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Developing drilling rate index prediction: A comparative study of RVR-IWO and RVR-SFL models for rock excavation projects

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Abstract. In the realm of rock excavation projects, precise estimation of the drilling rate index stands as a pivotal factor in strategic planning and cost assessment. This study introduces and evaluates two pioneering computational intelligence models designed for the prognostication of the drilling rate index, a pivotal parameter with direct implications for cost estimation in rock excavation projects. These models, denoted as the Relevance Vector Regression (RVR) optimized with the Invasive Weed Optimization algorithm (IWO) (RVR-IWO model) and the RVR integrated with the Shuffled Frog Leaping algorithm (SFL) (RVR-SFL model), represent a groundbreaking approach to forecasting drilling rate index. The RVR-IWO and RVR-SFL models were meticulously devised to harness the capabilities of computational intelligence and optimization techniques for drilling rate index estimation. This research pioneers the integration of IWO and SFL with RVR, constituting an unprecedented effort in forecasting drilling rate index. The primary objective of this study was to gauge the precision and dependability of these models in forecasting the drilling rate index, revealing significant distinctions between the two. In terms of predictive precision, the RVR-IWO model emerged as the superior choice when compared to the RVR-SFL model, underscoring the remarkable efficacy of the Invasive Weed Optimization algorithm. The RVR-IWO model delivered noteworthy results, boasting a Variance Account for (VAF) of 0.8406, a Mean Squared Error (MSE) of 0.0114, and a Squared Correlation Coefficient (R^2) of 0.9315. On the contrary, the RVR-SFL model exhibited slightly lower precision, yielding an MSE of 0.0160, a VAF of 0.8205, and an R2 of 0.9120. These findings serve to highlight the potential of the RVR-IWO model as a formidable instrument for drilling rate index prediction, particularly within the framework of rock excavation projects. This research not only makes a significant contribution to the realm of drilling engineering but also underscores the broader adaptability of the RVR-IWO model in tackling an array of challenges within the domain of rock engineering. Ultimately, this study advances the comprehension of drilling rate index estimation and imparts valuable insights into the practical implementation of computational intelligence methodologies within the realm of engineering projects.

Keywords: drilling rate index; invasive weed optimization algorithm; relevance vector regression; rock geomechanical properties; shuffled frog leaping algorithm

1. Introduction

Within the domain of rock excavation projects, the critical decisions regarding the selection of drilling, excavation, and support systems are intricately linked to several key factors. These factors encompass the specific production requirements, the nature of the operation, equipment availability, and the distinctive characteristics of the rock formations involved in the project. One of the pivotal parameters that substantially influences these choices is the drilling rate index. This metric holds a central role in the meticulous strategic planning of excavation and support methods, influencing the efficiency and cost-effectiveness of the entire project. Among the various parameters considered for assessing the drilling rate index, Uniaxial Compressive Strength (UCS) assumes a fundamental role. UCS serves as an indispensable measure of a rock's resilience and stability, particularly when the context involves drilling and excavation operations (Zaid 2021a, Zaid *et al.* 2020). It is this very parameter that stands as a linchpin in the process of estimating the drilling rate index, given its profound impact on the mechanical behavior of the rock material. Over the course of numerous research studies, the prediction of drilling performance has entailed a comprehensive exploration of diverse rock parameters, with UCS consistently taking precedence as the most commonly utilized metric for evaluating the drilling rate index (Akün and Karpuz 2005). In addition to the evaluation of UCS, the study of P-waves, also known as primary waves, offers valuable insights into the mechanical properties of the rock mass (Sadique *et al*. 2022, Zaid 2021b, Zaid 2021c, Zaid *et al.* 2022). P-waves induce particle motion within the rock mass, propagating in the direction of wave transmission. This phenomenon provides critical information regarding the rock's elasticity and behavior under the influence of these waves, enhancing our understanding of its mechanical properties. Such insights are immensely valuable in forecasting the drilling rate index, a task that hinges on the assessment of a multitude of rock parameters. These parameters include the composition of the rock, quantified by factors like quartz content, porosity, and apparent porosity, along with the measurement

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of P-wave velocity, which serves as a valuable indicator of the rock's tensile strength (Kahraman 1999). To predict drilling performance accurately, various empirical tests have been employed as well. These tests encompass a wide array of methods, including Taber abrasion, impact strength index (ISI), point load strength, cone indenter number, Schmidt rebound hardness, Shore scleroscope hardness, texture coefficient (TC), coefficient of rock strength, specific energy (SE), rock brittleness, and the Cerchar abrasivity index (CAI) (Kahraman *et al*. 2003). Furthermore, the application of regression analysis has been a prevalent technique in research endeavors, focusing on unraveling the intricate relationship between the physical properties of rocks and the drilling rate index (Yarali and Soyer 2013). While these preceding efforts have undoubtedly contributed valuable insights to the field, the existing analytical models often grapple with the complexity of the dataset. This challenge has spurred a growing interest in delving deeper into the intricate interactions between the drilling rate index and other variables. Researchers are increasingly driven to propose more precise and dependable models for its estimation (Khandelwal and Armaghani 2016).

