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Optimizing Underground Coal Mine Safety: Leveraging Advanced Computational Algorithms for Roof Fall Rate Prediction and Risk Mitigation

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Abstract
The utilization and consumption of coal in various nations have emphasized the pivotal role played by coal mines. However, aside from the substantial contribution of coal mines, miners, engineers, and craftsmen in this industry have long been exposed to numerous risks and financial losses resulting from roof collapses in underground coal mines. Hence, due to the heightened sensitivity surrounding this issue, the accurate and low-error forecasting and assessment of the roof fall rate (RFR) are deemed crucial and of utmost importance. Nonetheless, due to the intricate and uncertain inherent characteristics of the rock formations, assessing the RFR has encountered multiple challenges that cannot be precisely approximated through traditional methods. In this paper, algorithms such as the harmony search algorithm (HS) and the invasive weed Optimization algorithm (IWO) are harnessed to address the aforementioned challenges. To model the RFR, a total of 109 data points were used, incorporating input parameters such as primary roof support (PRSUP), depth of cover (D), coal mine roof rating (CMRR), mine height (MH), and intersection diagonal span (IS). For effective data analysis and model development, the dataset was split into two separate groups: one for training and the other for testing. Specifically, 80% of the data was used to build the model, while the remaining 20% was allocated for model evaluation and validation. Based on the outcomes of three statistical metrics R^2, MSE, and RMSE, it is evident that the deployment of HS and IWO algorithms demonstrates high performance, with predicted values closely aligning with actual ones. Consequently, the utilization of intelligent algorithms in the field of rock engineering is positioned as a potent tool for researchers and engineers. In conclusion, a sensitivity analysis is carried out with the help of the @RISK software as a means of ranking the influence that the input parameters have on the output of the model. Its results indicate that among different parameters, the CMRR parameter with a sensitivity degree of 0.11 has the most impact on the model, even with the smallest change in this parameter, a significant change is made in the model output.

Keywords Roof fall rate (RFR) · Harmony search algorithm (HS) · Underground coal mine · Invasive weed optimization algorithm (IWO) · Sensitivity analysis

1 Introduction

The mining industry has recently emerged as a significant economic driver for the nation. However, due to the intricate and costly nature of underground mining, it is imperative to anticipate the various factors affecting mining through a range of techniques before commencing excavation and ore extraction. While underground mining poses numerous risks, coal mines stand out with the highest financial and life-related risks [1–5]. In recent years, roof collapses have been a leading cause of mining accidents. Research indicates that out of every 100 roof collapses in underground mines, coal mines account for a substantial 18.8%, a significant proportion compared to all underground mines. Given the elevated risk associated with underground coal mining, researchers have undertaken a variety of studies in this domain [6–12]. Palei and Das carried out a study utilizing statistical and regression methods to assess the risks of roof

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collapses in underground coal mines using the room and pillar method. Similarly, Ghasemi et al. assessed the potential for roof collapses in coal mines by utilizing the room and pillar approach. They employed several influencing factors and semi-quantitative methodologies to analyze Iran's Tabas coal mines [13]. Ghosh and Sivakumar investigated the hazards resulting from roof collapses in the Rajendra underground coal mine situated in the southeast of India, using the direct method (field method) [14]. Oraee et al., aiming to predict rock falls, utilized computer modeling (UNWEDGE software) to examine the impact of roof discontinuities in Iran's Ashkeli coal mine [15]. Prusek et al., combining experimental techniques and expert methods, analyzed the risk of rock falls in coal mines [16]. Wang et al. assessed the risks of landslides and falls in China's Shanxi underground coal mine through field tests [17]. Kang et al. used a large-scale physical model to closely simulate rock falls during underground coal mining. They subsequently compared and evaluated the results against numerical and field methodologies, finding a notable degree of agreement across the different approaches and a commendable level of accuracy in the rock fall model [18]. Abousleiman et al. used experimental observations to estimate the rate of roof collapses in an underground coal mine. To validate the discrete element method (DEM), they compared it with experimental methods. The findings indicated that both methods yielded an acceptable degree of concurrence [19]. Osouli and Bajestani investigated the influence of humidity variations on coal mine roof collapses, employing field, laboratory, and numerical methodologies [20]. Mark et al. scrutinized two American underground coal mines utilizing the room and pillar mining technique, employing statistical analysis for stability and rock fall. They concluded that strategically placing rockbolt, especially at intersections, effectively prevented roof collapse [21]. Van der Merwe et al. employed numerical techniques to simulate the risk of rock falls in a South African underground coal mine. The software output suggested that the installation of rock bolts in weak rock areas significantly mitigated rock falls [22]. Osouli and Shafii explored the rock mass characteristics of Illinois coal mine roofs and their impact on roof collapses, considering significant rock engineering parameters [23]. Numerous incidents resulting in miner fatalities and financial losses due to roof collapses in underground coal mines across different countries have underscored the critical and sensitive nature of analyzing and predicting rock fall hazards. Therefore, analysis and prediction RFR with low error and high accuracy seems important. However, due to the inherent complexity and uncertainty associated with stone properties, the use of traditional methods, including experimental, analytical and numerical methods, has low accuracy. Furthermore, some prior research employed field methods, which incurred time and high costs. In certain situations, the feasibility of field testing was hindered by insufficient equipment and engineer fatigue. Consequently, given these challenges, methods that can accommodate uncertainties in rock properties should be prioritized. In today's rapidly advancing technological era, smart methods represent a significant and innovative alternative to traditional approaches across various fields. Unlike conventional methods, which often rely on linear and static models, smart methods are equipped with the ability to adapt to complex and dynamic environments. These advanced techniques can comprehensively account for the myriad of multifaceted factors that influence model outcomes, providing a more accurate and holistic analysis. Furthermore, smart methods excel in managing uncertainties in input parameters, a common challenge in many modeling processes. By effectively addressing these uncertainties, they ensure greater reliability and robustness in the resulting models. Consequently, these methods are not only more adaptable but also offer substantial benefits in terms of cost-effectiveness and efficiency, leading to the development of sophisticated nonlinear models that outperform traditional ones in both accuracy and practicality [24–33].

Recognizing the vital role of miners in underground coal mines, it is imperative to identify and mitigate high-priority risks to ensure the safety and well-being of miners during their work. Substantial research has been conducted to pinpoint operational risks in underground mine operation and devise effective management strategies. For instance, Liu et al. introduced the Root-State Hazard Identification (RSHI) for assessing and managing risks in underground coal mines. Their study classified roof beard hazards in this domain and distinguished between root hazards and state hazards. By applying the RSHI technique to six Chinese Yima coal mines, they determined that root risks take precedence and can be comprehensively identified using this approach [34]. Sari employed a probabilistic approach to assess operational risks in two Turkish underground coal mines, GLI-Tuncbilek and ELI-Eynez, aiming to minimize potential hazards. Utilizing statistical techniques such as time series (TS) analysis and multiple linear regression (MLR), the study predicted and evaluated operational risks for future events and accidents. The findings demonstrated the success of both models in this context, indicating that they can effectively determine risk levels in the forthcoming years [35]. Zhang et al. introduced an innovative evaluation method that combines uncertainty theory and variable weight theory to evaluate the level of operational risk associated with coal and gas. In this approach, variable weights (VW) for various parameters influencing risks in coal mining were determined using a segmented variable weight model based on the VW theory. Additionally, constant weights (CW) were established through the fuzzy analytic hierarchy process. The results demonstrated the method's effectiveness in evaluating and mitigating explosion risks in underground coal mining [36].

