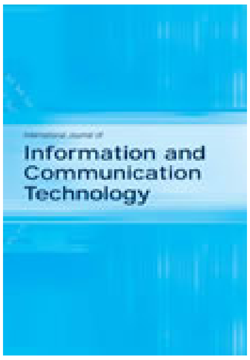

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Open pit slope stability monitoring based on machine learning improved by water wave optimisation algorithm

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Abstract: Aiming at the problem of insufficient prediction accuracy of traditional machine learning model in slope stability monitoring of open-pit mine, this paper proposes an improved machine learning monitoring method based on water wave optimisation (WWO). Firstly, the improved water wave optimisation algorithm is introduced to enhance the global search ability and balance the convergence speed and local extremum escape performance of the algorithm. On this basis, IWWO is used to optimise the machine learning method synchronously. Finally, the actual slope engineering data are introduced, and the prediction results of this model are compared with the calculation results of rigid body limit equilibrium method. The final results show that this method can identify the precursor of slope instability in real time, and provide reliable technical support for mine safety early warning.

Keywords: water wave optimisation algorithm; support vector machine; SVM; random forest; long short-term memory; open pit slope.

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1 Introduction

One of the key links in mine safety production is slope stability monitoring in open-pit mines. Apart from major economic losses, slope instability can cause major safety hazards (Li et al., 2022a). Slope stability has become more important with mining depth rising and geological conditions growing more complex. The traditional slope monitoring methods mainly rely on manual inspection and simple instrument monitoring, which have problems such as long monitoring cycles, incomplete data acquisition, and untimely warning (Li et al., 2022b). In recent years, with the rapid development of sensor technology and machine learning algorithms, data-driven slope stability monitoring methods have gradually become a research hotspot (Zhu et al., 2021). To satisfy the real engineering objectives, the conventional machine learning model still suffers several shortcomings in prediction accuracy and parameter optimisation efficiency, nevertheless.

Conventional approaches of slope stability monitoring mostly rely on hand inspection and basic instrument monitoring. Long monitoring cycles, insufficient data collecting, and early warning (Kumar et al., 2021) among other issues these approaches bring about Data-driven slope stability monitoring approaches have progressively attracted attention in recent years. For instance, Huang et al. (2024) put up a slope stability prediction system incorporating support vector machine (SVM), sparrow search algorithm (SSA), and principal component analysis (PCA). Nevertheless, the choice of kernel function parameters greatly influences the performance of SVM; so, the parameter optimisation method typically relies on experience or grid search, which is ineffective and easy to lead to local optimisation.

By combining several decision trees, RF enhances the prediction accuracy; nonetheless, the performance of the model depends much on the tree depth and feature subset selection. For instance, Demir and Sahin (2023) suggested to develop a Ranger algorithm-based classification model for slope stability evaluation. Still, the model performance is highly influenced by the tree depth of RF and feature subset choice. Usually depending on expertise or grid search, which is ineffective and easy to fall into local optimisation, the method of parameter optimisation relies on LSTM, being a recurrent neural network, can capture long-term dependencies in time series data; yet, the success of the model depends critically on the configuration of its hidden layer nodes. For the prediction of slope stability, for instance, Huang et al. (2023) creatively suggested a long-term and short-term memory deep learning method. But the performance of LSTM depends much on the environment of hidden layer nodes, hence the procedure of parameter optimisation mainly relies on experience or ineffective grid search.

Parameter optimisation makes extensive use of intelligent optimisation methods such DE, PSO and GA. Zhou et al. (2022) for instance suggested two SVM models, which were optimised using grey GWO and GA to forecast the possible soil liquefaction. When addressing high-dimensional and nonlinear problems, these algorithms still suffer with poor convergence speed and easy to fall into local optima, nevertheless. Strong global search capability and fast convergence speed are two benefits of the intelligent optimisation method based on water wave propagation and refraction, water wave optimisation (WWO) algorithm. For instance, based on WWO, Kaur and Kumar (2022) suggested a meta heuristic clustering approach. Nevertheless, the conventional WWO method still has significant issues when addressing challenging optimisation problems including illogical refraction probability and wavelength attenuation factor setting as well as inadequate escape capability of local extremum.

To solve the above problems, this study proposes a machine learning monitoring method based on improved WWO algorithm. Firstly, key monitoring data such as slope displacement, groundwater level, rainfall and geological structure are collected by multi-source sensors to build a comprehensive monitoring data set. Secondly, aiming at the parameter sensitivity of SVM, RF and LSTM models, IWWO algorithm is introduced to enhance the global search ability by dynamically adjusting the wavelength attenuation factor and nonlinear refraction probability; Combined with adaptive mutation strategy, the convergence speed and local extremum escape performance of the algorithm are balanced. On this basis, IWWO is used to synchronously optimise the kernel function parameters of SVM, the tree depth and feature subset of RF, and the hidden layer nodes of LSTM, and a multi model fusion mechanism is designed to improve the generalisation ability. Finally, the effectiveness and practicability of the proposed method are verified by the actual slope engineering data.

The main contributions of this study are as follows:

1 A machine learning monitoring method based on IWWO is proposed, which effectively solves the problems of insufficient prediction accuracy and low efficiency of parameter optimisation of the traditional machine learning model.

2 By dynamically adjusting the wavelength attenuation factor and nonlinear refraction probability, the global search ability of IWWO algorithm is enhanced.

3 Combined with adaptive mutation strategy, the convergence speed and local extremum escape performance of IWWO algorithm are balanced.

4 A multi model fusion mechanism is designed to enhance the generalisation ability of the model.

5 The effectiveness and practicability of the proposed method are verified by the actual slope engineering data.

2 Relevant technologies

2.1 Analysis of slope stability factors in open pit mine

1 Basic types of slope failure.

If there is a through fracture surface in the slope rock mass, the divided rock mass will be separated from the parent in various ways, which is called slope failure (Terbrugge et al., 2006). The slope can be divided into rock slope and soil slope according to its material composition. There are three main failure modes: collapse, landslide and lateral spread.

