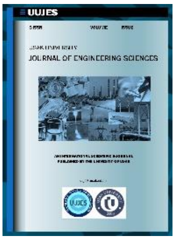

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Research article

AN ANN MODEL FOR PREDICTING SLUMP OF CONCRETE CONTAINING CRUSHED GLASS AND NATURAL GRAVEL

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Abstract

This study modelled the slump of concrete containing crushed glass and Bida Natural Gravel (BNG) based on deep learning algorithm using the MATLAB neural network toolbox. A total of 240 (150mm × 150mm × 150mm) cubes were cast from 80 mixes generated randomly using Scheffe's simplex lattice approach. Slump was measured for each of the experimental points of fresh concrete before filling in the moulds. The resulting batch for each mix was used as input data while the laboratory results for slump was used as output data for the ANN-model. Hence a shallow multilayer supervised Neural Network was developed to model these data. The developed model would be able to predict concrete slump containing 0% - 25% crushed glass as partial replacement for fine aggregate, water- cement ratio ranging from 0.45 – 0.78 and concrete grade M15 – M25. The architecture of the network contained 6 input parameters: water to cement ratio, water, cement, sand, crushed glass and BNG, 20 neurons in the hidden layer and slump in the outer layer. The adequacy of the developed model was measured using Mean Square Error (MSE) and Correlation Coefficient (R). Results showed that 6:20:1 model architecture for slump model had an MSE values for training, validation and testing as: $1.84e^{-2}$, $5.81e^{-3}$, $3.64e^{-3}$, $1.73e^{-3}$ respectively. Regression values for training, validation and testing are: 79%, 94%, 96% and 79%. The study concluded that a shallow multilayer Neural Network architecture with 20 neurons in the hidden layer is sufficient for predicting concrete slump.

Keywords: *BP-ANN; Bida Natural Gravel (BNG); Crushed glass; Mean Square Error (MSE), Regression; Slump*

1. Introduction

Concrete workability is an important parameter in concrete technology and construction. It is the ease by which fresh concrete can be mixed, transported, placed and compacted. Rheological parameters such as: cement paste and friction between the particles of the aggregate influence the workability of concrete [1]. Because of the complexities of the

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aforementioned associations, quantifying the workability of concrete has proven difficult. Slump test carried out in the laboratory or on the construction site, is most commonly used to determine the consistency of concrete. The slump test serves as a useful indicator of concrete workability as mixes vary from batch to batch even though it does not measure all factors that affect workability [2]. One of the elements that affects the mix design of concrete is the workability of the concrete. Concrete mix designs are created using empirical techniques or artificial intelligence (AI). For example, the American Concrete Institute (ACI) and the British Department of Environment (DoE) are models that were developed empirically. The most popular artificial intelligence techniques are ANN, Fuzzy analysis, and Genetic algorithms, which are computer-based techniques built on the idea of machine learning [3].

There exists a highly non-linear relationship between the several constituents of the glass concrete which affect the slump of the concrete. Artificial neural networks (ANNs) have exploded in popularity over the past two decades because of their capacity to learn from previous experiences and derive mathematical functions that are challenging to formulate using conventional computing techniques in order to establish relationship among variables. ANNs were inspired by how the human brain functions. The slump of high-performance concrete has been successfully predicted using ANN by [1], [4] and that of high-strength concrete [5], as well as the consistency of concrete containing metakaolin and fly ash [6] and fly ash and slag [7].

For various environmental and sustainable reasons, by-product materials of various kinds are frequently used as admixtures or replacements in concrete. Over the years, waste glass in particular has become more well-known for its use as a partial replacement for some or all of the fine or coarse aggregate in concrete. Every year, the world produces tonnes of waste glass. Because glass is not biodegradable, it cannot be disposed of in landfills. The use of waste glass as a partial substitute for aggregate in concrete can pave the way for the creation of an infrastructure system that is environmentally friendly, energy-efficient, and cost-effective [8]. Slump is a common indicator of concrete's workability. Using the slump cone test or other rheology tests, slump can be experimentally measured. However, conducting experiments involves significant financial outlays and labour costs. The production, transportation, and construction processes in the concrete industry can all benefit from a slump prediction model's lower costs [9].

