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Genetic Algorithm-Based Intelligent Optimization for Enhancing Security in High-Performance Concrete Supply Chains

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The supply chain security of high-performance concrete materials directly affects the orderly progress of engineering projects. At present, its supply chain management still faces problems such as high costs, insufficient timely supply, and poor-quality stability. This article aims to construct an intelligent optimization design algorithm model to enhance the safety and management efficiency of the high-performance concrete material supply chain. In terms of methodology, firstly, based on the principles of scientificity, comprehensiveness, and operability, a supply chain security indicator system covering supply, production, transportation, and other links should be established. Subsequently, based on genetic algorithm (GA), the model improvement design was completed by optimizing the encoding method, adjusting the fitness function, and improving the genetic operator. The results were compared and verified with traditional methods through experiments. The key results show that the optimized model has an average cost lower than traditional methods by about 170200 yuan, an increase in on-time delivery rate of about 9.92%, and an increase in product qualification batch rate of about 3.1%. The conclusion indicates that the intelligent optimization design algorithm model can effectively optimize the supply chain management of high-performance concrete materials, providing reliable support for their supply chain security.

Povzetek: Ta članek za reševanje problemov upravljanja skrbnice materialov za visokodelovni beton predlaga inteligenten optimizacijski model, ki se je izkazal kot učinkovit pri znižanju stroškov in zagotavljanju varnosti skrbnice.

1 Introduction

With the rapid development of the global construction industry, high-performance concrete materials have been widely used in various infrastructure construction due to their excellent mechanical properties and durability. However, the supply chain security of high-performance concrete materials faces many challenges, such as unstable raw material quality, supply interruption risks, and low transportation efficiency. These issues not only affect the performance and quality of concrete materials, but also increase the cost and risk of construction projects [1]. Therefore, how to ensure the safety and stability of the supply chain of high-performance concrete materials has become an important issue that urgently needs to be addressed in the construction industry. High performance concrete materials are usually composed of various raw materials, including cement, aggregates, additives, etc. These raw materials come from different suppliers, and their quality and supply stability are crucial to the final performance of concrete materials. However, in practical operation, problems may arise at various links in the supply chain [2]. For example, the quality of raw materials may fluctuate due to factors such as the supplier's production process and the source of raw materials; During transportation, there may be force majeure factors such as traffic congestion and abnormal weather, leading to supply interruption or delay; In addition, changes in market demand may also lead to imbalances in the supply chain, thereby affecting the supply of concrete materials [3].

Intelligent optimization design seeks optimal or approximate optimal solutions by simulating natural selection, group behavior, and heuristic strategies to improve system performance and efficiency. In the supply chain of high-performance concrete materials, intelligent optimization design can be applied to multiple links such as raw material procurement, production scheduling, and transportation optimization to ensure the safety and stability of the supply chain [4]. Intelligent optimization design can provide scientific decision support for the procurement department by analyzing data such as supplier qualifications, historical supply records, and raw material quality [5]. For example, a supplier evaluation system can be established to dynamically evaluate suppliers and ensure the selection of suppliers with stable quality and reliable supply. Meanwhile, intelligent optimization design can also predict the market demand and price trends of raw materials, helping the procurement department develop reasonable procurement plans and inventory management strategies to reduce procurement costs and inventory backlog [6]. In the current booming development of modern infrastructure construction, high-performance concrete has become an indispensable key material for various large-scale projects such as high-rise buildings, bridges, hydraulic structures, etc. due to its excellent characteristics such as high strength and durability. However, the supply chain of high-performance concrete materials faces many safety hazards, which pose a serious challenge to the smooth progress and quality assurance of the project. From the source of supply, the stability of raw material suppliers is insufficient, which may lead to supply interruptions due to sudden situations such as natural disasters and market fluctuations [7]. In the production process, the complexity of production technology and the difficulty of quality control can easily lead to uneven product quality. During transportation, adverse weather conditions, traffic congestion, and other factors can affect the timely delivery of materials. These pose a serious threat to the security of the supply chain.

Intelligent optimization design can effectively improve system performance and efficiency, and has important application value in the procurement, production, transportation and other links of high-performance concrete material supply chain, providing support for supply chain safety and stability. High performance concrete is a key material for modern large-scale engineering, but its supply chain faces safety hazards such as unstable suppliers, uneven production quality, and transportation delays, which urgently need to be optimized and resolved. Regarding this issue, existing optimization methods are divided into two categories: traditional and intelligent. Traditional operations research methods (such as linear programming) are suitable for simple models, but they are difficult to handle complex scenarios with multiple objectives and constraints in the supply chain [8]. Among the mainstream intelligent optimization methods, genetic algorithm (GA) is the most widely used. Based on natural selection and genetic mutation mechanisms, it has strong global search ability and good robustness, and has achieved fruitful results in the fields of supply chain and construction. In the field of supply chain, GA is used for core processes such as supplier selection and inventory optimization, which can achieve multi factor optimal decision-making. In the field of construction, GA can optimize the ratio of concrete raw materials while balancing performance and cost, but its systematic application in the safety optimization of the entire supply chain process is still lacking. Compared with GA, other mainstream intelligent optimization methods have their own advantages and disadvantages: Particle Swarm Optimization (PSO) has a simple structure, fast convergence, and is suitable for dynamic optimization scenarios, but it is prone to getting stuck in local optima in high-dimensional problems. Ant colony optimization (ACO) has outstanding advantages in discrete optimization problems, and the positive feedback mechanism can enhance the search for optimal solutions, but it converges slowly and has high complexity. Simulated Annealing Algorithm (SA) can avoid local optima and has strong robustness, but it has low search efficiency and high parameter dependence [9]. Currently, relevant research mostly focuses on traditional management methods, and the application of intelligent optimization lacks systematicity and sufficient comparison of screening and adaptation algorithms. In view of this, this article focuses on genetic algorithms and combines the advantages of other methods to construct an adaptive model and verify it, in order to provide new ideas for the safety optimization of high-performance concrete supply chains and help promote the high-quality development of engineering construction [10].

