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An Improved SPEA2 Algorithm with Local Search for Multi-Objective Investment Decision-Making

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Abstract: Enterprise investment decision-making should not only consider investment profits, but also investment risks, which is a complex nonlinear multi-objective optimization problem. However, traditional investment decisions often only consider profit as a goal, resulting in an incorrect decision. Facing the high complexity of investment decision-making space, traditional multi-objective optimization methods pay too much attention to global search ability because of pursuing convergence speed and avoiding falling into local optimum, while local search ability is insufficient, which makes it difficult to converge to the Pareto optimal boundary. To solve this problem, an improved SPEA2 algorithm is proposed to optimize the multi-objective decision-making of investment. In the improved method, an external archive set is set up separately for local search after genetic operation, which guarantees the global search ability and also has strong local search ability. At the same time, the new crossover operator and individual update strategy are used to further improve the convergence ability of the algorithm while maintaining a strong diversity of the population. The experimental results show that the improved method can converge to the Pareto optimal boundary and improve the convergence speed, which can effectively realize the multi-objective decision-making of investment.

Keywords: investment decision; multi-objective optimization; SPEA2; local search

1. Introduction

Enterprise investment planning is constrained by many conditions. In addition to the limitation of investment budget, there are also some complicated economic constraints, which are mutually restrictive [1]. It has drawn more and more attention regarding how to determine the investment plan scientifically and how to create the greatest value with limited funds. The existing decision-making methods of production and investment projects in enterprises mainly include the net present value (NPV) method [2], payback period method [3], cost–benefit analysis [4], Monte Carlo simulation approach [5], probability tree method [6], dynamic programming method [7], shortest path method [8,9], incremental effect evaluation method [10] and so on. These methods have their own advantages and are widely used, whereas they also have shortcomings, which can not meet the criteria of reasonable and scientific evaluation [11]. In addition, these methods are mainly based on single-objective decision-making, which is profit maximization. The advantages of single-objective decision-making method are simplicity and ease of understanding. Nevertheless, the investment of enterprises is affected by many factors, which often contradict each other [12], as a single-objective decision-making method often fails to measure the whole scheme comprehensively, which makes decision-making difficult and even leads to incorrect decision-making. The decision-making methods mentioned above regarding production investment of enterprises mostly focus on optimization in terms of economic benefits of projects, while the investment of production projects of enterprises is influenced by many factors, and the reliability (project risk) is one of the important factors [13]. Improving the evaluation index of project investment decision-making and adopting multi-objective optimization decision-making method for comprehensive decision-making of enterprise production investment projects are important ways to achieve comprehensive and rational decision-making analysis. This paper establishes a multi-objective evaluation index system based on investment profit, investment risk and environmental costs, and makes multi-objective optimization decision for investment projects.

For complex nonlinear problems such as multi-objective optimization, the traditional analytical method is difficult to solve. In the early stages, multi-objective optimization problems are often transformed into single-objective optimization problems by weighting [14], and solved by mathematical programming, and yet the optimal solution can only be obtained with one weight at a time, which is sensitive to the weight value or the order given by the objective. In order to solve the problem of simple weighting, Stevic et al. [15] proposed a new approach based on a combination of the simple additive weighting (SAW) method and rough numbers, which is used for ranking the potential solutions and selecting the most suitable one. Badi et al. [16] used best-worst method and multi-attribute ideal-real comparative analysis to realize multiple criteria decision-making. Pamucar [17] proposed the full consistency method for determining weight coefficients. Based on full consistency method, Nunic [18], Bozanic [19], and Pamucar [20] proposed a series of improved methods to improve the reliability of multi-objective results. In addition, the new artificial intelligence algorithm [21,22] can also find the optimal weight. The essence of these methods is to find the optimal weight. At present, the evolutionary algorithm (EA) is considered as an effective method to find the optimal Pareto optimal solution set for multi-objective optimization. The evolutionary algorithm is a kind of adaptive global optimization probabilistic search algorithm which simulates the evolution process of organisms in natural environment. The evolutionary algorithm operates on the whole population at the same time, and can search multiple solutions in parallel in a single run of the algorithm. It has strong versatility and can deal with complex multi-objective optimization problems, which are difficult to be solved by traditional optimization methods. In recent years, many excellent multi-objective evolutionary algorithms (MOEA) have been proposed one after another, and good results have been achieved in solving multi-objective optimization problems [23]. The representative algorithms are NSGAII [24–26], SPEA2 [27–30], PAES [31–33] and so on [34–36]. The slow convergence speed and low precision of multi-objective evolutionary algorithm have become the fatal weakness that affects the performance of the algorithm. One of the reasons for this weakness lies in the evolutionary algorithm itself, which is a probabilistic algorithm that is better at global search but less capable of local search [37]. Most evolutionary algorithms expand the range of random search in order to prevent the algorithm from falling into local convergence, while the price of that is to weaken the ability of local search. Especially when the search space is very irregular, the phenomenon of convergence to the global optimal solution is particularly obvious. The feasible solution space of multi-objective decision-making problem of enterprise investment is often very complex and nonlinear [38]. It is not easy to converge to Pareto optimum when using traditional multi-objective optimization theory to optimize. Therefore, it is necessary to put forward a new method to solve the multi-objective decision-making problem of enterprise investment.

