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ORIGINAL ARTICLE

Developing a least squares support vector machine for estimating the blast-induced flyrock

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Abstract
In blasting operations, the main purpose is to provide appropriate rock fragmentation and to avoid adverse effects such as flyrock and vibration. This paper presents the applicability of least squares support vector machines (LS-SVM) for estimating the blast-induced flyrock. For comparison aim, support vector regression (SVR) was also employed. The case study was carried out in the Gole-E-Gohar iron mine of Iran in which the values of burden to spacing ratio, hole length to burden ratio, subdrilling, stemming, charge per delay, rock density and powder factor were measured for 90 blasting operations. The mentioned seven parameters were used as the independent or input parameters in modeling, while, the values of flyrock distance were assigned as the models output. To train the models, 72 datasets were adopted and then the remaining 18 datasets were adopted to test the models. The models performance was compared by several statistical criteria such as *R* square (R^2) and mean square error (MSE). According to obtained results, the LS-SVM with the R^2 of 0.969 and MSE of 16.25 can prove more useful than the SVR with the R^2 of 0.945 and MSE of 31.58 in estimation of blast-induced flyrock. At the end, sensitivity analysis was also performed and according to the results, powder factor and rock density were the most effective parameters on the flyrock in this case study.

Keywords Blasting · Flyrock · LS-SVM · SVR

1 Introduction

The blasting is a cheapest and important method for fragmenting the rock mass in open-pit and underground mines. Although the main aim of this method in open-pit mines is rock fragmentation; however, some side effects of blasting such as flyrock (FR), backbreak and ground vibration are inevitable [1–7]. FR is defined as the rock propelled beyond the blast area by the force of an explosion [8]. Unsuitable blast-hole pattern, incorrect drilling, unwarranted specific charge, insufficient stemming and burden are the most important reasons to create FR [9, 10]. Additionally, the other blast design or controllable parameters such as powder factor (PF), stemming (ST), stiffness factor, spacing (S), charge per delay (CPD), subdrilling (SD), hole depth, and length are the effective parameters on the intensity of FR [11–13]. Besides controllable parameters, uncontrollable parameters also are the effective parameters on the intensity of FR, so that these parameters cannot be changed by engineers [14, 15].

As suggested in the literature [11, 12, 14], inaccurate prediction of FR can cause fatal and nonfatal accidents. Hence, accurate prediction of FR is a necessary work for the safety issues. Over the past years, soft computing method such as fuzzy logic (FL) and artificial neural network (ANN) have been widely employed for solving the engineering problems [16–22]. Amini et al. [23]

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anticipated the blast-induced FR in Soungun copper mine of Iran through support vector machine (SVM). They used several factors such as burden, hole diameter and PF as the independent parameters. Based on their obtained results, SVM can be introduced as an acceptable method in this field for the prediction of FR.

Back-propagation neural network and empirical models were employed for the FR prediction by Yari et al. [10]. They showed that the performance of back-propagation neural network was better than empirical models for the FR prediction. Monjezi et al. [3] offered a combination of ANN and genetic algorithm (GA) for estimating the FR. They applied several input parameters such as PF, ST and CPD for developing the ANN-GA model. Based on their obtained results, the ANN-GA with the R square (R^2) of 0.89 can be introduced as an acceptable and reliable model in this field.

In the other study, ANN and fuzzy interface system (FIS) were presented for estimating the FR by Ghasemi et al. [12]. In their research, PF, CPD, ST, S and burden were used as the input parameters. The obtained R^2 by FIS was achieved as 0.96, while the R^2 by ANN was obtained as 0.94 which prove both are capable of predicting the FR. A comprehensive study to estimate FR was done by Trivedi et al. [24] using adaptive neuro fuzzy inference system (ANFIS), ANN and regression models. Based on their obtained results, the accuracy of ANFIS was superior to those of ANN and regression models. In the present study, the feasibility of least squares support vector machines (LS-SVM), as a new soft computing-based model in this field, is investigated. In addition, support vector regression (SVR) and linear regression (LR) are employed and their results are compared to LS-SVM results.

