ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
Vol. 10, Issue 8, August 2023

Effective Performance of Aggregates from Recycled Concrete Subjected to Blast Load: A Numerical Simulation

Shirbe, A. J, Abejide, K., Ahmed A.,Abejide, O. S. , Ketkukah, T.S.

Department of Civil Engineering, Ahmadu Bello University, Zaria. Nigeria.
Department of Civil Engineering, Ahmadu Bello University, Zaria. Nigeria.
Department of Civil Engineering, Ahmadu Bello University, Zaria. Nigeria.
Department of Civil Engineering, Ahmadu Bello University, Zaria. Nigeria.
Department of Civil Engineering, University of Jos, Jos. Nigeria.

ABSTRACT: A computational model based on an Artificial Neural Network (ANN) was designed and developed using the most representative variables to predict performance of aggregates from recycled concrete. The ANN architecture was of the supervised type containing: an input layer, a hidden layer with 13 neurons and an output layer that includes the sigmoid activation function with symmetrical properties for optimal model convergence. The ANN model was fed-back in its learning with training data until it became perfected, and due to the experimental results obtained, it is a valid prediction option that can be used in future blasting of ore deposits with similar characteristics using the same representative variables considered. Therefore, it constitutes a valid alternative for predicting blast explosions on concrete, given that it has been experimentally validated, with moderately reliable results, providing higher correlation coefficients than traditional models used, and with the additional advantage that an ANN model provides, due to its ability to learn and recognize collected data patterns. In this way, using this computer model one can obtain satisfactory results that allow us to predict breakage in similar scenarios, providing an alternative for evaluating the costs that this entails as a contribution to the work.

KEYWORDS: blast loads, aggregates, modeling, reuse and simulation

I.INTRODUCTION

Blast load effect on buildings and building components has received considerable attention in recent years. This is mainly due to the increase in blast events resulting from different accidents and terrorism activities targeting important structures in different parts of the world. Over the last decades considerable attention has been raised on the behavior of engineering structures under blast or impact loading. The use of explosives by terrorist groups around the world that target civilian buildings and other structures is becoming a growing problem in modern societies. Usually the casualties from such a detonation are not only related to instant fatalities as a consequence of the direct release of energy, but mainly to structural failures that may occur and could result in extensive life loss. Disasters, have demonstrated the need for a thorough examination of the behavior of structures subjected to blast loads [1].

Due to the vast amount of concrete being produced and the huge amount of demolition waste from old concrete structures and also from explosions, recycling concrete has become a necessity. In order to save space at landfills and disposal dumps, it is important to take care of this waste in an environmentally friendly way. Recycled concrete aggregates are simply crushed old concrete elements and then screened for a possibility of appropriately treating and reusing such waste as aggregates in new concrete, especially in engineering applications. The cost and risk involved may not allow testing or evaluation of blasts in concrete structures. Thus, a numerical evaluation using mathematical modelling approach will give a realistic and somewhat adequate implications of the use of recycled concrete whose aggregates had earlier been subjected to blast loads.

The aim of this presentation is to indicate a simple and reliable numerical and analytical method to predict the behavior of blast pressure wave propagation and damage of recycled concrete from residues of concrete subjected to blast loadings using Artificial Neural Network (ANN).

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The objectives herein are to:

(i) Formulate the numerical method for predicting the behaviour of blast pressure wave propagation of recycled concrete from residual of concrete subjected to blast loads.

(ii) Develop the numerical method for predicting the behaviour of blast pressure wave propagation of recycled concrete from residue of concrete subjected to blast loads.

(iii) Development of analytical curves to quickly predict Recycled concrete from bridge deck and buildings spall damage.

This presentation investigates and develops dynamic models that combines sufficient accuracy with computational efficiency for structures affected by blast wave loads due to an external explosion. A model of a concrete bridge deck as in [2] is created and simulated using Artificial Neural Network (ANN). The bridge deck is subjected to blast of different wading and will be studied to determine if it can be re-used for construction. However, the limitation of this study is that we are working with numerical simulations of blast loads without recourse to laboratory experimentation.

II. LITERATURE REVIEW

A. Concrete

Concrete is a name applied to any compositions consisting of sand, gravel, crushed stone, or other coarse material, bound together with cement materials, such as, lime or cements and with or without admixtures. Concrete solidifies and hardens after mixing and placement due to a chemical process known as hydration. The water reacts with the cement, which bonds the other components together, eventually creating a hard and stone like material.

