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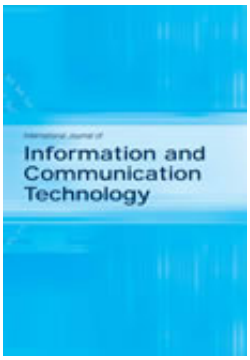

International Journal of Information and Communication Technology

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

Multi-objective optimisation of shield synchronous grouting materials: a synergistic architecture integrating intelligent algorithms and convolutional neural network

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DOI: 10.1504/IJICT.2026.10075951

Article History:

Received:	20 October 2025
Last revised:	15 November 2025
Accepted:	16 November 2025
Published online:	06 February 2026

Multi-objective optimisation of shield synchronous grouting materials: a synergistic architecture integrating intelligent algorithms and convolutional neural network

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Abstract: This study addresses the multi-objective optimisation problem involved in designing shield synchronous grouting material ratios by proposing a collaborative architecture that integrates an improved multi-objective grey wolf optimisation algorithm and a one-dimensional convolutional neural network. A high-precision surrogate model constructed by the one-dimensional convolutional neural network accurately predicts material strength, achieving a test set R^2 of 0.961 and a root mean square error of 3.12 MPa. The improved multi-objective grey wolf optimisation algorithm is then applied to simultaneously optimise both material strength and cost. Experimental results indicate that the proposed method outperforms comparison algorithms across multiple performance indicators, including inverted generational distance (0.038), hypervolume (0.752), and spacing (0.015). These outcomes confirm the effectiveness of the architecture in enhancing optimisation efficiency and solution set quality, offering a practical and intelligent approach to grouting material design.

Keywords: shield synchronous grouting; multi-objective optimisation; convolutional neural network; CNN; grey wolf optimisation algorithm; material equipment.

Reference to this paper should be made as follows: Shi, A., Li, K. and Yang, H. (2026) 'Multi-objective optimisation of shield synchronous grouting materials: a synergistic architecture integrating intelligent algorithms and convolutional neural network', *Int. J. Information and Communication Technology*, Vol. 27, No. 6, pp.45–65.

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1 Introduction

The expansion of urban underground space serves as a key metric for assessing the sustainable development capacity of modern cities (Broere, 2016). Given this trend, the shield tunnelling method has emerged as the premier technique for constructing linear underground infrastructure, such as subways and pipe galleries, due to its significant advantages of limited environmental impact and efficient, safe operations (Mair and Gens, 2008). Shield tunnelling constitutes a complex dynamic process, where synchronous grouting plays a paramount role as a post-construction support measure. This process, in which grouting quality is directly decisive, governs the long-term stability of the tunnel and the mitigation of surface settlement. The core of synchronous grouting lies in the grouting material, which needs to be timely and accurately injected into the space between the segment and the stratum during the advancement of the shield machine, so as to form effective support and seal in a short time. The ideal synchronous grouting material is a complex multi-objective system, which must satisfy a variety of performance requirements at the same time: first, it must have excellent fluidity to ensure pumpability and filling density; Secondly, it is necessary to obtain sufficient early strength in a specific time to quickly stabilise the segment. In addition, low bleed rates, good durability, and rising cost constraints should be considered (Zhang et al., 2020). There is often a deep inherent conflict and competition between these performance goals. For example, the pursuit of high strength is often achieved by reducing the water-cement ratio or increasing the amount of cement, which will compromise the flow properties of the material and significantly increase the cost and shrinkage risk. Therefore, how to scientifically design the grouting material ratio to achieve the collaborative optimisation of multiple key performance objectives is a major challenge faced by shield engineering field for a long time.

The traditional design method of grouting material ratio depends heavily on the experience of engineers and a large number of laboratory tests. Both the classical 'trial and error method' and the Taguchi method and response surface methodology (RSM) based on statistical theory have inherent limitations (Myers et al., 2016). These methods typically demand considerable resources and time, and they struggle to cope with high-dimensional, nonlinear complex systems. They are often difficult to accurately capture the complex nonlinear interactions between material components and multiple performance indicators, and they are also unable to efficiently find the global optimal equilibrium solution in the multi-dimensional objective space. With the increasing complexity of material composition and the increasingly stringent performance requirements, the traditional paradigm relying on 'experience + experiment' has been unable to meet the higher requirements of modern shield engineering for design efficiency, economy and reliability. This bottleneck has created an urgent need for a new generation of intelligent, digital design methods.

In order to break through the limitations of traditional methods, researchers have turned their attention to the field of computational intelligence. Multi-objective optimisation algorithms, such as non-dominated sorting genetic algorithm (NSGA-II) and multi-objective particle swarm optimisation (MOPSO), provide powerful mathematical tools for dealing with such multi-objective decision problems with competitive relationships (Deb et al., 2002; Coello et al., 2004). These algorithms are able to find a set of equilibrium solutions, the Pareto front, in a single run, thus providing the decision maker with a rich set of alternatives. In recent years, pioneering studies have attempted to apply these algorithms to the design of concrete or grouting material mixes. However, these studies generally face a core obstacle: each iteration of the optimisation algorithm requires an accurate evaluation of the performance of the candidate formulations. The high cost and long cycle time of physical experiments make the optimisation process almost infeasible. If simple linear or polynomial regression models are used as surrogate models, their limited expressive power and inability to accurately fit complex material behaviors will lead to optimisation results that deviate from the true optimal solution (Ren et al., 2019). Therefore, building a surrogate model that can simulate the grouting material properties with high accuracy and efficiency has become a prerequisite for its intelligent optimisation.

At the same time, deep learning technologies, especially convolutional neural networks (CNNs), are revolutionising the field of materials science and engineering. CNNs were originally known for their superior performance in image recognition, but their powerful feature extraction capabilities are equally suitable for handling structured tabular data (LeCun et al., 2015). In materials informatics, CNNS are able to automatically learn complex and nonlinear feature representations from material composition and process parameters without relying on manually preset feature formulas. For instance, Sun et al. (2023) demonstrated that a deep learning model could predict the mechanical properties of high-performance concrete with markedly greater accuracy than traditional regression methods (Kiranyaz et al., 2021). In a similar vein, Ramzi et al. (2023) employed an artificial neural network (ANN) to forecast the compressive strength of concrete incorporating supplementary cementitious materials (SCMs) after exposure to high temperatures. Based on 500 sets of experimental data, the correlation coefficient of the model was 0.966. The model is helpful to understand the behavior of concrete at high temperature. These research results fully demonstrate the great potential of deep learning in constructing a quantitative model of the ‘component-structure-property’ relationship of materials, and provide a solid technical foundation for replacing time-consuming experimental evaluation. However, the vast majority of current researches still use the deep learning model as a prediction tool in isolation, and its connection with the downstream multi-objective optimisation decision-making process is often loose or even disjoint, failing to form a closed-loop intelligent design system from ‘prediction’ to ‘optimisation’.