2 Case study

2.1 General information

The datasets utilized in this research were collected from the Gole-E-Gohar iron mine, which is located at the 55 km southwest of Sirjan in Kerman province of Iran. It is located at the latitude between 55°11′50″ E and 55°12′40″ E and the longitude between 29°03′00″N and 29°07′00″N and at 1750 m above the sea level. The Gole-E-Gohar deposit lies at the center point of a triangle containing the Kerman, Shiraz and Bandar Abbas cities, being about 280 km away from each of them. This reserve comprises six separate anomalies in an area with 10 km length and 4 km width (Fig. 1). The total estimated ore reserve of this mine is equal to about 1135 Mt. Drilling and blasting approach is regularly utilized to break the rocks in the Gole-E-Gohar iron mine [14, 25, 26]. However, FR phenomenon is one of the most side effects due to blasting in the current mine.

2.2 Site geology

The Gole-E-Gohar complex is located in the northeast margin of the Sanandaj-Sirjan tectonic-metamorphic belt in the marginal compact zone recognized as the Salt Lake of Khairabad. The litho-stratigraphy of the outcropped rock units in this area

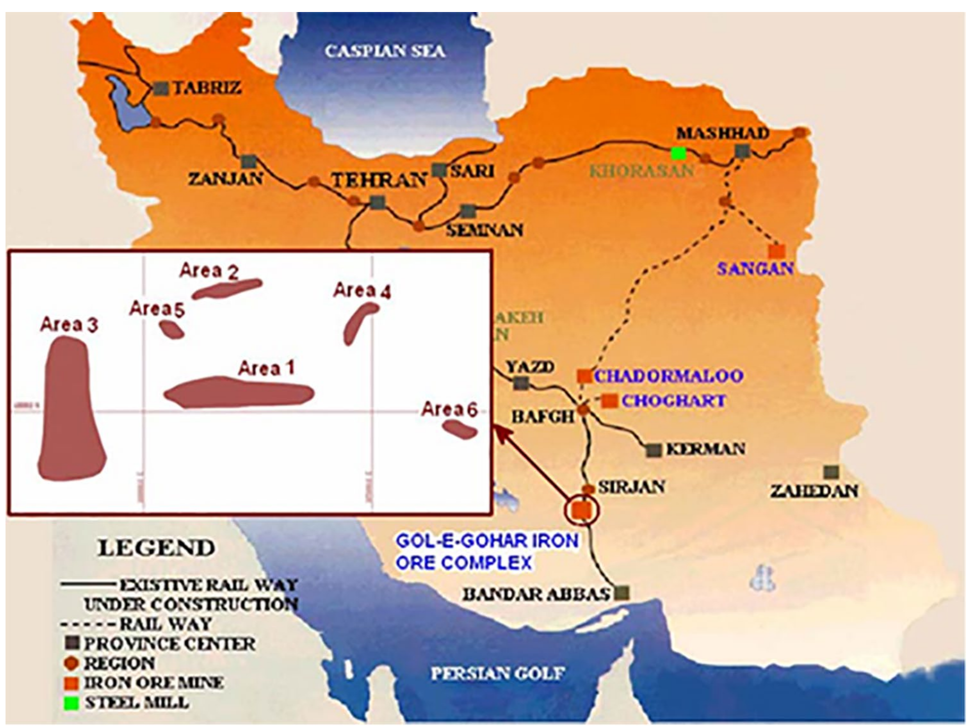


Fig. 1 Location of the Gole-E-Gohar iron ore complex and related anomalies

is composed of Paleozoic metamorphic units, Mesozoic and Cenozoic sedimentary units and Quaternary alluvial materials. The Gole-E-Gohar iron mine is lied in the metamorphic rocks of Paleozoic period that upright compose of three parts including lower, middle and upper pieces. The underneath (lower) part comprises the series of gneiss, mica schist, amphibolite and quartz schist. After that, there exists the middle (mean) part that composes of successions of marble, mica schist, greenschist and graphit schist units. Finally, the upper one consists of marble, dolomite and calcite rocks [14].

