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Genetic Programming based Prediction of the Angle of Draw: A Key Parameter in Underground Coal Mine Subsidence

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Abstract

Subsidence associated with underground coal mining is a significant geotechnical concern in many coal-producing regions. The extraction of coal over large areas from underground often leads to the collapse of overlying strata into the goaf, subsequently causing surface subsidence. The extent of this subsidence varies widely across mines, depending on several factors, including mine geometry, geological discontinuities, physico-mechanical properties of the overlying strata, extraction method, seam thickness, and depth of working. Among these, the angle of draw (AoD) plays a critical role in delineating the subsidence-affected zone, particularly in underground coal mining. Accurate prediction of AoD is essential for safe mine planning and the mitigation of subsidence-related hazards. In the present study, a comprehensive field investigation was conducted to collect mine operational parameters from various underground coal mines. Using this dataset, Genetic Programming (GP) was employed to model the relationship between AoD and key mining and geological parameters. The developed GP model demonstrated a strong correlation between predicted and measured AoD values, with a coefficient of determination (R) = 0.7921, highlighting the model's predictive capability. Additionally, a sensitivity analysis (SA) was performed to identify the most influential input parameters affecting AoD. The analysis indicated that, while all five input variables significantly impact AoD, the compressive strength of overlying strata exhibited the highest influence (sensitivity score = 0.98). The findings of this study provide a data-driven approach to predict the angle of draw in underground coal mines, offering valuable insights for improved mine design, extraction strategies, and surface infrastructure protection.

1. Introduction

Mining has been essential to human progress and continues to grow due to increasing global demand for minerals [1]. India, one of the major coal-producing countries of the world, has produced 997.826 MT of coal in the year 2023-24 [2]. Coal mining in India primarily revolves around the extraction of shallow coal deposits, with more than 95% of its total coal production coming from opencast mining operations. In India, approximately 98% of underground coal production is extracted using the Bord & Pillar mining method, while only about 2% is obtained through the long wall mining technique. Subsidence is a main hassle related to underground coal mining, inflicting harm to the surface and structures present on it [3]. Subsidence is crucial in underground mining because it can cause surface instability, leading to safety hazards, infrastructure damage, and environmental impacts [4] . As minerals are extracted, the ground above may sink or collapse, creating risks for miners working below ground and potentially damaging the surface

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features like buildings, roads, and ecosystems. Prediction of subsidence is essential to ensure mine safety, minimise environmental harm, and protect surrounding infrastructure.

Subsidence can be predicted through instrumentation and continuous monitoring of strata movement resulting from voids created by coal extraction. Appropriate modifications in underground extraction planning can help minimize the potential impacts of subsidence. Subsidence can be mitigated by selecting suitable support systems, such as leaving rib and sill pillars, using steel and wood supports, cable bolting, or stowing the goaf with sand, cement-mixed tailings, or waste rock. The magnitude of subsidence depends on several factors, including the mining method, depth of the coal seam, geological conditions, quantity of coal extracted, pillar design and roof support, water infiltration and hydrostatic pressure, surface loading and construction, time-dependent behavior, and environmental and climatic conditions. The angle of draw, also known as the limit angle (A), is the outward angle between the normal to the seam at the panel edge and a line connecting the panel edge to the point on the surface where subsidence reduces to zero, as illustrated in Figure 1. Beyond the angle of draw, surface subsidence is generally negligible.

All surface subsidence is confined within this angle of draw, making it a critical factor in underground coal mining. The angle of draw has important implications for both safety and productivity, as it defines the area where surface deformation is most likely to occur due to mining activities.

