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Original Paper

Mix Ratio of High-strength Concrete Based on Chaotic Particle Swarm Optimization

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Abstract

The optimization of the mix ratio of high-strength and high-performance concrete needs to solve the variable design problem of many factors. The purpose of this paper is to study the optimal design of high-strength concrete mix proportions based on chaotic particle swarm optimization. This paper introduces the research background and significance of this paper, the research status of deep learning prediction, concrete compressive strength prediction and intelligent design of concrete mix ratio at home and abroad, and introduces the relevant theoretical basis, mainly including the concept of high strength concrete and chaotic particle swarm algorithm. A multi-objective optimization model for high-strength and high-performance concrete based on experimental data is proposed. Each part of the model is introduced in detail, and the system established by the intelligent design model of concrete mix ratio proposed in this paper is firstly introduced briefly, then the various functions of the system are explained, and finally the system is given method, and select a real building concrete production mix data set for testing. The optimized high-strength and high-performance concrete has higher strength and a slump of 216.4mm.

Keywords

chaotic particle swarm, high strength concrete, mix ratio optimization, optimal design

1. Introduction

As one of the indispensable materials in engineering construction, concrete is the basis for the realization of engineering blueprint. After decades of efforts and development, my country's concrete production has basically achieved large-scale and intensive (Lindelof, Said, & Ahmed, 2019). With the rise of infrastructure construction, the demand for concrete is gradually increasing, and for a long time in the future, the output of concrete will remain high and grow to a certain extent (Gupta & Bellary, 2018). In order to control the construction budget of the project, it is a basic problem to be solved in the field of engineering materials to use appropriate raw materials and to produce concrete that meets the design requirements in a stable, high-efficiency and low-polluting manner through the optimal mix ratio. The development of concrete engineering informatization will become an inevitable trend. Using the rapid learning ability of computers, we can improve production efficiency. Through the auxiliary application of computers, we can write the application program of concrete mix ratio, and reasonably optimize the design for practical engineering requirements (Firoozi, Dehestani, & Neya, 2018).

The optimization of mix ratio design has always attracted the attention of practitioners. From the beginning, the most suitable mix was selected based on the collection of a large number of data experiments, and then the design goal was based on the compressive strength of concrete. optimization to obtain a better mix ratio (Nosheen, Qureshi, Tahir, et al., 2018). Asen and Dehestani (2021) studied the effect of mix design parameters on chloride diffusion and reinforcement corrosion in concrete. The effects of parameters such as cement, water-binder ratio, slump, aggregates, and characteristic compressive strength were analyzed using response surface methodology (RSM). Regression analysis was used to evaluate mixes with each concrete. To validate the regression analysis and study the effect of reinforcement corrosion on beam bending behavior, finite element software was used. Corrosion was applied to selected beams and load-displacement plots were obtained by analyzing four laboratory samples. These figures show good agreement between numerical and experimental results. Duman, Li, Wu, et al. (2020) discusses an improved hybrid particle swarm optimization and gravitational search algorithm (PSOGSA) combined with chaotic mapping (CPSOGSA), applying a composite benchmark function, to solve the OPF problem of stochastic wind power and flexible AC transmission systems (facts). Numerical studies are used to illustrate the effectiveness of the proposed CPSOGSA method relative to other methods such as moth swarm algorithm and whale optimization algorithm. With the help of algorithm optimization calculation, we can find certain rules, and then apply the rules to the optimization calculation of concrete mix ratio and the real-time monitoring of concrete engineering quality (Falliano, De Domenico, Ricciardi, et al., 2018).

In this paper, based on the performance of concrete, the chaotic particle swarm algorithm is combined to build a concrete mix optimization model. The model can combine the existing empirical formulas as constraints, such as sand ratio, water-cement ratio, concrete strength, etc. The lowest unilateral cost is taken as the optimization objective function, the optimal solution of the mix ratio is solved, and the result of the most economical scheme after the concrete mix ratio is optimized is obtained. Based on the concrete performance model and concrete mix ratio optimization model obtained above, the properties and prices of concrete raw materials in the given example are used as the input of the model, and the prediction data of concrete strength, slump, and the unilateral price of concrete are output to explore the optimization model reasonableness and suitability.