B. Recycled Concrete Aggregates (RCA)

Due to the vast amount of concrete being produced and the huge amount of demolition waste from old concrete structures, recycling concrete has become a necessity. And to save space at landfills and disposal dumps, it is important to take care of this waste in an environmentally friendly way. Recycled concrete aggregates are simply crushed old concrete elements, and it can be used in various applications.

At this moment, concrete made with RCA is not commonly used for structural purposes. Studies have shown that an increase in the amount of RCA leads to a decreasing performance of the concrete. Problems with high water absorption and low elastic-modulus are suggested to be the main problems. The range of water absorption in RCA used as coarse aggregate is 3.5 % to 9.2%, while water absorption for natural aggregate concrete (NAC) is 0.5% to 5%[3].This can lead into micro cracks in the cement paste and a lower workability of the concrete. The quality of the origin concrete is also difficult to control. In a Spanish article[4],it is mentioned that comparing studies about RAC can be difficult because of the uncertainty of the origin of the concrete that has been recycled. There are examples of using it in buildings, for example, the Shanghai ecological building[5]. And in the enterprise park at Stapleton in Denver, Colorado[3].

In many areas, especially around some of the larger cities in the world, sources of natural virgin aggregates like sand and gravel has been depleted[6]. This has become an environmental problem, because aggregates are now transported over longer distances. So preserving natural resources by using RCA is environmentally desirable. In 2010 it was noted that 1 ton of concrete per human being was produced in the world, and with a world population of approximately 7 billion people the answer gives amount of demolition waste concrete [3]. This is one reason for creating a technology, which can handle this problem. The production of cement is one of the largest contributors to CO_2 emissions[7], when looking at the production of construction materials. The global production of cement was in 2010 over 3.3 billion tons, and it stood for about 5% of the anthropogenic CO_2emissions. To produce cement, a process named calcination is necessary. In this process limestone is heated and chap into calcium oxide and CO_2. This is an inevitable process for making cement and it is the opposite of the carbonating process, which lowers the steel protecting alkaline level in concrete.

C. Explosions and Blast

An explosion is defined as a large-scale, rapid and sudden release of energy. Explosions can be categorized on the basis of their nature as physical, nuclear or chemical events. In explosions, energy may be released from the catastrophic failure of a cylinder of compressed gas, volcanic eruptions or even mixing of two liquids at different temperatures.

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International Journal of AdvancedResearch in Science, Engineering and Technology
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Explosive materials can be classified according to their physical state as solids, liquids or gases. Solid explosives are mainly high explosives for which blast effects are best known. They can also be classified on the basis of their sensitivity to ignition as secondary or primary explosive. The latter is one that can be easily detonated by simple ignition from a spark, flame or impact. Materials such as, mercury fulminate and lead oxide are primary explosives.

The detonation of a condensed high explosive generates hot gases under pressure up to 300 kilo bar and a temperature of about 3000-4000^{0}C. The hot gas expands forcing out the volume it occupies. As a consequence, a layer of compressed air (blast wave) forms in front of this gas volume containing most of the energy released by the explosion. Blast wave instantaneously increases to a value of pressure above the ambient atmospheric pressure. This is referred to as the side-on overpressure that decays as the shock wave expands outward from the explosion source.After a short time, the pressure behind the front may drop below the ambient pressure

In the present study, the focus will be on building structures, as these have proven to be the most common targets of terrorist attacks with the use of explosive devices. Nevertheless, the procedure that should be followed in the case of different structural elements is practically the same. The first step in designing a building to sustain blast loading is the definition of the type and weight of the explosive for which the design will be performed. Several types of explosives are available nowadays, any of which could be used for conducting an attack against a structure. In the majority of the cases, solid explosives will be used in improvised explosive devices (IED), because of their transportability, relatively easy manufacturing and the possibility of their placement in vehicles that could be moved in the vicinity, adjacent or within (for example, underground garages) a building. The wide variety of explosives has led to the adoption of a universal quantity, which is used for all necessary computations of blast parameters. TNT (Trinitrotoluene) was chosen as its blast characteristics resemble those of most solid type explosives. An equivalent TNT weight is computed according to Equation (1) below that links the weight of the chosen design explosive to the equivalent weight of TNT by utilizing the ratio of the heat produced during detonation (ref):

$$W_e = W_{exp} \frac{{H_{exp}}^d}{{H_{tnt}}^d} \quad (1)$$

Where
W_e: TNT equivalent weight [kg]
W_{exp}:weight of the actual explosive [kg],
${H_{exp}}^d$:heat of detonation of the actual explosive [MJ/kg], and
${H_{tnt}}^d$: heat of detonation of the TNT [MJ/kg].