To address these challenges, computational intelligence approaches have emerged as a rapid and viable solution, particularly when the underlying relationships between dependent and independent variables are uncertain (Armaghani *et al.* 2014). In the realm of drilling engineering, artificial intelligence techniques have played a significant role in several research projects, such as those conducted by (Asteris *et al.* 2021, Mohamad *et al*. 2017, Mohamad *et al*. 2020, Parsajoo *et al*. 2021, Zhou *et al.* 2020). These initiatives have showcased the potential of computational intelligence in addressing the complexities of drilling rate index estimation and have opened new avenues for tackling challenges within the domain of rock engineering. For instance, Khandelwal and Armaghani (2016) applied regression analysis in conjunction with a hybrid genetic algorithm and artificial neural network (ANN) for the estimation of the drilling rate index. Notably, their model focused on rock geomechanical properties, specifically Brazilian tensile strength (BTS) and UCS. Fattahi and Bazdar (2017) presented alternative models for drilling rate index estimation, utilizing an ANN-based approach. Ru *et al*. (2019) introduced a novel model that combines the Monte Carlo simulation (MCS) with the least square support vector machine (LSVM) to predict the drilling rate index. In a similar vein, Sakız et al. (2021) proposed a fuzzy inference system method for estimating the drilling rate index, drawing on CAI properties and rock strength. In conclusion, the dynamic field of rock excavation projects is continually evolving, with the selection of drilling, excavation, and support systems becoming increasingly informed by an array of factors, including the fundamental properties of the rock mass. As our understanding of these complexities deepens, computational intelligence techniques offer promising avenues for the development of precise and reliable models that can enhance the estimation of the drilling rate index, ultimately contributing to the success of rock engineering projects.

In the realm of estimating the drilling rate index, ANN emerge as an alternative method, but they introduce distinct challenges in their design, potentially leading to stochastic events during model construction. Additionally, ANN exhibits certain limitations, notably a relatively sluggish learning rate. In contrast, support vector regression (SVR) offers a more global and deterministic approach; however, it presents its own complexities in the selection of an appropriate kernel function and the fine-tuning of crucial parameters like insensitivity (ε) and penalty weight (C). Contrastingly, relevance vector regression (RVR) offers a unique perspective. Unlike SVR, RVR refrains from imposing restrictions on basis functions, granting increased flexibility in the modeling process (Fattahi 2021). Furthermore, the RVR approach simplifies the tuning procedure by necessitating adjustments to a single variable, σ (kernel width). Consequently, the sparse RVR approach exhibits the potential for broader generalization compared to SVR, all while requiring fewer computational resources.

This study delves deep into the realm of estimating the drilling rate index, employing sophisticated analytical techniques. It notably enhances the RVR method by integrating two optimization algorithms: the shuffled frog leaping algorithm (SFL) (RVR-SFL model) and the invasive weed optimization algorithm (IWO) (RVR-IWO model). This amalgamation of RVR with IWO and SFL facilitates the identification of the most appropriate user-defined parameter values. The model's performance is rigorously evaluated, drawing on insights garnered from existing literature. To gauge the model's effectiveness in estimating the drilling rate index, a comprehensive statistical error analysis is conducted.

2. A synopsis of the methodologies employed in this study

2.1 RVR

The RVR is a probabilistic approach rooted in Tipping's Bayesian technique (Tipping 2001) and has demonstrated its efficacy in a variety of regression prediction tasks (Fattahi 2020a, Fattahi 2020b). Much like SVR, the RVR model employs kernel functions to transform low-dimensional data into high-dimensional data. For the single-output case (*t*), $t=(t_1,\dots,t_N)^T$ with multiple inputs (*x*), $\{x_n,t_n\}_{n=1}^{N}$. The model's objectives are summarized as follows

$$t_n = y\left(x_n, w\right) + e \tag{1}$$

where , *w* represents the weight vector, and *e* denotes random noise. Furthermore, *y(x)* is expressed as

$$y\left(x,w\right)=\sum_{i=1}^{N} w_i K\left(x,x_i\right)+w_0=\sum_{i=1}^{N} w_i \Phi\left(x\right) \tag{2}$$

where $\Phi\left(x\right)=\left[1,K\left(x,x_1\right),K\left(x,x_2\right),\dots,K\left(x,x_N\right)\right]$.

