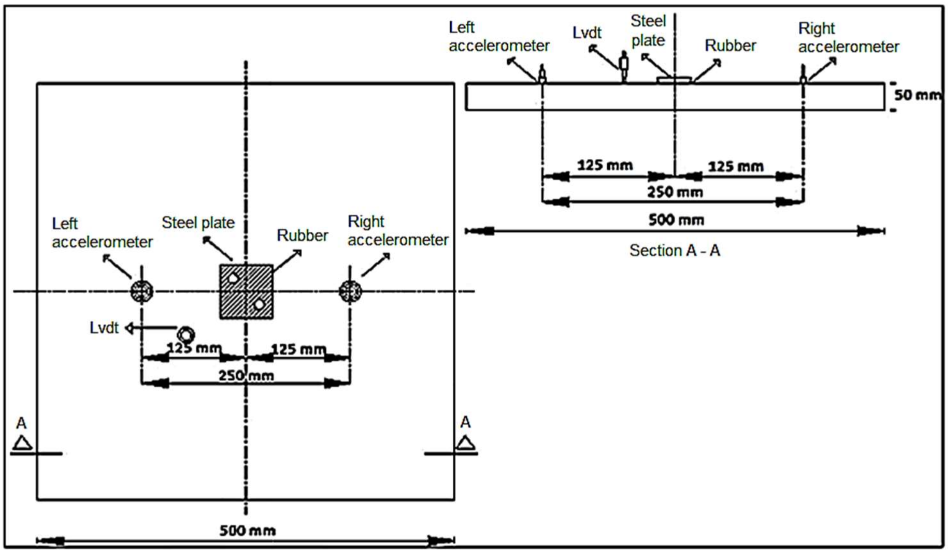

Fig. 4 – Positions of the equipment.

ICP typed dynamic load cell is utilized to measure the impact load values. This load cell exists in the edge part of the steel hammer. So, it is able to determine impact load values for each drop of the hammer. The load cell has capacity to determine big signals in a short period of time. While measurement range of the load cell is up to 88.96 kN, working temperature is between -54 and +121 ^{o}C.

Drop numbers and durations are measured by optic photocells during impact experiments. An electronic screen that is situated on the left side of the test setup display the drop numbers and durations for each drop movement. There is a locking mechanism to restrain the rebound of the hammer in the test setup. Optic photocells are also used to enable this mechanism locking mechanism of the test setup. By this way, the measurements are taken for single drop of the hammer.

As sudden dynamic loading is applied on test specimens, a dynamic data logger system is used in the experimental study. The data-logger has 138 dB dynamic measurement range, 16 kHz maximum sampling speed, 24 bit adc resolution and 12 vdc power input with a working temperature between -20 and +50 ^{o}C. Finally, test data is converted into time histories of acceleration, displacement and impact load values by using the software in the computer. Location of the test equipment in a test specimen is presented in Figure 4.

3. Experimental results

Test specimens are placed in the test setup and experimental study is performed for the same amount of impact energy (4.125x9.81x0.6 = 24.28 joule) due to the constant value of drop height and mass of the hammer.

Each test specimen is painted to white color to observe crack and damage development in a better way. S7 test specimen in the test setup is shown as an example in Figure 5.

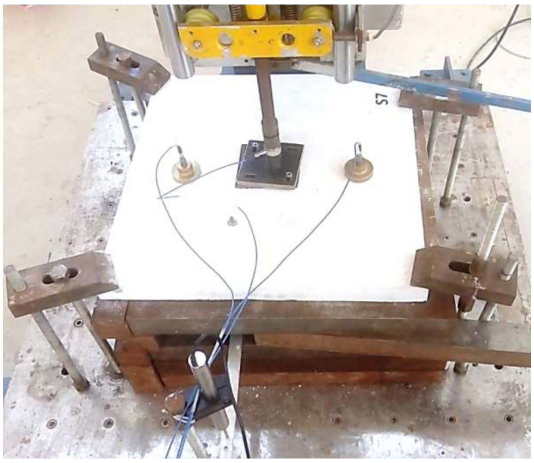

Fig. 5 – S7 test specimen.

