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RESEARCH ARTICLE

Reliability analysis on civil engineering project based on integrated adaptive simulation annealing and gray correlation method

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ABSTRACT Dynamic reliability is a very important issue in reliability research. The dynamic reliability analysis for the project is still in search of domestic and international research in the exploration stage. By now, dynamic reliability research mainly concentrates on the reliability assessment; the methods mainly include dynamic fault tree, extension of event sequence diagram and Monte Carlo simulation, and et al. The paper aims to research the dynamic reliability optimization. On the basis of analysis of the four quality influence factors in the construction engineering, a method based on gray correlation degree is employed to calculate the weights of factors affecting construction process quality. Then the weights are added into the reliability improvement feasible index (RIFI). Furthermore, a novel nonlinear programming mathematic optimization model is established. In the Insight software environment, the Adaptive Simulated Annealing (ASA) algorithm is used to get a more accurate construction subsystem optimal reliability under different RIFI conditions. In addition, the relationship between construction quality and construction system reliability is analyzed, the proposed methods and detailed processing can offer a useful reference for improving the construction system quality level.

KEYWORDS civil engineering, dynamic reliability, grey relational degree, adaptive simulated annealing algorithm

1 Introduction

In a civil engineering project, managers consider not only the cost and time, but also the quality and reliability. Civil engineering project reliability analysis has become an essential part of the construction process. The reliability of the civil engineering project can be affected by many factors that are dynamic change. Therefore, it is necessary to study dynamic reliability problems of the civil engineering project.

In dynamic reliability, the current researchers in this field find the dynamic reliability technology could be applied to the reliability and availability, security, maintainability, diagnosis, and quality management areas and so on [1]. In reference [2], after modeling the bridge-vehicle system, the uncertainties of the vehicles are produced using Gaussian probability distribution function and the statistical parameters of the response is extracted by Monte-Carlo simulation. The results, which are based on the confidence intervals and the variance of the statistical parameters, are obtained to study the effects of uncertainties on the dynamic response of the bridge. In addition, the probabilities of failure are calculated to illustrate a quantitative measure for the simulated statistical results. The most effective parameters on the uncertainty of the bridge response are also presented in this paper [2]. In reference [3], the statistical inferential procedures for composite dynamic systems are developed here based on a Burr type-XII distribution with a power-trend hazard rate function. Point estimates of the Burr type-XII parameters, and interval estimates of the baseline survival function are obtained based on the maximum-likelihood estimates, and the Fisher information matrix. A test procedure is presented for examining the relationship between the hazard rate function and the number of failed components. The performance of the proposed method is then evaluated by means of an extensive Monte Carlo simulation study. An example is finally presented for illustrative purpose [3].

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In reference [4], the authors study a multi-state weighted k-out-of-n: G system model in a dynamic setup. In particular, they study the random time spent by the system with a minimum performance level of k. Their method is based on ordering the lifetimes of the system's components in different state subsets. Using this ordering along with the Monte-Carlo simulation algorithm, they obtain estimates of the mean and survival function of the time spent by the system in state k or above. They present illustrative computational results when the degradation in the components follows a Markov process [4]. In reference [5], the authors propose a novel approach to the dynamic estimation of rater reliability in regression (DER3) using multi-armed bandits. This approach is specifically suited for real-life crowd sourcing scenarios, where the task at hand is labeled or rating corpora to be used in supervised machine learning, and the annotations are continuous ratings, although it can be easily generalized to multi-class or binary classification tasks. They demonstrate that DER3 provides high-accuracy results and at the same time keeps the cost of the rating process low. Although their main motivating example is the recognition of emotion in speech, their approach shows similar results in other application areas [5]. In reference [6], a practical method is developed for estimating the performance of highly reliable dynamic systems in random environment. This method uses concepts of unvaried extreme value theory and a relatively small set of simulated samples of system states. Generalized extreme value distributions fit to state observations and used to extrapolate Monte Carlo estimates of reliability and failure probability beyond the data. Numerical examples involving Gaussian and non-Gaussian system states are used to illustrate the implementation of the proposed method and assess its accuracy [6]. In reference [7], LU Ning set project total cost goal, then system optimal reliability was obtained; at the same time, he set the system reliability goal, then the optimal cost of the system was obtained; besides, the paper established mathematical model through computer programming to achieve the optimal allocation of the system. Compared with other scholars who adopted minimal paths or minimal cut sets, this method improved the computational speed greatly [7]. In reference [8], SU Chun analyzes in detail the dynamic reliability modeling method, then got the advantages and disadvantages of each evaluation method, and pointed out the development direction of dynamic reliability [8]. In reference [9], WANG Cheng described the reliability of the giant concrete construction system. On the basis of fuzzy set and membership function, the author calculated the reliability, and proposed and designed fuzzy analysis of integrated system suited for the Three Gorges project [9]. In reference [10], Enrique Castillo used sensitivity analysis methods to optimize the objective function, the initial value, dual variables the system of the system, and the method is suitable for nonlinear programming, linear problem, finally the sensitivity analysis method was applied in civil engineering reliability allocation [10]. In Ref. [11], LU Wenzhou proposed the concept of civil engineering project system vulnerability, and aimed at the room to ramp up its fragility adopting agile management technology and key chain technology to optimize the design of lean civil engineering project system. But there was no concrete index to evaluate the system reliability [11]. In reference [12], WANG Qian Qian adopted the random process and the Gauss Legendre integral formula of the combination of precise integration method, and analyzed the dynamic reliability of compound random vibration system by the specific examples [12]. In reference [13], DUAN Rong Xing presented a comprehensive study on the evaluation of data communication system (DCS) using a dynamic fault tree approach based on fuzzy set, the results showed that the proposed method is more flexible and adaptive than conventional fault tree analysis for fault diagnosis and reliability estimation of DCS [13]. In reference [14], ZHANG Xiao Jun integrated Pro/E, ANSYS and Isight to establish response surface approximate mathematical model to optimize the reliability of machine tool bed design [14]. In reference [15,16], some different regression models were used to analyze the relevant experimental data [15,16].

