Optimisation decision model of enterprise financial risk management combining stochastic demand

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Abstract: To address the problems of complex financial activities and difficult cross-control risks in the environment of stochastic collaborative innovation, we propose an enterprise financial risk management model for implementing stochastic collaborative innovation from multiple perspectives of the environment, human factors, technology, organisation, and process. On this basis, the relevant random influence factor set is analysed and summarised as a basis for enterprise financial risk management and evaluation. Given the Pareto effect for the enterprise financial risk management factor set, combined with the enterprise financial risk management model and element set, an optimisation decision model of enterprise financial risk management combining the random demand function is proposed. Through the case study of product design in an enterprise, the scientificity and effectiveness of the model are verified.

Keywords: product design; stochastic collaborative innovation; enterprise financial risk management; risk evaluation; random set theory; radial basis function.

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1 Introduction

The financial management of securities enterprises is a highly complicated economic system. As the income and risk of investment are random, the decisions of enterprises are often uncertain (Aven and Aven, 2015; Nasr, 2011). In the proposed mean-variance enterprise financial risk management model, the investment income and risk are effectively quantified to drive the development of enterprise financial management (Mustapha and Adnan, 2015; Cocoşilă, 2014). Subsequently, the solution to the enterprise financial risk management model has emerged, and artificial intelligence algorithms have been extensively applied (Sanford and Moosa, 2012). Stochastic demand is an artificial intelligence algorithm where interplay and interaction are stimulated among butterflies. Characteristics such as adaptability, autonomy, and parallelism of animal behaviours, as well as parallel distributed processing, strong robustness are used (Hitomi, 2013; Korshikova, 2012). In addition, the algorithm itself has limitations, including the insufficiencies such as slow convergence, prone to falling into local extremum in the optimisation process (Durante, 2014; Zainutdinov, 2013). Many researchers have proposed some ideas for improvement from various perspectives, mainly including the combination with other algorithms, the adjustment of algorithm parameters, and the integration with some functions of other algorithms, etc. (Bekenova and Abduldayeva, 2012).

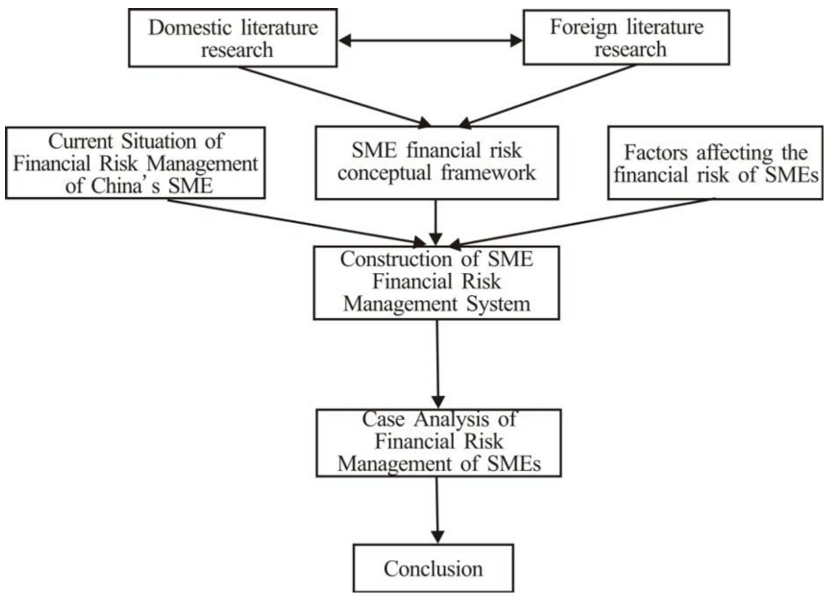
Since the 1990s, American scholars have confined the risk management object to pure risk from a narrow perspective and focused on risk handling. In general, as foreign financial risk research started early, the theoretical system was relatively complete, the application field was wide, and the research results were abundant and systematic. In summary, foreign studies mainly focus on the methodology and strategy of handling financial risks. However, there is a lack of the corresponding mechanism analysis and empirical research on the root cause, development process, and financial management of small and medium-sized enterprises (SMEs). The domestic literature on financial risk management of SMEs is often limited to a specific perspective or aspect. Domestic scholar Zhong Qin mainly focused on the long-term financial risk prevention management of SMEs in his study on the characteristics, causes, and prevention of financial risk of SMEs. In the study of financial risk identification and control of SMEs, risk prevention and control are mainly for the internal and external causes of the financial risk in SMEs. In the ‘on the financial risk management of SMEs in China’. In ‘SMEs’, Kong Lingyong expounded the prevention of financial risk in SMEs from the perspective of business operation and maintenance. Yao Jianghong discussed the financial risk prevention of SMEs. In the ‘research on the identification and control of industrial financial risks’, the financial risk prevention of SMEs were considered mainly from the perspective of internal control.

