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Performance prediction of Roadheaders using Support Vector Machine (SVM), Firefly Algorithm (FA) and Bat Algorithm (BA)

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Abstract
Roadheaders play a crucial role in the excavation processes of tunnels and mines, offering efficient and precise cutting capabilities. The performance prediction of a roadheader is essential for optimizing operations and ensuring project success. By understanding the various factors that influence performance, implementing predictive models, and continuously improving machine design and operational strategies, the potential of roadheaders can be maximized. This article delves into the intricacies of performance prediction for roadheaders, exploring methods, case studies, challenges, and future directions in this critical aspect of tunneling and mining operations. The primary objective of this study is to develop models that can predict the Instantaneous Cutting Rate (ICR), which is defined as the production rate during the actual cutting period (measured in tons or cubic meters per cutting hour), based on the properties of the rock formations being excavated as well as machine parameters. In this research, the Instantaneous Cutting Rate of roadheaders at the Tabas coal mine was analyzed by examining the characteristics of both the rock and the machinery involved. Additionally, this study employed Firefly Algorithm (FA), Bat Algorithm (BA) and Support Vector Machine (SVM), which were assessed using coefficient of determination (R^2), root mean square error (RMSE), mean squared error (MSE) and mean absolute error (MAE).The obtained results for Firefly Algorithm (FA) are found to be as R^2 = 0.9104, RMSE = 0.0658, MSE= 0.0043 and MAE= 0.0039, for Bat Algorithm (BA) are found to be as R^2 = 0.9421, RMSE = 0.0528, MSE= 0.0027 and MAE= 0.0024, and for Support Vector Machine (SVM) are found to be as R^2 = 0.8795, RMSE = 0.0762, MSE= 0.0058 and MAE= 0.0052, respectively. It can be concluded that while predictive models produce satisfactory results, the Bat Algorithm (BA) demonstrates a higher level of precision and realism in its outcomes.

Keywords:
performance prediction, roadheaders, instantaneous cutting rate, firefly algorithm, bat algorithm

1. Introduction

In certain contexts, mechanical or mechanized excavation presents a viable alternative to conventional excavation and blasting techniques, with a notable increase in its application for the development of underground spaces in contemporary practices (**Aydan et al., 2014**). Mechanized methods offer several advantages over traditional approaches, including enhanced excavation speed, improved production efficiency, greater safety, and reduced need for supplementary excavation, lower maintenance requirements, and decreased personnel demands. Among the various mechanized excavation equipment, roadheaders demonstrate significant effectiveness in handling rocks with low to medium resistance (**Kahraman et al, 2017**). This capability, combined with techniques such as Partial-face Excavation and Selective Excavation, has contributed to the widespread adoption of these machines in both mining and tunneling operations. The primary objective of implementing mechanized excavating systems within the construction and mining sectors is to supplant the traditional methods of excavation and blasting with a more efficient and continuous approach (**Teymen, 2021**). This transition aims to enhance the accuracy, speed, and cost-effectiveness of excavation operations, thereby improving overall production efficiency. Additionally, the adoption of such systems leads to a decrease in maintenance requirements and a reduced need for labor personnel (**Ulusay et al., 2014**). These benefits, coupled with recent advancements in equipment performance and machine reliability, have resulted in an increasing market share for miners utilizing mechanized systems in the mineral products industry (**Rostami et al, 2024**). Consequently, accurately forecasting the performance of these devices is crucial, as it directly influences production rates, accelerates operations, and ultimately enhances project profitability. Roadheaders offer significant advantages, including enhanced productivity, reliability, mobility, flex-

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ibility, safety, selective excavation capabilities, reduced strata disturbances, a smaller workforce, and lower capital and operational expenses. To realize these advantages and ensure the effective application of roadheaders, it is essential to accurately predict the machine's performance. This process typically involves considerations related to machine selection, production rates, and pick (bit) consumption.

The selection of the machine is based on the dimensions of the tunnel and the geological conditions, including the size and shape of the profile, the condition of the floor material (in terms of its resistance to the machine's weight and ground pressure), and the slope, among other factors. Furthermore, performance prediction primarily focuses on evaluating the Instantaneous Cutting Rate (ICR), which is defined as the production rate during the actual cutting period (measured in tons or cubic meters per cutting hour), and the Pick Consumption Rate (PCR), which indicates the number of picks replaced per unit volume or weight of rock excavated (expressed as picks per cubic meter or cubic meters per pick). Mechanical excavation of rocks and coal is extensively utilized globally. Since the 1960s, roadheaders have been frequently employed for rock excavation in both tunnel and roadway projects within the mining sector. Roadheaders represent sophisticated excavation equipment that is extensively utilized in both tunneling and mining activities, primarily owing to their high efficiency and accuracy. The ability to forecast the performance of roadheaders is vital for the optimization of project schedules and financial expenditures. This article examines the multiple elements that affect roadheader performance, approaches for precise prediction, techniques for data gathering and analysis, practical case studies that highlight successful implementations, as well as the challenges and prospective developments within this domain. A comprehensive understanding of the complexities involved in predicting roadheader performance is critical for improving project results and fostering advancements across the industry (**Guo et al., 2024**). Evaluating the performance of a roadheader is crucial for effective planning and accurate cost estimation when undertaking tunnel or roadway projects. Numerous researchers have proposed predictive models to assess the performance of roadheaders, **Table 1** presents a selection of these models. In the present study, a novel approach for predicting the performance of roadheaders is proposed to improve the accuracy of statistical analysis results. This paper aims to develop new models for roadheader performance prediction specifically in the Tabas coal mine, employing advanced techniques such as Support Vector Machine (SVM), Firefly Algorithm (FA), and Bat Algorithm (BA). The incorporation of optimization algorithms in this research is motivated by the necessity to identify solutions that adhere to specific constraints and address the problem at hand. Although the potential solutions to the problem may be numerous, optimization algorithms are designed to identify the most optimal solution.

Table 1. Roadheader performance prediction models

Author	Model
Gehring (1989)	$ICR = \frac{719}{\sigma_c^{0.78}}$ $ICR = \frac{1739}{\sigma_c^{1.13}}$
Bilgin et al. (1990)	$ICR = 0.28P(0.974)^{RMCI}$ $RMCI = \sigma_C \left(\frac{RQD}{100}\right)^{2/3}$
Rostami et al. (1995)	$ICR = k\frac{P}{SE_{opt}}$
Copur et al. (1998)	$ICR = 27.511e^{0.0023RPI}$ $RPI = \frac{PW}{\sigma_C}$
Thuro and Plinninger (1999)	$ICR = 75.7 - 14.3\ln(\sigma_C)$
Balci et al. (2004)	$ICR = k\left[P/(0.37UCS^{0.86})\right]$ $ICR = k\left[P/(0.41UCS^{0.67})\right]$
Tumac et al. (2007)	$ICR = 81.21SH^{-0.78}$ $ICR = 109.25\sigma_C^{-0.72}$
Ocak and Bilgin (2010)	$ICR = 510588\sigma_C^{-2.1779}$
Ebrahimabadi et al. (2011)	$ICR = 30.75RMBI^{0.23} RMBI =$ $= e(UCS/BTS)(RQD/100)^3$
Abdolreza and Yakhchali (2013)	$ICR = 1.759UCS + 0.501\alpha +$ $+ 0.636RQD - 4.839BTS - 22.127$
Kahraman and Kahraman (2016)	$ICR = -2.92I_s - 0.79A_w + 22.95$
Kahraman et al. (2019)	$NCR = -8.58\ln\ln NPI + 55.06$

2. Materials and methods

Optimization algorithms employ a methodical approach to identify the best solution for a specified problem. This is achieved through a repetitive examination of the search space. Typically, these algorithms utilize mathematical methods, and the solutions they produce may be either deterministic or probabilistic. Selecting the appropriate objective function is a critical step in the implementation of optimization algorithms. In certain cases, multiple objectives may be addressed concurrently within the optimization framework; these scenarios are referred to as multi-objective problems (**Kaur et al., 2019**). A common approach to tackle such challenges involves constructing a new objective function as a linear combination of the original objectives, where the significance of each function is dictated by the weights assigned to them. Each optimization problem comprises several independent variables, known as design variables. The goal of the optimization process is to identify the design variables that will either minimize or maximize the objective function (**Jawed and Sajid, 2022**).

Optimization algorithms serve as vital instruments in addressing intricate challenges across a multitude of sectors and fields. These algorithms are specifically crafted to identify the most advantageous solution from a collection of viable options, thereby rendering them indispensable for enhancing efficiency and reducing expenses. This article investigates various categories of optimization algorithms, their practical applications in real-world contexts, the essential elements that underpin their operation, and the approaches used to assess their effectiveness. Furthermore, it explores the obstacles encountered by these algorithms and highlights emerging trends that are influencing the evolution of optimization methodologies.