Table 1 provides estimates of the produced heat of detonation of some common explosives [8]. These values can be used for the calculation of the equivalent TNT weight with the use of Equation (1).

Table 1:Indicative values of heat of detonation of common explosives

Name of explosive	**Heat of detonation[MJ/kg]**
TNT	4.10 – 4.55
C4	5.86
RDX	5.13 – 6.19
PETN	6.69
PENTOLITE 50/50	5.86
NITROGLYCERIN	6.30
NITROMETHANE	6.40
NITROCELLULOSE	10.60
AMON. / NIT.(AN)	1.59

As an explosive charge detonates in urban areas the surroundings, and relative placement of the explosion, affects the loading on the structures. As shown in Figure 1, they can be distinguished in three basic types, which depend on the relative position of the explosive source and the structure to be protected, that is, on the height,*H** above ground, where the detonation of a charge, *W*, occurs, and on the horizontal distance, *RG*, between the projection of the explosive to the ground and the structure. These three explosion types are:

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International Journal of AdvancedResearch in Science, Engineering and Technology
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(a) ***Free-air bursts***: The explosive charge is detonated in the air; the blast waves propagate spherically outwards and impinge directly onto the structure without prior interaction with other obstacles or the ground.

(b) ***Air bursts***: The explosive charge is detonated in the air, the blast waves propagate spherically outwards and impinge onto the structure after having interacted first with theground; a Mach wave front is created.

(c) ***Surface bursts***: The explosive charge is detonated almost at ground surface, the blast waves immediately interact locally with the ground and they next propagate hemi-spherically outwards and impinge onto the structure.

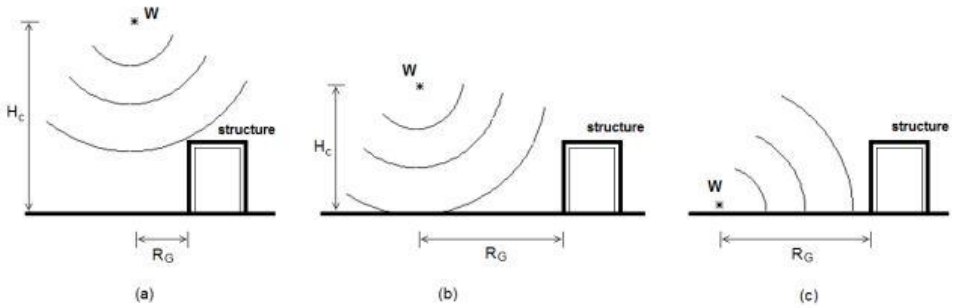

Figure 1: Types of external explosions and blast loadings; (a) Free-air bursts, (b) Air bursts, and (c) Surface bursts [9]
.

D. Use of Artificial Neural Network (ANN)

ANNs are composed of many simple interconnected processing elements called neurons or nodes. Each node receives an input signal with information from other nodes or external stimuli, processes it locally through an activation or transfer function and generate an output signal that is sent to other nodes or external outputs as shown in Figure 2. There has been a growing interest in obtaining adequate predictive models in mines. Among the possible alternatives available, Artificial Neural Networks are increasing used. In this paper we will use the most common type of ANN trained with Multilayer Perceptron algorithms (MLP).