2.3 Drilling and blasting operation details

The staggered pattern was applied in the drilling and blasting operation of the Gole-E-Gohar iron mine. The ammonium nitrate and fuel oil (ANFO) was also utilized as the main explosive material and drilling cuttings was applied for the stemming object. The delay time between the first and second rows was 80 ms whereas; 50 ms delay time was applied between other rows. Number of rows in each blasting pattern is 2–7 and holes number per row is 10–20. Blast-hole diameter is 251 mm and bench heights are in the range of 5–15 m. In the current Iron mine, all of the blast holes are perpendicularly drilled using the crawler mounted INGERSOLL-RAND DMH rotary machine. After the blasting, loading of the blasted materials is performed through P&H AL 1900 shovels. In addition to, 85 metric ton Euclid dump trucks are applied for hauling object.

2.4 Measurement and collection of datasets

A total number of 90 datasets were recorded based on the actual measurement of the blasting parameters on the benches at the Gol-E-Gohar mine. Surveying process was immediately conducted after the completion of drilling to measure the bench geometry, blast holes coordinates and lengths, etc. Moreover, all of the FR occurrences were considered and surveyed based on the field observations during the blasting operations. According to this, it was proved that the highest FR distance was frequently occurred in the first blast row due to the bursting mechanism of the face. Conventional surveying was also used for the FR distance measuring utilizing the global positioning system (GPS). Accordingly, the highest horizontal space of the landed fragments with the related free face was regarded as the FR distance in the corresponding blasting pattern. Based on the above field measurements, a perfect database including all of the most effective variables on the FR distance such as blast geometrical and geomechanical characteristics along with time delays and explosive properties were prepared. Therefore, seven influential parameters, i.e., burden to spacing ratio (*B*/*S*), hole length to burden ratio or stiffness factor (*H*/*B*), subdrilling (SD), stemming (ST), charge per delay (CPD), rock density (RD) and powder factor (PF) are considered as the input parameters for prediction of FR distance. Statistical descriptions of the prepared database utilized for FR modeling distance and the variables related symbols are given in Table 1. Moreover, Table 2 shows the samples of datasets applied in the models development.

3 Development of the predictive models

In this paper, a new LS-SVM model is designed for the prediction of FR. SVM is one of the machine learning methods based on statistical learning theory. LS-SVM was presented by Suykens et al. [27], so that is a modify algorithm of SVM. In this approach, minimization of square error is important. In the presented research work, the existing datasets, discussed in the previous section, are divided into two sets, a training set with 80% of all datasets; includes 72 datasets and an independent testing set with 20% of all dataset; includes 18 datasets.

3.1 Support vector regression (SVR)

SVR is one of the strong methods in prediction fields. In this method, input data are transformed by linear function from original space into high-dimension space [28]. The prediction function of SVR is linear function as shown below [29]:

$$f(x) = \sum (a_i - a_i^*)K(x_i, x) + b, \tag{1}$$

Table 1 Statistical description of the prepared database and variables related symbols

Type of data	Parameters	Unit	Symbol	Min	Mean	Max	Std dev.	Variance
Input	Burden to spacing ratio	–	*B*/*S*	0.67	0.81	0.85	0.044344	0.001966
	Stiffness factor	–	*H*/*B*	1.31	2.85	3.83	0.760378	0.578175
	Subdrilling	m/m^3	SD	0.02	0.03	0.06	0.013204	0.000174
	Stemming	m	ST	2	5.45	9.8	1.613808	2.604377
	Charge per delay	kg/ms	CPD	14.7	82.14	175.5	43.70743	1910.34
	Rock density	g/cm^3	RD	1.85	3.57	4.6	0.873754	0.711922
	Powder factor	kg/ton	PF	0.13	0.23	0.33	0.035191	0.001238
Output	Flyrock distance	m	FR	10	29.84	70	13.41717	180.0204

