Computers and Concrete, *Vol. 24, No. 6 (2019) 555-560*
DOI: https://doi.org/10.12989/cac.2019.24.6.555

Prediction of rebound in shotcrete using deep bi-directional LSTM

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(*Received May 31, 2019, Revised November 26, 2019, Accepted December 1, 2019*)

Abstract. During the application of shotcrete, a part of the concrete bounces back after hitting to the surface, the reinforcement or previously sprayed concrete. This rebound material is definitely not added to the mixture and considered as waste. In this study, a deep neural network model was developed to predict the rebound material during shotcrete application. The factors affecting rebound and the datasets of these parameters were obtained from previous experiments. The Long Short-Term Memory (LSTM) architecture of the proposed deep neural network model was used in accordance with this data set. In the development of the proposed four-tier prediction model, the dataset was divided into 90% training and 10% test. The deep neural network was modeled with 11 dependents 1 independent data by determining the most appropriate hyper parameter values for prediction. Accuracy and error performance in success performance of LSTM model were evaluated over MSE and RMSE. A success of 93.2% was achieved at the end of training of the model and a success of 85.6% in the test. There was a difference of 7.6% between training and test. In the following stage, it is aimed to increase the success rate of the model by increasing the number of data in the data set with synthetic and experimental data. In addition, it is thought that prediction of the amount of rebound during dry-mix shotcrete application will provide economic gain as well as contributing to environmental protection.

Keywords: deep neural network; LSTM; prediction; rebound; shotcrete

1. Introduction

Shotcrete is a type of concrete that is carried with pressure by means of a pneumatic hose or pipe and placed in place at high speed with simultaneous compression (Wang *et al.* 2018, Wang *et al.* 2019). Spraying concrete ensures that the concrete is perfectly bonded to the substrate, fills all cavities, cracks and pits and doesn't require any molding because it cures instantly (Hubáček *et al.* 2013). The flexibility of shotcrete makes it an effective alternative to traditional concrete in, concrete repair, tunnel coating and rock support (Yu *et al.* 2018). It can be used in a variety of civil engineering applications and projects ranging from mining, slope stabilization, concrete repair and anchored retaining walls to construction of tunnels and other underground structures sensitive to different forms of physical and chemical attack affecting durability, in cases where a complex form of element is required and molding is difficult to make (Armengeud *et al.* 2018, Baricevic *et al.* 2018, Galan *et al.* 2019).

Application of shotcrete involves a range of complex procedures including pumping, spraying shotcrete and its effect on the receiving surface (rebound, dynamic compression, etc.) (Ginouse and Jolin 2015). Two methods are employed in shotcrete applications: wet and dry. Although both techniques have advantages and disadvantages, their suitability depends on individual practice (Galan *et al.* 2019).

In the wet mix, the pre-mixed concrete is conveyed by a high-speed closed hose system and then sprayed through the nozzle using high-pressure air (Yun *et al.* 2018). The dry mix is more specific than the wet mix because the components (sand, aggregate and binder) are placed in the machine in a dry or slightly humid state. The dry mix, which is conveyed by the compressed air, is pneumatically transmitted to the nozzle where water is added through a hose (Armengeud *et al.* 2018). The operator is responsible for controlling the flow of water to the main concrete, it plays an important role on the composition of the shotcrete (Duarte *et al.* 2019). If the operator misuses the nozzle in spraying application, it causes extra concrete consumption as a result of impacting the mesh surface instead of the desired thickness (Vandewalle 2000).

