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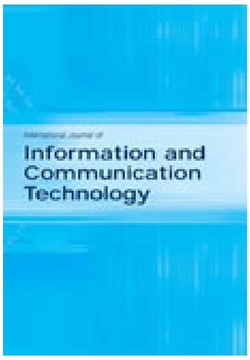

International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

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DOI: 10.1504/IJICT.2025.10072943

Article History:

Received:	21 June 2025
Last revised:	14 July 2025
Accepted:	15 July 2025
Published online:	08 September 2025

Optimisation of rare earth mining using intelligent optimisation algorithms

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Abstract: Rare earth resources, as a strategic key mineral resource for the nation, require efficient and sustainable development. Traditional mining sequence planning methods struggle to comprehensively coordinate the complex interplay of multiple factors. To address these challenges, this study employs a genetic algorithm to efficiently solve the model, aiming to generate an overall optimal or satisfactory mining sequence plan under given constraints. Research validation indicates that the proposed method can more effectively balance the long-term and short-term benefits of a mine's entire lifecycle and better adapt to the spatial complexity of geological conditions in mining areas. Additionally, the study explores key parameter settings for the algorithm and potential improvement strategies to enhance solution performance. This research provides new theoretical support and effective intelligent decision-making tools for the scientific formulation of mining plans for rare earth mines, holding significant theoretical value and practical guidance implications.

Keywords: intelligent optimisation algorithms; genetic algorithms; rare earth mines; mining areas.

Reference to this paper should be made as follows: Liu, X., Yi, L. and Zheng, M. (2025) 'Optimisation of rare earth mining using intelligent optimisation algorithms', *Int. J. Information and Communication Technology*, Vol. 26, No. 32, pp.53–67.

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1 Introduction

Rare Earth Elements serve as strategic resources supporting the development of high-tech industries and the transition to clean energy, and their sustainable development has become a global focus. According to the US Geological Survey, China accounts for 37% of global rare earth reserves and over 60% of production (Summaries, 2021). However, southern ion-adsorption-type rare earth deposits, which are found in weathered crust layers with strong spatial variability in ore grades, are highly prone to causing soil erosion and radioactive contamination during extraction (Wang et al., 2018). Traditional mining sequence planning relies on human experience and static models, making it difficult to balance economic benefits, resource utilisation, and environmental protection in a dynamic manner (Moldoveanu and Papangelakis, 2016). Especially in the current context of heightened price volatility and stricter environmental regulations, there is an urgent need to develop adaptive optimisation methods to achieve scientific management of the entire mining lifecycle.

Mining sequence optimisation fundamentally falls under high-dimensional combinatorial optimisation problems. Early studies primarily employed mathematical programming methods: Rocchi et al. (2011) utilised a proprietary mixed-integer linear programming tool named Blasor for open-pit strategic coal mine planning, rapidly assessing the necessary joint optimal underground development strategies and mining sequences across several longwall mining areas. Since the 21st century, intelligent optimisation algorithms have made significant strides in the mining planning field due to their flexibility in handling nonlinear constraints. have made significant progress in the field of mine planning. Alipour et al. (2017) applied genetic algorithms to a hypothetical two-dimensional (2D) copper ore body model. The ore body is characterised by a two-dimensional (2D) block array. Similarly, the corresponding two-dimensional GA array is used to represent the solution space of the OPPS problem. Then, a fitting function was defined based on the objective function of the OPPS problem to evaluate the solution domain. Fathi et al. (2021) introduced a novel hybrid method combining two artificial intelligence techniques to estimate iron ore grades; this method is based on a single-layer extreme learning machine and particle swarm optimisation, designed using drill hole locations, depths, and information from the ore body, and applied to ore grade estimation on a block model basis.

Research on the optimisation of rare earth mining has long lagged behind that of traditional mineral species. Existing literature primarily focuses on improvements to hydrometallurgical processes or tailings pollution control, with insufficient research on intelligent decision-making for mining sequences. Ion-adsorption-type rare earth ore bodies exhibit a planar distribution pattern, with strict spatial dependencies between mining sites, and require dynamic responses to fluctuations in the market value of multiple rare earth elements (Yang et al., 2013).

