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A NEW DEEP LEARNING ACCELERATED BLAST LOADING EFFECT ANALYSIS OF FRP RETROFITTED CONCRETE SLAB

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Abstract. *Sudden rapid release of energy in blast loading results in complex material behaviour in the surrounding. The study on these destructive events and its serious impact is only increasing day by day due to its geopolitical importance. Traditionally concrete structures have been used for many blast-resistant structures. It is well known that retrofitting reinforced concrete (RC) slabs with exterior fiber-reinforced polymer (FRP) improves blast resistance, reduces displacements and cracking, and helps to collect debris. Even with modern sophisticated computational tools there are still issues with accurate and efficient prediction of the results through numerical simulation. In this work we propose a machine learning assisted blast loading analysis model than can predict maximum displacement of the FRP retrofitted reinforced concrete (RC) slab subjected to blast loading from the standard input parameters including the features of the blast loading, reinforced concrete slab as well as FRP retrofitting. The dataset is collected from the literature which includes several experimental as well as numerical data. A deep learning model is trained with these data and its performance is tested for prediction of the maximum displacement. The model is seen to perform satisfactorily within acceptable engineering errors. Another advantage is that after training the prediction is extremely fast and can save a lot of time. Also, if the training sample includes variations of cases across several possible scenarios the machine learning can be quite robust.*

Keywords: Blast loading, FRP Retrofitted Slab, Machine learning.

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1 INTRODUCTION

Explosive-induced occurrences caused by subversive blasts and unintentional explosions have grown over time [1, 2, 3, 4, 5]. Understanding the behaviour of structures subject this short duration extreme loading is crucial for development of protection structures in affected area. Reinforced concrete structures (both military as well as civilian) has been widely used in such scenarios all over world. To mitigate the effects of airblast loads on buildings, cost-effective structural-engineering solutions may include: retrofitting existing structural members with externally bonded (EB) or near surface mounted (NSM) FRP plates [5, 6, 7, 8, 9]; or the use of innovative materials such as ultra-high performance fibre concrete (UHPFC) for the construction of new structural members. Therefore, its performance in terms of maximum displacement or stress is an active subject of research. Design guidelines for air-blast loading, such as TM 5-855-1(1986) [7], TM 5-1300(1990) [8], UFC 3-340-02 (US Department of Defense, 2008) [9], and ASCE/SEI 59-11(2011) [10] only provide combinations of estimated detonation distances and explosive charges that are likely to produce spall damage [11].

Recent years have seen the development of numerical approaches such as classic finite element methods, meshfree methods, and hybrid finite element meshfree methods to model spall damage in structural components subjected to near field or contact explosions [12]. Jacques [13] used a Shock Tube Testing Facility to perform detailed experimental research on RC slabs modified with carbon fiber-reinforced polymer (CFRP). A total of thirteen distinct specimens were subjected to sixty simulated explosions while taking into account one-way and two-way components, simple and fixed boundary conditions, and various fibre arrangement schemes. In [14] slabs reinforced with carbon FRP plates were tested in addition to ultra-high performance fibre concrete (UHPFC) to see the response in case of blast loading. Numerical investigation of the effectiveness of GFRP retrofitting to the slabs were reported in the [15] for concrete slabs subject to blast pressure. Tolba [16] exposed eighteen two-way RC slabs to 33.4 kilogramme and 22.4 kg ANFO charges, respectively (Ammonium Nitrate Fuel Oil). The blast response of one-way RC slabs retrofitted with varied amounts of CFRP strips was examined by Maazoun et al [17]. Five slabs were loaded using an explosive driven shock tube (EDST) and detonated with 40 g of C4. The maximum displacement of each specimen was predicted using the SDOF approach, and the findings were compared to the experimental data, with errors ranging from 5% to 14% for retrofitted slabs.

Some numerical methodologies have been developed in addition to analytical ones for determining maximum displacements of FRP retrofitted RC slabs. Lin and Zhang [18], for example, investigated the efficiency of retrofitting RC slabs with GFRP against blast loading using the finite element modelling (FEM) programme LS-DYNA. The numerical model was tested on two experimental data points using GFRP retrofits, yielding maximum displacement errors of 0.8 percent and 14.8%. The use of rigorous studies for modelling the reaction of FRP retrofitted RC components subjected to blast loading offers a once-in-a-lifetime chance to replace costly and dangerous structural blast trials [19]. Currently, both analytical and numerical methods are employed to simulate structures subjected to blast loading. Although these techniques reduce the cost and safety risks associated with experimental blast loading, they necessitate significant theoretical knowledge, modelling effort, computing time, and continual validation.