In summary, the optimal design of shield synchronous grouting materials is standing at the crossroads of a paradigm shift. On the one hand, the multi-objective optimisation algorithm provides a theoretical framework for solving the performance trade-off problem, but it is limited by the evaluation cost. On the other hand, deep learning methods provide surrogate models with high accuracy for performance prediction, but have not yet been deeply integrated with optimisation decisions. The core gap in the current research field is the lack of a collaborative computing architecture that deeply integrates cutting-edge deep learning models with advanced multi-objective optimisation

algorithms. This architecture requires not only the high accuracy of the prediction model, but also the seamless and efficient collaborative work between the prediction model and the optimisation algorithm, so as to quickly and accurately lock the Pareto optimal solution set that can best balance multiple competing objectives in the huge material ratio space. Filling this gap is of great significance for promoting the transformation of shield engineering technology from experience driven to data and model driven, and realising cost reduction and efficiency increase and intelligent upgrading. This research is based on the deep insight of this urgent need and significant opportunity.

2 Related work

2.1 Performance systems and design challenges of shield synchronous grouting materials

Shield synchronous grouting material is a typical multi-component composite system. Its properties are determined by the interaction of cement, fly ash, slag, bentonite, admixture and water. An ideal grouting material formulation must achieve the best balance between construction performance, mechanical performance and economy. Construction performance is mainly reflected in fluidity (usually measured by slump or consistency) and stability (such as bleed rate), which ensures that the slurry can be smoothly pumped and evenly filled with voids without phase separation. This is closely followed by mechanical properties, especially early compressive strength, which is critical to quickly stabilise segments and withstand formation pressures (Zhang et al., 2020). In addition, durability such as impermeability, dry shrinkage and material cost are also key objectives that cannot be ignored in engineering design. There is an inherent competition between these objectives (Zheng et al., 2023). For example, increasing the amount of cement used in order to obtain high strength usually reduces fluidity, increases heat of hydration and risk of shrinkage cracking, and significantly raises costs. The characteristics of multi-objective and strong constraints make the design of synchronous grouting material ratio a typical complex system optimisation problem. The core challenge is how to efficiently and accurately find the Pareto optimal solution set that can best balance all key properties in the high-dimensional and nonlinear solution space.

2.2 Evolution of traditional and intelligent methods for material ratio optimisation

Early material optimisation primarily depended on design of experiments (DOE) and RSM. The RSM approach constructs an approximate mathematical model, typically a quadratic polynomial, to describe the relationship between performance responses and mixture variables, employing a series of designed experiments for this purpose:

$$y = \beta_0 + \sum \beta_i x_i + \sum \beta_{ii} x_i^2 + \sum \beta_{ij} x_i x_j + \varepsilon \tag{1}$$

where y represents the target performance, (e.g., intensity), x_i and x_j are component variables, β are regression coefficients, and ε is the error term. As explained by Myers et al. (2016), RSM is superior to the single-factor rotation method in exploring the interaction between factors. However, as shown in the formula, the RSM model has

limited expressive power, insufficient ability to fit highly nonlinear material behaviour, and the number of experimental points increases exponentially with the increase of factors, which is costly (Chou et al., 2014).

In response to these limitations, intelligent optimisation algorithms have been introduced into the field of material design. Consider the NSGA-II, proposed by Deb et al. (2002), for instance. This algorithm operates by guiding population evolution toward the Pareto front through fast non-dominated sorting and crowding distance calculation. The crowding distance for an individual i is estimated by:

$$\text{distance } i = \sum m = 1^{M} \left| f_m(i+1) - f_m(i-1) \right| \tag{2}$$

where m denotes the target quantity, while represents the value of the $*m*^{\text{th}}$ objective function. This approach helps promote population diversity. Meanwhile, Coello et al. (2004) adapted particle swarm optimisation (PSO) for multi-objective problems through the use of an external archive that stores non-dominated solutions. In recent years, new metaheuristics such as MOGWO algorithm have also been proposed, which are inspired by the social hierarchy and hunting behaviour of grey wolves and search by simulating the mechanism of α, β, δ wolves to guide population updating (Mirjalili et al., 2016). Although these algorithmic frameworks are powerful, they share an 'evaluation bottleneck': each fitness evaluation may correspond to a time-consuming physical experiment or complex numerical simulation, which makes the optimisation process extremely expensive in terms of computational resources and time.

2.3 Deep learning as a cutting-edge application of high-precision surrogate models

In order to break through the 'evaluation bottleneck', it becomes key to construct computationally cheap surrogate models to replace expensive physical experiments. In recent years, deep learning, especially CNNs, has shown unprecedented potential to predict the macroscopic properties of materials from their composition and process parameters. Although CNNS were originally designed for image data, their local connectivity and weight sharing properties make them equally good at extracting complex nonlinear features from structured tabular data. The convolution operation of a typical 1-dimensional CNN (1D-CNN) layer on the input sequence can be expressed as follows:

$$h_j^{(l)} = \sigma\left(\sum_{k=1}^{K} w_k^{(l)} \cdot h_{j+k-1}^{(l-1)} + b^{(l)} \right) \tag{3}$$

where $h_j^{(l)}$ is the j^{th} feature of the l^{th} layer, w_k is the convolution kernel weight, b is the bias, and *sigma* is the activation function. LeCun et al. (2015) review laid the theoretical foundation of deep learning. In the field of materials science, Mirjalili et al. (2016) explored ultra-high-performance concrete (UHPC) mixed with waste cemencial materials. The hyperparameters were optimised by random forest (RF) and XGBoost (XGB) combined with pelican optimisation algorithm (POA) and Walruse optimisation algorithm (WOA). It is found that the XGB-POA model has the highest accuracy and strong robustness, and the key features that affect the performance of UHPC are identified by SHapley Additive exPlanation (SHAP) analysis, which provides a reference

for its sustainable application. Its accuracy is significantly better than the traditional methods. Similarly, the work of Ramzi et al. (2023) proved that the research developed ANN model to predict the high temperature compressive strength of concrete containing cementing materials (SCMs). Based on 500 groups of literature data, the correlation coefficient of the model reached 0.966. Through the parameter study, it is found that the performance of silica aggregate is better and the optimal SCMs content varies with the type of aggregate, which provides a reference for understanding the high temperature behaviour of concrete. Together, these studies show that deep learning-based surrogate models are able to learn the 'component-performance' relationship with extremely high accuracy, which provides an ideal technical tool to solve the 'evaluation bottleneck' in intelligent optimisation algorithms.