The objectives can be formally stated as $p\left(t_n\left|x_n\right.\right)=N\left(t\left|y\left(x_n\right),\sigma^2\right.\right)$. The likelihood is expressed as

$$p\left(t\left|w,\sigma^2\right.\right)=\frac{1}{2\pi\sigma^2}\exp\left\{-\frac{1}{2\sigma^2}\left\|t-\Phi(x)w\right\|\right\} \tag{3}$$

where $w=(w_0,w_1,...,w_N)$, Φ is the $N\times(N+1)$ design matrix, and $t=(t_1,t_2,...,t_N)$. The posterior distribution over weights is defined as

$$p(w\left|t,\alpha,\sigma^2\right.)=\frac{p(t\left|w,\sigma^2\right.)p(w\left|\alpha\right.)}{p(t\left|\alpha,\sigma^2\right.)}= \\ \frac{1}{2\pi^{(N+1)/2}}\left|\Sigma\right|^{-1/2}\exp\left\{-\frac{1}{2}(w-\mu)^T\Sigma^{-1}(w-\mu)\right\} \tag{4}$$

$$\Sigma=\left(\sigma^{-2}2\Phi^T 2\Phi+A\right)^{-1} \tag{5}$$

$$\mu=\sigma^{-2}\Sigma\Phi^T t \tag{6}$$

with $A=diag(\alpha_1,\alpha_2,...,\alpha_N)$. Tipping (2001) introduced the following probability distribution over the training targets

$$p\left(t\left|\alpha,\sigma^2\right.\right)=(2\pi)^{-N/2}\left|C\right|^{-1/2}\exp\left\{\frac{1}{2}t^T C^{-1}t\right\} \tag{7}$$

where the covariance is represented as $C=\sigma^{-2}I+\Phi A^{-1}\Phi^T$. For a comprehensive understanding of the RVR method, readers can refer to the detailed explanation in (Nisha and Pillai 2013).

2.2 IWO algorithm

The IWO is categorized as one of the meta-heuristic techniques. It draws inspiration from the behavior of weeds colonizing their environment, and it was first introduced by Mehrabian and Lucas (2006). The essence of IWO's design revolves around the emulation of how weeds seek out the best locations to grow and reproduce. Notably, the IWO algorithm exhibits a simplified structure, remarkable robustness, and a reduced dependency on input parameters. In the realm of the IWO algorithm, the entire population is represented by a collection of "weeds," where each weed symbolizes a potential solution to a given problem, typically referred to as a feasible problem solution (Zhou *et al.* 2015). These "weeds" are distributed across the entire search area, and each of them generates new "weeds" based on a specific cost feature. This iterative process continues until the predetermined number of "weeds" is attained. Importantly, only those "weeds" with a higher cost of reproduction are allowed to produce "seeds," while the others are systematically removed. The process persists until a "weed" emerges with the most favorable cost, ultimately representing the ideal solution (Zhou *et al.* 2015). A more comprehensive understanding of the IWO method can be found in the original work by Mehrabian and Lucas (2006).

Within the context of this research, the IWO algorithm plays a crucial role in determining the critical parameter for the RVR model. This choice significantly influences the performance and effectiveness of the RVR model in the prediction and estimation tasks. The flowchart of the IWO algorithm is provided in Fig. 1.

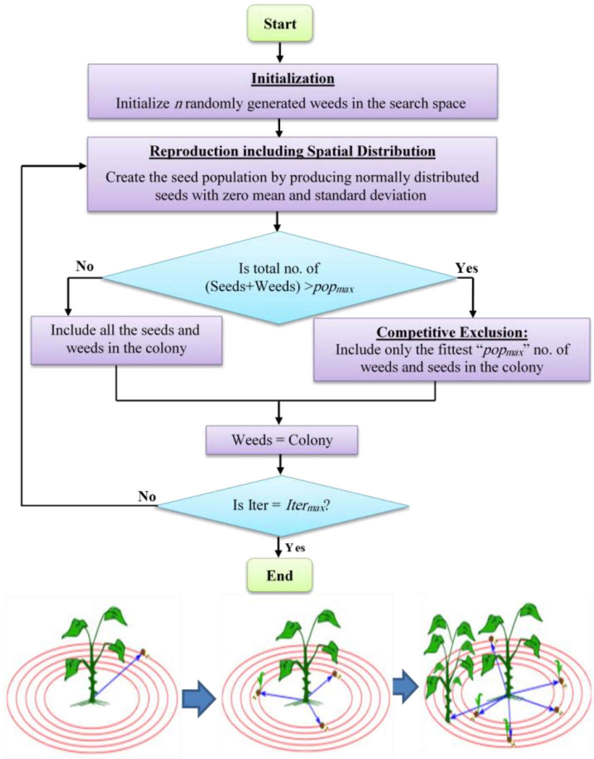


Fig. 1 IWO algorithm flowchart

The versatility of the IWO method extends across various domains, where it has been effectively employed for forecasting and optimization purposes. For example, in a study conducted by Huang *et al.* (2019), a novel model was developed using the IWO algorithm in conjunction with an ANN. This model aimed to predict the tensile strength of rock materials, demonstrating the adaptability of IWO in various applications. Another illustration of IWO's versatility can be observed in the work of Moayedi *et al.* (2019), where a novel approach was introduced for slope stability monitoring. This approach combined neuro-fuzzy techniques with the elephant herding optimization algorithm and the IWO algorithm. The results of this study provided evidence of the IWO algorithm's effectiveness in achieving optimization goals and improving performance. Furthermore, the applicability of the IWO method extends to geotechnical engineering, as demonstrated by Nagaraju *et al.* (2020).