In light of the aforementioned difficulties, using waste glass in concrete can aid in the development of a construction that is both cost-effective and environmentally friendly. In their 2017 study, Sadiqul et al. [8] used glass powder as a partial cement replacement to examine the strength of concrete. Additionally, Zainab and Enas [10] conducted research on the use of recycled waste glass as a substitute for some of the fine aggregate in concrete. Shayan and Xu [11] discovered the possibility of replacing aggregate or cement with up to 30% of glass powder without having a negative long-term impact. However, modelling approach was not used in these works. In the light of this, a computational model of slump of concrete containing crushed glass (0 – 25%) used as partial replacement for fine aggregate using back propagation ANN (BP-ANN) was developed in this study.

2. An Overview of the Effect of Crushed Glass on Concrete Slump

Glass is a solid inorganic substance which can be transparent or translucent, hard and brittle. Glass is 100% recyclable in theory and can be recycled indefinitely without losing any quality [12]. The recycling of waste glass and other industrial byproducts has advanced significantly in the construction sector. In addition to saving landfill space, recycling this waste by turning it into aggregate also lessens the need to extract raw materials for construction work [13]. Numerous research studies have been conducted because these alternatives necessitate in-depth analysis of their impact on concrete's properties.

No alkali-silica reaction was found with particle sizes up to 100 µm, according to Corinaldesi et al. [14], indicating the viability of using waste glass as fine aggregate component in concrete and mortar. By late ages, there is a significant increase in the compressive strength of concrete containing waste E-glass, but as the glass content increases, workability is observed to decline, according to Chen et al. [15]. According to Metwally [16], adding finely milled waste glass to concrete mixtures had a negative impact on workability but significantly improved the mechanical properties of concrete over time. Zainab and Enas [10] substituted crushed glass for the sand at 10%, 15% and 20%. They reported that slumps of waste glass concrete specimens decreased with increases in the waste glass content. They posited that this was influenced by the waste glass grain shapes. In spite of the reduction in slump, they observed that the concrete mixtures had considerably good workability.

3. Materials and Method

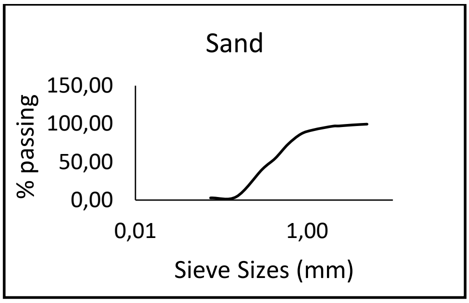
3.1 Materials

Materials used for this research work are; sand, cement, Bida gravel (maximum 20 mm size), water and waste glass (passing through British Standard sieve of size 2.0 mm). Ordinary Portland Cement grade 42.5N (Normal hardening and 28-day compressive strength of 42.5 N/mm^2) was used for this research. Fine aggregate was sourced from Minna area of Niger state. Bida gravel was gotten from Bida area in Niger state. The gravel was washed in 5 mm British Standard sieve [22] to remove sand content. In addition, "washing and sieving is the preferred method for aggregates which may contain clay or other materials likely to cause agglomeration of particles" [22]. The washed gravel was oven-dried at 105^oC until constant mass was achieved [22]. Portable water was gotten from the civil engineering laboratory. In accordance to requirements of BS EN 1008:2002, water used for mixing was free from impurities, odourless and colourless. Waste glass was sourced from the mechanical engineering central workshop at the Federal University of Technology, Minna.

Table 1 Physical properties of the aggregates

Physical Properties	Sand	CG	BNG
Fineness Modulus	2.7	2.5	6.4
Absorption (%)	2.68	2.60	2.37
Specific gravity	2.6	2.51	2.68
Density (kg/m^3)	1515	1453	1663
AIV (%)	-	-	16.56

Note: CG – Crushed glass; BNG – Bida Natural Gravel; AIV: Aggregate Impact Value



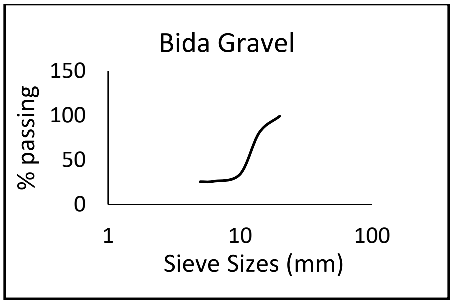


Fig. 1 Partcicle Gradation Curve of Sand **Fig. 2** Particle Gradation Curve of Bida Gravel

3.2 MATLAB neural network toolbox

The MATLAB software includes a toolbox called Neural Network (NN). It is a technical computing language with high performance. The tool box encompasses visualization, computation and programming in an environment that is simple to utilize while using common mathematical notations to express issues and solutions. In order to implement a back propagation neural network algorithm for the study, MATLAB software (version R2022b) was used.