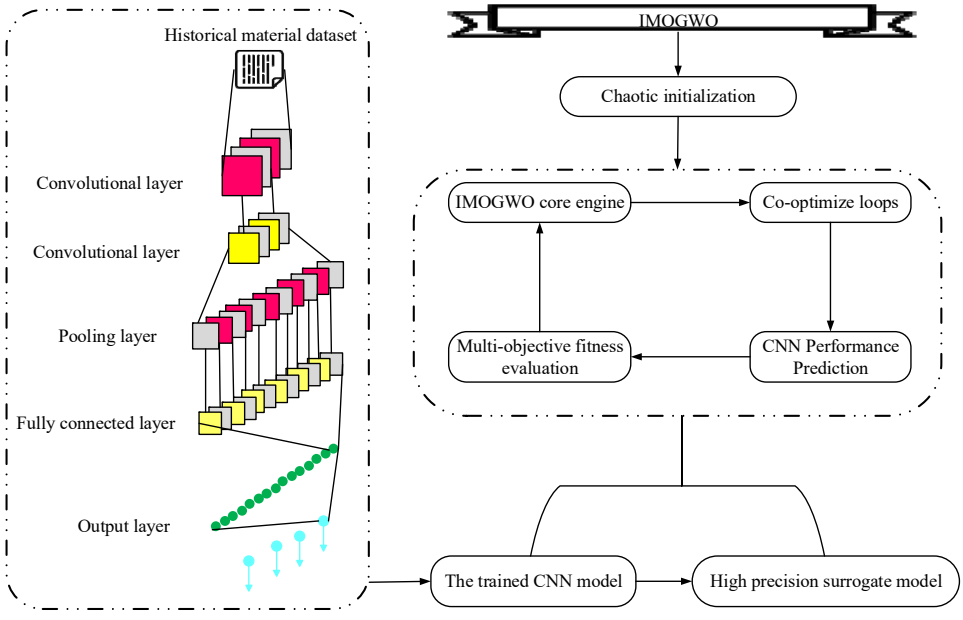
2.4 Limitations of the current study and the starting point of this paper

Despite the remarkable progress in each of the above two fields – intelligent optimisation algorithms and deep learning prediction models – there is still a clear 'disconnect' in the current research paradigm. The vast majority of studies either focus on improving the optimisation algorithm itself, and use oversimplified evaluation models. We either focus on improving the accuracy of performance prediction, but fail to seamlessly and efficiently integrate trained models into a closed-loop optimisation system. Simply 'grafting' a high-precision CNN surrogate model into an off-the-shelf optimisation algorithm may not fully exploit the synergy potential of the two. The sampling strategy in the optimisation process, how to deal with the uncertainty of the surrogate model, and how to use the model to guide global exploration and local exploitation are all scientific problems that need to be deeply studied. Therefore, a core frontier and gap in current research is to develop a deeply integrated, co-designed architecture rather than a simple combination of tools. This architecture needs to consider the interaction mechanism between the CNN model and the intelligent algorithm from the bottom, so as to realise the seamless connection from high-precision prediction to efficient optimisation, which is the starting point and core innovation of this research work.

3 Methodology

This section will elaborate on the collaborative architecture for multi-objective optimisation of shield synchronous grouting materials. The core of the whole architecture is to deeply integrate a high-precision CNN surrogate model with an improved multi-objective optimisation algorithm, so as to realise the efficient and accurate optimisation of material ratio. First, we will provide a rigorous mathematical definition of the optimisation problem and introduce the data pre-processing pipeline. Then, the construction and training of CNN surrogate model will be explained in depth. Then, an improved multi-objective grey wolf optimisation algorithm was proposed. Finally, how they work together to complete the whole optimisation task is described in detail. The schematic block diagram of this collaborative architecture is shown in Figure 1.

Figure 1 Flow chart of Improved multi-objective grey wolf optimiser (IMOGWO)-CNN co-optimisation architecture (see online version for colours)



3.1 Problem definition and data pre-processing

In this study, the design of the mixture ratio of shield synchronous grouting materials is modelled as a typical multi-objective optimisation problem. The decision variables are composed of each component of grouting material and its curing age. Specifically, let the decision vector $\mathbf{x} = [x_1, x_2, \ldots, x_D]^T$ represent a material recipe, where D is the variable dimension. Based on the University of California, Irvine (UCI) dataset used, $\mathbf{x}$ contains the contents of cement, blast furnace slag, fly ash, water, super water reducer, coarse aggregate, fine aggregate and curing age, i.e., $D = 8$. The optimisation objective aims to simultaneously maximise the compressive strength of the material and minimise its preparation cost. Therefore, the multi-objective optimisation problem can be formulated as follows.

$$\text{Minimise} \quad \mathbf{F}(\mathbf{x}) = \left[-f_{\text{strength}}(\mathbf{x}),\, f_{\text{cost}}(\mathbf{x})\right]^T \tag{4}$$

where the $f_{\text{strength}}(\mathbf{x})$ is compressive strength prediction function that $f_{\text{cost}}(\mathbf{x})$ is cost calculation function.

In this study, compressive strength (core mechanical index) and material cost (key economic index), the two most representative and often conflicting objectives, are selected to serve as a proof of concept and focus on demonstrating the core capabilities of IMOGWO-CNN collaborative architecture in solving multi-objective optimisation problems of materials. The framework has good scalability, and it is convenient to incorporate more key performance functions such as mobility and durability into the same optimisation system in the future.