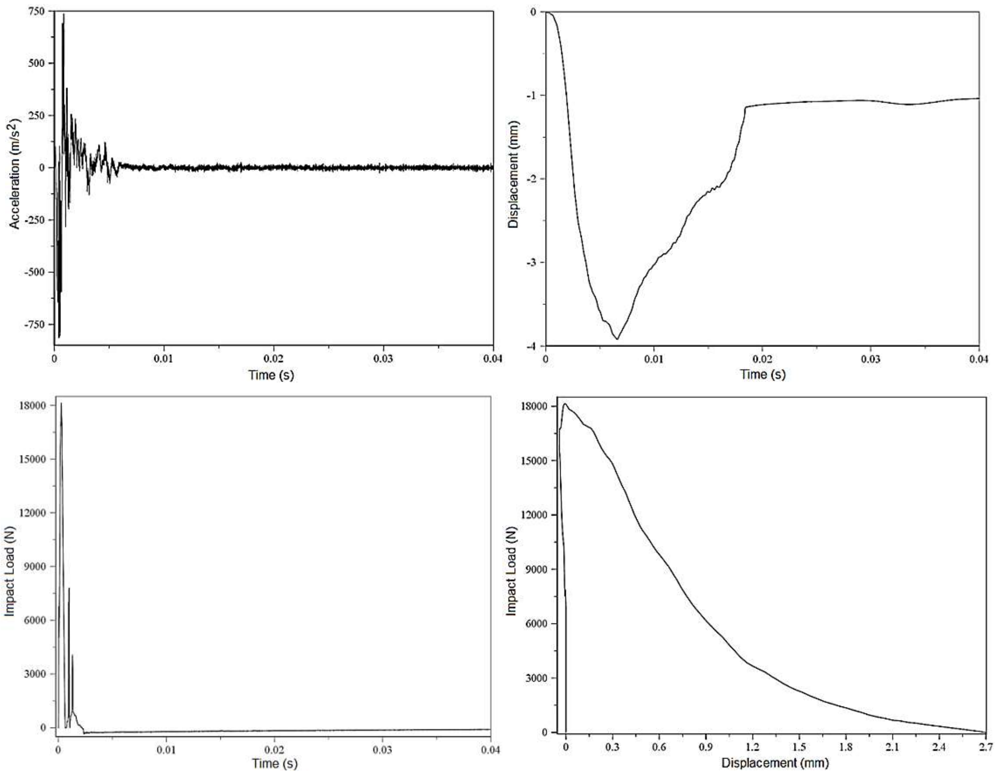

Fig. 6 – Graphs for S1 specimen.

Time histories of acceleration, displacement and impact load values are obtained for the test specimens during experimental part of the study. In addition, load-displacement curves are generated while considering the same time intervals for impact load and displacement values. Examples of acceleration-time, displacement-time, impact load-time and impact load-displacement curves for the first drop of Specimen 1 are depicted in Figure 6. Failure damage situations of the specimens are obtained in the final step of the experimental study. Crack widths increase and some mortar pieces separate from test specimens in failure damage situation. Furthermore, maximum displacement value is measured and the specimens are not able to resist against impact loading anymore. Test specimens in failure damage situation are shown in Figure 7.

After completing the experimental part of the study, acceleration, displacement and impact load values are recorded by data-logger for each drop movement of the hammer. Accelerometers are symmetrically placed on the specimens to validate acceleration values. It is seen that there aren't big differences between the values of left and right accelerometers. Maximum acceleration, displacement and impact load values that are obtained by measurement devices in the experimental program are presented for each test specimen in Table 3 [20].