To optimize the dynamic reliability of engineering project, first of all, the author analyzed factors which affected construction quality, including the human condition, methods, machinery, and materials. This study obtained the weights of various affecting factors by gray relational degree and determined the reliability improvement feasible index (RIFI) where RIFI = $\omega_i L_i$. For quality, reliability, first, the system reliability optimization model is established. Secondly, a cost function is established to analyze the changing trend of reliability in different reliability improvement feasible index (RIFI) conditions. This method avoided the disadvantages of previous studies which ignored the importance of project quality and quantified the quality level simply [11].The traditional reliability optimization methods mostly adopt the traditional genetic algorithm, particle swarm optimization (PSO) algorithm by computer programming, but this study called corresponding engineering calculation software without human interventions by the Isight software to give less calculating. This study used the adaptive simulated annealing algorithm and produced new creation, it computed the difference of the objective function, and then it accepted or abandoned in the process until found the optimal solution which most closed to target.

2 Analyzing some factors affecting quality

2.1 Some factors of affecting the quality

Human influence is a very most important factor in the project; it involves every stage of the project and affects other factors. Project participants include decision makers of the project, the designers, producers and managers, construction supervision, the government quality inspection personnel, material supplier and relevant functional departments human and so on [17]. Improving the reliability of the staff is very important to improve the reliability of the whole system. The professional level of the project owner, quality supervision party, the supplier, project management, government officials and other project participants will affect the quality level of the whole project.

2.2 Material factors

In the construction engineering project, materials, mainly involve all kinds of engineering materials, prefabricated parts, components and finished products and semi-finished products. The construction engineering quality depends on whether its materials are in accordance with the relevant specification and whether the storage meets the material storage requirements or store appropriately.

2.3 Method factors

There are three kinds of method factors in construction, one is the construction technology and construction operation in the process of construction; The other is the management method involving construction organization and management, the construction schedule, construction personnel arrangement, construction site layout and so on; the last one is what contract mode will be adopted from parallel contract, project general contract, and design and construction subcontract. If there are incorrect or improper construction methods in the construction organization arrangement, it is likely to cause project quality problems like damaging the interests of the owner, making the construction take more quality maintenance responsibility. Therefore, in order to carry out the project successfully, and it must formulate strict construction standard and construction management system.

2.4 Mechanical factors

Mechanical factors include Earthmoving machinery, transportation machinery, hoisting machinery and the finished or semi-finished products processing machinery and so on [18]. The control of construction machinery quality has great effect on time, quality, and safety of civil engineering projects. Choosing appropriate construction machinery according to different construction technology, and checking the performance of construction machinery and mechanical performance regularly, maintaining the machinery regularly can avoid abrasion. To ensure the construction machinery is in the best working condition in the process of construction so that it will avoid the construction accidents and reduce the cost of construction machinery busywork.