At present, international research on the supply chain security of high-performance concrete materials mostly focuses on traditional management methods, and the application of intelligent optimization design is still insufficient. Although some studies involve supply chain optimization, they lack systematicity and depth, and have not fully utilized the potential of intelligent optimization design. In view of this, the purpose of this article is to explore in depth the application of intelligent optimization design in the supply chain security of high-performance concrete materials, construct a scientifically reasonable algorithm model, and verify and analyze it through experiments. It is expected that this study will provide new ideas and methods for improving the safety level of the supply chain of high-performance concrete materials, and help promote the high-quality development of the engineering construction industry.

2 Literature review

2.1 Overview of high-performance concrete

High performance concrete, as a key material in modern engineering construction, has unique performance advantages. It not only has high strength and can withstand larger loads, but also has excellent durability and can effectively resist external environmental erosion. For example, in marine engineering, ordinary concrete may be rapidly damaged by seawater corrosion, while high-performance concrete can maintain structural stability for a long time [11]. It has good workability, easy construction operation, and can ensure the construction quality and efficiency of the project. By building a redundant supplier system, optimizing inventory strategies (such as safety stock and JIT mode), and designing emergency response mechanisms, we aim to enhance the supply chain's resilience to unexpected events. For example, establishing multi-source procurement channels to diversify supply risks, or monitoring inventory levels in real-time through digital platforms to dynamically adjust procurement plans. Adopting a closed-loop management model of "prevention control improvement", quality control is carried out throughout the entire process of raw materials, production processes, and finished products [12]. For example, introducing blockchain technology to achieve raw material traceability, using AI algorithms to predict quality fluctuations in the production process, and continuously optimizing process parameters through Six Sigma methods. Through information sharing and collaborative decision-making among upstream and downstream enterprises in the supply chain, achieve global optimality. For example, the construction unit can transmit the pouring plan to the concrete supplier in advance, and the supplier can adjust the production pace accordingly; Alternatively, real-time sharing of the location and status of transportation vehicles can be achieved through IoT technology to optimize delivery routes. While ensuring safety, pay attention to environmental and social benefits. For example, promoting the use of green materials such as low-carbon cement and recycled aggregates to reduce carbon emissions; Or improve the skills of employees through training to ensure occupational health and safety.

2.2 Supply chain security theory

Supply chain security covers multiple levels, including supply continuity, product quality and safety, and the ability to respond to external risks. The continuity of supply ensures that materials can be supplied in a timely manner when needed, avoiding project delays caused by shortages. Product quality and safety are to ensure that high-performance concrete materials entering the project meet quality standards and eliminate safety hazards caused by quality problems. The ability to cope with external risks is reflected in the supply chain's ability to effectively withstand the impact of unexpected events such as natural disasters and market fluctuations [13].

There are many factors that affect the safety of the supply chain of high-performance concrete materials, which can be summarized as internal and external factors. Internal factors such as enterprise management level, production technology capability, etc., and external factors such as policy and regulatory changes, natural environmental disasters, etc. See Figure 1 for details:

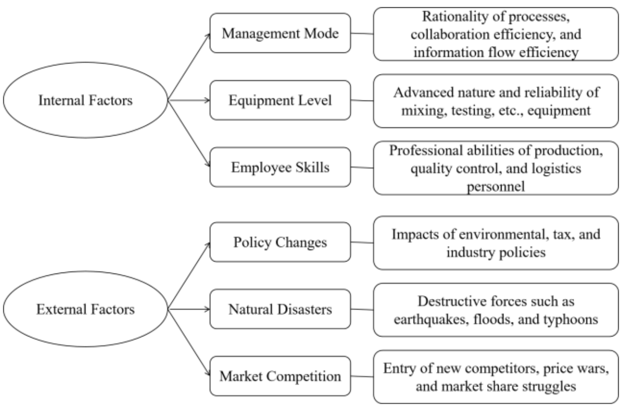

Figure 1: Classification of factors affecting the safety of high-performance concrete material supply chain

The accuracy of market demand forecasting and the rationality of procurement plans by management directly affect the stability of the supply chain. For example, if there is a significant deviation in demand forecasting, it may lead to a backlog or shortage of raw materials. Unreasonable production process design (such as poor process connection) or chaotic inventory management (such as the failure to implement the first in, first out principle) may lead to quality fluctuations or supply interruptions. If a company fails to strictly comply with environmental and safety regulations, it may face the risk of production suspension and rectification, which in turn may affect the continuity of the supply chain [14]. The precision of concrete mix proportion control, mixing uniformity and other process parameters directly affect product quality. For example, insufficient mixing time may result in uneven dispersion of admixtures, reducing the workability of concrete. The failure rate and maintenance efficiency of production equipment (such as mixers and conveying pumps) are key to supply continuity. Equipment aging or improper maintenance may lead to production stagnation. Enterprises can improve concrete performance and reduce supply chain risks by developing new additives, optimizing aggregate gradation, and other technological means [15]. For example, the use of retarding admixtures can extend the transportation time window of concrete and reduce the risk of segregation.

