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Original Article

Impact Analysis of a Concrete Beam via Generative Adversarial Networks

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Abstract - *This study investigates the behavior of a concrete beam under impact loading. For this purpose, the beam specimen is produced for this purpose, and impact experiments have been performed using a drop weight test setup. Besides, several measurement devices such as an accelerometer, dynamic load cell, optic photocells and data logger are also utilized in the experimental study. The constant input energy is implemented on the concrete beam specimen, and measurements are collected for each hammer drop. In the numerical part of the study, a novel deep learning model called Generative Adversarial Network (GAN) that has the ability to generate synthetic data without human intervention has been designed. GANs create an artificial intelligence agent to compete against another artificial intelligence agent in order to generate new samples with desired properties. GANs are used to produce synthetic data with the same statistical distribution as the experimental acceleration and impact load values acquired from the experiments. When experimental (real) and numerical (synthetic) values are compared, it is discovered that the suggested numerical model has produced consistent results in creating synthetic experimental values for the specimen. So, it is thought that the proposed numerical could be evaluated in the prediction of impact experiments.*

Keywords - *Concrete beam, Test setup, Impact loading, GANs, TVAE.*

1. Introduction

Concrete is a construction material comprised of cement, fine and coarse aggregates with water. Concrete has a significant role in all branches of civil engineering due to its advantages, such as durability, high compression strength and resistance to high temperatures. Concrete technology relates to its practical application, especially in the building industry all around the world. For instance, concrete technology is used in structural members such as foundations, columns, beams and slabs in building construction. Low-velocity impact loading may affect structural members during their service periods [1-3]. As the duration of the impact loading is very short, structural responses are different from other loading types. Although dynamic effects such as seismic and wind loads are considered in the design of structural members, the effect of sudden impact loading is ignored. The impact effect on structural members can be defined as impulsive dynamic loading that occurs during a short time span. Impact scenarios can be given as crane accidents, falling rocks, vehicle collisions, explosion-induced shock waves etc.

The calculation of the capacities of the structural members becomes more important when the effects of sudden impact loading are considered. Because of the difficulties in designing the test setup and high-cost measurement devices, there are not many experimental studies about the impact effects on the structural members in the literature [4-6]. However, researchers have suggested that a drop weight test setup is the best way to seek the impact behavior of several test specimens produced from different materials [7-9]. Drop weight is applied to the specimen by a vertical striker from a certain height. In addition, the limits of impact experiments have been defined by the regulations in ASTM E 23 [10].

Deep learning is the new frontier in artificial intelligence, which uses neural networks and deep learning algorithms to learn from vast amounts of data and solve complex problems. Compared to shallow learning techniques, deep learning has a greater degree of flexibility and can better approximate many nonlinear functions. Recent years have seen rapid adoption of deep learning techniques in many applications. The main reasons for this are the increasing computational power and the availability of large training datasets that allow for model building. One of the newest applications of deep learning is to create synthetic tabular data that is close to or equal to the original data distribution using Generative Adversarial Networks (GANs). GANs [11] are artificial intelligence algorithms that generate realistic data to be used for training deep neural networks. They consist of two neural networks: the generator and the discriminator. The generator takes random input noise and tries to generate realistic-looking data, while the discriminator takes input data from the generator and tries to learn how to recognize fake data. GANs have gained popularity in recent years due to their success in extracting features from synthetic data without any manual feature engineering needed. They can be used to generate synthetic data and have been successfully applied in different fields like generating text, speech, images, and video.

To develop synthetic structural brain networks, Barile et al. [12] employed generative adversarial networks. The structural characteristics of newly produced brain networks are analyzed, and their influence on categorization performance is studied to determine their quality. Huang et al. [13] used a generative adversarial network to generate time-dependent traffic sensor data by transforming the traffic time series data creation problem into an image generation challenge. They claimed that the suggested model might greatly enhance traffic data assignment accuracy when compared to previous models using various statistical methodologies. Posilovic et al. [14]. Introduced a novel deep learning Generative Contradiction Network model for producing realistic ultrasonic B-scans with flaws in various places. They also demonstrated that the data provided improves the performance of deep convolutional neural object identification networks. Yang et al. [15] trained generative adversarial networks in subsurface research and engineering using high-resolution core pictures with a restricted field of view and their equivalent huge structure images. The model was tested using real-world pictures, and the model-generated images showed good agreement with the real-world pore structures.