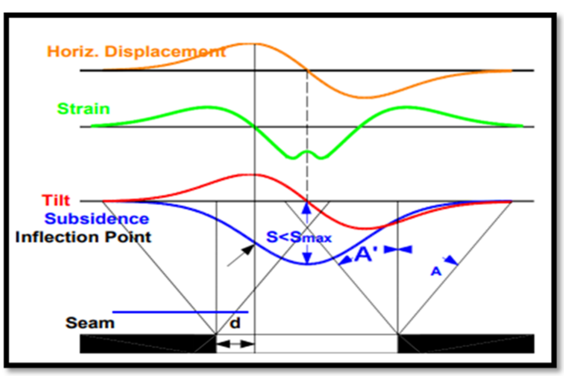

Figure 1. Factor schematic diagram of angle of draw

Recent studies on mining-induced subsidence primarily employ empirical methods, regression analyses, and numerical modeling techniques such as FEM, FLAC3D, and UDEC to investigate stress redistribution, displacement, and ground deformation caused by underground excavation [5,6]. These studies have enhanced understanding of subsidence mechanisms, overburden behavior, and ground response under different mining conditions. However, their application is generally site-specific, as model parameters are often calibrated for local geological and mining settings, and uncertainty in predicted results is seldom quantified. In recent years, artificial intelligence and machine learning techniques have increasingly been applied to subsidence prediction, mainly focusing on parameters such as maximum subsidence, surface tilt, and horizontal strain [7]. Despite these developments, direct modeling of the angle of draw has received limited attention in recent literature, and its relationship with governing mining and geomechanical parameters remains insufficiently explored. Notably, no Gaussian Process-based framework has been proposed to develop a closed-form predictor for the angle of draw or to conduct systematic input sensitivity analysis, particularly for Indian bord and pillar coal mines. The present study addresses this research gap by developing a Gaussian Process-driven prediction model and performing a structured sensitivity assessment.

In this study, an extensive field survey was conducted to record several parameters related to subsidence. Genetic Programming (GP) was used by taking survey data as input to develop a simple relationship between the most effective parameters and AoD. The concept of Genetic Programming (GP) is based on the Darwinian principle of survival and reproduction of the fittest [8]. GP has found widespread engineering applications over the past two decades (Hosseini and Nemati, 2015). In earth science engineering, GP has been used for various predictions, including back break in opencast mines [9]; fly-rock assessment from blasting [10]; subsidence prediction due to underground mining [11]; strength assessment of intact rocks [12,13]; evaluation of rock mass deformation modulus [14]; prediction of tensile and compressive strength of limestone [15]; fly rock assessment due to blasting [10]; ground vibration modeling for Jharia coalfields [16]; and prediction of heat stress hazards in underground mines [1]. To the authors' knowledge, GP has not yet been applied to predict the angle of draw in underground coal mines. Therefore, the authors recognize its wide, versatile, and successful application in geosciences, and this study is likely the first to apply GP in the field of angle of draw prediction in underground coal mines.

2. Effects of angle of draw

In underground coal mining, the angle of draw (AoD) represents the inclination at which the overlying strata begin to fracture and undergo displacement as a result of mining activities. This parameter is critical for understanding ground behavior above and around the mined-out area and has significant implications for mine stability and mine personnel safety. Furthermore, accurate knowledge of the AoD is essential for optimizing mining operations and minimizing adverse environmental impacts.

2.1. Ground Stability

2.1.1. Overlaying Strata Failure

The angle of draw governs the lateral extent of ground affected by strata collapse above underground excavations. A steeper AoD enlarges the destabilized zone, thereby intensifying surface subsidence and stress redistribution within the overburden. Numerical modeling studies have demonstrated that overburden stiffness and coal seam dip angle exert a direct influence on AoD and the magnitude of subsidence [17,18].

2.1.2 Stress on Support Systems

An increase in AoD expands the deformation zone surrounding underground openings, resulting in higher strain within the rock mass. Consequently, enhanced ground support systems such as rock bolts, wire meshes, and steel beams are required to prevent roof failure and maintain safe working conditions [19].

2.1.3. Gas Outburst Risk

Higher coal seam dip angles, which are often associated with increased AoD values, elevate the risk of gas outbursts by shifting hazardous zones upward and enlarging unstable rock regions. These conditions necessitate the implementation of improved gas management and control strategies to ensure mine safety [20,21].