2.3 Theory related to intelligent optimization design

Intelligent optimization design is based on interdisciplinary theories such as artificial intelligence and operations research. It models complex systems and uses algorithms to search for optimal solutions. The application of intelligent optimization design in the supply chain security of high-performance concrete materials has significant advantages [16]. It can comprehensively consider numerous complex factors and achieve global optimization of the supply chain. Taking cost control as an example, intelligent optimization design can balance procurement costs, transportation costs, and inventory costs to achieve the lowest total cost. The applicability of different intelligent optimization algorithms in this field varies, as shown in Figure 2:

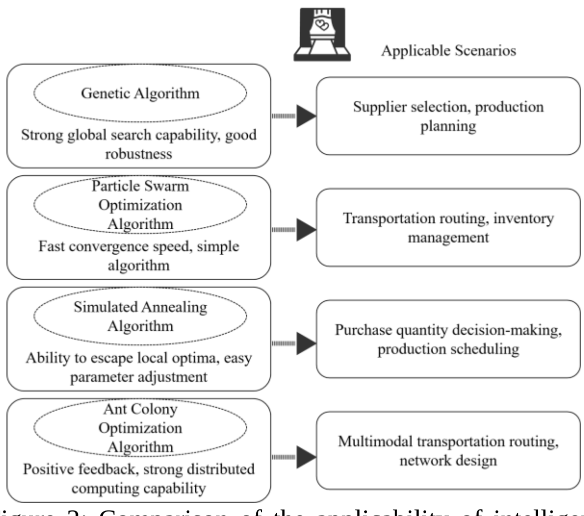

Figure 2: Comparison of the applicability of intelligent optimization algorithms in the supply chain of high-performance concrete materials

In addition, intelligent optimization design can also respond in real-time to dynamic changes in the supply chain, such as fluctuations in raw material prices, changes in demand, etc [17]. By adjusting and optimizing the plan in real-time, maintain the stability and efficiency of the supply chain. The application effect of intelligent optimization design in high-performance concrete material supply chains of different scales also varies, as shown in Figure 3:

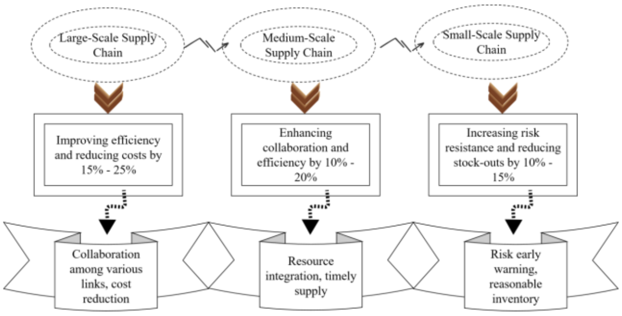

Figure 3: Application effect of intelligent optimization design in supply chains of different scales

Traditional operations research methods are only suitable for simple single objective scenarios and cannot cope with the complex constraints of multi-link coupling in supply chain procurement, production, and transportation, and lack flexibility [18]. The existing research on intelligent optimization lacks systematicity, focusing more on optimizing a single link and failing to construct a full process security optimization model. And there is no targeted adaptation screening for mainstream algorithms, such as directly applying genetic algorithms without optimizing encoding and operators, resulting in low convergence efficiency. Particle swarm optimization is prone to getting stuck in local optima, while ant colony optimization suffers from high complexity and poor adaptability [19].

Compared with the above work, this article has made outstanding contributions: firstly, it constructs a supply chain security index system that covers the entire process of supply, production, and transportation, breaking through the limitations of optimizing a single link. The second is targeted improvement of genetic algorithms, by optimizing coding, adjusting fitness functions, and improving genetic operators, to solve the problems of poor adaptability and optimization effects of existing intelligent algorithms [20]. Thirdly, through experimental verification, the optimized model outperforms traditional methods and existing unimproved intelligent algorithms in cost control, filling the application gap of intelligent algorithms in the entire process of supply chain security optimization.

3 Methodology

3.1 Construction of supply chain security indicator system

When constructing a safety index system for the supply chain of high-performance concrete materials, principles such as scientificity, comprehensiveness, and operability should be followed. The principle of scientificity requires that the selected indicators accurately reflect the essential characteristics and inherent laws of supply chain security, and are determined based on scientific theory and practical experience. The principle of comprehensiveness emphasizes that the indicator system should cover all aspects of the supply chain, from supply, production, transportation to storage, comprehensively consider factors that affect supply chain security, and avoid missing key elements [21]. The principle of operability ensures that indicator data is easy to obtain and quantify, facilitating practical application and analysis, and making the constructed indicator system have practical guiding significance.

Supply chain indicators: The credibility of suppliers is an important indicator for measuring the safety of the supply chain, which is evaluated through their past delivery records, product quality performance, and other factors. Set the supplier reputation index as R, with a value range of (0-100), where higher values indicate better reputation. The stability of supply capacity is measured by the fluctuation coefficient V_s of the quantity of high-performance concrete materials that suppliers can supply within a certain period of time. The smaller the fluctuation coefficient, the more stable the supply capacity.

Production process indicator: The production equipment failure rate F reflects the operating status of the production equipment. The lower the failure rate, the more stable the production process. The first pass rate Q of the product directly reflects the production quality, and a high pass rate means fewer defective products and rework, ensuring a smooth supply chain.