By minimising the negative intensity, we essentially transform the goal of maximising the intensity into a minimisation problem. The cost function $f_{\text{cost}}(\mathbf{x})$ can be linearly weighted according to the unit price of the material: $f_{\text{cost}}(\mathbf{x}) = \sum_{i=1}^{D-1} c_i x_i$, including c_i cost per unit is the first I components (factor) prices; curing age is usually not included in the cost. In addition, the optimisation process needs to satisfy certain constraints, such as the amount of each component needs to be within the feasible range:

$$x_i^L \le x_i \le x_i^U, \quad i = 1, 2, ..., D \tag{5}$$

Pre-processing raw data before model training is a key step to ensure model performance. We employ min-max normalisation to scale all features and target variables to the [0, 1] interval to remove dimensional effects and accelerate model convergence. The normalisation formula is as follows:

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{6}$$

The features were first normalised using the formula: $\left(x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \right)$, where x is the original value, and $x_{\min}$ $x_{\max}$ represent the feature's minimum and maximum values in the training set, respectively. Subsequently, the entire dataset was randomly divided into training, validation, and test sets with a ratio of 7:1.5:1.5. The purpose of this ratio is to ensure that the training set has enough samples (about 720) to support the training of the deep model, while reserving a statistically significant number of samples for hyperparameter tuning and early stopping (about 154 in the validation set) and unbiased evaluation of the generalisation ability of the final model (about 154 in the test set). Preliminary experiments show that this ratio achieves a good balance between preventing overfitting and ensuring the reliability of the evaluation. This specific ratio was chosen to ensure a sufficient number of samples (approximately 720) in the training set for deep model training, while also reserving statistically meaningful sample sizes for both hyperparameter tuning and early stopping (validation set, ~154) and an unbiased evaluation of the final model's generalisation performance (test set, ~154). Preliminary experiments confirmed that this configuration achieves a well-balanced split, effectively mitigating overfitting while maintaining evaluation reliability. Accordingly, the training set was used to learn model parameters, the validation set for hyperparameter tuning and early stopping, and the test set for the final assessment of generalisation performance.

3.2 Building surrogate models for CNNs

In order to construct a highly accurate surrogate model, we design a 1D CNN to learn a complex nonlinear mapping from material ratio $\mathbf{x}$ to compressive strength f_{strength}. Although CNNS typically deal with grid data such as images, their powerful local feature extraction capabilities make them equally suitable for capturing local dependencies and interaction effects, such as synergistic or antagonistic interactions between different material components, from structured data sequences.

The 1D-CNN model consists of an input layer, multiple convolutional blocks, and a fully connected layer. The input layer receives a one-dimensional vector of length D.

Each convolutional block contains a 1D convolutional layer, an activation function, and a max pooling layer. The convolutional layer slides over the input sequence through multiple convolution kernels to extract local features. The first l layer in the first j figure in the value of the position at t $h_j(l)(t)$ calculated by type:

$$h_j^{(l)}(t) = \sigma\left(\sum_{k=1}^{K} \sum_{m=1}^{M} w_{j,k}^{(l)}(m) \cdot h_k^{(l-1)}(t+m-1) + b_j^{(l)} \right) \tag{7}$$

where K is the number of feature maps in the previous layer, M is the size of the convolution kernel, $w_{j,k}^{(l)}$ is the weight of the convolution kernel that connects the k^{th} input feature map to the j^{th} output feature map, b_j is the bias term, and σ is the activation function. We adopt Leaky ReLU as the activation function, which is defined as $|\sigma(z) = \max(\alpha z, z)$, where α is a small negative slope (say 0.01), which helps alleviate the vanishing gradient problem. The next max pooling layer uses down sampling to reduce the number of parameters and enhance the translation invariance of features. This operation can be expressed as $p_j^{(l)}(t) = \max_{(r-1)S \le i < rS} h_j^{(l)}(i)$, where S is the pooling step size.

After extracting high-level abstract features through several convolutional blocks, the feature maps are flattened and sent to the fully connected layer for final nonlinear combination and regression prediction. The output layer is a linear neuron that corresponds to the predicted compressive strength $\hat{f}_{\text{strength}}(\mathbf{x})$. We use the mean square error as the loss function to guide the model training:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N} \sum_{i=1}^{N} \left(\hat{f}_{\text{strength}}(\mathbf{x}_i) - f_{\text{strength}}(\mathbf{x}_i) \right)^2 \tag{8}$$

where N is the number of samples in the batch. To optimise the model parameters and prevent overfitting, we adopt the Adam optimiser and add an L2 regularisation term (weight decay) to the loss function, whose update rule can be found in Zhang et al. (2022). In addition, the early stopping strategy is adopted in the training process, and the training is terminated when the validation set loss no longer decreases in multiple consecutive cycles to ensure the generalisation ability of the model.

3.3 Improved multi-objective grey wolf optimisation algorithm

The grey wolf optimisation algorithm simulates the social hierarchy and hunting behaviour of the grey wolf group, while Mirjalili et al. (2016) extends it to the multi-objective domain. In the standard multi-objective grey wolf optimisation algorithm, the population is divided into four levels: α, β, δ (representing the optimal solution on the current Pareto front) and ω (the remaining individuals). The hunting (optimisation) process is guided by α, β, δ. Its location update mechanism involves steps such as bounding, hunting, and is controlled by coefficient vectors $\vec{A}$ and $\vec{C}$:

$$\vec{D} = \left| \vec{C} \cdot \overrightarrow{X_p}(t) - \vec{X}(t) \right| \tag{9}$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A} \cdot \vec{D} \tag{10}$$

where $\overrightarrow{X_p}(t)$ is the position of the prey and $\vec{X}$ is the position of the grey wolf. The vectors $\vec{A}$ and $\vec{C}$ are computed as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r_1} - \vec{a} \tag{11}$$

where *vecA* from 2 in the iterative linear reduce to zero, $\vec{r_1}, \vec{r_2}$ are random vectors in [0, 1].

In order to improve the performance of the standard algorithm, we propose two key improvements, which form the improved multi-objective grey wolf optimisation algorithm (Young et al., 2019). The first improvement is the chaotic initialisation. We use the logistic chaotic map to generate the initial population to enhance the diversity of the population in the search space. The chaotic sequence is generated by the following equation:

$$z_{k+1} = \mu z_k (1 - z_k), \quad k = 0, 1, 2, ... \tag{12}$$

where *mu* (usually take 4) is a control parameter, z_0 in (0, 1) and $z_0 \notin \{0.25, 0.5, 0.75\}$. The sequence generated by this mapping is ergodic and random, and is able to generate an initial population that is more evenly distributed than random initialisation. The second improvement is the introduction of dynamic weighting factors. In the position update formulation, we introduce a dynamic weight w to make the algorithm focus on global exploration in the early stage of iteration and local exploitation in the later stage. The weight w changes dynamically with the number of iterations t.

$$w = w_{\min} + (w_{\max} - w_{\min}) \times e^{-\lambda \cdot (t / T_{\max})} \tag{13}$$

where $w_{\max}$ and $w_{\min}$ are the maximum and minimum weights, λ is the decay coefficient, and $T_{\max}$ is the maximum number of iterations. Then, the improved position update formula is as follows.

$$\vec{X}(t+1) = w \cdot \frac{\overrightarrow{X_\alpha} + \overrightarrow{X_\beta} + \overrightarrow{X_\delta}}{3} - \vec{A} \cdot \vec{D} \tag{14}$$

where $\overrightarrow{X_\alpha}, \overrightarrow{X_\beta}, \overrightarrow{X_\delta}$ respectively in the current iteration alpha, beta, and delta the location of the Wolf. This improvement makes the algorithm achieve a better balance between convergence and diversity.