To address these challenges, this paper proposes an adaptive genetic algorithm framework (AGA-OSO) that integrates geological constraints with multi-objective decision-making. The core innovation lies in constructing a geological-economic-environmental coupled optimisation model: economic objectives incorporate rare earth price time series predictions to maximise discounted cash flow; resource objectives introduce a rare earth oxid comprehensive recovery rate function; environmental objectives quantify surface disturbance costs based on GIS ecological sensitivity analysis. A three-dimensional voxel chain encoding mechanism is designed to map mining field topological relationships (such as ore body dip angle and slope stability constraints) to chromosome gene loci. At the algorithmic level, a dynamic adaptive strategy is adopted: crossover probability is adjusted based on population entropy feedback, mutation probability is regulated via a nonlinear simulated annealing mechanism to prevent premature convergence, and a feasible solution repair operator is integrated to handle complex constraints. To address geological uncertainty, a sequential Gaussian simulation is integrated to generate a grade distribution scenario tree, and a conditional value at risk model is used to generate a Pareto front solution set, providing decision-makers with risk-controlled optimisation solutions.

2 Relevant technologies

2.1 Rare earth mining

The formation and evolution of rare earth deposits are controlled by complex geological structural movements and surface geochemical processes. Unlike the concentrated occurrence of traditional metal ore bodies, ion-adsorption-type rare earth deposits often exhibit a planar distribution within weathered crust layers, with their mineralisation mechanisms originating from the chemical weathering of granitic or volcanic rocks under humid and hot climatic conditions (Bai et al., 2022). Primary rare earth minerals undergo hydrolysis and leaching, after which rare earth ions are selectively adsorbed by clay minerals such as kaolinite and illite, forming secondary ore deposits of industrial value. This unique occurrence state results in ore bodies exhibiting a spatially distributed pattern characterised by widespread dispersion and localised enrichment. The thickness, grade, and elemental composition ratio of the ore layers exhibit significant variability both vertically and horizontally. The extraction of such resources essentially involves the directed extraction and enrichment of ion-adsorbed rare earth elements within geological bodies. The theoretical core lies in elucidating the coupled relationship between ore body spatial heterogeneity, mining dynamics response, and resource recovery efficiency (Li et al., 2022).

The theoretical framework for rare earth mining must integrate three dimensions: geological resource characteristics, mining technology constraints, and environmental system interactions. From a geological perspective, the heterogeneous structure of ore bodies necessitates the establishment of a detailed three-dimensional resource model, with the key challenge being the quantification of the spatial correlation of grade distribution (Zhang et al., 2022). While traditional Kriging interpolation can characterise regionalised variable trends, it is insufficient for describing the abrupt boundaries and nested structures of weathered crust deposits, necessitating the introduction of geostatistical modelling (such as sequential indicator modelling) to reconstruct the uncertainty field of ore bodies. The mining technology dimension focuses on the uniqueness of chemical mining: injecting electrolyte solutions (such as ammonium sulphate) into the ore layer via injection wells, utilising ion exchange principles to desorb rare earth ions, and then collecting the leachate for precipitation and purification. The theoretical essence of this process is the coupling of solid-liquid two-phase reaction kinetics and seepage mechanics. Leaching efficiency is constrained by multiple factors, including the permeability coefficient of the ore layer, solution concentration gradient, adsorption-desorption equilibrium constants, and groundwater conditions (Xu et al., 2021). In practice, it is necessary to optimise the layout of injection wells, leaching intensity, and recovery cycles to balance short-term extraction rates and long-term resource recovery rates rare earth mining.

The theoretical foundation of mining sequence decision-making stems from system optimisation principles, requiring the coordination of the dynamic interactions among the resource, economic, and environmental systems. The resource system aims to maximise the overall recovery rate of rare earth oxide (REO), with its theoretical bottleneck lying in the synergistic extraction of co-occurring elements – due to the strong adsorption capacity of high-value heavy rare earth elements such as terbium and dysprosium, improper mining sequences may result in their residual presence within clay crystal lattices. The economic system aims to maximise the net present value over the entire lifecycle, necessitating the construction of a price-cost linkage model: rare earth prices fluctuate sharply due to global supply chain dynamics (such as magnetic material demand), policy quotas, and the impact of alternative technologies, while mining costs increase non-linearly with mine depth, terrain slope, and environmental protection investments. The environmental system emphasises minimising ecological disturbance, with its theoretical core being the quantification of the negative externalities of 'leaching-loss' (He et al., 2021). Ammonium sulphate leaching causes ammonia nitrogen to infiltrate aquifers, leading to water eutrophication, while large-scale topsoil stripping exacerbates soil erosion risk (Mwewa et al., 2022). Theoretical studies indicate that environmental costs grow exponentially with mining intensity, necessitating the prioritisation of ecological barrier construction and post-closure rehabilitation plans in temporal planning.