3 Calculating the weights of some factors affecting quality

There are many methods to determine the weight, such as the entropy weight method, factor analysis, and cluster analysis. This study adopts the gray correlation method to gain weight matrix in this section, then gets the similarity coefficient, determines the deviation degree, difference of sequence and the gray correlation coefficient, the gray correlation degree, finally the study normalizes the weight affecting quality. The expert scoring method is adopted to make a remark of each factor, then the author determine a unified marking criterion, then use the gray theory to determine the gray correlation degree of each affecting factor, and then find out the weight. When we evaluate quality affecting factor, we consider various influencing factors of every construction process according to the current quality specification standards. Assuming that we invited four experts to participate in the evaluation, the evaluation experts can identify the second-level indexes which affect construction quality to test, according to the analysis of the different factors in the previous section, the establishment of the index system of the two levels as shown in Table 1.

Table 1 Quality affecting factor indicators

first class indicators	second class indicators
human factors	constructors' technical management the supervisions' work depth and breadth suppliers' quality supervisory personnel's power
material factors	building material quality equipment materials quality
method factors	construction technology and construction operation level construction management level engineering contracting way
mechanical factors	mechanical quality level machinery advanced degree

Each factor that is qualified will be with no penalty and which is not qualified will penalize one point on a base of 10 points. By that analogy, we can draw the marking table of four experts for the four factors affecting quality.

Assume that the four factors are judged by four experts according to the evolving standard. The result is as shown in Table 2.

Table 2 Experts' evaluation of quality affecting factors

factors	expert1	expert2	expert3	expert4
human	5	6	7	7
material	7	8	6	6
method	8	8	5	7
mechanical	9	8	7	8

Then the author gets an evaluation matrix:

$$R = \begin{bmatrix} 5 & 6 & 7 & 7 \\ 7 & 8 & 6 & 6 \\ 8 & 8 & 5 & 7 \\ 9 & 8 & 7 & 8 \end{bmatrix}.$$

1) Establishes evaluation weight matrix

$$R_\omega = \begin{bmatrix} 0.17 & 0.19 & 0.28 & 0.25 \\ 0.24 & 0.27 & 0.24 & 0.21 \\ 0.28 & 0.27 & 0.20 & 0.25 \\ 0.31 & 0.27 & 0.28 & 0.29 \end{bmatrix}.$$

2) Calculate the similarity coefficient and similarity matrix. The similarity coefficient uses R_{bd} to indicate similarity of the evaluation results between expert b and expert d. The similarity coefficient can be derived as shown in Eq. (1),

$$R_{\mathrm{bd}} = 1 - \left(\frac{1}{m}\sum_{i=1}^{k}(\omega_{bi} - \omega_{di})^2\right). \tag{1}$$

Then the similarity matrix can be obtained as follows:

$$R_{bd} = \begin{bmatrix} 1 & 0.973 & 0.930 & 0.839 \\ 0.973 & 1 & 0.941 & 0.955 \\ 0.930 & 0.941 & 1 & 0.967 \\ 0.839 & 0.955 & 0.967 & 1 \end{bmatrix}.$$

3) The deviation of weight value uses Q_b to indicate which means that the expert b deviates the comprehensive evaluation of all experts. The deviation value can be derived as shown in Eq. (2).

$$Q_b = \sum_{i=1}^{k} R_{bi}. \tag{2}$$

So the result is: Q = (3.742, 3.869, 3.838, 3.761).

The relative deviation uses p_b to indicate that the value that expert b deviate from maximum deviation degree $Q_{\max}$, its' expression is as Eq. (3).

$$p_b = (Q_{\max} - Q_b)/Q_{\max} \times 100\%. \tag{3}$$

So after calculating, we can get: p = (0.0328, 0.000, 0.0080, 0.0279). Experts' assessment deviation values that not exceed 5% are considered valid; we judge the value $p < 0.05$, so we consider expert evaluation results to be valid.

4) Calculates the difference of sequence

According to the expert evaluation results, the most important affecting factors can be taken as a benchmark when calculates the sequence difference. Judging from the weight matrix, mechanical factor has the greatest impact on quality. g4j indicates that the jth factor is how important to the most important affecting factors, the specific data as shown in Table. 3.

Table 3 Sequence difference

	factor	expert1	expert2	expert3	expert4
Δ_{41}	human	0.14	0.08	0	0.04
Δ_{42}	material	0.07	0	0.04	0.08
Δ_{43}	method	0.03	0	0.08	0.04
Δ_{44}	mechanical	0	0	0	0

5) Calculates the gray correlation coefficient; the gray correlation coefficient can be defined as Eq. (4).

$$D_{4j} = \frac{m + \beta M}{\Delta_{4j} + \beta M} \tag{4}$$

For the formula, M is a biggest sequence difference, m is the smallest sequence difference, let β be 0.5. We can draw from the Table. 3 that M is 0.14 and m is 0, then the gray correlation coefficient can be identified as Table. 4.

