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Original scientific paper

Prediction of Rebound Amount in Dry Mix Shotcrete by a Fast Adaboosting Neural Network

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Abstract: In this study, a new machine learning approach has been proposed to predict the rebound causing loss of material in shotcrete using the ensemble learning method. In shotcrete application, the amount of rebound material was obtained for use in a dataset. In this study, the shotcrete mixes that contain an additive of fly-ash, silica fume, and polypropylene fiber were produced besides simple shotcrete. Each mix was sprayed onto 2 wooden panels measuring 45 × 45 × 15 cm in size. The rebound material resulting from the spraying process was collected, weighed and recorded as data. The highest rebound was observed for the plain sample and the lowest for samples with substituted silica fume. Dependent and independent parameters were identified in the dataset produced as a result of experimental studies. Hyperparameters producing optimum results in the training of the model were identified for the model and boosting method. The dataset was split into training and testing sets by 80% and 20%, respectively. As a result, the model achieved a prediction performance of 84.25%. To test the performance of the proposed model, traditional machine learning algorithms were compared on the same dataset. Consequently, the proposed model was observed to have the highest accuracy.

Keywords: adaboosting; dry-mix shotcrete; ensemble learning; neural network; rebound

1 INTRODUCTION

Today, limited natural resources have begun to diminish driven by rapid growth of population, and consequently, approaches such as reduction of waste and/or reuse of waste as raw materials have started to gain importance. Structural wastes are among the heaviest and the most voluminous wastes produced in the cities [1]. The recycling of this waste is essential for reducing the volume of accumulated waste and reduction of natural resources. The construction sector is a main player in terms of impact on environment [2].

Shotcrete, a special type of concrete, a concrete placement method in which a mix carried through a pneumatic hose or pipe under pressure is sprayed onto a surface at high speed [3-7], is different from the standard concrete mix not only in terms of the composition of the mix, but also in terms of its application to the structure [8]. It is applied onto surfaces using a dry- or wet-mix process [7, 9]. The dry-mix process is very specific contrary to the wet-mix process since the components (sand, aggregate, and binder) are added to the machine in dry or slightly humid form and are conveyed via a pneumatic hose to the end where water is added [10]. The rebound that occurs during the application of shotcrete causes a waste material problem.

Rebound which is described as that part of the sprayed material (consisting of sand, cement and mainly of coarse aggregate) that has not adhered to the substrate or failed to cling to the surface and has fallen [11-12] is an important element in the spraying application. The rebound effect as an indirect measure of the quality of shotcrete is expressed as the ratio of the mass of concrete loss caused by rebound to the total mass of concrete. Rebound causes loss of coarse aggregate, hence leading to lower mechanical performance [13].

Both techniques have advantages and disadvantages [7], and rebound effect is the most relevant one among the disadvantages [13]. If the operator holds the nozzle perpendicular to the surface and makes small circular motions, pieces of aggregate bounce off the surface and cement paste starts to build up and constitutes an adhesive surface on which the next shotcrete material will compact. For this reason, some rebound is necessary and expected. This is a fine line between too little rebound and too much rebound. In case of too little rebound, mortar may be insufficient to penetrate into the superficial pores and the adherence between the shotcrete and the substrate may be insufficient. Too much rebound increases material costs excessively [12]. Loss of significant material subject to the rebound of fresh concrete, and low--quality shotcrete continue to be disadvantages [14].

Rebound is higher in a dry-mix process than in a wet-mix process [12]; for this reason, mix designs are disposed to reduce rebound [10]. Such losses give rise to effects on the cost of work, the environment and overconsumption of material; they are richer in terms of cement content and are therefore inclined to create an in-situ mix in the place where they are exposed [15]. The rebound resulting from the application process substantially affects economic efficiency and environment [11]. It is one of the main concerns of the shotcrete industry due to reduction of rebound material losses and improvement of material properties, and significant effects on material cost and wastage [4, 8]. Since the first days of the shotcrete process, the reduction of rebound losses and improvement of material quality have been the main targets of this important and very active industry [4].