This paper introduces the Tabular Vector Autoencoder (TVAE) that has been applied to tabular data to generate synthetic data via deep neural networks with a limited number of layers and parameters [16]. The model is trained using GANs training algorithm, which can be written as an optimization problem on the output layer of TVAE or its discriminator function, where the objective is minimizing cross-entropy between real labels [17]. TVAE can also decrease the amount of data processed by performing evolutionary operations at different points in time with different subsets of training data as input, significantly decreasing computation time [18–24].

A concrete beam is manufactured, as well as 3 cubic samples in the first place. 28-days curing period has been completed, and the constant input impact energy is applied to the beam specimen. Accelerometers, dynamic load cells, data loggers and optic photocells are employed in the experimental study. Impact tests have been continued until the specimen reaches a failure damage situation. Time histories of acceleration and impact load values are also determined due to the measured values by test devices.

In the numerical analysis section, the TVAE model has been performed to experimentally reduce the time and cost of obtaining acceleration and impact load data from the beam specimen. The model has been used to generate 5000 synthetic beam data using real acceleration and impact load values obtained from a limited number of experiments. To verify whether the created synthetic beam data have been consistent with the real data, the cumulative sums and statistics per feature of the synthetic beams generated from the actual data from the experiments have been compared. Evaluation is consistent with cumulative sums per feature and statistical distribution, providing evidence that synthetic data generated by the model is accurate when compared with real experimental data.

2. Experimental Study

2.1. Test Specimen and Materials

In the experimental part of the study, a concrete beam is produced in the laboratory. While the section sizes of the beam are 100x150 mm, the length of the specimen is 710 mm. A mold of the specimen is produced from plywood material consisting of thin wood layers with a thickness of 21 mm.

The compression strength of the cubic samples is targeted at 35 MPa in the design phase of a concrete mixture. Material amounts and percentages by weight for 1 m^3 concrete are given in Table 1. A concrete mixing machine is used to produce concrete in laboratory conditions. A total of 3 cubic samples are manufactured as well. After lubrication of the molds of the beam specimen and cubic samples, the concrete mixture is poured into the molds and vibration is performed in the end. The curing period is completed in 28 days. Afterwards, the cubic samples were tested under axial load to decide the compression strength value. Finally, the average compression strength value is determined as 36.2 MPa, close to the targeted strength value. A cubic sample in the concrete testing machine is presented in Figure 1.

Fig. 1 Cubic sample

Table 1. Material amounts

Material	Amount (kg)	Weight (%)
Cement (42.5R)	400	16.7
Gravel (5-15 mm)	1020	42.7
Sand (0-5 mm)	770	32.2
Water	200	8.4

2.2. Test Devices

A drop weight test setup is utilized to implement impact loading on the test specimen during the experimental study. Similar test setups have been designed to investigate the impact effect on several materials and test specimens for such studies in the literature. In the test setup, various amounts of masses can be applied from a certain drop height up to 2500 mm. Thus, potential energy is converted into kinetic energy at the impact moment. High-strength steel plates are used to produce the base platform of the test setup, which weighs almost 500 kg. A vertical striker that is named a hammer is placed between two slides of the test setup. The hammer is also manufactured from steel material. Besides, the geometry of the impact hammerhead is taken constantly, just like the drop height and mass of the hammer.

Measurement devices are used to obtain experimental data during impact tests. For example, piezoelectric accelerometers are used to determine the acceleration values from four points of the concrete beam specimen. These accelerometers are capable of measuring vibrations without any loss. The accelerometers are placed into the yellow brass apparatuses using mechanical anchors from 150 and 250 mm distances of impact point by considering the left and right of the axis of symmetry.

A dynamic load cell that successfully obtains the dynamic effects in impact experiments is fixed in the edge part of the steel hammer. Thus, the load cell moves with the hammer and measures the value of impact loading for each drop. Impact load values with even small waves for a very short span can be measured by the load cell.

Optic photocells are also used in the experimental study. In this way, drop durations in milliseconds and drop numbers are determined. These values are simultaneously monitored on the electronic screen. Besides, optic photocells obstruct the second load transfer from the hammer after rebound movement.