In summary, the IWO algorithm's adaptability and efficiency make it a valuable tool in various fields, offering innovative solutions to optimization and estimation challenges. Its ability to mimic the behavior of weeds colonizing their environment allows it to find optimal solutions to complex problems, making it a valuable asset in the realm of computational intelligence and optimization techniques.

2.3 SFL algorithm

The SFL algorithm derives its inspiration from the foraging behavior of frogs as they seek out sources of food, a concept originally introduced by Eusuff and Lansey

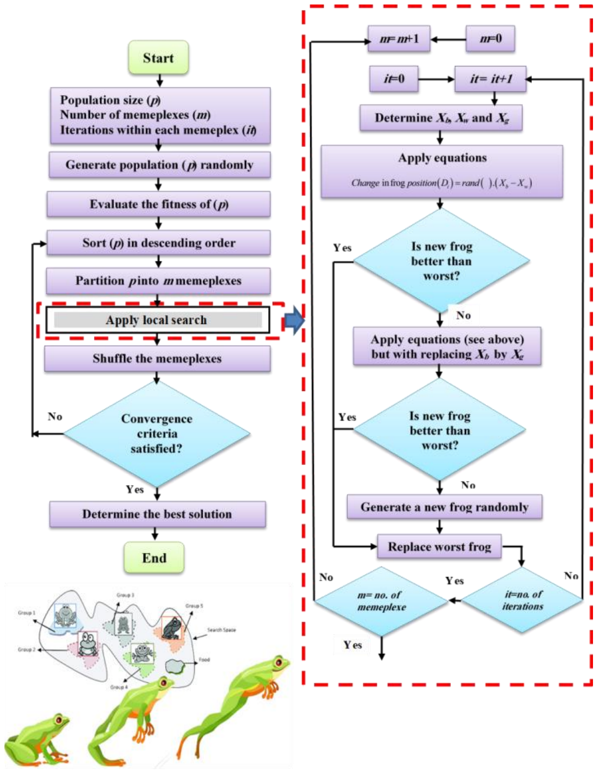


Fig. 2 Flowchart of the SFL algorithm

(2003). In this algorithm, a population of frogs is initially dispersed, each frog embarking on its quest to locate areas with an abundant food supply. As they continue their search for sustenance, frogs are periodically separated and subjected to a process akin to natural selection and evolution. To gain a deeper understanding of the SFL algorithm and its mechanics, one can refer to the comprehensive descriptions and explanations provided by (Amiri *et al*. 2009, Eusuff *et al.* 2006) (See Fig. 2).

In the specific context of this research, the SFL algorithm assumes a crucial role in the selection of parameters for the RVR model. This involvement significantly influences the performance and overall efficacy of the RVR model, ensuring that it operates at its optimal capacity. The remarkable versatility of the SFL algorithm is demonstrated by its diverse range of applications across a wide array of fields. For instance, Mahmoudi *et al.* (2016) introduced a novel approach that melds the SFL algorithm with SVR. The goal of this fusion was to predict water quality parameters, showcasing the SFL algorithm's adaptability in tackling environmental and quality-related challenges. Additionally, the study conducted by Moayedi *et al.* (2020) exemplifies the SFL algorithm's potential. In this particular case, the algorithm was coupled with an ANN to estimate soil shear strength, a critical factor in geotechnical and civil engineering applications. In the realm of drilling operations, optimizing drilling parameters is of paramount importance to achieve the highest possible rate of penetration when drilling a well.

While various optimization methods are available, discovering a mathematically sound and reliable model for maximizing the penetration rate has proven to be an enduring challenge. The study conducted by Yi *et al.* (2014), which incorporated the SFL algorithm, addressed this issue by estimating real-time penetration rate optimization. This demonstrated the algorithm's adaptability and effectiveness in the field of drilling engineering. Furthermore, the work of Eusuff and Lansey (2003) proposed an innovative model founded on the SFL algorithm, which was developed to optimize the design of water distribution networks. This application of the SFL algorithm showcased its adaptability and versatility in addressing complex optimization problems, particularly within the domain of civil engineering and infrastructure design.

In summary, the SFL algorithm, inspired by the natural foraging behavior of frogs, stands as a versatile and adaptable tool with applications that span a multitude of fields. Its capacity to emulate the process of natural selection and its suitability for addressing intricate optimization problems make it a valuable asset in the world of engineering and beyond.