Sufficient modelling is required to determine the factors affecting the study in experimental studies, provide the same conditions during repetition of the experiment, consider laboratory facilities and ensure reliability of the data obtained. However, besides the insufficient laboratory conditions, the technical difficulties and cost encountered during the experiment complicate the experimental study. Due to such difficulties experienced in experimental studies, it is preferred to search for suitable alternatives. Today, environments where experiments and simulations can be performed using various parameters can be created by neural network methods.

In this study, the focus has been placed on the rebound that occurs during shotcrete application, and a means to simulate and make analysis using the model developed to predict the amount of rebound in order to substantially prevent material loss has been presented.

2 RELATED WORK

Shotcrete is a better and more economical alternative to the conventional casting techniques [16]. The rock support in mining and tunneling is probably the most important application of shotcrete, but at the same time, it may be used in various construction structural repair, slope stabilization, shell structures, rehabilitation studies, refractory linings, swimming pools, and works in which the assembly of a mold is difficult. In industrial practices, it offers various advantages such as good adhesion with the substrate, rapidly-increasing resistance during curing, good compaction properties, the opportunity not to use a mold, and ease of application in confined spaces [2, 7, 8, 10, 15, 17, 18].

Despite the wide scope of application and advantages, shotcrete has some disadvantages, with rebound effect being the most relevant [13]. Rebound is harmful for the environment and causes excessive material consumption. In addition, rebound may lead to an in-situ mixture which has more cement content and therefore causes more contraction [19]. The lower the rebound rate, the better the quality of shotcrete will be [14]. For this reason, reduction of rebound loss and improvement of material quality has been the main targets to improve the shot [19].

Reduction of losses caused by material rebound during placement has remained one of the biggest challenges of the industry due to its significant effects on cost and the characteristics of the in-situ material. [17]. Mix designs are aimed at reducing rebound [10].

In the literature, a correlation has been established between various factors such as the placement method of shotcrete and its rheological properties, and assessments have been made in order to improve understanding of the relationship between fresh concrete properties, and particularly the losses resulting from rebound. In the studies carried out, it is reported that rebound affects not only the cost but also the properties of in-situ material negatively [4, 11, 15, 16, 17, 19]. In the study which researches the effects of the fine particle composite additives and nanomaterials in cement materials on the strength of mortar samples [20], it has been demonstrated that super fine additives (nano-SA) and nanomaterials do not only improve the workability and compressive strength of the shotcrete but also significantly reduce the rebound ratio. In a study which was conducted to examine the strength of dry-mix shotcrete produced with coarse recycled concrete aggregates (CRCA) [2], a marked reduction has been observed in the rebound effect with the addition of recycled aggregates. In another study in which the effect of substitution of natural coarse aggregates with coarse recycled aggregates on the durability performance of shotcrete is examined [13], a positive result has been achieved, with reduction of rebound due to addition of recycled aggregates to dry-mix shotcrete. In another study [21], shotcrete with various plastic viscosity values was modeled in Abaqus CAE software package for finite elements in a manner to obtain optimum rebound values in shotcrete mixes. It is reported that the amount of concrete that bounced decreased in line with the increase in viscosity value, and that there is a stable correlation between spraying angle, spraying height and viscosity of concrete. In another study designed to determine the slump, cost and compressive strength of shotcrete in different ages [3], a series of 3-layer Back Propagation Neural Network (BPNN) models of different network architectures were developed.

In this study, certain studies assessing the rebound characteristic of shotcrete [2, 4, 12, 14, 15, 16, 17, 20, 22] have been examined, and in the light of the cited studies, it has been set as a basic target to develop a model that could predict the amount of rebound that causes the loss of material and affects the quality of shotcrete. Bearing this in mind, the machine learning method that predicts the rebound amount using the Adaboost algorithm, an ensemble learning method, is proposed in this study as a new approach in this study.

