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Prediction of Flyrock Throw Using Gaussian Process Regression Machine Learning Models

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***Abstract* – Flyrock is a by-product of blasting that can pose dangers to man, equipment, infrastructure, and neighbouring mining communities. As such, there is the need to minimise the throw of flyrock using predictive tools. Hence, in this research, the GPR is used for flyrock throw prediction. The results from the different GPR models were compared with those of BPNN, namely LM, BR and SCG algorithm. The accuracy of prediction is Matern 5/2 GPR with R^2 of 1.00 and RMSE of 0.000386, then SEGPR with R^2 of 1.00 and RMSE of 0.000386; and then RQGPR with of R^2 of 1.00 and RMSE of 0.000387 with the last EGPR with R^2 of 0.99 and RMSE of 0.14.**

***Keywords* – Flyrock, BPNN, Gaussian Process Regression, SDG, Mining.**

I. INTRODUCTION

Flyrock is the rock mass that is ejected far from the mining zone when the blast is initiated. The first parameters usually considered are: burden, blast-hole diameter, depth, powder factor spacing, stemming, type of explosive material, and sub-drill being controllable parameters during flyrock prediction. Additionally, rock properties that the blast engineer cannot influence are uncontrollable parameters such as compressive joint spacing and tensile strength of rock. Hence the blast engineer has to vary the first parameters to minimise the flyrock throw distance. Various empirical equations were devised to envisage flyrock resulting from the blasting operation [1], [2]. Empirical models were developed based on several field experimented effective parameters on flyrock, namely, hole diameter, the density of explosive, stemming, burden, the initial launch velocity of ejected material, powder factor, and hole length. As a result, these empirical equations capacity of performance prediction is not very efficient in many cases [2],[3].

Amongst the efficient tools for predicting these outcomes is Artificial Neural Network (ANN), Multiple Linear Regression (MLR), Fuzzy Interface System (FIS), Fuzzy Rock Engineering System (FRES), Hybrid Dimensional Analysis Fuzzy Inference System, (H-DAFIS) Support Vector Machine, (SVM) Gene Expression Programming (GEP), Extreme Learning Machine, (ELM), Biogeography-Based Optimization (BBO) [3], [4]-[7], [9]. The aforementioned techniques are applicable in various areas of science and engineering disciplines not excluding mining specifically flyrock throw distance prediction. The complex nature of the flyrock prediction call for rigorous and reliable techniques for its prediction [2].

The Gaussian Process Regression (GPR) algorithm is used in spatial statistics, geostatistics, machine learning, image analysis, and other fields where multivariate statistical analysis. [10] used GPR to predict the porosity and permeability of petroleum well southern basin of the South Yellow Sea using petrophysical well log data adjacent to each other with data from nearby well of similar rock characteristics. Based on these developments a more accurate flyrock model is required for practical purposes in the field of flyrock prediction. As a result, the progenies of GPR machine learning techniques were applied in this study to predict flyrock emanating from blast operations. Growing population demands increased infrastructure – water, sewerage, energy generation, and distribution, transport, and housing, and workspaces. The challenge of answering to the needs of buildings and construction have enormous climate change effects due to competition between housing infrastructure, quarrying, and mining activities. The coexistence of quarrying and mining industries and cities and communities has resulted in encroachment [11].

This paper examines how accurately predicting flyrock throw distance ahead of and or during mining and quarrying operations using GPR can lead to achieving industry, innovation, and infrastructure goals (SDGs 9 and 11).