Table 2 Samples of datasets applied in the models development

No.	*B*/*S* (−)	*H*/*B* (−)	SD (m/m^3)	ST (m)	CPD (kg/ms)	RD (g/cm^3)	PF (kg/ton)	FR (m)
1	0.81	1.77	0.02	4.2	46.22	1.85	0.21	20
2	0.79	3.18	0.03	8	25.23	3.9	0.25	25
3	0.85	3.18	0.03	7.4	74.98	4.21	0.27	35
4	0.78	3	0.05	3	140.21	3.85	0.31	70
5	0.82	2.89	0.05	5.8	125.36	4.31	0.29	45
6	0.67	3.75	0.06	4	143.98	4.05	0.13	10
7	0.75	3.83	0.05	5	125.3	4.6	0.33	10
8	0.67	3.5	0.06	3	175.5	4.38	0.17	30
9	0.81	1.31	0.02	4.4	74.21	1.85	0.23	30
10	0.8	2.25	0.05	4	125.26	3.64	0.33	65

where b is the deviation of regression prediction and a_i is Lagrange multiplier and K is the kernel function. Using minimizing an adjusted function, the Lagrange multipliers are created as follows:

$$R(f) = \frac{1}{2}\|\omega\|^2 + c\sum_{i=0}^{n} L(f(x_i) - y_i), \tag{2}$$

where $\|\omega\|^2$is determined of model complexity. Then, c is a tradeoff between complexity of SVR and training error. Furthermore, L is defined by (3):

$$L(f(x) - y) = \begin{cases} 0 & \text{if}|y - f(x) \leqslant \varepsilon| \\ |y - f(x)| - \varepsilon & \text{otherwise} \end{cases}, \tag{3}$$

where ε is insensitive loss function that is as a radius around the training data. More explanations regarding SVR model can be obtained in many studies [30, 31]. In this paper, kernel function for SVR is Gaussian radial basis function. The values of predicted FR by SVR for testing datasets are shown in Table 3. The performance of developed SVR will be discussed in Sect 4.

3.2 3.2. Least squares support vector machine (LS-SVM)

The computational cost in optimization approaches has high cost especially in the prediction of FR examples. SVM method is one of the most effective modeling processes that has been employed in nonlinear system [32]. One of the powerful methods based on nonlinear regression is LS-SVM. In this model, the feature space is where the inputs are mapped by LS-SVM in infinite-dimensional. LS-SVM is transformed by Mercer's theorem and positive kernel. In this approach, problem is solved by the formula of LS-SVM in dual space using a least-squares cost function. There are two parts in the training process, kernel parameter selection, and the cost function parameter tuning. Suppose the N sample$\left\{x_k, y_k\right\}_{k=1}^{N}$, $x_k \in \mathbb{R}^P$ is input vector and $y_k \in \mathbb{R}$ is output vector. The main objective is to estimate a model of the following Eq. [33]:

$$y = \omega^T \varphi(x) + b + e, \tag{4}$$

where $\varphi(.) : \mathbb{R}^p \rightarrow \mathbb{R}^{nh}$ is transformed to feature space with high-dimension. The e is supposed to be independent and identically distributed with a mean of zero and constant variance. The problem of optimization is formulated by a tuning cost function [34] that presented in Eq. (5). It is one of the restrictions in the LS-SVM model.

Table 3 The comparison between the measured and the predicted FR by SVR model

No. of data	Measured FR	Predicted FR	No. of data	Measured FR	Predicted FR
1	40	40.20	10	20	24.66
2	40	41.20	11	25	28.66
3	30	35.91	12	20	26.97
4	40	38.01	13	25	33.37
5	35	39.27	14	35	35.88
6	30	36.67	15	10	16.92
7	35	39.35	16	10	18.36
8	30	36.37	17	10	18.89
9	30	32.46	18	15	21.95

$$\min_{\omega,b,e_k} \frac{1}{2}\omega^T\omega + \gamma\frac{1}{2}\sum_{k=1}^{N} e_k^2 \quad s.t. \begin{cases} y_k = \omega^T\varphi(x_k) + b + e_k & k = 1, ..., N \\ \omega^T\varphi(x_k) = a\omega^T\varphi(-x_k) & k = 1, ..., N \end{cases} \tag{5}$$