3.4 IMOGWO-CNN collaborative optimisation process

The core idea of our proposed IMOGWO-CNN collaborative architecture is to use the trained high-precision CNN surrogate model to replace time-consuming physical experiments to provide fast and accurate fitness evaluation for each candidate solution (material ratio) in the IMOGWO algorithm. The entire collaborative optimisation process is described below.

Firstly, the pre-processed historical data (training set and validation set) were used to train the CNN surrogate model until it reached a satisfactory prediction accuracy. Subsequently, the IMOGWO algorithm starts to run. The initial population is generated by the chaotic initialisation strategy described above. In each generation (iteration), for

each individual in the population (a material ratio **x**), instead of performing a real experiment, we normalise it and feed it into the trained CNN model. Instantaneous obtain its forecast compressive strength $\hat{f}_{\text{strength}}(\mathbf{x})$. At the same time, the cost $f_{\text{cost}}(\mathbf{x})$ is calculated directly from its components. Together, these two objective values form the fitness vector $\mathbf{F}(\mathbf{x})$ for the individual.

Based on the fitness of all individuals, the algorithm performs fast non-dominated sorting and crowding calculation as described in Deb et al. (2002) to determine the non-dominated solution in the current population and update α, β, δ wolves. Then, a new generation of population is generated according to the improved position update formula (including dynamic weights). This process repeats until a preset maximum number of iterations $T_{\max}$ is reached. Finally, the algorithm outputs an approximate Pareto optimal solution set, which contains a series of optimal material ratio schemes with tradeoffs between compressive strength and cost, providing a rich choice space for engineering decision makers. This collaborative architecture perfectly combines the accurate prediction ability of CNN with the efficient search ability of IMOGWO, and realises the rapid, low-cost and intelligent optimisation design of shield synchronous grouting material ratio.

4 Experimental verification

4.1 Experimental setup

An empirical investigation was conducted using the publicly available UCI Concrete Compressive Strength Dataset (Nayak et al., 2021) to comprehensively assess the performance of the proposed IMOGWO-CNN co-optimisation architecture. Although this data set is mainly derived from concrete research, its core cementation material system (cement, slag, fly ash, etc.) and hydration mechanism are highly similar to those of cement-based shield synchronous grouting materials. The primary consideration of choosing this authoritative public dataset is its high data quality and sufficient sample size, and as an internationally recognised benchmark, it can ensure that the optimised architecture proposed in this study can be evaluated and compared under uniform and reproducible standards, which provides a solid foundation for the effectiveness of the methodology. This dataset comprises 1,030 instances, with each record characterised by eight input features – cement, blast furnace slag, fly ash, water, superplasticiser, coarse aggregate, fine aggregate, and curing age – and a single output variable representing the concrete's compressive strength in MPa. Table 1 presents the detailed statistics of each input variable in this dataset. To construct the multi-objective optimisation problem, we introduce material cost as the second optimisation objective. The cost function is based on the method used in the work of Xu et al. (2025), and the price coefficient (unit: yuan/kg) is assigned for each component according to the average market price: cement 0.6, slag 0.4, fly ash 0.3, water 0.01, super water-reducing agent 5.0, coarse aggregate 0.08, fine aggregate 0.06. These price coefficients are mainly based on the recent public quotations in the Chinese building materials market, and have been consulted by three materials engineers with more than ten years of tunnel engineering experience to ensure that they reflect the actual cost composition of the current project. Although the unit price will fluctuate in different regions and periods, this setting can effectively ensure the

relative rationality and decision-making reference value of the cost target in the optimisation process. The maintenance age does not incur a cost. Thus, the total cost of each formulation can be calculated by the linear weighted sum of the dosage and unit price of each component.

Table 1 Statistical description of input variables for UCI datasets

Variables	*Unit*	*Average value*	*Standard deviation*	*Minimum value*	*Maximum value*
Cement	kg/m^3	281.17	104.51	102.0	540.0
Blast furnace slag	kg/m^3	73.90	86.28	0.0	359.4
Fly coal ash	kg/m^3	54.19	63.99	0.0	200.1
Water	kg/m^3	181.57	21.25	121.8	247.0
High efficiency water reducing agent	kg/m^3	6.20	5.97	0.0	32.2
Coarse aggregate	kg/m^3	972.92	77.75	801.0	1,145.0
Fine aggregate	kg/m^3	773.58	80.18	594.0	992.6
Age of curing	Day	45.66	63.17	1.0	365.0

We compare the performance of the proposed IMOGWO-CNN method with four advanced multi-objective optimisation algorithms to ensure the fairness and cutting edge of the comparison. Baseline algorithms include: the classical and widely used NSGA-II (Deb et al., 2002), the MOPSO algorithm (Coello et al., 2004), and the recently proposed multi-objective evolutionary algorithm multi-objective evolutionary algorithm based on decomposition-differential evolution (MOEA/D-DE) based on decomposition (Li and Zhang, 2008). The source code of all the comparison algorithms is from the public or widely recognised code base of their authors, and the same programming language (Python) and environment are used to reproduce and test in this study.