II. OVERVIEW OF FLYROCK THROW PREDICTIONS

Hasanipanah *et al.* (2017) [12] employed Regression Tree (RT) and Multiple Linear Regression (MLR) models for the prediction of flyrock distance caused by blasting in the Ulu Tiram quarry, in Malaysia with a reasonable degree of accuracy. Besides, the forecast of flyrock with top-notch accuracy the essential task to investigate blast safety zone was also estimated nevertheless there is high subjectivity. Hasanipanah and Amnieh (2020) [13] proposed a Fuzzy Rock Engineering System (FRES) framework to expertly appraise the parameters that affect flyrock. [14] also developed a Fuzzy Interface System (FIS) model to predict blasting works in Gol-E-Gohar iron mine, Iran with a reasonable degree of precision. Nonetheless, because of the complex and perplexing nature of FIS, only high professionals with knowledge in machine learning can comfortably handle that model effectively. [15] also predicted and subsequently optimised flyrock and back-break impacts that may reduce damage on facilities and equipment especially flyrock. In the study conducted by [15] an Artificial Neural Network (ANN) was developed to predict flyrock and back-break resulting from blasting using, 97 blasting operation data in Delkan iron mine, Iran. Regarding this methodology, the ability to select the correct hidden layers and output layers is time-consuming and requires expert knowledge.

[6] investigated flyrock of Soungun Copper Mine, Iran to check the accuracy of Support Vector Machines (SVM) in the prediction of flyrock, obtained results of SVM were compared with that of the Artificial Neural Network (ANN). The issue with SVM is the tendency to fit data sets to a predetermined line of best fit which could be misleading. [16] predict flyrock induced by blasting through a novel tactic based on the combination of differential Evaluation Algorithm (DE) and Dimensional Analysis algorithm (DA). DA is at its infancy stage and it is utilised by only a tiny nucleus of the scientific and research community. [17] used Hybrid Dimensional Analysis Fuzzy- Inference System (H-DAFIS) to predict blast-induced flyrock throw distance in surface mining, by fitting it in a dimensional analysis procedure and Mamdani's fuzzy inference system approach with promising results. But the choices between various rules applied in H-DAFIS can be a very daunting task. [18] also implemented Gene Expression Programming (GEP) for predicting flyrock throw distance and to optimise blasting data for minimisation with Firefly Algorithm (FA). Optimising the flyrock throw distance may seem to be a great success but lacks practicality. This is because the optimised result did not give insight into the input parameters contributing to its success.

[20] functionalised Artificial Neural Network (ANN) by training ninety-five (95) datasets of experimental blasts conducted in four (4) opencast limestone mines in India. Thirty (30) datasets have been used for testing and validation after sixty-five (65) were used to train the neural network. ANN has predicted Flyrock throw distances, Multi-Variant Regression Analysis (MVRA) and further calculated using motion analysis of flyrock projectiles and compared with the observed data based on ProAnalyst a motion-video and image analysing software. The unnerving task of determining the ANN structure and eagle eye search using ProAnalyst is time-consuming. Additionally,[21] in estimating flyrock throw distance in bench blasting through blast-induced pressure measurements in rock introduced a methodology to determine the blast-induced pressure–time in conjunction with pressure probe. It has been shown that the induced pressure measurement yields better accuracy for the prediction of flyrock distance. But the cost of production downtime due to the installation of the pressure probe for every blast is a drawback. [22] predict flyrock induced by blasting through a novel approach based on the combination of Imperialist Competitive Algorithm (ICA) and Artificial Neural Network (ANN) all of which require professional skills for practical implementations.

[23] advanced a new hybrid intelligent system of Extreme Learning Machine (ELM) optimized by Biogeography-Based Optimization (BBO) for prediction of flyrock throw distance ensuing from blasting in a mine. In the BBO-ELM system, the role of BBO is to optimize the weights and biases of ELM. The idea of only reducing the flyrock throw through optimisation is impractical. The pioneering of Artificial Intelligence (AI) and Machine Learning (ML) including Gaussian Process Regression (GPR) by many researchers highlighted the proficiency of soft computing methods in solving various engineering areas, particularly in the field of mining and geotechnical applications [4]-[5], [9],[10], [24- 26].