2.2 Extraction Planning

2.2.1. Mining Sequence

The AoD plays a significant role in determining the sequence and timing of coal extraction. Steeper angles require careful planning and scheduling; in some cases, the adoption of retreat or longwall mining strategies is necessary to limit excessive stress redistribution and instability in the surrounding strata [22].

2.2.2. Production Rate

A shallow AoD promotes higher production rates due to improved ground stability, whereas a steep AoD enlarges the deformation zone, necessitating slower extraction, additional support, and continuous monitoring to mitigate collapse risks [23,24]. Optimized coal-drawing techniques can help maintain extraction efficiency even in steeply inclined seams [25].

2.3 Risk of Seismic Activity

2.3.1. Rock bursts

Steep AoD conditions are associated with elevated stress concentrations within the rock mass, thereby increasing the likelihood of violent rock bursts that pose a serious threat to mine safety [26].

2.3.2. Seismic monitoring

Mines characterized by large AoD values require comprehensive seismic monitoring systems to detect microseismic activity. Such systems enable early warning and timely mitigation of seismic hazards associated with mining-induced stress changes [27].

3. Methodology

Genetic programming is an adaptive computational technique that uses a population of potential solutions represented as tree-like structures (mathematical functions or expressions). It evolves these solutions over successive generations to find the most accurate predictors. In underground coal mining, the angle of draw is governed by several independent variables and exhibits pronounced sensitivity to even small variations in these parameters.

The study was carried out in three main stages. First, a detailed field survey was conducted, and data were collected from underground coal mines across different coal fields. Second, a genetic programming (GP) model was developed using the collected field data. Finally, the efficiency of the prediction model was assessed. The investigation focused on mechanized underground coal mines where coal was extracted using the bord-and-pillar mining method with caving. A comprehensive field survey strategy was designed to collect data from the underground mines over a three-year period, which was then used as input for the GP model. The model established relationships between input and output variables, and its performance was evaluated using fitness functions. The methodology of this study is schematically illustrated in Figure 2.

4. Site details and data collection

A site has been identified where underground coal is being extracted using the bord-and-pillar mining method, in combination with caving. The depth (D) of each panel is calculated using the surface reduced level (RL) and the seam floor, determining the vertical distance to the coal seam. Each panel's width (W) and working thickness (T) are obtained from the underground working plans. Additionally, the angle of draw (AoD), which predicts how overlying rock will move as coal is extracted, is recorded through surface subsidence monitoring stations. The degree of discontinuity for each mining panel is evaluated based on the presence and characteristics of joints and faults within the coal seam and surrounding strata. Discontinuities such as joints, fractures, and faults can significantly impact the stability of the mine and the extraction process. These features are identified and assessed through geological surveys, borehole data, and mapping of the seam. Data are being collected from different mines, including panel width, panel working thickness, panel depth, coal compressive strength, degree of discontinuity, and angle of draw.