Mahdevari et al. utilized the TOPSIS fuzzy method to evaluate risks in three underground coal mines (Heshoni, Hajdak, and Baniz) located in Kerman province, Iran. The aim was to manage and reduce operational and dynamic risks impacting the health and safety of mine workers. The study identified and classified a total of 86 risks, prioritizing them into eight categories, including geochemical, managerial, electrical, geomechanical, chemical, mechanical, environmental, social, personal, and cultural. Given the uncertainties in coal mines, the application of the TOPSIS fuzzy method emerged as a reliable technique for effectively managing and reducing potential and significant risks to enhance the safety and health of workers and engineers in underground coal mines [37]. Shi et al. employed the improved Analytical Hierarchy Process (IAHP) to quantitatively investigate the risk of methane explosion in an underground coal mine. Their findings indicated that explosion, frictional, and electrical sparks were the primary ignition risks in coal mines [38]. Palei and Das employed a regression model in their research to predict the risks of roof collapse in coal mines during the board and pillar extraction method. Their findings indicated that unmaintained roofs present multiple hazards, and as the depth of the mining workshop increases, the likelihood of significant collapse events becomes higher [39]. Matloob et al. focused on prioritizing and highlighting operational risks during coal mine extraction using machine learning (ML) and artificial intelligence (AI). The results indicated that the application of modern techniques in assessing coal mine risks leads to higher accuracy [40]. Kursunoglu assessed the risk of dust explosion in coal mines and employed fuzzy risk matrix and Pareto analysis methods for risk management. Identifying 17 crucial factors for this phenomenon in underground coal mines, the research suggested preventive measures. Among these factors, flammable gases were identified as the most significant risk [41]. Tripathy et al. used logistic regression, SVM, KNN, and decision tree methods to predict risks in coal mines, categorizing risk assessment into very high, high, medium, and low risk levels and emphasizing high-grade risks [42]. Miao et al. analyzed explosion risks in the Babao underground coal mine in China using Fuzzy Bayesian Network (FBN). The study ensured data reliability by examining expert weights through the Fuzzy Analysis Hierarchical Process (FAHP) method. The findings indicated that FBN simulation provides a practical and highly accurate method for identifying the causes of gas explosion ignition in coal mines and managing them [43]. Li et al. creatively identified all effective factors in the risks of working in an underground coal mine using data mining and Bayesian network methods. Critical path and sensitivity analysis determined six important risk factors and their related parameters for enhancing safety and health in underground coal mines [44]. Aghababaei et al., based on rock engineering systems, assessed the risk of roof collapse and damaged areas in coal mines before and after mining by retreating from the high wall surface. Four classes (moderate, critical, dangerous, and safe areas) were identified to preemptively address operational risks. The findings showed the possibility of identifying and reducing the risks of critical areas with high accuracy to develop detailed operational plans to control roof collapse. [45]. Direk conducted a study using the Fault Tree Analysis (FTA) method to determine the factors contributing to roof collapse in an underground coal mine in Turkey. Associated risks were calculated using ReliaSoft BlockSim-7 software [46]. The primary and leading causes of accidents and roof collapse risks in underground coal mines were conclusively identified. The results underscored that utilizing the fault tree analysis method enables the accurate identification of risks for underground mine [46]. Gurjar et al. aimed to comprehend the significance of each parameter in the occurrence of roof collapse during retreat mining in a coal mine. The study initially identified all parameters influencing roof collapse, followed by the development of a workable framework for roof collapse risk assessment and management using semi-quantitative methods. The Bagdeva underground coal mine in Kurba, South East India, specifically its main panel, served as the application site for this technique. Multiple retreat mining scenarios and associated risks were evaluated, providing valuable insights [47]. Li et al. introduced a Bayesian network-based quantitative technique for gas explosion risk assessment in the Babao underground coal mines in China. The fuzzification process involved the development of the Fuzzy Hierarchical Analysis Process (FAHP) approach, incorporating both objective and subjective knowledge from experts. The research not only identified the most critical risk factor but also demonstrated that the Bayesian network method can effectively be employed for preventing gas explosions in coal mines [48].

In the present study, the prediction and evaluation of Roof Fall Rate (RFR) leveraged two potent algorithms, Harmony Search (HS) and Invasive Weed Optimization (IWO). The application of these algorithms is specifically designed to offer a more precise and efficient alternative to traditional methodologies, which often suffer from being time-consuming, resource-intensive, and limited in their scope. Traditional methods typically involve extensive manual calculations, lengthy processing times, and often fail to account for the complex and dynamic nature of the systems they aim to model. In contrast, optimization algorithms leverage their iterative processes to systematically explore a broad range of potential solutions. They can continuously adapt and refine their approaches based on new data or changing conditions, thereby achieving results that are not only more accurate but also more tailored to the specific problem at hand. These algorithms are particularly promising for addressing uncertainties in fields like rock mechanics.

They are adept at navigating complex solution spaces, which allows for a deeper and more nuanced understanding of the problems being studied. By analyzing various scenarios and potential outcomes, optimization algorithms help to better manage the uncertainties inherent in these fields, leading to more robust and reliable models. In industries such as rock engineering, mining, and energy exploration, where precise and well-informed decision-making is critical, the systematic and adaptive nature of optimization algorithms represents a substantial advancement. These algorithms facilitate more accurate predictions and effective solutions by thoroughly analyzing all possible variables and outcomes. This shift towards using optimization algorithms marks a significant improvement in the ability to predict and manage complex systems, enhancing decision-making processes and ultimately leading to better operational efficiency and success in these demanding industries.

2 Parameters and Database Description

When analyzing data to estimate the RFR, two key factors greatly influence the model's output. These factors include the selection of input parameters and the quantity of input data. The more carefully you select the parameters, the more significant their impact on the model's output. Likewise, having a larger volume of real data leads to a more precise model analysis. In such cases, the resulting model can be employed with greater confidence in real-world projects.

As a result, this paper aims to utilize a comprehensive dataset related to roof fall risk (RFR) for the entire mine, not limited to specific intersections. The dataset used in this study consists of 109 data points, which cover various sections of the mine, including both entries and intersections. Of these data points, 80% (87 data points) were used for model construction, while the remaining 20% (22 data points) were allocated for model validation. The input and output parameters are described as follows [49]:

RFR: RFR is a crucial output parameter used to evaluate the safety and structural stability within underground mining environments. This parameter quantifies the frequency of roof falls—incidents where sections of the mine's roof collapse—relative to the extent of the mine's advancement, known as drivage. Drivage is a measure of the linear distance a mine has advanced over a period, typically calculated by converting annual production figures (excluding longwall production) into linear feet of tunnel progression. To calculate RFR, the total number of roof falls that have occurred within a specific period is divided by the corresponding drivage. This calculation yields a rate that reflects how often roof falls are occurring relative to the expansion of the mine. A higher RFR indicates a greater frequency of roof falls, suggesting potential issues with mine stability and highlighting areas that may require immediate attention to prevent further incidents. RFR is not just a statistical measure but a vital tool for mine engineers and safety managers. It allows them to pinpoint high-risk areas within the mine where the likelihood of roof falls is elevated. By analyzing RFR trends over time, engineers can identify patterns that might indicate worsening conditions, such as deteriorating geological structures or inadequate support systems. This insight enables the implementation of targeted safety measures, such as reinforcing mine roofs, adjusting mining methods, or even redesigning mine layouts to mitigate risks. Moreover, the RFR metric plays a critical role in the continuous monitoring and improvement of mining safety protocols. It provides a quantitative basis for comparing the effectiveness of different safety interventions and mining techniques. Mines with a low RFR are typically seen as having better safety records, which can contribute to improved operational efficiency, reduced downtime due to accidents, and a safer working environment for miners. In summary, RFR is a key indicator in the mining industry, essential for assessing and managing the risks associated with underground mining operations. Its accurate calculation and regular monitoring are fundamental to maintaining the safety and integrity of mining activities, ensuring that high-risk areas are identified and addressed promptly to prevent roof falls and safeguard the lives of miners [50].

Coal mine roof rating (CMRR): The CMRR is a crucial input parameter that significantly affects the likelihood of roof collapses. Developed by Molinda and Mark [51], this rating system assesses the quality of the rock in the mine roof, a key factor in roof stability. The CMRR scale ranges from 0 to 100, where 0 represents very poor quality and 100 represents excellent quality. This rating takes into account various natural factors, such as:

- Discontinuities and joints: The presence and orientation of fractures and separations within the rock mass.
- Fractures and faults: Larger-scale breaks that can undermine the rock's structural integrity.
- Rock strength: The intrinsic strength of the rock material, influencing its ability to support overburden.
- Presence of subterranean water: Water within the rock can weaken the structure, increasing collapse risk.

High-quality rock with fewer discontinuities and greater strength will have a higher CMRR, indicating a lower risk of roof collapse. Conversely, poor-quality rock with numerous discontinuities and lower strength will have a lower CMRR, indicating a higher risk [52].

Primary roof support (PRSUP): In underground coal mines, roof bolts play a crucial role as the primary support mechanism, designed to protect miners from the substantial weight of the rock above. These bolts are essential for stabilizing the mine roof and ensuring the safety of the work environment. The failure of these support systems can have serious consequences, including significant financial costs and potential human losses resulting from roof collapses. Such collapses not only endanger the lives of miners but also lead to costly repairs and operational disruptions. The PRSUP parameter is specifically designed to evaluate the density and effectiveness of the roof bolt system in place. This parameter provides a measure of how well the roof bolts are performing their intended function of supporting the mine roof and preventing collapses. The effectiveness of the roof bolts is crucial for maintaining the stability of the underground workings and ensuring the safety of the mining operations. The PRSUP parameter is defined by a particular equation, which quantifies the support system's characteristics based on various factors related to the density and performance of the roof bolts [39]. This equation helps in assessing whether the current roof support measures are adequate or if additional support is necessary to enhance mine safety and operational efficiency. The following equation provides the detailed definition of the PRSUP parameter [53, 54]:

$$PRSUP = \frac{L_b \times N_b \times C}{14.5 \times S_b \times W_e} \tag{1}$$

- W_e: Entry width (meters).
- S_b: Row distance between roof bolts in the mine roof (meters).
- L_b: Roof bolt length (meters).
- C: Roof bolt capacity (kilonewtons).
- N_b: is the number of bolts used in each row of roof bolts.