III. MATERIALS AND METHODS USED

I.Methods

Over the years, empirical methods have been developed for flyrock throw prediction. Some of the relations would only be stated but the in-depth empirical predictions would not be considered in this paper since its in-depth can be found in [2],[3],[6],[9] [12], [22]. Amongst the empirical relations developed for flyrock throw prediction are as follows:

An empirical model was established by [30] based on hole diameter as in Equation 2.1 and [29], [31] the co-relation to estimate the maximum distance (Lmax) of flyrock throw from the also based on blast hole diameter (D), as shown in equations 2.2 and 2.3.

$$L_{max} = 30.745D^{0.66} \tag{2.1}$$

$L_{max} = 260 \times (\frac{d}{25})^{2/3}$ (2.2)

$Tb = 0.1 \times D^{2/3,}$ (2.3)

Where,

L_{max} = Maximum flyrock distance, meters (m)

D = Blasthole diameter, millimeters (mm)

Tb is the size of rock fragment in meters.

[28] further developed Equation 2.4 detailing how the specific charge influence flyrock throw distance when it is greater than 0.2 kg/m3. The maximum flyrock distance, for a specific charge > 0.2 kg/m3 may be estimated from the following equation [2]:

$L_{max} = 143 \text{ x } d \text{ x } (q - 0.2)$ (2.4)

Where,

L_{max} = Maximum throw (m)

d = Hole diameter (ins)

q = Specific charge (kg/m3).

[32] suggested an empirical Equation 2.5 to predict flyrock distance based on stemming length and burden as follows:

$L = 155.2 \times d^{-1.37}$ (2.5)

where;

L is the ratio of stemming length to burden and

d is the distance travelled by the rocks in meters.

[33] proposed equations 2.6, 2.7 and 2.8 for the maximum flyrock throw distance. Air resistance, wind direction and speed are ignored since their impacts were minimal [34].

$R1 = \frac{V0 \text{ x } (2\sin 2\Theta)}{g}$ (2.6)

$V_0 = \frac{(10d \text{ x } 2600)}{(Tb \text{ x } \rho r)}$ (2.7)

$Tb = 0.1\ \boldsymbol{\rho}^{2/3}$ (2.8)

Where,

R1 is the distance travelled (m) by the rock along a horizontal line at the original elevation of the rock on the face,

V0 is the initial velocity of the flyrock, is the angle of departure with the horizontal, and

g is gravitational constant,

d is hole diameter in inch,

Tb is the size of rock fragment (m), and

ρ is the density of rock in g/cm^3.

[35] proposed a flyrock throw model based on Equation 2.8.1 which takes into account charge per delay, burden, nature of the rock, and the angle of the launch of the flyrock throw [35] .

$L = (k^2 /9.8) (\frac{\sqrt{m}}{B})^{2.6} \times (\sin 2\theta)$ (2.8.1)

Where,

L is maximum throw (m),

m is charge mass per delay (kg),

B is the burden (m),

θ is launch angle from horizontal (45 degrees),

k is a constant, 13.5 for soft competent rock, 27 for hard competent rock.

The development and use of empirical have been surpassed by AI techniques including Gaussian Process Regression (GPR).

II.Gaussian Process Regression

Gaussian Processes (GPs) are a probabilistic approach to learning in kernel machines that is principled, practical, and practical. A Gaussian Process Representation (GPR) is a collection of random variables, any predetermined number of which has a joint multivariate Gaussian Process. [36]. The Gaussian distribution is commonly applied to vectors, but it can also be applied to functions. As a result of prior understanding of the data and functional connections, there is usually no need for a validation process for generalisation. As a result, GP regression models can deduce the predictive distribution associated with the test input [36],[37].

Because they naturally deal with noisy measurements, unevenly distributed observations, and fill small gaps in the data with high confidence while assigning higher predictive uncertainty in sparsely sampled areas, GPRs have been proposed as measurement models and for model-based failure detection in robotics. However, many robotics applications necessitate non-standard GP models. . In mobile robot localisation, regression with input-dependent noise outperforms state-of-the-art techniques [27], [10].