where $b \in \mathbb{R}$ and γ is a tuning constant and a will be a determined constant which can obtain either -1 or 1. The nonlinear function is constrained using $a = 1$ or $a = -1$ is second of restriction. We assume K is a positive-defined kernel function. Due to the Mercer's theorem$K(x_i, x_j) = \varphi(x_i)^T\varphi(x_j), i, j = 1, ..., N$. The nonlinear function $\varphi(.)$ is not explicitly calculated. In kernel functions K, that is used via implicitly. The dual solution is defined by following Eq. [35]:

$$\left[\begin{array}{c|c} \Omega + \gamma^1 I_N & 1_N \\ \hline 1_N^T & 0 \end{array}\right] \left[\frac{a^k}{b^k}\right] = \left[\frac{y^k}{0}\right] \tag{6}$$

and

$$\Omega_{i,j} = K(x_i, x_j) = \exp\left(-\left\|x_i - x_j\right\|_2^2 \Big/ \sigma^2\right), \tag{7}$$

where $\Omega_{i,j}$is the inputs of positive definite kernel matrix. In Eq. 6, $1_N = [1, ..., 1]^T \in \mathbb{R}^N$. In this paper, according to Eq. 7, we use radial basis function (RBF) and σ is an adjusting parameter. In Eq. 5, the tuning cost function is calculated by Lagrange multipliers. The declaration result for the predicted f is defined by the following:

$$\hat{f}(x) = \sum_{t=1}^{N} a_t K(x_t, x) + b \tag{8}$$

For better understanding, Fig. 2 also illustrates the flowchart of proposed LS-SVM model. As mentioned above, one of the effective parameter in LS-SVM is γ that defined as a tuning constant. For selecting the best value for the γ, different values were evaluated and shown in Table 4. Based on obtained results it was found that $\gamma = 1000$ had the highest performance in testing datasets. Hence, the value of 1000 was selected for the γ in this study. In the next step, the optimum value of σ^2 should be selected. For this work, the different values were evaluated and given in Table 5. According to these results, it was found that $\sigma^{2=550}$ had the highest performance in testing datasets. Therefore, the value of 550 was selected for the σ^2 in this study. The values of predicted FR by LS-SVM for testing datasets are presented in Table 6. The performance of developed LS-SVM will be also discussed in Sect 4

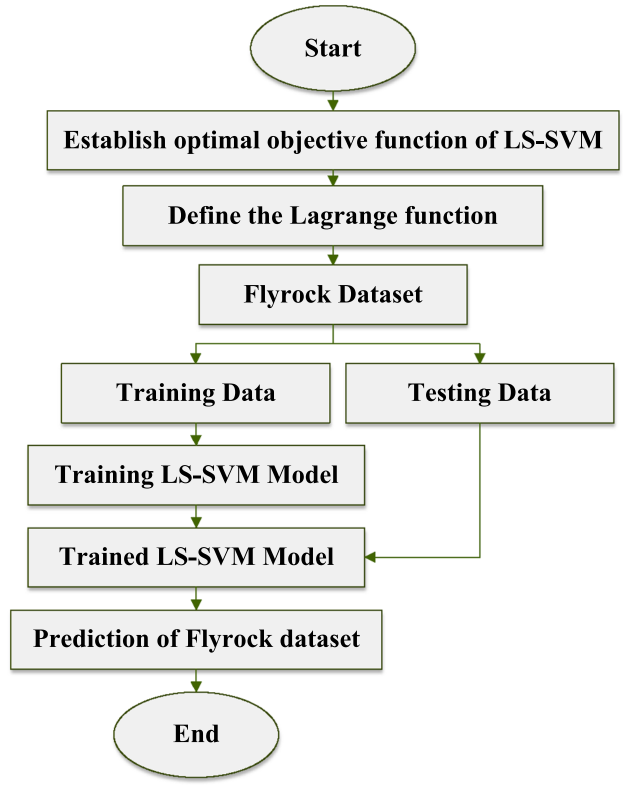


Fig. 2 The flowchart of proposed LS-SVM model

Table 4 Obtained LS-SVM results for different γ values

γ	LS-SVM	
	R^2 train	R^2 test
1	0.7469	0.9032
10	0.8491	0.9427
100	0.8913	0.9490
500	0.9004	0.9640
1000	0.9043	0.9653
1100	0.9048	0.9648
1200	0.9053	0.9642
1300	0.9058	0.9635
1400	0.9063	0.9627
1500	0.9067	0.9619
2000	0.9085	0.9572
3000	0.9111	0.9472