Table 4 Grey correlation degree

factor	expert1	expert2	expert3	expert4
human	0.33	0.47	1	0.64
material	0.5	1	0.64	0.47
method	0.7	1	0.47	0.64
mechanical	1	1	1	1

6) Calculate the gray correlation degree

The γ4j can be calculated as γ4j = [0.61, 0.653, 0.703, 1] (j = 1, 2, 3,4). After normalized, the weight can be obtained: [W1, W2, W3, W4,] = [0.206, 0.220, 0.237, and 0.337].

4 Reliability optimization process descriptions

4.1 Calculates RIFI

Reliability improvement feasible index (RIFI) is the reliability improvement feasible index, its calculation formula can be defined as RIFI = $\omega_i L_i$. ω_i is the weight of the factor, L_i is elastic coefficient, which means System′s ability that can maintain or improve performance under different environmental conditions. In this paper it refers to the construction subsystem′s stable ability under human, methods, materials, machinery four different factors affecting quality. RIFI is influenced by the quality factor weight and the elasticity coefficient at the same time. The evaluation of RIFI relations is as shown in Table 5.

Table 5 Evaluations of RIFI relations

the range of RIFI	evaluation relations
RIFI ⩾ 0.8	excellent
0.7 ⩽ RIFI ⩽ 0.79	Very good
0.5 ⩽ RIFI ⩽ 0.69	good
0.2 ⩽ RIFI ⩽ 0.49	general
RIFI < 0.2	bad

4.2 Establishes the model

If the construction subsystem is composed of six working procedures, the reliability relationship block diagram is shown in Fig. 1.

In Fig. 1, Procedure 1 and procedure 2 are in series relationship, procedure 3 and procedure 4 are in the series relationship too, and then procedure 1, 2 and procedure 3, 4 are in parallel relationship. Then procedure 5, 6 are in series with procedure1, 2, 3, and 4. In this study, the reliability concept is applied to reflect project quality. One of the important measures of reliability, the reliability function $R(t)$ is employed for the quantification. When $t = 0$, that is at the work completion time, the reliability level $R_i(0)$ (or $R(i)$) can be defined as the quality of the its work package. Moreover, the nonlinear cost-reliability function should be set up. According to the principle of reliability block diagram and reliability calculation methods, the construction subsystem reliability can be obtained as Eq. (5).

$$R(S) = [1-(1-R(1))(1-R(2))][1-(1-R(3)) \times (1-R(4))]R(5)R(6). \tag{5}$$

The objective function can be defined as Eq. (6).

$$\begin{aligned} F(\mathrm{S}) &= \mathrm{Max}\ R(\mathrm{S}) = \mathrm{Max}\ R(\mathrm{S}) \\ &= [1-(1-R(1))(1-R(2))][1-(1-R(3)) \\ &\quad \times (1-R(4))]R(5)R(6). \end{aligned} \tag{6}$$

The constraint can be defined as Eq. (7), (8), (9).

$$\sum_{i=1}^{6} T_i \cdot \left\{ \tan\left[\frac{\pi}{2} \cdot \frac{R(i)}{R(i)_{\min}}\right]\right\}^{(1-RIFI)} \leqslant C, \tag{7}$$

$$L_i \leqslant R_i \leqslant U_i, \tag{8}$$

$$\sum_{i=1}^{6} T_i \leqslant 3000. \tag{9}$$

In these constraints, $i = 1, 2, \ldots, 6$. Each work package has a basic cost index $T(i)$ which stands for the expenditures when the work is done at the minimum quality level. The work packages and their basic cost indexes are summarized in Table 6, C is the lowest cost, let it be 4000. L_i is the minimum reliability value that is 0.5, and the U_i is the highest reliability value that is 0.95. The model calculates the optimal value when it meets the Eqs. (7–9) constraints above.

5 Sensitivity analysis

5.1 Variance-based sensitivity analysis approach

Global sensitivity analysis method mainly includes: the variance analysis, regression analysis, scatter diagram method, Morris, screening method and the method based on variance, etc. The global sensitivity analysis method, analysis of variance has restrictions on the distribution of the output, the regression analysis demanded to know the relationship between input and output of the form, the scatter plot and Morris cannot compare the size of sensitivity, only the method based on the variance can meet the above requirements.