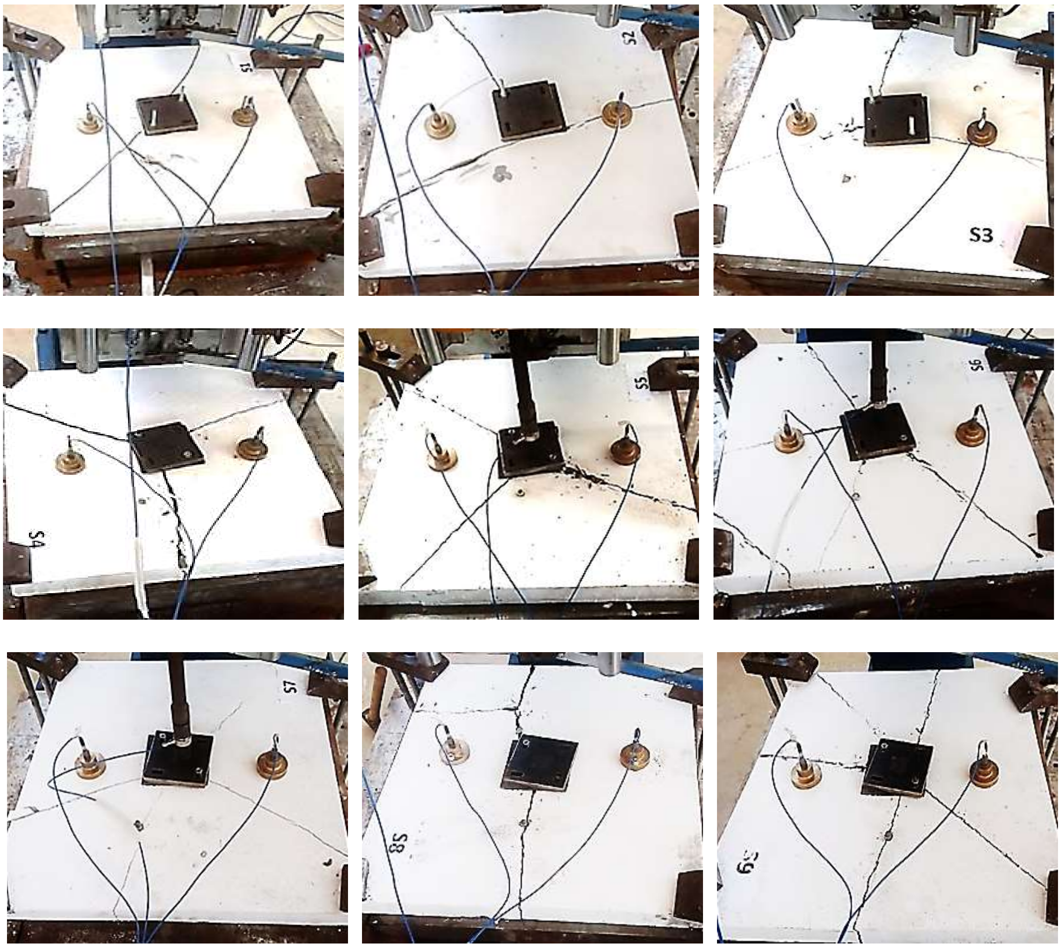

Fig. 7 – Failure of test specimens.

Table 3

Experimental results

Specimen no	Left acceleration (m/s^2)		Right acceleration (m/s^2)		Max. displacement (mm)	Max. impact load (kN)
S1	-813.64	736.30	-794.41	723.72	8.90	18.13
S2	-693.24	741.88	-736.68	677.56	8.52	18.01
S3	-730.50	690.02	-685.93	719.34	9.04	17.59
S4	-980.60	938.97	-962.56	935.17	7.07	21.30
S5	-958.80	1017.24	-994.61	937.49	6.90	20.98
S6	-977.64	996.26	-936.42	978.83	7.26	22.04
S7	-1363.03	1228.97	-1213.58	1284.62	6.17	25.24
S8	-1176.24	1260.10	-1163.42	1208.74	6.32	24.95
S9	-1255.95	1384.60	-1249.04	1345.53	5.98	25.53

4. Numerical analysis

In this section of the study, the prediction of maximum acceleration and displacement values of the S1, S6 and S9 test specimens are predicted by ANN analysis. These selected specimens have the biggest compression strength values for each type of mortars. The biggest acceleration values that are measured from two symmetrical accelerometers are considered in the analysis. Since, a constant level of impact energy is applied on the specimens for each drop, similar impact load values are obtained by the load cell that is placed in the edge part of the hammer. Because of this reason, numerical analysis is performed for maximum acceleration and displacement values.