This parameter helps estimate the robustness of the support system, with higher PRSUP values indicating stronger support systems capable of preventing roof collapses.

Intersection diagonal span (IS): Intersections in the mine, where different tunnels or entries converge, are particularly susceptible to roof collapses. The span of these intersections significantly impacts roof stability, as larger spans can lead to increased loads and higher collapse risks [49]. The IS parameter is used to calculate the span of the intersection diagonal in underground mining environments by summing the lengths of the two intersecting diagonals. This calculation is crucial for understanding the dimensions of the intersection openings within the mine. By implementing strategies to reduce the span of these intersections, such as creating smaller apertures, the potential for rock falls can be significantly decreased. Smaller intersection openings help in enhancing the stability of the mine structure, thereby reducing the risk of collapses and improving overall safety. Figure 1 illustrates the process for calculating the intersection opening, providing a visual guide to the method used for measuring the IS parameter. This visual representation aids in comprehending how the span of the intersection diagonal is determined and emphasizes the importance of managing intersection sizes to maintain structural integrity and mitigate hazards in mining operations.

Depth of cover (D): The depth of cover, or the thickness of the overlying rock above the mine, is another critical factor influencing roof stability. As the depth increases, both vertical and horizontal stresses within the rock mass also increase. This heightened stress can compromise the stability of the mine roof, making it more prone to collapse. Mines operating at greater depths are generally less stable and pose higher safety risks, potentially leading to fatalities and substantial financial losses if collapses occur.

Mining height (MH): The height of the mine entry, known as mining height, is a critical factor influencing the likelihood of roof falls in underground mining operations. According to research conducted by Fotta and Mallett [55], there is a direct correlation between increased mining height and the risk of roof collapses. As the height of the mine entry rises, it results in larger unsupported spans within the mine. These larger spans are more prone to collapse under the weight of the overlying rock, thus increasing the risk of roof falls. Figure 2 provides a visual depiction of the dangers associated with rock falls in the roof of an underground coal mine. It also illustrates how roof bolts can be employed as a mitigation measure to reduce these risks. By providing

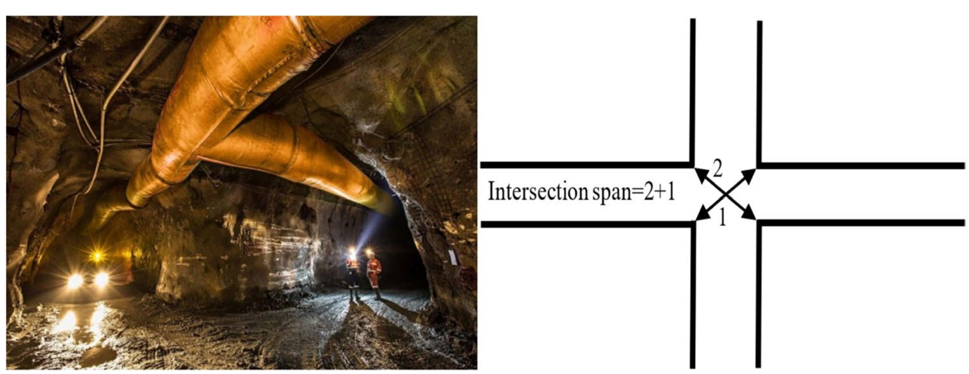


Fig. 1 Illustration of how to calculate intersection diameters in underground mines [49]

additional support, roof bolts help stabilize the mine roof and minimize the potential for collapses, thus enhancing the safety and stability of the mining environment.

To analyze and construct the RFR model, Table 1 displays some of the inputs and output data values in their actual form. It should be noted that the values of the parameter IS in Table 3 are equal to the input width for intersection locations.

Before engaging in modeling, it is highly effective to analyze the input and output data to formulate a functional equation. Consequently, descriptive statistics regarding inputs and output data, encompassing minimum, average, maximum, mode, median, range, and standard deviation, can be presented, as depicted in Table 2.

To gain a more thorough and comprehensive understanding of the data's descriptive statistics, they can be visually depicted. For this purpose, Fig. 3 presents a histogram of the input and output data using SPSS software.

In addition to offering statistical descriptions of both input and output data, it is essential to interpret the correlations between these variables to fully grasp their effects on the model's output. Correlation quantifies the extent to which the input data and output data are related. A negative correlation implies an inverse relationship, where

Fig. 2 Visual representation of rock falling from the roof in an underground coal mine [56]

Table 1 Portion of inputs and output data values [49]

No	Inputs					Output
	D (ft)	MH (ft)	PRSUP	IS (ft)	CMRR	RFR
1	400.00	7.00	3.93	60.00	50.00	0.66
2	350.00	5.50	4.55	65.00	45.00	5.69
3	350.00	3.50	8.80	62.00	44.00	0.00
4	400.00	7.00	2.46	60.00	75.00	0.00
5	350.00	3.50	4.36	62.00	44.00	0.00

Table 2 Descriptive statistics of inputs and output data

Type	Parameters	Maximum	Mean	Minimum	Std. Deviation	Mode	Median	Range
Input	D (ft)	1100	448.8532	150	223.20232	500	400	950
	IS (ft)	78.40	63.4477	50	5.60759	63	63	28.4
	MH (ft)	10	6.2890	3	1.94252	7	6.5	7
	PRSUP	14.67	5.7056	2.46	2.29179	5.90	5.32	12.21
	CMRR	78	47.7248	28	11.10461	50	45	50
Output	RFR	31.82	2.7508	0	5.25176	0	0.52	31.82

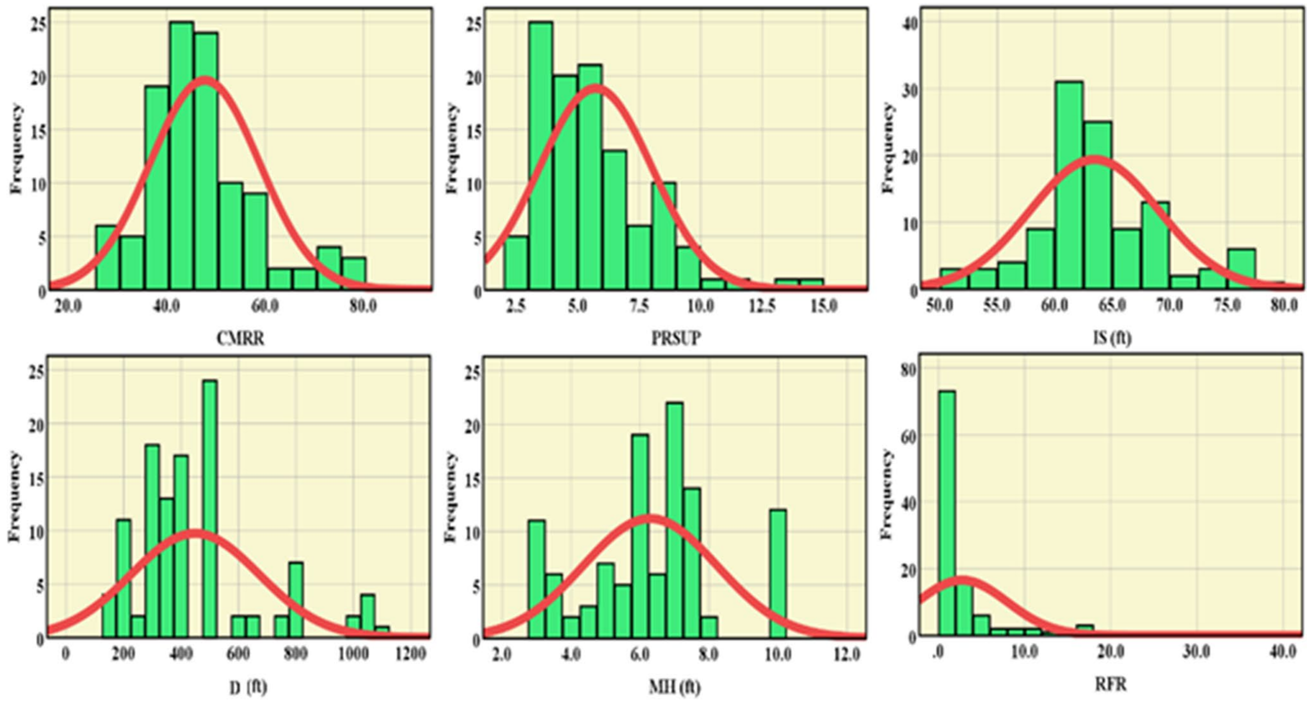


Fig. 3 Histogram chart illustrating input and output parameters

an increase in one variable corresponds with a decrease in another. Conversely, a positive correlation indicates a direct association, meaning that as one variable increases, the other also tends to increase. Understanding these correlations helps in comprehending how changes in input variables influence the model's output and can guide adjustments to improve model accuracy and performance. The strength of this correlation is essential for data analysis, where a high correlation (close to 1) suggests a strong connection between variables, and a low correlation (near zero) indicates a weak connection. Figure 4 illustrates the correlation between the input parameters (CMRR, PRSUP, IS, DOF, MH) and the output parameter (RFR). Although the correlations between the input parameters (CMRR, PRSUP, IS, DOF, MH) and the output parameter (RFR) were relatively weak, we proceeded with these parameters due to the complex and non-linear nature of underground mining environments. In such settings, weak correlations do not necessarily imply that the parameters lack predictive power. Advanced algorithms such as HS and IWO are specifically designed to handle noisy and weakly correlated data, enabling the detection of underlying patterns that traditional methods might overlook. This approach has been validated in previous studies where similarly weakly correlated parameters were used in predictive models, yielding robust results. For instance, Razani, Yazdani-Chamzini [49] has demonstrated that even in cases of weak correlations, intelligent algorithms can accurately model complex systems by considering non-linear relationships and multiple influencing factors.