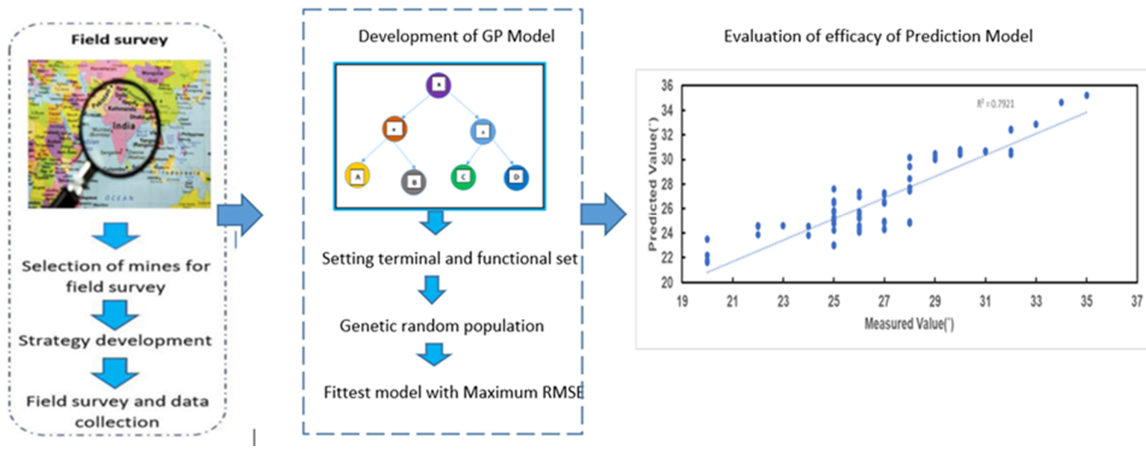

Figure 2. Methodology of the study

5. Prediction of Angle of Draw by GP

The angle of draw in underground mines depends on various independent variables, and the relationships among them are complex and non-linear. Recognizing the capability of genetic programming to address such complexity, this study employs GP to predict the angle of draw in underground coal mines. Genetic programming and genetic algorithms are conceptually similar; however, GP operates on a tree-based structure, whereas genetic algorithms function on a binary system. Genetic programming (GP) starts with randomly generated computer programs, which are combinations of mathematical functions and variables suited to the problem at hand [30]. Through iterative crossover and mutation operations, GP evolves toward an optimal solution by maximizing the fitness function [12].

The resulting GP tree represents the mathematical relationship between parameters, constants, and predefined functions, typically expressed in the LISP programming language. For example, a simple representative output tree of the function (A+B) X (C+D) is shown in Figure 3.

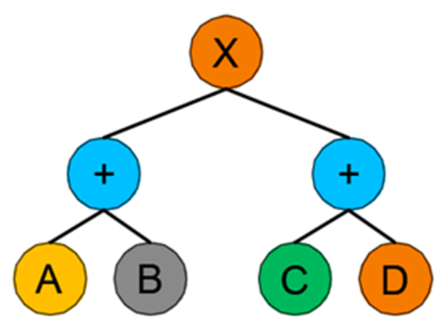

Figure 3. GP tree structure of (A+B) X (C+D)

In GP, input and output variables, along with their associated mathematical functions, are pre-defined within the computer program. The most effective input variables among the pre-defined set are automatically selected to generate the best pattern, and unrelated variables are eliminated so that the performance of the program is not reduced. GP has advantages over other AI tools due to its simpler coding process and quicker identification of the optimal solution. The basic steps in GP involve defining the terminal and functional sets, selecting a fitness function, setting control conditions for the run, and establishing criteria to terminate the process. A sample flowchart of GP is shown in Figure 4.