The core challenge facing the current theoretical framework is the transmission of uncertainty across multiple scales. At the micro-scale, the heterogeneous distribution of clay mineral adsorption sites makes it difficult to precisely calibrate leaching kinetic parameters; at the meso-scale, the ambiguity of ore body boundaries often results in estimation errors exceeding 20% for recoverable reserves; at the macro-scale, sudden changes in external market and policy environments must be addressed. These uncertainties are transmitted through the mining system at each level, ultimately amplifying into instability in resource benefits and environmental risks. Therefore, modern mining theory is evolving from deterministic planning to a stochastic-robust optimisation paradigm, with the breakthrough point being the construction of a 'geological-engineering-environmental' coupled digital twin. Through multi-agent simulation, it pre-simulates system responses under different timing strategies, providing a decision-making foundation for intelligent optimisation algorithms.

2.2 Genetic algorithm

The essence of genetic algorithms is an intelligent search paradigm that simulates biological evolutionary mechanisms, with its core theoretical framework based on population genetics and the principle of natural selection (Katoch et al., 2021). During the exploration of the solution space, the algorithm encodes candidate solutions as chromosomes – for example, the order of rare earth mining can be represented as a string of integers $g = (g_1, g_2, \ldots, g_n)$, where $g_i \in [1, T]$ identifies the mining year of unit i. This encoding transforms high-dimensional combinatorial optimisation problems into an evolutionary process of gene sequences. Its theoretical advantage lies in avoiding local optima traps through parallel population search. The fitness function $F(g)$ quantifies the quality of the solution, providing a basis for selection pressure.

The evolutionary driving force stems from three genetic operators: selection simulates survival of the fittest, and a roulette wheel strategy is adopted to make the selection probability of an individual proportional to its fitness:

$$P_{select}(g_k) = \frac{F(g_k)}{\sum_{j=1}^{N} F(g_j)} \tag{1}$$

The crossover operator mimics genetic recombination, with single-point crossover exchanging parent chromosome segments with probability p_c to break through local solution constraints. The mutation operator randomly disturbs gene values with low probability p_m to inject diversity and maintain the evolutionary potential of the population.

Convergence theory is the mathematical foundation of genetic algorithms (Alhijawi and Awajan, 2024). Using a Markov chain model, it can be proven that when the elitism strategy forces the retention of the optimal solution in each generation, the algorithm converges to the global optimal solution with probability 1. The convergence speed is regulated by the population size N and operator parameters:

$$t_{conv} \propto \frac{\ln(1/\varepsilon)}{\ln\left(1 - \left(p_c \cdot p_{mut}^{eff}\right)^{1/d}\right)} \tag{2}$$

where ε is the convergence threshold, d is the solution space dimension, and p_{mut}^{eff} is the effective mutation probability. In rare earth optimisation, large-scale discrete decision variables require adaptive adjustment of p_c and p_m.

Mining constraint processing theory is key to engineering applications. A repair operator is designed to address mining sequence conflicts. Environmental constraints are incorporated into fitness through the penalty function method:

$$F'(g) = F(g) - \lambda \cdot \max(0, SDI - \Gamma) \tag{3}$$

where λ is the penalty coefficient and Γ is the ecological threshold. This theoretical framework converts hard constraints into soft optimisation objectives, balancing feasibility and search efficiency.

Cutting-edge developments focus on multi-objective optimisation and uncertainty modelling. The NSGA-II algorithm uses non-dominated sorting to stratify populations:

$$Rank(g) = \left|\{g' \mid g' \prec g\}\right| \tag{4}$$

where $g' \prec g$ indicates g' controls g, combining crowded distance to maintain Pareto frontier diversity. In response to rare earth price fluctuations and grade uncertainty, robust optimisation theory introduces scenario tree weighting:

$$Rank(g) = \left|\{g' \mid g' \prec g\}\right| \tag{5}$$

where ξ_s represents the geological scenario and π_s represents its probability. This has driven the evolution of genetic algorithms from static optimisation to dynamic decision-making, establishing their core role in complex mine planning.