This paper's primary objective can be conceptually divided into three fundamental processes: data processing, the division of data into two groups for training and testing, and model development and evaluation. For a clearer comprehension, this concept is diagrammatically presented in Fig. 5.

3 Advanced Algorithms Employed in This Study

3.1 The HS Algorithm

In 2001, Geem and his colleagues introduced the HS Algorithm to address complex engineering problems and optimize solutions [57]. This innovative algorithm is specifically designed for continuous space optimization. The algorithm takes inspiration from the process of creating music and seeking extraordinary harmonies within it.

In the musical context, the goal is to discover attractive and pleasing harmonies, analogous to the concept of harmony in music. Likewise, in engineering problems and optimization processes, the goal is to find the optimal solution based on a defined objective function. In music, the beauty of the produced harmony depends on the chosen notes, and similarly, the HS algorithm aims to produce a beautiful and

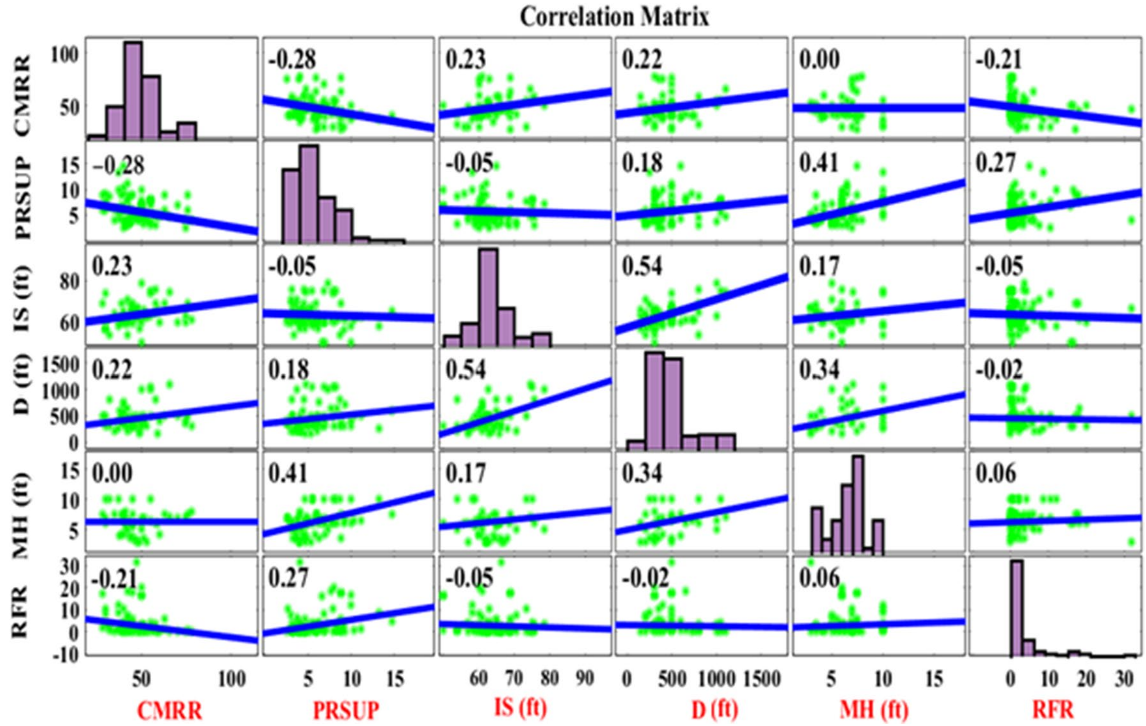
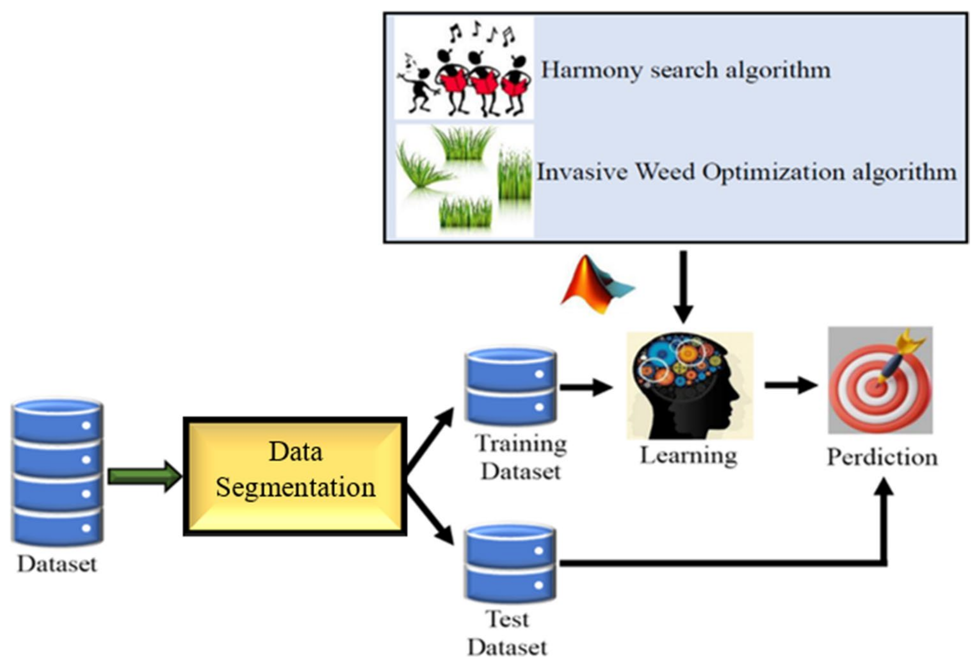


Fig. 4 Visualization of correlation between input and output parameters

Fig. 5 Flowchart demonstrating the process of building and testing the model



harmonious solution. Musicians, when creating music, strive to improve their previous harmonies, draw from past experiences, or venture into uncharted musical territory.

Musicians, during this creative process, can produce new harmonies even without prior experience. They may select any note within their allowed range, and when combined with other notes, this forms a harmony vector. If the produced harmony is favorable, it is stored in the musician's memory, increasing the likelihood of producing better harmonies in subsequent performances [58].

At the heart of the HS algorithm lies the "harmony memory," which contains a set of harmony vectors, each representing a musical composition. Each musical instrument, representing a decision variable, can select a note within its allowed range, and this contributes to a vector of harmonies. If the quality and beauty of this new harmony surpasses previous experiences, it is stored in the harmony memory (HM). The process of creating harmonies is repeated until an exceptional harmony is found in the memory.

To generate a new vector of variables, known as a harmony vector, the HS algorithm employs one of three rules:

A) Selecting a value from HM.
B) Selecting a value from the neighborhood of a HM value.
C) Randomly choosing a value for the variable from the allowed range (outside the HM).

In summary, the HS algorithm comprises five fundamental steps [57, 59]:

Step 1: Problem definition and algorithm parameter initialization, including defining the optimization problem, specifying the number of decision variables (N), setting their value ranges, determining harmony memory consideration rate ($HMCR$), pitch adjustment rate (PAR), bandwidth (bw), harmony memory size (HMS), and the algorithm's termination criterion (maximum number of iterations) (k).
Step 2: Beginning of the HM's construction. The memory is first filled with created vectors in a random fashion, with the number of vectors generated being equal to the size of the HM. Both the original HM and the values that correspond to the objective function are saved in the memory. The structure of the HM is represented by Eq. 2 [57].

$$HM = \begin{bmatrix} x_{1,1} & \cdots & x_{1,N} \\ \vdots & \ddots & \vdots \\ x_{HMS,1} & \cdots & x_{HMS,N} \end{bmatrix} \tag{2}$$

In Eq. 2, each row corresponds to an N-variable harmony, and HMS is the size of HM.