Because GPR does not estimate the hyperparameter jointly using gradient-based optimisation, but rather alternates each step in a sampling-based approach, it is employed before modeling local noise rates. Another way to simulate non-stationarity is to employ a combination of GPRs, with each GPR assigned to a specific location, similar to how GPR mixture models may model straight discontinuities by placing auxiliary GPRs on both sides of the discontinuity. The GPRs that represent the process on either side of the disjointedness are then used to investigate them [36]. The following are some examples of extra sub-classification of gaussian process regressions based on their covariant functions:

For a training data set of the form: $\{(x_i, y_i); i=1, 2..., n\}$ where $x_i \in Rd$ and $y_i \in R$

A linear regression model of the form in equation 2.9

$$y=x^T\beta+\varepsilon \tag{2.9}$$

A. Rational Quadratic Gaussian Process Regression, GPR

The Rational Quadratic GPR kernel allows the model data by variation at multiple scales. The algorithm of the rational quadratic GPR is illustrated as follows in Equations 2.10 to 2.12 [27]. The linear regression model, where K (X, X) is parametrised looks as follows [10]:

$$K(x,x)=\begin{pmatrix} k(x_1,x_1) & k(x_1,x_2) & \cdots & k(x_1,x_n) \\ k(x_2,x_1) & k(x_2,x_2) & \cdots & k(x_2,x_n) \\ \vdots & \vdots & \vdots & \vdots \\ k(x_n,x_1) & k(x_n,x_2) & \ldots & k(x_n,x_n) \end{pmatrix} \tag{2.10}$$

The Rational GPR Model becomes an Equation. 2.11:

$$(xi\ , xj\ |\theta) = \sigma_f{}^2\,(1 + \frac{r^2}{2\propto\ \sigma_l{}^2}) \tag{2.11}$$

Where:

$r = \sqrt{(xi\ -\ xj)^T\ (xi\ -\ xj)}$

θ is the maximum a posteriori estimate.

σf is the signal standard deviation.

∝ is the non-negative parameter of the covariance.

B. Exponential Gaussian Process Regression, EGPR

Exponential Gaussian Process Regression (EGPR) is similar to the Squared Exponential Gaussian Regression (SEGPR) except that the Euclidean distance is not squared. Exponential GPR replaces inner products of basis functions with kernels slower than the S E GPR. The EGPR handles smooth functions well with minimal errors, but it does not do well with discontinuities. The algorithm of the median EGPR as illustrated in equation 2.12[27].

$$(xi\ , xj\ |\theta) = \sigma_f{}^2\,\exp\left(-\frac{r}{\sigma_l}\right) \tag{2.12}$$

Where: $r = \sqrt{(xi\ -\ xj)^T\ (xi\ -\ xj)}$

C. Matern 5/2 Gaussian Process Regression, GPR

The Matern 5/2 kernel takes spectral densities of the stationary kernel and creates Fourier transforms of the Radial Basis Function (RBF) kernel. The Matern 5/2 kernel does not have the concentration of measure problems for high dimensional spaces. Sample functions from Matérn 5/2 forms are |ν – 1| time differentiable. Thus, the hyperparameter ν can control the degree of smoothness. The algorithm of the matern 5/2 GPR is illustrated as in Equation 2.13[10], [27].

$$(xi,xj|\theta)=\sigma_f{}^2\left(1+\sqrt{5r}+\frac{\sqrt{5r}}{3}\right)\exp\left(-\sqrt{5r}\right) \tag{2.13}$$

D. Square Exponential Gaussian Process Regression, SEGPR

SEGPR is a function space expression of a Radial Basis Function (RBF) regression model with infinitely many basis functions. The Squared Exponential GPR is also identical to the Exponential GPR except that the Euclidean distance is squared as shown in Equation 2.14. A fascinating feature utilizing the Square Exponential GPR is it replaces inner products of basis functions with kernels. The advantage to this feature is handling large data sets in higher dimensions will unlikely produce huge errors. Also, it handles discontinuities well. The algorithm of the squared exponential GPR as illustrated as follows.