Optimization algorithms are diverse in nature, each designed to tackle particular categories of problems. Notable examples include genetic algorithms, simulated annealing, particle swarm optimization, and linear programming. These algorithms utilize mathematical frameworks and computational methods to progressively refine solutions until an optimal result is achieved. In practical scenarios, optimization algorithms find applications across various sectors, including finance, logistics, engineering, and healthcare, where they serve to optimize processes, allocate resources effectively, and improve decision-making. A comprehensive understanding of the mechanisms underlying these algorithms and their real-world applications is crucial for professionals aiming to harness their advantages in addressing complex problems and enhancing decision-making processes (**Jawed and Sajid, 2022**).

2.1. Firefly Algorithm

The Firefly Algorithm represents a metaheuristic optimization approach that draws inspiration from the intriguing behaviors exhibited by fireflies in their natural environment. Utilizing the concepts of light intensity and attraction, this algorithm has garnered significant attention for its efficacy in identifying optimal solutions across a range of fields. This article aims to explore the core principles, operational mechanisms, applications, benefits, and comparative analyses of the Firefly Algorithm, thereby offering a thorough insight into this novel optimization technique. As scholars persist in investigating the possible applications of the Firefly Algorithm, its flexibility and adaptability are becoming increasingly apparent (**Yang, 2009**). The capacity of the algorithm to adeptly traverse intricate optimization terrains has established it as an essential resource in disciplines including engineering, finance, and data science. By leveraging the principles of light intensity and attraction, the Firefly Algorithm presents a distinctive methodology for addressing problems, which consistently captivates and motivates researchers globally. As investigations into the possible uses of the Firefly Algorithm progress, its flexibility and adaptability are becoming increasingly apparent. The Firefly Algorithm employs a novel strategy that draws inspiration from the natural behaviors exhibited by fireflies, particularly their distinctive flashing patterns, to facilitate the optimization process (**Kumar et al., 2018; Rajan and Malakar, 2015**). This biologically inspired technique enables the exploration of a broad spectrum of solutions, leading to the identification of optimal results across various contexts. Its capacity to adapt and evolve in response to changing conditions distinguishes the Firefly Algorithm as a versatile and powerful instrument for addressing intricate optimization problems (**Gandomi et al., 2011**).

The Firefly Algorithm draws its inspiration from the social behavior exhibited by natural fireflies that congregate in sizable groups, and it is recognized as one of the most effective algorithms for addressing combinatorial optimization challenges (**Gandomi et al., 2011**). Various algorithms derive from the firefly algorithm, all of which operate as multi-agent systems wherein the agents emulate artificial fireflies, mirroring the behavior of their natural counterparts. The firefly algorithm exemplifies collective intelligence, demonstrating that agents with limited individual capabilities can collaborate effectively to attain impressive outcomes (**Rokh et al., 2024**). The flowchart of FA is shown in **Figure 1**.

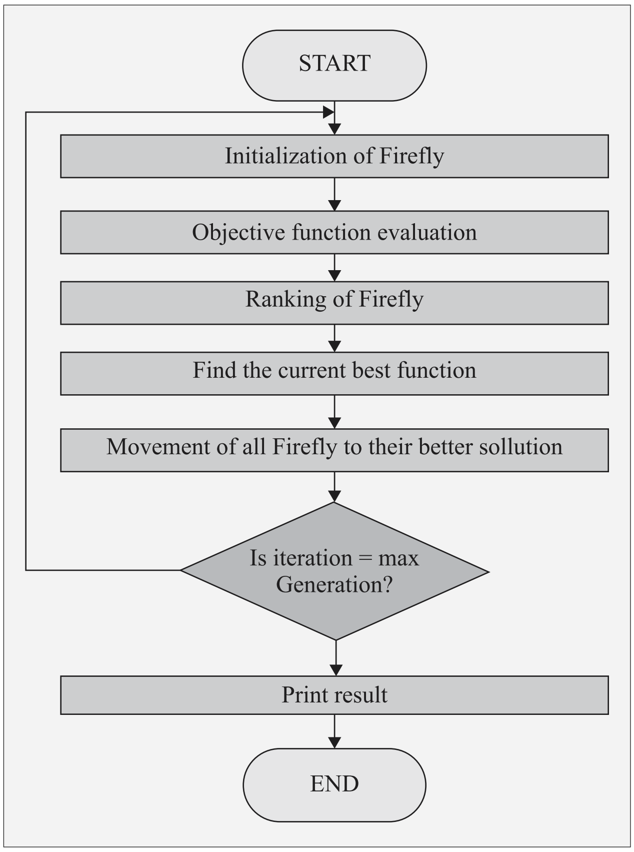

Figure 1. The flowchart of FA (**Kumar et al., 2018; Rajan and Malakar, 2015**)

The Firefly Algorithm (FA) seeks to identify the optimal solution by simulating the behavior of a group of fireflies. Each firefly is assigned a value that reflects the fitness of its position, which serves as a representation of the concentration of firefly pigments. The algorithm updates the positions of the fireflies through successive iterations. Specifically, each iteration consists of two primary phases: the pigment updating phase and the movement phase. During the movement phase, fireflies are attracted to their neighbors that exhibit a higher concentration of pigments. Consequently, through repeated iterations, the collective group of fireflies converges towards a more optimal solution (**Khan et al., 2016**). This algorithm represents an innovative approach grounded in collective behavior, drawing inspiration from the social interactions observed among fireflies in their natural environment. In the firefly algorithm, the search mechanism involves a comparative analysis among all fireflies. When a firefly emits less light than another, it is compelled to move towards the brighter one. This behavior results in a clustering effect around the firefly that emits more light. In subsequent iterations of the algorithm, if a firefly with greater luminosity is present, the other fireflies will again be drawn towards it. The search process is defined by a predetermined maximum number of iterations (**Kumar and Kumar, 2021**). In this algorithm, the optimization process initiates randomly by distributing a population of n fireflies across various locations within the search space. Initially, each firefly possesses an identical quantity of luciferin, denoted as l. Each iteration of the algorithm comprises two distinct phases: one for updating the luciferin levels and another for adjusting the positions of the fireflies. The amount of luciferin of each worm in each repetition is determined according to the fitness value of that worm's location (**Wang, 2024**). In this way, in each iteration, according to the amount of elegance and in proportion to that, an amount is added to the current Luci Frain of the cream. In addition, in order to model the gradual decline with time, a value of the current Luciferin is reduced by a factor less than 1. In this way, the relationship of updating Lucy Frein is presented as follows:

$$l_j\left(t+1\right)=\left(1-\rho\right)l_j\left(t\right)+\gamma^{J_j(t+1)} \tag{1}$$

Where $J(x_i(t)$, $l_{i(t-1)}$, $l_i\left(t\right)$ represents the new luciferin value, the prior luciferin value, and the fitness associated with the position of worm i during iteration t of the algorithm. The parameters ρ and γ are constants that are utilized to simulate the gradual decrease and the influence of fitness on the luciferin dynamics.

In the movement phase, each worm probabilistically advances toward a neighboring worm that exhibits a higher lucy frein (**Gandomi et al., 2013**). This mechanism facilitates the worms' tendency to gravitate toward those neighbors that possess greater luminosity. For each firefly i, the likelihood of transitioning to the more luminous neighbor j is articulated as follows:

$$P_j(t)=\frac{l_j\left(t\right)-l_i\left(t\right)}{\sum_{k\in N_i(t)}l_k\left(t\right)-l_i\left(t\right)} \tag{2}$$

Where $N_i(t)$ represents the set of fireflies neighboring firefly i at time t, if it is assumed that firefly j is chosen by firefly i (with a probability p derived from **Equation 2**), the motion equation of the firefly in a time-discrete format can be expressed as follows:

$$x_i\left(t+1\right)=x_i\left(t\right)+s\left(\frac{x_j\left(t\right)+x_i\left(t\right)}{\parallel x_j\left(t\right)-x_i\left(t\right)\parallel}\right) \tag{3}$$

Where $x_i\left(t\right)$ is the next m vector of firefly i›s location at time t, ||.|| represents the Euclidean smooth operator and s is the step size of the movement. Assuming r_0 as the initial neighborhood range for each firefly, the range of each firefly›s neighborhood is revised in accordance with **Equation 4**.

$$r_d^i\left(t+1\right)=\min\left\{r_s,\max\left\{0,r_d^i\left(t\right)+\beta\left(n_t-\left|N_i\left(t\right)\right|\right)\right\}\right\} \tag{4}$$

Where β is a constant parameter and n_t is a parameter to control the number of neighbors.