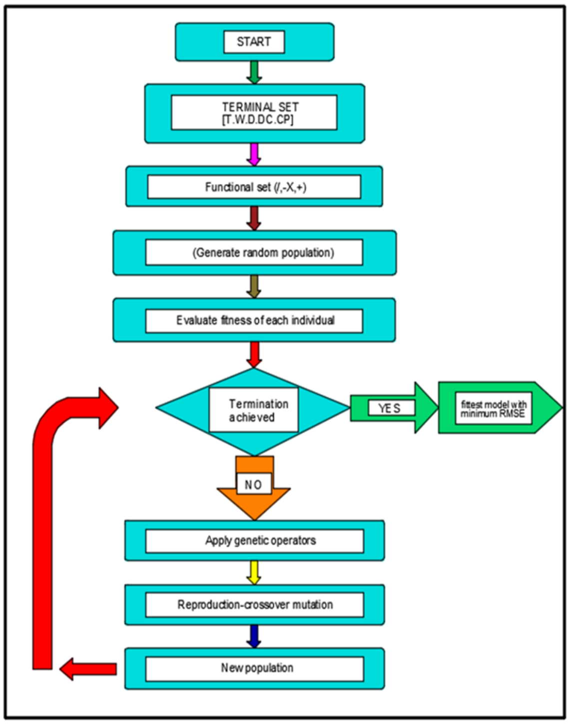

Figure 4. Sample flowchart of GP

6. Data collection and overview

A comprehensive dataset of 243 panels was compiled from multiple underground coal mines across various coalfields in India, all operating under the bord-and-pillar method with caving. For each panel, key geological and mining parameters were documented, including panel width (W, m), depth of cover (D, m), working thickness (T, m), coal compressive strength (CP, MPa), degree of discontinuity (DD), and the corresponding measured angle of draw (AoD, degrees). This diverse and robust dataset provides a reliable basis for developing and validating the predictive models.

The dataset was randomly partitioned into training datasets and testing data sets to ensure unbiased model development and performance evaluation. All input variables were normalized prior to model training to maintain scale consistency and enhance the stability and convergence of the predictive models. The ranges for these variables are:

Table 1. Different parameters used for the development of GP model

Parameters	SD	MEAN	Range	
T (m)	1.18	2.84	1.47	8
D (m)	101.38	167.90	43	534
C (Mpa)	6.91	22.51	23	45
W (m)	55.46	110.42	42	370
DD	0.13	0.36	0.1	0.7
A()	0.13	0.38	6	38

At first, the data was analyzed using multiple regression to obtain a set of equations. The multivariate regression analysis (MVRA) Table 2 is given below:

Table 2. Multivariate regression analysis

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.648							
R Square	0.420							
Adjusted R Square	0.399							
Standard Error	5.767							
Observations	243							
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	10.786	2.626	4.107	0.000	5.594	15.978	5.594	15.978
Thickness(m)	0.719	0.446	1.612	0.109	-0.163	1.601	-0.163	1.601
Depth(m)	0.010	0.005	1.871	0.063	-0.001	0.021	-0.001	0.021
Compressive Strength,(MPa)	0.639	0.081	7.871	0.000	0.479	0.800	0.479	0.800
With of Panel(m)	-0.026	0.009	-2.777	0.006	-0.045	-0.008	-0.045	-0.008
Degree of Discontinuance	-0.833	3.829	-0.218	0.828	-8.403	6.736	-8.403	6.736

The equation thus obtained is as below:

$$AoD = 0.72 \times T + 0.01 \times D + 0.64 \times C - 0.02 \times W - 0.83 \times DD + 10.78 \quad (1)$$

Where are:

T= Thickness (m),

W=Width (m),

D=Depth(m),

C= Compressive strength (Mpa),

DD= Degree of Discontinuity(nos).

The coefficient of determination of the above equation was found to be 0.42, which shows a poor predictability of AoD. Also, as per the P-value null hypothesis, the C and W input parameters have a P-value less than 0.05, which implies that the C and W are the most influential parameters.

It is evident from the above equation that MVRA is not proving to be an efficient tool for the prediction of AoD. Therefore, in this study, genetic programming is conducted using the Gene Xpro 5.0 software. The total dataset obtained from the field survey is randomly divided into a proportion of 80% and 20%, and used as training and testing datasets, respectively. Seven mathematical functions {X, /, +, -, Exp, ^2, ^3} are used in the model to attain maximum R^2 and minimum error between the actual and predicted dependent variable. However, GP model considered 6 mathematical functions {+, -, X, /, Exp, ^2} to attain the maximum R^2 value. The run control settings used in the GP model are shown in Table 1.