4 Results and discussion

In the present paper, two soft computing-based models, i.e., SVR and LS-SVM were proposed for estimating the FR. In modeling, seven different parameters including *B*/*S*, *H*/*B*, SD, ST, CPD, RD and PF were adopted as the models input parameters. For selecting the most effective parameters on the FR,

Table 5 Obtained LS-SVM results for different σ^2 values

σ^2	LS-SVM	
	R^2 train	R^2 test
1	0.9999	0.7067
10	0.9739	0.8680
100	0.9200	0.8908
150	0.9160	0.9058
200	0.9135	0.9232
250	0.9115	0.9372
300	0.9100	0.9474
350	0.9086	0.9545
400	0.9082	0.9593
450	0.9078	0.9624
500	0.9075	0.9642
550	0.9073	0.9690
600	0.9067	0.9657
650	0.9050	0.9658
700	0.9033	0.9656
750	0.9018	0.9653
800	0.9013	0.9648
850	0.9008	0.9644
900	0.9004	0.9639
950	0.9000	0.9633
1000	0.8996	0.9628

sensitivity analysis is performed in the present study based on the following Eq. [36]:

$$r_{ij} = \frac{\sum_{k=1}^{n} \left(y_{ik} \times y_{ok} \right)}{\sqrt{\sum_{k=1}^{n} {y_{ik}}^2 \sum_{k=1}^{n} {y_{ok}}^2}}, \tag{9}$$

where y_i and y_o are the input and output parameters, respectively. The intensity of input parameters on output depends the amount of r_{ij} and the most effective parameter has the highest value of r_{ij}. According to obtained results, the PF with r_{ij} of 0.947 was considered as the most effective parameter on FR. More details regarding the sensitivity analysis results are shown in Fig. 3.

To further evaluate the performance of the SVR and LS-SVM models, several criteria, i.e., variance account for (VAF), mean squared error (MSE), mean absolute bias error (MABE) and R^2 were computed. These criteria are formulated as below [37–40]:

$$\mathrm{VAF} = \left[1 - \frac{\mathrm{var}\left(M_i - P_i\right)}{\mathrm{var}\left(M_i\right)} \right] \times 100 \tag{10}$$

$$\mathrm{MSE} = \frac{1}{n} \times \sum_{i=1}^{n} \left[\left(M_i - P_i\right)^2 \right] \tag{11}$$

$$\mathrm{MABE} = \frac{1}{n} \times \sum_{i=1}^{n} \left| M_i - P_i \right| \tag{12}$$

$$R^2 = \frac{\left[\sum_{i=1}^{n} \left(M_i - M_{\mathrm{mean}}\right)^2 \right] - \left[\sum_{i=1}^{n} \left(M_i - P_i\right)^2 \right]}{\left[\sum_{i=1}^{n} \left(M_i - M_{\mathrm{mean}}\right)^2 \right]}, \tag{13}$$

where M_i are the measured FR values, P_i are the predicted FR values obtained from the predictive models, and var is the variance sign. The performance of the predictive model according to the mentioned criteria is excellent if VAF, MSE, MABE and R^2 are 100%, 0, 0 and 1, respectively. Table 7 shows the values of the mentioned criteria obtained from the SVR and LS-SVM models. Furthermore, the scatter plots of FR predicted by the predictors for both training and testing datasets are demonstrated in Figs. 4 and 5. Here (from Table 7; Figs. 4, 5) it is observed that both SVR and LS-SVM prediction models performed satisfactorily; however, the LS-SVM is more

Table 6 The comparison between the measured and the predicted FR by LS-SVM model

No. of data	Measured FR	Predicted FR	No. of data	Measured FR	Predicted FR
1	40	39.67	10	20	22.64
2	40	40.90	11	25	27.73
3	30	33.58	12	20	25.13
4	40	37.87	13	25	31.12
5	35	37.86	14	35	35.20
6	30	35.57	15	10	14.17
7	35	39.10	16	10	16.20
8	30	34.63	17	10	16.56
9	30	29.97	18	15	19.44