3 Forecasting of drilling rate index using RVR-SFL and RVR-IWO

3.1 Database features

An essential prerequisite for this study is the inclusion of a dataset with broad geographic representation to facilitate the development of intelligence-based models for predicting the drilling rate index. To achieve this, datasets from a prior study (Yarali and Soyer 2013) were employed, encompassing real values of the drilling rate index and geomechanical properties of various rocks. A sample of this dataset used in the current investigation is provided in Table 1. Further statistical information regarding the datasets is presented in Table 2. The rationale for selecting these input parameters is elaborated upon in (Yarali and Soyer 2013). The dataset, comprising the values of 29 samples of metamorphic, igneous, and sedimentary rocks, was randomly divided into two subsets: 80 percent of the dataset (23 data points) was allocated for the training dataset used in model construction, and the remaining 20 percent (6 data points) was reserved for the testing dataset, employed for evaluating the models' performance. Additionally, the drilling rate index can be ascertained by employing Fig. 3c after measuring S20 (determined through the Swedish Stamp Test, as depicted in Fig. 3(a)) and SJ values (as illustrated in Fig. 3(b)).

3.2 Algorithms configuration

Building upon the foundation laid in Section 2, the IWO and SFL algorithms are employed to optimize the kernel parameter σ of the RVR. Subsequently, the RVR-SFL and RVR-IWO models are developed within the MATLAB environment. The precision of outcome prediction is closely tied to the σ value. The flowchart detailing the hybrid RVR with SFL (RVR-SFL) and IWO (RVR-IWO) is depicted in Fig. 4. Both the SFL and IWO are instrumental in determining the optimal parameter for RVR. Tables 3 and 4

Table 1 An excerpt from the dataset used in modeling (Yarali and Soyer 2013)

Input parameters					**Output parameters**
Shore scleroscope hardness (SSH)	Diametral point load strength index (Is→(50)) (MPa)	BTS (MPa)	UCS (MPa)	Axial point load strength index (Is↓(50)) (MPa)	Drilling rate index
55.1	5.16	8.1	117.9	4.92	48
35.9	4.41	7.9	98.4	4.23	61
53.4	3.29	6.1	64.5	3.31	66
36.45	3.23	6.7	75.6	2.59	69
41.8	4.35	6.2	67.6	2.22	65
52.2	2.97	6.8	82.5	3.17	68

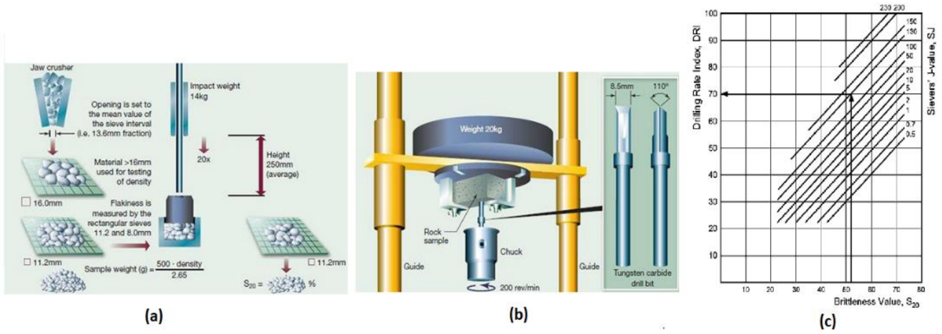


Fig. 3 (a) The S20 (The brittleness test) (Dahl 2003), (b) The SJ (The Sievers'J miniature drill test) (Dahl 2003) and (c) The diagram for estimating the drilling rate index using SJ and S20 (Bruland 1998)

Table 2 Statistical breakdown of the datasets

Parameters	Minimum	Maximum	Avarage
$Is_{(50)}$↓ (MPa)	1.88	7.51	4.143
$Is_{(50)}$ → (MPa)	1.37	7.65	4.008
SSH	23.1	85.3	49.98
BTS (MPa)	2.6	16.5	7.96
UCS (MPa)	28.6	182.1	91.82
Drilling rate index	35	86	62.75

Table 3 Controlled variables employed in executing the SFL algorithm

Descriptions	**Value**
Parents number (q)	Max. (round(0.3*nPopMemeplex), 2)
Offsprings number (alpha)	3
Memeplexes number (nMemeplex)	5
Memeplex Size (nPopMemeplex)	10
Max. iteration (Max_It)	900
Max. number of sub-iterations (beta)	5

outline the controlled parameters used in executing the SFL and IWO algorithms.

Fig. 5 visually represents the convergence characteristics of the IWO and SFL algorithms throughout the process of seeking the minimal prediction error. Notably, after 230 iterations for the IWO algorithm and 400 iterations for the SFL algorithm, the cost approaches its minimum point. These results underscore the efficiency and convergence properties of the algorithms.