Table 3. Parameters used in the GP Model

GP parameters	Values
Terminal parameters	W, D, CP, DD, T
Fitness function	RMSE
Chromosomes	80
Number of genes	3
size	5
Linkage function	Addition
Maximum tree depth	535
Stopping criteria	243

After inserting the independent and dependent variables as given in Table 1. and selecting the mathematical functions, the following equation is obtained for predicting the angle of draw in underground coal mines. The optimal GP output model in a tree structure is displayed in Figure 5.

$$AoD = (C * 1.77 * T) + [(W - 5.29 - (DD * e^{\left(-\frac{5.95}{(H+T)}\right)})] \quad (2)$$

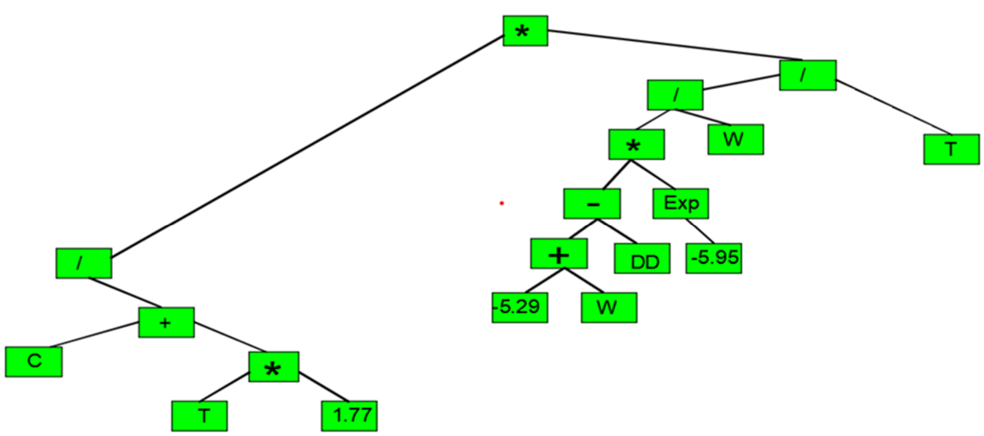

Figure 5. Final Expression Tree generated by GP

7. Sensitivity analysis

Sensitivity analysis is essential for comprehending the relationship between input and output variables. By determining which input variable is most important, the angle of draw can be controlled more efficiently and with less work[31].

The influence of each input parameter on the angle of draw (AoD) was evaluated using the

Cosine Amplitude Method (CAM). CAM calculates the cosine similarity between input and output vectors, producing standardized sensitivity coefficients ranging from 0 (no effect) to 1 (strongest influence). It is particularly effective for nonlinear and complex relationships, such as those in the Genetic Programming (GP) model, where traditional linear methods may not adequately capture parameter effects. CAM was selected because it provides an intuitive comparison of input importance, manages correlated and nonlinear variables, and is computationally efficient for limited field datasets. Unlike ANOVA, which assumes linearity and independence, CAM can account for interrelated or nonlinear parameters typical of geotechnical systems.

Each input variable's sensitivity to the output is assessed in this study using the Cosine Amplitude Approach, whose mathematical expression is given in Equation 3 [9,32].

$$R_{ij} = \frac{\sum_{k=1}^{n}(x_{ik} \times x_{jk})}{\sqrt{\sum_{k=1}^{n} x_{ik}^2 \times \sum_{k=1}^{n} x_{jk}^2}} \quad (3)$$

Where are:

R_{ij} = sensitivity of an input variable,

x_i = input variable,

x_j= output variable,

n= number of datasets.

The input variables are independent and have no overlapping as T, W and Dare are measurable parameters, whereas the width is the only designed parameter and depth and thickness are natural. The other parameter that is compressive strength is the geo-technical property of the coal and DD is independent and site specific. Therefore, the cosine amplitude method will be most suitable to identify the impact of individual input parameters on the AoD. The impact of each input variable on AoD is illustrated graphically in Figure 6. The sensitivity analysis results indicate that compressive strength is the most significant factor (0.99) affecting the angle of draw, followed by the width of the panel (0.98), thickness (0.96), degree of discontinuity (0.95), and depth of the working (0.91). The sensitivity analysis results appear to be accurate in all respects.**Error! Reference source not found.**

The results obtained with CAM were similar to that of MVRA and P-value as discussed above i.e. C and W are the most important parameters for predicting the AoD.