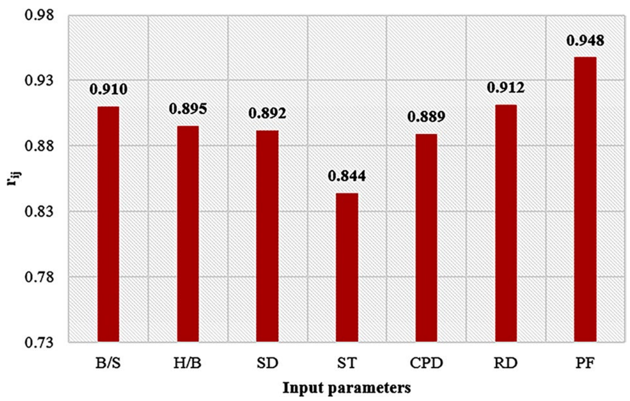


Fig. 3 The sensitivity analysis for selecting the most effective parameters on the FR

accurate model to estimate the FR and has better generalization capability. Respectively, the amount of R^2 for the LS-SVM and SVR models were obtained as 0.969, 0.945 which demonstrate that the degree of association between the measured and predicted FR values by LS-SVM is better than SVR. For better understanding, Fig. 6 shows the actual and predicted FR values for only testing datasets.

5 Conclusion

It is a well-established fact that the inaccurate prediction of FR can cause fatal and nonfatal accidents in and around the mines. Therefore, precise prediction of FR is a significant issue for decreasing the environmental side effects in mines. This paper explores the possibility of using the LS-SVM to create a precise model for predicting FR in the Gole-E-Gohar iron mine, Iran. The LS-SVM results have been also compared with the actual data and SVR model. In LS-SVM and SVR models, seven input parameters comprising *B*/*S*, *H*/*B*, SD, ST, CPD, RD and PF were used, while the FR parameter was considered as the models output. Totally, a database including 90 datasets were collected from the Gole-E-Gohar mine and the mentioned input and output parameters were precisely measured. In modeling, 80% of all data (72 datasets) were assigned for training the models and the remained data (18 datasets) were assigned for testing the models. Models performance was assessed with statistical criteria such as MSE, MABE, VAF and R^2. Based on obtained results from LS-SVM and SVR models, it was found that both models performed satisfactorily; however, the LS-SVM was more useful than SVR in estimation of scour blast-induced FR and had the capacity to generalize. In the other words, LS-SVM model with the R^2 of 0.969 had the better ability to estimate the FR over the SVR with the R^2 of 0.945. In the work presented in this paper, sensitivity analysis was

Table 7 The values of criteria used for evaluating the predictors

Predictor	Criteria							
	R^2		MSE		VAF (%)		MABE	
	Train	Test	Train	Test	Train	Test	Train	Test
SVR	0.906	0.945	18.81	31.58	90.44	91.02	3.45	4.94
LS-SVM	0.907	0.969	18.77	16.25	90.55	94.05	3.43	3.46