The theoretical advantages of genetic algorithms in mining scheduling optimisation stem from their unique search strategy (Sohail, 2023). Compared to local search algorithms (such as simulated annealing), which are prone to getting stuck in local optima, genetic algorithms enable parallel search across the population to simultaneously explore multiple regions of the solution space, significantly reducing the risk of missing the global optimum; when dealing with non-convex, non-continuous objective functions in rare earth mining (such as net present value models considering price jumps), their ability to operate without derivative information avoids the mathematical limitations of traditional optimisers. For strong temporal dependency constraints between mining units (such as mining sequence requirements for slope stability), feasibility rules (feasibility rule) or repair operators (repair operator) can be used to integrate constraint handling into the evolutionary process: the former penalises invalid solutions in fitness evaluation, while the latter actively adjusts chromosome structures to satisfy constraints, with both ensuring the engineering feasibility of solutions. Additionally, the algorithm's convergence theory indicates that under the elitism strategy, when the variance of intergenerational population fitness approaches zero, the algorithm converges to the global optimal solution with probability 1. This characteristic provides theoretical reliability for long-term planning in rare earth mining areas.

The theoretical evolution of genetic algorithms has always revolved around balancing the contradiction between exploration and exploitation. Exploration capability refers to the algorithm's potential to discover new solution regions, regulated by the crossover rate and mutation rate; exploitation capability reflects the algorithm's efficiency in conducting fine-grained searches in the vicinity of high-quality solutions, dependent on the intensity of selection pressure (Gad, 2024). In rare earth mining optimisation, traditional genetic algorithms with fixed parameters often face a dilemma: high exploration leads to slow convergence, while high exploitation triggers premature convergence. To address this, the adaptive genetic algorithm (AGA) was developed, with its core theoretical breakthrough being a dynamic feedback regulation mechanism – real-time adjustment of crossover and mutation probabilities based on population diversity (such as gene entropy values). For example, when the population tends toward homogeneity, the AGA increases the mutation rate to enhance exploration capability; when the population is highly dispersed, it reduces the mutation rate and enhances selection pressure to accelerate exploitation. This mechanism significantly enhances the algorithm's robustness under the complex spatial constraints of rare earth ore bodies, positioning it at the forefront of theoretical research for solving large-scale temporal optimisation problems.

The theoretical development of genetic algorithms is currently deeply integrated with machine learning (Khatri et al., 2023). In the rare earth mining field, acceleration strategies based on surrogate models are gaining traction: neural networks or Gaussian process regression are used to approximate computationally expensive fitness functions, replacing part of the real evaluation to reduce computational load. In multi-objective optimisation, the Non-Dominated Sorting Genetic Algorithm (NSGA-II) maintains solution set diversity through hierarchical sorting and density comparison, providing decision-makers with the Pareto optimal frontier. These theoretical innovations collectively drive the evolution of genetic algorithms from static optimisation tools to intelligent decision-making engines, laying the foundation for addressing multi-scale uncertainty challenges in rare earth mining areas.

3 Mathematical model

The essence of the optimisation problem for the mining sequence of rare earth ore deposits lies in determining the optimal opening and closing sequence of each mining unit (mine field) under the constraints of geological conditions, technical limitations, and environmental capacity, with the aim of maximising the comprehensive benefits over the entire lifecycle. The mining area is defined as being divided into n mining units, with a planning period of T years. The core decision variable is a binary matrix $X = [x_{it}]_{n\times T}$, where $x_{it} = 1$ indicates that mining unit i is mined in year t, and 0 otherwise. This variable must satisfy the uniqueness constraint: each mining unit can only be mined once.

The objective function integrates three dimensions: economic benefits, resource efficiency, and environmental costs. The economic objective aims to maximise the net present value (NPV), which requires consideration of dynamic rare earth prices and mining costs:

$$\max f_1(X) = \sum_{t=1}^{T} \frac{1}{(1+r)^t} \left(\sum_{i=1}^{n} x_{it} \cdot Q_i \cdot p_t - C_t(X) \right) \tag{6}$$

where Q_i represents the REO reserves of unit i, p_t is the predicted rare earth price for year t (influenced by market supply and demand and policy regulation), and r is the discount rate. Mining costs C_t include ore leaching, solution collection, and environmental protection investments, with values increasing nonlinearly with the geographical location of the mining unit (e.g., slope, depth) and cumulative disturbed area.

The resource objective aims to improve the comprehensive recovery rate of rare earths, with a focus on addressing the loss of high-value heavy rare earth elements (HREE):

$$\max f_2(X) = \sum_{k=1}^{K} w_k \cdot \eta_k(X) \tag{7}$$

where K represents the target rare earth element type (e.g., neodymium, dysprosium, terbium), w_k is the weight of element k (determined by market value and strategic importance), and η_k is its recovery rate function. The value of this function depends on the mining sequence. Therefore, a sequence buffering mechanism must be designed to balance leaching kinetic efficiency (Halim et al., 2021).

