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Research on optimization model of concrete proportioning based on particle swarm algorithm in construction engineering technology

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ABSTRACT

Particle swarm algorithm, as a kind of population intelligent optimization algorithm, shows great potential in solving multivariate and nonlinear optimization problems due to its simple and efficient characteristics. The article constructs a concrete ratio optimization model in construction engineering technology, which is supported by particle swarm algorithm as the main technology. The model also integrates the least squares support vector regression algorithm, which makes it not only simple ratio optimization, but also has the function of concrete performance prediction. The relative error of the model in predicting the physical properties of concrete is small, less than 5%, which improves the reliability of concrete proportioning. The concrete samples generated by the model with five different ratios have better physical properties for daily needs. In the durability test, the concrete sample with proportion 4 showed the best performance in terms of mass loss rate and impermeability, which were 3.52% (after 400 cycles) and 156.44C (after 56d), respectively. And all the concrete samples used were in the range of proportional qualification and the cost was 5.99% to 28.61% lower than the comparison method.

Keywords: construction engineering technology; particle swarm algorithm; least squares support vectors; ratio optimization models

1. Introduction

Architectural concrete construction is an essential part of house construction. Concrete as a commonly used construction materials, its ratio directly affects the quality and service life of the project. Concrete ratio refers to the engineering design requirements and the actual situation, to determine the proportion of cement, sand, aggregate and mixing materials in concrete to ensure the strength, durability and performance of concrete [1-2]. Concrete proportioning must meet four basic requirements: structural design of the strength class, the ease of concrete construction, the

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engineering environment on the durability of concrete requirements and economic principles [3]. The economic principle refers to the need to save cement to reduce the cost of concrete. The determination of the mixing ratio needs to take into account the requirements and conditions of different projects, and should be reasonably planned at the design stage. The basic parameters of concrete proportioning are water-cement ratio, unit water consumption and sand rate. On the basis of meeting the strength and durability of concrete, the ratio of cement dosage to water dosage, i.e., water-cement ratio, is determined, which is conducive to the implementation of the construction process [4-5]; on the basis of meeting the required ease of concrete construction, the water consumption per unit is determined according to the type and specification of the coarse aggregates, and the sand rate should be determined on the basis of the principle that the quantity of sand in the aggregates should fill up the voids of the stone and be slightly enriched [6-8]. Among them, sand and gravel aggregate is the filler in concrete, which can increase the strength and stability of concrete [9]. At the same time, admixtures such as slag powder, quarry dust powder, fly ash, and steel-glass fiber reinforced active powder can be added in appropriate amount according to the need to improve the performance of concrete [10-13]. Determination of concrete proportion and adjustment of construction proportion are then important to ensure the quality of concrete, and the steps are not to be confused. It should follow the steps of determining the concrete strength class and environmental requirements, determining the water-cement ratio, determining the water consumption per unit, determining the sand rate, calculating the amount of each constituent material in the concrete, and checking the reasonableness and feasibility of the design of concrete ratios [14], in order to ensure the quality of concrete.

However, in the actual construction of a building project, the concrete proportion may need to be adjusted to meet specific project requirements and site conditions. Therefore, it is urgent to construct an optimized concrete proportioning model, which can save cost while giving the best proportioning solution efficiently.

Concrete proportioning optimization mainly focuses on optimizing the ratio between the mixtures according to the objective requirements. Literature [15] evaluated the optimization of mix proportioning of engineered ground polymer composites under multi-objective optimization technique using response surface methodology and the results showed that the proportioning performance was in good agreement with the predicted result performance. Whereas, literature [16] mentioned that the response surface methodology is able to provide suitable approximations for blend optimization and statistical inference and analysis of variance are applicable for cementitious material proportioning optimization. Literature [17], on the other hand, applies response surface methodology to optimize rubber concrete proportioning by developing an ANOVA model. Concrete proportioning is related to the performance of concrete, which depends on indicators such as cement type, aggregate type, filler, and water reducer dosage. Literature [18] constructed a dynamic optimization model to optimize the proportioning design of high performance concrete by simultaneously checking all the constraint properties of the proportioning design. Literature [19], on the other hand, combined machine intelligence algorithms, individual learners, and integrated learners to predict and optimize the strength of industrial wastes to obtain consistently high performance concrete. Whereas, literature [20] used an integrated machine learning model to predict the modulus of elasticity and physicochemical properties of concrete formulated with recycled concrete aggregates and provide optimization for the design of the optimal concrete ratio. In addition, literature [21] optimized the sand grade configuration by means of improved Andreasen and Andersen filling model to obtain the optimum filling density. Further, literature [22] designed a hybrid intelligent system of artificial intelligence and meta-heuristic algorithms to optimize the proportioning of recycled aggregate concrete mixtures, and then the optimal proportion was obtained through a multi-objective optimization model constructed by combining artificial intelligence algorithms and multi-objective firefly algorithms. Whereas, literature [23] utilized a multi-objective particle swarm algorithm under the combination of machine learning and meta-heuristic algorithm to optimize the concrete ratios and obtained the best ratios. Similarly, literature [24] particle swarm algorithm optimization to obtain the optimum ratio of solid content and cement admixture of cement paste filler mixes based on strength and workability at minimum cost is also a multi-objective optimization study.

The study, based on the current research status of concrete ratio optimization in construction engineering technology, learns that particle swarm algorithm is less applied in the intelligent optimization design of concrete ratio. Therefore, the article designed the intelligent optimization model of concrete ratio by integrating the particle swarm algorithm of least squares support vector. In addition, the study prepared the raw materials of ceramic foam concrete (cement, fly ash, ceramic foam, etc.), and the concrete samples were obtained through the production process as well as the algorithmic proportioning. Combined with the research scheme designed in this paper, the research on the optimization effect of concrete proportioning based on particle swarm algorithm is carried out in terms of performance, durability and cost of concrete samples.

2. Current status of research on optimization of concrete proportioning in construction engineering technology

2.1. Proportioning design of concrete

As a multiphase material, concrete's complex composition leads to its complex properties. On the one hand, concrete can be prepared by a worker with the ability to manipulate a trowel and mix cement, aggregates and water, and concrete produced by this crude method is usable for many less demanding construction projects. The production of a specific, dense, homogeneous, high-quality and economical concrete, on the other hand, requires a high level of knowledge and skill.