The Square Exponential GPR Model becomes:

$$(xi\ ,\ xj\ |\theta) = \sigma_f{}^2\ \exp\left[-\frac{1}{2}\frac{(\mathrm{xi}-\mathrm{xj})^{\mathrm{T}}\ (\mathrm{xi}-\mathrm{xj})}{\sigma\mathrm{l}^2}\right] \tag{2.14}$$

IV. LOCATION AND DATA COLLECTION

A. Location

Gold Fields Ghana Limited, Damang (GFGLD) is in south-western Ghana, approximately 300 km by road, west of Accra, the capital, at a latitude 5° 11’ N and a longitude 1° 57’ W. The GFGLD’s concession lies to the north of and joins the Tarkwa concession, which is located near the town of Tarkwa as shown in Fig. 1[39]. The area is served with good access roads and an established infrastructure. The Mine is further aided by the main road connecting to the port of Takoradi, about 90 km to the southeast. The data for this research was obtained from this subsidiary of GoldFields Ghana [38].

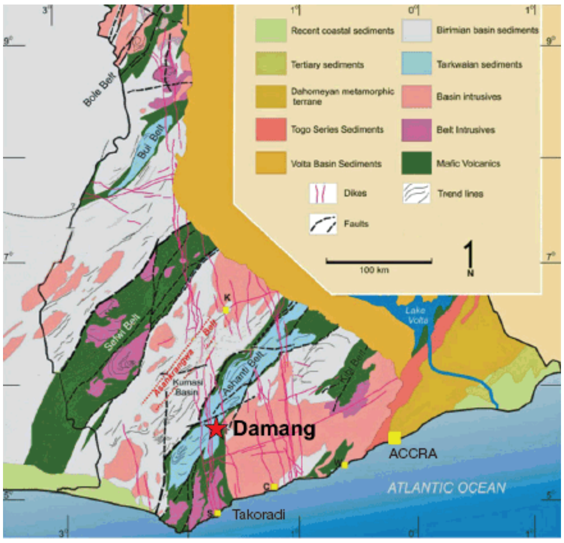

Fig. 1: Location of Gold Fields Ghana Damang Mine [39] .

B. Data Collection

Data on drill and blast parameters was gathered and utilised to calculate flyrock. The total number of records in the database was 2 629. Explosives Specific Gravity, Hole Diameter, Burden, Spacing, Hole Depth, Subdrill, Powder Factor Rate Charged per bcm, Stemming, Velocity of Detonation, VOD, and Explosive Charge were the input parameters, with flyrock being the output, as indicated in Table 1. This secondary data was gathered over the course of two years, from April 2018 to March 2020. During data splitting, 80 percent training and 20 percent testing were used in the modeling since this offered the best prediction with the least amount of error compared to alternative data processing ratios.

The good rock mass (70-90), fair rock (50-70) mass, poor rock mass (25-50), and very poor rock mass (<25), respectively. The following drill patterns used for the various domains are designated as follows 3.5 m by 3.5 m for (phyllites and diorites) 3.7 m by 4.3 m (all waste zones), and 3.8 m by 3.8 m at a depth of 9 m and 6 m as and when needed.

Table 1 Input and Output Parameters

Input Parameters		
Parameter	**Symbol**	**Range**
Subdrill (m)	D_s	0.2 - 2
Hole depth (m)	HD	3 - 10.8
Stemming length (m)	ST	1.0 - 4.0
Hole diameter (mm)	D	115 - 140
Powder Factor (kg/m^3)	P. F	0.3 – 1.5
Spacing (m)	S	3 - 6
Burden (m)	B	3 - 6
Column Charge (Kg)	Q	2 - 30
Explosive Gravity (kg/m^3)	Sg	1.00 -1.15
Velocity of Detonation (m/s)	VOD	3600 - 4900
Charge per BCM ($/BCM)	CPBCM	0.8 -3.8
Output Parameter		
Flyrock	FR	30- 5000

V. RESULTS AND DISCUSSIONS

The modelling was carried out using machine learning models in MatLab using Hewlett-Packard (HP) laptop with Intel(R) Core (TM) i7-1065G7 CPU @ 1.30GHz (8 CPUs), 1.5GHz, Memory: 8192 MB RAM. The predictive accuracy of the various spawns of GPR was explored, and the best-performing progenies were selected.