The existing local search algorithm is improved from the hill climbing method. Local search algorithm has been widely used, and many improved algorithms [39–42] have been derived. However, the simple local search algorithm has an important defect that can not be solved. Once the search process falls into the local optimum, the algorithm process will end at that point. At this time, it may get a bad result, not the global optimum. Therefore, the local search algorithm is easy to fall into local optimum and the global search ability is limited. This paper proposes an improved SPEA2 algorithm based on local search for multi-objective decision-making of enterprise investment. With strong global search capability, an external population dedicated to local search is set up separately for each iteration to generate a non-dominant set. Local fine-tuning operation is carried out to improve the convergence speed of the algorithm. In addition, this paper also improves the crossover operator and partially individual update strategy, which effectively improves the convergence ability of the algorithm and overcomes the shortcomings of poor local search ability. The purpose of this paper is to propose a new local search algorithm to solve the problem that multi-objective investment optimization is easy to fall into local optimum. Compared with the traditional method of simplifying multi-objective optimization to single-objective optimization, the multi-objective optimization algorithm based on local search proposed in this paper can obtain the optimal Pareto solution set, which can provide a more comprehensive reference for investment decision-making. On the other hand, the traditional multi-objective method of investment decision-making is difficult to converge to Pareto solution set due to lack of local search, which affects the accuracy and reliability of investment decision-making. The results imply that this method can realize the optimization of multi-objective investment decision very well, and the convergence speed of the optimization results is faster and the results are more accurate than the traditional multi-objective optimization methods.

2. Methodology

Multi-objective optimization problems can be described as:

$$\begin{aligned} \min \quad & F(X) = (f_1(X), f_2(X), ..., f_m(X)), \\ \text{s.t.} \quad & g_i(X) \leqslant 0, i = 1, 2, ..., p, \\ & h_j = 0, j = 1, 2, ..., q, \end{aligned}$$

where $X = [x_1, x_2, ..., x_n]$ is the decision variables, and f_i is the ith optimization objection. Pareto domination is one of the main concepts of multi-objective optimization. The concepts of Pareto domination and Pareto solution set are as follows:

Pareto dominance: If A and B are any two different individuals in an evolutionary population, with A dominating B (AΦB), the following two conditions must be satisfied:

(1) For all sub targets, A is not worse than B, that is $f_k(A) \leqslant f_k(B)\ k = 1, 2, ..., m$.

(2) There is at least one sub goal that makes A better than B, which is $\exists l \in \{1, 2, ..., m\}$, $f_k(A) < f_k(B)$.

Pareto-optimal set: The Pareto optimal solution set P^* is the set of all Pareto optimal solutions, which is defined as follows:

$$P^* \triangleq \{X^* | \neg\exists X \in X_f : X\Phi X^*\}, \tag{1}$$

where X_f is variable space.

2.1. The Basic Theory of SPEA2

SPEA2 is an efficient multi-objective optimization genetic algorithm proposed by Zitzler et al. It is based on the concept of Pareto domination for fitness allocation and selection operations, and uses the niche method and external archiving elite retention mechanism. The specific flowchart is shown in Figure 1.

Although SPEA2 has some advantages over other multi-objective algorithms, its genetic evolution operation has strong randomness. In this way, the search range can be enlarged, the algorithm will not fall into local convergence, but the local search ability is insufficient. After reaching nearby regions of the Pareto optimal solution, the optimization efficiency of SPEA2 often decreases dramatically, and sometimes the Pareto optimal solution can not even be searched.