In this paper, the optimal decision operator is introduced into the basic stochastic demand algorithm to overcome the defects of the basic stochastic demand algorithm such as slow optimisation and low convergence accuracy in the later stage. In addition, the ideas of improving self-adaptive vision and step length are adopted to accelerate the convergence. The experiments suggest that the stochastic demand algorithm has more superior optimisation capacity. The optimisation of the enterprise financial risk management model by stochastic demand algorithm can achieve better solution results.

2 Optimisation decision framework of enterprise financial risk management

In this paper, the causes of financial risk formation are analysed in detail. Multiple aspects of internal and external factors of financial risks and the necessity of financial risk management in SMEs are analysed. The framework of this paper is shown in Figure 1.

Figure 1 Optimisation decision framework of enterprise financial risk management



3 Enterprise financial risk management model

Assuming that there are n types of optional assets in the capital market, which are denoted as $S_i(i = 1, 2, \cdots, n)$. It is noted that an investor holds M funds to purchase n types of assets, where the proportion of the n types of assets, i.e., S_i in the M funds corresponds to x_i. In a certain period, the income rate of the investor acquiring the asset S_i is denoted as r_i, and the corresponding prediction risk is q_i. Hence, an enterprise financial risk management model can be established.

In a specific investment period, the investor's total income is V, i.e.:

$$V = \sum_{i=1}^{n} M x_i r_i \ s.t. \sum_{i=1}^{n} x_i = 1, x_i \geq 0, i = 1, 2, \cdots, n \tag{1}$$

In a specific investment period, the maximum risk in all assets is taken as the investment risk R, i.e.:

$$R = \max_{1 \le i \le n} Mx_i q_i \ \ s.t. \sum_{i=1}^{n} x_i = 1, x_i \ge 0, i = 1, 2, \cdots, n \tag{2}$$

In the enterprise financial management, transaction expenses are generated in the transaction process, which is denoted as T; the transaction expense rate of asset S_i is p_i. It is stipulated in the model that: when the purchase amount does not exceed the fixed value $u_i(i = 1, 2, \cdots, n)$, the transaction expense is u_i; when the purchase amount exceeds the fixed value u_i, the transaction expense is calculated as Mx_i, i.e.:

$$Tx_i = \begin{cases} 0, & x_i = 0 \\ u_i p_i, & 0 < Mx_i < u_i \\ (Mx_i) p_i, & Mx_i > u_i \end{cases} \tag{3}$$

In a specific investment period, by maximising the total income and minimising the risk, we adopt the method of weight addition $\rho(0 \langle \rho \langle 1)$. The multi-target enterprise financial risk management problem is converted into a single-target enterprise financial risk management model. Hence, the enterprise financial risk management model can be obtained as follows:

$$\max F(x) = \rho \sum_{i=1}^{n} \left(Mx_i r_i - T(x_i) \right) + (1 - \rho),$$

$$\left\{ \max_{1 \le i \le n} \{ Mx_i q_i \} \right\} s.t. \begin{cases} \sum_{i=1}^{n} x_i = 1 \\ 0 \le x_i \le 1, i = 1, 2, \cdots, n \\ 0 \langle \rho \langle 1 \end{cases} \tag{4}$$

where ρ represents the weight of the investment income, $1 - \rho$ represents the weight of the investment risk. The value of ρ can be determined according to the investor conditions.