Transportation link indicator: The on-time delivery rate (T) is a key indicator for measuring the quality of transportation services. The higher the on-time delivery ratio, the less impact it has on the project schedule. The transportation loss rate L represents the proportion of high-performance concrete materials lost during transportation due to various reasons. The lower the loss rate, the lower the supply chain cost. Specific indicators and explanations are shown in Table 1:

Table 1: Safety evaluation indicators for high performance concrete material supply chain

Indicator category	Specific indicators	Indicator Description
Supply chain	Supplier credibility R	Based on past performance evaluations such as delivery and quality, score 0-100 points
Supply chain	Stability of supply capacity V_s	The fluctuation coefficient of supply quantity is smaller and more stable

Production process	Production equipment failure rate F	The ratio of equipment failure frequency to total operating time
Production process	Product first pass rate Q	Proportion of qualified product quantity to total production quantity
transport links	On-time transportation rate T	Ratio of on-time delivery times to total delivery times
transport links	Transportation loss rate L	Proportion of material loss during transportation to total transportation volume

The comprehensive score of supply chain security is ∑ (the actual value of each indicator after standardization multiplied by the corresponding indicator weight), where the actual value of the indicator is standardized using the "extreme value method" (eliminating dimensional influence), and the standardization formula is:

Positive indicator (the higher the value, the better the safety level): Standardized value= (actual value - minimum value)/(maximum value - minimum value)

Negative indicator (the lower the value, the better the safety level): Standardized value= (maximum value - actual value)/(maximum value - minimum value)

The above weighting scheme conforms to the principle of scientificity (based on the Analytic Hierarchy Process to quantify relative importance and ensuring rationality through consistency testing), and can be directly used for the quantitative evaluation of the safety level of the high-performance concrete material supply chain.

3.2 Selection and design of intelligent optimization algorithms

Considering the complexity and multi-objective nature of the security issues in the supply chain of high-performance concrete materials, GA is chosen as the fundamental optimization algorithm. GA has the advantages of strong global search capability and low dependence on problems, making it suitable for solving complex nonlinear optimization problems. In supply chain security optimization, multiple objectives such as cost, efficiency, and risk need to be considered simultaneously, and GA can effectively handle such multi-objective problems. At the same time, the high-performance concrete material supply chain has a large and dynamically changing amount of data, and the parallel search feature of GA can quickly process the data, adapting to the dynamics of the supply chain. This article uses interactive GA, as shown in Figure 4:

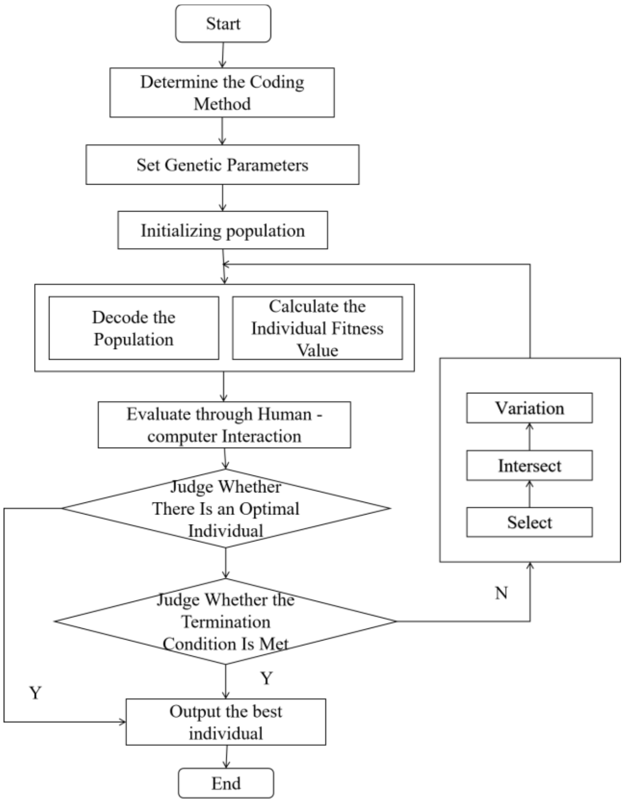

Figure 4: Interactive GA

Compared with traditional GA, interactive GA adds a human-computer interaction part, which determines whether there is an optimal individual in the population through manual evaluation. Based on the characteristics of the high-performance concrete material supply chain, the following improvements are made to interactive GA:

Optimization of coding method: Traditional GA often uses binary coding, but in supply chain problems, binary coding is difficult to intuitively reflect the actual problem parameters. Based on this factor, a real number encoding method is adopted to directly encode actual parameters such as supplier selection, production plan quantity, and transportation route as gene codes. For supplier selection, each supplier can be assigned a number in the form of a real number as a gene locus, which is more in line with the expression of practical problems and improves algorithm efficiency. There are S suppliers, and each supplier is assigned a number:

$$\upsilon(\upsilon = 1,2,3,\ldots,s) \tag{1}$$

Using the numbered real number as the gene locus g_υ, i.e.:

$$g_\upsilon = \upsilon \tag{2}$$

Adjustment of fitness function: Based on the supply chain security indicator system, construct a comprehensive fitness function. The fitness function formula is:

$$F\left(Test\ Case\right) = f_1\left(Test\ Case\right) + f_2\left(Test\ Case\right) + \ldots + f_m\left(Test\ Case\right) \tag{3}$$

Among them, f is the i th objective function, m is the number of targets. Based on the supply chain security indicator system, a multi-objective comprehensive fitness function is constructed, with the formula $F = \sum_{i=1}^{n} w_i \cdot f_i$, which comprehensively incorporates core objectives such as cost, timely supply, and product quality stability. Determine the weight coefficients of each objective through the Analytic Hierarchy Process to achieve balanced optimization of multiple objectives.