In this context, investigation of prediction of the rebound during shotcrete application can be said to be important in environmental, economic and technical terms. When the literature about shotcrete is investigated, it is seen that many investigators have studied mechanical properties, application, rebound, etc. of shotcrete. Some of these studies reported in the literature include the factors affecting the quality of shotcrete (Brennan 2005), problems with testing and preparation under lab conditions of shotcrete (Hubáček *et al.* 2013), freeze-thaw damage in shotcrete and the effects of freeze-thaw on the physical and mechanical properties of shotcrete (Wang *et al.* 2019), the influence of the mixture consistency on the bond strength of deformed reinforcing bars encased with shotcrete (Trujillo *et al.* 2018), investigation of the mixture design of wet-mix shotcrete in terms of mechanical properties of shotcrete and

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http://www.techno-press.org/?journal=cac&subpage=8
ISSN: 1598-8198 (Print), 1598-818X (Online)

rebound (Liu *et al.* 2017), the effects of various additives on the rheological properties of high-performance wet-mix shotcrete (HPWMS) and wet-mix shotcrete (WMS) (Yun *et al*. 2015a, Yun *et al.* 2015b), investigation of characteristics such as air content, spacing factor, and air-void specific surface area of both fresh and hardened wet-mix shotcrete with mineral additives before spraying operation (Yun *et al.* 2018), the effect of high geothermal environment on deformation of shotcrete and the effect on shrinkage of fiber materials applied on shotcrete in hot and dry environments (Cui *et al.* 2017), the effect of adding fiber and nanomaterials to shotcrete on the mechanical properties and rebound of shotcrete (Khooshechin and Tanzadeh 2018), investigation of shotcrete mixtures with steel fiber and amorphous metallic fiber (Yang *et al.* 2017), the relationship between mass distributions of the sprayed and replaced material and rebound (Ginouse and Jolin 2016), determination of slump, cost and compressive strength at different ages of shotcrete with varying quantities of water, steel fibers and silica fume using Back Propagation Neural Network (BPNN) model (Muhammad *et al*. 2015), rebound of shotcrete (Pfeufer and Kusterle 2001, Ballou 2003, Ginouse and Jolin 2015), the effect of mineral admixtures on rebound of fiber reinforced dry-mix shotcrete (Bindiganavile and Banthia 2001), the effect of mineral admixtures on rebound of shotcrete (Wolsiefer and Morgan 2003), the relationship between fresh dry-mix shotcrete properties and rebound and the effect of supplementary cementitious materials (SCMs) on rebound (Armengaud *et al*. 2017), the effect of rebound and fibers (macro-synthetic plastic fibers and steel fiber) in shotcrete on rebound behavior (Kaufmann *et al.* 2013).

Datasets comprise observations that contain attributes or multiple linked variables (Shin *et al.* 2016). The rapid use of technology in all disciplines has significantly increased the number of data in datasets (Muhammad *et al.* 2015). Inference, classification and estimation processes are performed with artificial neural networks using data sets (Courbariaux *et al.* 2015). With deep learning, which is a sub-model of Artificial Neural Networks, crowded data can be interpreted rapidly with high accuracy. Various deep learning algorithms are used according to the type of problem and the desired result when developing deep learning applications. Previous studies reported in the literature include object detection (Cai *et al.* 2016), prediction, recognition of sound (Graves *et al.*2013) and text (Samui *et al.* 2018), character analysis (Dewa *et al.* 2018), classification (Samui *et al.* 2018), interpretation (Quang and Xie 2016) by deep learning algorithms. Also, Deep Learning Algorithms are applied successfully on images (picture and video) except for data sets so they provide the opportunity to collaborate with disciplines such as health (Acharya *et al*, 2017), construction (Alshehhi *et al.* 2017), agriculture (Chunjing *et al.* 2017).

In the current study, the process from the preparation of shotcrete to its application was addressed as a whole and it was aimed to predict rebound by considering all the parameters. In this context, this study investigated the use of the deep neural network model Long Short-Term Memory (LSTM) in the predictability of the rebound material of shotcrete, the application of which is progressively increasing, and this study is believed to contribute to the literature. In the study, a model carrying out the prediction procedure by deep neural network was proposed to investigate predictability of the amount of the material that bounces off and is not used in the dry-mix shotcrete application. The data required for the training of the model were obtained from experimental studies. These experimental studies are difficult and costly so there were 120 experimental data in the dataset. 90% of the data in the dataset was used to train the model and 10 % to test the model. After the parameters to be used in the proposed prediction model were identified, the model was trained and the test data were applied. Predicting the amount of rebound material, the model is thought to contribute to protecting the environment as well as minimizing production costs.