A. GPR Modelling

Rational Quadratic, Square Exponential, Matern 5/2, and Exponential Gaussian Process Regression models were trained and validated at speeds ranging from 290 to 10 000 observations per second. The fundamental functions were made constant, and the isometric kernel and optimisation isotropic parameters were employed, as well as automated kernel scaling, sigma kernel, and standard kernels. R^2 and RMSE are statistical methods used to evaluate the performance of models. Equations 2.15 and 2.16 are used to express the relationships.

B. Performance Metrics

The performance metrics for analysing the study results are coefficient of determination (R^2) and Root Mean Square Error (RMSE) as illustrated in equations 2.15 and 2.16 [10].

$$R = \frac{\sum_{i=1}^{n}\left(t_i - \bar{t_i}\right)\left(p_i - \bar{p_i}\right)}{\sqrt{\sum_{i=1}^{n}\left(t_i - \bar{t_i}\right)^2} \times \sqrt{\sum_{i=1}^{n}\left(p_i - \bar{p_i}\right)^2}} \qquad (2.15)$$

The R^2 is obtained using equation 2.16

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(t_i - \bar{p}_i\right)^2} \qquad (2.16)$$

Where
t is the measured constraint value,
p is the predicted constraint value,
$\bar{t_i}$ is the mean measured parameter value,
$\bar{p}_i$ is the mean predicted parameter value, and
n is the total number of the data point.

C. Comparative Analysis of Techniques

The efficacy of GPRs in forecasting flyrock coming from blasting activities was tested by examining their progenies and comparing them to some ANN approaches. .

D. Training and Testing of GPR Techniques

The various daughters of GPRs were examined. These were the corresponding coefficients of determinations and RMSEs: For training, Square Exponential GPR 0.99 and 0.11; Rational Quadratic GPR 1.00 and 0.11; Matern 5/2 GPR 1.00 and 0.14; Exponential GPR 1.00 and 10.55. In testing, the corresponding coefficients of determinations and RMSEs are, Square Exponential GPR 1.00 and 0.000387; Rational Quadratic GPR 1.00 and 0.000387; Matern 5/2 GPR 1.00 and 0.000386; Exponential GPR 0.99 and 0.14. these results indicated the superb predictive capability of the GPRs as shown in Figs. 2 and 3.

E. Artificial Neural Network (ANN) Techniques

The training 80% of data and testing 20% was done using Levenberg-Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG) algorithm. The analysis was optimal for 11 inputs, 10 hidden layers, 2 output layers, and 1 output.

The training session was done using the Levenberg-Marquardt algorithm to model using Artificial Neural Network (ANN) and this was the outcome obtained R2 of 0.99 and RMSE of 6.01. Bayesian regularization algorithm was used to model using Artificial Neural Network (ANN) and the outcome received was R2 of 0.99 and RMSE of 0.068. Scaled Conjugate Gradient algorithm was used to model using Artificial Neural Network (ANN) and the outcome was R2 of 0.88 and RMSE of 100.50.

The testing was equally done using Levenberg- Marquardt algorithm was used to model using Artificial Neural Network (ANN) and this was the outcome obtained R^2 of 0.99 and RMSE of 16.12. Bayesian regularization algorithm was used to model using Artificial Neural Network (ANN) and an outcome got was R^2 of 0.99 and RMSE of 0.11. Scaled Conjugate Gradient algorithm was used to model using Artificial Neural Network (ANN) and this was the outcome obtained R^2 of 0.88 and RMSE of 100.50.