Step 3: Generating a New Harmony from the HM. In this step, a new harmony is created in the format of $x_1^{new}, x_2^{new}, \ldots, x_n^{new}$. This process is guided by three key rules: a) selection from memory, b) adjustment of the selected memory value, and c) random selection. Equation 3 outlines the implementation of these rules [57, 60–62]:

$$x_1^{new} = \begin{cases} x_i\prime = x\prime \in \{x_i^1, x_i^2, \ldots, x_i^{HMS}\} & with\ probabiliy\ HMCR \\ x_i\prime = x_i\prime \in x_i & with\ probabiliy\ (1 - HMCR) \end{cases} \tag{3}$$

Within the parameters of the permitted range of modifications, Eq. 3 selects one of the memory values with the probability of HMCR, while simultaneously generating a random value with the probability of (1-HMCR). In simpler terms, a random number is initially generated within the [0,1] range, and if it is less than HMCR, one of the values from memory is chosen. Otherwise, a random value is generated within the variable's change limits.

The HMCR value should be chosen within the range [0,1). An HMCR value of 1 leads to a localization of the problem into a local optimum. On the other hand, a value of 1-HMCR prevents the occurrence of local optima and promotes memory diversity. Any value selected from the memory can produce a new variable during a local search within its vicinity, governed by a radius of bw and the probability of PAR. When the selected value from the memory is used, it is directly incorporated into the new harmony without any alterations with a 1-PAR probability. The resulting value for each variable in the new vector is then checked to ensure it falls within the allowable range; otherwise, the nearest allowable value is substituted. Mathematically, the adjustment for each parameter can be expressed through the following relationship:

$$\begin{aligned} x_i\prime = x_i\prime \pm u(-1,+1) \times bw & \quad with\ probabiliy\ HMCR \\ x_i\prime = x_i\prime & \quad with\ probabiliy\ HMCR \times (1 - PAR) \end{aligned} \tag{4}$$

where u(-1, + 1) represents a uniform distribution ranging from -1 to 1, and bw signifies the bandwidth within an arbitrary and continuous interval. For a clearer understanding of these concepts, Fig. 6 provides a visual representation of how HMCR and PAR behave mathematically.

Step 4: Updating HM. In the event that the freshly generated harmony is superior to the quality of the least desirable harmony stored in the memory, the value of the associated objective function is replaced, and the harmony that is stored in the memory that is the least favorable is discarded.
Step 5: Repetition of the third and fourth steps continues until the algorithm reaches its defined termination condition. Generally, the algorithm's completion criterion is based on satisfying a specific condition or reaching the maximum number of iterations.

For the purpose of providing a concise description, Fig. 7 of the flowchart illustrates the entire operation of the HS algorithm.

3.2 IWO Algorithm

The IWO algorithm was conceived and introduced by Mehrabian and Lucasc in 2007, drawing inspiration from nature [63].

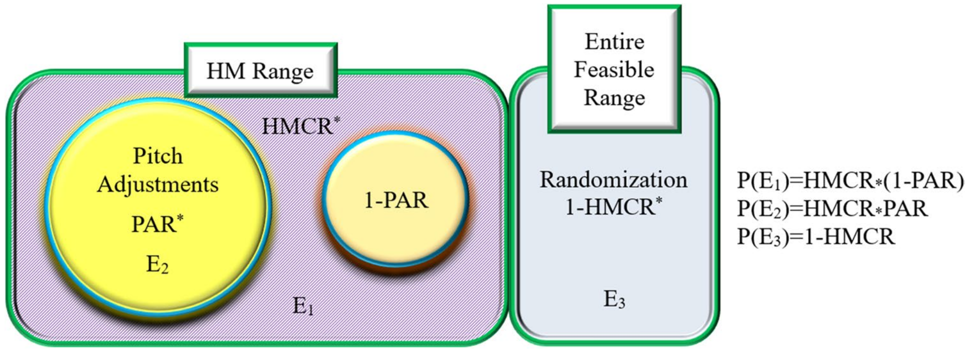


Fig. 6 Illustration of HMCR and PAR behavior [57]

In botanical terms, a weed is a plant that thrives in undesirable locations and poses a significant threat to crops, hindering their growth. This algorithm, although elegantly straightforward, is remarkably efficient and rapid in discovering optimal solutions. It leverages the fundamental and innate characteristics of weeds, such as survival competition within a colony. The algorithm's procedural steps are elucidated below.

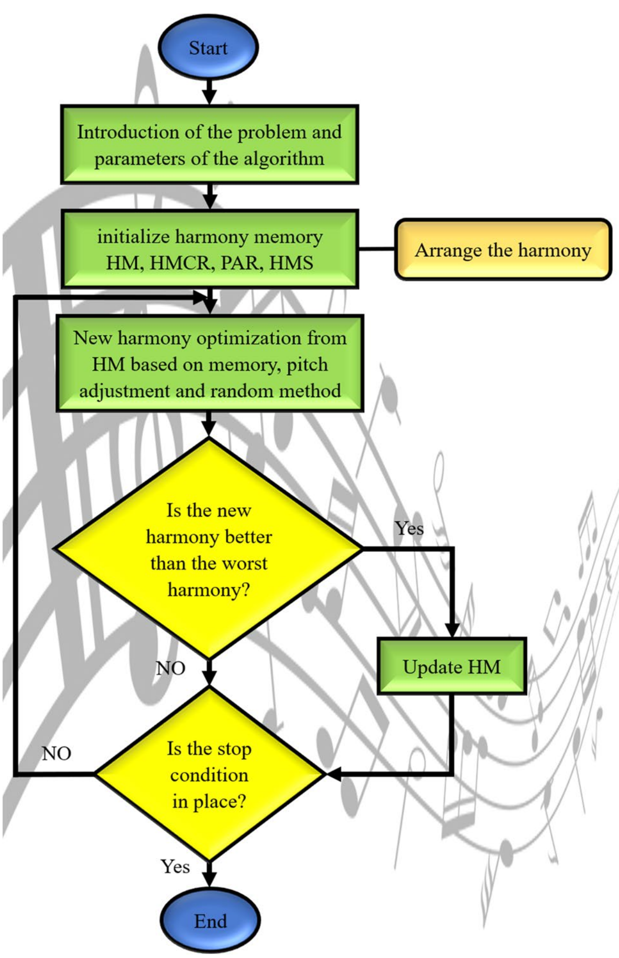


Fig. 7 Flowchart of the HS algorithm [57]

3.2.1 Determining the Initial Population and Reproduction

Initially, a limited population is created by randomly distributing individuals across the problem-solving space. After that, every individual in this population produces seeds in accordance with the specific capabilities that it possesses. The number of seeds each plant can produce follows a linear scale, ranging from the minimum to the maximum seed count. Weeds with superior adaptation produce a greater number of seeds. The relationship for seed production is expressed through the following equation:

$$Seed_n = \frac{f - f_{min}}{f_{max} - f_{min}}\left(S_{max} - S_{min}\right) + S_{min} \tag{5}$$

where $Seed_n$ represents the number of generated seeds, f denotes the current weed's compatibility, f_{max} and f_{min} signify the highest and lowest compatibilities within the current population. Additionally, S_{max} and S_{min} represent the maximum and minimum allowable seed production, respectively. A straightforward and understandable graphic representation of the linear relationship between seed production and compatibility is presented in Fig. 8 [63].

In this context, higher compatibility equates to the production of more seeds, facilitating swifter optimization and the attainment of the objective function. This is visually represented in Fig. 9.

3.2.2 Spatial Dispersion

During this phase, the generated seeds are dispersed randomly within the multidimensional problem space. While the distribution follows a normal function and has a value of zero for its average, the standard deviation of the distribution goes through a number of different stages of change. This method guarantees that the seeds, distributed randomly, stay closely located to their parent plants. The standard deviation (σ) value decreases progressively from its initial value ($\sigma_{initial}$) to the final value (σ_{final}) with each iteration. A mathematical expression that can be used to describe the

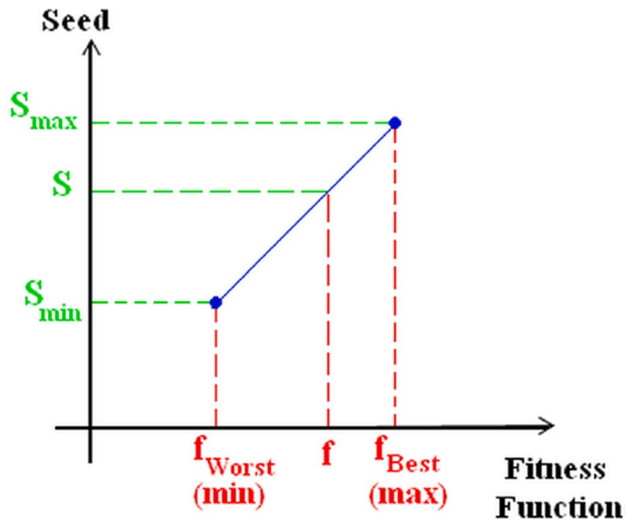


Fig. 8 Compatibility vs seed production relationship [63]

link between these parameters and the standard deviation is shown in Eq. 6:

$$\sigma_{iter} = \frac{\left(iter_{max} - iter\right)^n}{\left(iter_{max}\right)^n}\left(\sigma_{initial} - \sigma_{final}\right) + \sigma_{final} \tag{6}$$

In the provided equation, $iter_{max}$ denotes the maximum number of repetitions, σ_{iter} signifies the standard deviation value during the operational stage, and n represents the modulation nonlinearity index or the nonlinear oscillation index.