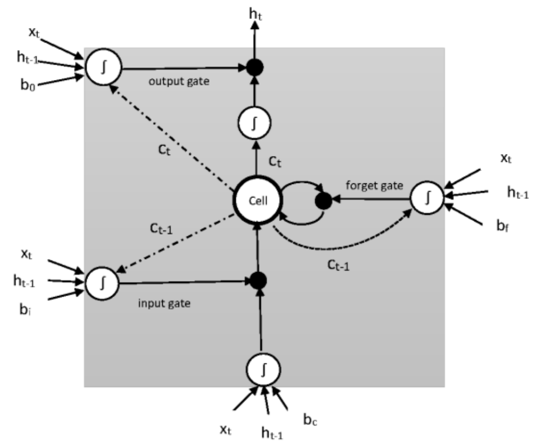


Fig. 1 LSTM cell architecture

In the first part of the study, a literature search was carried out to find previous studies on the amount of concrete bouncing off in shotcrete applications and factors affecting rebound. Thus, it was identified which data obtained from rebound experiments could be used in deep neural network model. In the second part, the architecture of the LSTM model to be used in the development of the deep neural network was described. Previous studies have shown that LSTM provides successful results in prediction operations with correct hyper-parameter selection. In the last part of the study, data preparation, training and testing procedures of the proposed model were explained.

2. Long short-term memory (LSTM)

LSTM is a powerful neural network structure that can model sequential information dynamically and contextually (Li *et al.* 2017). LSTM networks can seamlessly model the vast majority of problems associated with multiple input parameters. In addition, it provides great benefit in adapting time series operations in multivariate prediction problems in linear methods.

In the foundation of the LSTM neural network, there's a sequential input sequence represented by (x_1, ·····, x_t) and at the output, there is recursive y_t sequence calculated by the formulas in Eqs. (1) -(2). In LSTM cell structure is shown in Fig. 1, where i represents input gate, f forget gate, o

Table 1 LSTM symbols and definitions

Inputs	Outputs	Nonlinearities
x_t Input vector	c_t Memory from current block	σ Sigmoid
c_{t-1} Memory from previous block h_{t-1} Output of previous block	h_t Output of current block	tanh Hyperbolic tangent b Bias
W: weight matrix		

output gate and c cells. The values represented in the LSTM cell structure are found by the formulas given in Eqs. (3)-(4)-(5)-(6) and (7) (Xue *et al.* 2018).

The definition of the inputs, outputs and Nonlinearities of the LSTM structure is given in Table 1.

$$h_t = LSTM\left(h_{t-1}, x_t ; W\right) \tag{1}$$

$$y_t = W_{hy} h_t + b_{y,} \tag{2}$$

$$i_t = \sigma\left(W_{xi}\, x_t + W_{hi}\, h_{t-1} + W_{ci}\, c_{t-1} + b_i\right) \tag{3}$$

$$f_t = \sigma\left(W_{xf}\, x_t + W_{hf}\, h_{t-1} + W_{cf}\, c_{t-1} + b_f\right) \tag{4}$$

$$c_t = f_t\, c_{t-1} + i_t \tanh\left(W_{xc}\, x_t + W_{hc}\, h_{t-1} + b_c\right) \tag{5}$$

$$o_t = \sigma\left(W_{xo}\, x_t + W_{ho}\, h_{t-1} + W_{co}\, c_t + b_o\right) \tag{6}$$

$$h_t = o_t \tanh\left(c_t\right) \tag{7}$$

3. Modelling

3.1 Data preparation

In order to estimate the amount of rebound in shotcrete, the parametric data from previous experimental studies were used. Spyder software was used in the preparation, processing, training and prediction of data. Representation on the temperature map of experimental parameters to be used in multivariate single output model is given in Fig. 2 and description of the data in variables is given in Table 2.