Collapse refers to the fall of slope rock and soil due to tensile fracture, including small-scale rock fall and large-scale mountain collapse. The crushed stone after collapse is piled up at the foot of the slope, forming an obvious angle of repose. Sometimes, collapse fragments may continue to move and evolve into debris flow (Stacey et al., 2003).

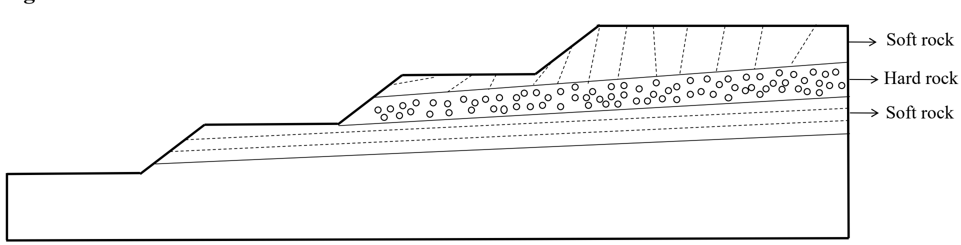
Landslide refers to the rock and soil sliding down along a specific sliding surface, which usually shows shear failure. Landslide can be divided into smooth type and arc type. The sliding surface may be a simple straight line or a more complex combination shape. During the sliding process, the sliding mass may disintegrate into fragments, form slumping, or further develop into debris flow or mud flow.

Lateral spread is a special phenomenon of slope failure, which usually occurs when there is a weak layer below. This kind of weak layer may lead to the loss of support of rock and soil above it due to its plastic deformation or flow characteristics, thus causing the overall failure. Generally, the occurrence of lateral spread is due to the significant deformation or movement of the weak layer at the lower part of the slope under the external pressure or self weight, resulting in the lateral displacement of the rock and soil above. In this case, the rock and soil mass may move forward as a whole, or split into multiple blocks and drift towards the area in front of the slope. The soft rock below is squeezed into the split blocks under pressure, resulting in the block showing an inverted shape, which is one of the main differences between the lateral spread and the ordinary landslide (Abdulai and Sharifzadeh, 2021).

2 Influence of geological conditions on slope stability of open pit mine.

Formation lithology plays an important role in slope formation (Chen et al., 2023). This factor has a decisive impact on the stability of the slope, especially in different geological ages and environmental conditions, the formation of rock mass structure is different. The different lithology directly affects the strength and deformation failure form of rock. Relatively speaking, hard rock is more stable, and the high and steep slope formed is less prone to landslide. Generally, rock and soil can be divided into soft rock and hard rock. Common soft rocks include mudstone and shale, which are characterised by low compressive strength, easy weathering and water erosion, and easy to soften. Its stability is significantly affected by lithological characteristics, so it must be fully considered in engineering design. In the natural environment, it is difficult for soft rock to form high and steep slopes, which are also affected by water and weathering, which increases the complexity of slope engineering. Common types of hard rock include siliceous rock, calcium siliceous rock, etc. These rock formations often present complex interlaced state, forming unique and diverse lithologic combination characteristics. In the case of complex rock structure, the contact area between rock layers increases, and the interaction between rock masses is more complex. Generally speaking, the layered rock slope with hard rock combination is more stable than that with soft rock. Each slope is composed of different rock layers, and rock layers with different strengths are combined to form five combination forms: hard rock, hard rock with soft rock, soft hard interbedding, soft rock with hard rock, and soft rock, as shown in Figure 1.

Figure 1 Strata combination



Weak intercalation has a significant impact on slope stability, which plays an important role in slope design and evaluation. In rock mechanics, rock mass is composed of structural plane and structural body. Weak intercalation is a thin layer of weak structure between hard rocks, which is common in fracture fracture zones. The thickness and dip angle of the weak interlayer are positively correlated with the displacement of the slope. The greater the thickness and dip angle, the more significant the displacement. The thickness and dip angle are negatively correlated with the safety factor, and the greater the angle, the lower the safety factor. For example, when the dip angle increases from 25° to 35°, the horizontal displacement of the slope increases by 0.321m, the vertical displacement increases by 0.257 m, and the safety factor decreases by 0.22. Similarly, the layer thickness increases from 2.5 m to 3.5 m, the horizontal displacement increases by 0.088m, the vertical displacement increases by 0.111m, and the safety factor decreases by 0.11.

The structure of slope reflects the relative position of rock strata in the whole slope. The combination relationship between this structure and rock strata determines the type and stability of slope. According to the geometric relationship between the dip and dip of rock strata and the aspect and angle of the slope, the slope can be divided into five different types, and each type corresponds to different geological characteristics and potential risks. If the angle between the rock layer and the slope is small, the slope is easy to lose stability and form a consequent slope. The structural plane of this kind of slope is usually a sliding boundary. In contrast, the included angle of oblique slope, cross slope and reverse slope is larger and more stable. The reverse slope has the largest included angle and is the most stable slope type.

In areas with complex geological structures and active tectonic movements, slopes are often unstable (Fleurisson, 2012). The density distribution of geological structure is closely related to the formation mode of slope instability, including folds and faults (joints and faults). The geological structure characteristics will affect the stability of the slope. Neotectonic movement may lead to changes in slope shape, state and hydrogeological conditions, increasing the risk of instability. Generally speaking, the stability of slope is poor in areas with complex geological structure, serious folds and frequent tectonic activities. Open pit slope structure can be divided into simple structure, medium structure, complex structure and extremely complex structure according to geological complexity.