3 PREPARATION OF DRY-MIX SHOTCRETE

In this study, it was aimed to predict the amount of rebound material described as waste material during shotcrete application. In line with this aim, the amount of rebound material has been obtained through an experimental application for use in a dataset of the Adaboost algorithm, an ensemble learning method. In the light of this purpose, the four main series of dry mix shotcrete mix have been produced including plain, silica fume, fly ash and polypropylene fiber. All series other than the plain sample were internally split into 2 series. The samples in the series are given in Fig. 1. In silica fume samples, cement was substituted by silica fume by 10 and 20%. In fly ash samples, cement was substituted by fly ash at the same ratios (10% and 20%) by volume, and mixes were produced. By the addition of polypropylene fiber into the concrete mix at the rates of 5 kg/m^3 and 10 kg/m^3, dry-mix shotcrete samples with polypropylene fiber added were produced. Each mix was sprayed onto 2 wooden panels measuring 45 × 45 × 15 cm in size.

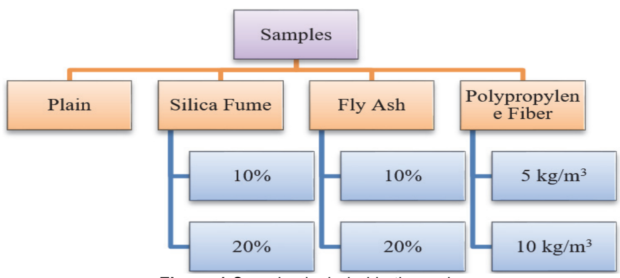

Figure 1 Samples included in the series

In shotcrete mixes, cement type CEM II 42.5 was used, and cement dose was selected as 500 kg/m^3. The physical, chemical and mechanical properties of cement are given in Tab. 1.

Table 1 Properties of cement [23]

Chemical Characteristics / %		Mechanical and Physical Characteristics	
$S0_3$	2,77	Compressive Strength 2 Days / N/mm^2	23.9
CI	0,012	Compressive Strength 28 Days / N/mm^2	48.1
Insoluble Residue	0,50	Initial Setting Time / min	139
Loss on Ignition	3,13	Autoclave Expansion / mm	0.36

In shotcrete application, the largest aggregate grain size was selected as 8 mm. Crushed stone aggregates of 0 - 5 mm and 5 - 8 mm dimensions were used. 80% of the aggregate was adjusted to be between 0 - 5 mm, and 70% thereof between 5 - 8 mm. The granulometry curve of the aggregate mixture used in the concretes produced is given in Fig. 2.

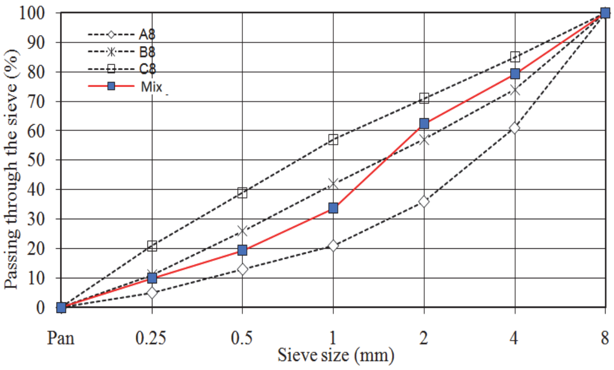

Figure 2 Granulometry curve of the aggregate mixture

Water/cement ratio was adjusted by the operator with the help of a valve at the end of the hose. Weight was relied upon in preparing the dry-mix. As a chemical additive, a setting accelerator powder concrete admixture designed for the production of dry system shotcrete was used. The setting accelerator admixture was added to the mixtures at a rate of 7% of the total binder dosage. The water used in shotcrete application was potable mains water. In the study, fly ash (FA) obtained from Seyitömer Thermal Power Plant was used. The properties of the fly ash are given in Tab. 2.