3.2. Setup

For the training and testing of the methods, a system with an Intel i7 processor with a frequency of 3.2 GHz and a memory of 12 GB was used. All experiments were performed on a graphics processing unit (GPU). The model is implemented in python using Keras library with TensorFlow backend.

Table 2 Parameters and description required for prediction of rebound

Variate	Description
*s*_thickness	Shotcrete thickness
cement	Amount of cement
*r*_ concrete	Amount of concrete required
*p*_ concrete	Amount of concrete produced
water	Amount of water
*a*_ concrete	Amount of shotcrete concrete admixture
aggregate	Amount of aggregate
*o*_ experience	Operator’s experience
fiber_1	Amount of fiber
fiber_2	Amount of fiber
rebound	Rebound

3.3 LSTM model

The proposed learning algorithm for recurrent neural networks is based on the Stochastic Gradient Descent (SGD) and back-propagation through time (BPTT). BPTT is a back propagation algorithm that is widely used in modeling and training of multi-layer neural networks. SGD is an efficient optimization algorithm model used to search the point optimal value of lost functions. After searching procedure, gradient and lost function of Eq. (8) are calculated using BPTT algorithm

$$h^{(t)} = f\left(Ux^{(t)} + Wh^{(t-1)}\right) \tag{8}$$

During design stage of the model, hyper parameter groups were formed for the model to provide high success. In each iteration of learning, using back propagation process, gradient is calculated retrospectively using $\frac{\partial J}{\partial w_1}, \dots, \frac{\partial J}{\partial w_9}$ and weight values are updated as $w_1 = w_1 - \alpha(\frac{\partial J}{\partial w_1} + \cdots)$.

In this calculation, the higher the number of data, the longer it takes to calculate. To solve this problem; the data set is divided into groups and the learning process is performed on these selected groups. However, due to the small number of elements in the training data set, all the elements in the data set were used simultaneously to

Index	s_thickness	r_ concrete	p_ concrete	water	cement	a_ concrete	aggregate-0	aggregate-1	fiber_1	fiber_2	o_ experience	rebound
0	0.05	1708	2904.76	133.365	500	35	1565.48	670.918	0	0	3	132.894
1	0.1	3416	5809.52	266.73	1000	70	3130.95	1341.84	0	0	3	261.856
2	0.05	1708	2904.76	133.365	500	35	1565.48	670.918	5	2	4	165.867
3	0.1	3416	5809.52	266.73	1000	70	3130.95	1341.84	10	4	4	345.934
4	0.05	1708	2904.76	133.365	500	35	1565.48	670.918	9	2	4	219.745
5	0.1	3416	5809.52	266.73	1000	70	3130.95	1341.84	18	4	4	435.778