ANN analysis is one of the applications of the artificial intelligence. An artificial neural network is kind of a computing system which is inspired by human brain and processes information in the end. Neural networks are capable of learning and correlating large datasets obtained from experimental studies of computer simulations. ANN analysis imitates the human brain activities and generates new information by using the learning algorithms.

Self-learning capacities in the ANN analysis yield accurate results by using the existing data. ANN analysis is considered to be an effective alternative solution way in specific problems having sufficient data. Main advantages of ANN can be counted as learning events, classifying and making decisions by evaluating the similar events. Because of these capabilities, many researchers have been performed ANN analysis in several engineering applications [21].

ANN analysis is composed of connected units named as neurons which are attached to each other with different influence levels. Basically, a neuron receives the signal, processes it and transfer to the connected neurons. Thus, a large number of interconnected neurons collaborate with each other to solve the problem. Because of this reason, statistical data tools are used to model this complicated relationship between inputs and outputs. Finally, ANN analysis is trained to recognize input patterns and yield appropriate output responses.

Generally, the network is made of an input layer of neurons, one or several hidden layer of neurons and output layer of neurons. In these layers, neurons are fully interconnected by weights as presented in Figure 8. Number of the neurons can be different according to type of the problem. Neurons receive data from outside environment in the input layer. Afterwards, the data is transferred to neurons in the hidden layer which is situated between input and output layers. Finally, neurons in the output layer receive processed information and produce the network results to an external output.

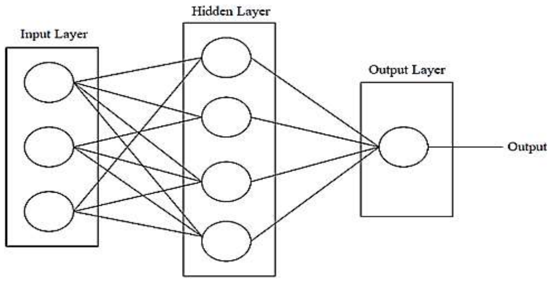

Fig. 8 – ANN architecture.

A proper architecture design shall be constituted in the ANN model. Even though, multilayer ANN models are usually proposed by researches, it is noted that ANN models with only one hidden layer is also capable of estimating results successfully [22]. Owing to its simplicity and universal approximation capacity, feed-forward, back propagation algorithm is used in the prediction of the experimental maximum acceleration and displacement values of the RC slabs.

Back propagation algorithm defines a systematic way to update the synaptic weights of multilayer, feed-forward supervised networks composed of input, hidden and output layers. This algorithm seeks the minimum of the error function in weight space using the method of gradient decent. The problem is divided into training and testing datasets after collecting the necessary data. Finally, correlation coefficient is calculated to evaluate the relationship between experimental and numerical results. The higher correlation coefficient value represents the better suitability between the experimental and predicted values.

To predict the maximum acceleration and displacement values by ANN analysis, neural network toolbox of the Matlab software is used to apply a multilayer feed-forward back propagation neural network to the dataset. In accordance with this purpose, several Matlab subroutines have been developed to reach the optimum result. While mass of the hammer, drop height and support conditions are considered as constant inputs, output parameters are maximum acceleration and displacement values. A hidden layer is also situated in the architecture of the network. Drop numbers of the slabs constitute the total sets. A total of 30, 32 and 36 drops are performed on each specimen. While many of the data is used for training set, the rest is used for testing set in the ANN analysis.