Table 2 The chemical properties of the fly ash / % [24]

	SiO_2	Al_2O_3	Fe_2O_3	CaO	MgO
Fly ash	54.30	20.71	9.34	4.62	4.45
	SO_3	K_2O	Na_2O	Ignition loss	SO_3
Fly ash	0.49	1.97	0.63	7.06	0.49

Silica fume (SF) from Antalya EtiElektrometalurji A.Ş. Ferrochrome facility was used as silica fume. The properties of the silica fume are given in Tab. 3.

Table 3 The properties of the silica fume / % [25]

Oxide	SiO_2	Al_2O_3	Fe_2O_3	CaO
Silica Fume	81.40	4.47	1.40	0.82
MgO	SO_3	K_2O	Na_2O	KK
1.48	1.35	NA	NA	7.06

Polypropylene fiber additive 19 mm in length and 18 - 20 µm in diameter was used as fiber additive. The aggregate, cement, additive material, silica fume, fly ash, polypropylene fiber and water that were used in the application were weighed to determine mixing ratios. For each concrete mixture, 14 wooden panels measuring 45 cm × 45 cm with two compartments were prepared in accordance with [26] standard. The thickness of the concrete to be sprayed on the test panels was specified as 15 cm. Shotcrete mixture was calculated based on [27] standard. The amounts of materials in 1 m^3 of shotcrete are given in Tab. 4.

Table 4 The amounts of materials in 1 m^3 of shotcrete

Mix Type	Cement	Fly Ash	Silica Fume	Fiber	Accelerat or additive	Aggregates	
						0 - 5 mm	5 - 8 mm
	kg/m^3						
Plain	500.00	-	-	-	35.00	1423.64	355.91
10% Fly Ash	450.00	34.52	-	-	33.92	1424.79	356.20
20% Fly Ash	400.00	69.03	-	-	32.83	1425.94	356.49
10% Silica Fume	450.00	-	37.26	-	34.11	1424.59	356.15
20% Silica Fume	400.00	-	74.52	-	33.22	1425.53	356.38
Polypropy lene Fiber	500.00	-	-	5	35.00	1423.64	355.91
Polypropy lene Fiber	500.00	-	-	10	35.00	1423.64	355.91

Cement and aggregate were blended in the shotcrete mixer in dry form, and a homogenous mix was obtained. After the dry mix was blended homogenously in the concrete mixer, (Fig. 3) the accelerator additive was added by pouring it into the bucket of the sprayer, and the mix was sent to the distribution component via compressed air, and conveyed to the sprayer tip inside a house with an inner diameter of 58 mm. The mix was humidified by 4% in the aggregate mixer to avoid congestion of the hose and prevent dust formation. A polyethylene nylon cover was laid beneath the panels to collect the bouncing material during the spray application.

Figure 3 Preparation of the mixture

All shotcrete mixes were sprayed onto the panels by the same operator at the same distance and at the same angle (Fig. 4). Each mix was sprayed to 2 pores of the panels with pores measuring 45 × 45 × 15 in size. In each series, the rebound material resulting from the spraying process was collected on a polyethylene nylon cover, weighed (Fig. 4) and recorded as data. Then, fresh shotcrete densities were determined according to [28] standard.

Figure 4 Shotcrete application and collecting the rebound material

The parameters used in the prediction model proposed in the study are presented in Tab. 5. The resulting dataset was split into training and testing sets by 80% and 20%, respectively.

Table 5 The parameters used in the prediction model

Samples		Unit Volume Weight / gr/cm3	Rebound Material / gr
Plain	-	2.175	4032.50
Fly Ash	10%	2.173	3827.50
	20%	2.280	3870.00
Silica Fume	10%	2.232	3125.00
	20%	2.142	3087.50
Polypropylene Fiber	5 kg/m3	2.248	3692.50
	10 kg/m3	2.237	3305.00

4 PROPOSED MODEL

4.1 Preparation of Dataset

The parameters have been created in two stages in the dataset. In the first phase, silica fume, fly ash and polypropylene fiber quantities, additives and aggregate quantities, which are the necessary parameters for the application of spraying concrete were saved. In the second phase, the volume of units obtained from the study, the weight and the back-tab amount were saved. All the resulting parameters formed the dataset as shown in Tab. 6.