The mechanical properties of rock refer to the ability of rock to resist external stress, including gravity, cohesion, internal friction angle, etc. Gravity refers to the weight per unit volume of material, which has an important impact on the slope stability of open-pit coal mine, mainly reflected in the following aspects:

- Compaction degree of soil: Higher compaction degrees – that is, more compact filling between soil particles – usually indicate high capacity weight soil. The degree of compaction of soil determines the shear strength and stability of the slope of an open-pit coal mine directly. Higher shear strength of the high capacity weight soil makes it more suited for slope stability. The stability of an open-pit coal mine slope depends much on the soil mass with high capacity weight having limited permeability and good anti scouring ability. The low permeability soil with strong anti-erasure capacity can efficiently stop the penetration and erosion of water flow, lower the loss and erosion of slope soil, and increase the stability of slope. The soil with high capacity weight typically exhibits low deformation characteristics, that is, the deformation generated by external force is minor. This helps the slope's stability since smaller deformation of the slope soil results in smaller displacement and deformation energy, therefore lowering the risk of slope sliding or collapse.

Stability of an open-pit coal mine slope depends critically on cohesion. It immediately influences the internal structure and interaction of slope soil, thereby influencing the stability of the slope as whole. The following describes specifically how cohesiveness affects the slope stability of an open-pit coal mine: improve the soil's cohesiveness. Cohesiveness improves the cohesiveness of soil, helps the particles to cluster together to create binding force, and influences the attraction between the individual soil particles. This cohesiveness helps to increase the general stability of soil and stop the movement and sliding of its particles.

Cohesiveness increases the closely linked together soil particles, therefore lowering the soil's porosity and so slowing down the water penetration rate. This helps to preserve the stability of the slope, lessens the saturation of the soil, and avoids the sharp shift of the moisture content in the ground.

Boost the shear strength of soil by means of cohesion since it raises the friction resistance and interaction force among the soil particles. This implies that the soil is more difficult to shear failure from outside load, thereby enhancing the lateral force resistance of the slope.

Larger cohesiveness can help the soil particles to be more firmly linked, therefore lowering the erosion and denudation of water on soil. This preserves slope integrity and stability and helps to slow down the gully of the slope's growth speed. The ratio between the maximal shear strength and the vertical pressure the soil or rock mass can resist under external shear force determines the internal friction angle. One of the crucial factors defining the shear strength of rock mass or soil. It affects the slope stability of open-pit coal mines significantly; this is demonstrated here: One of the main factors to characterise the shear strength of rock mass or soil is internal friction angle. Because the increased internal friction angle allows soil or rock mass to resist more shear force, the shear failure of either material is more challenging. Larger internal friction angles so often suggest more stability of the slope.

- Influence the anti sliding ability of slope: The internal friction angle directly affects the friction resistance between soil or rock mass. Larger internal friction angle means higher friction resistance, which increases the anti sliding ability of soil or rock mass. In the open-pit slope, the larger internal friction angle can reduce the probability of landslide or sliding and improve the stability of the slope.

In geotechnical engineering, in order to simplify the calculation and improve the efficiency, the physical parameters of the whole soil layer can be converted by weighted average. It is assumed that f_i is the calculation amount of the i^{th} soil layer, x_i is the physical index of the i^{th} soil layer, h_i is the thickness of the i^{th} soil layer, and f is the comprehensive value of the calculation amount of each soil layer. The calculation quantity f_i is in direct proportion to the physical parameter index x_i of soil layer and the thickness h_i of soil layer. Equation (1) gives the relationship among the three:

$$f_i = ax_ih_i \tag{1}$$

where a is a constant.

$$f = \sum_{i=1}^{n} f_i \tag{2}$$

where n is the number of layers of the whole soil layer. Assuming x_m is the weighted physical index of each soil layer, then:

$$f = ax_m \sum_{i=1}^{n} h_i \tag{3}$$

$$x_m = \frac{f}{a\sum_{i=1}^{n} h_i} = \frac{\sum_{i=1}^{n} f_i}{a\sum_{i=1}^{n} h_i} = \frac{\sum_{i=1}^{n} x_ih_i}{\sum_{i=1}^{n} h_i} \tag{4}$$

According to the above formula, the mechanical parameters of soil layer are weighted.

3 Influence of slope shape on slope stability of open pit mine.

The shape of slope has a significant impact on its stability, especially the slope angle and height. Slope angle and height are one of the key factors determining slope stability (Bednarczyk, 2017).

Slope angle refers to the angle between the slope and the horizontal ground, which has a significant impact on the stability of the slope. The size of slope angle directly affects the free state and stress distribution of slope front. The increase of slope angle may cause a series of slope stability problems. First, a larger slope angle will expand the range of slope tension zone, resulting in more cracks and tension on the surface of slope. With the expansion of these tension bands, the risk of slope surface slip increases. At the same time, the stress at the toe of the slope will also be concentrated due to the increase of slope angle. This stress concentration will lead to the increase of shear stress, especially in the bottom area of the slope. The increase of shear stress may lead to shear failure of rock and soil layers inside the slope, which further aggravates the risk of slope instability. Mining operations in the open pit slope could alter the topography, change the slope angle, and thereby influence the slope stability.

Among the main determinants of slope stability is slope height. Higher stress concentration in the toe and other important locations results from the considerable rise in self weight pressure of soil and rock under high slopes. The shear stress and vertical pressure of the slope will be much raised by the increase of self weight pressure, therefore increasing the likelihood of slope deformation and landslip. Furthermore, the higher gravity stress of the slope will generate more shear pressure on the interior rock and soil layer, which will cause sliding surface or fault to develop, therefore compromising the general stability of the slope. In open-pit mines, mining operations could cause variations in slope height; hence, it is essential to routinely assess the slope stability and implement appropriate reinforcement actions to guarantee slope safety.