Data normalization needs to be performed to restrain problems arising from overvalued cumulative amounts in the problem. So, normalization operation has been applied to the datasets by Eq. (1). Inputs and outputs are normalized between (-0.9:0.9) range after normalization. In the equation, z_n, z_i, z_{min} and z_{max} represent the calculated normalized value, the related i. value, the minimum value the maximum value in the set respectively.

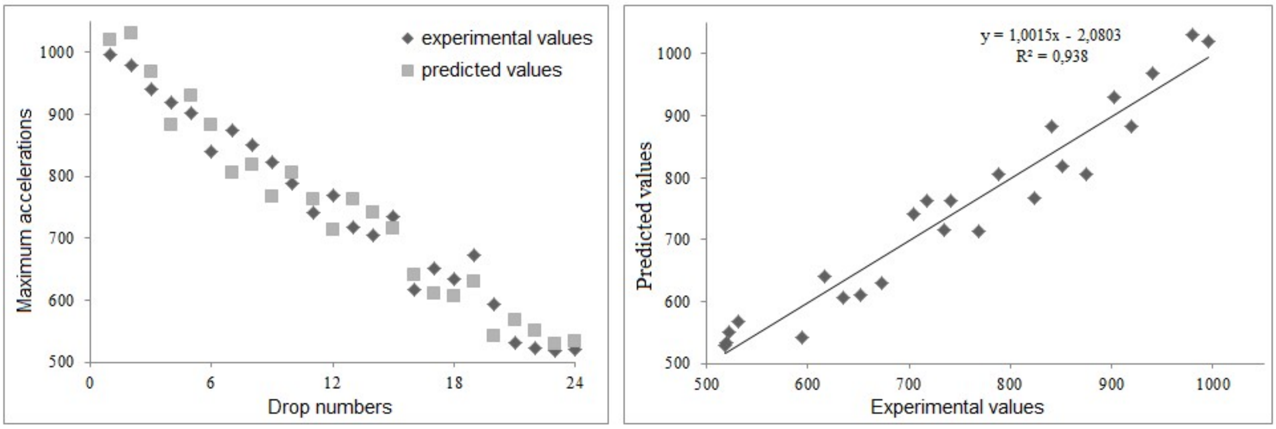

Fig. 9 – Dispersion of training set for acceleration values of S6.

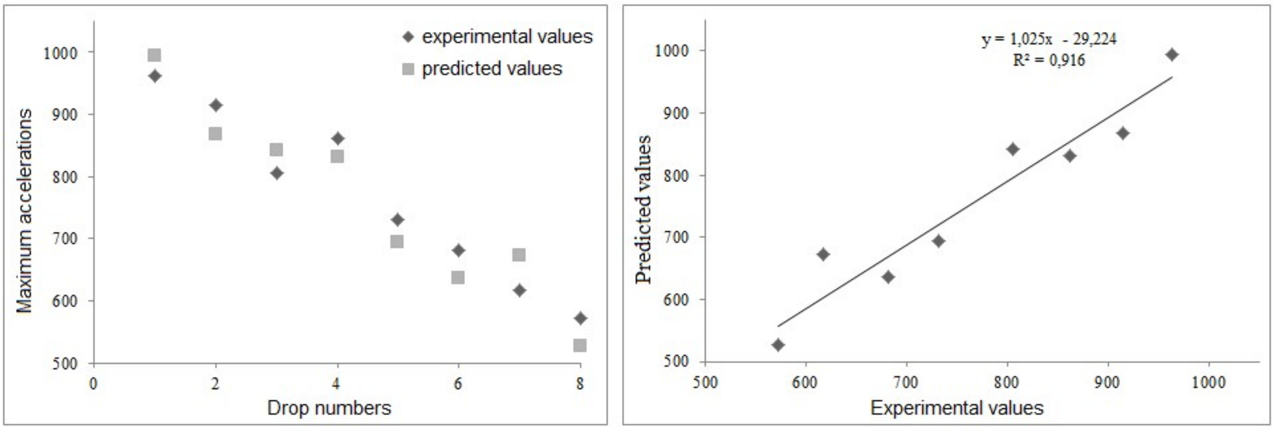

Fig. 10 – Dispersion of testing set for acceleration values of S6.