Table 6 Parameters and definitions in the dataset

Definition	Description
v_weight	Unit Volume Weight
s_fume	Amount of Silica Fume
v_ask	Fly Ash Quantity
a_ concrete	Amount of Spray Concrete Additives
aggregate	Aggregate Amount
fiber	Amount of Fiber
p_fiber	Polypropylene Fiber
rebound	Rebound

4.2 Development of Model

Ensemble Learning is an approach aimed at bringing together independently trained algorithms in prediction, prediction, and classification problems [29]. It is also a hybrid machine learning that allows the neural network trained with multiple algorithms to achieve a single result with different techniques. There are three different methods of ensemble learning: bagging, stacking and boosting [30].

Bagging: a method that generally considers homogeneous weak learners [31]. They learn independently of each other in parallel and combine after some sort of deterministic mean-taking process [32].

Stacking: stacking, which often considers heterogeneous weak learners, learns them in parallel [33]. It then combines them, training a meta-model to extract a prediction based on different weak model predictions [34].

Boosting: in boosting, which often considers homogeneous weak students, the basic model depends on the previous model. In this way learners combine following a deterministic strategy. The Boosting method runs faster and consumes less memory [35].

Adaboosting, one of the effective methods of Ensemble Learning, has been used in the proposed neural network model. The design of the model is given in Fig. 5.

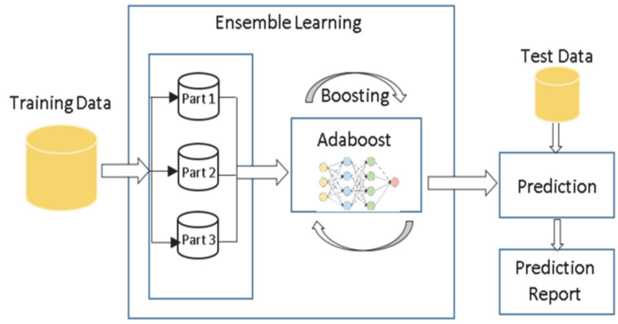

Figure 5 The proposed ensemble learning model

In the process of developing the model, the data set of n samples and n features as $D=\{(x_i,y_i)\}(|D|=n,\ x_i\in R^m, y_i\in R)$ is given. Here, an ensemble learning model is used to estimate a single output towards an aggregate function ϑ, $\{f_1, f_2, f_3, ..., f_k\}$, which aggregates the inductors of K (Eq. 1).

$$\hat{y}_i = \vartheta(x_i) = G(f_1, f_2, f_3, ..., f_k) \tag{1}$$

Here, $\hat{y}_i \in R$ is for the regression problem and $\hat{y}_i \in Z$ is for the prediction problem. In the dataset, the weight distribution of the th-boosting in the iteration is expressed as $W_t = \{w^1{}_t, w^2{}_t, w^3{}_t, ..., w^n{}_t\}(t = 1, 2, 3, ..., T)$, which is initially set without error. This means that the weight of Y is given a value of $1/n$ in the first iteration when $t = 1$, and will be adaptively updated in later iterations. For a new input sample, it calculates the predicted value of each weak back tab amount to +1.0 or −1.0. Projected values are weighted by the stage value of each of the weaker learners. The prediction for the ensemble model is taken as a sum of weighted predictions. If the sum is positive, the first class is predicted, while the second class is predicted if the sum is negative (Eq. 2).

$$l_t^i = \begin{cases} 1 \text{ if } f_t(x_i) = y_i \\ -1 \text{if } f_t(x_i) \neq y_i \end{cases} \tag{2}$$

Each sample has a weight in the learning dataset. After each learning process, the weights of the samples are updated again, taking into account the classification error of the classifier. A weighted average based on the accuracy of each classifier is selected to classify a new sample and the prediction is performed. The final stage Adaboost classification result is made by the combination of classification results in α. The formatted Adaboost algorithm used in the proposed model is given in Tab. 7.