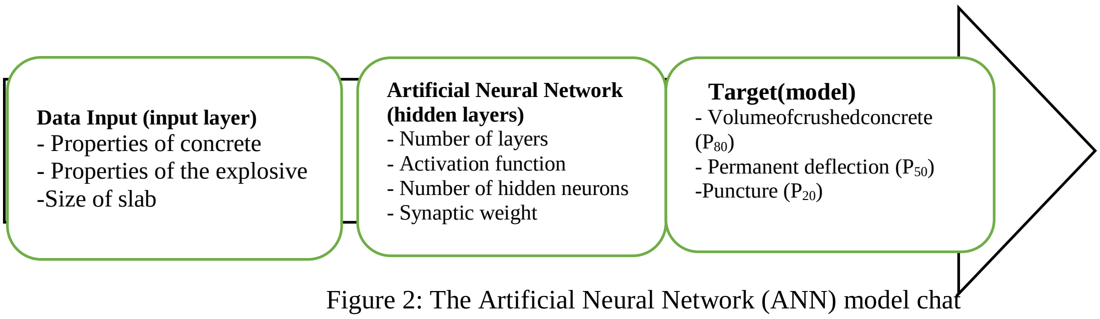

Figure 2: The Artificial Neural Network (ANN) model chat

III. METHODOLOGY FOF THE ANN MODEL

In order to achieve the objective desired herein, the following methodology is employed, which consists of several parts and is shown in Figure 6. This methodology consisted of compiling the data from a study spalling of concrete subjected to blast loading [2]. MATLAB libraries were used to obtain the design, then ANN was evaluated using various descending gradient algorithms [10]to obtain the optimal design and thus validate the results of volume of crushed concrete(P_{80}), Permanent deflection(P_{50}) and Puncture(P_{20})of the model with the actual values contained in the study data and with the statistical parameters obtained from the multiple linear regression model.

A. Data Collection

Blasting parameters were taken from the study in [2], which consists of five samples of blast field tests of FRC and reinforced concrete specimens which were performed in cooperation with the Czech Army corps and Police of the Czech Republic in the military training area Boletice. These make up the following blasting parameters: It is worth mentioning that 37 samples were taken for the training of the network and 10 for the respective testing. The following training parameters are shown in Table 2: The variables are Length, Width, Thickness, Concrete grade, Fiber content, Steel grade, Kilograms of charged Explosives, were taken as input variables as well as P_{80}, P_{50}, P_{20} as variables of output, since the Volume of crushed concrete, Permanent deflection, and Puncture remain constant in data collection. In the Table 1, values of P_{20}, P_{50}, and P_{80} were obtained using image analysis method to determine size distribution which consist of three phases: selecting the sampling site, imaging, and image analysis. The sampling phase involves the selection of sites to obtain samples that represent the blasted concrete.

Table 2: Parameters used in ANN

Specimen no.	1	2	3	4	5
Concrete grade	C30/37	C30/37	C55/67	C55/57	C30/37
Fibers	-	4.5kg/m^3	-	4.5kg/m^3	9.0kg/m^3
Steel grade	500MPa	500MPa	500MPa	500MPa	500MPa
Length	6m	6m	6m	6m	6m
Width	1.5m	1.5m	1.5m	1.5m	1.5m
Thickness	0.3m	0.3m	0.3m	0.3m	0.3m
TNT value	25kg	25kg	25kg	25kg	25kg
Puncture	0.43m^2	0.26m^2	0.02m^2	-	-
Vol. of crushed concrete	0.23m^3	0.15m^3	0.20m^3	0.05m^3	0.06m^3
Permanent deflection	0.31m	0.37m	0.28m	0.30m	0.26m

B. Design and Experimentation of ANN

Once the input data is obtained, including concrete properties and blasting design, explosives and the diameter of the breakage using blasting, we design the feed-forward neural network of the supervised type, considering the reliable and representative data avoiding the overfeeding of the ANN in order to achieve the desired learning. In the design of the architecture, we tested the number of layers and neurons that will make the ANN work properly for training using the data in Table 1. Figure 3 shows the diagram of the ANN design with a hidden layer.