3.3 Methods

3.3.1 Concrete mix

A total of 80 mixes generated randomly using Scheffe's simplex lattice approach. Slump was measured for each of the experimental points of fresh concrete in accordance with specifications in [23]. For training, 80% of the data was used while 15% and 5% were used for validation and testing, respectively. A simplex lattice approach developed by Scheffe [17] was deployed to generate 80 experimental mix combinations. Following that, the contents of water, cement, sand, and BNG in kg/m^3 were determined using the absolute volume method. Concrete slump was modelled using the water-cement ratio (w/c), cement, sand, crushed glass, and BNG content as input data and the slump for the 80 experimental points as output data.

3.3.2 Developing the feed forward neural network

The following parameters were used as input data when creating the neural network for slump: the weight of cement (C), the weight of water (W), the weight of sand (S), the weight of crushed glass (CG), the weight of BNG and the water-cement ratio (W/C). To find out their impact on the slump of the resulting concrete, different material quantities were used. Other parameters required for the model development, such as the number of hidden layers, number of neurons in hidden layers, and learning rate, were determined as the model was simulated.

3.3.3 Developing the neural based model

Creating a database of examples and training a neural network on the results of a series of experiments on a material is the fundamental approach for creating a neural-based model of material behaviour. The trained neural network would have enough knowledge of the material behaviour to qualify as a material model if the experimental results contain the pertinent information about the material behaviour. Such a trained neural network should be able to approximate the results of other experiments in addition to being able to replicate the experimental results it was trained on [18]. Back-propagation networks (BPN) are the foundation of the majority of studies that used ANN to simulate material behaviour. According to Pala et al. [19], the back propagation algorithm is a gradient descent technique which minimizes error for a specific training pattern by adjusting the weights by a small amount at a time. It is one of the well-known training algorithms for the multi-layer perceptron (MLP). The BPN learns by calculating the error and propagating the result back through the network after comparing the target output of each input pattern with the output it generates from each input pattern. After the network has been trained, the project's input parameters are given to it so it can run. The weight values and thresholds that were set during training are then used by the network to compute the node outputs. The coefficient of determination R^2 is used to evaluate the trained network's accuracy. The coefficient, which indicates the strength of the linear association between x and y, is a measure of how well the independent variables took into account the measured dependent variable. The strength of the prediction relationship increases with R^2 value. It is helpful because it shows how much of one variable's variance (fluctuation) can be predicted from another.

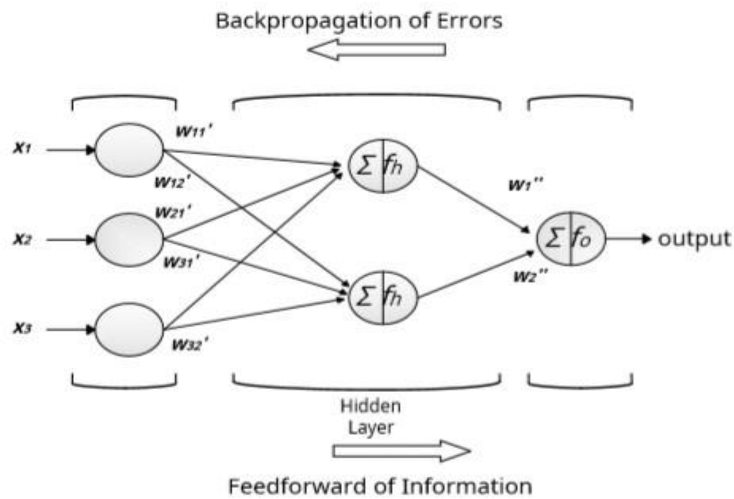


Fig. 3 Back propagation and forward propagation [20]

4. Results and discussion

4.1 Slump and compacting factor

These parameters are indicators of the workability of a concrete mix. Concrete slump between 0 and 25mm indicates very low degree of workability. For a value between 25 and 50mm slump, it indicates a mix of low workability. Medium workability is between 50 and 100mm slump and concrete mix with high workability ranges from 100 to 175mm slump. The slump and compacting factor for the 80 mixes are presented in Appendix 1. These values are the features from which the ANN model for slump was developed. According to B.S 1881-103 [21], the normal range of compacting factor for fresh concrete lies between

0.8 and 0.92. It is normally useful for mixes with low workability where the slump test is not satisfactory. Water to cement ratio, water, cement, sand, crushed glass and BNG content were used as input for the feed-forward network while slump was the output.