Table 7 Formatted Adaboost Algorithm

Input: training set $D = \{(x_i, y_i)\} (|D| = n, x_i \in R^m, y_i \in R)$

T : 100 // total number of iterations

Initialize: $W_1^i = 1;$ and; $W_t = \left\{ \frac{1}{n}, \frac{1}{n}, \frac{1}{n}, ..., \frac{1}{n} \right\}$ $F = \phi$

For $t = 1, 2, 3, …, T$

»Take a sample R_t « S_n using W_t

»Make a classifier f_t using R_t

»Compute: E_t and $\alpha = 0.5 >> \left(\frac{1 - E_t}{E_t} \right)$

»Update weight: $w_{t+1}^i = \text{normalize}\left(w_t^i * \exp(\left(-\alpha_t * I_t^i \right)) \right)$

Output: Ensemble $F_t = \{f_1, f_2, f_3, ..., f_t\}$ and $\alpha = \{\alpha_1, \alpha_2, \alpha_3, ..., \alpha_t\}$

Throughout the Adaboost training phase, there are a number of parameters that need to be adjusted for optimum performance. Brute force strategy was used to adjust the parameters of the Adaboost model and to obtain the best prediction results. These general and booster parameters are listed in Tab. 8 along with their values.

Table 8 Initial parameters of the model

Parameters	Value
learning_rate	0.1
gamma	0
n_estimators	100
silent	1
reg_alpha	0.01
reg_lambda	0.6

5 RESULTS

5.1 Rebound Results

The graph showing the rebound values of the shotcrete series in the study is presented in Fig. 6. The highest rebound was observed for the plain sample, whereas the lowest for samples with substituted silica fume. This result is in good agreement with previous results reported in the literature [36-38].

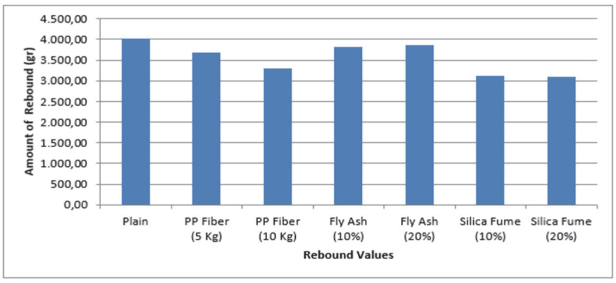

Figure 6 The rebound values of the series

5.2 Metric Evaluation

To determine the accuracy performance of the proposed model, metrics such as the coefficient of specificity (R) (Eq. 3), Mean Absolute Error (MAE) (Eq. 4), and Mean Error Square Root ($RMSE$) (Eq. 5) were used. Here the coefficient of specificity is an indication of the accuracy of the predictions they produce for the test data of the trained model with the training data. The closer the result is to 1, the more successful the model is. The fact that the value obtained from MAE and $RMSE$ metrics is close to 0 indicates that the error of the model is low.

$$R = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}} \tag{3}$$

$$MAE = \frac{1}{N} \sum_{n=1}^{N} | e_n | \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^{N} e_n} \tag{5}$$

5.3 Performance Evaluation

The proposed prediction model was implemented using the "scikit learn" and "mlxtend" libraries in the Spider. After the prior processing of data by data clearing and normalization technique, the classification model fed the data set. The K-cross validation technique was used for the model. Cross-validation is a process that involves the use of a built-in model against an independent dataset. The main reason for the application is to study how a model will perform on data it has not yet seen.

Due to the scarcity of data in the data set used, the 4 - cross-validation data set is divided into 4 sections where 3 parts are used in the training phase and 1 part in the testing phase. The results from the model are given in Tab. 9. Accordingly, the proposed model derived the most performance result from 3 different algorithms used for machine learning with an accuracy rate of 84.25%.