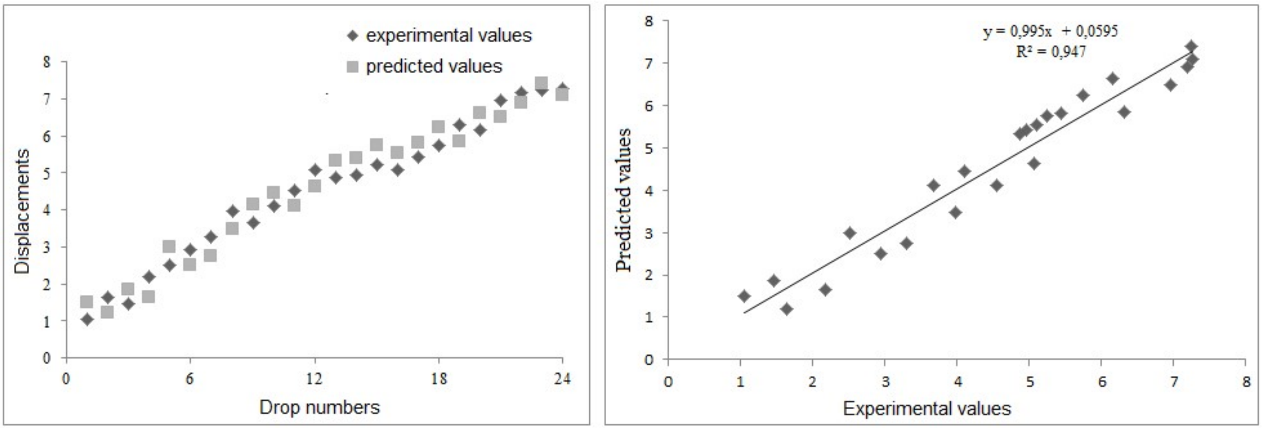

Fig. 11 – Dispersion of training set for displacement values of S6.

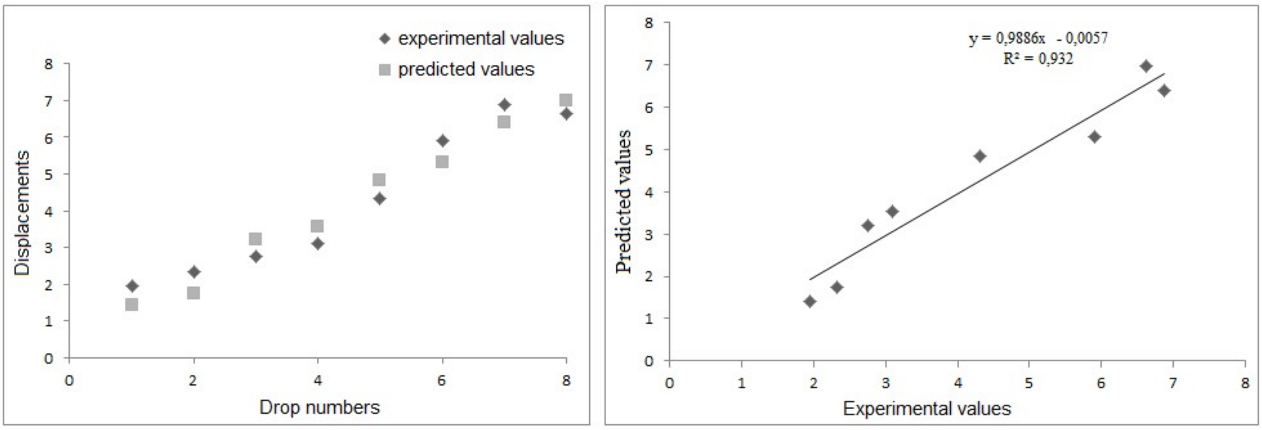

Fig. 12 – Dispersion of testing set for displacement values of S6.