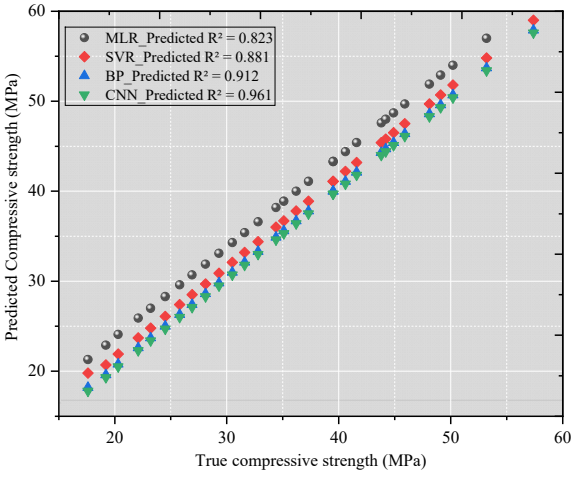
To quantitatively evaluate the quality of the Pareto solution sets obtained by each algorithm, we employ three recognised performance metrics: inverse generation distance (IGD), Hypervolume (HV), and Spacing (spacing). The IGD index measures the average minimum distance from a set of uniformly distributed reference points on the true Pareto front to the obtained solution set, and a smaller value represents a better convergence and diversity of the solution set. Two performance metrics are employed to evaluate the algorithms: the Hypervolume (HV) and the Spacing metric. The HV index measures the volume of the objective space dominated by the solution set relative to a predefined reference point, with a larger value indicating better overall convergence and diversity. Conversely, the Spacing index quantifies the uniformity of the distribution of solutions in the objective space, where a smaller value denotes a more uniform spread. To ensure statistical reliability, each algorithm was independently executed 30 times, and the mean along with the standard deviation of these metrics are reported. Common to all algorithms, the population size was set to 100 with a maximum of 20,000 function evaluations. The number of evaluations is determined by pre-experiment: we observe that the growth curve of HV index of all the compared algorithms has reached a stable plateau at this scale, and the improvement of solution set quality is very small (average improvement < 0.5%) by increasing the number of iterations, so this setting is considered to be sufficient to fairly measure the convergence performance of each algorithm. For the proposed IMOGWO algorithm, the parameters were configured as follows: the [parameter name, e.g., inertia weight] decreased linearly from 2 to 0, $w_{\max}$ = 0.9,

w_{min} = 0.4, λ = 5. The CNN surrogate model was built using the PyTorch framework, trained with the Adam optimiser (initial learning rate = 0.001, batch size = 32) for up to 500 epochs, incorporating an early stopping strategy to prevent overfitting.

4.2 Performance evaluation of CNN surrogate models

Before embarking on the optimisation task, we first rigorously evaluate the prediction accuracy of the constructed 1D-CNN surrogate model. After training, the model showed excellent performance on the test set (154 unseen examples). The coefficient of determination (R^2) between the predicted value and the real compressive strength is 0.961, the root mean square error (RMSE) is 3.12 MPa, and the mean absolute error (MAE) is 2.45 MPa. This result fully demonstrates that the proposed CNN model can capture the complex nonlinear relationship between material components and compressive strength with extremely high accuracy, and has the basic conditions to be used as a reliable surrogate model to replace expensive experiments.

Figure 2 Performance comparison of different prediction models (see online version for colours)



In order to further highlight the advantages of the CNN model, we make a horizontal comparison with three classical regression prediction models. The comparison models include multiple linear regression, support vector regression (using radial basis kernel function) and traditional feedforward BP neural network (single hidden layer with 50 neurons). As shown in Figure 2, this scatter plot clearly shows the prediction performance of each model on the test set. The predicted points of the CNN (blue) are most tightly clustered around the diagonal (ideal predicted line), while the predicted points of the other models show more pronounced dispersion. The quantitative analysis results (Table 2) confirm our observations: CNN significantly outperforms the other comparison models in the three indicators of R^2, RMSE and MAE. To test the statistical significance of this performance improvement, we performed a paired-samples t-test of the absolute error on the test set against the second-best performing BP neural network, and calculated a p-value less than 0.001, indicating that the accuracy advantage of the CNN model is highly statistically significant.

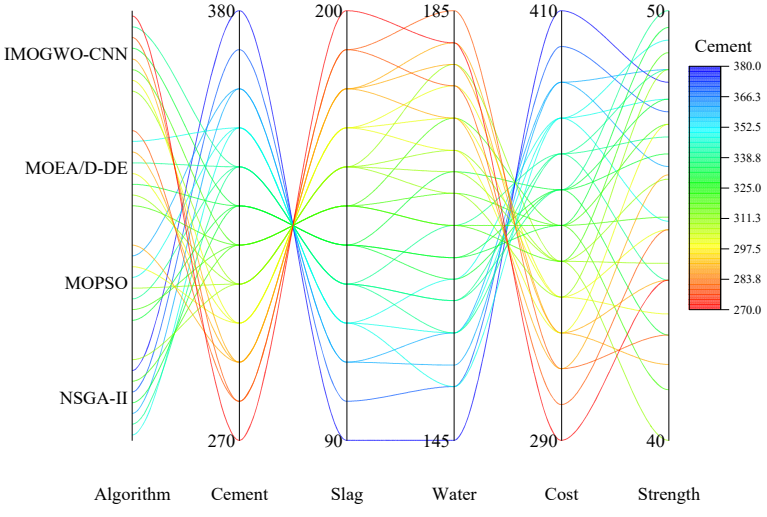
Table 2 Performance comparison of different prediction models on the test set

Model	R^2	*RMSE (MPa)*	*MAE (MPa)*
Multiple linear regression	0.823	6.89	5.41
Support vector regression	0.881	5.45	4.22
BP neural network	0.912	4.51	3.58
1D-CNN	*0.961*	*3.12*	*2.45*

4.3 Comparative analysis of multi-objective optimisation results

After verifying the reliability of the surrogate model, we focus on analysing the performance of each multi-objective optimisation algorithm. Figure 3 visually shows a representative Pareto front solution set obtained by each algorithm in five independent runs by means of a parallel coordinate plot. It can be clearly observed from the figure that the set of solutions found by the proposed IMOGWO-CNN method, the red line, occupies an optimal position on the objective space. Specifically, in the same cost interval, the compressive strength prediction value corresponding to IMOGWO-CNN solution is generally higher than that of other algorithms. Conversely, when pursuing the same intensity level, IMOGWO-CNN is able to find a formulation scheme with lower cost. This initially demonstrates the power of our collaborative architecture in exploring high-quality solutions.