2.2. Bat Algorithm (BA)

The bat algorithm is founded on the echolocation capabilities exhibited by microbats. Approximately 1,240 distinct species of bats exist, collectively representing 20% of all mammalian species. The echolocation mechanism employed by smaller bats functions as a sophisticated perceptual system, wherein ultrasonic waves are emitted to capture echoes. By analyzing the emitted and returned waves, the bat's brain and nervous system are capable of constructing a detailed representation of its environment (**Alsalibi et al., 2021**). This remarkable ability enables microbats to locate their prey even in complete darkness. The sound intensity generated by these bats reaches 130 dB, utilizing frequencies ranging from 15 kHz to 200 kHz for hunting purposes, in contrast to the human auditory range of 20 Hz to 20 kHz. To accurately interpret the information gathered, bats must distinguish their own emitted sounds from the echoes they receive (**Boudjemaa et al, 2020**). Microbats employ two primary techniques to achieve this differentiation: one involves echo detection through short time intervals, allowing these bats to discern their emitted sounds based on timing relative to the reflected sounds. Echolocation utilizing extended periodic cycles: these bats emit a continuous sound while differentiating between pulses and echoes through frequency modulation. They possess the ability to adjust the pulse of any emitted frequency in accordance with their flight velocity. Consequently, the echoes received remain within the appropriate auditory range. The Bat Algorithm, which draws inspiration from the echolocation abilities of bats, has established itself as a significant metaheuristic optimization method within the realm of computational in-

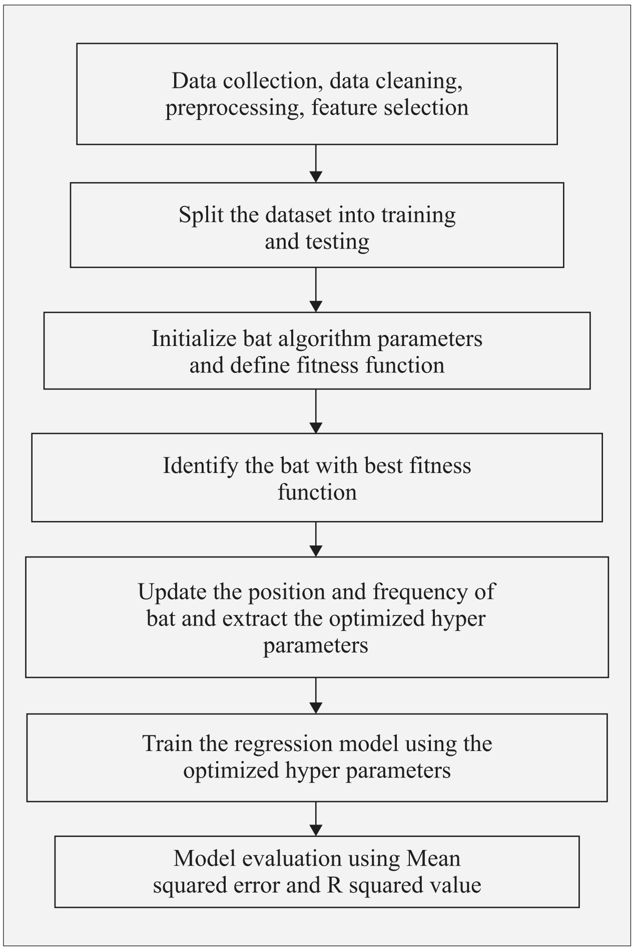

Figure 2. The flowchart of BA (**Maity, 2023**)

telligence. This article offers a thorough examination of the Bat Algorithm, detailing its development, clarifying its algorithmic structure and operational principles, exploring its wide-ranging applications in different fields, assessing its effectiveness in comparison to other optimization algorithms, and contemplating future advancements and research opportunities. By investigating the theoretical underpinnings and practical applications of this groundbreaking algorithm, readers will acquire a detailed insight into its functionalities and its potential influence on addressing intricate optimization challenges (**Alsalibi et al., 2021**). The flowchart of BA is shown in **Figure 2.**

The Bat Algorithm represents an innovative methodology that draws inspiration from the natural behaviors exhibited by bats to effectively identify optimal solutions. By emulating the echolocation techniques employed by bats to detect their prey, this algorithm provides a fresh perspective on problem-solving, demonstrating significant efficacy across various practical applications. Through an integrated approach that balances exploration and exploitation, the Bat Algorithm exhibits adaptability and evolution, rendering it a flexible instrument for addressing a diverse array of optimization problems. Its growing prominence in the optimization domain can be attributed to its capacity to adeptly navigate intricate problem landscapes and swiftly converge on optimal solutions by harnessing the distinctive behaviors of bats.

The Bat Algorithm's novel approach to addressing challenges has rendered it an indispensable resource across multiple sectors, including engineering and finance, where the identification of optimal solutions is essential for achieving success. This algorithm not only excels in discovering the best possible outcomes but also provides a distinctive viewpoint on the problem-solving process. By emulating the natural echolocation techniques of bats, the Bat Algorithm exemplifies the significance of adaptability and creativity in overcoming complex issues. Its proficiency in navigating intricate problem landscapes distinguishes it as a vital instrument for industries in pursuit of advanced solutions. The Bat Algorithm distinguishes itself as an essential resource for industries in pursuit of advanced solutions due to its proficiency in navigating intricate problem domains. This algorithm is adaptable and can be utilized across various optimization challenges, rendering it a significant asset for both researchers and practitioners. Inspired by the natural echolocation capabilities of bats, the Bat Algorithm exemplifies the effectiveness of adaptation and innovation in addressing complex issues. Its rapid convergence towards optimal solutions is achieved through a balanced approach of exploration and exploitation, further enhancing its utility in diverse applications. The Bat Algorithm, inspired by the echolocation techniques employed by bats in their natural environment, serves as a metaheuristic optimization method. This algorithm adeptly navigates the dual requirements of exploring novel solutions while simultaneously exploiting established ones, thereby enhancing overall efficiency. Its distinctive methodology positions the Bat Algorithm as a formidable instrument for tackling a wide range of optimization issues across various sectors. Renowned for its rapid convergence towards optimal solutions, the algorithm effectively mirrors the foraging behavior of bats, making it particularly useful for addressing intricate optimization challenges. As the Bat Algorithm progresses, it is giving rise to a range of novel and intriguing applications. Its adaptability spans various fields, including engineering design, financial modeling, and healthcare optimization, thereby facilitating innovative solutions across multiple sectors. By investigating these new applications, researchers can fully realize the Bat Algorithm's potential in addressing real-world challenges with accuracy and effectiveness. In summary, the Bat Algorithm exemplifies the creativity inherent in nature-inspired computing, providing a flexible and effective method for tackling optimization issues. As scholars continue to enhance and broaden the scope of this algorithm, its significance and utility are expected to expand across a variety of disciplines. By remaining informed about ongoing developments and embracing opportunities for further innovation, we can leverage the distinctive strengths of the Bat Algorithm to confront increasingly intricate problems and foster a future where computational intelligence leads to transformative advancements (**Boudjemaa et al, 2020**).

This algorithm is predicated on three fundamental rules: First, bats possess the ability to gauge distances through echolocation, enabling them to differentiate between potential prey and stationary obstacles. Second, bats engage in a random search for food, characterized by a speed denoted as v_i, a direction represented by x_i, a minimum frequency f_{min}, a wavelength λ, and an initial sound intensity A_0. Furthermore, they can autonomously modify the wavelength of their emitted signals and adjust their pulse emission rate in response to the proximity of their prey. Third, while the loudness of the emitted sounds can vary, it is assumed to transition from an initial level A_0 to a minimum level A_{min}.

Each bat relies on the velocity vi^t and position xi^t at iteration t within a d-dimensional search or solution space. Among all the bats, there exists a singular optimal solution denoted as x*. Consequently, the three laws discussed in the preceding section can be determined using the following **Equations**:

$$Fi = fmin + (fmax - fmin) \tag{5}$$

$$Vi^{t=}vi^{t-1} + (xi^{t-1} - x^*)fi \tag{6}$$

$$Xi^t = xi^{t-1} + vi^t \tag{7}$$

A random vector β€ is generated from a uniform distribution over the interval [0,1]. In this context, either wavelength or frequency may be utilized for implementation purposes. The parameters fmin = 0 and fmax = 100 are established, which are contingent upon the specific dimensions of the problem being addressed.

Initially, each bat is allocated a random frequency selected uniformly from the range [fmin, fmax]. Consequently, it can be characterized that the bat algorithm functions as a frequency scaling mechanism, facilitating an effective balance between exploration and exploitation. The pulse duration and emission frequency create an inherent system for automatic area management and scaling, ultimately guiding the process toward optimal solutions (**Chaudhary and Banati, 2019**).

2.3. Support Vector Machine (SVM)

A Support Vector Machine (SVM) is a type of supervised machine learning algorithm that classifies data points, which are represented as coordinates in a multidimensional space, by employing a line or hyperplane for separation. This classification ensures that data points located on the same side of the line exhibit similarity and are categorized into the same group (**Cortes and Vapnik, 1995**). When new data points are introduced, they are assigned to one of the pre-existing groups based on their position within the defined space. Initially, we analyze the data classification in scenarios where the samples are linearly separable (**Vapnik, 1995**). In instances of linear separability, it is essential to identify the optimal line or hyperplane that effectively distinguishes between the two classes. In the expression w.x+b=0, the vector w is called the weight vector, which is perpendicular to the separating hyperplane, and b is the Bias value. The boundary planes are defined as follows:

$$H^+ : w.x + b = +1 \tag{8}$$

$$H^- : w.x + b = -1 \tag{9}$$

The configurations observed on these planes are situated at the minimal distance from the optimal hyperplane, referred to as support vectors. The region delineated by the two hyperplanes, H+ and H-, is known as the Margin (**Vapnik, 1998**). The flowchart of SVM is shown in **Figure 3**.