All measured values are transferred to the data logger by low-noise connection cables. The data logger rapidly collects the measured data and sends them to the software in the computer without any loss. Afterwards, the results are evaluated in the computer environment, and acceleration-time and impact-load time graphs are generated in the end.

A high-strength steel loading plate and the neoprene rubber layer are placed on the middle point of the specimen, in other words, the contact point between the hammer and the specimen. Thus, impact loading is distributed through the beam section, and local fragmentation is prevented. The value of thickness is 10 and 5 mm for the loading plate and the rubber layer, respectively. A schematic diagram of the test setup can be seen in Figure 2.

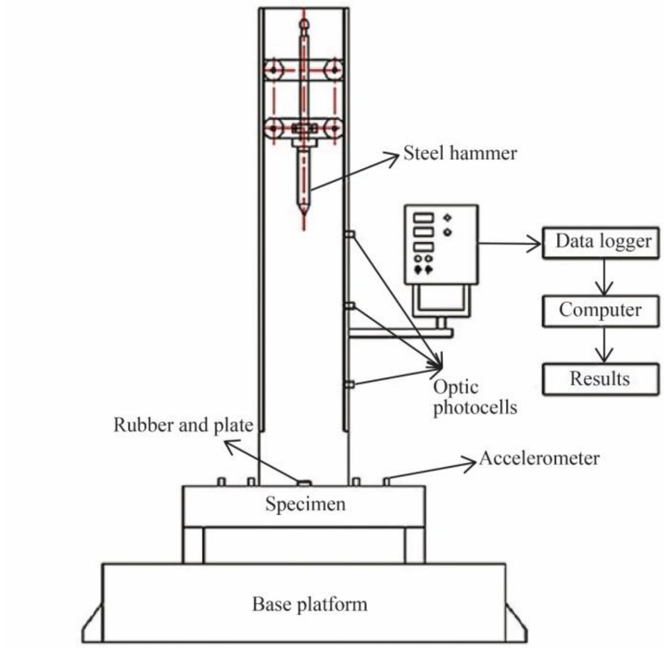

Fig. 2 Test setup

3. Experimental Results

The beam specimen has been tested under constant impact energy because of the constant values of the mass and drop height. While the mass of the hammer is 4 kg, the drop height is 800 mm in the experimental study. Before generating impact experiments, the specimen was painted white in order to observe fractures in a better way. Then, the specimen is placed in the test setup, and support conditions are provided at both ends. The concrete beam specimen is shown in Figure 3.

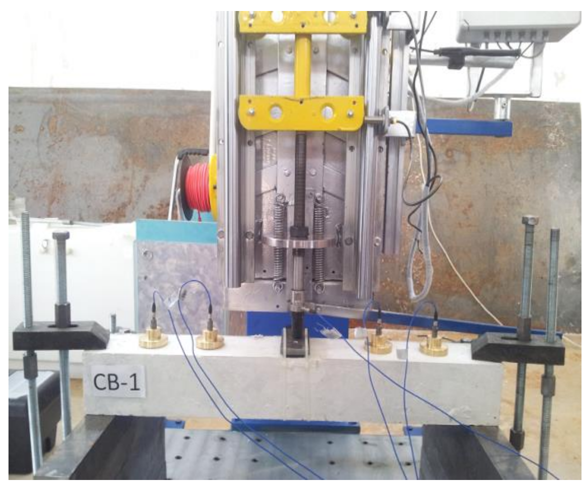

Fig. 3 Test specimen

Fracture development of the beam specimen has been observed during the experimental study under low-velocity impact loading. Damage development and failure of the specimen are exhibited in Figure 4.