Concrete proportioning design has moved towards multi-objective joint. Multi-objective joint design is different from the previous single-objective ratio design, its design guidelines are based on a number of concrete performance indicators derived from the total indicators to judge the merits of the concrete ratio, from a number of ratios to determine the optimal ratio, which should be with the help of optimization methods. In practice, the difficulty of multi-objective joint design lies in the establishment of mathematical relationships between material properties and concrete performance indicators, as well as the criteria for judging the advantages and disadvantages of concrete ratios.

2.2. Analysis of the current status of ratio optimization

In the field of optimal design of high-performance concrete proportioning, there are mainly methods proposed by the American Concrete Institute (ACI) and the Laboratoire de la Centre de la Passeporte de la Passeporte (LCPC) in France. In recent years, with the development of artificial intelligence technologies such as artificial neural networks (ANNS) and evolutionary algorithms, the intelligent and optimal design technology of concrete proportioning has also been greatly developed.

The means of implementation of artificial neural network technology in concrete proportion design uses the method of simulating the real system by using orthogonal design test as a learning sample to simulate the complete test. At the same time, some of the test data are used as the research object to simulate the real system by self-organized neural network classification calculation, which constitutes the learning sample to obtain satisfactory results.

Genetic algorithm, from the successful concrete proportion data, generalizes the range of values of various raw material dosages, and takes the cost of concrete materials as the optimization objective function. The mathematical planning problem of constrained optimization is transformed into a genetic algorithm model, with real numbers encoded to represent the chromosome bit strings of an individual, enabling combinations of operators such as league league random selection operator, complete arithmetic crossover operator, and non-uniform variation operator, to complete the genetic operation, programmed to compute and obtain the optimal solution.

However, most of the current researches in the optimization of concrete proportioning are single-objective, such as economy or strength. With the rapid development of concrete, the composition of concrete is becoming more and more complex, and the improvement of the quality of concrete and the diversification of the use of concrete makes the original concrete proportioning design method no longer applicable, and its proportioning design has also changed greatly. Therefore, this paper designs a concrete proportioning optimization model based on particle swarm algorithm for diversified design.

3. Research materials and methods

3.1. Research materials

1) Cement. Big Eagle brand 42.5 ordinary silicate cement was used, the chemical composition of the cement is shown in Table 1, and the physical and mechanical performance indexes are shown in Table 2.

Table 1. Chemical composition of cement/%

CaO	SiO_2	Al_2O_3	Fe_2O_3	MgO	SO_3	Na_2O	K_2O	LOSS
54.94	26.74	8.25	3.04	2.09	2.05	0.15	0.22	1.37

Table 2. Physical and mechanical properties of cement

<table>
<tr><th rowspan="2">Fineness/%</th><th rowspan="2">Water consumption/%</th><th colspan="2">Setting time/min</th><th colspan="2">Resistance to pressure/ MPa</th><th colspan="2">Folding strength/ MPa</th><th rowspan="2">Stability</th></tr>
<tr><th>Initial setting</th><th>Final setting</th><th>3d</th><th>28d</th><th>3d</th><th>28d</th></tr>
<tr><td>2.8</td><td>26.3</td><td>155</td><td>260</td><td>25.3</td><td>39.2</td><td>6.28</td><td>9.15</td><td>Qualify</td></tr>
</table>

2) Fly ash. Class I fly ash was used, the chemical composition of fly ash is shown in Table 3 and the activity index is shown in Table 4.

Table 3. Chemical composition of fly ash/%

Al_2O_3	CaO	Fe_2O_3	MgO	SiO_2	LOSS
17.94	2.98	4.66	1.65	64.08	2.21

Table 4. The active index of fly ash

28d Resistance to pressure/MPa	1	2	3	4	5	6	Mean	Activity
Mixed sand	39.8	39.1	42.1	40.6	41.3	41.7	40.8	104.08
Cement sand	37.4	37.2	40.6	39.5	40.2	40.3	39.2	

3) Ceramic granules. Ceramic particles selected by the self-developed coal slurry - self-combustion gangue ceramic particles. The bulk density of granule is 450kg/m^3, which belongs to ultra-light granule, and the barrel compression strength and 1h water absorption rate are better than the technical index of artificial lightweight aggregate, which meets the national standard requirements.

4) Foam. The foaming agent in this test is animal protein foaming agent, through the screening experiment, finally choose the dilution ratio of 1:20 foaming agent, the foam density produced by physical foaming through the foaming machine is 36.14kg/m^3.

5) Water reducing agent. Admixture of appropriate amount of water reducing agent can reduce the mixing water under the premise of ensuring that the slump of concrete mix remains unchanged. The test water reducing agent adopts polycarboxylic acid water reducing agent, the dilution ratio of mother liquor is 1:4, the dosage is 2% of the mass of cementitious material, and the water reducing rate is 20%.

6) Foam stabilizer. The foam stabilizer used in this test was selected as hydroxypropyl methyl cellulose ether. It is a semi-synthetic, inactive, viscoelastic polymer, belonging to a kind of nonionic cellulose mixed ether, in the form of white powder. The dosage of this test is 0.02% of the mass of the gelling material.

7) Water. Tap water at room temperature was used in this test.

3.2. Foam concrete production process

The ceramic foam concrete was prepared according to the concrete ratios provided by the optimization model. The concrete process is as follows:

1) Mix the weighed cement and fly ash evenly and set aside.

2) Weigh the mixing water, cellulose ether and water reducing agent, and pour the cellulose ether and water reducing agent into the mixing water in turn and mix well.

3) Pour the above two materials into the foam concrete mixer in turn and mix for 2 min.

4) At the same time, use the foaming machine to prepare foam from the foam agent, mix into the corresponding volume of foam, and mix fully for 1min.

5) Pour the weighed pre-wetted and saturated surface dry state of ceramic granules into the mixer and mix well for 2min to get the ceramic foam concrete mix.

6) After the preparation of ceramic foam concrete, the slurry should be poured into the corresponding molds brushed with oil in advance, note that this test selects vibration-free, self-leveling molding, and scrape off the excess slurry on the surface with a spatula to make the surface flat.

7) Molded specimens at a temperature of (20 ± 3) ℃, relative humidity greater than 90% of the curing box maintenance 48h after demolding, and then continue to maintain to the specified age, for the relevant physical and mechanical properties of the test.

3.3. Methods of Physical Properties Research

3.3.1. Compressive strength. The test compressive strength in 100kN electro-hydraulic servo pressure testing machine to complete, the specimen destructive load is greater than 20% of the full range of the press and less than 80% of the full range of the press. Compressive strength should be calculated according to formula (1):

$$f = \frac{F}{A} \tag{1}$$

Eq:
f is the compressive strength of the specimen/MPa.
F is the maximum destructive load/N.
A is the compressed area of the specimen/mm2.