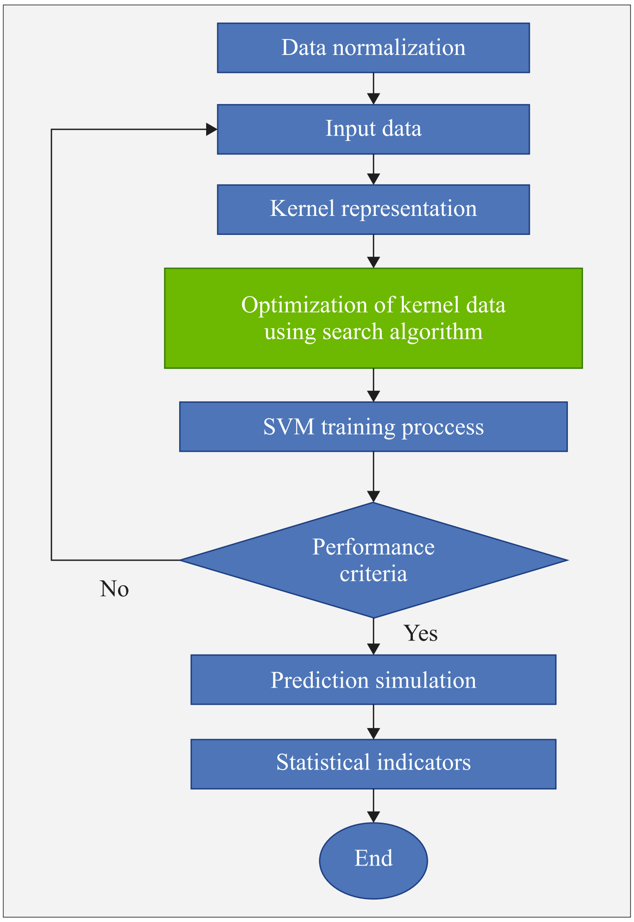

Figure 3. The flowchart of SVM (**Álvarez-Alvarado et al., 2021**)

2.4. Description of Study Area

The Tabas coal mine, recognized as the largest and the sole fully mechanized coal mining operation in Iran, is positioned in the central region of the country, close to the city of Tabas in the South Khorasan Province, approxi-

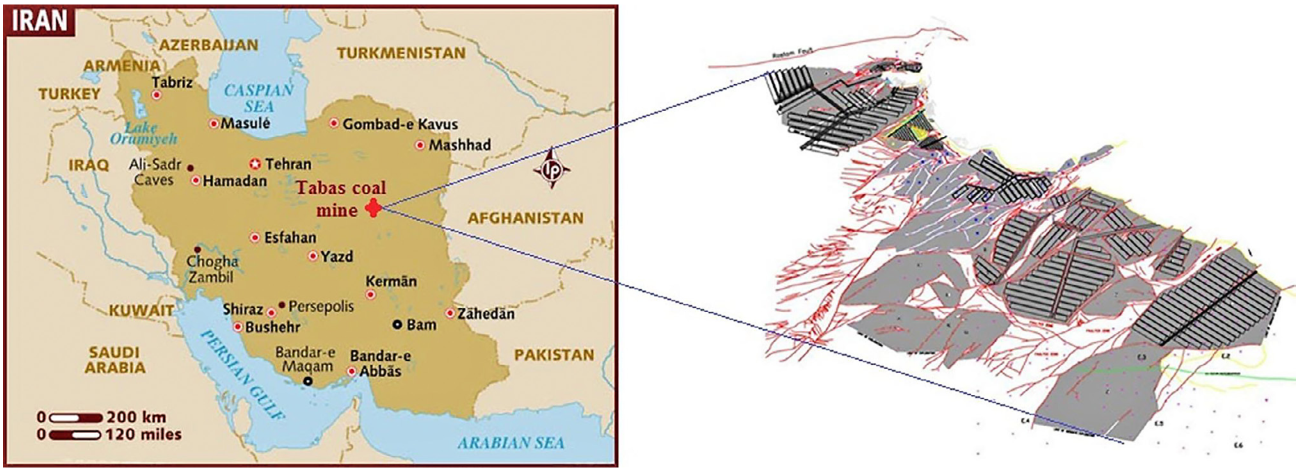

Figure 4. Position and region of Tabas coal mine (**Shirani Faradonbeh et al., 2017**)

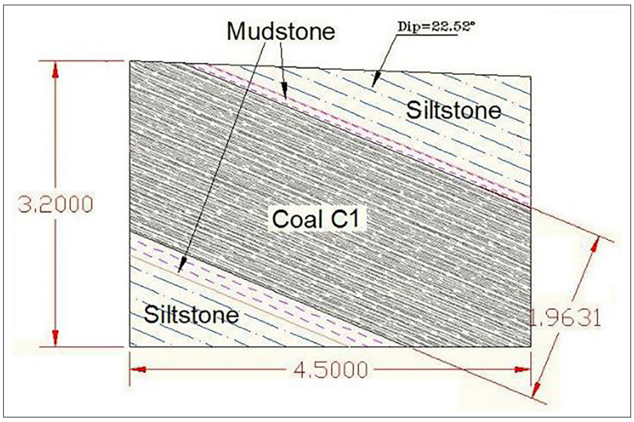

Figure 5. A common perspective of the rock formations (all measurements are in meters) (**Ebrahimabadi et al., 2011**).

Table 3. Descriptive statistic of database (**Ebrahimabadi, 2010**)

Variable	N	Min.	Max.	Mean	SD	Variance
UCS (MPa)	62	14.10	28.20	19.61	5.47	29.985
BTS	62	3.60	5.30	4.08	0.30	0.093
RQD (%)	62	18	28	19.70	1.81	3.291
Alpha (°)	62	39	54	47.12	4.83	23.393
SE	62	4.38	6.62	5.30	0.86	0.740
ICR (m3/h)	62	14.60	46.20	28.75	10.23	104.774

Table 2. Input and output variables of the predictive models

Input	UCS, BTS, RQD, Alpha, SE
Output	ICR

mately 75 kilometers from southern Tabas. The location and area of the Tabas coal mine are illustrated in **Figure 4**.

The Tabas coal mine is a prominent entity in the field of mining and resource extraction, boasting a historical legacy that traces back to its inception. Situated in an area renowned for its abundant mineral resources, the Tabas coal mine has been instrumental in shaping the economic framework of its region. A common perspective of the rock formations is shown in **Figure 5**.

2.5. Database

Input and output variables of the predictive models in the Tabas coal mine are shown in **Table 2** and the descriptive statistics of data are shown in **Table 3**.

2.6. Evaluation criteria

Some researchers used many evaluation criteria (**Nabavi et al., 2023; Nabavi et al., 2024; Kazemi et al., 2023**). In the context of decision-making, the formulation and application of explicit evaluation criteria are essential for directing choices and evaluating results. These criteria act as standards for measuring performance, effectiveness, and overall success. This article examines the core elements of evaluation criteria, including their definition, importance, and essential components. By recognizing the value of developing robust evaluation criteria, both individuals and organizations can refine their decision-making processes, increase transparency, and attain desired results with improved accuracy (**Kazemi et al., 2023**).

The present research utilized Coefficient of Determination (R^2) , Root Mean Square Error (RMSE), mean squared error (MSE) and mean absolute error (MAE) to assess the accuracy and efficiency of the models, as outlined in **Equations 10, 11, 12** and **13**. The preferred values for these indicators are one for R^2 and zero for RMSE. Moreover, distribution diagrams and comparative graphs of observational versus computational values were incorporated to further compare and analyze the results (**Afradi and Ebrahimabadi, 2020**).

2.6.1. Coefficient of Determination

The Coefficient of Determination is a critical metric that assesses the explanatory capacity of a model, revealing the extent to which independent variables ac-count for variations in the dependent variable. The overall variation in the dependent variable is the sum of the variation explained by the regression model and the variation that is not accounted for. This coefficient provides insight into the potential correlation between two data sets in future scenarios. It estimates the likely outcomes of a specified parameter in the future, based on a mathematical model that is derived from existing data (**Ebrahimabadi and Afradi, 2024**). The Coefficient of Determination serves as a standard for evaluating the effectiveness of the regression line in accurately representing the variables involved (**Afradi et al., 2024**). A regression line that successfully intersects all data points demonstrates a high degree of representational accuracy, whereas a line that strays from the points indicates a lower degree of accuracy. In essence, the Coefficient of Determination reflects the alignment between observed and predicted values, which can be assessed through various parsing and fitting methodologies. It quantifies the fraction of total variance in observed values that is explained by the predicted values. The Coefficient of Determination varies from zero to one, with a maximum value of one signifying that the predicted values perfectly match the observed values (**Afradi and Ebrahimabadi, 2021**).