From all these works it is observed that blast loading experiments as well as numerical simulations are quite resource intensive and may be prohibitive in certain different conditions. On the other hand, a machine learning model can be developed to predict the response from initial input features such as geometry, loading as well as material conditions. Machine learning model learns quite reasonably from the input parameters and predicts the response in a considerably less time. It is evident from some very recent research works in this field. A comprehensive historical dataset and an appropriate machine learning model is described beautifully in [20]. Our model adds some additional data through numerical experiment and tests the performance of a fully connected deep neural network for maximum displacement prediction application. In this present study we use an autoencoder based generative model to predict the response of the concrete slab under blast loading.

2 MACHINE LEARNING MODEL

2.1 Dataset

The dataset for the machine learning model is collected from the literature. Several experimental and numerical studies were collected from previous research and the 11 input features are selected. They include geometry, loading and some features related to material quantity and property. The details are listed in table 5. FRP orientations configurations are shown in Fig. 1. The output is maximum displacement at the center of the slab for each corresponding input feature is selected. An Abaqus model was also developed, and some data has been generated from that. The modelling of the Abaqus has been done using concrete damaged plasticity (CDP) for concrete, Johnson cooks model for steel. Sample of property data is shown in shown in table 1,2 and 3 respectively. Sample FRP properties are described in table 4 adapted from [15]. The finite element model in Abaqus has been validated with the [15].

Young Modulus (MPa)	Poisson's ratio	Viscosity parameters	
19700	0.19	0.001	
Dilation angle	Eccentricity	$\mathrm{fb0/fc0}$	$\mathbf{K}$
38	1	1.12	0.666

Table 1: Mechanical properties of CDP

Compressive behaviour	Compression damage		
Yield stress ($\mathbf{kPa}$)	Crushing strain	Damage parameter	Crushing strain
15000	0	0	0
20197.804	.0000747307	0	$7.47307\mathrm{E}-05$
$30000;609$	0.0000988479	0	$9.88479\mathrm{E}-05$
40303.781	0.000154123	0	0.000154123
50.007 .692	0.000761538	0	0.000761538
40236.090	0.002557559	0.195402	0.002557559
20236.090	0.005675431	0.596382	0.005675431
5257.557	0.011733119	0.894865	0.011733119

Table 2: Compression damage properties of CDP

The Hashin damage criteria is also used for damage of FRP laminates as described in the

Tensile behaviour	Tension damage		
Damage parameter (kPa)	Cracking strain	Damage parameter	Cracking strain
1998.930	0	0	0
2842.000	0.00003333	0	0.00003333
1869.810	0.000160427	0.406411	0.000160427
862.723	0.000279763	0.69638	0.000279763
226.254	0.000684593	0.920389	0.000684593
56.576	0.00108673	0.980093	0.00108673

Table 3: Tensile damage properties of CDP

GFRP	Longitudinal modulus	$27500\mathrm{MPa}$
	Transverse modulus	$1300\mathrm{MPa}$
	Shear modulus	$270\mathrm{MPa}$
	Poisson's ratio	0.23
	Longitudinal tensile strength	$410.2\log\dot{\varepsilon}_{11} + 459.2\mathrm{MPa}$
	Longitudinal compressive strength	$0.318\mathrm{GPa}$
	Transverse tensile strength	$146.5\log\dot{\varepsilon}_{22} + 17.2\mathrm{MPa}$
	Transverse compressive strength	$10500\mathrm{KPa}$
	In-plane shear strength	$6.2\log\dot{\varepsilon}_{12} + 7.9\mathrm{MPa}$
	Density, ρ	$2,100\ \mathrm{kg/m^3}$
	Thickness	$1.3\ \mathrm{mm}$
3* Epoxy	Tensile strength	$54\mathrm{MPa}$
	Elastic modulus	$3100\mathrm{MPa}$
	Maximum elongation	5%

Table 4: Properties of FRP

following equation. Fibre tension $(\sigma_{11} \geq 0)$:

$$F_f^t = \left(\frac{\sigma_{11}}{X^T}\right)^2 + \alpha\left(\frac{\tau_{12}}{S^L}\right)^2$$

Fibre compression $(\sigma_{11} < 0)$:

$$F_f^c = \left(\frac{\sigma_{11}}{X^c}\right)^2$$

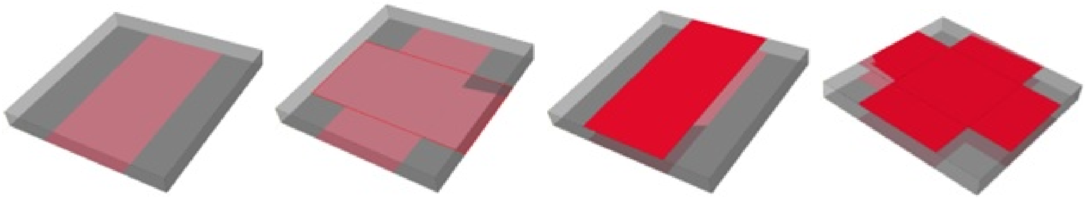
Matrix tension $(\sigma_{22} \geq 0)$:

$$F_m^t = \left(\frac{\sigma_{22}}{Y^T}\right)^2 + \left(\frac{\tau_{12}}{S^L}\right)^2$$