2. Research on Optimal Design of Mix Proportion of High Strength Concrete Based on Chaos Particle Swarm Optimization

2.1 High-strength Concrete

High performance concrete can be said to be a new type of concrete (Ismail, Jaeel, Alwared, et al., 2021). At present, the most common technical way to prepare high-strength and high-performance concrete is to add reactive mineral admixtures, superplasticizers and other admixtures into concrete. This also means that the general rules to be followed in the preparation of high-strength and high-performance concrete are: (1) the water glue is relatively low; (2) the raw materials are of good quality and the content of impurities is low; (3) additional active mineral admixtures are added; (4) Add superplasticizer and other admixtures as needed. It can be seen that the extensive use of mineral admixtures in the preparation of high-strength and high-performance concrete can not only improve concrete performance, but also reduce the amount of clinker cement; The greenhouse effect is also conducive to the protection of the environment and the formation of a good production cycle because of the reasonable disposal and utilization of a large number of industrial wastes as mineral admixtures. In conclusion, high performance concrete can save cement, turn industrial waste into treasure, prolong the service life of engineering structures, and ultimately protect the ecological environment and natural resources. Therefore, high-performance concrete should also be a sustainable "green concrete" (Oeb, Poa, Mtt, et al., 2020; Kambham, Ram, & Raju, 2019).

2.2 Chaos Particle Swarm Optimization

Compared with other algorithms, the basic particle swarm optimization (PSO) has the advantage of faster search, but it also has disadvantages such as being easy to fall into the local optimal solution (Nejati, Ahmadi, & Edalatpanah, 2019). Many scholars have continuously improved the traditional particle swarm optimization, and proposed particle swarm optimization with shrinkage factor, particle swarm optimization with dynamic neighborhood, etc. (Chiniforush, Gharehchaei, Nezhad, et al., 2021). The chaotic particle swarm optimization (CPSO) is a hybrid particle swarm algorithm that adds the chaos principle to the particle swarm optimization. It combines the global optimal search ability of the chaotic search and can better overcome some of the shortcomings of the particle swarm optimization. Compared with other algorithms, chaotic particle swarm optimization is simpler, easier to implement, and has better global search ability. It has been proved that CPSO has better optimization ability and evolution efficiency than basic PSO algorithm (Sheludko, 2018; Kaya, Gümüü, Abdülkadir, Aydilek, et al., 2021).

Chaos is a common phenomenon in nonlinear systems (Bilal & Ztürk, 2021). Chaos is a phenomenon with a subtle internal structure. Chaos movement has the characteristics of craftsmanship, randomness and regularity. To a certain extent, it follows its own laws across all situations without repetition (García-Ródenas, Linares, & López-Gómez, 2021). Chaos search has inherent randomness and initial value sensitivity. Inherent randomness means that the motion law of chaotic motion is irregular, similar to randomness; initial value sensitivity means that if the chaos search is through some equations after many iterations, it is more sensitive to the original value.

The basic particle swarm optimization algorithm is prone to oscillate around the local optimal solution in the solution space, so the basic particle swarm optimization algorithm is improved, and the chaos algorithm and the particle swarm optimization algorithm are parallelized. Therefore, during initialization, the method of chaos is used to select several positions with better values as initial particles, which can speed up the operation speed of the algorithm (Yousri, Allam, Eteiba, et al., 2020; Shirani & Safi-Esfahani, 2020). The algorithm flow is as follows:

Step 1: Chaos initialization forms the position and velocity of particles, and calculates the initial individual particle end and global end of the particle swarm. The optimal number of chaotic variables is selected as the initial particle population.

Step 2: Taking the current particle position as the chaotic variable, update the chaotic sequence and calculate and evaluate the F1 suitability.

Step 3: Update the particle swarm according to the initial particle swarm, update the particle position and velocity, and calculate and evaluate the F2 suitability to satisfy the flexible resource constraints according to the rules.

Step 4: Compare the two fitnesses F1 and F2. Keep the best solution. Update local particle optima and total optima.

Step 5: If the maximum number of repetitions is reached, return the total optimal gbest solution, otherwise go to step 2.

3. Investigation and Research on Optimal Design of High Strength Concrete Mix Proportion Based on Chaos Particle Swarm Optimization

3.1 Multi-objective Optimization Model Design of High-strength and High-performance Concrete

(1) Constraints

Set the water-binder ratio, sand ratio, water-reducing agent (kg), silica fume (kg), and fly ash (kg) in $1m^3$ high-strength high-performance concrete (kg) to be 1x, 2x, 3x, 4x, 5x respectively. Restrictions:

$$x_i^{(l)} \le x_i \le x_i^{(u)} \tag{1}$$

In the formula, $x_i^{(l)}$, $x_i^{(u)}$ (i=5, 4, 3, 2, 1) represent the water-binder ratio, the sand ratio and the lower and upper limits of the material.