In the following **Equation 10**, X_i and Y_i, respectively, are the computational and observational values of the time step i, N is the number of time steps, $\overline{x}$ and $\overline{y}$ are the average of computational and observational values, respectively.

$$R^2 = \frac{\sum_{i=1}^{N}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\overline{x})^2\sum_{i=1}^{N}(y_i-\overline{y})^2}} \qquad (10)$$

2.6.2. Root mean squared error (RMSE)

Root mean square error is a function associated with the fit or objective function, and it is fundamentally the square of the mean squared error. This index measures the absolute deviation between predicted and actual values. Its values can vary from zero to infinity, with a lower RMSE indicating a superior simulation; the most favorable outcome is a value of zero. The expression for this statistical index is delineated in **Equation 11**.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i y_i)^2} \qquad (11)$$

2.6.3. Mean Squared Error (MSE)

The Mean Square Error (MSE) is a measure that computes the average of the squared differences between the predicted and observed values. MSE is attained as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i y_i)^2 \qquad (12)$$

2.6.4. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a statistical measure that quantifies the average size of the absolute discrepancies between predicted values and their corresponding actual values. Mean Absolute Error (MAE) is a commonly employed statistical measure that offers a straightforward and comprehensible assessment of a predictive model's accuracy. It calculates the average size of the errors present in a series of predictions, disregarding their directional nature. Consequently, MAE emphasizes only the magnitude of the differences between predicted outcomes and the actual observed results, treating all errors uniformly, irrespective of whether they represent overestimations or underestimations. MAE is attained as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}| x_i - y_i y_i \qquad (13)$$

2.7. *Data preprocessing*

Prior to the application of algorithms, it is crucial to preprocess the data to ensure its cleanliness, normalization, and readiness for modeling. The preprocessing procedures encompass the following steps:

1. Data Cleaning:

a) Elimination of missing or inconsistent data points. In instances where missing values are significant, interpolation or imputation techniques may be employed.

b) Identification and removal of outliers to prevent extreme values, which could skew the model, from being included in the training dataset.

2. Normalization:

The range of variables, such as Machine Parameters and mining data, can exhibit considerable variation. To standardize the features and mitigate the risk of any single feature disproportionately influencing the model due to differences in scale, normalization or standardization is applied. This process typically involves transforming the data to a range between 0 and 1 or adjusting the data to achieve a zero mean and unit variance.

3. Feature Selection:

Certain features may lack contribution to the model›s predictive capability or may introduce extraneous noise. Techniques for feature selection, including correlation analysis, mutual information assessment, and recursive feature elimination (RFE), are utilized to identify and retain the most pertinent features for prediction.

4. Data Splitting:

The dataset is partitioned into three subsets: training, validation, and testing. Generally, 80% of the data is allocated for training the model, 10% for validation, and the remaining 10% for final testing. The training subset is employed to develop the model, the validation subset is utilized for hyperparameter tuning, and the testing subset is reserved for assessing the model›s performance on previously unseen data.

3. Results

3.1. ICR Prediction in Tabas coal mine by FA

Initialization typically occurs through a random process. The firefly search algorithm comprises four distinct steps. Initially, a new function, denoted as alpha, is introduced to modify the initial value of the parameter α; it is important to note that this step is optional within the firefly algorithm. The second step involves the implementation of the fitness function f(s). In the third step, the order function FA organizes the population of fireflies based on their respective fitness values. The fourth step entails the function for identifying the best firefly, which selects the most suitable candidate from the population. Lastly, the motion function FA facilitates the movement of fireflies within the search space, directing them towards more attractive solutions. The entire firefly search process is governed by the maximum evaluation limit set by the fitness function.

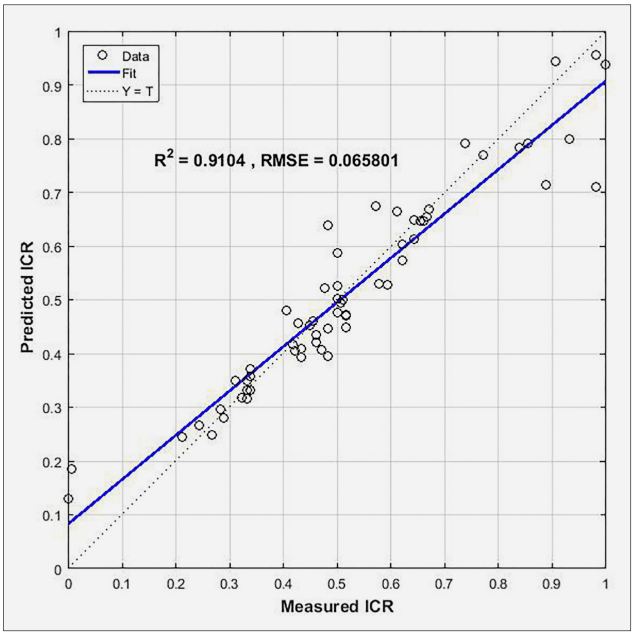

Figure 6. Distribution diagram obtained by FA

The predictive model is illustrated through the distribution diagram and the matching diagram of the measured ICR values, as well as the target and predicted ICR values, as depicted in **Figures 6** and **7**, respectively.

3.2. ICR Prediction in Tabas coal mine by BA

There are several assumptions and simplifications for the bat algorithm, including the following:

1. Echolocation: all bats use echolocation to sense distance and also "know" the difference between food/prey and obstacles in the background. This capability allows them to move easily in complex environments.

2. Random movement and frequency tuning: bats fly randomly with speed v_i at position x_i. They can automatically adjust the frequency (or wavelength) of their emitted pulses and change the pulse emission rate $r \in [0, 1]$ according to the proximity to their target. These features make it easier for bats to move towards closer targets or avoid obstacles.

3. Changes in loudness: although loudness can change in many ways, we assume that the loudness de-

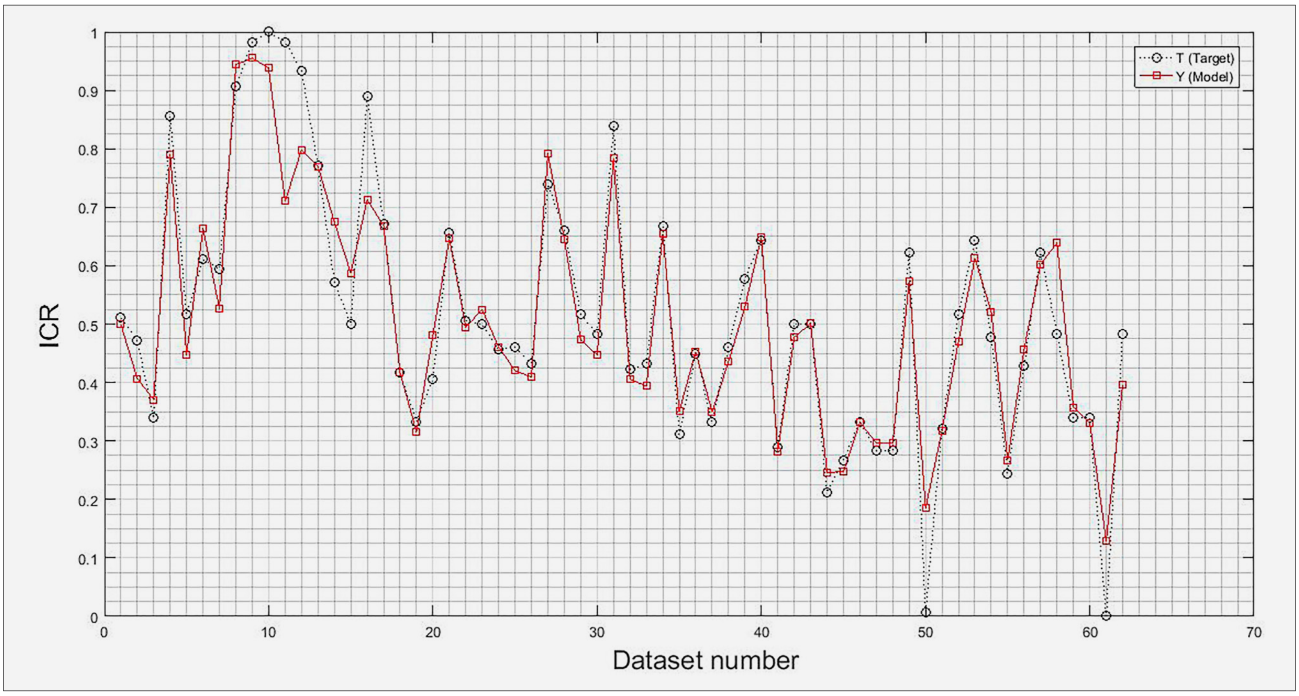

Figure 7. Matching diagram obtained by FA

creases from a large (positive) value A_0 to a minimal value A_{min}. These assumptions are used in the algorithm to simplify and simulate the real behavior of bats.