Table 4 Controlled variables employed in executing the IWO algorithm

Descriptions	**Values**
Final Std. Deviation (Δ_{final})	0.001
Max.of seeds around each weed (S_{max})	5
Max. of weeds (P_{max})	100
Min.of seeds around each weed (S_{min})	1
Nonlinear ratio (pow)	2
Initial Std. Deviation ($\delta_{initial}$)	1
Max. iteration (MaxIt)	900
Initial seeds number (N_{Weed})	100

3.3 Assessment of model performance

It is common practice in data-driven system modeling methodologies to utilize several preprocessing techniques aimed at eliminating potential outliers, addressing missing data, and rectifying inaccuracies. These preprocessing steps are carried out before any computations, ensuring that the raw data derived from the database is well-suited for modeling (Fattahi 2016). An essential step in the preprocessing phase involves the normalization of all data samples to a standardized range, typically within [0, 1]. This normalization process is achieved through the application of a linear mapping function, represented by the equation:

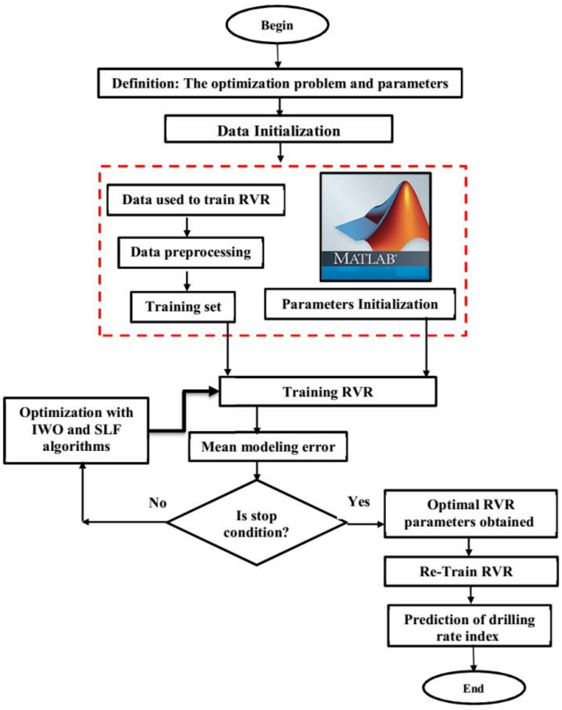


Fig. 4 Procedure of the IWO and SFL algorithms for optimizing RVR parameters

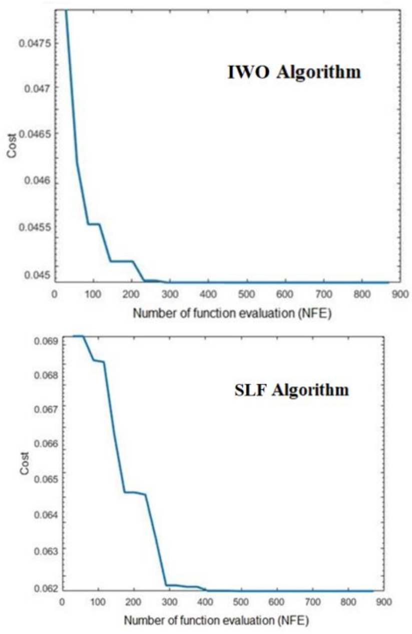


Fig. 5 Convergence behavior of the IWO and SFL algorithms

$$x_M = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

where:

- x represents the original value in the dataset.
- x_M denotes the mapped value.
- x_{min} and x_{max} signify the minimum and maximum values from the original input, respectively.

Normalization enhances the suitability of the data for training and significantly contributes to the accuracy of prediction.

For the evaluation of the RVR models' performance, key accuracy measures have been employed, drawing from prior research (Fattahi 2018, Fattahi *et al.* 2021, Fattahi and Zandy Ilghani 2021).These measures include:

Mean Square Error (MSE), defined as

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(t_k - \hat{t}_k)^2 \tag{9}$$

where t_k and $\hat{t}_k$ represent the measured and estimated values, respectively, and nn represents the sample size.

Squared Correlation Coefficient (R^2), given by

$$R^2 = 1 - \frac{\sum_{k=1}^{n}(t_k - \hat{t}_k)^2}{\sum_{k=1}^{n} t_k^2 - \frac{\sum_{i=1}^{n}\hat{t}_k^2}{n}} \tag{10}$$

Variance Account For (VAF), which is defined as

$$VAF = \left[1 - \frac{\operatorname{var}(t_k - \hat{t}_k)}{\operatorname{var}(t_k)}\right] \tag{11}$$

These performance evaluation metrics play a crucial role in assessing the accuracy and reliability of the RVR models, ensuring that the predictive capabilities of the models are in line with established criteria and standards.