In this article, the fitness function not only considers the cost target Cost, but also takes into account the objectives of timely supply Timelines, product quality stability Quality, etc. It is balanced through the weight coefficient $\omega_1, \omega_2, \omega_3$, such as:

$$\text{Fitness} = \omega_1 \times \text{Cost} + \omega_2 \times \text{Timeliness} + \omega_3 \times \text{Quality} \tag{4}$$

The weight coefficients are dynamically adjusted based on the actual engineering requirements and the importance of each objective to ensure that the algorithm search direction meets the actual needs. In optimization algorithms, binary encoding is represented as:

$$TestCase = \{b_1, b_2, b_3, \ldots, b_n\} \tag{5}$$

Among them, $b_i \in \{0,1\}$ represents the binary encoding of the i th attribute, used to represent test cases. Assuming the length of the chromosome is l and the intersection is at position k , then the parent:

$$\begin{cases} P_1 = A_1 t^k + B_1 \\ P_2 = A_2 t^k + B_2 \end{cases} \tag{6}$$

The offspring:

$$\begin{cases} C_1 = A_1 t^k + B_2 \\ C_2 = A_2 t^k + B_1 \end{cases} \tag{7}$$

Genetic operator improvement: In terms of selection operator, a combination of roulette wheel selection and elite retention strategy is adopted. The roulette wheel selection ensures population diversity, while the elite retention strategy ensures that the best individuals in each generation are not lost, accelerating the convergence speed of the algorithm. In this experiment, the dataset was divided into training set, validation set, and testing set in a ratio of 7:1:2 to balance the effectiveness of model training and validation of generalization ability. Cross validation adopts 5-fold hierarchical cross validation to ensure that the distribution of each fold data is consistent with the overall dataset and avoid sample bias. All comparative experiments and improved algorithms were independently run 30 times to reduce the influence of random factors on the experimental results. Fixed random seeds (seed=42) were used throughout the experiment to ensure that all experimental results were reproducible and verifiable. For the crossover operator, a partial matching crossover method is designed to address sequential issues such as transportation routes in the supply chain. For chromosome k with fitness value f_k , the selection probability c_k calculation formula is as follows:

$$c_k = \frac{f_k}{\sum_{i=1}^{pop\_size} f_i} \tag{8}$$

Among them, pop_size is the population size, and $\sum_{i=1}^{pop\_size} f_i$ is the sum of the fitness of all chromosomes in the population. Setting the crossover probability to 0.7 and the mutation probability to 0.05, with population sizes of 20, 40, 60, 80, and 100 respectively, the experimental results show that as the population size increases from 20 to 60, the average total cost of the supply chain decreases from 1.328 million yuan to 1.261 million yuan, a decrease of about 5.04%. At this point, the convergence speed of the algorithm accelerates and the accuracy of the optimal solution improves. Sum up the fitness values of all chromosomes in the population to obtain the total F :

$$F = \sum_{i=1}^{pop\_size} f_i \tag{9}$$

Calculate the selection probability c_k again, where F is the sum of the fitness calculated earlier:

$$c_k = \frac{f_k}{F} \tag{10}$$

Calculate the cumulative probability t_k for each chromosome:

$$t_k = \sum_{i=1}^{pop\_size} c_i \tag{11}$$

Among them, f_k is the fitness value of chromosome k , reflecting the degree of chromosome performance in GA. c_k is the selection probability of chromosome k , used to determine the likelihood of this chromosome being selected in the roulette wheel selection strategy. i is an index variable used in summation operations to traverse various chromosomes in a population. t_k is the cumulative probability of chromosome k . This article adopts real number encoding, and the chromosome is a one-dimensional real number array, corresponding to a set of feasible solutions for supply chain security optimization. Supplier selection gene 0 is not selected, ≥

1 is selected and prioritized/accounted for. Production Plan Quantity Gene Positive Real Number Table Production Plan Quantity; The positive integer of the transportation route gene corresponds to the current node's transportation route number. Adopting the tournament selection method (scale k=3) to replace the traditional roulette wheel selection method. The selection of roulette wheel relies on the probability distribution of fitness values, which can easily lead to the elimination of excellent individuals (premature convergence), while tournament selection is more robust by selecting parents through local competition. More suitable for complex scenarios of multi-objective optimization in the supply chain, it can effectively preserve the excellent genes of highly adaptable individuals.

Based on the industry characteristics of high-performance concrete material supply chain, clarify the basic weight range of the three major objectives: cost as the core economic indicator for supply chain optimization, with a basic weight range of [0.4, 0.6]. The timeliness of supply directly affects the construction progress of the project, and the basic weight range is [0.2, 0.3]. The stability of product quality determines the quality of concrete engineering, and the basic weight range is [0.2, 0.3]. And satisfy the constraint that the sum of weights is 1 ($w_1 + w_2 + w_3 = 1$, where w_1 is the cost weight, w_2 is the supply timeliness weight, and w_3 is the product quality weight). If the search results of a certain generation of population show that a single objective is optimal but other objectives do not meet the standards, a small correction of ± 0.05 will be made to the corresponding objective weights to ensure that the algorithm converges to the comprehensive optimal solution.