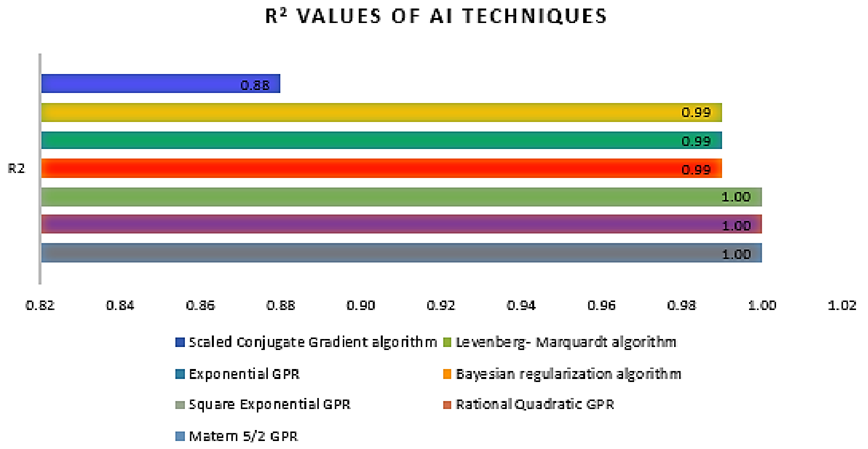

Fig. 2 Coefficient of Determination of AI Techniques

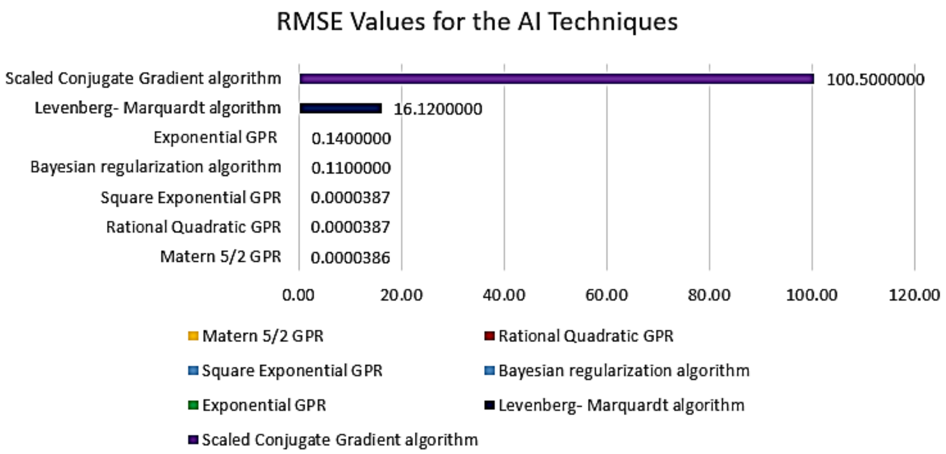

Fig. 3 RMSE Values of AI Techniques

VI. CONCLUSIONS AND RECOMMENDATIONS

A. Conclusions

The various functions of GPRs have been employed to anticipate flyrock throw arising from blasting operations.

Additionally, the excellent performance of the various types of GPRs are so appealing using coefficient of determination and Root Mean Square Error as yardsticks for measuring its performance. The order of accuracy of prediction are Matern 5/2 GPR topping with R^2 of 1.00 and RMSE of 0.000386, followed by SEGPR and RQGPR with R^2 of 1.00 and RMSE of 0.000386; R^2 of 1.00 and RMSE of 0.000387 with Exponential GPR with R^2 of 0.99 and RMSE of 0.14 as indicated in Figs. 2 and 3.

B. Recommendations

It can be recommended that:

i. When it comes to flyrock resulting from blasting operations, Gaussian Process regression models have great predictive potential.

ii. The GPR model may be used to accurately anticipate the extent of flyrock throw in quarries, mines, and communities that cohabit to achieve SDG 9.

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