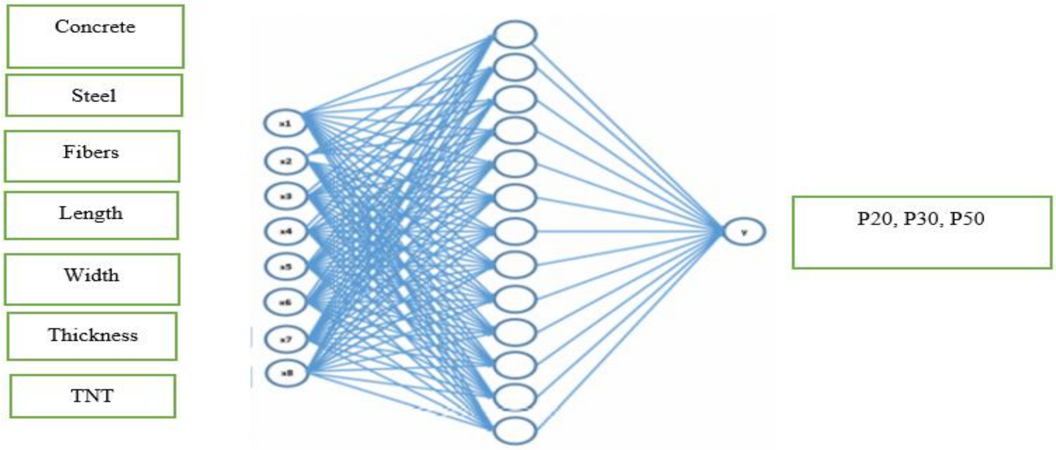

Figure 3: ANN Design

In order to determine the number of hidden layers, the studies conducted by [11] was used which show that any continuous function can be uniformly approximated by single layer hidden neural network models. The number of hidden layers and neurons in each layer affect the capacity of the model for generalization, that is, the accuracy in computing new examples [12]. Therefore, ANN in this work will only have a hidden layer as shown in Figure 3. The number of neurons in the hidden layer is determined based on two empirical formulas: firstly Hecht–Nielsen [13], based on the theorem of Kolmogorov [14], suggests that $2n + 1$ (where "n" is the number of input parameters) should be used as the maximum number of neurons for a hidden layer of a backpropagation network. Therefore, if the number of input parameters is $n = 8$, the number of hidden neurons should be $N \leq 17$. Finally, according to a second empirical formulae of [15], the number of neurons in the hidden layer must satisfy Equation (2)

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International Journal of AdvancedResearch in Science, Engineering and Technology
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$\sum_{i=0}^{n} C^{i}{}_{N} > K$ (2a)
Where:

$\sum_{i=0}^{n} C^{i}{}_{N}$>k (2b)

n: number of input parameters = 8; K: used dataset number = 47; N: number of hidden neurons to be determined; Resulting N >8. Therefore: 9≤ N ≤ 17.

These N values were used to determine the appropriate functioning of ANN, and to establish its architecture, which was evaluated for each N value, using two parameters; the root mean squared error and the correlation coefficient between predicted and actual values. Figure 3 shows the summary of the ANN design together with the input and output parameters to be obtained.

IV. RESULTS AND DISCUSSION

A. Experimental Results

Once the ANN architecture model was designed, it was implemented, beginning with the training stage and then with the validation of the ANN. Therefore, with the values obtained previously, train then the ANN, minimizing the root mean squared error with the training data and the values of "n" (number of neurons in the hidden layer) using the Descending Gradient Algorithm over a number of 1000 training cycles until the error is minimized. Figure 4 shows the root mean square error, which stabilizes as ANN training cycles increase, using the Descending Gradient Algorithm, for both training (blue curve) and testing data (orange curve).

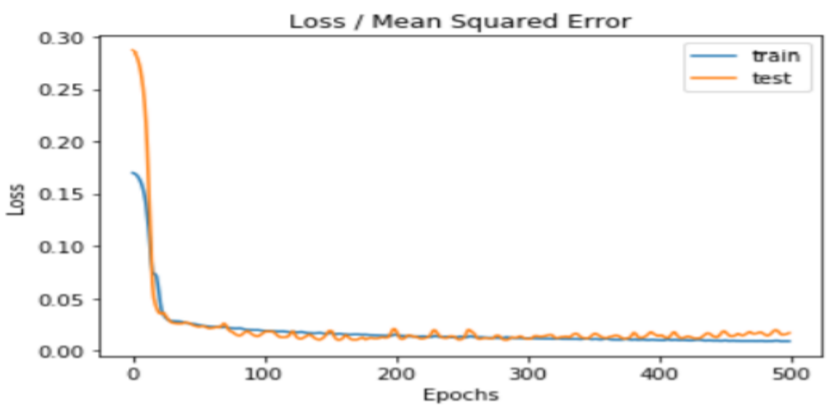

Figure 4: Root man square error vs the number of cycles

Analyzing Figure 4, and Table 3 gained from ANN simulations, (which presents the root mean square error values for each number of neurons obtained during network training using 1000 cycles), it is determined that with n = 8 we get a lower root mean squared average error (0.009994). Therefore, we use n = 8 in the ANN for the predictions of volume of crushed concrete (P_{80}), Permanent deflection (P_{50}) and Puncture (P_{20}). Then, we proceeded to compare them using training and testing data, and got the following results which was discuss on below:

Table 3. Number of simulations vs. hidden neurons.