3.3.2. Thermal Conductivity. The coefficient of thermal conductivity is defined as the amount of heat transferred through the unit area of the material along the direction of heat flow in a unit time under a unit temperature gradient, and the test is completed with the determination on the QTM-500 fast thermal conductivity meter. Thermal conductivity should be calculated according to formula (2):

$$\lambda = \frac{Qd}{A\Delta T} \tag{2}$$

Eq:
λ is the thermal conductivity of the specimen in W/(m-k).
Q is the heat flux/W.
ΔT is the temperature difference/K.
A is the heat area/m2.
d is the thickness of the specimen/m.

3.3.3. Dry density. Take a group of specimens, calculate the volume of each specimen V, the specimen will be placed at a temperature of (60 ± 5) ℃ drying oven drying to before and after the two times between the mass of 4h difference is not greater than 1g, after removing the specimen should be put into the dryer and in the specimen cooled to room temperature after weighing the specimen drying mass, accurate to 1g. dry apparent density should be calculated in accordance with the formula (3):

$$\rho_0 = \frac{m_0}{V} \times 10^6 \ \lambda = \frac{Qd}{A\Delta T} \tag{3}$$

ρ_0 is the dry apparent density in kg/m^3.
m_0 is the dry mass of the specimen/g.
V is the volume of the specimen/mm^3.

4. PSO-LSSVN based concrete proportioning optimization model

4.1. Basic Model of Particle Swarm Algorithm

4.1.1. Principles of the Particle Swarm Algorithm. The Particle Swarm Algorithm [25] is an effective method used to simulate the feeding behavior of birds, which considers the feasible solution space of the problem as a food region. Individuals of a flock of birds are abstracted as individual particles, and the process of the entire flock flying in search of food is represented mathematically:

1) Target search space range: a n-dimensional vector space R^n, consisting of n particles forming a swarm, and the position information of particle i is Eq. (4):

$$X_i = (x_{i1}, x_{i2}, x_{i3}, \ldots\ldots, x_{in}), i = 1, 2, 3, \ldots\ldots, n \tag{4}$$

2) Size of the population: the number of particles determines the size of the population, set to m, then this population can be expressed as equation (5):

$$M = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{5}$$

3) Position information: the distance each particle finds the target, the individual optimal position reached by particle i, and the global optimal position are expressed as follows:

$$f\left(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}\right) \tag{6}$$

$$p_{\_best_i} = \left(p_{i1}, p_{i2}, p_{i3}, \ldots\ldots, p_{in}\right) \tag{7}$$

$$g_{\_best_i} = \left(p_{i1}, p_{i2}, p_{i3}, \ldots\ldots, p_{in}\right) \tag{8}$$

4) Velocity information: the trajectory of the particle is determined by the size and direction of the flight speed, the flight speed of particle i can be expressed as equation (9):

$$V_i = \left(v_{i1}, v_{i2}, v_{i3}, \ldots, v_{in}\right) \tag{9}$$

5) The flight mode of the particle: the particle then iterates through Eq. (10) and Eq. (11) during the flight process to continuously update the individual optimal position and the global optimal position:

$$\begin{aligned} V_i(t+1) = \omega * V_i(t) + c_1 * r_1 * \left(p_{\text{-}best}(t) - X_i(t)\right) \\ + c_2 * r_2 * \left(g_{-best_i}(t) - X_i(t)\right) \end{aligned} \tag{10}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{11}$$

where in Eq. (10) ω is the inertia weight factor, c_1 and c_2 are learning factors, and r_1 and r_2 are random variables obeying a uniform distribution $U(0,1)$. The particles are able to move towards the individual and global extremes mainly controlled by these five parameters.

4.1.2. Basic processes:

1) Initialization parameters, including the number of population, position and velocity information of each particle, inertia weights, learning factors.
2) Calculate the adaptation value of individual particles.
3) Update the position information and velocity information of the particle itself.
4) Update the position information and velocity information of the global optimum.
5) Calculate the position and velocity information of the new generation of particles.
6) If the maximum number of iterations is reached, terminate the program and output the optimal values, otherwise go to 2).

4.1.3. Particle Swarm Algorithm Improvement. By adding parameters, optimizing them or combining them with other intelligent algorithms, particle swarm algorithms can effectively improve their performance, thus enhancing the efficiency and accuracy of the system [26]. It is summarized in the following 2 methods:

1) Improvement of inertia weights ω. Due to the existence of inertia weights ω, the flight speed and flight trajectory of the particles will keep changing, thus affecting the final flight position. The inertia weights ω are updated by linearly decreasing, i.e., the value of ω decreases as the number of iterations increases, and this update can be realized by Eq. (12):

$$\omega = \omega_{\max} - \frac{g\left(\omega_{\max} - \omega_{\min}\right)}{g_{\max}} \tag{12}$$

Where $\omega_{\max}$ represents the maximum weight value, i.e. the initial weight value. $\omega_{\min}$ represents the weight value of the last iteration, which is the final weight value. g represents the number of current iterations. $g_{\text{-max}}$ represents the maximum number of iterations. The second one uses adaptive weighting method, where the inertia weights are updated in the following equation:

$$\omega = \begin{cases} \omega_{\max} - \dfrac{(\omega_{\max} - \omega_{\min})*(f - f_{\min)})}{f_{avg} - f_{\min}} & f \leq f_{avg} \\ \omega_{\max} & f > f_{avg} \end{cases} \tag{13}$$

Where, $f_{\min}$ represents the maximum fitness value in the swarm and f_{avg} represents the average fitness value in the swarm, this inertia weight updating method balances the algorithm's ability to search locally and globally by assigning different weights to each individual particle.

2) Increase the qualification of particle flight speed $V_{\max}$ set the maximum flight speed in the particle swarm, which can make the particle swarm algorithm more effective to collect and add. The particle swarm velocity update method will be done as a range test, where the velocity of some particles with a velocity greater than $V_{\max}$ becomes $V_{\max}$, and the velocity of some particles with a velocity less than $V_{\max}$ becomes $V_{\max}$:

$$\begin{cases} V(V > v_{\max}) = v_{\max} \\ V(V < -v_{\max}) = -v_{\max} \end{cases} \tag{14}$$

3) Increase the compression factor c. Compression factor c affects the acceleration of particle swarm algorithm, can increase the compression factor c to accelerate the acceleration, the compression factor is set as Eq:

$$c = 2 / \left| 2 - \psi - \sqrt{\psi^2 - 4\psi} \right| \tag{15}$$

where ψ is taken as in Eq:

$$\psi = c_1 + c_2, \psi > 4 \tag{16}$$

Due to the addition of the compression factor c, the position update method of the particle swarm will have Eq. (11) changed to Eq. (17):

$$X_i(t+1) = X_i(t) + c * V_i(t+1) \tag{17}$$

4.2. Least Squares Support Vector Regression Algorithm

Since this study is for the optimization of concrete proportioning for construction projects, which requires the prediction of concrete sample performance and belongs to the category of regression problems, the following is mainly a brief introduction to the mathematical model of the least squares support vector machine regression algorithm [27].