3.2.3 Competitive Elimination

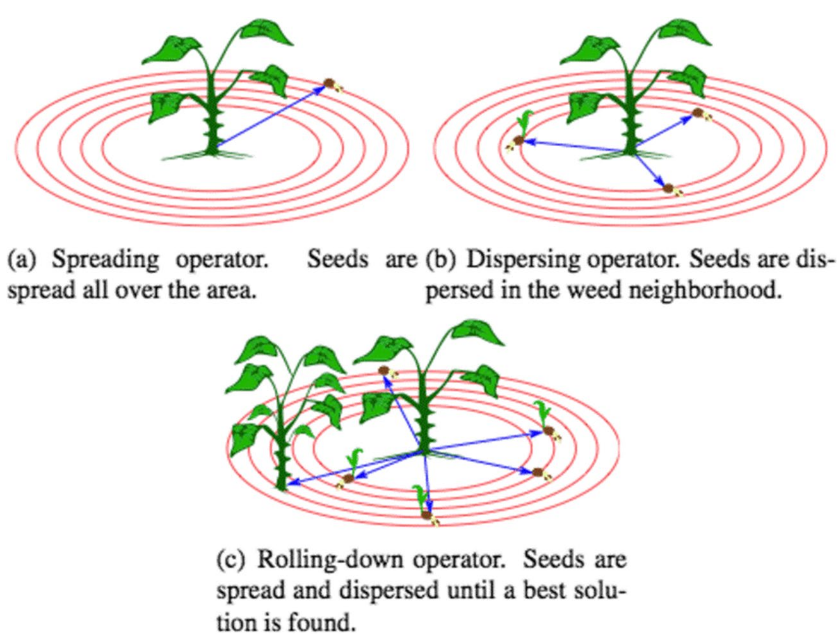
In the context of the Invasive Weed Algorithm, following multiple iterations, the seed count within the colony reaches its maximum threshold (P_{max}) through the process of reproduction. Once this threshold is met, a mechanism is initiated to cull the less robust seeds. After the maximum allowable seed count is achieved, each seed can give rise to new seeds, following the method outlined earlier, which are then dispersed across the problem space. After that, a score is assigned to each seed, and in the final stage, seeds that have received lower scores are trimmed in order to keep the seed population at its full potential. This process is repeated until the seeds gradually converge towards the seed that is ideal for the situation. In brief, Fig. 10 offers a visual depiction of the IWO algorithm's operational flow.

4 Predicting RFR Using HS and IWO Algorithms

As mentioned before, intelligent methods offer a potent alternative to traditional approaches, as they excel at constructing complex nonlinear models while accommodating variations in input parameters. Thus, this study leverages two robust algorithms, HS and IWO, to predict and estimate RFR in underground coal mines with minimal error and maximum accuracy.

For the modeling of RFR using HS and IWO algorithms, a substantial volume of data is essential to ensure

Fig. 9 Creating a new seed to achieve the objective function [64]



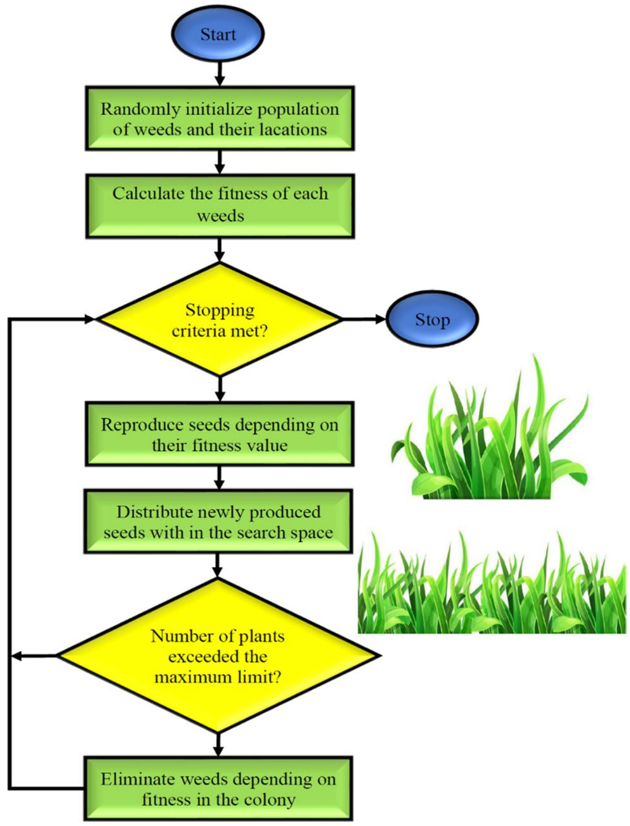


Fig. 10 Workflow of the IWO algorithm [63]

precision. As noted in the database section, this study utilizes 109 data points to model RFR. To yield accurate results, the data must be divided into two sets: training and testing. Specifically, 87 data points (equivalent to 80% of the dataset) are allocated to training and model construction, while the remaining 22 data points (20% of the dataset) are reserved for testing and validating the model.

Normalization of the input data is a critical step in the modeling process to ensure that all input data falls within a specific range. Normalization prevents outliers and ensures that the data is prepared for the development of an accurate model. Equation 7 illustrates the normalization process, transforming input data into the 0–1 range.

$$X_n = \left[\left(X_{mea} - X_{min}\right) / \left(X_{max} - X_{min}\right)\right] \tag{7}$$

In Eq. 7, the variables are defined as follows:

X_n: Represents the normalized data values.

X_{mea}: Stands for the real data values in their non-normalized and raw form.

X_{min}: Signifies the lowest data values.

X_{max}: Denotes the highest data values.

In this study, the initial form of the estimator function was derived from the theoretical foundations of the HS and IWO algorithms, which are designed to iteratively optimize complex, non-linear models. These algorithms aim to minimize the cost function by evaluating different parameter sets, allowing for the selection of the most accurate estimator. The equations were subsequently refined through a trial-and-error process to achieve optimal performance based on the model's training and testing data. This approach is consistent with similar studies in the field, where optimization algorithms like HS and IWO have been employed to handle multi-variable non-linear problems in rock mechanics and geotechnical engineering [65–69]. By following these methods, we ensured that the estimator function was optimized to minimize prediction error while accommodating the complexity of the dataset. As a result, Eq. 8 can be regarded as a highly effective model for predicting RFR, offering optimal performance based on the given data and the applied optimization techniques.

$$\begin{aligned} RFR = {} & 2\left(w_1 tan(CMRR)^{w_2}\right) - \left(w_3 tan(PRSUP)^{w_4}\right) \\ & - exp\left(w_5 tan(IS)^{w_6}\right) - \left(w_7 exp\left(tan(D)^{w_8}\right)\right) \\ & - \left(w_9 tan(MH)^{w_{10}}\right) - w_{11} \end{aligned} \tag{8}$$

where w_i represents weight variables evaluated by the HS and IWO algorithms. To quantify the model's performance, a performance function is expressed as Eq. 9.

$$F(v) = \sum_{i=1}^{m} \left(Y_{mea} - Y_{pre}\right)^2 \tag{9}$$

where:

Y_{mea} denotes the actual values.

Y_{pre} represents the estimated values obtained from the created model.

m signifies the number of data observations.

An essential consideration in constructing a highly accurate, low-error model is the examination of the hyper parameters for the HS and IWO algorithms. These parameters are user-defined and are determined through trial and error, akin to model construction. The values of these adjustment parameters for estimating RFR using HS and IWO algorithms are provided in Table 3.

Subsequently, following the formulation of the equation and the adjustment of algorithm parameters, the prediction model coefficients for estimating RFR using the HS and IWO algorithms are obtained through MATLAB software as represented by Eqs. 10 and 11. The created equations are created through trial and error and after building several difficult and complex models by the user.