Environmental objectives require minimising ecological disturbance risks, and the Surface Disturbance Index is introduced to quantify the impact:

$$\max f_3(X) = \sum_{t=1}^{T} \left(\alpha \cdot A_t^{new} + \beta \cdot \Delta P_t \right) \tag{8}$$

where A_t^{new} represents the newly mined area in year t, and ΔP_t represents the increase in ammonia nitrogen concentration in the watershed (due to leakage of the mining agent ammonium sulphate). Coefficients α and β are determined through GIS spatial overlay analysis: α is inversely proportional to the vegetation coverage and soil stability of the unit, while β is positively correlated with groundwater sensitivity. This model explicitly incorporates environmental costs into the optimisation objective, rather than imposing them as post-hoc constraints.

This mathematical model formalises the multi-objective optimisation problem of rare earth mining as:

$$\begin{cases} \max \left[f_1(X), f_2(X) \right] \\ \quad \min f_3(X) \\ \quad s.t. X \in \Omega \end{cases} \tag{9}$$

where Ω is the feasible solution space that satisfies all of the above constraints. Through weighted summation or Pareto optimal frontier generation strategies, multi-objective problems can be converted into single-objective optimisation frameworks that can be handled by genetic algorithms, laying the foundation for subsequent adaptive searches.

4 Adaptive genetic algorithm combining spatial topology coding and dynamic parameter adjustment

Given the challenges posed by the combination of explosive characteristics and multi-objective coupling in the optimisation of rare earth mining sequence, this section proposes an adaptive genetic algorithm (AGA-OSO) that integrates spatial topological encoding with dynamic parameter adjustment. The algorithm flow is illustrated in Figure 1. The core process begins with population initialisation: a three-dimensional voxel chain encoding strategy is employed to map the mining unit sequence into a chromosome structure. Specifically, each chromosome consists of n gene positions, where the gene position number corresponds to the mining unit number, and a gene value of $g_i \in \{1, 2, \ldots, T\}$ indicates the mining year of unit i. To ensure slope stability constraints, a topological sorting rule is introduced during the initialisation phase: when unit i is located below unit j, a feasible solution satisfying condition $g_j \geq g_i + \Delta t$ is forced to be generated to avoid excessive intervention by subsequent repair operators.

The key to genetic operations lies in balancing global exploration and local development capabilities (Khayrutdinov et al., 2022). The selection operator adopts a hybrid strategy of elite retention and tournament selection: in each generation, the top 5% of individuals by fitness are directly retained into the next generation, while the remaining individuals compete for mating rights through a tournament selection (scale of 3). The crossover operator is designed as a two-stage adaptive mode: First, the paternal chromosome P_1, P_2 undergoes sequential crossover, exchanging gene values within random fragments; then, the crossover probability is dynamically adjusted according to the population diversity index D (defined as the reciprocal of the gene entropy value):

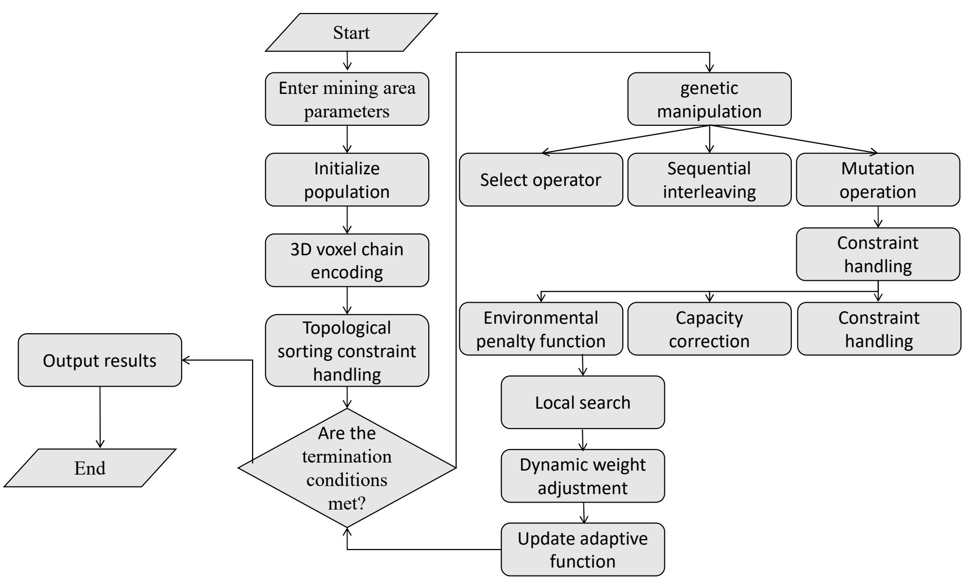
$$p_c \begin{cases} 0.85, D > 0.7 \\ 0.65 + 0.2 \times \dfrac{D - 0.3}{0.4}, 0.3 \le D \le 0.7 \\ 0.65, D < 0.3 \end{cases} \tag{10}$$