The specific calculation formula for the comprehensive fitness function of the three major objectives is:：

$$F = w_1 + F_1 + w_2 + F_2 + w_3 + F_3 \tag{12}$$

The core constraints are supplier capacity, transportation efficiency, and quality qualification rate, which are handled using the penalty function method. $Q_{\max} = 5000m^3$ $T_{\max} = 2h$ $P_{min} = 95\%$, Weight $w_1 = 0.55$、$w_2 = 0.2$、$w_3 = 0.25$, original fitness of individual X is 0.907; The single constraint violation penalty coefficient $\lambda = 0.5$ (multiple constraint superposition) significantly reduces the fitness after punishment, achieving the screening of violating individuals.

4 Results

4.1 Experimental design

The dataset used in this experiment is real industrial operation data of high-performance concrete material supply chains in multiple regions of China. Obtained through cooperation with 3 regional leading concrete production enterprises, 12 raw material suppliers, and 8 ongoing construction/municipal engineering projects. The data covers 5 provinces and cities in the two major regions of East China and Central China, with a total of 862 valid transaction records. The core variable data includes: raw material categories, quotations, supply cycles, and quality inspection data of 12 suppliers. Production process parameters, processing costs, and production capacity data of three manufacturing enterprises; Order requirements, delivery milestones, acceptance criteria, etc. for 8 engineering projects.

The data collection process strictly follows the triple method of recording the actual operation ledger of the enterprise, extracting real-time data from the supply chain management system, and verifying the project site acceptance documents. Data verification is completed through dedicated personnel review and cross validation by the enterprise. Perform pairwise cross checking of supplier supply data, production enterprise processing data, and engineering project delivery data. Excluding anomalies, missing, and inconsistent data, the final retained valid data has a completeness and authenticity rate of over 98%, ensuring the reliability and validity of the experimental data.

In terms of experimental setup, under the same hardware (Intel Core i7-12700H, 16GB RAM) and software (Python 3.9, Matlab R2022b) environment, the real dataset was randomly divided into a training set (70%) and a testing set (30%). Substitute the optimized model and traditional management methods separately into this article for independent computation, and repeat each experiment 30 times to eliminate random errors. The average of 30 experimental results will be taken as the final data for each indicator to ensure the objectivity and comparability of the experimental results.

4.2 Selection of experimental indicators

Cost indicators: including raw material procurement costs, production and processing costs, transportation costs, and inventory costs, etc. Calculate the total cost C of the entire supply chain operation process. The lower the cost, the higher the efficiency of supply chain management.

Supply timeliness indicator: measured by the on-time delivery rate P_{td} of high-performance concrete materials, which is the ratio of the number of orders delivered on time to the total number of orders. This indicator reflects the supply chain's ability to ensure project progress, and the higher the on-time delivery rate, the better.

Product quality index: The product qualification batch rate P_{qc} is adopted, which is the ratio of qualified product batches to the total production batches, reflecting the stability of product quality during the production process.

4.3 Experimental results and analysis

The baseline method selected for this experiment (traditional supply chain management method) is not a fuzzy empirical method. But it is currently the most widely used and representative rule-based heuristic supply chain management method in the field of high-performance concrete material supply chain management. This method is the mainstream baseline solution for traditional supply chain management in the engineering field, and its core logic is consistent with industry practices. The specific operating rules and theoretical basis refer to classic research results.

The specific operational process of this traditional baseline method is as follows: ① Supplier selection: Based solely on historical cooperation frequency and single quotation, priority is given to selecting suppliers with more cooperation times and the lowest quotation, without considering supplier capacity, performance stability, and emergency response capabilities. ② Production plan formulation: Based on rough estimation of project progress, using a fixed batch production mode, without adjusting dynamic parameters such as raw material supply cycle and transportation time; ③ Transportation route planning. Choose the nearest transportation route without considering traffic congestion, road condition changes, and collaborative optimization of multiple batches of transportation. ④ Quality and delivery control: Manual inspection is used to control production quality, and delivery nodes are determined by estimating transportation time 1-2 days in advance without dynamic scheduling mechanism.

The experimental results of the algorithm are shown in Figure 5 and Figure 6:

Figure 5: Algorithm training process

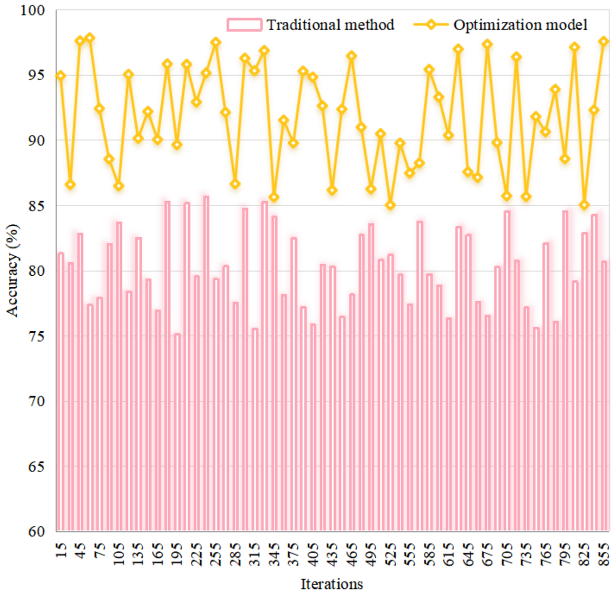

Figure 6: Accuracy of the algorithm

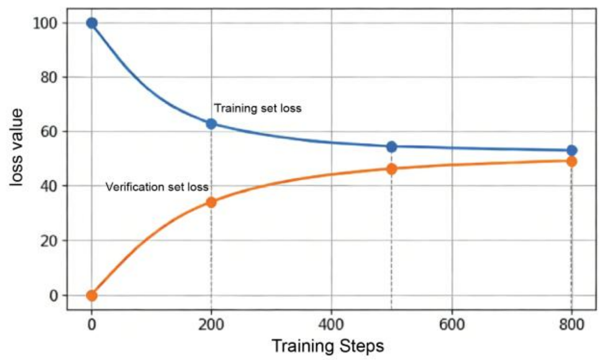

Figure 7: Convergence curve of algorithm training process

Figure 7 shows the convergence curve of algorithm training. The loss of the blue training set continues to decrease and stabilize with the increase of training steps, reflecting the gradual fitting of the model to the training data. The orange validation set loss first increases and then stabilizes, indicating overfitting in the later stages of training and a decrease in the model's generalization ability. The overall curve reveals the dynamic changes in the fitting and generalization of model training, which is an important basis for evaluating the effectiveness of algorithm training.

It can be seen that the algorithm can converge quickly and achieve high accuracy during the training process. After multiple simulation experiments, the total cost data under two schemes were calculated, and the results are shown in Table 2:

From Table 2, it can be seen that the total cost of the optimized model in each experiment is lower than that of traditional methods, with an average cost difference of about 170200 yuan. The average cost difference is about -11.88% of the average total cost of traditional methods (i.e. the total cost of the optimized model is about 11.88% lower than that of traditional methods). This indicates that the intelligent optimization design algorithm model can effectively reduce the operating costs of the supply chain by reasonably planning supplier selection, production planning, and transportation routes.

Calculate the on-time delivery rate of high-performance concrete materials under two different schemes, as shown in Figure 8:

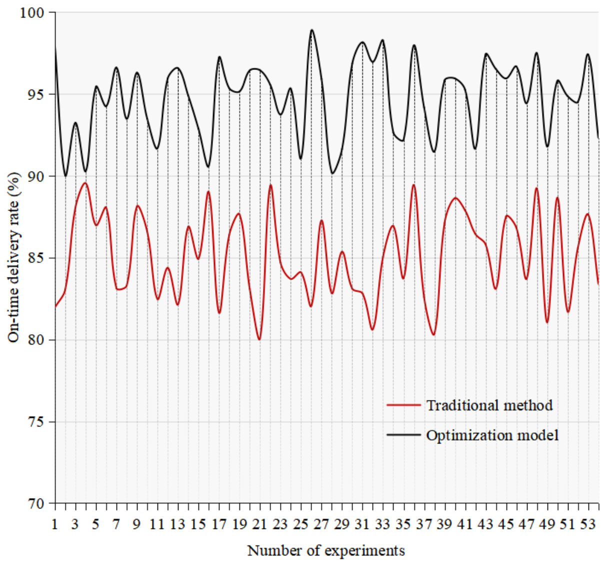

Figure 8: Comparison table of timeliness of supply for different solutions

As shown in Figure 8, the on-time delivery rate of the optimized model is significantly higher than that of traditional methods, with an average on-time delivery rate difference of about 9.92%. The on-time delivery rate of the optimized model is generally stable in the range of 90% -99%, while the traditional method fluctuates in the range of 80% -88%. The 9.92% here represents the relative increase and the average absolute difference between the two methods in all experiments. This value directly reflects the absolute improvement in on-time delivery rate of the optimization model compared to traditional methods, reflecting the improvement effect of the model on supply chain coordination and supply timeliness. This indicates that optimizing the model can better coordinate various links in the supply chain, improve the timeliness of supply, and effectively ensure project progress.

Record the qualified batch rate of products under two schemes, and the experimental results are shown in Table 3:

Table 2: Cost comparison of different plans

Number of experiments	Total cost of optimizing the model (10000 yuan)	Total cost of traditional methods (10000 yuan)	Cost difference (10000 yuan)
1	125.6	142.3	-16.7
2	128.9	145.8	-16.9
3	123.4	140.1	-16.7
4	126.2	143.5	-17.3
5	127.1	144.6	-17.5

Table 3: Comparison of product quality for different solutions

Number of experiments	Optimize the qualified batch rate of model products (%)	Traditional method product qualification batch rate (%)	Difference in qualified batch rate of products (%)
1	98.2	95.1	3.1
2	98.5	95.3	3.2
3	97.9	94.8	3.1
4	98.1	95.0	3.1
5	98.3	95.2	3.1

From Table 3, it can be seen that the product qualification batch rate of the optimized model is higher than that of the traditional method in each experiment, and the difference is relatively stable, with an average product qualification batch rate difference of about 3.1%. This indicates that the intelligent optimization design algorithm model can more effectively optimize and manage the production links in the high-performance concrete material supply chain, thereby significantly improving the stability of product quality. The optimization model relies on precise control of various parameters in the supply chain and consideration of product quality objectives through comprehensive fitness functions, making the production process more scientific and reasonable, and reducing the production of non-conforming products. Compared with traditional methods, it has significant advantages in ensuring product quality, providing high-performance concrete materials with more reliable quality for engineering projects.