The set of training samples is given as $D = \{(x_i, y_i), i = 1, 2, 3, \cdots, n\}$, $x_i \in R^d$, $y_i \in R^d$. where y_i is the target value corresponding to the input vector x_i. The input set R^d is mapped to a high-dimensional feature space using a nonlinear mapping $\varphi(x_i)$. The regression function at this point is:

$$f(x) = \omega \cdot \varphi(x) + b \tag{18}$$

ω and b denote the weight vector and offset of the regression function, respectively. Unlike SVM, in utilizing the principle of structural risk minimization, LS-SVM chooses the square of error ξ_i as the loss function in the optimization objective, and at the same time, the constraints are changed to equational constraints, and the optimization problem of LS-SVM becomes:

$$\begin{gathered}\min \frac{1}{2}\|\omega\|^2+\frac{1}{2} C \sum_{i=1}^n \xi_i^2 \\ s.t. y_i\left[\omega \cdot \varphi\left(x_i\right)+b\right]-1+\xi_i=0, i=1, \cdots, n\end{gathered} \tag{19}$$

Where ξ_i also represents the error term. C for the penalty coefficient, also known as the regularization parameter, is mainly used to regulate the relationship between empirical risk and model complexity, generally the larger the value of C, the greater the penalty for exceeding the error range of the sample.

The Lagrange function is established to solve the above problem, namely:

$$\begin{aligned}L\left(\omega, b, \xi_i, a\right)= & \frac{1}{2}\|\omega\|^2+\frac{1}{2} C \sum_{i=1}^n \xi_i^2 \\ & -\sum_{i=1}^n a_i\left[y_i\left[\omega \cdot \varphi\left(x_i\right)+b\right]-1+\xi_i\right]\end{aligned} \tag{20}$$

where $a_i \in R$ denotes the Lagrange multiplier. The optimal solution satisfies the KKT (Karush-Kuhn-Tucker) condition, i.e., the partial derivatives of L with respect to ω, b, ξ_i, a are found separately and made equal to zero:

$$\begin{cases}\dfrac{\partial L}{\partial \omega}=0 \rightarrow \omega-\displaystyle\sum_{i=1}^n a_i y_i \varphi\left(x_i\right)=0 \\ \dfrac{\partial L}{\partial b}=0 \rightarrow \displaystyle\sum_{i=1}^n a_i y_i=0 \\ \dfrac{\partial L}{\partial \xi_i}=0 \rightarrow C \xi_i-a_i=0 \\ \dfrac{\partial L}{\partial a_i}=0 \rightarrow y_i\left[\omega \cdot \varphi\left(x_i\right)+b\right]-1+\xi_i=0\end{cases} \tag{21}$$

Elimination of ω and ξ_i by homoskedastic transformation of the above conditions leads to the following matrix form:

$$\begin{bmatrix}0 & Y^T \\ Y & Z Z^T+C^{-1} I\end{bmatrix}\begin{bmatrix}b \\ a\end{bmatrix}=\begin{bmatrix}0 \\ I\end{bmatrix} \tag{22}$$

Style:

$$\begin{cases}Z=\left[\varphi\left(x_1\right)^T y_1, \varphi\left(x_2\right)^T y_2, \cdots, \varphi\left(x_n\right)^T y_n\right] \\ Y=\left[y_1, y_2, \cdots, y_n\right]^T \\ I=[1,1, \cdots, 1]^T \\ a=\left[a_1, a_2, \cdots, a_n\right]\end{cases} \tag{23}$$

Combining the kernel function $K\left(x_i, x_j\right)=\varphi\left(x_i\right)^T \varphi\left(x_j\right)$ and ordering $\Omega=Z Z^T$ by the Mercer condition, then:

$$\Omega=y_i y_j \varphi\left(x_i\right)^T \varphi\left(x_j\right)=y_i y_j K\left(x_i, x_j\right) \tag{24}$$

From this equation (22) can be modified to a set of linear equations:

$$\begin{bmatrix} 0 & y_1 & \cdots & y_n \\ y_1 & y_1 y_1 K(x_1, x_1) + \dfrac{2}{c} & \cdots & y_1 y_n K(x_1, x_n) \\ \vdots & \vdots & \ddots & \vdots \\ y_n & y_n y_1 K(x_n, x_1) & \cdots & y_n y_n K(x_n, x_n) + \dfrac{2}{c} \end{bmatrix} \cdot \begin{bmatrix} b \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \tag{25}$$

The model parameters $\begin{bmatrix} b & a_1 & \cdots & a_n \end{bmatrix}^T$ can be solved using the set of training samples $D = \{(x_i, y_i), i = 1, 2, 3, \cdots, n\}$. The decision function of LS-SVM is finally determined as:

$$f(x) = \sum_{i=1}^{n} a_i K\left(x_i \cdot x_j\right) + b \tag{26}$$

4.3. PSO-LSSVN concrete proportioning optimization model construction

4.3.1. Optimization of key parameters. To optimize the hyperparameters of LS-SVM using the PSO algorithm, two important aspects need to be considered in the fusion of the two algorithms: the representation of the hyperparameters and the definition of the particle fitness function.

1) Representation of hyperparameters: for LS-SVM, since the kernel function form selected in this paper is RBF kernel function, there are two hyperparameters to be optimized, i.e., the regularization parameter C and the kernel parameter σ. When optimization is performed with PSO, it is required that each particle denotes the possible solution of the optimization problem, i.e., the combination of hyperparameters. Therefore, in the optimization process of LS-SVM, a two-dimensional vector is used to represent the combination of the two hyperparameters C and σ, i.e., the position of the i th particle can be represented as $X_i = (C_i, \sigma_i)$.