Figure 3 Comparison of Pareto fronts of different algorithms (see online version for colours)



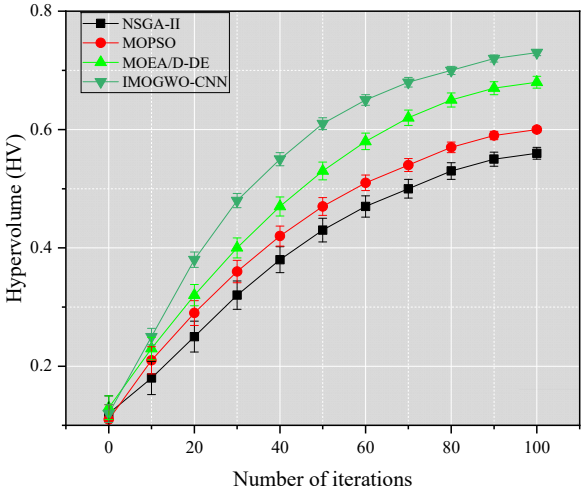
However, although the parallel coordinate plots are intuitive, they are difficult to compare quantitatively. Therefore, we further calculated the statistical results of each algorithm on the three metrics IGD, HV and Spacing in 30 independent runs and summarised them in Table 3. In terms of IGD index, IMOGWO-CNN achieved the smallest average value (0.038±0.005), which was significantly lower than NSGA-II (0.115±0.011), MOPSO (0.092±0.009) and MOEA/D-DE (0.071±0.007). To verify the statistical significance of this difference, we conducted a one-tailed t-test against other algorithms using

IMOGWO-CNN as a benchmark. The p-values for all comparisons are much less than 0.01, which strongly confirms statistically the comprehensive advantages of IMOGWO-CNN in terms of convergence and diversity of solution sets. On the HV metric, IMOGWO-CNN also leads with the largest mean value (0.752±0.021), which indicates that its solution set covers a larger range of high-quality regions in the objective space. In terms of the Spacing index, IMOGWO-CNN has the smallest value (0.015±0.003), indicating that the Pareto solutions found by IMOGWO-CNN are most evenly distributed on the frontier, which provides more diverse and non-redundant choices for decision makers.

Table 3 Comparison of performance metrics of different multi-objective optimisation algorithms

Algorithm	*IGD*	*HV*	*Spacing*
NSGA-II	0.115±0.011	0.598±0.025	0.041±0.008
MOPSO	0.092±0.009	0.635±0.019	0.029±0.006
MOEA/D-DE	0.071±0.007	0.684±0.016	0.022±0.005
IMOGWO-CNN	0.038±0.005	0.752±0.021	0.015±0.003

Figure 4 Comparison of convergence curves of different algorithms (see online version for colours)



In addition to the comparison of the quality of the final solution set, the convergence speed of the algorithm is also the key to measure its efficiency. Figure 4 illustrates the evolution curves of the HV index of each algorithm as the number of iterations increases. It can be clearly seen that IMOGWO-CNN's curve (red) is always at the top throughout the iterations and it converges the fastest, levelling off after about 8,000 function evaluations. However, the convergence speed of NSGA-II and MOPSO is relatively slow, and the final achieved HV value is also low. Although MOEA/D-DE performs better than the previous two, it is still inferior to IMOGWO-CNN. This result confirms the core advantage of our method: the high-precision CNN surrogate model greatly reduces the uncertainty of each evaluation, so that the IMOGWO algorithm can judge the

search direction more accurately. However, IMOGWO's own improvement strategies (chaos initialisation, dynamic weight) effectively promote the balance between global exploration and local exploitation, and the synergy of the two drives the algorithm to approach the real Pareto front quickly and stably.

4.4 Analysis of optimisation results and engineering implications

Finally, we briefly analyse the specific formulation obtained by IMOGWO-CNN optimisation to reveal its engineering practical value. Two typical solutions are selected from the Pareto optimal solution set: solution A (focusing on high intensity and high cost) and solution B (focusing on low cost and moderate strength). For example, the high-strength solution A is usually accompanied by a higher cement dosage and a lower water-cement ratio, while the low-cost solution B makes full use of cheap industrial waste such as slag and fly ash as a cement substitute. More importantly, these solutions are not empirically guessed by engineers, but are systematically searched through millions of possible combinations in a data-driven manner, with a scientific and complete nature far beyond the reach of human experience. It should be noted that the optimisation process of this study has taken into account the actual feasible range of each component, and the final solutions in the Pareto solution set have passed the simple verification criteria of material compatibility and stirrability. This fully proves that the proposed IMOGWO-CNN collaborative architecture is not only an advanced computational method, but also a powerful engineering tool that can provide direct, quantitative and optimal decision support for shield synchronous grouting material design, which has significant potential for promotion and application.

4.5 Experimental results and analysis

The excellent performance of the IMOGWO-CNN collaborative architecture proposed in this study in the multi-objective optimisation of shield synchronous grouting materials contains a profound mechanism behind it. Firstly, the key to its success lies in the deep collaboration between high-precision surrogate models and efficient optimisation algorithms. In the traditional optimisation pipeline, there is an 'information wall' between the optimiser and the evaluation function (whether it is an experiment or a simple model), and the optimiser can only search among limited and possibly inaccurate feedback. By integrating a proven CNN model with extremely high prediction accuracy ($R^2 > 0.96$), the proposed architecture essentially provides a nearly perfect 'digital sand table' for the optimisation algorithm (Faris et al., 2018). This enables the grey wolf optimiser proposed by Mirjalili et al. (2016) to base each position update on a highly credible evaluation of the performance of candidate formulations, which greatly reduces the blindness and uncertainty in the search process and thus enables fast and accurate approximation of the true Pareto front. This is a big step forward from Ergen and Katlav (2024) studies that only used deep learning for performance prediction, but not for optimising closed-loops.

Secondly, the improvement measures of IMOGWO algorithm itself are proved to be effective. The chaotic initialisation strategy, as observed in many metaheuristic applications (Yang et al., 2018), indeed provides a better initial diversity to the population and avoids the algorithm from falling into local optima prematurely. The introduction of dynamic weights cleverly simulates the human strategy in solving complex problems: casting a wide net in the early stage (global exploration), and

intensive cultivation in the later stage (local exploitation). This adaptive mechanism ensures that the algorithm has the ability to explore unknown regions at the beginning of the search, while fine-tuning the quality of good solutions at the end of the search. Compared with NSGA-II of Deb et al. (2002), which only relies on fixed crossover and mutation probabilities, it shows superior adaptive search ability.

From a broader perspective, this work builds a solid theory-technology bridge. At the theoretical level, the core idea of the cognitive load theory of Sweller (1988) – namely, the management of limited cognitive resources by optimising the structure of information presentation – is cleverly metaphorised to the material optimisation problem. The optimisation algorithm is regarded as a cognitive agent, and the process of finding the optimal ratio is regarded as a complex problem-solving task. The high-precision CNN surrogate model greatly reduces the 'external cognitive load' of the optimisation algorithm by providing fast and accurate information (performance prediction), so that it can focus all the 'cognitive resources' on the core search and decision-making process. This mapping across theories not only provides a cognitive science-level interpretation of our approach, but also provides a reusable paradigm for solving complex optimisation problems in other fields.