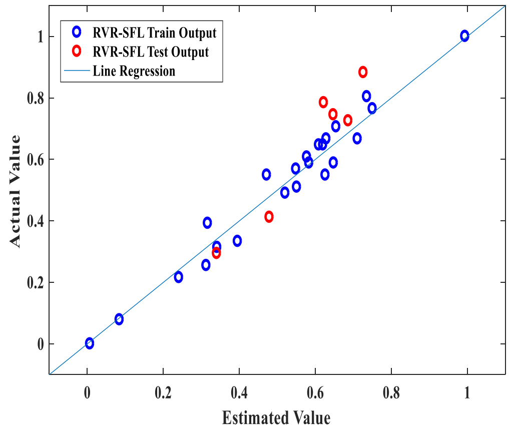
4. Discussions and results

This study introduced the RVR-IWO and RVR-SFL models for predicting the drilling rate index, utilizing five key input parameters: SSH, $Is_{(50)}$→, BTS, UCS, and $Is_{(50)}$↓. A comprehensive comparison of performance metrics between the two computational intelligence techniques, RVR-IWO and RVR-SFL, is presented in Table 5. During the testing phase, the IWO-RVR model exhibited notably superior precision, with a VAF of 0.8406, an R^2 of 0.9315, and an MSE of 0.0114. In contrast, the SFL-RVR model achieved an MSE of 0.0160, a VAF of 0.8205, and an R2 of 0.9120 for predicting the drilling rate index. This performance discrepancy underscores that, when compared to the SFL-RVR model, the IWO-RVR model excelled not only in computational efficiency but also in predictive capabilities.

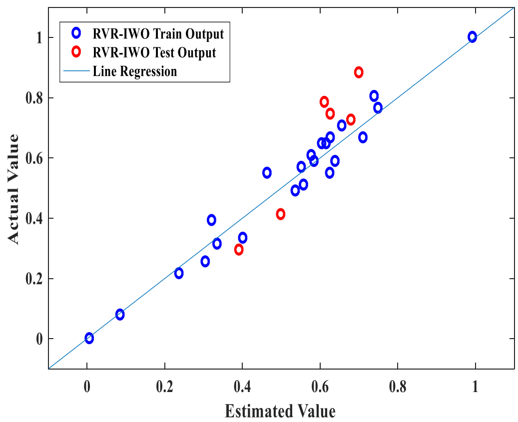
To further emphasize the difference in predictive performance between the RVR-IWO and RVR-SFL models, we provide a visual representation in Fig. 6, which shows a remarkably close agreement between the estimated and measured values. Fig. 7 reinforces the comparative aspect by presenting a direct comparison between the observed values from all datasets and the estimated values of the drilling rate index generated by the RVR-IWO and RVR-SFL models. While both models demonstrated their capability to predict the drilling rate index, as evidenced in this figure and Table 4, it is evident that the RVR-IWO model outperformed the RVR-SFL model in both training

Table 5 The key performance indices of both intelligence models

Model	Training phase			Testing phase		
	MSE	R^2	VAF	MSE	R^2	VAF
RVR-IWO	0.00204	0.9625	0.8712	0.0114	0.9315	0.8406
RVR- SFL	0.00207	0.9618	0.8708	0.0160	0.9120	0.8205



(a)



(b)

Fig. 6 Correlation between measured values and estimated values (a) RVR-SFL and (b) RVR-IWO

and testing datasets. Consequently, the IWO algorithm emerges as a more effective choice for enhancing the performance of the RVR model.

5. Limitations and future works

This study predominantly concentrated on predicting the drilling rate index by relying on rock geomechanical properties. It's crucial to acknowledge that additional factors, such as the performance of the drilling machinery or equipment, bit parameters, and other drilling variables like pressure parameters, warrant exploration and future prediction endeavors. Regarding the modeling aspect, further investigations can explore alternative hybrid RVR models for estimating the drilling rate index. Such models may encompass optimization algorithms like Green Herons Optimization-RVR, Dolphin Echolocation Optimization-RVR, Chicken Swarm Optimization-RVR, and Electromagnetic Field Optimization-RVR. Thus, the potential for assessing the suitability of these diverse optimization algorithms for predicting the drilling rate index based on rock geomechanical properties can be explored in future studies.

6. Conclusions

This paper has aimed to develop accurate, realistic, and user-friendly models for estimating the drilling rate index, a critical parameter in the context of rock excavation projects' strategic planning and cost assessment. Through the innovative integration of the RVR with the IWO in the RVR-IWO model and the RVR with the SFL in the RVR-SFL model, we have endeavored to advance the field of drilling engineering and computational intelligence. The performance of these models has been rigorously assessed using various evaluation metrics, including MSE, VAF, and R^2, in comparative experiments.