2) Fitness function: the fitness is a measure to evaluate the advantages and disadvantages of the position of the particles, and also indirectly portrays the generalization performance of the LS-SVM model. In this paper, we choose to utilize the mean square error of the prediction results as the performance index of the cost prediction model, which is mathematically defined as:

$$f = \frac{1}{n} \sum_{j=1}^{n} \left(y_j - \hat{y}_j\right)^2 \tag{27}$$

where y_j denotes the actual output value of the j nd sample. $\hat{y}_j$ denotes its model predicted value. f can be seen as a composite function of C and σ. When performing fitness evaluation, the smaller the error is the better the particle position, then the optimization problem can be described as:

$$\begin{gathered} \min_{C,\sigma} f = \frac{1}{n} \sum_{j=1}^{n} \left(y_j - \hat{y}_j\right)^2 \\ s.t. C \in [C_{\min}, C_{\max}], \sigma \in [\sigma_{\min}, \sigma_{\max}] \end{gathered} \tag{28}$$

Where $C_{\min}$, $C_{\max}$ and $\sigma_{\min}$, $\sigma_{\max}$ denote the minimum and maximum values of C and σ respectively. In the modeling process of LS-SVM, with the help of PSO searching in the range of values of C and σ to minimize the adaptation value f, then the solution vector (C, σ) is the optimal hyperparameters to be searched by LS-SVM.

4.3.2. Concrete proportioning optimization process. The concrete proportion optimization specific process is shown in Fig. 1. Through the preliminary study of PSO algorithm and LSSVM model above, the following modeling ideas can be formed:

1) Preprocess the historical data through sample clustering and indicator dimensionality reduction to form a sample matrix.

2) Determine the training data set and prediction data set.

3) Setting the range of values for parameters C and σ while using the PSO algorithm to initialize m particles to form a population $X=\{X_1, X_2, \cdots, X_m\}$, where $X_i=\{C_i, \sigma_i\}(i=1,2,\cdots m)$.

4) Combine the training dataset to calculate the particle fitness and compare it, set the individual optimal value $P_{best}(i)$ and global optimal value G_{best}, and update the velocity and position of each particle.

5) Iterate repeatedly until the end condition is satisfied.

6) Output the optimized hyperparameters C and σ and assign them to the LS-SVM prediction model.

7) Train the model with the training set and input the predicted sample data for model prediction to obtain the optimal results.

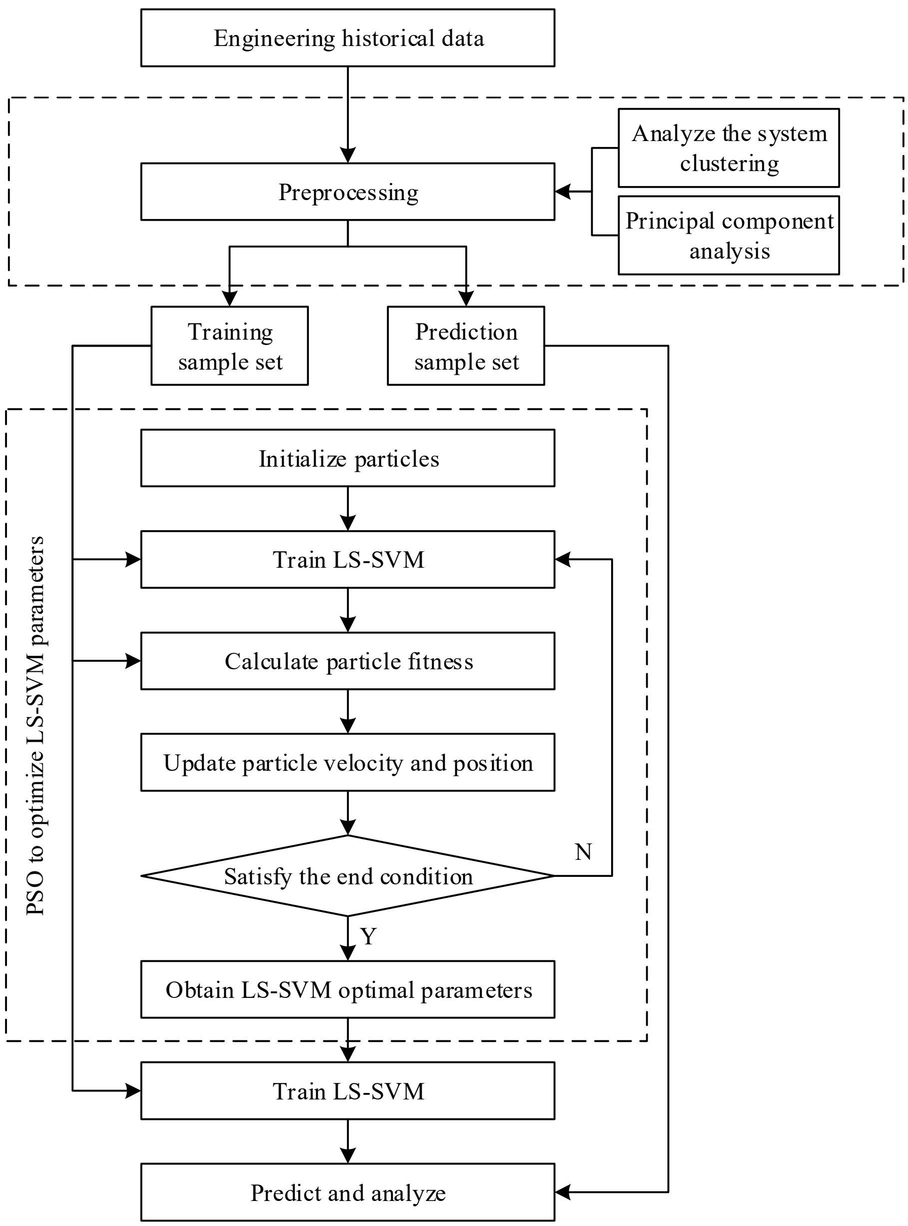

Fig. 1. The optimization flow chart of LS-SVM based on PSO optimization

4.4. *Application analysis of optimized model concrete proportioning*

4.4.1. Physical performance prediction. In this section, the PSO-LSSVN model was utilized to predict the 28d compressive strength, dry density, and thermal conductivity of vitrified foam concrete by regression fitting. Prior to the start of the experiment, by collecting literature, as well as consulting with relevant experts, 20 different raw material ratios of concrete were configured using the concrete raw materials described above, and the prediction model was built after machine learning.