The predictive model is illustrated through the distribution diagram and the matching diagram of the measured ICR values, as well as the target and predicted ICR values, as depicted in **Figures 8** and **9**, respectively.

3.3. ICR Prediction in Tabas coal mine by SVM

A Support Vector Machine (SVM) represents a robust and adaptable class of supervised machine learning algorithms, predominantly utilized for the classification of data points. Within the SVM framework, data points are depicted as coordinates in a multidimensional space, with each dimension corresponding to a specific feature of the data. This multidimensional representation enables SVM to effectively manage intricate datasets characterized by multiple features. The fundamental principle of SVM is to determine the optimal hyperplane that most effectively distinguishes between the various classes of data points. A hyperplane is defined as a flat affine subspace that is one dimension lower than its surrounding space; in a two-dimensional context, it manifests as a line, while in three dimensions, it appears as a plane. The objective of the SVM is to locate the hyperplane that maximizes the margin, which is defined as the distance between the hyperplane and the closest data points from each class. These closest points are known as support vectors, and they play a crucial role in the efficacy of the model. Training an SVM involves several essential steps:

1. Data Preparation: the initial phase entails preparing the dataset, which includes selecting pertinent features, addressing missing values, and normalizing or scaling the data as required.

2. Kernel Selection: SVMs can be categorized as linear or non-linear, contingent upon the characteristics of the data. For datasets that are linearly separable, a linear kernel suffices. Conversely, for more complex datasets where classes are not linearly separable, SVMs can utilize various kernel functions (such as polynomial, radial basis function (RBF), or sigmoid) to map the data into a higher-dimensional space where linear separation becomes feasible.

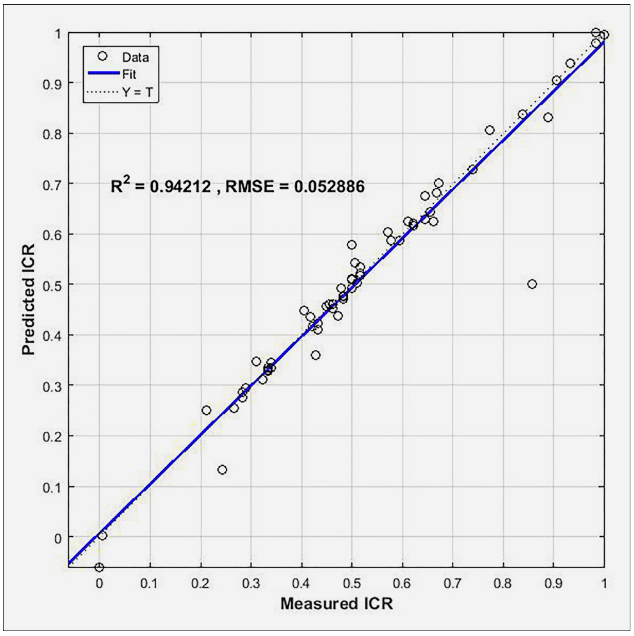

Figure 8. Distribution diagram obtained by BA

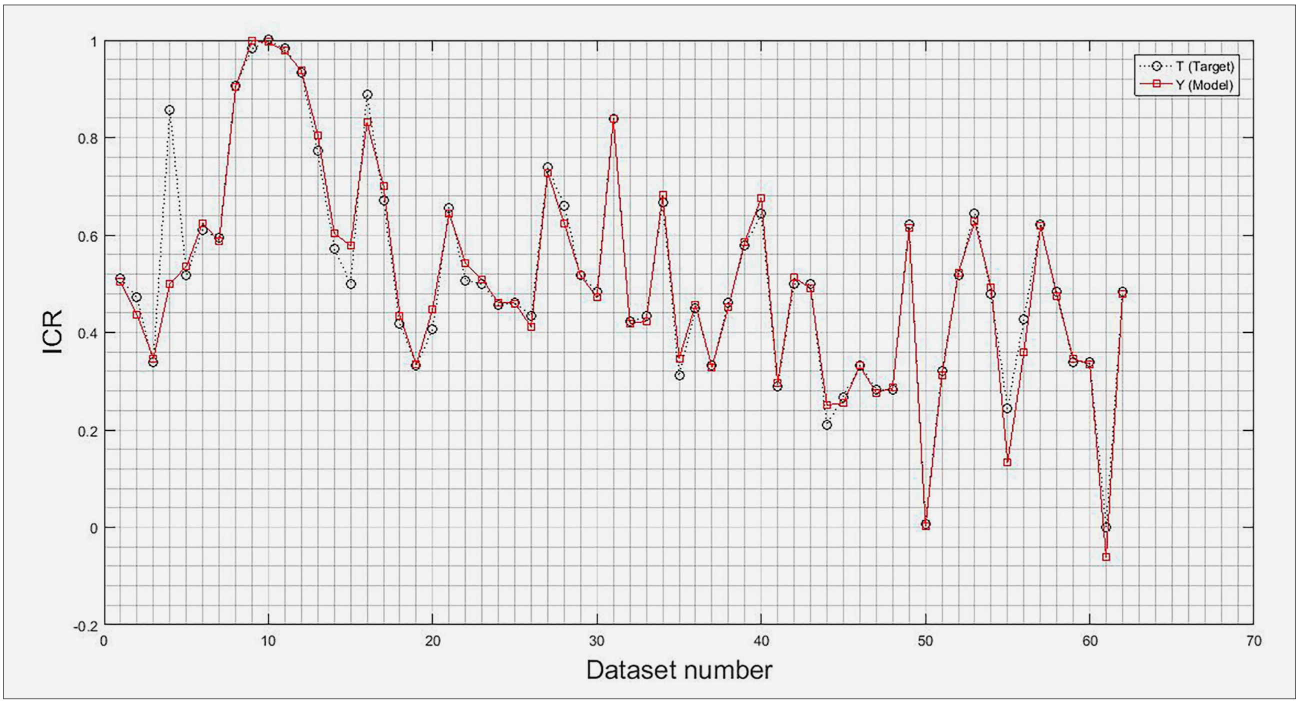

Figure 9. Matching diagram obtained by BA

3. Model Training: in the training phase, the SVM algorithm seeks to identify the optimal hyperplane by addressing a constrained optimization problem. This process involves maximizing the margin while concurrently minimizing classification errors. Techniques such as the Sequential Minimal Optimization (SMO) algorithm are typically employed to facilitate the optimization process.

4. Prediction Generation: after the SVM model has been trained, it is capable of making predictions based on new data inputs. The predictive model is represented by the distribution diagram and the correlation diagram of the measured ICR values, alongside the target and predicted ICR values, as shown in **Figures 10** and **11**, respectively.

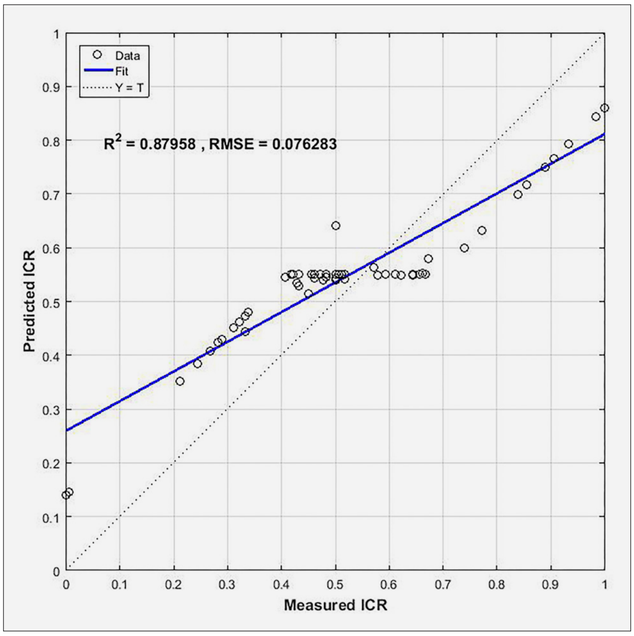

Figure 10. Distribution diagram obtained by SVM

3.4. *Results of the evaluation criteria for predictive models*

The results of the evaluation criteria of the prediction models are presented in **Table 4** and **Figure 12**. The results show that all models have excellent performance, with the difference that BA has better performance than the other models.