Variance-based sensitivity is to analyze the input influence to output variables. Assuming that we know one input variable values, then fix input variables and get a conditional variance of the output. The output of the unconditional variance and conditional variance differences reflect the influence of input variables to output. The sensitivity indexes contain the main effect in the sensitivity analysis of variance index, the total effect and interaction effect index [19].

Supposing that the model $y = f(x_1, x_2, \ldots, x_k)$, x_i is as uncertainty variables. When x_i is $\overline{x_i}$, conditional variance of the output is $V(y|\overline{x_i})$, when x_i is in certain value, $V(y|\overline{x_i})$ may be larger than the output of unconditional variance $V(y)$.To deal with this case, conditional variances in the

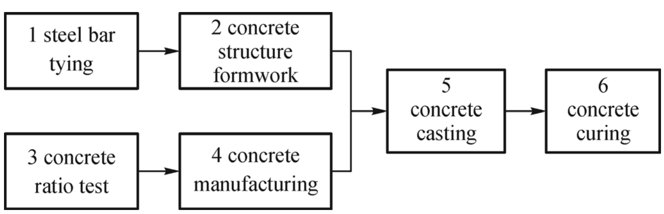

Fig. 1 Construction subsystem reliability relationship

range of change, x_i deserves average $E_{x_i}(V(y|\overline{x_i}))$. If the average of conditional variances is very small, it shows that x_i has much effect on the output (output of uncertainty is mainly determined by the uncertainty of the x_i). The formula can be drawn as followed:

$$V(y) = E_{x_i}\left(V_{x_i}(y|\overline{x_i})\right) + V_{x_i}\left(E_{x_i}(y|\overline{x_i})\right). \quad (10)$$

From the formula (1), the larger $V_{x_i}\left(E_{x_i}(y|\overline{x_i})\right)$ is, the more effect x_i on the output. The sensitivity index can be deduced as follows:

$$S_{x_i} = \frac{V_{x_i}\left(E_{x_i}(y|\overline{x_i})\right)}{V(y)}. \quad (11)$$

S_{x_i} is x_i first order sensitivity index or main effect, it represents the contribution of x_i.

The total effect index ST_{x_i} can be defined as follows:

$$S_{xi}^{T} = \frac{V(y) - V_{x_i}\left(E_{x_i}(y|\overline{x_i})\right)}{V(y)}. \quad (12)$$

S_{x_i} and ST_{x_i} are often used in sensitivity analysis as the sensitivity of indicators, S_{xi} is mainly used for the input variable importance sorting, and ST_{x_i} is mainly used for model simplification. Full effect indexes include the main effect of variables and mutual effect with other variables, so the difference between ST_{x_i} and S_{x_i} variables could be judged whether there is an interaction. Similar to the main effect and whole effect index, the interaction effect index can be defined as $S_{x_ix_j}$, $S_{x_ix_jx_k}$, respectively present second order and third order effect index. For example, second order interaction effect index is fixed two input variables; the change of the output variable reflects the two main effects of each variable and the interaction effect of the two variables [20].

The $S_{x_ix_j}$ computational formula can be written as:

$$S_{x_ix_n} = \frac{V_{x_ix_n}\left(E_{x_ix_n}(y|S_{x_ix_n})\right)}{V(y)} - S_{x_i} - S_{x_n}. \quad (13)$$

In a similar way, third order index computational formula can be written as:

$$S_{x_ix_nx_m} = \frac{V_{x_ix_nx_m}\left(E_{x_ix_nx_m}(y|S_{x_ix_nx_m})\right)}{V(y)} - S_{x_ix_m} - S_{x_nx_m} - S_{x_nx_m}. \quad (14)$$

The other advanced index is similar.

5.2 Computation method of the sensitivity indices

Using calculation formula to get S_{xi} and $S^{\mathrm{T}}{}_{xi}$ is very difficult. If $x_1, x_2, \ldots, x_n$ are independent of each other, you can use the monte Carlo method to estimate the value, the specific formula is as follows.N_1 and N_2 are as input vector of random sampling matrix, n is the frequency in sampling.

$$N_1 = \begin{pmatrix} a_{11} & \ldots & a_{1n} \\ \vdots & & \vdots \\ a_{m1} & \ldots & a_{mn} \end{pmatrix}, \quad (15)$$

$$N_2 = \begin{pmatrix} a_{11}{}' & \ldots & a_{1n}{}' \\ \vdots & & \vdots \\ a_{m1}{}' & \ldots & a_{mn}{}' \end{pmatrix}. \quad (16)$$

Solution related to the variables is based on the grouping variable method. Essence of this method is to put the relevant variables into a set, keep variables in groups are independent of each other, each variable is as a single independent variable, so that you can use this method to calculate the main effect index and the whole effect index of each group variable.