From the extensive analysis and results, we can draw the following key conclusions:

- Superiority of RVR-IWO: In the estimation of the drilling rate index, the RVR-IWO model outshines the RVR-SFL model, establishing its reputation as a more reliable and accurate choice. The IWO algorithm's success in enhancing the efficiency of RVR is evident, demonstrating its practical applicability in predicting drilling rate index with exceptional precision.
- Versatility of the RVR-IWO Model: This research underscores the RVR-IWO model's versatility and adaptability in addressing a wide array of rock engineering challenges. Beyond its remarkable performance in drilling rate index estimation, it holds promise for tackling a broader range of geomechanical problems, showcasing its potential to revolutionize rock engineering practices.

In conclusion, this study signifies a significant stride forward in the realm of rock excavation projects by offering advanced computational intelligence models that excel in predicting the drilling rate index. The RVR-IWO model, in particular, emerges as a powerful tool with the capacity to significantly enhance the precision and reliability of drilling rate index estimates. By advancing our understanding of drilling rate index estimation and its practical application, this research paves the way for more efficient and cost-effective rock excavation projects, ultimately contributing to the advancement of drilling engineering as a whole.

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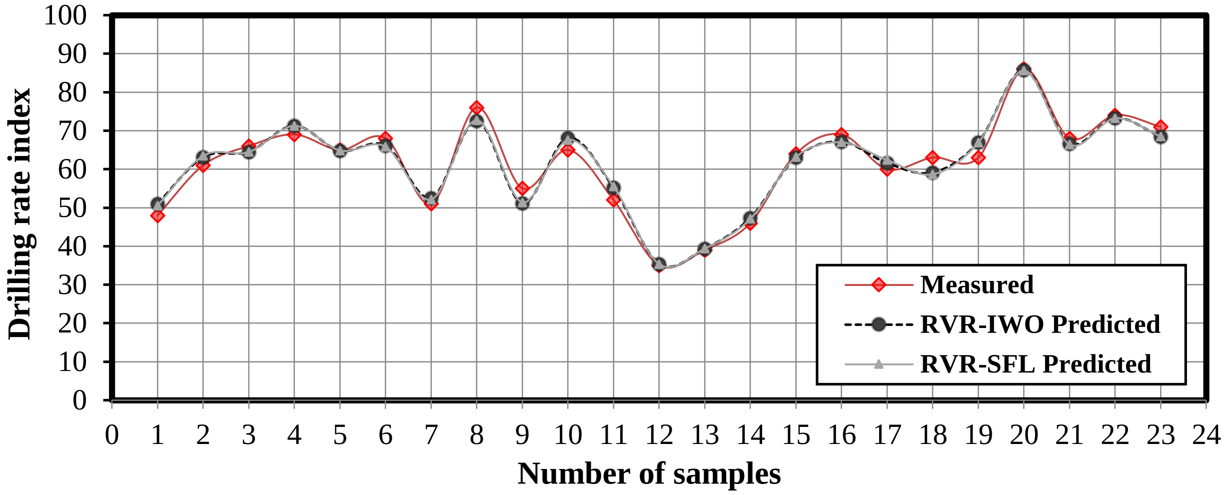
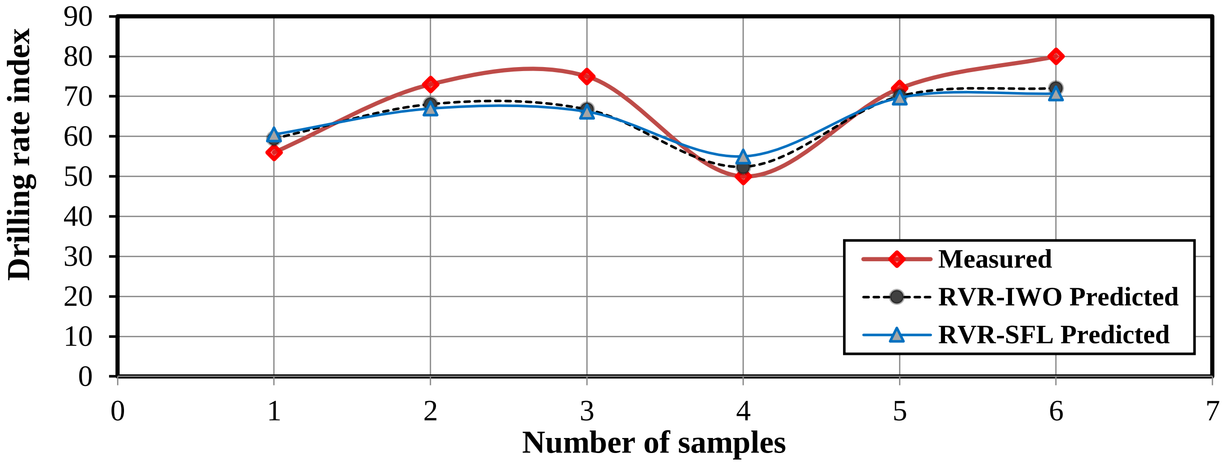


(a)



(b)

Fig. 7 Illustrating the prediction errors of the drilling rate index for (a) training and (b) testing datasets

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