4 Stochastic demand algorithm

In the basic stochastic demand (BRA), the artificial butterfly state is $X = (x_1, x_2, \cdots, x_n)$, where x_i is the optimisation variable of the objective function, and the food concentration at the current position of the artificial butterfly is the value of the objective function, i.e., $T = f(X)$. It represents the distance that the artificial butterfly can sense, the step is the maximum distance when the artificial butterfly moves, δ indicates the degree of crowding in the butterflies, Nf represents the number of artificial butterflies in the neighbourhood of an artificial butterfly X_k, and the total number of artificial butterflies is n.

The optimisation of artificial butterflies mainly depends on behaviours such as foraging, tailgating, clustering, randomisation, etc., where the optimal values are obtained through mutual cooperation between these behaviours.

1 *Foraging behaviour.* The current position of the artificial butterfly is denoted as X_i. In the field of view, a random search is performed to identify the position X_j, calculate the food density Y_j at the position X_j, and compare the food density at the two positions. If Y_j is greater than Y_i, the artificial butterfly moves in the direction of X_j with *step* as the step length. The movement formula is shown in equation (5); otherwise, a random behaviour is performed to further search for new positions randomly.

$$X_{inext} = X_i + rand() \cdot \frac{X_j - X_i}{\left\| X_j - X_i \right\|} \tag{5}$$

where X_{inext} represents the position of the artificial butterfly at the next moment; *rand*() represents the random number from 0 to 1 that complies with the uniform distribution.

2 *Tailgating behaviour.* The current position of the artificial butterfly is denoted as X_i. In the field of view of the artificial butterfly, a random search is performed to identify the optimal position of the artificial butterfly $X_{\max k}$ and calculate the food density Y_k at this position. If Y_k is greater than Y_i and the degree of crowding is low (i.e., the $X_{\max k}$ crowd factor δ, neighbouring artificial butterfly number Nf and the total number of artificial butterflies n meet $Nf / n \langle \delta$), the artificial butterfly $X_{\max k}$ moves one step length in the direction, which is represented as follows:

$$X_{inext} = X_i + rand(step) \cdot \frac{X_{\max k} - X_i}{\left\| X_{\max k} - X_i \right\|} \tag{6}$$

3 *Clustering behaviour.* The current position of the artificial butterfly is denoted as X_i. The field of view is taken as the radius, the number of artificial butterflies within the neighbourhood searched is Nf. If $Nf \neq 0$, the centre position X_c of the artificial butterfly is searched. The artificial butterfly moves to the centre position according to equation (7); if $Nf = 0$, the foraging behaviour is performed.

$$X_{inext} = X_i + rand(step) \cdot \frac{X_c - X_i}{\left\| X_c - X_i \right\|} \tag{7}$$

4 *Randomisation behaviour.* Randomisation behaviour is the default for foraging behaviour, namely, randomly selecting a position and moving in that direction within the field of view.

5 *Bulletin board.* The bulletin board card is used to record the position and state of the optimal artificial butterfly after each iteration, i.e., after each iteration, the current artificial butterfly and bulletin board are compared. If the current artificial butterfly state is superior, the bulletin board will be updated to transpose the current artificial butterfly.

The process of biological evolution in nature is always accompanied by gene mutations. In stochastic demands, butterflies gradually form new individuals with stronger vitality through mutations of genes, thereby adapting to changes in the environment. The principles of biological evolution (namely, genetic mutation) are introduced into stochastic demand. Where the position state (optimum value) of the artificial butterfly can no longer be optimised, the position information of the artificial butterfly is changed (mutated) to continue the optimisation, so that a more superior artificial butterfly state can be taken to achieve the purpose of stochastic demand convergence. The optimisation decision operator is a common mutation operator in genetic algorithms, which refers to the use of a uniform distribution of random numbers within a specific range to change the position of the original artificial butterfly individuals with a small probability. In the optimisation process, the current artificial butterfly position is first calculated. Subsequently, a random number (*uniformrandom*) is generated from the uniform distribution, and the random number is added to the current artificial butterfly state, i.e.:

$$X_i' = X_i + X_i \cdot uniformrandom \tag{8}$$

where X_i represents the position state of the artificial butterfly; *uniformrandom* represents the random number generated. The parameter threshold (*kesi* = 0.01) is set in advance as a critical condition for determining whether an optimisation decision is made because *step* is in the range of (0,0.1), i.e., each movement is less than 0.1. To exclude local extremum, we take *kesi* = 0.01 as the threshold in this paper. When the current state of the artificial butterfly (the optimal value) different from the previous state (the optimal value) is smaller than the threshold, the more superior artificial butterfly is kept. Other artificial butterflies perform the mutation behaviour, i.e., another optimisation decision random value is added to the artificial butterfly state to obtain a new artificial butterfly state. Subsequently, the butterfly search behaviour is performed until the global optimum is obtained.