The profile shape of landslide is closely related to the scale and development stage of landslide. The plane profile shape of the slope reflects the deformation area and overall appearance of the landslide, and is an important index to judge the external characteristics of the slope. Different landslide forms are related to the deformation state, and some forms may contribute to the further development of the landslide. Although the profile shape of landslide may change during the deformation process, it is very important to analyse the current landslide state and predict the slope stability. According to different profile shapes, landslides can be divided into five types: convex, concave, composite, straight and stepped. These forms have different characteristics and influences.

4 Influence of hydro meteorological conditions on slope stability of open pit mine.

The influence of water on slope mainly has two aspects: first, it increases the shear stress of slope soil; Secondly, it reduces the shear strength of soil.

a The impact of surface water on soil slope is mainly reflected in erosion, which usually has two forms: surface erosion and gully erosion. Areal erosion is a common form of erosion in soil slopes. Due to the loose soil layer on the slope, when rainwater flows along the slope, it will evenly scour the loose material, resulting in the erosion of the soil layer on the slope and gradually reduce, and the slope moves backward. Long term surface erosion will accumulate a large amount of soil at the foot of the slope, forming a thick accumulation layer. Gully erosion is a common form of surface erosion, which usually occurs on the slope with uneven terrain. This erosion form is mainly due to the existence of grooves and low depressions on the slope. When the precipitation is large, the water flow will gather in these low-lying places to form linear flow, and the erosion intensity will also increase. On the slope, this flow will accelerate the erosion of surface soil and rock, and gradually form rills, forming the so-called gully erosion. This erosion process will not only lose soil, but also lead to further aggravation of the terrain, which will have adverse effects on the ecological environment and land use. These erosion forms will make the soil slope surface subject to different degrees of erosion, thus affecting the stability of the slope and slope characteristics.

b The impact of surface water on rock slopes is small because they are generally stronger and less vulnerable to surface erosion. However, severe weathering and heavy rainfall may lead to the stripping of the surface layer, exposing the bedrock, and accelerating the weathering process, which will lead to the gradual thinning of the rock mass, the decline of strength, the increase and deepening of cracks, forming a vicious cycle. In addition, the blockage of surface water will increase the weight of rock mass and further increase the sliding force of slope. Landslide events usually occur in the period of rainfall or snow melting, and the seepage field distribution of the slope is changed by the infiltration of a large amount of water. The infiltration and accumulation of water lead to the rise of groundwater level, increase the water pressure, soften the potential sliding surface, reduce the shear strength and anti sliding force, and make the slope unstable.

c The influence of groundwater on sandy slope is very important. The sand slope is in a dry state, which is mainly supported by the friction between sand particles. However, the friction angle between sand particles will be reduced after rainwater infiltration, especially when the drainage is not smooth or there is an impermeable layer, the water fills the pores to form pressure, which reduces the effective stress and internal friction of the soil, resulting in a sharp decline in slope stability. In addition, the increase of water content in soil will also increase the sliding force of slope and further aggravate the risk of instability.

d Groundwater has dual effects on clay slope. The dry clay slope is relatively stable due to its high shear strength, but cracks may exist. During rainfall, water penetrates into clay through cracks, forming pore water pressure. This will increase the weight of the soil mass and the sliding force, and may cause the soil mass to be lifted and flow soil phenomenon, and eventually lead to slope instability and failure. The permeability of silty slope is between sand and clay. Although the cohesion and shear strength may be increased after rainwater infiltration, it also reduces the internal friction angle of soil and weakens the overall strength. With the increase of water content, the cohesion decreases and the shear strength decreases. When the buoyancy force exceeds the gravity, it may cause flowing soil phenomenon, leading to slope instability.

e Groundwater will produce pore water pressure in the pores of rock slope, which is related to the height of water head and perpendicular to the pore surface. High water head will cause large hydrostatic pressure, which will exert sliding thrust on the rock mass and reduce the stability of the rock mass.

f The hydrodynamic pressure produced by groundwater seepage depends on the flow volume, water density and hydraulic gradient. The pressure direction is consistent with the water flow, which may reduce the weight of the filler on the structural plane, or even take away the filler particles, increase the voids and reduce the stability of the rock.

2.2 WWO algorithm

WWO is an intelligent optimisation algorithm based on water wave propagation and refraction phenomenon, which simulates the variation of wavelength, wave height and energy during water wave propagation (Rajan et al., 2022). WWO realises global search and local development of optimisation problems by simulating physical phenomena such as propagation, refraction and breaking of water waves.

One of the fundamental ideas behind WWO algorithm is water wave propagation. With the increasing propagation distance, wavelength λ and wave height h will progressively fade in the process of water wave propagation (Shofner et al., 2016). One may write the attenuation law of wavelength and wave height by means of the following equation:

$$\lambda(t+1) = \lambda(t) \cdot \alpha \tag{5}$$

$$h(t+1) = h(t) \cdot \beta \tag{6}$$

where $\lambda(t)$ and $h(t)$ respectively represent the wavelength and wave height at the t^{th} iteration; α and β are attenuation factors. The wavelength determines the propagation range of water waves λ, and the wave height h determines the energy of water waves (Thomas et al., 2017). By dynamically adjusting the wavelength and wave height, WWO can achieve a balance between global search and local development.

Refraction happens when water waves run across barriers during propagation, therefore changing the direction of the refracted water waves. WWO mimicking the phenomena of water wave refraction improves the global search capabilities of the method. The following equation allows one to determine the direction of propagation of refracted water waves:

$$\theta_{new} = \theta_{old} + \Delta\theta \tag{7}$$

where θ_{old} is the propagation direction before refraction; θ_{new} is the propagation direction after refraction; $\Delta\theta$ is the refractive angle, usually following a certain probability distribution.