Table 3 Setting parameters for HS and IWO algorithms

Algorithms	Parameters	Value
HS algorithm	Maximum Number of Iterations	3000
	Pitch Adjustment Rate	0.19
	HM Consideration Rate	0.9
	Number of New Harmonies	50
	Bandwidth	0.01
	HMS	60
IWO algorithm	Maximum iterations	3000
	Initial population size	15
	Maximum population size	100
	Final value of standard deviation	0.05
	Maximum number of seeds	25
	Initial value of standard deviation	1.5
	Minimum number of seeds	0
	Variance reduction exponent	8

Also, the parameters have been completely optimized by coding done in MATLAB environment and optimizing the model

$$RFR = 2\left(-0.0423\tan(CMRR)^{0.4478}\right) - \left(-0.2172\tan(PRSUP)^{0.9998}\right) - exp\left(0.2132\tan(IS)^{1.227e-10}\right) - \left(-0.1230exp\left(\tan(D)^{0.0199}\right)\right) - \left(0.0147\tan(MH)^{1.0211}\right) + 0.9977 \quad (10)$$

$$RFR = 2\left(-0.2493\tan(CMRR)^{0.3998}\right) - \left(-1.1102\tan(PRSUP)^{1.0101}\right) - exp\left(-0.1852\tan(IS)^{-9.117e-8}\right) - \left(-0.095exp\left(\tan(DOF)^{0.0519}\right)\right) - \left(1.2147\tan(MH)^{2.5211}\right) + 1.0905 \quad (11)$$

An important point that should be mentioned is that in this article, due to the division of data into two groups of training and testing, cross-validation of data, large amount of data, having a stop condition in coding, data ordering, overfitting has been prevented.

5 Model Validation

In this study, the performance of the models developed using the HS and IWO algorithms was evaluated and validated using key statistical metrics, namely MSE (Mean Squared Error), R^2 (Coefficient of Determination), and RMSE (Root Mean Squared Error). Equations 12 through 14 provide the definitions for these statistical indicators. Within these equations, Y_{mea} represents the actual values, Y_{pre} represents the estimated values, and 'n' represents the number of data points used to assess the model [70–78].

Table 4 Model validation results for HS and IWO algorithms in training and testing phases

Algorithm	Description	R^2	MSE	RMSE
HS	Train	0.9517	1.22	1.10
	Test	0.9712	1.11	1.03
IWO	Train	0.9398	1.4887	1.2201
	Test	0.9637	1.3011	1.1406

$$R^2 = 1 - \frac{\sum_{k=1}^{n}\left(Y_{mea} - Y_{pre}\right)^2}{\sum_{k=1}^{n}\left(Y_{mea}^2\right) - \frac{\sum_{i=1}^{n} Y_{pre}^2}{n}} \quad (12)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{mea} - Y_{pre}\right)^2 \quad (13)$$

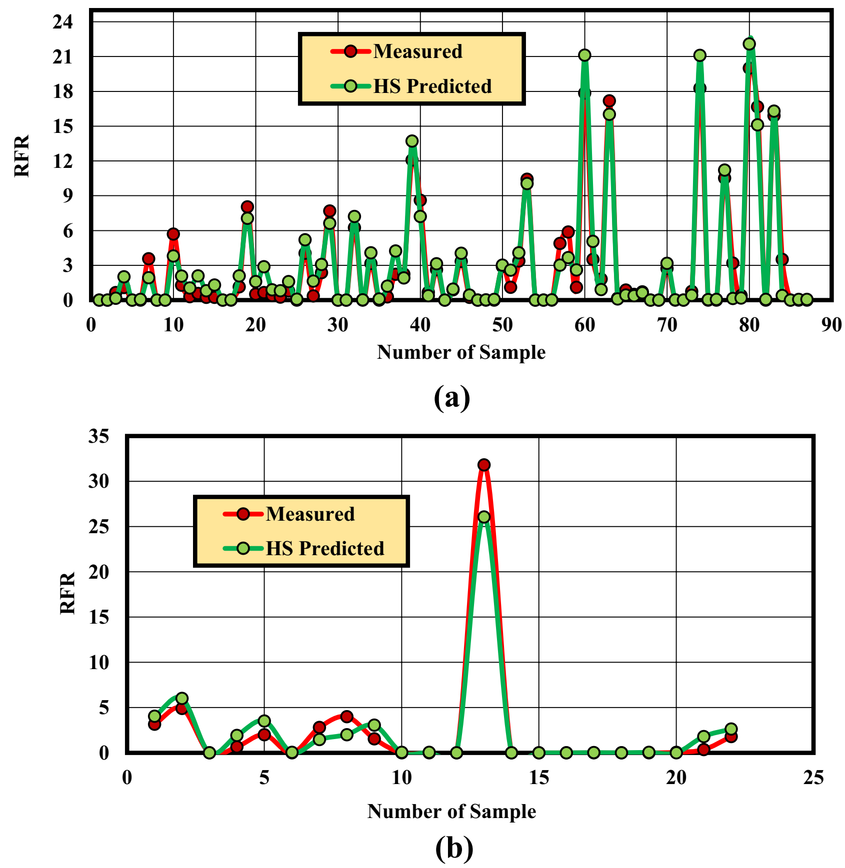
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{mea} - Y_{pre}\right)^2} \quad (14)$$

According to the interpretation of these statistical indicators, when R^2 values approach 1 and MSE and RMSE values approach zero, it signifies a model's high accuracy and low error. Table 4 presents the values of these statistical indices (R^2, MSE, and RMSE) for the RFR estimation models developed using the HS and IWO algorithms during both the training and testing phases.

Table 4 underscores the high accuracy and low error nature of the models designed for estimating and predicting RFR through the application of HS and IWO algorithms. To visually represent this aspect, Figs. 11 and 12 offer a comparative analysis of actual and predicted values produced by the models created by the HS and IWO algorithms during both the training and testing phases.

Figures 11 and 12 reveal a remarkable proximity between the actual data values and those predicted by the models. This demonstrates that the values of real data and the data generated by the models are closely aligned. In other words, the HS and IWO algorithms, with relatively minimal time and cost, can construct intricate non-linear equations that closely mirror field test results. Consequently, the prediction model emerges as an indirect yet highly effective approach for accurately estimating the RFR. It is important to note that if geological and geotechnical conditions closely resemble those in this study, the established model can be applied to similar investigations. In different geological conditions

Fig. 11 Comparative evaluation of actual and predicted RFR using the HS algorithm: (**a**) training phase, (**b**) testing phase



similar to the article, the same method can be adapted to other research studies by using HS and IWO algorithms and other intelligent algorithms, comprehensive analysis.

6 Sensitivity Analysis (SA)

The challenges encountered in the realm of rock engineering problems are typically multifaceted, involving a multitude of parameters to be addressed and optimized. Consequently, the utilization of the SA method proves to be a highly practical and comprehensive approach, offering engineers a deeper insight into the influencing factors of the model. The SA empowers industrialists and engineers to ascertain the extent to which input parameters affect the model's output. This method entails systematically and randomly altering a single input parameter while holding all other variables constant. By employing this process, it becomes possible to deduce the impact of the modified parameter on the model's output. This process is iterated for all input parameters until those with the most pronounced influence on the model’s output are identified. Given the intricate nature of evaluating and estimating RFR, SA, and the identification of pivotal parameters in effectuating the model’s output take on a pivotal role in understanding the model.

To put it succinctly, SA enables engineers and researchers to gauge the resilience of the model in response to changes in each individual input parameter. The ultimate objective of this analysis is to rank and prioritize input parameters according to their impact on the RFR model’s output, from the most influential to the least. In this research, which pertains to a highly intricate model, SA was executed on models crafted by both the HS and IWO algorithms. To attain this objective, @RISK software was employed to prioritize the input parameters, including CMRR, PRSUP, IS, D, and MH, based on their influence on the RFR model’s output.

The outcomes of the SA on the models developed by the HS and IWO algorithms are depicted in Figs. 13 and 14, respectively. As evident from the results generated by the @ RISK software, the CMRR parameter exerts the most substantial influence on the RFR model’s output. In essence, minute adjustments in the CMRR parameter result in the most significant alterations in the model's output. Hence, the CMRR parameter can be characterized as exceptionally sensitive and is rightly dubbed a pivotal parameter. Given this, engineers and researchers are advised to accord special attention to the CMRR parameter. An intriguing observation is that, in both models developed by the HS and IWO algorithms, the CMRR parameter is emphasized by being highlighted and bolded. In conclusion, understanding the pivotal

