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Construction of Financial Investment Risk Control Model Based on Improved Particle Swarm Algorithm

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Abstract. In order to solve the problem that the particle swarm algorithm does not have high search ability in the late iteration and the particles tend to fall into the local optimum when it is introduced into a nonlinear financial risk model (objective), a financial investment risk control model based on an improved particle swarm algorithm is proposed. Based on the optimization of inertia weights and the variation of individual position of each particle, an improved particle swarm algorithm is proposed. The particle swarm algorithm is used to select the optimal control parameters to minimize the total risk value of the financial system. The simulation results show that: in the traditional algorithm, the beginning stage drops faster, and the local optimal phenomenon appears soon, but the improved algorithm makes the particles jump out of the local optimal trap soon by improving the inertia weights and other values, so as to reach the optimal faster, and the convergence of the improved algorithm is advanced more than 5 generations. Conclusion: The improved particle swarm algorithm is better than the traditional particle swarm algorithm in terms of global optimization and search speed.

Keywords. Nonlinearity; Particle swarm; Risk control; Global optimization

1. Introduction

In China, solving the financial problems of SMEs and promoting the legalization and normalization of private finance are hot topics in the economy. Internet finance undoubtedly provides a new way to solve these two problems at the same time [1]. With the help of Internet finance, China's financial reform will bring significant changes to the financial business structure and the overall financial structure. In the current era of Internet banking development, the main forms are third-party payment, P2P loan mode, fund-raising mode and micro finance mode, which are supported by Alibaba micro finance group [2]. Compared with the traditional financial industry, the cost benefit of the Internet financial industry is very small. Through online marketing, you can quickly and completely reach potential customers and quickly and continuously launch products [3].

The rapid development of Internet technology has solved the problem of imbalance of low-cost data, and the accumulation and analysis of historical data have improved the accuracy and transformation value of data. These technologies have made great

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contributions to the development of Internet finance. The development of the Internet, especially the development of search technology, data mining technology and platform design, has promoted the gradual improvement of information symmetry and spatial smoothness. Data generation, data mining, data security and search engine technology based on Internet technology are strong advocates of Internet finance [4]. Therefore, promoting data consistency is an important initiative to increase efficiency, reduce costs and even improve risk management [5].

2. Literature review

In the field of financial risk control models, there are mainly two categories in terms of implementation methods. One is the financial risk control model based on statistical methods, and the other is the financial risk control model through artificial intelligence methods. Li, X. et al. used the Bayesian model average method to model credit risk, and experiments show that on a real credit risk database provided by rating agencies, the regression model using the Bayesian model average method is better than the basic regression model in accuracy and performance [6]. Yin, M. et al. used linear support vector machine classifier, combined genetic algorithm and particle swarm optimization algorithm to select parameters, and used discriminant analysis to identify the bankruptcy level of bank customers. Research shows that this method can better identify bankrupt customers than the original model [7].

Liu, L and others pointed out that open-source threat intelligence can be stored in the network security knowledge map in a structured way, such as the text description of network attacks [8]. The network security knowledge map is crucial to help security analysts detect network threats, because it stores a large amount of network threat information in the form of semantic triplets and can query this information. Xu, Y. et al. proposed a novel big data prevention technology for financial system risks in order to reduce the severity and frequency of financial system risks in the new era [9]. Combined with big data mining technology and artificial intelligence algorithm, this technology can monitor the financial market in real time and prevent suspicious information. This technology realizes the close combination of big data and financial market, reduces the cross infection of financial systemic risk, and improves the controllability of financial systemic risk

In this paper, an improved algorithm is proposed through the adjustment of random inertia weights and the variation of individual positions, and based on applying the improved particle swarm optimization algorithm to the financial risk system, the optimal parameter allocation of the author's algorithm is illustrated through experiments, so as to reduce the total value of risk of the financial system.

3. The research methodology

3.1 Financial risk system modeling based on the standard particle swarm algorithm

Traditional particle swarm optimization algorithms mainly originated from the study of biological population behavior, by analyzing the interaction of behavior between individuals, so as to search for the optimal position in the population space [10]. Each particle represents a potentially feasible solution, and each particle has two attributes: the current position x_i and speed v_i, noting the individual particle optimal position as $p_{\text{best}}(i)$, $g_{\text{best}}(i)$ denotes the optimal position of the whole population. The resulting relationship between the position and velocity of each particle is given in equations (1)(2) below.