5 Feasibility of stochastic demand algorithm

Five typical functions are used for the test. The operating platform is Matlab 2012b on the Windows 7 operating system, with the computer operating frequency 2.8 GHz, the operating memory 4 GB, and the operating system is 64-bit.

1 $\max f(x, y) = \frac{\sin(x)}{x} \cdot \frac{\sin(y)}{y}$, other $-1 < x, y < 2$

2 $\max f(x, y) = -\left[\sum_{i=1}^{5} i \cdot \cos\left((i+1)x + i\right)\right]\left[\sum_{i=1}^{5} i \cdot \cos\left((i+1)y + i\right)\right]$, other $-10 \le x, y \le 10$

3 $\min f(x, y) = x^2 + y^2 - 10(\cos 2x + \cos 2y) + 20$, other $-5.12 \le x, y \le 5.12$

4 $\min f(x, y) = \frac{1}{4{,}000}\left(x^2 + y^2\right) - \cos(x)\cos\frac{y}{\sqrt{2}} + 1$, other $-600 \le x, y \le 600$

5 $\min f(x, y) = \left(x^2 + y^2\right)^{0.25}\left\{\sin^2\left[50\left(x^2 + y^2\right)^{0.1}\right] + 1\right\}$, other $-100 \le x, y \le 100$.

The settings of each parameter in the simulation are as follows: the total number of artificial butterflies *fishnum* = 100, the maximum number of iterations max*gen* = 100, the maximum number of attempts *try_number* = 100, the size of the initial field of view *Visual* 1 = 1, the step length *step* = 0.1, the factor of the crowding degree *delta* = 0.618, the threshold *kexi* = 0.01, and the coefficient *a* = 0.6. The basic stochastic demand algorithm (BRA) and adaptive optimisation decision (AOD) are used to optimise the five test functions, respectively. The simulation is performed 20 times, and target convergence is accurate to 0.00001. The test functions run independently under the convergence accuracy for 20 times, and the mean of the 20 simulation convergence iterations is taken as the average number of convergent iterations. The success rate is equal to the number of operations with the target accuracy divided by the total number of experiments, and the test results are shown in Table 1.

Table 1 suggests that compared to the AOD, the stochastic demand (BRA) has significantly improved the optimisation effect of the five test functions. The five functions selected fall into local extremum, in particular, the local extremum distribution of function 2, function 3, and function 4 is very wide. However, from the perspective of optimisation effects, BRA has a strong capacity to get out of local extremum, which can prevent the artificial butterfly from falling into local extremum and improves the optimisation accuracy of the algorithm effectively. Some optimal values up to the theoretical value of the function also suggest that the BRA has a more robust performance, stronger convergence, and higher optimisation accuracy. In terms of convergence speed, the convergence speed of the function in the BRA optimisation process is significantly improved. Functions 4 and 5 have a relatively large definition domain. Although they have more local extremums, they can also reach convergence quickly, which suggests that BRA has a relatively strong global search capability. In terms of stability, 20 independent operation tests are performed for each function, where BRA has a very high success rate. This also suggests that BRA has basically overcome the disadvantage of being trapped in local extremum, indicating the stability of BRA. Figures 2–4 show the curve of the optimisation process for test functions 1–5, respectively.