Figures 2 and 3 show the prediction effects of 28d compressive strength, dry density and thermal conductivity of the samples used, respectively. Combined with the two graphs analysis: from the prediction model results, for its 28d compressive strength prediction results for the maximum absolute error of 0.07, the maximum relative error of 1.42%, analyze its 28d compressive strength prediction of the results of the larger may be due to one hand, the sample itself the test value of the smaller. On the other hand, the 28d compressive strength prediction results have a complex relationship with the seven raw material ratios. For the dry density and thermal conductivity, the absolute errors of the predictions of the model in this paper ranged from 0.08 to 2.33 kg/m^3 and 0.001 to 0.022 W/(m·k), respectively. The relative errors of the prediction of the three physical properties are within 5%, so the model in this paper has a certain reference value for the prediction of the physical properties of concrete.

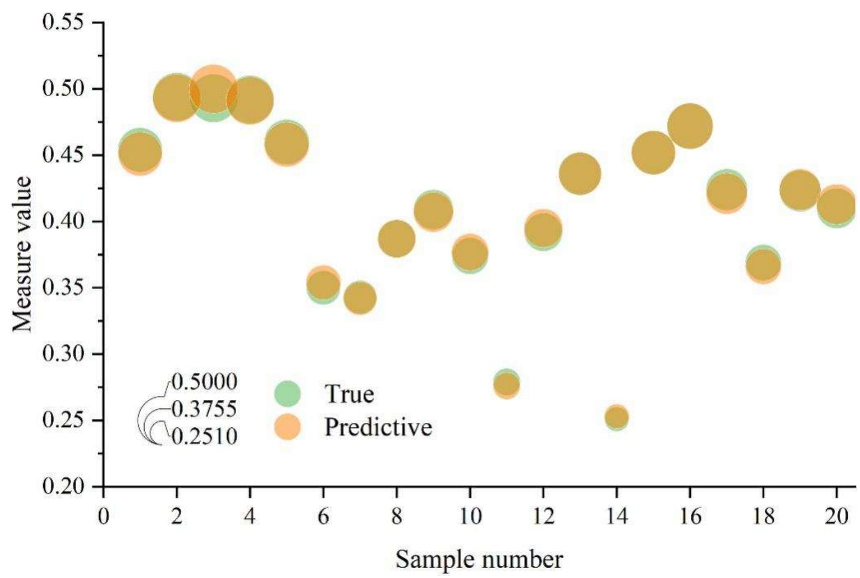

Fig. 2. The resistance to pressure is predicted

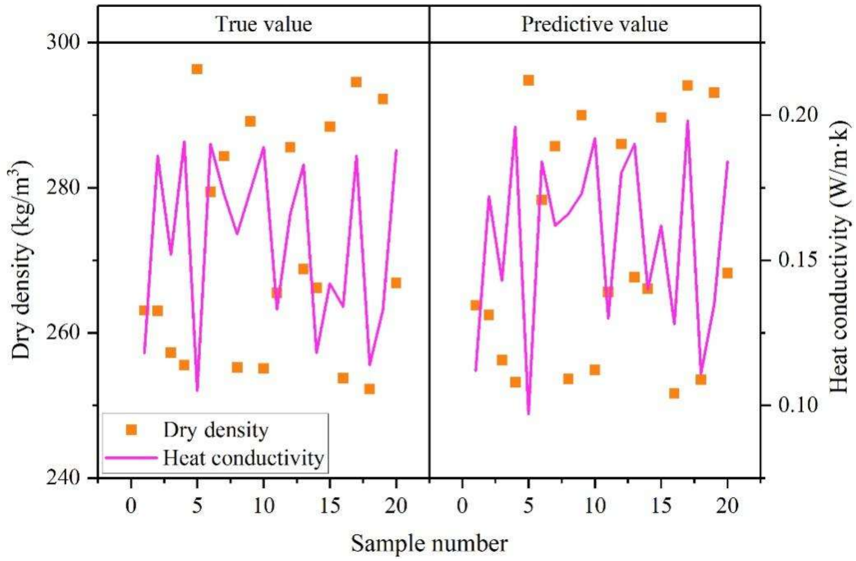

Fig. 3. Dry density and heat conduction coefficients are calculated

4.4.2. Usable performance testing. In this section, five concrete samples with different proportions of raw materials were generated using the PSO-LSSVN model. The specific proportions of each concrete sample are shown in Table 5. After the concrete samples were made, the physical properties of the concrete, including compressive strength, dry density, and thermal conductivity, were determined according to the methods described above. For the accuracy of the experiment, each proportion of concrete samples was measured five times according to the above method and the average value was taken.

Table 5. Concrete proportions of concrete samples

Raw material	Formula 1	Formula 2	Formula 3	Formula 4	Formula 5
Cement	70%	75%	80%	80%	85%
Fly ash	10%	7%	7%	6%	5%
Pottery grain	10%	10%	6%	6%	4%
Foam	9%	7%	5%	4%	4%
Water reducer	0.5%	0.5%	1%	2%	1%
Stabilizing agent	0.5%	0.5%	1%	2%	1%
Water	Moderation	Moderation	Moderation	Moderation	Moderation

Figure 4 illustrates the physical properties of the different concrete samples. The folded line in the figure represents the average measured value of each index, and the shaded area is the relative error of the five tests. As can be seen from the figure, the physical properties of the five groups of samples have a good performance, with the compressive strength, dry density, and thermal conductivity distributed in the range of 0.487-0.624 MPa, 200.6-255.31 kg/m, and 0.204-0.274 W/(m·k), respectively. It is worth mentioning that the ration 4 has the best performance in all the measured indexes and has a large potential for application.