The refractive probability P_r can be calculated using the following equation:

$$P_r = \exp\left(-\frac{\Delta\theta^2}{2\sigma^2}\right) \tag{8}$$

where σ is the standard deviation of the refractive angle. WWO can dynamically change the search direction during the search process by including refraction probability, therefore avoiding local optima's trap.

The energy in water waves progressively decays during their propagation. The water waves will fragment (Zhou et al., 2019) when the energy drops below a particular level. WWO mimicking the phenomena of water wave breaking improves the local development capability of the method. One can characterise the situation under which water waves break by the following equation:

$$E(t) < E_{threshold} \tag{9}$$

where $E(t)$ is the water wave energy at the t^{th} iteration; $E_{threshold}$ is the energy threshold.

When water waves break, WWO generates new water waves, and the wavelength and wave height of the new water waves can be calculated using the following equation:

$$\lambda_{new} = \lambda_{initial} \cdot \gamma \tag{10}$$

$$h_{new} = h_{initial} \cdot \delta \tag{11}$$

where $\lambda_{initial}$ and $h_{initial}$ are the initial wavelength and wave height; γ and δ are random factors.

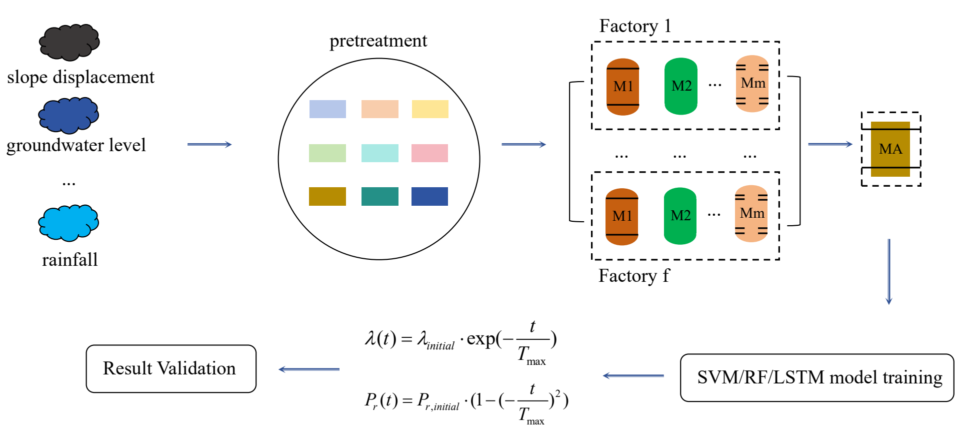
WWO can do fine search in local areas by modelling the phenomena of water wave breaking, so enhancing the local development capacity of the method (Zhou et al., 2020).

By mimicking physical events including water wave propagation, refraction, and fragmentation, WWO enables both local growth of optimisation issues and worldwide search.

3 Multi model parameter optimisation and fusion method based on improved WWO algorithm

The key to monitoring the stability of open-pit mine slopes is to collect real-time data on slope displacement, groundwater level, rainfall, and geological structure through multiple sensors, and predict potential instability risks based on machine learning models. However, the parameter sensitivity of traditional machine learning models such as SVM, random forest RF, and long short-term memory network LSTM severely restricts their prediction accuracy and generalisation ability. Therefore, this study proposes a multi model parameter synchronisation optimisation and fusion method based on the IWWO algorithm. This method enhances global search capability by dynamically adjusting wavelength attenuation factor and nonlinear refraction probability, and combines adaptive mutation strategy to balance convergence speed and local extremum escape performance, ultimately achieving collaborative improvement of multi model parameter optimisation and fusion mechanism. The model framework diagram of this method is shown in Figure 2.

Figure 2 Model structure diagram (see online version for colours)



3.1 Multi source data collection and preprocessing

By using displacement sensors, water level gauges, rain gauges, and geological exploration equipment to collect slope displacement $D(t)$, groundwater level $W(t)$, rainfall $R(t)$, and geological structural parameters G, a multidimensional time-series dataset is constructed. To eliminate dimensional differences, the data is standardised using maximum minimum normalisation:

$$x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{12}$$

For time series data (such as displacement and water level), sliding windows are used to segment them into time series samples with a window length of T and a step size of Δt, ultimately forming a feature matrix $X \in \mathbb{R}^{N\times(d_D+d_W+d_R+d_G)}$, where N is the number of samples and d_* is each data dimension.

3.2 Design of IWWO algorithm

The traditional WWO has shortcomings in balancing global search and local development (Singh et al., 2019). This study improves it from three aspects:

- Dynamic wavelength attenuation factor: Wavelength λ controls the search range, and the initial value $\lambda_{initial}$ decays exponentially with the number of iterations t.

  $$\lambda(t) = \lambda_{initial} \cdot \exp\left(-\frac{t}{T_{\max}}\right) \tag{13}$$

  where $T_{\max}$ is the maximum number of iterations, which makes the algorithm focus on global exploration in the early stage and local development in the later stage.

- Nonlinear refraction probability adjustment: Refraction probability $P_r(t)$ determines the frequency of search direction adjustment, and the initial value $P_{r,initial}$ decreases nonlinearly with iteration:

  $$P_r(t) = P_{r,initial} \cdot \left(1 - \left(-\frac{t}{T_{\max}}\right)^2\right) \tag{14}$$

  This design avoids premature convergence of the algorithm to local optima.

- Adaptive mutation strategy: mutation probability $P_m(t)$ dynamically adjusts local disturbance intensity:

  $$P_m(t) = P_{m,initial} \cdot \left(1 - \frac{t}{T_{\max}}\right) \tag{15}$$

3.3 Multi model parameter synchronous optimisation

Using IWWO to synchronously optimise the key parameters of SVM, RF, and LSTM, the specific process is as follows:

- SVM kernel function parameter optimisation: The optimisation objective is Gaussian kernel parameter γ and penalty coefficient C, individual encoding is $v_i = [\gamma_i, C_i]$, and the fitness function is to minimise the mean square error (MSE) of cross validation:

$$Fitness\left(v_i\right) = \frac{1}{K}\sum_{k=1}^{K}\left(y_k - \hat{y}_k\left(v_i\right)\right)^2 \tag{16}$$

where K is the cross validation fold, and $\hat{y}$ is the k^{th} fold predicted value.