Figure 2 Curve of optimisation process for function 1 and function 2

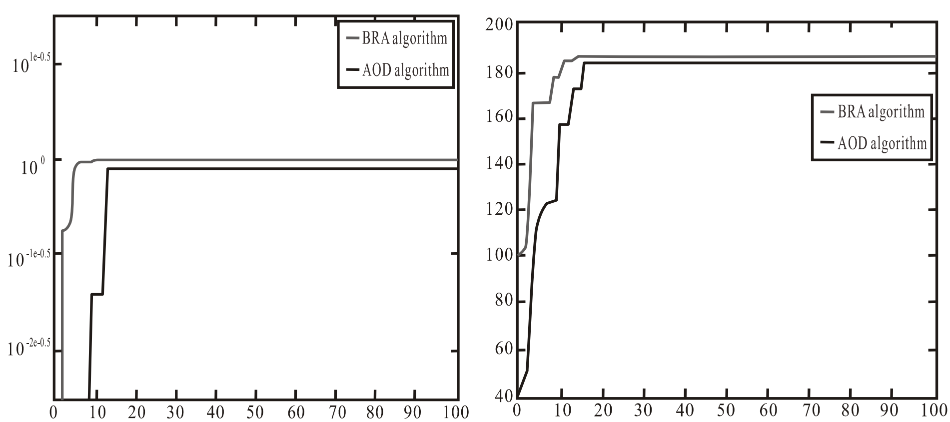


Table 1 Test results

	Test function 1		*Test function 2*		*Test function 3*		*Test function 4*		*Test function 5*	
	BRA	*TOA*	*BRA*	*TOA*	*BRA*	*TOA*	*BRA*	*TOA*	*BRA*	*TOA*
Optimal solution	0.999999	1.000000	185.476207	186.730909	0.000052	2.5249e-11	0.029693	0.002569	2.870749	0.002569
Worst solution	0.999997	1.000000	184.068875	1,786.730121	0.000816	1.09445e-10	2.870749	0.012599	2.968775	0.002573
Average value	0.999998	1.000000	184.772541	186.730515	0.000434	6.7347e-11	1.450221	0.007584	2.919762	0.002571
Average convergence number of iterations	146		1,614		9,230		5,045		7,040	
Success (%)	72,100		8,098		7,488		3,480		25,100	

Figure 3 Curve of optimisation process for function 3 and function 4

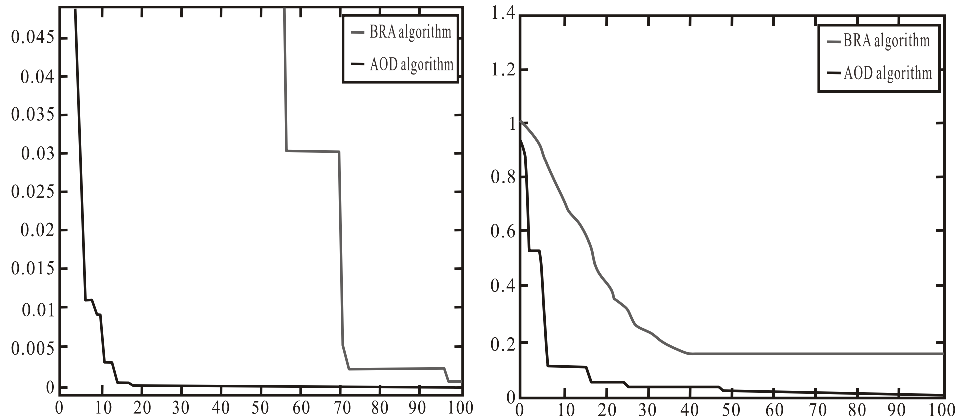
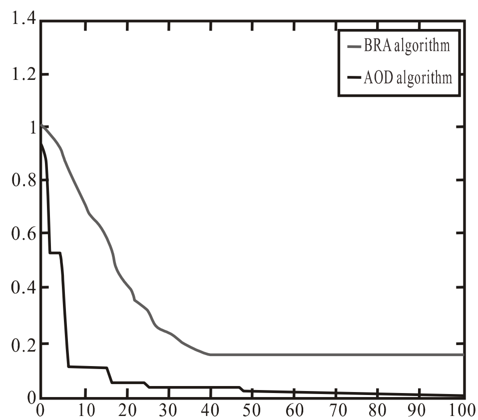


Figure 4 Curve of optimisation process for function 5



The above optimal path diagram shows that the stochastic demand algorithm has a better optimisation effect, and the AOD is slower and less accurate than the basic stochastic demand algorithm (BRA).