4.2 ANN model

The model for slump was trained with a shallow neural network in the MATLAB neural network toolbox. A shallow network is a multi-layer supervised learning network with one hidden layer. In supervised learning, the weights associated with each neuron in each layer are initialized and activated with an activation function before it is fed to another neuron in the next layer. This is called the feed forward network. At the output layer, the error associated with the feed-forward network is calculated. To minimize this error and improve on the accuracy of the network, the weights are adjusted using techniques such as: stochastic gradient descent, batch method and the mini-batch method. This process is referred to as backward propagation. In this study, the stochastic gradient descent technique was adopted. The network architecture was made of 80 observations, 6 features in the input layer 1, 20 neurons in the hidden layers and 1 feature in the output layer of the network. The parameters used in training the models are presented in Table 2.

Table 2 Training parameters for the ANN model

Parameter	Configuration
Input Data	w/c, water, cement, sand, crushed glass and BNG
Output Data	Slump
Maximum number of Epochs	1000
Validation Checks	6
Target Gradient	1×10^{-7}
Training Algorithm	Levenberg-Marquardt
Activation Function	Hidden layer – Sigmoid; Output layer – Linear
ANN Architecture	6 : 20 : 1
Performance Check	Mean Square Error (MSE) and Regression

Fig. 4 shows the network architecture of the models. Six (6) input data: water to cement ratio, water, cement, sand, crushed glass and BNG content were passed to the network as input and the slump was the response for the output layer. A total of 80 observation points were used to train the network. 80% of the data were used to train the network, 15% were used for validation and 5% were used for testing. Additional 50 secondary data synthesized from the laboratory results were used to further test the network.

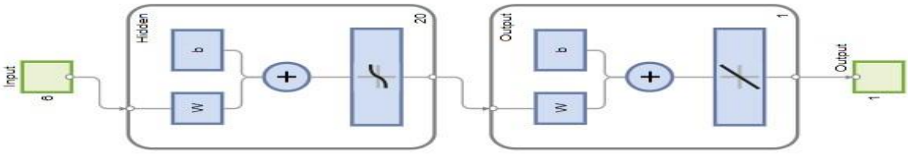


Fig. 4 Network architecture of the shallow neural network model

Table 3 Training result based on Mean Square Error (MSE) and Regression (R)

	Observation	MSE	R
Training	64	$1.84e^{-2}$	0.79
Validation	12	$5.81e^{-3}$	0.94
Test	4	$3.64e^{-3}$	0.96
Additional Test	50	$1.73e^{-3}$	0.79

The performance of the model based on MSE and Regression is presented in Table 3. The MSE values for training, validation and testing are: $1.84e^{-2}$, $5.81e^{-3}$, $3.64e^{-3}$ and $1.73e^{-3}$ respectively. Regression values for training, validation and testing are: 79%, 94%, 96% and 79%. The regression values imply that the model is quite satisfactory. Regression plots based on the training, validation and testing of data are presented in Appendix 2.

5. Conclusion

The following are the conclusions of this study:

1. To accurately predict the slump of concrete, a shallow multilayer neural network architecture with 20 neurons in the hidden layer is sufficient.
2. The experimental values and the model values for slump have a correlation based on the regression MSE and regression values.
3. ANN is a more potent predictor than models based on linear regression.
4. Future studies should explore the optimization of hyper-parameters to further enhance the predictive accuracy of ANN models for concrete slump.