Mean Squared Error by Number of Simulations						
Number of hidden neurons	**1**	**2**	**3**	**4**	**5**	**Average**
10	0.013934	0.010181	0.010772	0.011604	0.013516	0.012001
12	0.014779	0.010263	0.00894	0.0091	0.009728	0.010562
15	0.011681	0.009246	0.009824	0.012855	0.010517	0.010825
17	0.012474	0.011985	0.008593	0.008027	0.008891	0.009994
20	0.009478	0.00777	0.012028	0008874	0.012441	1774.808

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International Journal of AdvancedResearch in Science, Engineering and Technology
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Figures 5 and 6 show a comparison among the ANN and MLR models of which, the ANN model depicts the greatest correlation according to R^2 = 0.87 and R^2 = 0.81 in training and testing respectively, as well as the other statistical parameters of the ANN model take values close to the real Volume of crushed concrete P_{80} according to Table 4.

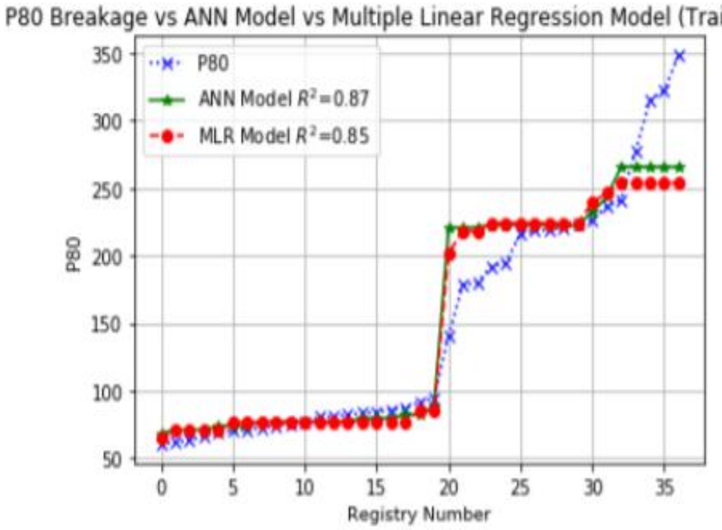

Figure 5: P80 Breakage vs. ANN model vs. the Multiple Linear Regression (MLR) model (training).

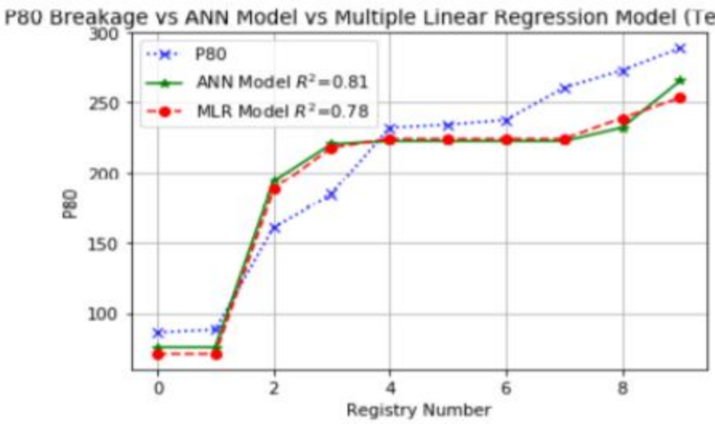

Figure6: Volume of crushed concrete (P_{80}) Breakage vs. ANN vs. MLR model (Testing).

Table 4. Comparison Table real P_{80}, ANN P_{80} and MLR P_{80} (Training and Testing).

	Training			**Testing**		
Statistical parameters	P_{80} (Real)	P_{80} (ANN)	P_{80} (MLR)	P_{80} (Real)	P_{80} (ANN)	P_{80} (MLR)
Correlation coefficient R^2		0.87	0.85		0.81	0.78
Mean(mm)	148.1	150.2	148.11	204.61	195.36	193.65
Standard deviation	85	80.8	78.98	68.86	61.99	63.27
Coefficient of variation	0.58	0.54	0.53	0.33	0.32	0.32

ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
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Figures 7 and 8 show a comparison among ANN and MLR models of which the ANN model depicts the greatest correlation according to R^2 in training and other statistical parameters of the ANN model take values close to the real Permanent deflection P_{50} according to Table 4.