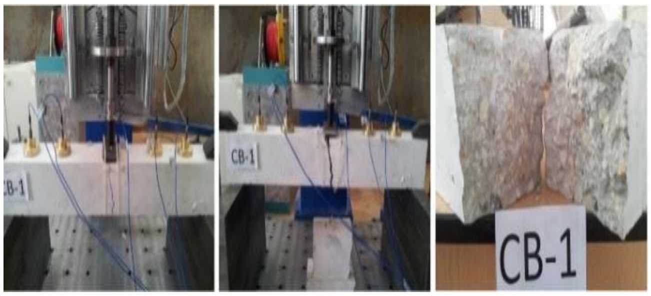

Fig. 4 Damage development of the specimen

Values of acceleration and impact load are also followed for each drop of the steel hammer. Impact experiments have been completed after reaching a total of 32 drops by the hammer. Besides, the average drop duration is measured as 424 msec. Experimental values of maximum accelerations and impact loads are given in Table 2.

Table 2. Experimental results

Drop Number	Max. Acceleration (m/s^2)		Max. Impact Load (kN)
	From 150 mm	From 250 mm	
1	2154	1874	12.1
2	2138	1813	11.9
3	2089	1852	12.0
4	2065	1763	11.7
5	2034	1733	11.8
6	2041	1703	11.8
7	2013	1665	11.5
8	2024	1683	11.3
9	1987	1591	11.1
10	1934	1624	11.2
11	1965	1573	11.0
12	1923	1518	10.9
13	1863	1447	10.7
14	1648	1413	10.3
15	1665	1424	10.2
16	1621	1407	10.0
17	1597	1337	9.7
18	1586	1305	9.8
19	1562	1183	9.5
20	1554	1134	9.5
21	1517	1115	9.2
22	1539	1108	9.3
23	1483	1084	9.1
24	1451	1062	8.9
25	1412	1023	8.9
26	1397	1054	8.7
27	1405	1016	8.6
28	1367	981	8.6
29	1324	927	8.4
30	1279	954	8.3
31	1233	905	8.0
32	1157	871	7.8

Time-dependent acceleration and impact load values are converted into acceleration-time and impact load-time graphs. The examples for the first drop of the hammer where maximum values are obtained are shown in Figure 5.