Appendices

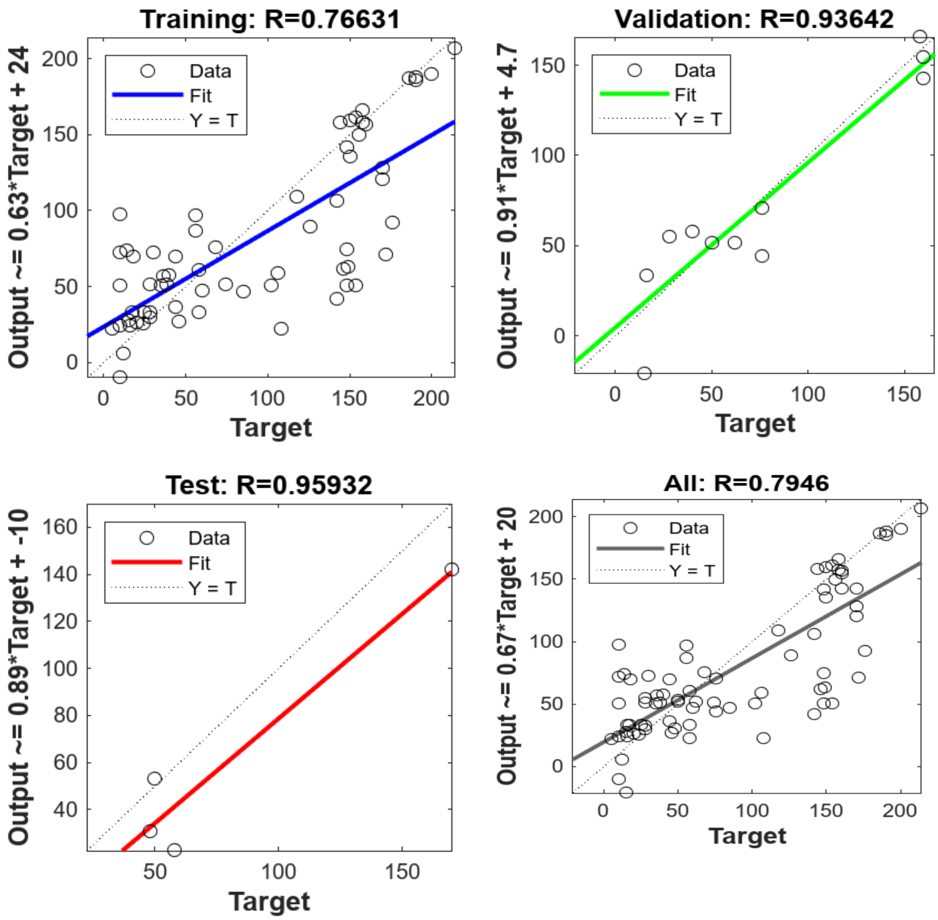
Appendix 1 Slump and compacting factor of fresh concrete

S/N	W/C	Water (kg)	Cement (kg)	Sand (kg)	Crushed Glass (kg)	BNG (kg)	Slump (mm)	Compacting Factor
1	0.45	1.61	3.58	7.32	0.39	16.41	12	0.87
2	0.50	2.84	5.68	5.5	0.61	13.02	190	0.90

3	0.78	3.35	4.27	5.87	1.04	14.69	214	0.99
4	0.60	2.06	3.43	5.9	1.48	15.7	142	0.96
5	0.65	2.68	4.13	5.55	1.11	14.18	186	0.94
6	0.66	2.9	4.39	6.62	0.47	15.1	190	0.97
7	0.52	2.56	4.88	5.71	0.85	13.97	158	0.97
8	0.58	2.19	3.8	5.89	1.28	15.25	40	0.95
9	0.63	2.34	3.74	5.74	1.31	15.01	44	0.99
10	0.55	2.11	3.83	6.5	0.72	15.38	28	0.92
11	0.50	1.95	3.9	6.66	0.68	15.63	16	0.91
12	0.58	2.75	4.78	5.53	0.9	13.69	170	0.97
13	0.55	2.35	4.27	5.75	1.15	14.69	118	0.98
14	0.53	1.84	3.5	6.6	0.94	16.05	10	0.90
15	0.60	2.52	4.2	5.71	1.07	14.43	158	0.96
16	0.51	2.1	4.09	6.56	0.61	15.25	18	0.94
17	0.50	2.31	4.62	6.19	0.65	14.57	76	0.96
18	0.59	2.23	3.79	6.12	1.02	15.19	28	0.93
19	0.55	2.35	4.27	5.81	1.09	14.69	56	0.97
20	0.60	2.26	3.77	5.81	1.29	15.19	50	0.92
21	0.52	2.4	4.58	6.1	0.68	14.43	76	0.94
22	0.49	2.01	4.13	6.64	0.58	15.38	28	0.93
23	0.51	2.22	4.33	6.18	0.82	14.89	35	0.97
24	0.50	1.95	3.9	6.61	0.73	15.63	15	0.90
25	0.56	2.39	4.26	6.07	0.8	14.63	10	0.87
26	0.54	1.97	3.66	6.55	0.84	15.73	5	0.94
27	0.57	2.3	4.01	6.12	0.89	14.93	38	0.94
28	0.55	2.66	4.83	5.62	0.88	13.83	160	0.97
29	0.54	2.45	4.56	5.73	1.01	14.36	150	0.97
30	0.56	2.54	4.51	5.71	0.97	14.22	144	0.94
31	0.54	2.07	3.85	6.27	0.98	15.44	28	0.94
32	0.56	2.26	4.03	5.82	1.22	14.99	30	0.88
33	0.59	2.35	3.99	5.8	1.18	14.86	56	0.96
34	0.61	2.42	3.96	5.73	1.2	14.74	170	0.96
35	0.57	2.08	3.62	6.18	1.12	15.55	20	0.96
36	0.54	2.31	4.29	6.15	0.78	14.76	40	0.99
37	0.56	2.15	3.82	6.19	1	15.32	48	0.97
38	0.55	2.22	4.04	6.15	0.92	15.05	148	0.99
39	0.58	2.44	4.24	5.73	1.11	14.56	148	0.97
40	0.52	2.14	4.08	6.23	0.91	15.18	62	0.93
41	0.59	2.32	3.91	5.79	1.23	14.95	148	0.94