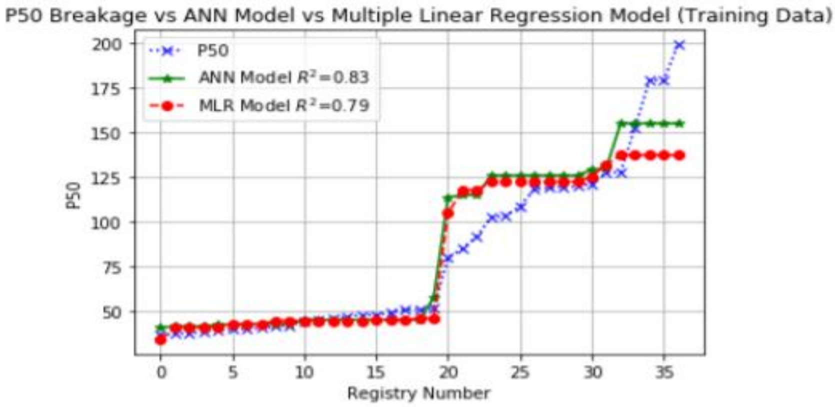

Figure 7: Permanent deflection (P_{50}) vs. ANN model vs. MLR model (training)

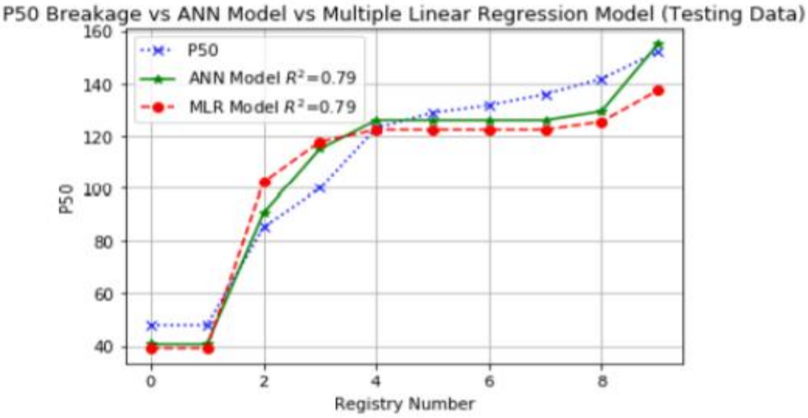

Figure 8: P_{50}vs ANN vs MLR model (testing)

Table 4. Comparison table real P_{50}, ANN P_{50} and MLR P_{50} (Training and Testing).

	Training			Testing		
Statistical parameters	P_{50} (Real)	P_{50} (ANN)	P_{50} (MLR)	P_{50} (Real)	P_{50} (ANN)	P_{50} (MLR)
Correlation coefficient R^2		0.83	0.79		0.79	0.79
Mean(mm)	81.36	85.03	81.36	109.37	107.47	105.06
Standard deviation	46.53	45.34	41.59	35.87	36.56	33.91
Coefficient of variation	0.57	0.53	0.51	0.32	0.34	0.32

Figures 9 and 10 show a comparison of the ANN and MLR models of which the ANN model depicts the greatest correlation according to R^2 in training, while in testing an R^2 with similar values is shown, good results have been obtained for the prediction of Puncture to top surface P_{20} according to Table 5.

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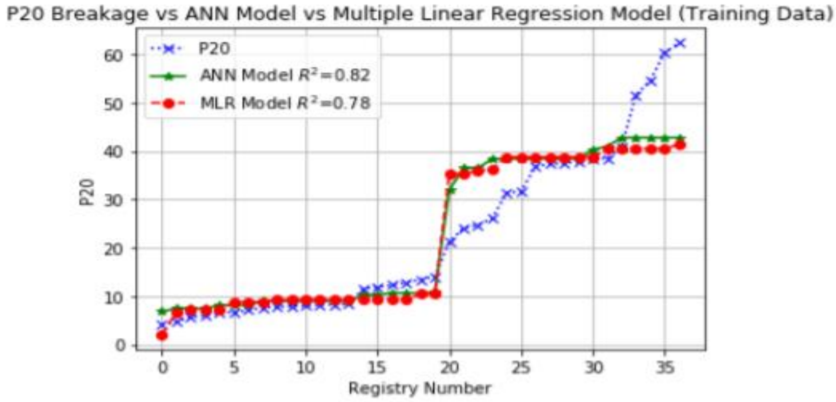

Figure 9: P_{20}vs ANN model vs MLR model (training)