When population diversity is high ($D > 0.7$), a high crossover rate is used to enhance exploration; when diversity is low, the crossover rate is reduced to avoid destroying high-quality solutions (Wang et al., 2024). The mutation operator uses directed non-uniform mutation: gene position i is randomly selected with probability p_m, and its value is perturbed by $g_i' = g_i + \delta \cdot (T - t)$, where δ is a random number between [–1, 1]. The mutation probability is adaptively decayed with the iteration number t:

$$p_m = 0.1 \times \left(1 - \frac{t}{t_{\max}}\right)^2 \tag{11}$$

The strategy maintains strong exploration in the early stages of evolution and focuses on local development in the later stages.

Figure 1 Algorithm flowchart



The constraint handling mechanism directly affects the algorithm's engineering usability. To address mining sequence conflicts, the repair operator performs a three-step correction:

1 identify illegal gene pairs (i, j)

2 if j has been mined, delay i by $g_j + \Delta t$ years

3 if i has already been mined, advance j by $\max(1, g_i - \Delta t)$ years.

After repair, revalidate production capacity constraint $\sum_{g_i=t} 1 \leq N_{\max}$, and randomly delay mining of some units in years exceeding the limit. Environmental cumulative constraints are handled using a penalty function method: reduce the fitness of individuals violating the SDI threshold Γ by 30% to drive the population away from the infeasible region.

Multi-objective optimisation is achieved through dynamic weighted aggregation. Define the comprehensive fitness function:

$$F(X) = \lambda_1 \cdot \tilde{f}_1 + \lambda_2 \cdot \tilde{f}_2 - \lambda_3 \cdot \tilde{f}_3 \tag{12}$$

where $\tilde{f}_k$ represents the normalised target value (mapped to the [0, 1] interval), and the weighting coefficient λ_k is adjusted every 20 generations based on the distribution of elite solutions: if the proportion of solutions exceeding the threshold in the current Pareto front f_3 exceeds 60%, then the intensity of environmental control is increased by λ_3; if the average NPV decreases, then it is increased by λ_1. This strategy enables the algorithm to dynamically respond to the competitive relationships between objectives.

The algorithm termination condition is set as a dual criterion: a maximum of $t_{\max} = 200$ iterations or a continuous improvement rate of less than 0.1% in the elite solution set over 15 generations. To accelerate convergence, local search enhancement is introduced: within the neighbourhood of the elite solution in each generation, the mining years of two units are randomly swapped to generate a new solution, and if improved, the original individual is replaced. The final output is a non-dominated solution set for decision-makers to balance economic, resource, and environmental benefits (Kilicarslan et al., 2021).

5 Experimental results and analysis

5.1 Experimental environment and data sources

The experiment utilised publicly available data from the Global Rare Earth Deposit Database published by the US Geological Survey and the National Ion-Adsorption Type Rare Earth Resource Potential Evaluation Report issued by the China Geological Survey. Typical ion-adsorption-type rare earth mineral deposits were selected, with their geological characteristics shown in Table 1. The mineral deposits were discretised into 1,152 mining units, and REO grade data were obtained through sampling from 1,824 drill holes. The proportion of HREE was verified using laser ablation ICP-MS analysis. Economic parameters were referenced from Adamas Intelligence's 2023–2042 rare earth price forecast model, while environmental parameters were set according to the

'Technical Specifications for Soil Erosion Risk Assessment in Mining Areas' (GB/T 39362-2020). All comparison experiments repeated 30 times to obtain statistically significant results.