Fig. 2 Parameters used to predict the amount of rebound

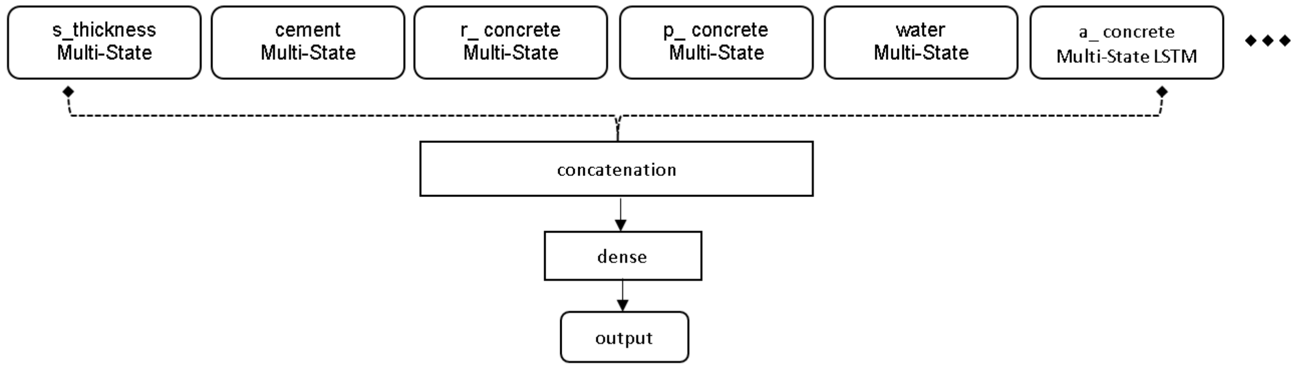


Fig. 3 Structure of LSTM model

Table 3 Parameters and hyper-parameters used in deep neural model

Hyper Parameters and Parameters	Case study
Train data set	108 (90%)
Test data set	12 (10%)
Input	11
Batch size	8
Epochs	50
Learning rate	0.001
Layers	4
Output	1

calculate batch gradient.

In back propagation, new weight value is calculated as follows: the difference is found by taking the reverse derivative and this value is multiplied with learning ratio parameter, the result of which is subtracted from the weight value. The learning rate parameter in this calculation is used as 0.01 in the first two epochs, and reduced to 0.001 in the following epochs. In addition, the total epoch number of the model was determined as 50. In general, the hyper parameters used to model proposed prediction neural network and input-output parameters are given in Table 3.

Algorithms that generate a lot of oscillation and noise, such as SGD, are normalized with exponential weight average and their oscillations are decreased. The success rate of the educated model is given by the formula given in Eq. (9), where a_i refers to real data, p_i prediction data, N the total of predicted rebound data. If $a_i=p_i$ it is taken as 1; if $a_i \neq p_i$, then it is taken as 0. The structure of the formed model from dataset to output is shown in Fig. 3

$$A_{cc} = \sum_{i=1}^{N} 1(a_i = p_i) \tag{9}$$

4. Experiment results and discussions

4.1 Evaluation for forecast result

Performance of the trained network was evaluated using Root Mean Square Error (RMSE) given in Eq. (10) and Mean Squared Error (MSE) given in Eq. (11). In Eqs. (10)-(11), A_i refers to estimation data and P_i refers to the data measured. RMSE finds the average square root of the squares of the difference between the real and the predicted value. MSE measures the total of squares of the difference between the real and the predicted values in the prediction set.

$$RSME = \sqrt{\frac{\sum_{i=1}^{n} (A_i - P_i)^2}{n}} \tag{10}$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (A_i - P_i)^2 \tag{11}$$

Table 4 Accuracy and loss performance of model

Dataset	Accuracy (%)	MSE	RMSE
Training Set	93.2	0.046	0.2144
Test Set	85.6	0.061	0.2469

Table 5 Comparison with other deep learning and machine learning algorithms

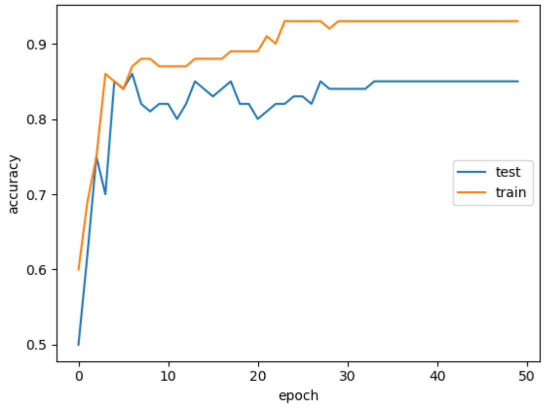
Model	Accuracy (%)		MSE		RMSE	
	Training	Test	Training	Test	Training	Test
Our LSTM Model	93.2	85.6	0.046	0.2144	0.061	0.2469
DBN	92.6	80.4	0.097	0.3540	0.510	0.2641
SVM	90.0	80.7	0.120	0.3454	0.220	0.3544
BP Neural Network	87.5	75.6	0.154	0.452	0.164	0.4521
SAE	85.7	72.8	0.162	0.521	0.178	0.552