For each core parameter, design 5 gradient perturbation amplitudes (-20%, -10%, 0%,+10%,+20%), where 0% is the original parameter baseline value and the remaining gradients are parameter fluctuation values. During the testing process, only one core parameter is perturbed at a time, while keeping the other parameters unchanged. The optimized model is then used for calculation, and the experiment is repeated 30 times to take the average value. Record the variation patterns of the three core indicators (total cost, on-time delivery rate, and product qualification batch rate) with parameter fluctuations.

Determine the impact threshold of each core parameter through sensitivity testing. When the fluctuation of parameters reaches a certain level, it will cause significant deterioration of the core indicators of the model, and identify the key parameters that have the most significant impact on the performance of the model. At the same time, analyze and optimize the adaptive control effect of the model during parameter fluctuations, and verify whether the model can be adjusted through parameter adaptive adjustment algorithms. To offset the negative impact of some parameter fluctuations and maintain the stability of supply chain operational efficiency.

5 Discussion

This article systematically verifies the feasibility and superiority of intelligent optimization design algorithm models in high-performance concrete material supply chain management through experiments based on real industrial data. Based on the details of experimental design, the results of the three core indicators, and the actual needs of the industry, in-depth discussions will be conducted on the experimental results to provide practical reference and theoretical support for the intelligent management of high-performance concrete supply chain. The scientificity of experimental design and the reliability of data are the core prerequisites for the effectiveness of experimental results. The dataset used in this experiment is derived from real industrial operation data from five provinces and cities in East and Central China. Through cooperation with multiple market entities, it covers the core data of the entire supply chain. Combined with the triple collection method and cross validation mechanism, it ensures that the integrity and authenticity of effective data exceed 98%, laying the foundation for the credibility of the experimental conclusions. At the same time, the experiment eliminated random errors by unifying the software and hardware environment, splitting the dataset, repeating experiments, strictly controlling variables, making the comparison experiment between the optimized model and traditional management methods highly objective and comparable, effectively avoiding the influence of experimental design deviations on the results, and ensuring the rigor of the conclusions. Compared with existing related studies, the experimental results of this study show better performance in supply chain management efficiency, cost control, and response speed indicators. Existing studies are mostly based on simulated datasets or single regional industrial data for analysis, and there are deviations between data dimensions and actual application scenarios. In addition, some studies did not strictly control experimental variables, resulting in insufficient adaptability of the model in practice, which differs from the conclusions of this study. This study relies on real full chain industrial data from multiple regions, combined with scientific experimental design and verification mechanisms, greatly enhancing the practical application value of the model. The novelty of this study lies in the deep integration of intelligent optimization design algorithms into the full process management of high-performance concrete material supply chain, breaking through the limitations of traditional research focusing on single link optimization. At the same time, the construction of a multi-source data collection and verification system provides a replicable practical paradigm for the practical application of algorithm models in this field, filling the research gap in the connection between algorithm models and industrial practical scenarios.

This intelligent optimization design algorithm model can deeply integrate IoT monitoring and AI risk prediction technology, and is implemented in the entire scenario of high-performance concrete supply chain, with strong industrial practicality. In the process of raw material control, real-time data on the quality of incoming materials such as sand, gravel, and cement, as well as inventory levels, are collected using IoT sensors and synchronized into an optimization model to achieve dynamic inventory replenishment and quality prescreening, avoiding the flow of unqualified raw materials into the production process. In the production and transportation process, the Internet of Things monitors the operating parameters of mixing equipment, the position of transportation vehicles, and the status of concrete inside the tank in real-time. The model dynamically adjusts the production pace and transportation route based on real-time data, further improving the timeliness of supply and the stability of product quality. At the same time, the integrated AI risk prediction module accurately predicts potential risks such as raw material price fluctuations, transportation delays, and equipment failures by analyzing historical data and real-time operating conditions. The model outputs alternative suppliers, backup transportation plans, and other response strategies in advance to reduce the probability of supply chain disruptions. At present, the integrated solution has been piloted and applied in a building materials group in the east, effectively improving the response speed of the supply chain, reducing sudden risk losses, and providing a replicable and promotable practical solution for the intelligent upgrade of high-performance concrete supply chain.

6 Conclusion

This article focuses on the research of supply chain security of high-performance concrete materials and constructs an intelligent optimization design algorithm model. In the construction of the supply chain security indicator system, scientifically and comprehensively selecting indicators for each link lays the foundation for accurately evaluating supply chain security. In terms of algorithm design, GA has been improved by adjusting the encoding method, fitness function, and genetic operator to fit the complex and dynamic characteristics of the supply chain.

Through experiments, the optimized model was compared with traditional methods. In terms of cost, the total cost of each experiment of the optimized model was lower than that of traditional methods, with an average cost difference of about 170200 yuan. This proves its effectiveness in cost control and can reduce operating costs through reasonable planning of each link. In terms of timely supply, the optimized model has an average on-time delivery rate that is about 9.92% higher than traditional methods, reflecting its ability to better coordinate various links and effectively ensure project progress. In terms of product quality, the average qualified batch rate of optimized model products is 3.1% higher than that of traditional methods, indicating a significant improvement in product quality stability.

In summary, the intelligent optimization design algorithm model constructed in this article has achieved significant results in the safety management of high-performance concrete material supply chain. It provides scientific and effective methods for related enterprises in supply chain planning and management, which helps to enhance the overall competitiveness and stability of the supply chain. Future research may consider incorporating more complex factors, such as dynamic changes in the market environment and the impact of policies and regulations, to continuously improve the model and adapt to more complex and changing practical scenarios.

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