$$v_{i+1} = \omega v_i c_1 \text{rand}(j)(p_{\text{best}}(i) - x_i) + c_1 \text{rand}(j)(g_{\text{best}}(i)) \tag{1}$$

$$x_i = x_i + v_i \tag{2}$$

Among them c_1, c_2 is a constant representing the influence factor of the particle, the rand( ) Randomized.j defined in [0,1], the ω Represents the inertia weight, which can reflect the relationship between the inertia and velocity of particles. In the early stage, in order to increase the global search ability, a larger inertia weight is allocated, but in the later stage, the goal is the accuracy of local search, so a smaller weight is used according to ω To improve the search ability, then ω The expression for this is equation (3) below.

$$\omega = \omega_{\text{end}} + (\omega_{\text{start}} - \omega_{\text{end}})\left(1 - \frac{t}{T_{max}}\right) \tag{3}$$

Among them, $\omega_{\text{end}} = 0.4$, $\omega_{\text{start}} = 0.9$, the current number of iterations is denoted by t, $T_{\max}$ is the maximum number of iterations allowed in the iteration process.

Although the standard particle swarm algorithm has many advantages, but in the iterative process, when the particles on behalf of their own iterative parameters: their own position, the single optimal position of the history of the optimal position, the optimal solution of the whole group and so on are using the same update method, the particles are prone to stagnate in the late stage, or find the optimal solution prematurely and so on, which leads to the parameters of the financial risk model can't produce the next optimal result quickly. Therefore, the author proposes to change the inertia weight setting method, using random numbers to dynamically represent the inertia weights, and introducing the pigeon flocking algorithm to represent the variation of the particle position, so as to infer the parametersc Jumping out of the optimal position is not only conducive to jumping out of the local optimum, but also ensures the diversity of the population to the greatest extent, while avoiding the result of premature convergence.

3.2 Particle Swarm Algorithm Improvement

3.2.1 Optimization of inertia weights

It can be inferred from formula (1) that the influence of historical information on iterative update is controlled by inertia weight. In traditional algorithms, inertia weight mostly adopts linear decline strategy, resulting in low search efficiency and premature local optimization. In order to improve these problems, many scholars have proposed a variety of ways: fixed inertia weight, weight decreasing strategy, fuzzy inertia weight strategy, random inertia weight strategy, nonlinear weight decreasing strategy based on power function, dynamic inertia weight strategy, and improved particle swarm optimization BP (Back Propagation) algorithm. Among these methods, the randomness strategy is better. On the basis of maintaining the diversity of the population, the global search ability of the algorithm is improved pertinently, so that particles can jump out of the local optimum and avoid falling into premature convergence. The definition of random weight is as follows (4):

$$\omega(t) = \frac{\omega_{max}(T_{max} - t) + \omega_{min}}{T_{max}} \text{rand } (j) + \sigma \cdot \text{rand } (j) \tag{4}$$

Among them ω_{max} denotes the maximum value of the randomized weights, the ω_{min} represents the minimum value. t is the current iteration number, the T_{max} is the maximum number of iterations.

3.2.2 Individual positional variation based on improved pigeon flocking algorithm

In the PSO (Particle Swarm Optimization) algorithm, the change trend of the optimal position of different particles will draw a trajectory chain with the increase of the number of iterations, which can represent the optimal position value. However, excessive aggregation of particles and local areas will lead to premature convergence, so the search ability of the algorithm is weak at this time. The author proposes an improved pigeon swarm algorithm by changing the mutation strategy of the particle position to achieve the particle jumping out of the local optimum.

The pigeon flocking algorithm makes the search direction of particles clear, improves the search speed, and has the advantages of high computational accuracy, but the variation strategy of the map compass operator and landmark operator is not clear enough, and these two operators are in two different operation stages; the map compass operator is introduced for the purpose of the initial stage of the particle position and velocity; and the role of the landmark operator is to target particles far away from the target, and the process of each iteration is to remove the particle by half. halved at each iteration. Because the map-compass operator is a balancing factor, which is related to the search speed and development capability, an optimization method is proposed to introduce a linear variation strategy, which can dynamically represent the trend of the map-compass operator as the following equation (5): The map-compass operator can be dynamically expressed as the following equation (5): The map-compass operator can be dynamically expressed as the following equation (5): The map-compass operator is a balancing factor, which is related to the search speed and development capability.

$$R = \left(R_{min} + R_{max}\frac{n}{T_{max}}\right)(1 + p_r(\text{rand } (j))) \tag{5}$$

Among them, R_{max}, R_{min} represent the maximum and minimum values of the compass factor, the p_r denotes the linear variation probability. On this basis, a search operator is proposed as follows in equation (6).

$$z_i^t = v_i^{t-1} - \delta \text{rand } (j) x_i^{t-1} + \text{rand } (j)\delta + \text{rand } (j)\delta x_{\text{centerd}}^{t-1} \tag{6}$$

Among them δ which has a domain of definition at (0,1) ,represents the over factor.