4.2 Experiment result

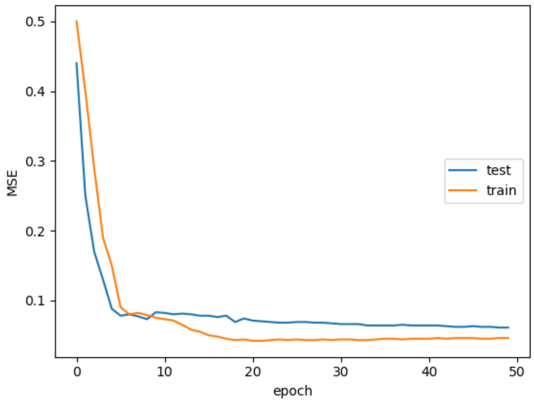
Since the data in the hyper parameters are similar to each other, they show a fluctuating condition in the success graph. It is not possible to change the data here so the batch value was changed to get a clearer graph for the problem. Fig. 3 shows the performance graph obtained for each epoch using the prediction model proposed on the dataset, 90% of which was used for training and 10% for testing.

In the graph, it is seen that the model was trained after the 30th epoch. In the test process, the success reaches a maximum value and a stable graph at the 35th epoch. The success and error performance obtained at the end of training and testing are also given in Table 4.

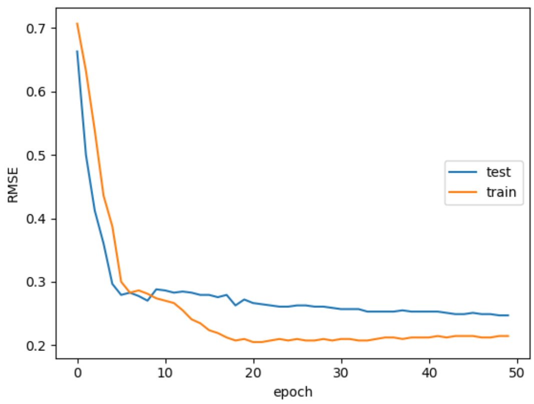
The performance of accuracy from the proposed LSTM model has been compared with other deep learning and



(a) accuracy by epochs



(b) MSE by epochs



(c) RMSE by epochs

Fig. 4 Performance from the proposed LSTM model (Blue curve: from the training; Orange curve from the test)

machine learning techniques. It was used Deep Belief networks (DBN), Support Vector Machine (SVM), Backpropagation (BP) Neural Network and Sparse auto encoder (SAE) in the comparison. The same dataset as the proposed model was used in the training and testing of the models. In the performance comparison shown in Table 5, our proposed model achieved the highest accuracy.

4. Conclusions

In this paper, a deep learning (DL)-based solution is developed for prediction rebound. 120 rows of data obtained from previous experiment and 12 different parameter values were included in the dataset. Due to the small number of the dataset, 90% of the data in the dataset was used for training and 10% for testing. A prediction accuracy of 93.2% was obtained in the proposed training process and of 85.6% in the training process. The difference of 7.6% between success performances of training and testing is due to the limited number of test data. At the end of the study, it was demonstrated that LSTM deep neural network models with accurately identified hyper parameters can give successful results when used in prediction processes.

As the most suitable weight values that will increase the success rate in deep neural networks are calculated step by step, the performance in the first epochs is low. Due to the limited number of data in the dataset, the number of epochs was kept low. If the number of data and epochs are increased, the success rate will also increase. Therefore, in the next study to be conducted on LTSM model developed, the number of data in dataset will be increased with synthetic data. Furthermore, by using "Transfer Learning" methods, it is aimed to increase the success rate by transferring attributes. Improvements to be made in future work will be used with the same hyper parameter values on the trained model in the study. Thus, the success rate of the developed model in prediction of rebound will be obtained.

Acknowledgments

The data used in this paper was obtained from the project 111M335 financially supported by Scientific and Technological Research Council of Turkey (TUBİTAK).

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