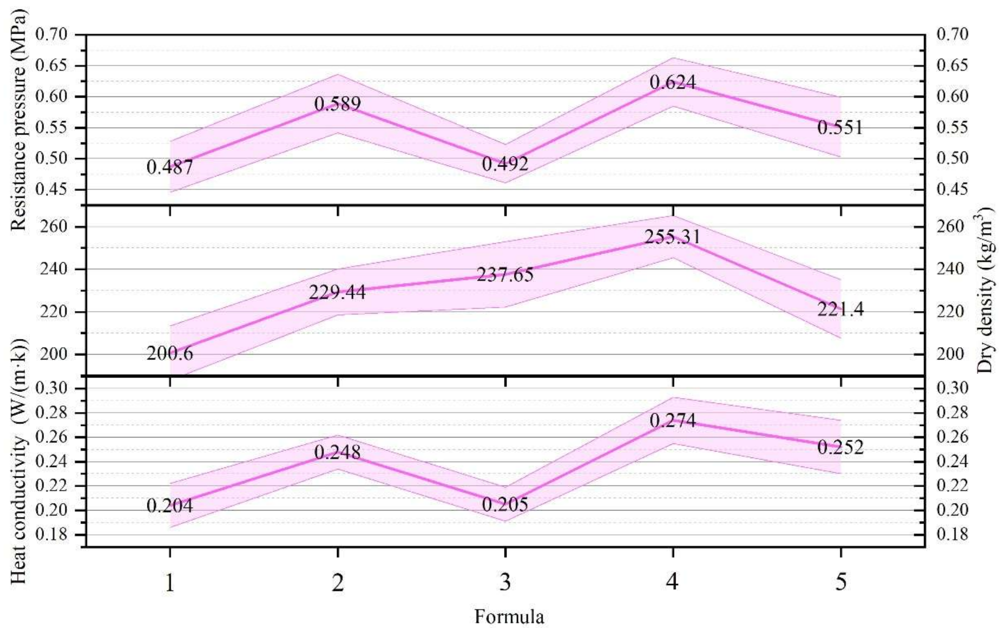

Fig. 4. Physical properties of different concrete samples

4.4.3. Durability assessment. This section of the experiment focuses on durability testing of concrete configured with five different raw material ratios using the PSO-LSSVN model above. The test indexes include frost resistance and permeability.

The frost resistance of concrete refers to its ability to resist damage during freeze-thaw cycles. The frost resistance of concrete is particularly important in cold or temperature changing environments, as it directly affects the durability and service life of concrete structures. And concrete permeability refers to its ability to resist liquid penetration, which is an important indicator for evaluating the durability of concrete. Poor permeability of concrete can increase the intrusion of moisture, chemical solvents and other harmful substances, increase the destructive effects of freezing and thawing, corrosion and reinforcement corrosion, and reduce the service life of concrete structures.

The experiments were carried out according to the experimental study of the fast freezing method in the Standard for Long-term Properties and Durability Test Methods for Ordinary Concrete (GB/T 50082-2009), and the change rule of the mass loss rate of concrete with the freeze-thaw cycle is shown in Figure 5. In the concrete freeze-thaw cycle, the mass loss rate of the specimen decreases to less than 5%, and the concrete is regarded as frozen. Analyzing the data in the figure, it can be seen that after 400 freeze-thaw cycles of the five concrete samples designed by the model in this paper, the mass loss rate of concrete under each proportion is within 5%, which meets the requirements specified in the Standard for Long-term Performance and Durability Test Methods for Ordinary Concrete. Among them, the concrete samples under proportion 4 have a lower mass loss rate than the rest of the proportion, which is only 3.52% after 400 freezing cycles, which is lower than the rest of the proportion by 10.78% to 14.72%.

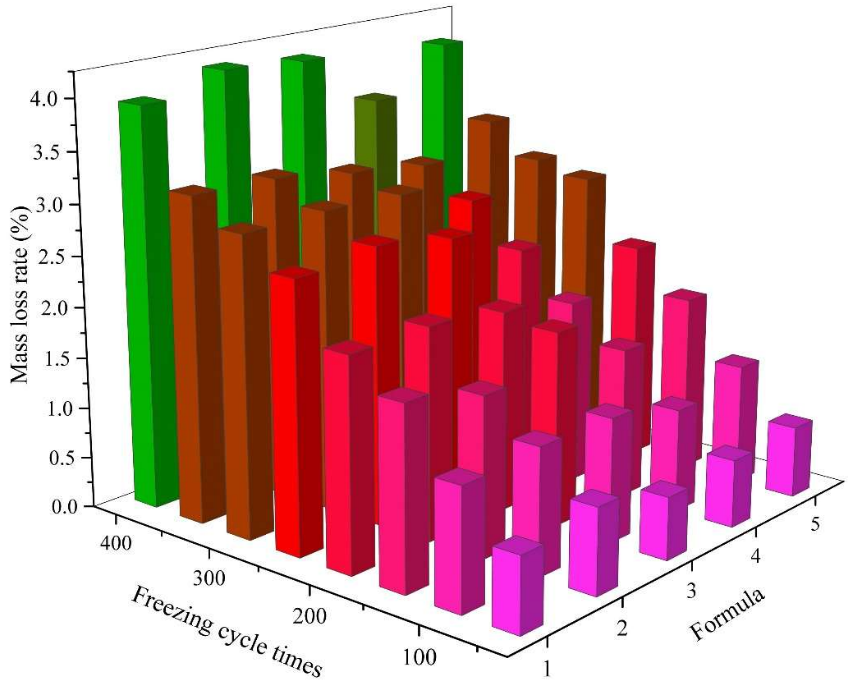

Fig. 5. The quality loss rate varies with the freeze and thaw cycle

In addition, according to the ASTM C1202 standard, the resistance of concrete to chloride permeation can be graded according to the magnitude of the electrical flux, with smaller fluxes indicating better resistance to chloride permeation. The chloride ion flux method was used to characterize the permeability of the concrete samples.

The results obtained for the permeability of the five types of concrete are shown in Fig. 6. From the figure, it can be seen that the ratio 4 concrete electric flux has low chloride ion permeability from 28d (277.25C), and the 56d concrete electric flux further decreases (156.44C). The remaining four samples designed by the optimized model have higher fluxes than ration 4, but they are all below 500C and exhibit very low chloride permeability. This indicates that the concrete samples designed by the model in this paper have better impermeability, with Ratio 4 being the most effective.

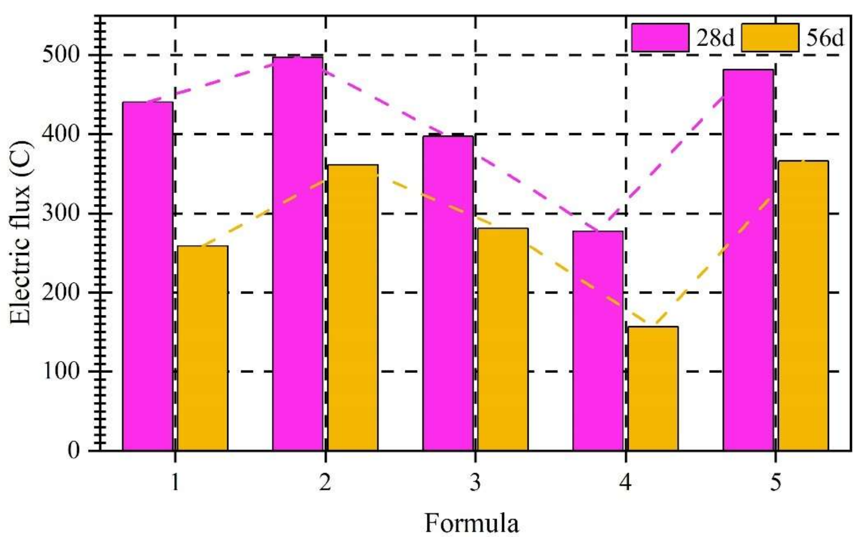

Fig. 6. The anti-permeability results of five concrete are obtained

4.4.4. Proportioning compliance and costs. In this section, the model of this paper (PSO-LSSVN) and NSGA-II are applied to stochastically solve the feedstock ratios five times to obtain the Pareto optimal solution set. The five sets of final ratios obtained by the two algorithms are used to calculate the predicted values of feedstock oxide content, and then the values of each comparison parameter are obtained and compared with the actual manual ratios.