In order to avoid the phenomenon of local optimization of particles in the late iteration, a variation factor is introduced to represent the change of position. Because of the siphon effect, which causes a large number of particles to gather at a certain optimal position, the particles that meet the conditions of variation are operated: the variation particles are singled out, which not only ensures the diversity of the population, but also increases the ability of global search. Equation (6) is improved as follows (7) (8).

$$x_i = \frac{v_i^{t-1} + \text{rand }(j)\delta x_{g_{\text{best}}} + \text{rand }(j)\delta x_{\text{centerd}}^{t-1} - c\text{rand }(j)}{1 + \delta\text{rand }(j)x_i^{t-1}} \tag{7}$$

$$c = min(b_1 - a_1, b_2 - a_2, \cdots, b_n - a_n) \tag{8}$$

Among themc represents the variation factor in the mutation process,the threshold range is the smallest among all particles, and the firsti The definitional domain of a particle is denoted by$\mathrm{b_n - a_n}$Representation. The formula of the variation rate is the following equation (9).

$$n = (p_{m,max} - p_{m,min})\left(\frac{k}{n}\right)^2 + (p_{m,min} - p_{m,max})\left(\frac{2k}{n}\right) \tag{9}$$

Among them$\mathrm{p_{m,max}}$, $\mathrm{p_{m,max}}$represent the minimum and maximum variability, respectively, and the number of iterations is denoted byk denotes the maximum number of iterations to useN indicated.

3.2.3 Individual optimal position update based on improved pigeon swarm algorithm and EMPSO algorithm

In the process of solving the problem of premature convergence of particles, the electromagnetic like mechanism in the concept of electromechanical discipline is introduced, and a hybrid set optimization algorithm EMPSO (Expectation Maximization and Particle Swarm Optimization) is proposed. The value of the charge quantity is used to represent the individual optimal particle and the group optimal particle respectively, so that the interaction between particles can be clearly expressed and premature convergence can be avoided. The specific charge amount and resultant force calculation method is as follows (10) (11):

$$q_i = \exp\left(-n\frac{f(p_{\text{best}}) - f(g_{\text{best}})}{\sum_{i=1}^{m}\left(f(p_{\text{best}}) - f(g_{\text{best}})\right)}\right) \tag{10}$$

$$F_i = \begin{cases} \sum_{j \neq i}^{m} (p_j - p_i) q_i q_j, & f(p_j) < f(p_i) \\ \sum_{j \neq i}^{m} (p_i - p_j) q_i q_j, & f(p_j) \geqslant f(p_i) \end{cases} \tag{11}$$

Combining the pigeon flocking algorithm Eq.(8) yields the optimal position of an individual calculated as the following equation (14).

$$p_i = z_i^i - \lambda \frac{F_i}{\|F_i\|} \boldsymbol{R}_{\mathrm{RNG}}, i = 1,2,\cdots,NP \tag{12}$$

Where RRNG is a vector representing the feasible step size, and its components represent the corresponding movement facing the upper boundary or the lower boundary respectively.

4. Analysis of results

In order to verify the impact of the improved algorithm on the performance, the test functions: Sphere function, Rastigrin function, Sumsquares function and Zakharov function are used to conduct simulation experiments on the two algorithms respectively to verify the performance of the two algorithms. The standard definitions of the four benchmark functions are as follows.

The Sphere function is as follows (13):

$$f(x) = \sum_{i=1}^{D} x_i^2 \tag{13}$$

Rastigrin function is as follows (14):

$$f(x) = \sum_{i=1}^{D} \left(x_i^2 - 10\cos\left(2\pi x_i\right) + 10\right) \tag{14}$$

Sumsquares function is as follows (15):

$$f(x) = \sum_{i}^{D} i x_i^2 \tag{15}$$

The Zakharov function is as follows (16):

$$f(x) = \sum_{i=1}^{D} x_i^2 + \left(\sum_{i=1}^{D} 0.5ix_i\right)^2 + \left(\sum_{i=1}^{D} 0.5ix_i\right)^4 \tag{16}$$

Sphere is a unimodal quadratic function,f(x)=0 represents the global minimum. Because there is only one minimum point, it is difficult to find the optimal value; Rastigrin is a multimodal function, which can collect a large number of local extreme points; Sumsquares and Zakharov functions are also functions with multiple peaks. For the experimental simulation process, the transformation range of inertia weight is [0 4,0. 9],$p_{max} = 0.6$，p_{min} =0.3, the threshold value of the random function is (0,1), and the maximum number of iterations is 100. Spehe, Sumsquares, Rastigrin and Zakharov functions clearly show the trend transformation between the number of iterations and the fitness value, as shown in Figure 1 to Figure 4.