Table 9 Comparison of model prediction performance

Classifiers	Accuracy / %	R	MAE	$RMSE$
Random Forest	65.35	0.60	0.365	0.452
SVM	75.35	0.75	0.290	0.372
Decision Tree	80.75	0.81	0.201	0.313
Proposed Model	84.25	84.34	0.1254	0.2135

The comparison of the proposed model's test data and prediction data is given in Fig. 7. Here it has been shown 84 predicted data, versus 84 actual data contained in the dataset. Likewise, the predictions made by the proposed model and other traditional machine learning algorithms are superimposed as shown in Fig. 8.

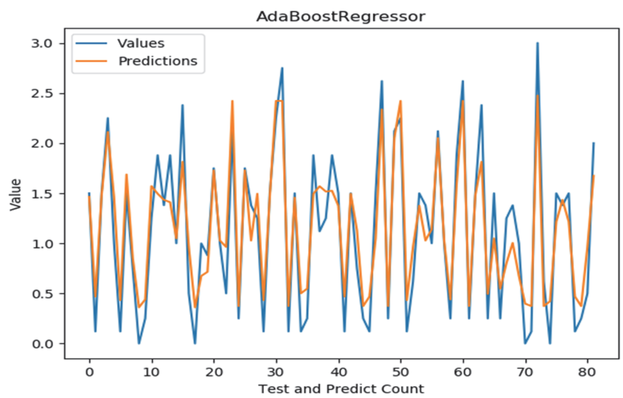

Figure 7 Comparison of test and predict values

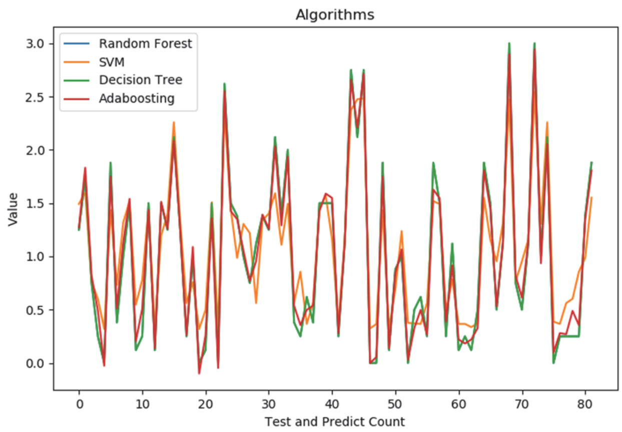

Figure 8 Comparison of Adaboosting with traditional machine learning algorithms

6 CONCLUSIONS

One of the significant problems of shotcrete is the rebound that occurs when the mix carried under pressure via a pneumatic hose or pipe hits the surface at high speed and bounces back. This rebound that takes place during the application may lead to problems such as loss of material, lower quality shotcrete layer. In this context, the research of methods and practices that will reduce rebound is important for achieving in-situ material quality and low production cost, and economic gains as well as for reducing environmental problems.

In the study, a new approach is proposed to predict the amount of rebound taking into account shotcrete mixes produced with mineral additives (fly ash, silica fume) and polypropylene fiber through machine learning methods that produce successful results in prediction applications. In view of rebound results, the highest rebound was observed for the plain sample. The plain sample is followed by samples with substituted fly ash of 20%. The lowest values were obtained for samples with substituted silica fume. The rebound decreased particularly with increasing amounts of silica fume. The rebound of shotcrete with silica fume was lower than other mixtures due to the highly cohesive nature of silica fume.

The Adaboost algorithm, an ensemble learning method, has been used for estimating the amount of rebound concrete in shotcrete applications that include different additives. First of all, dependent and independent parameters were identified in the dataset produced as a result of experimental studies. The dataset was split into 4 parts, 3 of which were used for training, and 1 for testing. Hyperparameters producing optimum results in the training of the model were identified for the model and Boosting method. As a result, the model achieved a prediction performance of 84.25%. To test the performance of the proposed model, traditional machine learning algorithms were compared on the same dataset. Consequently, the proposed model was observed to have the highest accuracy.

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