Matrix compression $(\sigma_{22} < 0)$:

$$F_m^c = \left(\frac{\sigma_{22}}{2S^T}\right)^2 + \left[\left(\frac{Y^C}{2S^T}\right)^2 - 1\right]\frac{\sigma_{22}}{Y^C} + \left(\frac{\tau_{12}}{S^L}\right)^2$$

where X^T and X^c are the longitudinal tensile and compressive failure strengths; F_f^t, F_f^c, F_m^t and F_m^c are the failure indices for different failure modes. S^L and S^T are the longitudinal and transverse shear failure strengths, respectively; Y^T and Y^C are the transverse tensile and compressive failure strengths, respectively; α is a coefficient that defines the contribution of the shear stress to the fibre tensile initiation criterion. σ_{11}, σ_{22} and τ_{12} are the components of the effective in-plane stress tensor. 80 samples are collected from literature including 20 experimental and 60 numerical results. Additionally, 40 numerical results are from Abaqus finite element modelling. A train-test split of $4:1$ is considered. The machine learning model trained with these datasets is described below.



(a) (b) (c) (d)

Figure 1: Configurations of FRP on concrete slabs

Data	Mean/Count	Standard Deviation
Slab length (m)	1.6	1.14
Slab width (m)	1.1	0.86
Slab Thickness (m)	0.1	0.05
Slab support condition (simple /Fixed)	$43/47$	-
Concrete Compressive Strength (MPa)	46.52	31.67
Steel Yield Strength	445.12	93.26
Reinforcement Ratio	0.009	0.0074
Scaled Distance (m/kg $^{1/3}$)	2.12	3.60
Fiber tensile strength (MPa)	1478.6	860.35
Fiber cross section (mm ^{2})	528.2	320.16
Fiber Orientation (I, II, III, IV, V)	$20/20/20/20/20$	-
Maximum Displacement (mm)	20.34	7.3

Table 5: Input and Output Features (similar to [20])

2.2 Model Architecture

The machine learning model consists of a simple Multi-Layer Perceptron (MLP). The architecture is shown below in Fig. 2. It consists of several fully connected deep neural network with decreasing depth. The activation function consists of Leaky Relu shown in Fig. 3. And it is attached to each of the first three hidden layers.

The Data 1 to Data 5 (only 5 boxes are shown instead of actual 11 just for convenience) shown are actually input values and it consists of 11 data such as slab length, width, thickness, Slab support condition (simple or fixed), concrete compressive strength, steel yield strength, reinforcement ratio, scaled distance of detonation, FRP tensile strength, FRP cross sectional area and orientation. The total number of parameters of this model is around 5500. The summary of the model parameters is shown in table 6.