- F-tree depth and feature subset optimisation: The optimisation parameters are maximum tree depth $d_{\max}$ and feature subset ratio f_{ratio}, individual encoding $v_i = [d_{\max,i}, f_{ratio,i}]$, and fitness function maximising out of bag (OOB) accuracy:

$$Fitness\left(v_i\right) = \frac{TP + TN}{TP + TN + FP + FN} \tag{17}$$

- LSTM hidden layer node optimisation: The optimisation parameters are the number of hidden layer nodes h_{units} and dropout rate $p_{dropout}$, individual encoding $p_{dropout}$, and fitness function minimising the MSE of the validation set:

$$Fitness\left(v_i\right) = \frac{1}{N_{val}}\sum_{j=1}^{N_{val}}\left(y_j - \hat{y}_j\left(v_i\right)\right)^2 \tag{18}$$

3.4 Multi model fusion mechanism

To improve generalisation ability, design a dynamic weight fusion strategy:

- Weight allocation: Dynamically allocate weights based on the MSE of each model on the validation set:

$$w_m = \frac{MSE_m^{-1}}{\sum_{m=1}^{3} MSE_m^{-1}} \tag{19}$$

- Fusion prediction: The final slope stability prediction value is a weighted sum:

$$\hat{y}_{fusion} = w_{SVM} \cdot \hat{y}_{SVM} + w_{RF} \cdot \hat{y}_{RF} + w_{LSTM} \cdot \hat{y}_{LSTM} \tag{20}$$

- Weight update: Introduce a sliding window mechanism to periodically recalculate weights based on the latest monitoring data to adapt to dynamic environmental changes.

This method achieves global and efficient optimisation of multiple model parameters through the IWWO algorithm, and combines dynamic fusion mechanism to fully explore the nonlinear modelling ability of SVM, the robustness of RF, and the temporal dependence of LSTM. It significantly improves the accuracy and real-time performance of slope stability prediction, providing reliable technical support for mine safety warning.

4 Model instance verification based on WWO algorithm for improving machine learning

In this section, actual slope engineering data is introduced and used as test set samples, which are input into the trained model to evaluate the actual stable state of the slope and further verify the generalisation ability of the model in this paper. Meanwhile, the stability of the slope was calculated using the rigid limit equilibrium method. Finally, the predicted results of the model in this article will be compared and verified with the results calculated by the rigid limit equilibrium method. This comparison can evaluate the accuracy and reliability of the model in practical engineering, further verifying its generalisation ability and practicality.

4.1 Overview of mining area and analysis of engineering geological characteristics

A certain open-pit coal mine is located in the transitional zone between piled up terrain and low hilly terrain. The elevation of the ore field is between 1,022 m and 1111 m, with a relative height difference of 89m. The preliminary design is an open-pit mine with a scale of 10.0 Mt/a, with a surface width of 1.9–3.3 km from north to south, a length of 3.6–4.0 km from east to west, and a surface area of 12.282 km^2; The bottom is 1.6–2.5 km wide from north to south and 3.2–3.8 km long from east to west, with a bottom area of 9.23 km^2. The mining elevation is 880–1096 m, the mining depth is 70–216 m, and the final slope angle of the open-pit mine is 22–26º. The open-pit coal mine experienced a landslide on November 5, 2013. The landslide occurred on three flat surfaces ranging from 1024 to 988 in the range of 3,900–4,400. The landslide body is about 500m long, 230m wide, with an area of 10.6×104 m^2 and a volume of 208×104 m^3. On November 4, cracks appeared and settlement occurred in 1024. The upper flat plate did not show any bottom bulges or cracks, but there was a bottom bulge phenomenon at the bridge construction site, indicating signs of landslide. This landslide is a bedding landslide. The physical and mechanical indicators of rock and soil mass are the basis for quantitative analysis of slope stability, as shown in Table 1.

Table 1 Physical and mechanical indicators of rock and soil mass

Rock formation	*Bulk density (KN/m^3)*	*Cohesion (KPa)*	*Internal friction angle (º)*
Disposal of materials	18	15.13	14
Fine sand, silt	20.8	0	26.9
Mudstone	19.6	50	25
Weak layer	18.6	5	9
Medium coarse sandstone	23.9	850	29
Coal seam	12.2	100	30

4.2 Slope stability analysis based on rigid limit equilibrium method

The principles for selecting and calculating profiles are as follows:

1 Selecting a profile requires careful consideration of representativeness and comprehensiveness – that is, of several kinds of slope characteristics.

2 The profile's design should be as perpendicular as feasible to the direction of the slope steps to faithfully depict the geometric structure of the hill.

3 Selecting profiles should take drilling and monitoring point location into account to guarantee data completeness and accuracy.

4 Profiles should be made up around slopes near significant buildings and facilities to guarantee the stability of these locations.

5 High risk areas: Profile should be set up to track possible hazards in places where landslides have happened or where there is a really high degree of risk.

6 Profiles should be made up to grasp the slope conditions under various geological situations when they alter greatly.

7 Selection of a suitable profile depends on the slope's service length to guarantee its stability over its whole service life.

These ideas guarantee that the choice of profiles can represent the real state of the slope and offer correct and trustworthy data to enable the stability analysis and safety evaluation of the slope. Eight computational profiles were established in the Northern Gang, namely A1-A1′, A2-A2′, A3-A3′, A4-A4′, A5-A5′, A6-A6′, A7-A7′, and A8-A8' section; Two profiles have been established on the western slope, namely the C1 to 1′ and C1 to 2′ profiles; Dongbang established 5 profiles, namely B1-B1′, B2-B2′, B3-B3′, B4-B4′, and B5-B5′.