3.5. *Sensitivity analysis (SA)*

Sensitivity analysis functions as a systematic technique for determining the input parameters that have the most significant impact on the resulting outputs. The cosine amplitude method, as outlined by **Yang and Zang (1997)**, can be utilized to aid in this assessment. This methodology is encapsulated in **Equation 14.**

$$R_{ij=}\frac{\sum_{l=1}^{n}(b_{il}\times yb_{jl})}{\sum_{l=1}^{n}b_{il}^{2}\sum_{l=1}^{n}b_{jl}^{2}} \tag{14}$$

In this framework, b_i represents the input parameters and b_j indicates the output parameters, with n denoting the overall count of datasets. The results of the sensitivity analysis in **Figure 13** and **Table 5.**

3.6. *Convergence curves of objective function*

In the fields of optimization and numerical analysis, convergence refers to the process by which an iterative

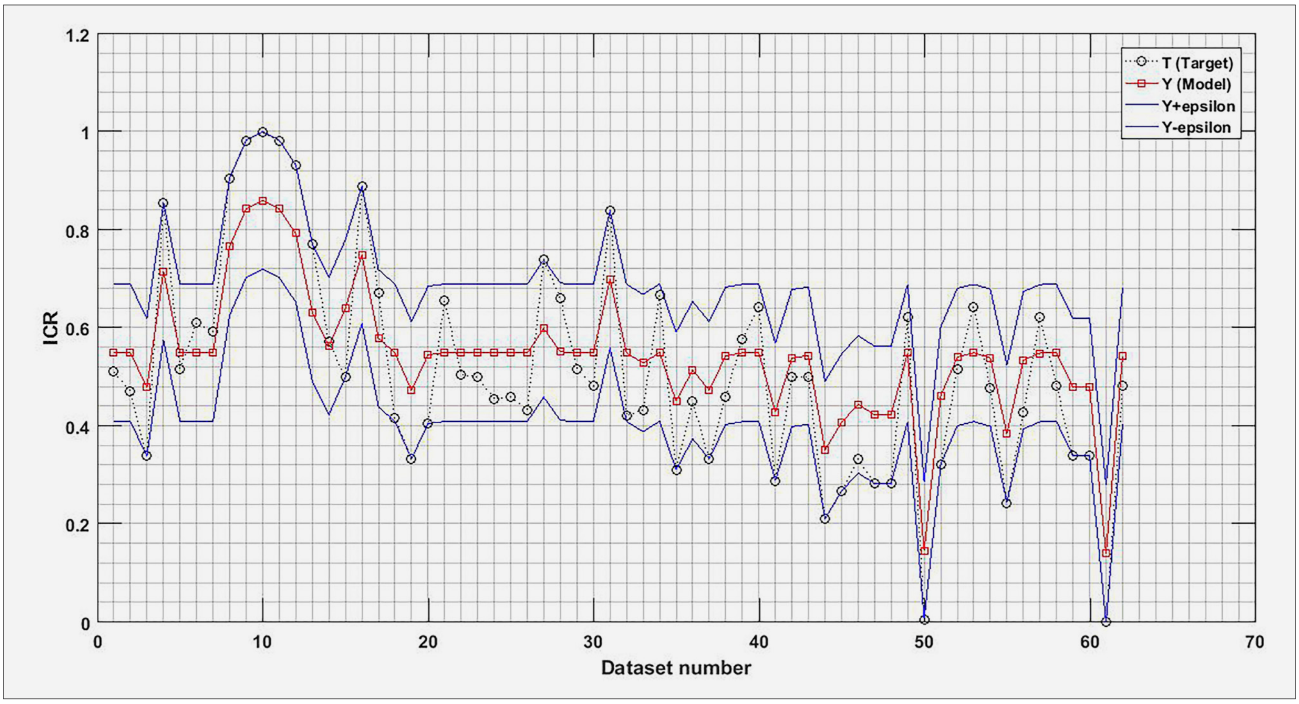

Figure 11. Matching diagram obtained by SVM

Table 4. Results of the evaluation criteria for predictive models

Model	R^2	RMSE	MSE	MAE
FA	0.9104	0.0658	0.0043	0.0039
BA	0.9421	0.0528	0.0027	0.0024
SVM	0.8795	0.0762	0.0058	0.0052

algorithm gradually approaches a definitive solution or a specific value as the number of iterations increases. This concept is fundamental to understanding how algorithms behave over time and is crucial for assessing their effectiveness and reliability. When an algorithm is said to converge, it means that as we perform more iterations, the results produced by the algorithm become increasingly close to the true solution or the desired outcome. This can be visualized as a sequence of approximations that narrows down towards a target value, whether that

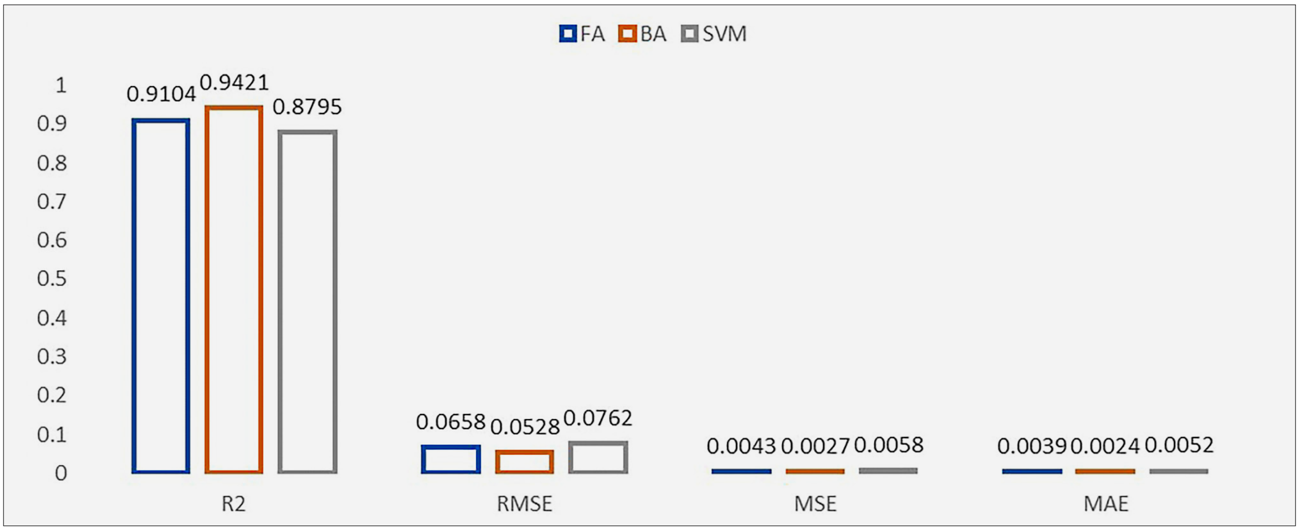

Figure 12. Evaluation criteria

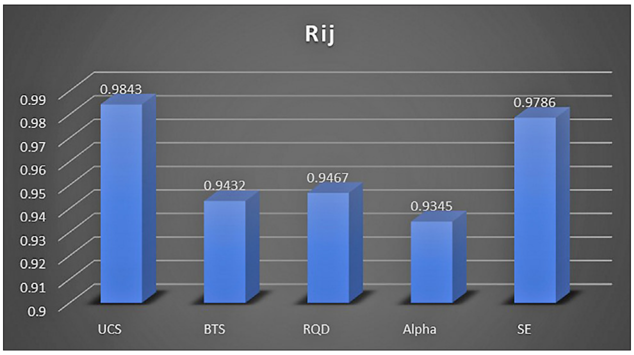

Figure 13. Schematic of parameter sensitivity analysis

Table 5. Sensitivity analysis

Input parameters	R_{ij}
UCS	0.9843
BTS	0.9432
RQD	0.9467
Alpha	0.9345
SE	0.9786

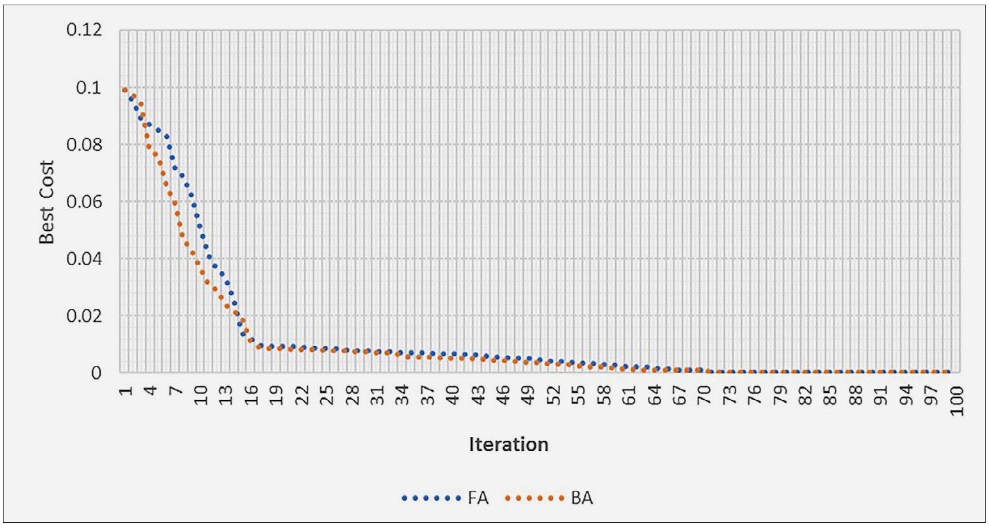

Figure 14. Convergence curves of objective function

be a root of a function, an optimal point in a multidimensional space, or a solution to a system of equations. Convergence curves of objective function are shown in **Figure 14**.