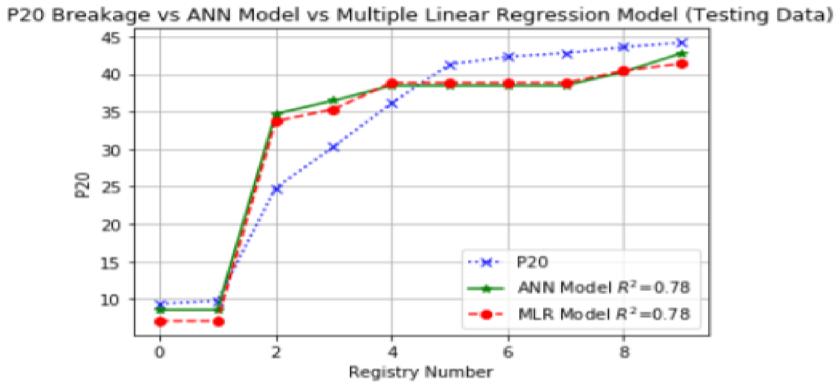

Figure 10: P_{20}vs ANN vs MLR model (testing)

Table 5. Comparison table real P_{20}, ANN P_{20} and MLR P_{20} (Training and Testing).

	Training			Testing		
Statistical parameters	P_{20} (Real)	P_{20} (ANN)	P_{20} (MLR)	P_{20} (Real)	P_{20} (ANN)	P_{20} (MLR)
Correlation coefficient R^2		0.82	0.78		0.78	0.78
Mean(mm)	22.38	22.93	22.38	32.45	32.49	32.01
Standard deviation	17.09	15.27	15.15	12.92	12.13	12.65
Coefficient of variation	0.76	0.66	0.67	0.39	0.37	0.39

The values obtained from the correlation coefficient R^2 of each studied ANN model (P_{20}, P_{50} and P_{80}) are quite acceptable and the breakage can be controlled in such a way that performance and costs can be improved.

B. Discussion

The use of n = 8 in the ANN for the prediction of volume of crushed concrete (P_{80}), Permanent deflection (P_{50}) and Puncture (P_{20}) were compared using training and testing data in which the ANN model shows a significant coefficient of correlation $R^2 = 0.87$ and $R^2 = 0.81$ in actual and predicted respectively, thus, the statistical parameter of the ANN model take values close to the actual volume of crushed concrete P_{80}, Table 4.

Comparing the ANN and MLR models of which ANN model shows a significant correlation with respect to R^2 in prediction, while in actual an R^2 values with more similarities were observed, better results were obtained for the prediction of puncture to top surface P_{20} as shown in Table 5. The coefficient of correlation R^2 for each ANN studied models (P_{20}, P_{50}, and P_{80}) are quite significant and the failure can be avoided by improving the performance and costs.

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V.CONCLUSION AND RECOMMENDATION

A. Conclusion

On the basis of the results obtained from this study, it wasobserve that using the proposed ANN model herein, we get an increasing coefficient of correlation (R^2), which is from 2% to 4 % over the Multiple Regression Linear (MLR) in the comparisons made with the training data, while this percentage increase varies from 0% to 2% with the testing data over MRR, which is mainly due to the sample size. In addition, it is observed that the correlation coefficients in the training models decreases in comparisons to volume of crushed concrete (P_{80}), Permanent deflection (P_{50}) and Puncture (P_{20}) ($R^2 = 0.87$, 0.83 and 0.82). This is because the main input variables are focused on the target of volume of crushed concrete (P_{80}), and thus decreases the effect on the variables Permanent deflection (P_{50}) and Puncture(P_{20}). Therefore, the model obtained is an alternative to the one presented in the earlier work by [16]and shows moderately reliable results. However, it is important to continue monitoring the blasting records to feed the site database and ensure greater representation of the parameters in order that the model can have a greater extension for further predictions than it is currently assumed, especially if working with various types of concretes with other peculiarities. In the present study, we considered several training algorithms according to [10]. In order to evaluate performance, the Momentum algorithm was selected because it reaches the global minimum and a marked stability in the root mean square error before the other algorithms. Concerning the linear models of the different variables,volume of crushed concrete (P_{80}), Permanent deflection (P_{50}) and Puncture (P_{20})it is concluded that their results have a moderate linear adjustment, but it tends to decrease in accuracy when the data testing has a well-marked dispersion. However, the ANN model “learned from the data” to obtain a variability, which is remarkable like the real data under study. In future study we hope to use the ANN model with other real data from different testing grounds, verifying the prediction efficiency and evaluating their associated costs.

B. Recommendations

Although the ANN and MLR models have an acceptable degree of correlation, in the comparison curves, a marked difference is observed in the final fragmentation part of real P_{80}, P_{50} and P_{20} with respect to the preceding values, this is due to the possibility of the absence of some input parameter that may have been omitted in the data collection, which remains a future work, in which it is recommended to increase the number of input parameters in order to obtain an even and more accurate model in real life situations.

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