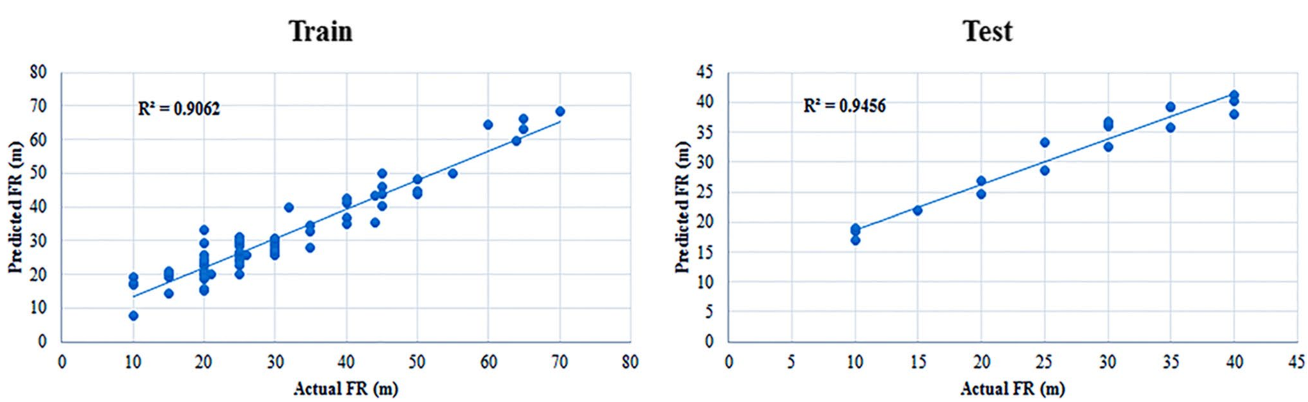


Fig. 4 The performance of the SVR to estimate the FR

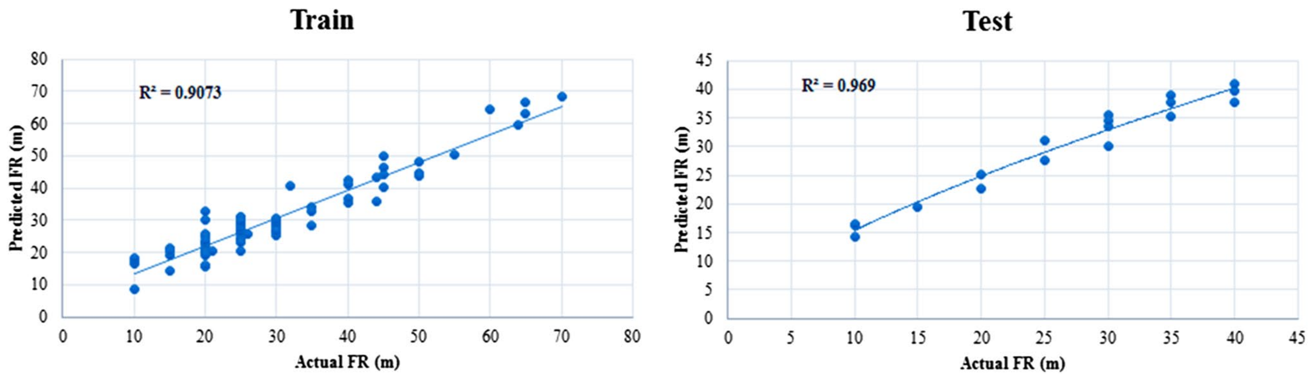
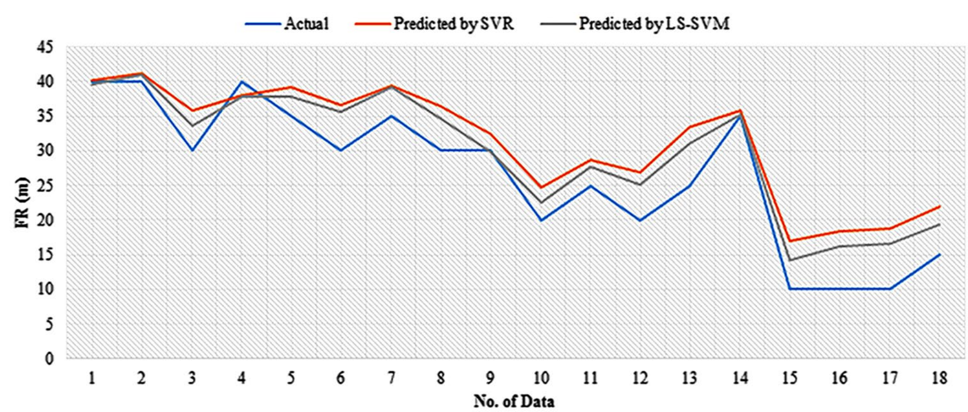


Fig. 5 The performance of the LS-SVM to estimate the FR

Fig. 6 The comparison between the actual and predicted FR



also performed and according to the results, PF and RD were the most effective parameters on the FR in this case study. As a conclusion, obtained results demonstrate that the proposed LS-SVM model in this study can be applied with confidence for future research works for estimating the FR induced by mine blasting.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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