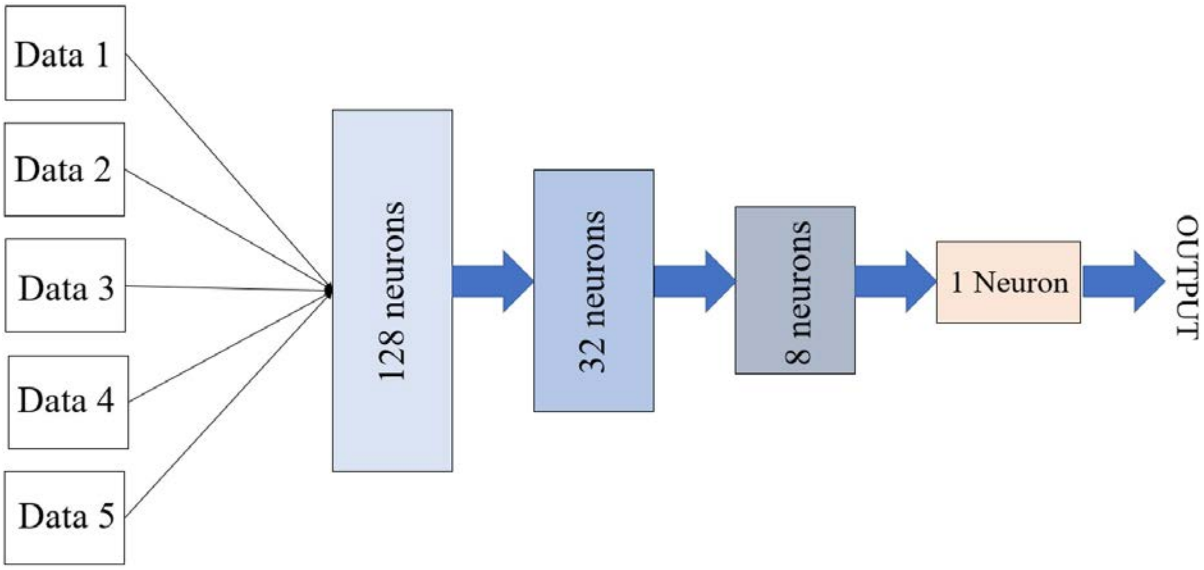


Figure 2: Configurations of FRP on concrete slabs

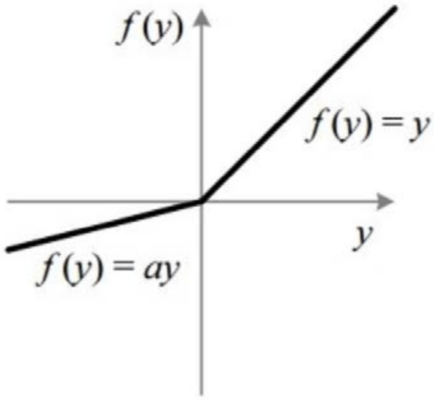


Figure 3: LeakyReLu activation function

3 RESULTS

Different kind of regression model as well as machine learning models are for the accuracy of the predicted output i.e. the maximum displacement. The Error of root mean square error of the different models are also compared for performance measure.

$$RMS = \sqrt{\frac{\sum_1^n (y_i - \widehat{y_l})^2}{n}}$$

Correlation between actual outputs and predicted outputs is also represented by goodness-of-fir coefficient and is given by:

$$R^2 = \left(1 - \frac{\sum_1^n (y_i - \widehat{y_l})^2}{\sum_1^n (y_i - \bar{y})^2}\right)$$

The comparison of values of RMS and R^2 is given in table 7 . Similarly, the output of machine learning model to that of actual is compared in Fig. 4.

Layer (type)	Output Shape	Param #
Dense	(None, 128)	1152
LeakyReLU	(None, 128)	0
Dense	(None, 32)	4128
LeakyReLU	(None, 32)	0
Dense	(None, 8)	264
LeakyReLU	(None, 8)	0
Dense	(None, 1)	9
Total params: 5,553		
Trainable params: 5,553		
Non-trainable params: 0		

Table 6: Model trainable parameters

Model	RMS	R^2
Linear Regression	31.5	0.29
Linear SVM	29.3	0.24
Quadratic SVM	14.2	0.52
Random Forest	11.5	0.87
MLP deep learning	10.1	0.89

Table 7: Comparison of performance of various models

4 CONCLUSION

The maximum displacement of reinforced concrete slabs subjected to blast stress is predicted using a machine learning model in this work. Following a comprehensive search of relevant literature, a dataset of 120 points was arranged. The consistent dataset had eleven features: slab length, width, thickness, Slab support condition (simple or fixed), concrete compressive strength, steel yield strength, reinforcement ratio, scaled distance of detonation, FRP tensile strength, FRP cross sectional area and orientation. The validated regression RF model was developed using the fully connected layers based MLP model. It is seen to perform satisfactorily with reasonably accuracy. It is also worth to note that the time of computation is also significantly fast.

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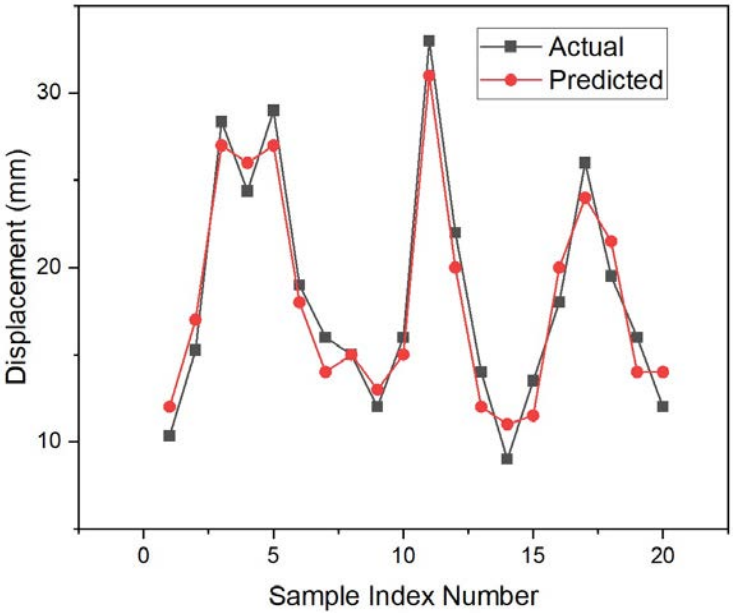

Figure 4: Comparison of actual and predicted displacement

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