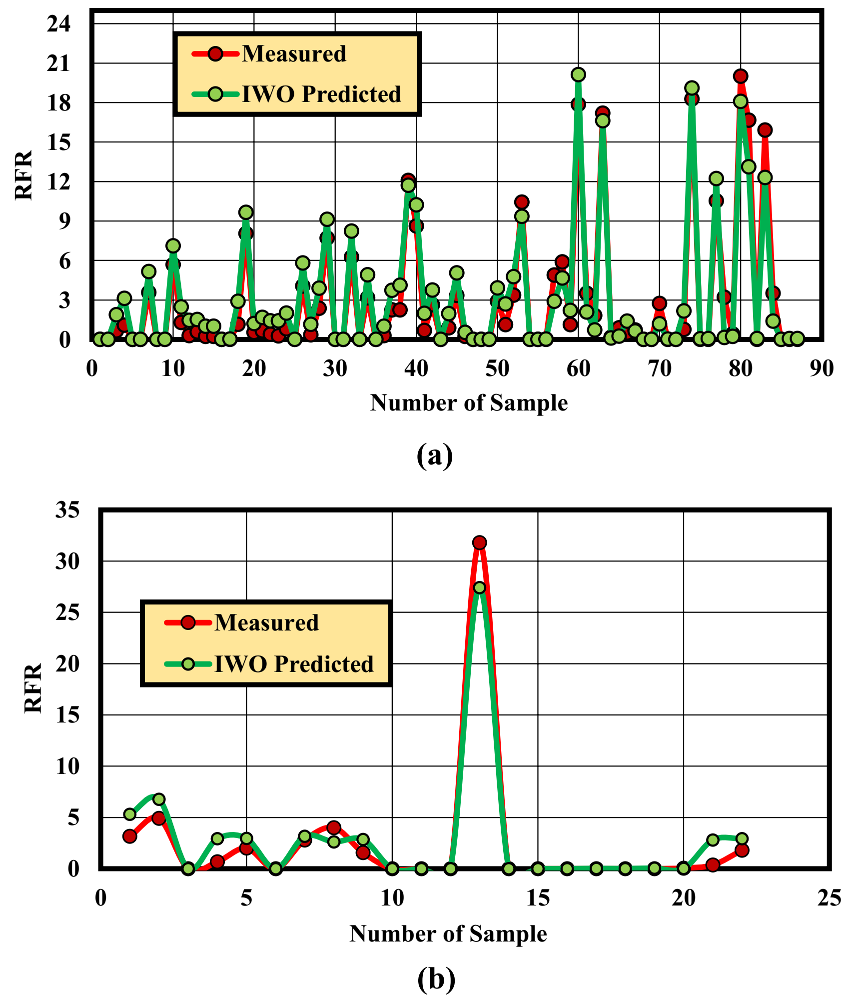


Fig. 12 Comparative evaluation of actual and predicted RFR using the IWO algorithm: (**a**) training phase, (**b**) testing phase

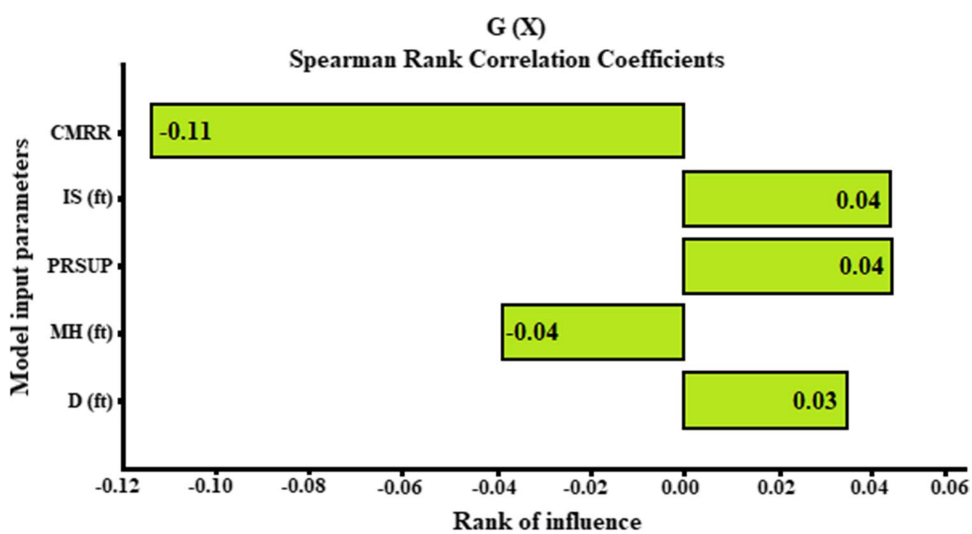


Fig. 13 The SA results using the HS algorithm

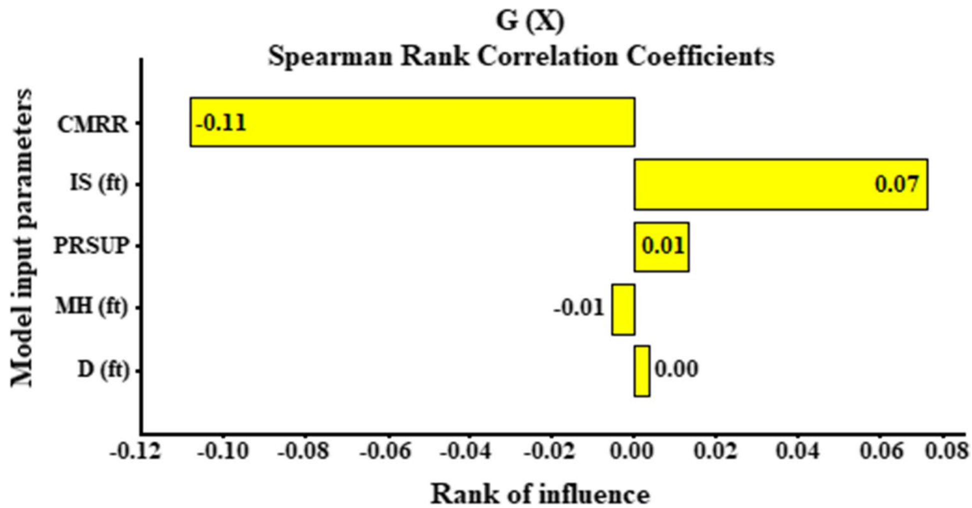


Fig. 14 The SA results using the IWO algorithm

parameter's role in the model can significantly enhance project accuracy and performance.

7 Discussion and Conclusions

Mining, particularly underground coal mining, is an inherently hazardous industry, posing significant threats to the safety and well-being of miners. Roof collapses in these mines have become a major concern for mining engineers, necessitating a deep understanding of the factors that contribute to such incidents. To effectively reduce workplace hazards, a comprehensive understanding of the main variables that contribute to roof collapse is essential. The use of conventional methods to calculate Roof Fall Risk (RFR) in coal mines faces challenges due to inherent uncertainty and variability in rock properties that further complicate these issues. This study introduces the use of intelligent algorithms as a promising solution to this problem, serving as a reliable tool to predict and address challenges related to rock mechanics and geotechnical structures while accommodating uncertainties and inherent variations in rock properties.

The HS and IWO algorithms were employed in this research to build a robust model that not only considers the inherent uncertainties associated with rock properties but also minimizes the time and cost associated with predicting roof collapse rates in underground coal mines. This model was developed using 109 data points, with input variables including CMRR, MH, D, PRSUP, and IS. Of these data, 87 (or 80%) were allocated for model building using the RES approach, while the remaining 22 data points (20%) were reserved for model evaluation and validation. The performance of the models built with HS and IWO algorithm approaches was evaluated using statistical criteria such as MSE, R^2, and RMSE. The findings demonstrated that the HS and IWO algorithm-based methods have a highly favorable performance in predicting roof collapse rates, making the model viable for operational projects. The insights derived from this research reveal significant implications for rock engineering. For instance, using intelligent algorithms, engineers can estimate the amount of roof collapse in underground mines and assess the stability of various underground spaces. This leads to informed decision-making, simplifies mining and construction operations in terms of timing and budget compliance, and enhances the stability of rock structures. Following the results, the study identifies the CMRR parameter, analyzed using @RISK software, as the most effective in shaping the model's output. CMRR emerges as a pivotal parameter for engineers and researchers, where even minor changes can significantly impact results and outputs. Consequently, this study underscores the importance of focusing on the CMRR parameter to ensure the stability of underground coal mines.

The application of these intelligent methods in stone structures holds the potential for fundamental improvements in mining engineering, geotechnics, and rock mechanics. These methods can overcome the limitations of traditional approaches and provide engineers and practitioners with precise and practical tools. The insights and results presented in this paper can serve as a valuable resource for mining engineers and industry stakeholders, ultimately enhancing the safety, efficiency, and cost-effectiveness of mining and construction operations. Intelligent algorithms are not only effective in the accurate prediction of RFR in stone structures but also present a cost-effective and uncertainty-accounting alternative to traditional regression analysis methods. Their versatility allows for their use in various rock engineering projects, ensuring accuracy, reducing errors, and enabling successful project completion within set timeframes. This highlights their significance as a preferred approach over conventional methods, particularly when dealing with different types of rocks or geological conditions.

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Data Availability All data and models generated or utilized during the study are included in the published paper, and the code generated or used during the study can be obtained from the corresponding author upon request.

Declarations

Ethical Approval None of the authors conducted studies involving human participants or animals for this paper.

Informed Consent Informed consent was obtained from all individual participants included in the study.

Conflict of Interest The authors declare no competing interests.

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