(2) Objective function

Due to the complex nonlinear relationship between the amount of raw materials and the properties of concrete, a multivariate nonlinear model was established between the properties of high-strength and high-performance concrete and the amount of raw materials. Now let y be the concrete performance index, x1,...,xk be the amount of various raw materials, then the multiple regression model of concrete performance prediction can be expressed by the following formula:

$$y = b_0 + b_1 \cdot f_1(x_1,..., x_k) + b_2 \cdot f_2(x_1,..., x_k) + ... + b_n \cdot f_n(x_1,..., x_k) \quad (2)$$

where all fi(x1,...,xk) are defined nonlinear functions of the independent variables xj(j=1,...,k).

3.2 High-strength Concrete Intelligent Mix Ratio Design System

Combined with the concrete mix design model and related algorithms proposed in this paper, this paper designs a concrete intelligent mix design system. The concrete intelligent mix design system mainly includes functional modules: compressive strength prediction module and mix design module. Among them, the concrete mix ratio design module includes several sub-modules, namely: user input module, expert scoring table scoring module and mix ratio fine-tuning module.

3.3 Optimization Examples

A certain type of steel concrete requires high-strength and high-performance concrete of C80. The cement is ordinary Portland cement, the strength grade is 50, the density is 3.3g/cm3, the fine aggregate is river sand, the fineness modulus is 2.9, the density is 3.01g/cm3, the coarse aggregate is crushed stone, the particle size is 10~15mm, Density 1.55g/cm3, M provincial grade silica fume (SF), apparent density 2t/m3, specific surface area about 25m2/g, water demand 121%, activity index 115%, using first-grade fly ash, apparent density It is 2.1g/cm3. In this test, the commonly used polycarboxylate water-reducing agent is used in China, and the slump of the field trial mix is required to be 15~25cm. The market prices of materials are as follows: cement 0.35 yuan/kg, sand 0.025 yuan/kg, stone 0.045 yuan/kg, water 0.003 yuan/kg, polycarboxylate water reducer 4.8 yuan/kg, silica fume 1.8 yuan/kg, fly ash 0.01 yuan/kg.

4. Analysis and Research on Optimal Design of High-strength Concrete Mix Ratio Based on Chaotic Particle Swarm Algorithm

4.1 High-strength Concrete Intelligent Mix Ratio Design System

The intelligent design of high-strength concrete mix ratio is the core function of this system, which is completed by coordinating and calling four sub-modules. The detailed process is described as follows: (1) Input information in the user input module. The system performs fuzzy matching in the historical database according to the user’s input information to obtain the appropriate mix ratio. (2) Score the matching mix ratios in the scoring module of the expert scoring table, and push out the mix ratio with the highest score as the benchmark mix ratio according to the score. (3) The mix ratio fine-tuning module is called, and the chaotic particle swarm algorithm is used to fine-tune the mix ratio. (4) After the fine-tuned mix ratio meets the constraints of the expert knowledge base, the multi-objective optimization model of high-strength and high-performance concrete is used to calculate its 28d compressive strength. If the result meets the user’s needs, calculate its unit cost and push the fine-tuned mix ratio to the user; otherwise, fine-tune the mix ratio with the highest score. The flow chart of intelligent design of high-strength concrete mix ratio is shown in Figure 1.