6 Optimisation decision process of enterprise financial risk management

When solving the target optimisation with constraint conditions, we use the penalty function method to convert the constraint problem into the unconstrained one to obtain the solution to the original nonlinear constraint problem. The basic idea of the penalty function method is as follows: the penalty function is established based on the constraints of the constraint problem, and the penalty factor σ is introduced to the original target function to form a new unconstrained augmented target function. The solution to the unconstrained augmented target function is the one to the original problem.

In this paper, the outlier penalty function method is used, i.e., the points that meet the condition are retained, while those that fail to meet the constraint condition are eliminated. As the iteration changes, the penalty factor and the penalty force are increased. To solve the problems of constraint enterprise financial risk management model, we introduce the outlier penalty function as follows:

$$\max F(x) = \rho \sum_{i=1}^{n} \left(Mx_i r_i - T\left(x_i\right) \right) + (1-\rho)\left\{ \max_{1 \le i \le n} \left\{ Mx_i q_i \right\} \right\} - \sigma \left(\sum_{i=1}^{n} x_i - 1 \right) \tag{9}$$

where $\sigma = 8^k (k = 1, 2, \cdots)$.

The modelling flow chart is shown in Figure 5. The specific steps are as follows:

1 Initialise the state of the artificial butterfly: butterfly size (*fishnum*), initial position, number of iterations (max*gen*), number of attempts (*try_number*), etc.

2 Set the artificial butterfly food concentration function based on the enterprise financial risk management model, and use the penalty function method to convert the constrained enterprise financial risk management model into a single target unconstrained enterprise financial risk management model.

3 Calculate the field of view and step length: the field of view *Visual*1 and the corresponding step length are obtained according to the average position distance between the current artificial butterfly and other artificial butterflies. The distances from the current artificial butterfly to the optimal and the closest artificial butterfly are calculated, respectively, which are denoted as *Visual*2 and *Visual*3. The corresponding step length is calculated at the same time.

4 Perform optimisation behaviours: each artificial butterfly chooses to perform clustering and tailgating behaviour with the field of view *Visual*1 and the corresponding step length, and implement the foraging behaviour with *Visual*2 and *Visual*3 as the field of view, respectively. The superior one is adopted.

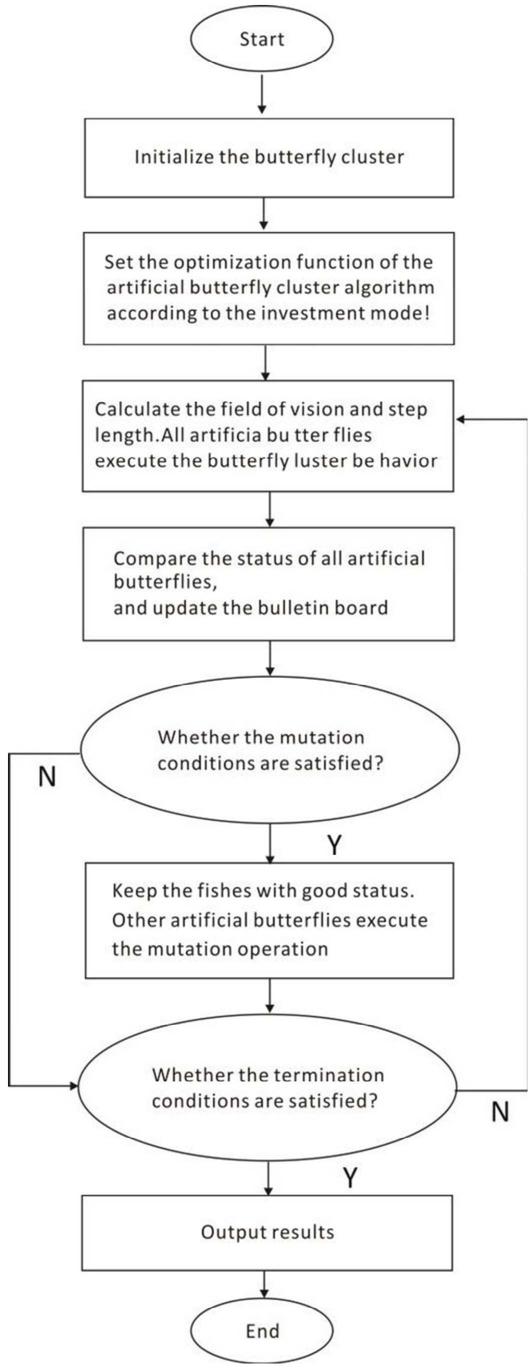
5 Update the bulletin board: the optimal value of the initial artificial butterfly state is updated and kept on the bulletin board. The position information of the optimal value is recorded to determine whether the optimal value meets the accuracy requirement. If so, the optimisation is ended; otherwise, proceed to the next step.