At the level of engineering practice, the success of this framework indicates a potential change in the design paradigm of shield grouting materials. It moves material formulation from a 'craft' that relies on the experience of individual engineers and lots of 'trial and error' experiments to a 'science' based on data and models. As stated in Pan and Zhang (2021) when discussing smart civil engineering, the core of digital twin technology lies in the bidirectional mapping and interaction between high-fidelity models and physical entities. The CNN surrogate model in this framework can be regarded as a 'digital twin' of grotsing material formulation, while the IMOGWO optimisation process is a massive, low-cost, riskless 'virtual experiment' in this digital space. This lays a key technical foundation for realising the intelligent construction mode of 'materials-as-a-service' in the future. Engineering decision makers can directly select from the Pareto optimal solution set according to specific engineering constraints (such as cost upper limit and minimum strength requirement) to realise scientific decision-making.

Despite the good results achieved by the collaborative architecture proposed in this study, there are still some inherent limitations. First of all, the training and validation of the model completely rely on the data set acquired under standard laboratory conditions. Although UCI datasets provide high-quality benchmarks, there are significant differences between the laboratory environment and the real shield tunnel construction site. The performance of on-site grouting materials is coupled by many complex factors, such as formation pressure, underground hydrology, uniformity of mixing equipment, and grouting process parameters. However, these dynamic variables have not been fully considered in the current model. In order to improve this limitation, a field monitoring system can be established, and the formation environmental data can be collected in real-time by embedding pressure sensors, moisture monitors and other equipment and they are included as new feature variables into the model input. At the same time, transfer learning technology can be used to pre-train the model infrastructure using laboratory data, and then fine-tune the model through a small amount of field measured data, so as to enhance the adaptability and prediction accuracy of the model under actual engineering conditions. Secondly, the optimisation framework currently targets the static performance index of the material, that is, the final performance at a specific curing age. However, in engineering practice, time-varying behaviours such as the early strength development law

of grouting materials and the time-varying loss characteristics of fluidity are also crucial, and current models are not able to capture and optimise these dynamic processes. To solve this problem, time series analysis method can be introduced to extend 1D-CNN to an architecture that can process time series data (such as CNN-LSTM hybrid model), and the prediction model of material properties over time can be established by collecting performance data at different time points. At the same time, the time-varying performance indicators, such as one-day, three-day, seven-day strength development rate and flow retention rate, are incorporated into the optimisation objective, so as to realise the multi-stage collaborative optimisation of the material life cycle performance. In addition, as a high-performance prediction tool, the internal 'black box' characteristic of CNN model is still a challenge that cannot be ignored. In the absence of intuitive physical explanations, trust barriers still need to be overcome for the engineering community to fully trust and adopt the recipes recommended by the model. To improve model transparency, interpretable AI techniques can be introduced, such as Shapley additive explanations (SHAP) and local interpretable model-agnostic explanations (LIME) methods. The contribution of each input feature to the final prediction result was quantified. At the same time, combined with the prior knowledge in the field of materials science, the optimal formula recommended by the model can be physically interpreted, the synergy or antagonism between key components can be pointed out, and the confidence evaluation can be provided for each recommended formula, so as to enhance the understanding and trust of engineers and technicians in the decision-making of the model.

Based on the findings of the current research and the development trend of the field, many directions are worth exploring in the future. An important direction is to develop cross-scale material design and optimisation models that link material microstructural features, such as pore distribution acquired through image analysis, with macroscopic property predictions, enabling co-design from microscopic mechanism to macroscopic properties. Another frontier is to explore few-shot learning or transfer learning strategies to solve the common problem of scarcity of high-quality data in the civil engineering field, so that reliable optimisation solutions can be obtained quickly for new projects or novel materials with only a small amount of experimental data. At the same time, reinforcement learning is introduced into the dynamic adjustment of grouting materials, and an adaptive system that can interact with the construction site environment in real-time and continuously optimise itself is constructed, which represents a possible path to truly intelligent construction. Finally, from the perspective of systems engineering, the material optimisation model is combined with the overall schedule, cost and carbon emission management objectives of the project to construct a comprehensive decision support system for sustainable infrastructure construction, which will have far-reaching social and economic value.

5 Conclusions

In this study, the deep CNN is successfully integrated with the improved multi-objective grey wolf optimisation algorithm, and a novel collaborative computing architecture is constructed to solve the complex problem of intelligent optimisation design of shield synchronous grouting materials. Through systematic experiments and comparative analysis, we draw the following core conclusions:

1 Architecture effectiveness: the proposed IMOGWO-CNN architecture is shown to be highly effective. It significantly outperforms a variety of advanced multi-objective optimisation algorithms, including NSGA-II, MOPSO and MOEA/D-DE, and achieves statistically significant improvements in several key indicators such as inverse generation distance, hypervolume and spacing. This confirms the great potential of highly accurate surrogate models in deep collaboration with advanced optimisation algorithms.

2 Theoretical contribution: this work goes beyond the pure combination of techniques and builds a theory-technology bridge connecting cognitive science (cognitive load theory) and materials informatics. By viewing the CNN surrogate model as a tool to reduce the 'extrinsic cognitive load' of the optimisation process, we provide a new perspective on understanding the intelligent solution of complex optimisation problems in a paradigm that is highly reusable and extensible.

3 Methodological innovation: the chaotic initialisation and dynamic weight strategy introduced in IMOGWO algorithm are proved to be effective in balancing global exploration and local exploitation, thereby accelerating convergence and improving the quality of solution set. At the same time, the successful application of 1D-CNN on structured material data further consolidates its dominant position in accurate prediction of material properties.

4 Practical implications: this study provides a powerful digital design tool for the field of shield engineering. The framework can quickly generate a series of formula schemes that achieve the optimal trade-off between compressive strength and material cost, greatly shorten the research and development cycle, reduce the experimental cost, and provide a practical technical path for realising the intelligent, accurate and efficient grouting material design, which has broad engineering application and promotion prospects.

Going forward, incorporating field variables into the model, considering the time-varying nature of performance, and enhancing the interpretability of the model will be key steps to move this framework from theoretical research to full-scale engineering practice.

Acknowledgements

This work is supported by the Anhui Province Action Plan for Cultivating Young-Middle-aged Teachers Excellent Young Teacher Cultivation Project (No. YQYB2023083) and the Anhui Province Higher Education Natural Science Research Project (No. 2023AH052818).

Declarations

All authors declare that they have no conflicts of interest.

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