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

Training function in the ANN analysis is selected to be scaled conjugate gradient (scg) and 4000 iterations have been performed to obtain the optimum result. The performance of the network is evaluated by the experimental and predicted maximum acceleration and displacement values together. The results of both training and testing sets are revealed for S6 specimen as an example between Figures 9 and 12.

Determination coefficients (R^2) are calculated for training and testing sets to exhibit the relationship between experimental and ANN analysis results. Suitability level of the experimental and predicted values is obtained by these coefficients. A perfect fit is obtained when the coefficient approaches to 1.0. The values of the coefficients are given for each test specimen in Table 4.

Table 4

Determination coefficients

Test specimen	Max. accelerations		Max. displacements	
	Training	Testing	Training	Testing
S1	0.916	0.903	0.925	0.917
S6	0.938	0.916	0.947	0.932
S9	0.943	0.921	0.949	0.936

5. Conclusions

As impact loading is the least known one among other loads, it is usually ignored in the design phase. However, structural members may be exposed to low velocity impact effect during their service periods. So, it is important to consider impact effects which may lead to substantial damages in a short span of time.

This study has focused on the dynamic behavior of the slabs that are manufactured by different types of grout mortars under impact loading. For this purpose, a drop test setup is developed. Each test specimen has been tested under a constant level of impact energy in the test setup. Impact experiments have been continued until failure damages are observed on the specimens.

When the experiments on the specimens are evaluated, it is seen that rigidity of test specimens has important effect on the acceleration values. Maximum acceleration values are determined for S9 test specimen having the highest rigidity due to the compression strength and modulus of elasticity values. The same tendency is also determined for the impact load values. Impact load values get bigger as the compression strength and modulus of elasticity values increase.

Lvdt is used to measure the displacement values of the specimens. The biggest displacement value is measured from S1 test specimen that has the lowest compression strength value. Total drop numbers and durations are determined by optic photocells. Because, same level of impact energy is implemented on the specimens, similar drop durations are obtained. However, there are differences between drop numbers owing to the change in compression strength values of the specimens. So, the biggest drop numbers are obtained for S7, S8 and S9 test specimens.

After completing the experimental program on the specimens, ANN analysis that is able to predict experimental values rapidly is performed to predict the maximum acceleration and displacement values for the selected specimens having the biggest compression strength values for each mortar type. For this purpose, a computer program is generated to compare experimental and numerical analysis. Afterwards, determination coefficients which are evaluated as performance standards are calculated to exhibit the relationship between experimental and numerical values.

Due to the results of training sets in ANN analysis, values of the determination coefficients differ between 0.916 and 0.943 for acceleration values. On the other hand, determination coefficients are obtained between 0.925 and 0.949 for displacement values.

Since total data of training set is bigger than testing set for each test specimen, it is considered that number of the total data has significant effect on the success of the correlation. For instance, the most successful determination coefficients are determined for S9 specimen which has the most total data between the specimens.

Finally, it is evaluated that a significant model and a strong relationship have been established between experimental and numerical studies. Thus, it is thought that, ANN analysis could be an alternative approach to reduce work force, overcome the difficulties in the laboratory conditions and predict experimental results when the proper numerical model is established.

REFERENCES

[1] T. Yılmaz, N. Kıraç, Ö. Anil, Experimental investigation of axial loaded reinforced concrete square column subjected to lateral low-velocity impact loading, Structural Concrete, 2019, **20**(4), 1358-1378.

[2] M. Zineddin, T. Krauthammer, Dynamic response and behavior of reinforced concrete slabs under impact loading, International Journal of Impact Engineering, 2007, **34**(9), 1517-1534.

[3] H. Othman, H. Marzouk, An experimental investigation on the effect of steel reinforcement on impact response of reinforced concrete plates, International Journal of Impact Engineering, 2016, **88**, 12-21.