Relevant input sensitivity analysis has another problem that related to the random sampling. Assuming that a and b is not independent, and have a joint density function, the definition can be written as follows:

$$f_{ab}(a,b) = f_a(a) f_{b|a}(b|a), \quad (17)$$

first, Sampling from the f_a, and then according to the result of sampling to do the $f_{b|a}$ conditional sampling. Variables related to the construction project system in nonlinear multi-objective model are human factor weight, material factor weight, method factor weight, mechanical factor weight, environmental factor weight, it is often difficult to know their joint probability density function, but the scope of a variable affected by another variable can be determined. So we can use this way to produce relevant sampling.

5.3 example analysis

Based on the model of the construction project system as the research object, this model is established on the basis of the reliability calculation method and cost constraints. It has the characteristics of simple and quick. The model involves human factors weight, material factor weight, mechanical factor weight, method factor weight, environmental factors weight variables, and the model output is the system reliability. Construction project system sensitivity analysis was carried out on the input variable importance sorting, it can help identify the key or the improving research object; To evaluate the relationship between the input helps to improve construction project overall system reliability and determine the bottleneck factors; On the analysis of the model assumptions, it can help to verify the model. Input importance degree sort first, assuming that the input variables were not associated with the model, and assuming that each variable distribution is shown in Table 6.

Table 6 Work packages and basic cost indexes of the case study

No.	work package basic cost	index $T(i)$ (CNY)
1	steel bar tying	700
2	concrete structure form	870
3	concrete ratio test	900
4	concrete manufacturing	850
5	concrete casting	720
6	concrete curing	730

Table 7 Input variable distribution

input variable	distribution
human factors weight	[0.1–0.3] uniform distribution
material factor weight	[0.1–0.3] uniform distribution
mechanical factor weight	[0.2–0.4] uniform distribution
method factor weight	[0.1–0.3] uniform distribution
environmental factors weight	[0.1–0.3] uniform distribution

Through Matlab programming, when the sampling frequency is 1024, the calculated results are shown in Table 8. Due to the sensitivity analysis importance sequence is more important than the absolute value, so this kind of situation cannot be considered. Sensitivity sequence is shown in the Table 8:

Table 8 Sensitivity sequence

input variable	main effect index	sequence	total effect index	sequence
human factors weight	0.2462	5	0.3778	5
material factor weight	0.1781	4	0.2596	4
mechanical factor weight	0.0665	3	0.0467	3
method factor weight	0.0449	2	0.0230	1
environmental factors weight	0.0357	1	0.0336	2

Table 9 Parameter distribution

parameter	distribution
the biggest cost constraints	[4000–6000] uniform distribution
every job cost under the worst conditions	[700–1000] uniform distribution

We can get that human factors weight and material factor weight change have great influence on the construction project system from the Table 2.

Then analyze the model assumptions to determine that the output of the uncertainty is mainly affected by input uncertainty or the assumption of the model. This article assumes that the distribution is shown in the table below:

This article assumes that the biggest cost constraints and every job cost under the worst conditions. The main effect and total effect index and sequence results are shown in Table 10.

Table 10 Main effect and total effect index and sequence results

input variable	main effect index	sequence	total effect index	sequence
human factors weight	0.2908	7	0.2793	6
material factor weight	0.1123	6	0.2834	7
mechanical factor weight	0.0390	5	0.0338	3
method factor weight	0.0388	4	0.0450	4
environmental factors weight	0.0269	3	0.0470	5
the biggest cost constraints	0.0055	1	0.0021	2
every job cost under the worst conditions	0.0089	2	0.0019	1

It shows the biggest cost constraints and every job cost under the condition of the worst conditions have little impact on the model output from the Table 4, the impact need not be considered.

6 Adaptive simulation annealing (ASA) algorithm applications in dynamic reliability optimization of the civil engineering project

6.1 The basic feature of the ASA algorithm

The ASA algorithm is used to solve nonlinear programming problems of different types; it optimizes the non-different or discontinuous function as to obtain the function's optimal solution. At the same time, this algorithm has good robustness to ensure the stability of the system. What is more, a wide adaptability can be looked as a good resolution to complex nonlinear or linear programming problems. Besides, the global convergence makes the search more flexible. This method can deal with discrete, continuous and hybrid optimization design variables; In addition, the algorithm only needs the fitness function value to determine the search direction and scope without any requirements on the objective function and constraint conditions.