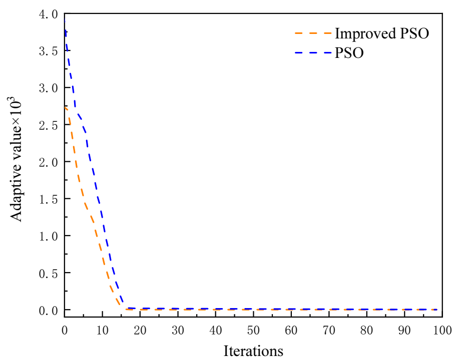

Figure 1. Change Trend of Fitness of Sphere Function

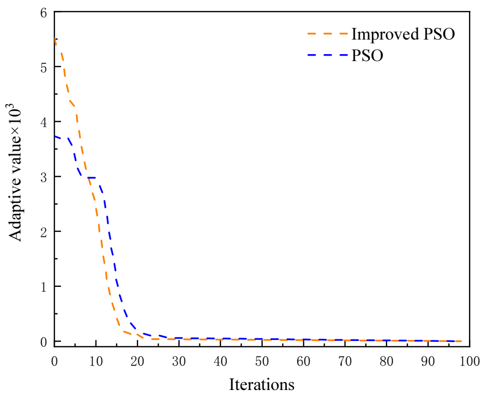

Figure. 2 Trend of fitness of Rastigrin function

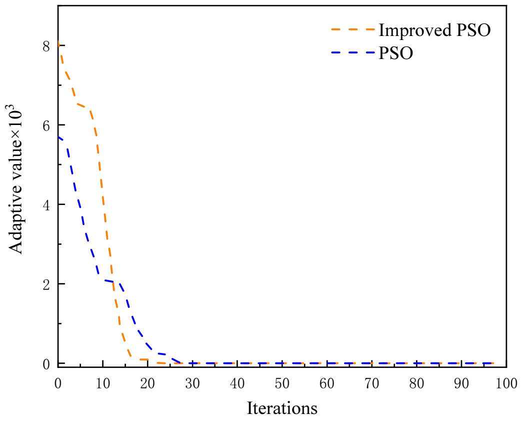

Figure. 3 Change trend of Sumsquares function fitness

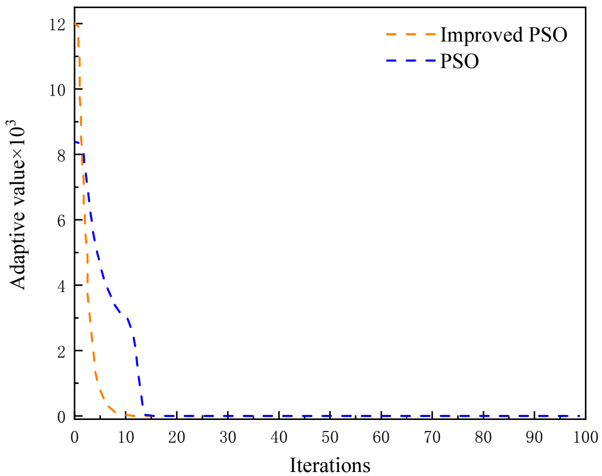

Figure. 4 Change trend of Zakharov function fitness

From the results in Figures 1 to 4, it can be seen that the optimized algorithm has a faster convergence speed, which largely solves the problem of falling into local optimum. It can be seen from Figure 1 that the PSO algorithm is slower than the improved algorithm to reach the optimal fitness value. It can be seen from Figure 2 that in the traditional algorithm, the decline is fast at the beginning, and the phenomenon of local optimum also appears quickly. But the improved algorithm makes particles jump out of the local optimum trap quickly by improving the inertia weight equivalence, so that they can reach the optimum faster [17]. In Figure 3, the PSO algorithm has low fitness at the beginning, but its convergence speed is slow. Although the improved algorithm fell into the local optimum, it quickly jumped out through the mutation strategy, thus speeding up the convergence speed. The effect is more obvious in Figure.4. The convergence algebra of the improved algorithm is more than 5 generations ahead of time.

From the simulation results, it can be concluded that the strategy adopted by the author to change the strength of particle inertia weights, the particle position variation and the change of the optimal position of the particles in the population can largely help the particles to jump out of the local optimum, solve the problem of slow convergence at the later stage, and show a better convergence performance.

5. Conclusion

On the basis of traditional methods, this paper introduces particle swarm optimization into the financial risk model, finds the mapping relationship between the particle position in the particle swarm optimization algorithm and the control factor c in the risk model, obtains the optimal control factor, and reduces the total risk value in the risk system to the greatest extent by optimizing the relationships between the particle attributes: inertia weight, individual position, individual optimal position variation, etc, On the basis of maintaining population diversity, the particle swarm can not only solve the problem of local optimization, but also maintain a good speed in the later stage.

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