According to the Design Code for Open pit Mines in the Coal Industry (GB50197-2015), the safety factor of non-working slope in the mining area should be adjusted based on the service life. When the service life is less than 10 years, it is recommended that the safety factor Fs should be between 1.1 and 1.2 to ensure sufficient stability of slopes with shorter service life. If the service period is between 10 and 20 years, the safety factor should be between 1.2 and 1.3. The slope at this stage requires a higher safety factor to cope with possible stress changes and environmental impacts. When the service period exceeds 20 years, the range of safety factor should be 1.3 to 1.5. Long term use of slopes requires a higher safety factor to ensure their sustained stability and resistance to the effects of time and natural erosion. These regulations ensure the safety and stability of slopes and provide specific guidance based on service life to address the different risks and challenges of non-working slopes in mining sites. Based on the slope type and service life, the safety reserve factor is determined to be 1.2.

The limit equilibrium method is commonly used in engineering to analyse slope stability, among which the Morgenstern Price method is a widely used slice method. Using the SLOPE/W module in GEO studio numerical simulation software, a slope model was established, and the safety factors of the selected typical profiles were calculated. Taking the five profiles in Dongbang as an example, the model materials were selected from Table 1. The Morgenstein Price (M-P) calculation method was used to search and calculate the circular sliding surface. The safety factors of B1-B1′ and B2-B2′ profiles are 2.532 and 1.129, respectively. The safety factors of B3-B3′, B4-B4′, and B5-B5′ profiles are 1.108, 2.298, and 1.239, respectively. According to the 'Design Standard for Open pit Mining Slope Engineering in Coal Industry' (GB51289-2018) and

'Design Code for Open pit Mining in Coal Industry' (GB50197-2015), the slope states of B2-B2′ and B3-B3′ profiles are basically stable, while the slope states of B1-B1′, B4-B4′, and B5-B5′ profiles are stable, as shown in Figure 3 to Figure 7.

Figure 3 B1-B1′ profile (see online version for colours)

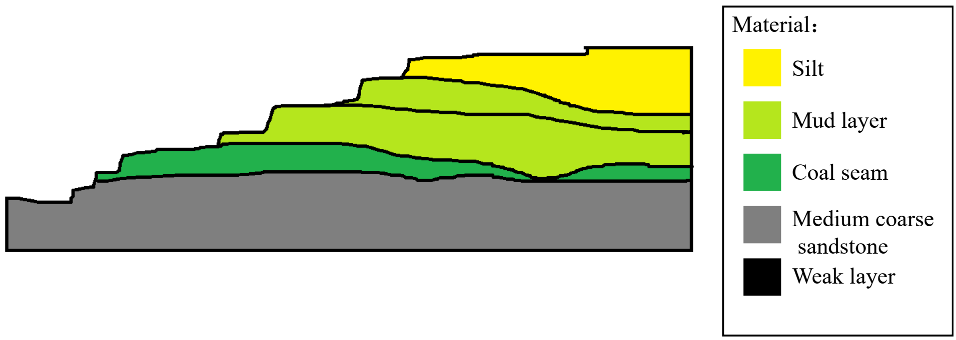


Figure 4 B2-B2′ profile (see online version for colours)

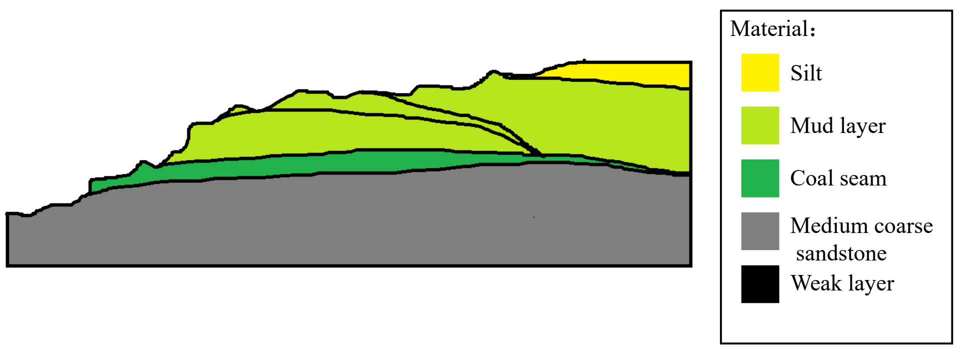


Figure 5 B3-B3′ profile (see online version for colours)

Figure 6 B4-B4′ profile (see online version for colours)