Comparative data for each batching parameter value is shown in Fig. 7, where the shaded portion of the figure in the corresponding color is the passing range in each batching. Figure 8 shows the concrete proportioning cost of the three methods. For the final proportioning results, the five times of raw material proportioning results obtained by this paper's algorithm can be better controlled within the qualified range, while the NSGA-II algorithm has different degrees of increase or decrease in the qualified range of each raw material proportioning compared with the manual proportioning. For the cost of raw materials, compared with the NSGA-II solved ratios and manual ratios, the final ratios obtained by using the algorithm in this paper can better reduce the cost of raw material ratios, with a reduction of between 5.99% and 28.61%.

Overall, compared with the NSGA-II algorithm and manual ratio adjustment, the results obtained by the algorithm in this paper ensure that all the control indexes of the raw materials are within the target range, and at the same time, the ratio cost can be controlled within a reasonable range. Therefore, the ratio adjustment scheme in this paper ensures the quality of raw materials, reduces the ratio cost and meets the actual production needs.

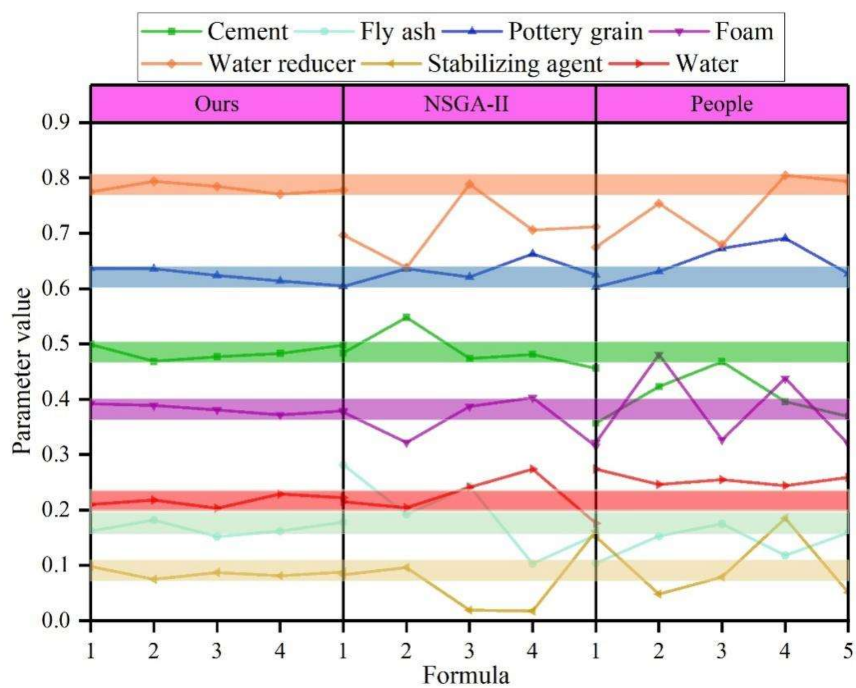

Fig. 7. The parameters of the ingredients are compared to the data

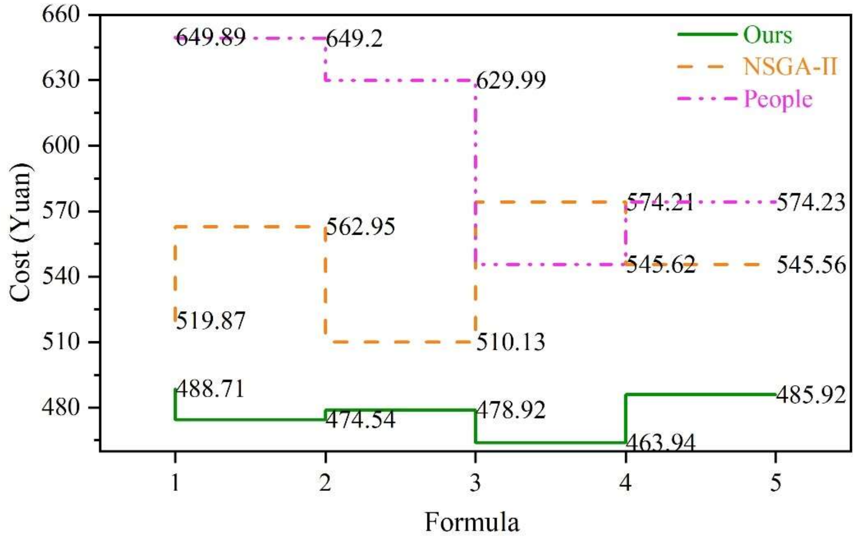

Fig. 8. The cost of the concrete ratio of the three methods

5. Conclusion

In this paper, a PSO-LSSVN concrete proportioning optimization model is constructed by integrating the particle swarm algorithm with the least squares support vector regression algorithm according to the principle and basic process of the particle swarm algorithm. The model integrates the features of high efficiency and accurate prediction of the optimization problems of the two algorithms. Combined with a number of experiments, the concrete designed by the optimization model is tested for its compressive strength, thermal conductivity, dry density, and durability, so as to achieve the optimization of low-cost and high-strength concrete ratios.

1) The absolute errors of the PSO-LSSVN model predictions of dry density and thermal conductivity ranged from 0.08 to 2.33 kg/m^3 and 0.001 to 0.022 W/(m·k), respectively.

2) The compressive strengths, dry densities, and thermal conductivities of the five concrete samples generated by the model were distributed in the ranges of 0.487 to 0.624 MPa, 200.6 to 255.31 kg/m, and 0.204 to 0.274 W/(m·k), respectively.

3) Meanwhile, the five samples have better durability performance and are 5.99% to 28.61% lower in raw material cost than NSGA-II solved proportioning and manual proportioning methods.

4) In all of the above performance test experiments, the proportion 4 concrete samples showed the best performance with the lowest required cost and the highest application potential.

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