4. Discussion

Optimization algorithms are essential tools in various fields, including engineering, economics, logistics, and artificial intelligence, as they provide a systematic methodology for identifying the optimal solution to a wide range of problems. The optimization process is characterized by a continuous exploration of the search space, which is the domain of all possible solutions. This exploration can be thought of as navigating through a landscape where the goal is to find the highest peak (maximum) or the lowest valley (minimum) that represents the best solution to the problem at hand.

Typically, optimization algorithms employ mathematical techniques to guide this exploration. These techniques can yield solutions that are either deterministic, where the same input will always produce the same output, or probabilistic, where randomness plays a role in the solution process. The choice between these approaches often depends on the nature of the problem and the desired characteristics of the solution.

A critical component of implementing optimization algorithms is the selection of an appropriate objective function. The objective function quantifies the goal of the optimization process, providing a measure that the algorithm seeks to minimize or maximize. The formulation of this function is crucial, as it directly influences the effectiveness and efficiency of the optimization process. In many cases, problems may involve multiple objectives that need to be considered simultaneously. These are known as multi-objective problems, which add a layer of complexity to the optimization task.

To manage the intricacies of multi-objective optimization, a common strategy is to create a new objective function that is a linear combination of the original objectives. This approach allows for the simultaneous consideration of multiple goals by assigning weights to each objective, reflecting their relative importance in the decision-making process. The weights can be adjusted based on the specific context of the problem, enabling a flexible approach to finding a balanced solution that satisfies various criteria.

Each optimization problem is defined by several independent variables, known as design variables. These variables represent the parameters that can be adjusted or controlled within the optimization framework. The primary aim of the optimization process is to determine the optimal values of these design variables that will either minimize or maximize the objective function. This involves not only finding the best solution but also ensuring that the solution adheres to any constraints or limitations that may be imposed by the problem context.

In summary, optimization algorithms are powerful methodologies that systematically explore the search space to identify optimal solutions. By leveraging mathematical techniques and carefully selecting objective functions, these algorithms can effectively tackle both single and multi-objective problems, ultimately guiding decision-makers toward the most favorable outcomes based on their specific goals and constraints. Due to their unique capabilities, roadheaders have found extensive application in various underground mining operations, including coal, gypsum, and potash extraction, as well as in tunneling projects for transportation infrastructure such as subways, highways, and railways. Their ability to operate continuously and with minimal disruption to surrounding areas makes them a preferred choice for many contractors and mining companies.

The performance of roadheaders is influenced by several factors, including the geological characteristics of the rock being excavated, the operational parameters of the machine, and the skill of the operator. Therefore, evaluating and predicting the performance of these machines is crucial for ensuring their optimal use. This involves analyzing factors such as cutting speed, advance rate, and the wear and tear of cutting tools, as well as understanding the rock mechanics involved in the excavation process.

By accurately assessing these performance metrics, operators can make informed decisions regarding the selection of appropriate equipment, the planning of excavation strategies, and the management of operational costs. Furthermore, predictive modeling and performance evaluation can help in identifying potential challenges and optimizing the overall efficiency of roadheader operations, ultimately leading to improved productivity and reduced downtime in underground projects. In summary, roadheaders are invaluable assets in the field of underground excavation, and their effective utilization hinges on a thorough understanding of their performance characteristics and the geological conditions in which they operate.

5. Conclusions

The role of roadheaders in the excavation of tunnels and mines is of paramount importance, as they deliver both efficient and precise cutting capabilities. Accurate prediction of roadheader performance is critical for optimizing operational processes and ensuring the success of projects. A comprehensive understanding of the factors influencing performance, along with the application of predictive models and ongoing enhancements in machine design and operational techniques, can significantly enhance the effectiveness of roadheaders. This article examines the nuances of performance prediction for roadheaders, highlighting methodologies, relevant case studies, challenges faced, and future prospects in this vital field of tunneling and mining.

This study employs a range of input parameters for the model, which includes rock quality designation (RQD), uniaxial compressive strength (UCS), Brazilian tensile strength (BTS), the Alpha angle that indicates the angle between the tunnel axis and the planes of weakness, and specific energy (SE), defined as the energy expended to excavate a unit volume of rock. The output of the model is represented by ICR.

Data obtained from sensors undergoes processing through algorithms and software to evaluate performance trends, detect possible problems, and enhance roadheader operations for improved efficiency. In this study, ICR at the Tabas coal mine was evaluated through an analysis of the properties of both the geological material and the equipment utilized. This study utilized the Firefly Algorithm (FA), Bat Algorithm (BA), and Support Vector Machine (SVM) for analysis, evaluating their performance through various metrics including the coefficient of determination (R^2), root mean square error (RMSE), mean squared error (MSE), and mean absolute error (MAE). The results indicated that the Firefly Algorithm (FA) achieved $R^2 = 0.9104$, RMSE = 0.0658, MSE = 0.0043, and MAE = 0.0039. In contrast, the Bat Algorithm (BA) yielded $R^2 = 0.9421$, RMSE = 0.0528, MSE = 0.0027, and MAE = 0.0024. The Support Vector Machine (SVM) produced $R^2 = 0.8795$, RMSE = 0.0762, MSE = 0.0058, and MAE = 0.0052. These findings suggest that while all predictive models exhibit commendable performance, the Bat Algorithm (BA) stands out for its superior accuracy and realism in the results obtained. For future research, it is suggested to explore other optimization algorithms, apply the models to different types of mines, or integrate machine learning techniques.

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SAŽETAK

Procjena radnih karakteristika strojeva za sukcesivni iskop pomoću metode potpornih vektora, algoritma krijesnice i algoritma šišmiša

Strojevi za sukcesivni iskop imaju ključnu ulogu u iskopima tunela i rudnika jer pružaju učinkovite i precizne mogućnosti iskopa. Procjena njihovih radnih karakteristika bitna je za optimiziranje operacija i osiguranje uspjeha u projektima. Uzimanjem u obzir različitih čimbenika koji utječu na izvedbu, implementacijom prediktivnih modela i stalnim poboljšanjem dizajna strojeva i operativnih strategija mogu se maksimalno povećati mogućnosti strojeva za sukcesivni iskop. Ovaj članak dublje istražuje radne karakteristike strojeva za sukcesivni iskop, istražuje metode, studije slučaja, izazove i buduće smjerove u ovome kritičnom aspektu iskopa tunela i rudarskih zahvata. Primarni je cilj ove studije razviti modele koji mogu predvidjeti trenutačnu brzinu rezanja (ICR), koja se definira kao stopa proizvodnje tijekom stvarnoga perioda rezanja (mjereno u tonama ili kubnim metrima po satu rezanja), na temelju svojstava stijenske mase koja se iskopava i tehničkih karakteristika stroja. U ovome istraživanju analizirana je trenutačna brzina rezanja strojeva za sukcesivni iskop u rudniku ugljena Tabas ispitivanjem karakteristika stijene i uključenih strojeva. Osim toga, ova studija primijenila je algoritam krijesnice (*firefly algorithm*, FA), algoritam šišmiša (*bat algorithm*, BA) i metodu potpornih vektora (*support vector machine*, SVM), koji su procijenjeni pomoću koeficijenta determinacije (R^2), korijena srednje kvadratne pogreške (RMSE), srednje kvadratne pogreške (MSE) i srednje apsolutne pogreške (MAE). Dobiveni rezultati za algoritam krijesnice (FA) iznose R^2 = 0,9104, RMSE = 0,0658, MSE = 0,0043 i MAE = 0,0039, za algoritam šišmiša (BA) iznose R^2 = 0,9421, RMSE = 0,0528, MSE = 0,0027 i MAE = 0,0024, a za metodu potpornih vektora (SVM) iznose R^2 = 0,8795, RMSE = 0,0762, MSE = 0,0058 odnosno MAE = 0,0052. Može se zaključiti da, iako prediktivni modeli daju zadovoljavajuće rezultate, algoritam šišmiša (BA) pokazuje višu razinu preciznosti i realističnosti.

Ključne riječi:
predviđanje učinka, strojevi za sukcesivni iskop, trenutačna brzina rezanja, algoritam krijesnice, algoritam šišmiša

Author's contribution

Arash Ebrahimabadi (PhD, Professor) formed the object and the subject of the research, proposed the idea, developed the idea for the work and the methodology for achieving results, analysis of the research, provided technical suggestions, project administration, supervision; conceptualization and wrote the article. **Alireza Afradi** (PhD) wrote the article, software; developed approaches and the presentation of the results.
All authors have read and agreed to the published version of the manuscript.