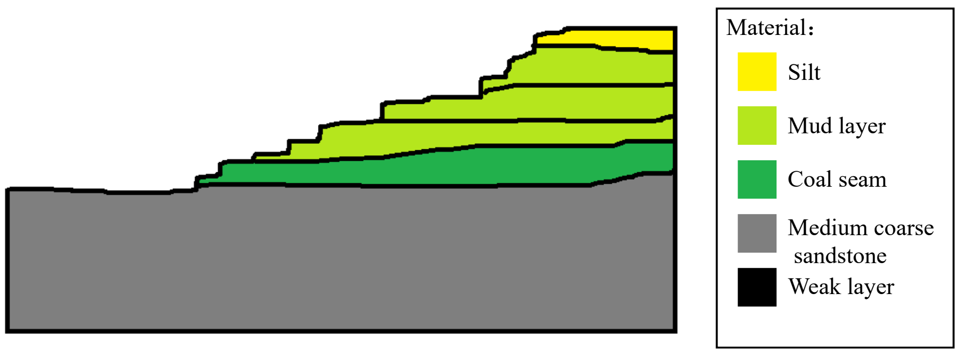
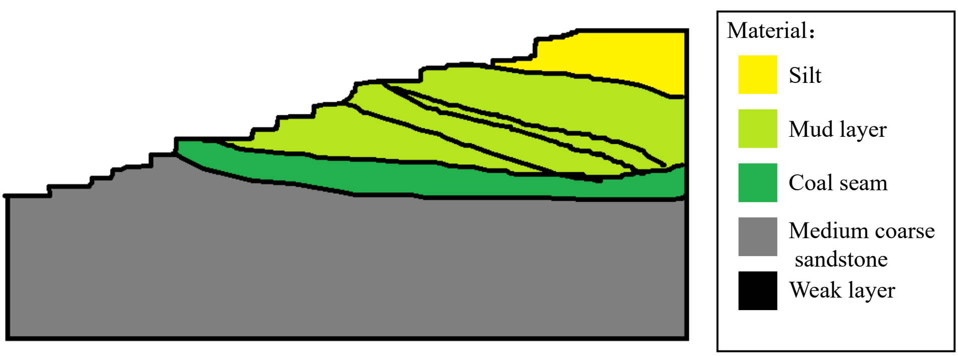


Figure 7 B5-B5′ profile (see online version for colours)



4.3 Improved machine learning model for slope stability evaluation based on WWO algorithm

Use the trained model to predict 15 actual slopes of a certain open-pit coal mine to demonstrate its generalisation ability and accuracy.

According to on-site data, the earthquake intensity (X_6) in the mining area is 4°, and the maximum daily rainfall (X_7) is 80mm. The quantified true values of other parameters are shown in Table 2. After inputting the normalised parameters of 15 samples into the trained model, the slope stability level can be directly obtained.

Table 2 Quantify the true values of model parameters

Serial number	X_1	X_2	X_3	X_4	X_5	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}
1	18.71	41.75	28.12	18.81	8.62	0	0	1	1	0	1	0
2	18.51	42.34	22.2	43.25	453.6	2	1	2	2	0	1	2
3	14.86	45.6	19.8	36.31	386.08	2	0	1	2	0	1	2
4	18.07	35	18.93	44.54	361.51	2	1	2	2	1	1	2
5	16.2	44.14	22.26	37.71	359.04	3	1	2	3	2	1	3
6	20	27.38	14.57	43.46	319.21	3	1	2	4	3	2	3
7	16.78	26.79	20.66	43.66	249.7	2	1	2	0	1	2	3

Table 2 Quantify the true values of model parameters (continued)

Serial number	X_1	X_2	X_3	X_4	X_5	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}
8	16.83	13.98	25.46	43.5	96.14	2	1	3	0	2	1	3
9	20.95	30.79	27.08	39.77	131.22	3	0	1	0	2	2	3
10	20.33	15.62	24.21	52.5	85.76	3	0	1	0	3	2	3
11	21.25	25.73	27.97	48.23	91.55	1	0	1	0	4	1	2
12	22.57	9.98	30.31	35.46	526.13	1	0	3	2	4	2	2
13	18.01	9.5	27.36	41.86	538.1	3	0	3	2	3	2	1
14	17.83	45.01	15.95	47.83	456.38	4	0	2	2	3	1	1
15	18.35	44.97	23.49	43.16	413.42	4	0	2	0	3	2	1

Table 3 Model prediction results

Slope number	*True state*	*Predicting status*
1	IV	IV
2	IV	IV
3	IV	IV
4	IV	IV
5	IV	IV
6	IV	IV
7	IV	IV
8	III	II
9	IV	IV
10	III	III
11	III	III
12	IV	IV
13	IV	IV
14	III	III
15	III	III

Table 3 shows that the output results of the model in this article are basically consistent with the actual results. Among all 15 slopes, the model accurately predicted 14, with only 1 prediction error. The only misjudgement is that a basically stable slope was incorrectly predicted as unstable, which may be due to the fuzzy boundary between these two states, indicating that the model has strong generalisation ability.

5 Conclusions

The stability monitoring of open-pit mine slopes is a key link in mine safety production. Traditional machine learning models have significant shortcomings in prediction accuracy and parameter optimisation efficiency, making it difficult to meet practical engineering needs. In response to this issue, this study proposes a machine learning monitoring method based on an improved WWO algorithm, which significantly improves the accuracy and real-time prediction of slope stability through multi-source data acquisition, multi model parameter optimisation, and fusion mechanism. Firstly, a comprehensive monitoring dataset was constructed by collecting key monitoring data such as slope displacement, groundwater level, rainfall, and geological structure through multiple sensors, and preprocessing operations such as standardisation and temporal alignment were carried out. Secondly, to address the parameter sensitivity issues of SVMs, random forests, and long short-term memory networks, an improved WWO algorithm is introduced. By dynamically adjusting the wavelength attenuation factor and nonlinear refraction probability, the algorithm's global search capability is enhanced; By combining adaptive mutation strategy, the convergence speed and local extremum escape performance of the algorithm are balanced. On this basis, IWWO was used to synchronously optimise the kernel function parameters of SVM, the tree depth and feature subset of RF, and the hidden layer nodes of LSTM, significantly improving the predictive performance of each model. To further enhance the generalisation ability of the model, this study designed a multi model fusion mechanism, which weights the prediction results of SVM, RF, and LSTM through a dynamic weight allocation strategy, fully utilising the advantages of each model to achieve more stable and accurate slope stability prediction. Finally, the effectiveness and practicality of the proposed method were verified through actual slope engineering data. The experimental results show that the method proposed in this paper can identify the precursors of slope instability in real time, and the predicted results are highly consistent with the calculation results of the rigid limit equilibrium method, which verifies the generalisation ability and engineering applicability of the model.

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Declarations

All authors declare that they have no conflicts of interest.

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