42	0.54	2.33	4.28	5.8	1.11	14.72	176	0.94
43	0.56	2.07	3.69	6.3	0.99	15.52	108	0.99
44	0.53	2.27	4.31	6.26	0.7	14.81	146	0.97
45	0.50	2.16	4.36	6.38	0.66	14.99	50	0.97
46	0.53	1.97	3.73	6.4	0.97	15.68	16	0.92
47	0.58	2.44	4.23	5.69	1.14	14.55	156	0.99
48	0.55	2.17	3.98	6.32	0.82	15.19	154	0.96
49	0.51	2.06	4.02	6.35	0.87	15.36	142	0.97
50	0.56	2.59	4.61	5.66	0.95	14.08	154	0.97
51	0.65	2.20	3.38	6.91	0.36	15.48	200	0.93
52	0.55	3.05	5.55	5.37	0.60	12.71	58	0.93
53	0.60	2.52	4.20	5.76	1.02	14.43	160	0.91
54	0.45	1.61	3.58	6.17	1.54	16.41	10	0.86
55	0.50	2.18	4.35	5.86	1.17	14.96	17	0.84
56	0.60	2.52	4.20	6.33	0.45	14.43	150	0.94
57	0.63	2.34	3.74	6.40	0.65	15.01	68	0.91
58	0.55	1.91	3.48	6.55	0.94	15.93	24	0.88
59	0.58	2.19	3.80	6.45	0.72	15.25	36	0.88
60	0.58	2.75	4.78	5.60	0.84	13.69	160	0.97
61	0.50	2.18	4.35	5.86	1.17	14.96	25	0.84
62	0.525	2.56	4.88	5.64	0.92	13.97	158	0.94
63	0.53	2.03	3.87	5.98	1.30	15.50	85	0.96
64	0.55	2.35	4.27	5.81	1.09	14.69	10	0.80
65	0.48	1.87	3.93	6.03	1.37	15.76	15	0.88
66	0.56	2.04	3.63	6.50	0.83	15.61	46	0.92
67	0.55	2.35	4.27	6.10	0.81	14.69	149	0.94
68	0.51	2.10	4.09	5.92	1.24	15.25	44	0.95
69	0.527	2.03	3.87	6.24	1.04	15.50	58	0.94
70	0.54	2.18	4.06	5.90	1.20	15.12	106	0.96
71	0.59	2.50	4.21	6.15	0.64	14.46	170	0.98
72	0.56	2.07	3.69	6.33	0.96	15.52	58	0.97
73	0.545	2.17	3.98	6.28	0.86	15.19	60	0.92
74	0.53	2.27	4.31	5.84	1.12	14.81	14	0.83
75	0.58	2.27	3.93	6.25	0.81	15.03	74	0.95
76	0.56	2.26	4.03	6.15	0.89	14.99	102	0.96
77	0.526	2.26	4.31	5.83	1.13	14.83	172	0.97
78	0.55	2.11	3.83	6.22	1.01	15.38	16	0.94
79	0.54	2.18	4.06	6.17	0.93	15.12	10	0.89
80	0.58	2.44	4.24	6.07	0.77	14.56	126	0.96

Appendix 2 Regression analysis for training, validation and testing of slump model



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