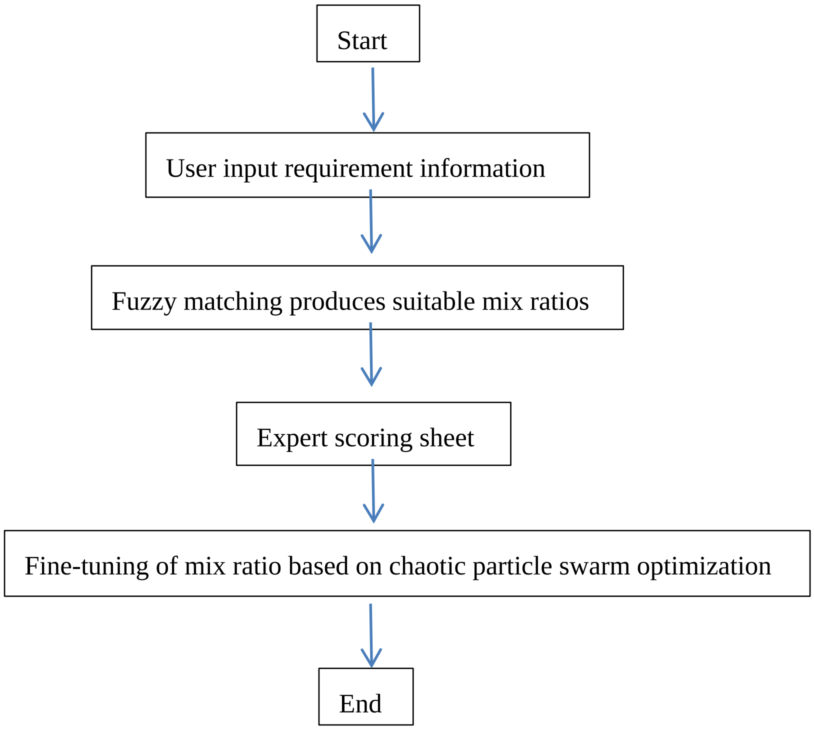

Figure 1. Flow Chart of Mix Ratio Intelligent Design

4.2 Mix Ratio Optimization Results

In the unit cubic concrete, the comparison between the optimized mix ratio and the experimentally determined mix ratio is shown in Figure 2. In the unit cubic concrete, the comparison between the optimized mix ratio and the experimentally determined mix ratio is shown in Table 1.

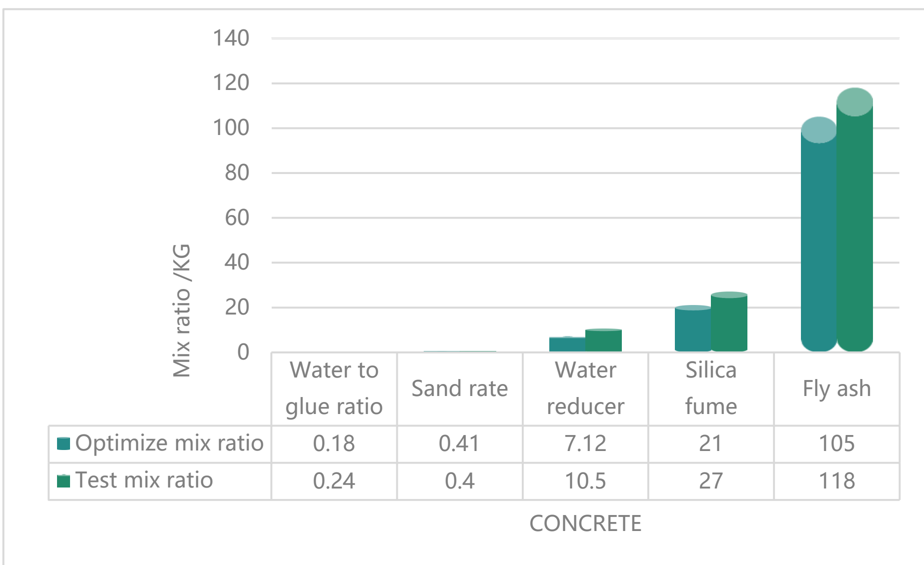

Figure 2. Comparison of Optimized Mix Ratios and Experimentally Determined Mix Ratios in Unit Cubic Concrete

Table 1. Comparison of Properties of Optimized and Experimentally Obtained Concrete

	28-day compressive strength	Initial slump	Material costs
Optimizing Forecast Values	91.08Mpa	216.4mm	277yuan
Test value	85.18Mpa	175.2mm	369.54yuan

It can be seen that the optimized mix ratio is basically consistent with that obtained from the trial mix, but the optimized high-strength and high-performance concrete has higher strength, greater slump and lower cost. The fitting prediction formula itself has errors, so the optimization results will inevitably have some small errors, but the optimization results have basically achieved the expected purpose.

In order to verify the permeability of high-strength and high-performance concrete under different mix ratios, the impermeability grade test of high-strength and high-performance concrete was carried out in this paper. The test results show that the high-strength and high-performance concrete has better impermeability, which is mainly due to its good compactness. The lower the water-cement ratio, the worse the permeability of concrete; fly ash and silica fume have a very important effect on improving the permeability of high-strength and high-performance concrete, in comparison, silica fume is more obvious than fly ash.

5. Conclusions

Considering the defects in the traditional artificial concrete mix design process, this paper designs an intelligent mix design model for concrete and designs a corresponding system. The process of concrete mixing is often manual trial mix, which will cost a lot of cost. Therefore, how to design an intelligent mix design model that can not only reduce the cost of concrete production, but also meet the requirements of its compressive strength is an urgent problem to be solved in the modern construction industry. Through the summary and analysis of the existing domestic and foreign experimental research results of high-strength and high-performance concrete, a performance-based optimization mathematical model of the mix ratio of high-strength and high-performance concrete is established. By comparing a variety of optimization methods suitable for high-strength and high-performance concrete mix ratio design, the most simple and optimal optimization design method is found. According to the proposed deep learning-based concrete intelligent mix design model, a concrete intelligent mix design system is established, which mainly includes two functions: concrete compressive strength prediction function and concrete intelligent mix design function. First, the system is briefly introduced, then the functions of the system are expounded, and finally the usage of the system is given.

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