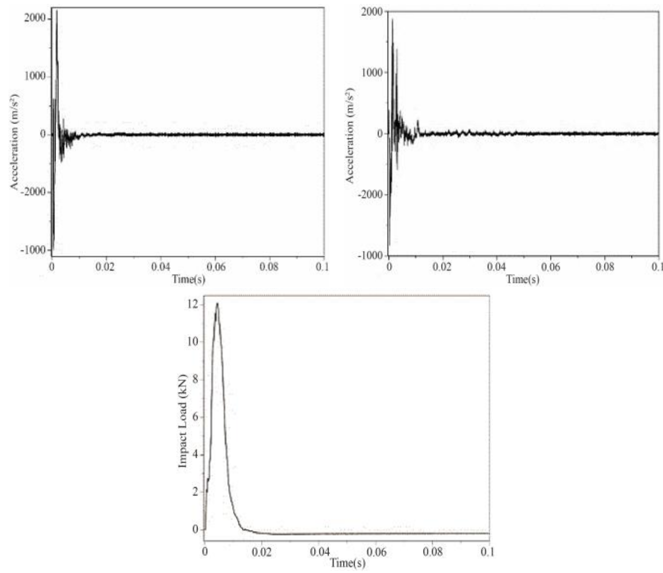

Fig. 5 Graphs for the first drop

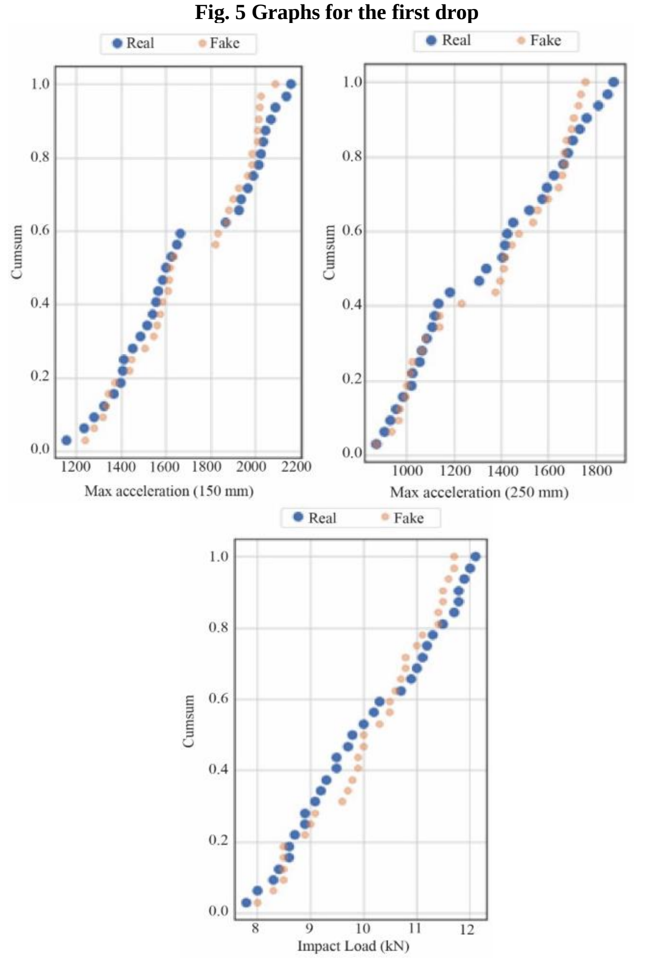

Fig. 6 Cumulative sums of real and synthetic beam data per feature

Table 3. Statistics of real and synthetic beam data

Statistics	Real Beam Samples		
	Max Acceleration (150 mm)	Max Acceleration (250 mm)	Impact Load (kN)
Min	1157	871	7.8
Max	2154	1874	12.1
Mean	1688.3	1348.2	10.1
St Dv	297.9	315.0	1.3
Statistics	**Synthetic Beam Samples**		
	Max Acceleration (150 mm)	**Max Acceleration (250 mm)**	**Impact Load (kN)**
Min	1157	871	7.8
Max	2154	1874	12.1
Mean	1682.7	1322.7	10.0
St Dv	288.8	307.9	1.3

4. Numerical Study

5000 iterations of the TVAE model in the Python programming language have been performed using the acceleration and impact load values gathered from thirty-three real beam samples as input data. Using the TVAE model, we have generated 5000 synthetic acceleration and impact load values for beam data that may be utilized for experiments. We have validated the TVAE model by comparing the obtained experimental and synthetic beam values. We first used cumulative sums per feature from real and synthetic data to validate the proposed model, as shown in Figure 6. From the figure, we have been able to get strong correlations between experimental and synthetic beam values. Second, as indicated in Table 3, we have examined the statistical values of real and synthetic beam data. This table has verified our TVAE model by demonstrating that the synthetic data properly represented the real data.

The TVAE model has been found to be a valuable tool for accelerating the experimental beam data acquisition process. The 5000 synthetic beam data generated by the model closely match the experimental beam data. This indicates that the TVAE model can be used to accurately predict a beam specimen's acceleration and impact load response.

5. Conclusion

Impact loading that acts on for a short period of time may cause significant damages as compared to other loading conditions. Contrary to other static and dynamic loads, impact loads are not considered in the traditional design of structural members. As developing test setups with necessary measurement devices for impact experiments is time-consuming and costly, numerical studies come forward as an alternative way when accurate models are generated in the computer environment.

It is purposed to make a study of the behavior of a concrete beam specimen under low-velocity impact loading. For this purpose, an experimental program is performed, and a constant impact energy level is implemented of the specimen in the first place. Acceleration and impact load measurements are taken from the specimen for each hammer drop. Impact tests are carried on until a failure damage situation is observed on the specimen.

A total of 32 drops have been applied to the beam specimen. The average drop duration is similar for each drop due to the constant mass and height of the hammer. When the experimental results are evaluated, it is seen that maximum acceleration and impact load values are obtained for the first drop of the hammer. In addition, acceleration and impact load values tend to decrease as cracks occur in the test specimen for further drops. As closer accelerometers are more affected by impact effects, bigger acceleration values are obtained from the accelerometers placed from a 150 mm distance from the impact point for each drop movement.

We have employed the TVAE model in the numerical section of the study to acquire the beams' acceleration and impact load values, which may be achieved by experiments in a cost-effective and time-saving way. We have been able to generate a large number of synthetic beam values, such as 5000, using a small number of experimental data as input. Based on the results, the model can accurately predict the impact behavior of a beam, including the acceleration and impact load values. The TVAE model and other GANs models can be used for other real engineering challenges for further investigation.

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