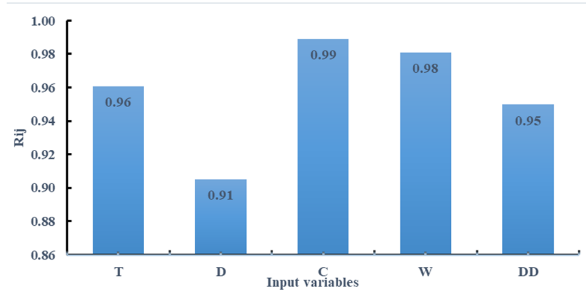

Figure 6. Results of SA obtained applying Cosine amplitude method

8. Results and discussion

An angle of draw prediction model for underground coal mines is developed with the help of genetic programming. Field studies were conducted in different underground coal mines to gather geotechnical parameters, which are used further as input parameters in the model.

This study uses a non-linear regression approach by genetic programming (GP) to predict the angle of draw in underground coal mines. The developed genetic programming model is capable of predicting the angle of draw at underground coal mines operated by the bord & pillar method of mining with caving. The performance of the GP model is evaluated by calculating the statistical performance indicators like correlation coefficient (R), coefficient of determination (R^2), and root mean square error (RMSE) (Table 3). The coefficient of determination (R^2) between the actual and predicted angle of draw (AoD) by applying genetic programming on training and testing data sets is obtained as 0.9637 and 0.9552, respectively (Figure 7 and Figure 8). Hence, it can be concluded that the equation developed by the GP model can be effectively used to predict the angle of draw for different coal fields of India.

Table 4. Performance indicator of the GP model

Performance indicator	Training data set	Testing data set
Correlation coefficient (R)	0.89	0.92
Coefficient of determination (R^2)	0.7921	0.85
Root mean square error (RMSE)	±1.43	±1.23

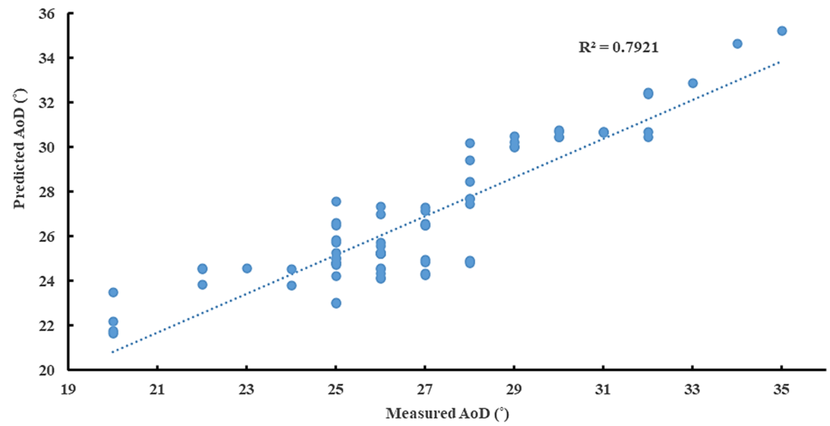

Figure 7. Actual vs predicted CP using GP on training dataset

The sensitivity analysis by the Cosine amplitude method revealed that all the considered independent variables have a high impact on the dependent variable (AoD), and their sensitivity weightage ranged from 0.91 to 0.99. It also revealed that the most sensitive parameter that affects the Angle of Draw is Compressive strength(C).

Sources of error may include measurement uncertainties, variability in overburden and coal seam properties, simplifications in input parameters, and operational variability. Recognizing these factors is important when interpreting predictions for engineering applications.

Sensitivity analysis using the Cosine Amplitude Method confirmed that all input variables significantly influence AoD, with sensitivity weights ranging from 0.91 to 0.99. Among them, the compressive strength of the overlying strata was the most influential parameter. Understanding the relative influence of each parameter, combined with error distribution analysis, allows engineers to identify areas requiring additional monitoring or conservative support designs, enhancing the practical application of the model in subsidence management.