6 Mutation operation: after the update of the bulletin board, if the current state of the artificial butterfly (optimal value) differs from the last optimisation state (optimal value) less than the threshold value $kexi = 0.01$, i.e., the critical condition is met, a random number with uniform distribution is generated. The superior artificial butterfly is retained, and mutation operation is performed on the poor artificial butterfly to avoid local extremum.

7 Determine whether to terminate the process: $gen = gen + 1$, if the convergence condition is met (the optimal value reaches the accuracy requirement) or the maximum number of iterations is reached, the optimisation process is terminated; otherwise, step 3 is performed.

The parameters are set as follows: $Visual = 2.5$, $step = 0.4$, the total number of artificial butterflies $fishnum = 100$, the maximum number of iterations $\max gen = 100$, the maximum number of attempts $try\_number = 100$, the factor of crowding degree *delta* = 0.6188, the threshold *kexi* = 0.01, and the coefficient *a* = 0.6. The data of the enterprise financial risk management model are shown in Table 2.

Figure 5 Model construction flow chart



For the three conditions as $\rho = 0.1$, $\rho = 0.3$, $\rho = 0.5$, the AOD and basic stochastic demand (BRA) are used to solve the enterprise financial risk management model, respectively, as shown in Table 3.

Table 3 shows that when $\rho = 0.1$, compared with the basic stochastic demand algorithm, the optimal value of the stochastic demand algorithm increases. The income V is increased by 0.9598% (22.1064% relative to 21.1466%), and the risk R value is decreased by 0.126% (0.7420% relative to 0.6160%). The optimisation effect of the model is significantly improved. When $\rho = 0.3$, the stochastic demand algorithm can improve the optimal value of the function and achieve better optimisation result. The income V is increased by 3.093%, and the risk R is decreased by 0.0176%, which is more favourable for investors to make the right judgment. When $\rho = 0.5$, the income V is increased by 0.175%, the risk R is decreased by 0.007%, and the optimisation effect is relatively good. When taken 0.1, 0.3, and 0.5 are taken for ρ, respectively, the corresponding model optimisation curves are shown in Figures 6 to 7.

Table 2 Enterprise financial risk management model parameters

	r_i	q_i	p_i	u_i
S_1	0.28	0.025	0.01	103
S_2	0.23	0.055	0.045	52
S_3	0.21	0.015	002	198
S_4	0.05	0	0	0
S_5	0.25	0.026	0.065	40

Table 3 Comparison of optimisation effects of enterprise financial risk management models

		X_1	X_2	X_3	X_4	X_5	$V(\%)$	$R(\%)$	$F(x)$
$\rho = 0.1$	AOD	0.2968	0.0532	0.4365	0.0070	0.2065	21.1466	0.7420	14.4641
	BRA	0.2464	0.0978	0.4033	0.0226	0.2297	22.1064	0.6160	14.9161
$\rho = 0.3$	AOD	0.4395	0.0564	0.2056	0.0000	0.3004	22.3737	1.0988	59.0526
	BRA	0.8270	0.0914	0.0000	0.0000	0.0782	25.4667	1.0812	61.2475
$\rho = 0.5$	AOD	0.8544	0.0000	0.1057	0.0000	0.1054	26.8413	2.1359	113.0533
	BRA	0.9999	0.0000	0.0000	0.0033	0.0000	27.0163	2.1289	122.0589