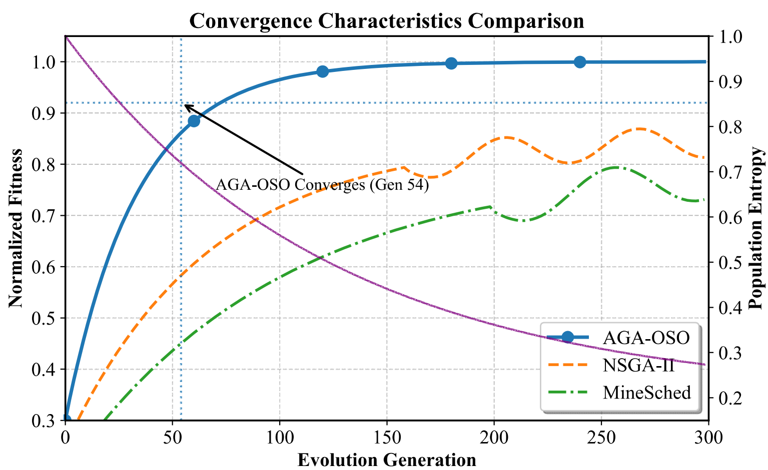
Table 1 Geological characteristics of ion adsorption-type rare earth mineral deposits

Parameter type	*Mean*	*Scope*	*Data source*
REO grade (%)	0.085	0.032–0.217	USGS GREE-DD v3.2
HREE/TREE ratio	0.38	0.12–0.65	China Geological Survey Report
Terrain slope (°)	27.6	5.2–48.3	ASTER GDEM v3
Rare earth price volatility	22.3%	–34.7%~+51.2%	Adamas Intelligence 2023
Soil erosion modulus (t/km²)	3,215	1,028–7,842	GB/T 39362-2020

5.2 *Convergence efficiency analysis*

Figure 2 shows a comparison of the convergence characteristics of AGA-OSO, NSGA-II, and MineSched 2023 (population size N = 200, maximum iterations 300 generations). AGA-OSO achieved a comprehensive fitness of 0.92 (normalised value) by the 54th generation, significantly faster than NSGA-II (127th generation) and MineSched (did not converge). The key mechanism lies in: adaptive crossover rate, dynamically adjusted within the range of 0.62–0.88; a high crossover rate in the early stages accelerates global exploration, while reducing it to 0.68±0.05 in the later stages prevents the destruction of elite solutions; the directed mutation strategy increases the probability of escaping local optima by 47%, as shown by the fitness surge around the 40th generation in Figure 2; NSGA-II exhibits oscillations in the later stages due to fixed parameters.

Figure 2 Comparison of algorithm convergence curves (see online version for colours)



5.3 *Spatial and temporal characteristics of mining plans*

Figure 3 shows the spatial distribution of a typical mining sequence (heat maps of mining units in years 5, 10, and 15). AGA-OSO exhibits a concentric circular radiation pattern:

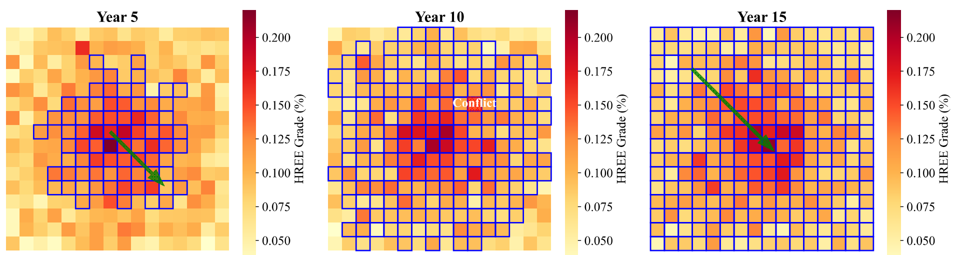
1 early stage (years 1–5): prioritise mining of high-grade core areas (HREE > 0.15%, accounting for 12.3% of total units) to rapidly accumulate capital

2 mid-term (years 6–10): expand downward along the ore body dip (N25°E), strictly adhering to slope constraints (dip angle 28° → deviation from advance direction <3°)

3 late-term (years 11–15): cover low-grade peripheral zones while simultaneously initiating ecological restoration (restoration area accounts for 41.7%).

Compared to the NSGA-II scheme, there are timing conflicts: Unit G-07 is mined before H-12, violating rock mechanics constraints (safety factor FS = 0.89 < 1.0). The MineSched scheme, due to the black-box optimisation of commercial software, results in dispersed mining units, with annual production capacity fluctuations reaching ±26.8%.