[4] R.M. Chakradhara, S.K. Bhattacharyya, S.V. Barai, Behaviour of recycled aggregate concrete under drop weight impact load, Construction and Building Materials, 2011, **25**, 69-80.

[5] T. Yılmaz, N. Kıraç, Ö. Anil, R.T. Erdem, G. Kaçaran, Experimental investigation of impact behaviour of rc slab with different reinforcement ratios, KSCE Journal of Civil Engineering, 2020, **24**(1), 241-254.

[6] N. Kishi, H. Mikami, K.G. Matsuoka, T. Ando, Impact behavior of shear-failure-type RC beams without shear rebar, International Journal of Impact Engineering, 2002, **20**(9), 955-968.
[7] E. Guades, T. Aravinthan, A. Manalo, M. Islam, Experimental investigation on the behaviour of square frp composite tubes under repeated axial impact, Composite Structures, 2013, **97**, 211-221.
[8] K. Liu, B. Liu, R. Villavicencio, Z. Wang, C.G. Soares, Assessment of material strain rate effects on square steel plates under lateral dynamic impact loads, Ships and Offshore Structures, 2016, **13**(2), 217-225.
[9] R. Ranade, V.C. Li, W.F. Heard, B.A. Williams, Impact resistance of high strength-high ductility concrete, Cement and Concrete Research, 2017, **98**, 24-35.
[10] ASTM E23-00, Standard test methods for notched bar impact testing of metallic materials, ASTM International, West Conshohocken, PA, 2002.
[11] J. Arros, N. Doumbalski, Analysis of Aircraft Impact to Concrete Structures, Nuclear Engineering and Design, 2007, **23**, 1241-1249
[12] S.N. Mokhatar, R. Abdullah, Computational Analysis of Reinforced Concrete Slabs Subjected to Impact Loads, International Journal of Integrated Engineering, 2012, **4**(2), 70-7d6.
[13] M. Zeinoddini, J.E. Harding, G.A.R. Parke, Axially pre-loaded steel tubes subjected to lateral impacts (a numerical simulation), International Journal of Impact Engineering, 2008, **35**(11), 1267-1279.
[14] H. Othman, H. Marzouk, Finite-element analysis of reinforced concrete plates subjected to repeated impact load, Journal of Structural Engineering, 2017, 14**3**(9), 1-16.
[15] R.T. Erdem, A.U. Öztürk, E. Gücüyen, Estimation of compression strength of polypropylene fibre reinforced concrete using artificial neural networks, Romanian Journal of Materials, 2016, **46**(3), 313-318.
[16] G.M. Kotsovou, D.M. Cotsovos, N.D. Lagaros, Assessment of RC exterior beam-column joints based on artificial neural networks and other methods, Engineering Structures, 2017, **144**, 1-18.
[17] R.T. Erdem, E. Kantar, E. Gücüyen, Ö. Anil, Estimation of compression strength of polypropylene fibre reinforced concrete using artificial neural networks, Computers and Concrete, 2013, **12**(5), 613-625.
[18] R.T. Erdem, Prediction of acceleration and impact force values of a reinforced concrete slab, Computers and Concrete, 2014, **14**(5), 563-575.
[19] J.B. Mander, M.J. Priestley, R. Park, Prediction of self-compacting concrete strength using artificial neural networks, European Journal of Environmental and Civil Engineering, 2016, **20**, 102-122.
[20] M. Berberoğlu, Experimental investigation of concrete slabs produced with cement based mortars under dynamic loads, M.Sc. Thesis, Manisa Celal Bayar University, Turkey, 2019.
[21] F. Demir, Prediction of elastic modulus of normal and high strength concrete by artificial neural networks, Construction and Building Materials, 2008, **22**, 1428-1435.
[22] G.A. Panagiotis, G.M. Vaseilios, Concrete compressive strength using artificial neural networks, Neural Computing and Applications, 2020, **32**, 11807-11826.

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