The optimisation curve of Figures 6 and 7 shows that the stochastic demand algorithm has higher optimisation accuracy, faster convergence, and better optimisation results. In summary, stochastic demand has a better optimisation capacity. The effect of financial risk management and whether the same measures can be taken to handle financial risks are inseparable from the evaluation of financial risk management benefits of enterprises. Enterprises should establish an evaluation team for financial risk management effect to assess the decision scheme of enterprise financial risk management, observe whether the financial risk management reduces the occurrence of enterprise financial risk accidents and whether it reduces the enterprise losses caused by risk accidents and summarise the enterprise financial risk management objectively. Evaluating the experience and lessons in management is conducive to reducing the risk accidents and further developing the enterprises. As the implementation of risk management measures can directly affect the efficiency of financial risk management decisions, any deviation in the implementation of risk management measures may lead to the failure of enterprise risk management.

Meanwhile, the degree of errors and deviations caused by enterprise financial risk decisions should be analysed and continuously improved to strengthen risk management.

Figure 6 Comparison graph of optimisation curve when $\rho = 0.1$ and $\rho = 0.3$

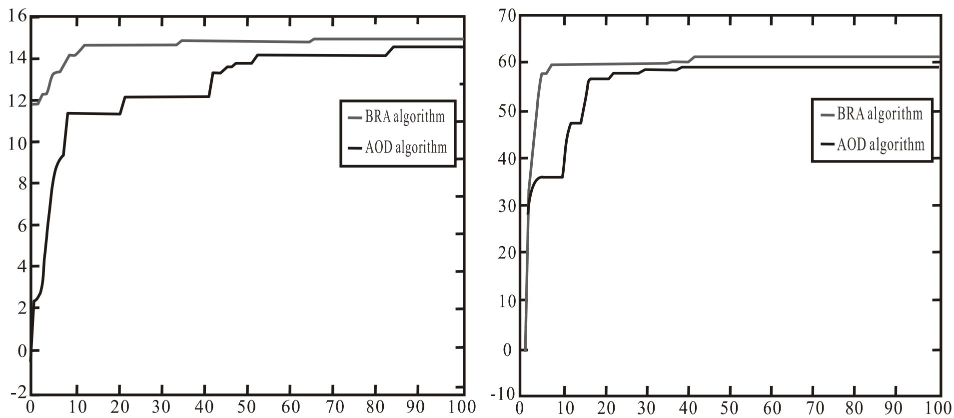
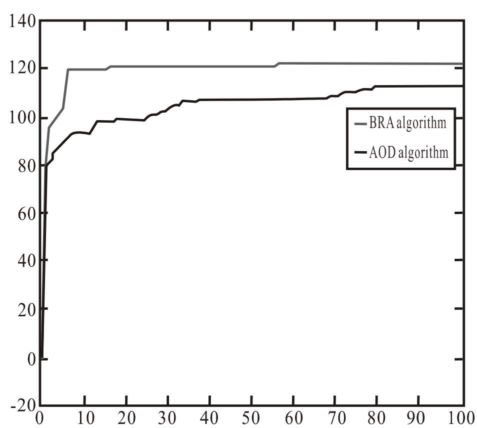


Figure 7 Comparison graph of optimisation curve when $\rho = 0.5$



7 Conclusions

The implementation of enterprise financial management capacity certification will help investors, creditors, suppliers, consumers, and other stakeholders judge enterprise financial management capability based on the certification results, thereby determining the value of enterprise investment and promoting continuous value creation of the enterprise. In this paper, an improved optimal decision operator is proposed. The optimal decision operator in the genetic algorithm is added to the basic stochastic demand. Hence, when the artificial butterfly falls into the local optimum, it may cause a sudden change in state and get out of the local extremum constraint, which has effectively improved the convergence accuracy of the algorithm. Meanwhile, the method of adaptive change of field of view and step size is used to realise the optimisation of large initial field of view and fast convergence, which prevents the artificial butterfly from fluctuating around the optimal value where the optimal value cannot be obtained. The stochastic demand algorithm is used to optimise the financial risk management model. The results of the solution show that as the optimal value of the model construction increases, the return on investment increases, and the risk decreases. Hence, the stochastic demand algorithm has a better optimisation capacity.

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