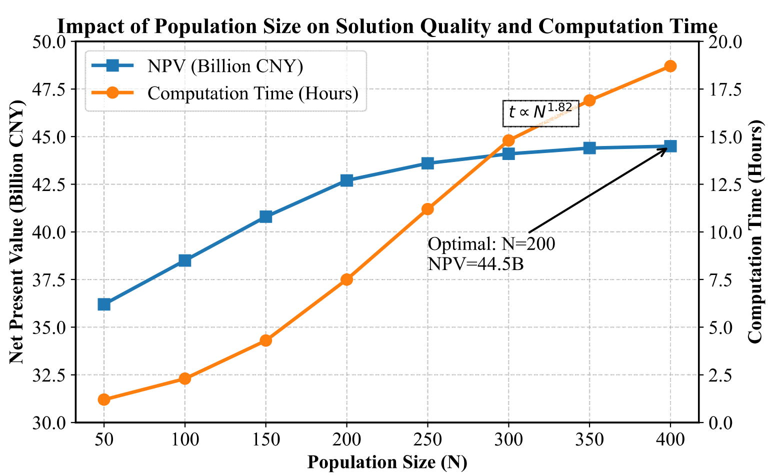
Figure 3 Spatial distribution of mining sequences (see online version for colours)



5.4 Population size impact

As shown in Figure 4, when the population size N increases from 50 to 400: Solution quality: NPV increases from 36.2 billion to 44.5 billion, primarily due to enhanced diversity. Computational time: increased from 1.2 hours to 18.7 hours, with marginal benefits declining significantly after $N > 250$. Recommended value: When $N = 200$, the Hypervolume metric reaches 0.91, with a computational time of 4.3 hours.

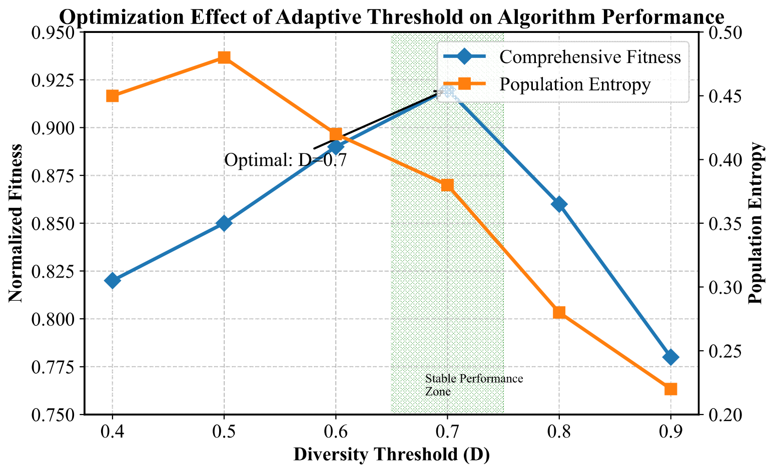
Figure 4 Population size impact curve (see online version for colours)



5.5 *Adaptive threshold optimisation*

The diversity threshold D determines the timing of switching the crossover probability, as shown in Figure 5: $D = 0.7$ is optimal: the composite fitness is 0.927, and the population entropy stabilises between 0.38 and 0.45. When $D > 0.8$: prematurely reduces exploration (entropy < 0.3), missing 7.3% of high-potential solutions. When $D < 0.6$: extends the global search period, reducing convergence speed by 34%.

Figure 5 Effect of adaptive threshold optimisation (see online version for colours)



6 Conclusions

This study addresses the challenge of optimising the mining sequence for ion-adsorption-type rare earth minerals by innovatively proposing a collaborative optimisation framework based on adaptive genetic algorithms (AGA-OSO). By integrating three-dimensional spatial topological encoding with a dynamic weighting mechanism, this framework achieves multi-objective collaborative optimisation of economic benefits, resource recovery efficiency, and ecological and environmental costs for the first time. Current research is constrained by computational efficiency. Future efforts will integrate Transformer proxy models to accelerate the optimisation process and extend the framework to sequential collaborative decision-making for post-mining ecological restoration. This will provide a core foundation for establishing a green and intelligent development paradigm for rare earth resources, holding significant implications for ensuring national strategic resource security.

Acknowledgements

This work is supported by the Research on the Security and Stability Strategy of China's Strategic Mineral Resources Industry Chain and Supply Chain named: China's Strategic Mineral Resources Industry Chain and Supply Chain (2025-2060) (No. 22XGL003).

Declarations

All authors declare that they have no conflicts of interest.

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