This study establishes the reliability model of nonlinear programming. If the paper uses a traditional algorithm, which will make the search process endlessly and the solution space will appear multiple optimal solutions; then search results stagnate in the locally optimal solution and it can′t get the optimal solution. Therefore, in this paper, the Annealing Simulated algorithm is improved to get an ASA algorithm to obtain the optimal reliability of engineering projects.

6.2 The basic steps and calculation results of the ASA algorithm

Construction process quality reliability value and construction system quality reliability can be obtained by modeling and ASA algorithm in Isight software when RIFI is different. So in this paper simulated annealing algorithm based on the gray correlation is to analyze the reliability of the project. Simulated annealing algorithm and genetic algorithm, artificial neural network algorithm, ant colony algorithm are compared in the Table 11 below:

The simulated annealing algorithm must carry on multiple iterations to find the optimal solution in the application process. Starting from the initial solution, it produces different kinds of data processing according to the parameters set. So it needs qualification to achieve the optimal value of objective function in the process of search. The qualification of the simulated annealing algorithm can be drawn as follows:

1) Initial solution

The initial value T_0 of Annealing temperature T has important effects on the global searching ability of the simulated annealing algorithm; setting of initial temperature also has an important effect on the optimal solution. If the temperature is higher, the probability of searching the global optimal solution is higher, but the search needs a long time; On the contrary, if the initial temperature is low, the time of searching for the optimal solution is shorter, but it will reduce the ability of searching for a global optimal solution. In the process of using a simulated annealing algorithm, the initial temperature of annealing tend to change many times, according to the related experimental results, but the simulated annealing algorithm dependence of the initial solution is not strong.

2) Speed of annealing

Annealing speed is one of the important parameters to reflect the process of the simulated annealing algorithm. Simulated annealing algorithm's global search ability and speed of annealing are inseparable. Speed of annealing can affect that the search is complete or not, at the same time, it avoids the solution trapped in local optimal solution, but the search process requires a certain computation time. When the simulated annealing algorithm is used to solve practical problems, it needs to set the appropriate attenuation function and annealing balance parameters according to the actual conditions and characteristics

3) Solution set

All feasible solution and infeasible solution form solution set, so the solution set delimits the initial temperature and scope of the solution. In unconstrained defined target calculation problem, the problem needs to meet the objective function, the solution set only contains a feasible solution. In the complex combination optimization problems, solution sets not only contains a feasible solution, there are some infeasible solution included in the solution set.

Adaptive Simulated Annealing algorithm steps are shown as follows:

Step 1: Sets the initial temperature as $t = t_0$ and initial state $s = s_0$ randomly, for $n = 0$.

Step 2:

1) Repeats

A) Produce a new state

B) *if* $\min\{1,\exp[-(C(s_j)-C(s))/t_n]\} \geqslant random[0,1]$, $s = s_j$

C) Until the sample stable and meet the criterion

2) Annealing $t_{n+1} = \text{update}(t_n)$,and $n + 1 = n$

Step 3: Until the algorithm is terminated and meets the criteria.

Step 4: Output algorithm search results.

The improved algorithm adapts to simulate degradation steps in Fig. 2:

The process to find the optimal solution in the Isight software is shown in Fig. 3:

Set different RIFI values and reliability results by using Isight are shown as Table 12.

All the work as the change of reliability improvement feasibility index trend as shown in Fig. 4.

From the Fig. 3, it can be learned that each work reliability is not correlated with reliability improvement feasibility index, RIFI doesn′t directly affect the reliability of each work.

RIFI in different environments, the reliability of the subsystem of the overall construction quality change trend are shown in Fig. 5 below:

Under the different RIFI condition, it is concluded that greater the value of RIFI, the higher the system reliability

Table 11 Algorithm compares

algorithm type	simulated annealing algorithm	genetic algorithm	artificial neural network algorithm	ant colony algorithm
characteristic	good robustness	less constraints	steady-state	good parallelism
	wide range of adaptability	large convergence probability	simple construction	good robustness
	less constraints	high adaptive ability	quick convergence	self-organizing system
	applicable to nonlinear programming problem	strong single point search ability	low climbing capacity	good positive feedback ability

