

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 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).

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