The GP model demonstrates a strong goodness of fit for both training and testing datasets; however, R^2 alone does not fully capture how prediction errors are distributed across the range of AoD values. Therefore, residuals were examined to understand the dispersion and potential bias in the predictions

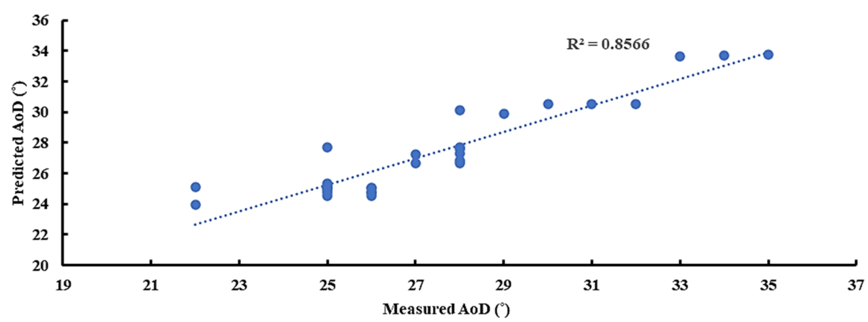

Figure 8. Actual vs predicted CP using GP on testing dataset

A relatively narrow RMSE (±1.43° for training and ±1.23° for testing) indicates that most deviations between measured and predicted AoD values are small, and the residual scatter plots show no systematic trend, suggesting the absence of bias in the model. The error behavior indicates that while the GP model performs robustly under most conditions, additional conservatism may be necessary in panels with unusually weak overburden or high discontinuity values. These insights enable mine planners to apply the model more safely, for example, by incorporating error bounds in protective pillar design, surface deformation risk assessment, and subsidence monitoring programs. Overall, combining statistical indicators with error distribution analysis significantly enhances the practical applicability and interpretability of the GP-based AoD prediction model.

Overall, the combination of statistical evaluation, error analysis, and sensitivity assessment demonstrates that the GP model provides reliable and actionable predictions of AoD for underground coal mining operations.

9. Conclusions

This study aimed to develop a simplified yet effective model for predicting the angle of draw (AoD) in underground coal mines across various coalfields. Genetic Programming (GP), a widely used artificial intelligence technique, was applied using five key geo-mining parameters as input variables. The AoD predicted by the GP model was compared with field-measured values from operational underground mines. Based on the analysis, the following conclusions are drawn:

Reliable AoD prediction: The angle of draw in underground coal mines can be reliably predicted using the equation derived through Genetic Programming. The correlation coefficients (R) between the GP-predicted and measured AoD were 0.89 for the training dataset and 0.92 for the testing dataset, demonstrating strong predictive capability.

Significant influence of input variables: Sensitivity analysis using the Cosine Amplitude Method revealed that all five input variables significantly influence the AoD. Among them, the compressive strength of the overlying strata exhibited the highest impact, with a sensitivity score of 0.99.

Engineering relevance: The ability to predict AoD using GP provides a valuable tool for implementing effective engineering controls aimed at mitigating the adverse effects of surface subsidence in underground mining operations.

Practical applicability: For new mining projects, GP-based models can be employed to forecast expected subsidence behavior across different panels by incorporating known geological and operational parameters. These predictions can assist engineers in designing appropriate support systems, identifying zones with a higher risk of surface disturbance, and optimizing mining strategies to minimize hazards.

In summary, Genetic Programming demonstrates strong potential as a predictive tool for subsidence-related parameters in underground coal mining. Its ability to capture complex, nonlinear relationships among influencing factors can contribute to enhanced safety, improved mine planning, and reduced environmental impacts.

Future Research Directions

Future studies could strengthen the current model by clearly identifying gaps in the quantitative modeling of the angle of draw, providing recommendations for standardized experimental and field-monitoring approaches, and offering targeted suggestions for integrating emerging technologies and interdisciplinary methods.

Statements & Declarations

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Competing Interest

The authors have no relevant financial or non-financial interests to disclose.

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