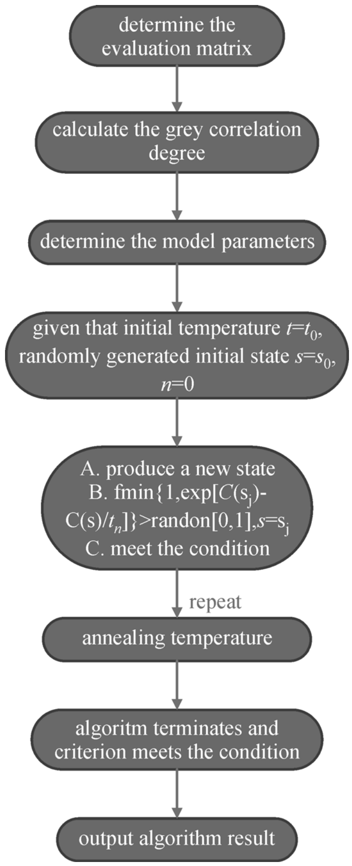

Fig. 2 improved ASA algorithm steps

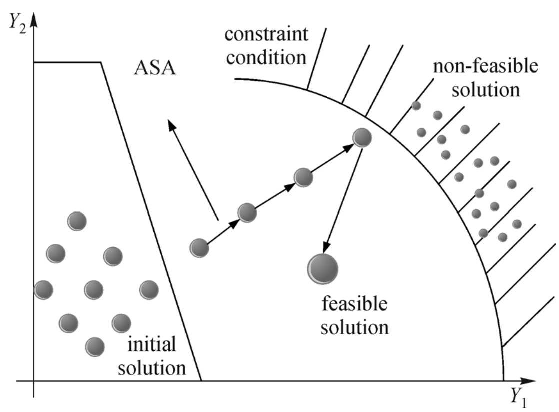

Fig. 3 optimization schematic

is. We can improve RIFI value to improve the reliability of the system. By this way, the reliability can provide a quantitative indicator to quantify the quality goal.

7 Conclusions

First, the affecting factors in the quality of construction engineering are analyzed in this paper. The gray correlation degree is taken to analyze the weight of human factor, material factor, mechanical factors, methods factors, etc. This method is an objective evaluation method and can avoid the drawbacks that the traditional calculation method of construction system depends on expert scoring method which is subjective. Based on this method, the optimal solutions of system reliability are obtained by using the ASA algorithm in Isight software. The above research shows that the greater the values of RIFI are, the higher system reliability is. That is to say, when the weight of construction procedures and the value of elastic coefficient are greater, the reliability will be higher. It also reflected

Table 12 The reliability results in the different RIFI condition

$R(i)/RIFI$	0.2	0.5	0.7	0.8
R (1)	0.90529	0.94778	0.92794	0.93740
R (2)	0.92031	0.90952	0.89977	0.82656
R (3)	0.87854	0.94371	0.94937	0.94604
R (4)	0.87245	0.88420	0.91044	0.90110
R (5)	0.92540	0.94479	0.94762	0.94521
R (6)	0.93468	0.93280	0.94613	0.93480
F (R) $_{\text{Max}}$	0.84513	0.87147	0.88606	0.89320

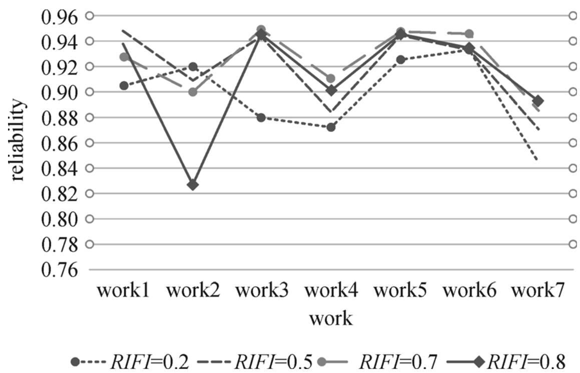

Fig. 4 work reliability

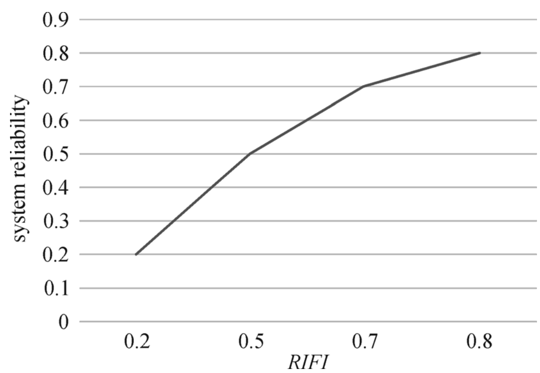

Fig. 5 system reliability

that quality is strongly correlated with reliability. In construction, we can effectively manage the construction quality by improving reliability, which enhances construction quality.

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