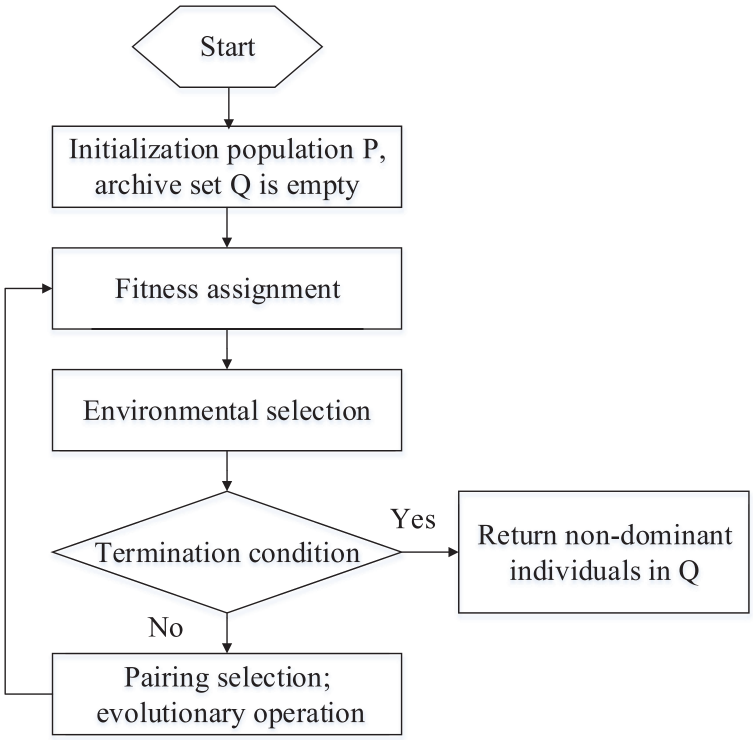


Figure 1. The description of the SPEA2 algorithm.

2.2. *Improved SPEA2*

In order to solve the problem of insufficient local search ability of the current SPEA2 algorithm, a local search method is proposed. This method has strong local search ability while ensuring global search ability. At the same time, improved crossover operator and individual update strategy are used to improve population diversity and speed of convergence.

2.2.1. Local Search Strategy

The standard SPEA2 evolutionary algorithm has strong randomness in genetic operation. Although this can increase the search range and avoid falling into local convergence, the local search ability is relatively poor. After reaching the nearby of Pareto optimal solution, the optimization efficiency of SPEA2 often decreases significantly, and sometimes even fails to converge to the Pareto optimal solution, and the solution set is not always the global optimal. In order to preserve the global search capability of SPEA2 and enhance the local search capability, we set up a separate population *L* to store the non-dominant set generated by each iteration. In addition, local fine-tuning of the internal individual in *L* is carried out to enhance the ability of neighborhood search. For binary coding, local search is to select a mutation near the end of the chromosome. The specific operation is as Figure 2.

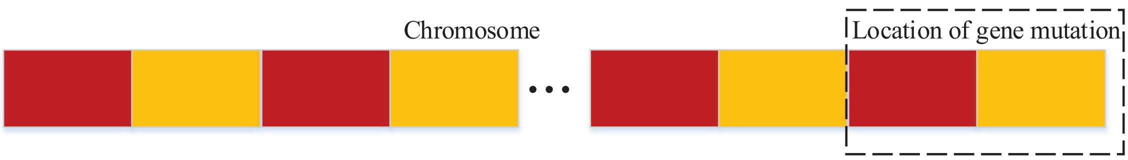


Figure 2. The description of the SPEA2 algorithm.

The paternal population of the next iteration is composed of population L and population P after fine-tuning of local search operation. Using simultaneous evolution of two populations can exchange the genetic information carried by excellent individuals among populations to break the balance within the population and realize the search near the optimal solution set. The diversity of alternative populations is richer than that of standard algorithms, and the chances of finding the optimal solution set will be greatly increased.

2.2.2. Crossover Operator

Conventional crossover operators only perform partial gene recombination of two individuals according to a certain crossover probability, regardless of whether the individuals to be operated are identical or similar. Obviously, the intersection of two individuals with high similarity is of little significance to population evolution, which will only bring population evolution to a standstill and increase the possibility of local convergence. In order to overcome this shortcoming, we judge the similarity of two individuals before crossing. It is only when the difference between two individuals reaches a certain degree that cross operation is carried out. In this paper, we use Euclidean distance of two chromosomes as a measure of individual similarity.

$$\text{Crossover} = \begin{cases} 1, & D_{ij} \geqslant T, \\ 0, & D_{ij} < T, \end{cases} \tag{2}$$

where D_{ij} represents the Euclidean space distance between two individuals, and T is the similarity thresholds. Number 1 indicates that there can be a crossover operator between two individuals, and number 0 represents no crossover.

2.2.3. Individual Updating Strategy

In order to further enhance the diversity of the population and reduce the risk of falling into local optimum in iteration, we "re-select" some inferior individuals of the population according to a certain proportion every several algebras, delete them, and re-initialize some individuals to join the parent population. This method is conducive to maintaining population diversity, improving search performance and effectively preventing premature emergence.

2.3. Evaluation Criteria

In order to evaluate the convergence performance of the algorithm, a closer evaluation method for convergence index is used in this work [43]. This method evaluates the approaching degree of the algorithm by calculating the minimum distance from the solution set to the reference set or the Pareto optimal solution set. The smaller the distance, the higher the approaching degree of the solution set. When evaluating the convergence performance of a multi-objective evolutionary algorithm, this method needs to determine the reference set P^*, which selects the known Pareto optimal solution set or the non-dominant set of past generations. $P^* = \text{Nondominated}(\text{U}_{t=0}^{\text{T}}\text{NDSet}^t)$, where NDSet^t is the non-dominant set of tth generation. Because the Pareto optimal solution set is generally difficult to determine, the reference set P^* usually takes the non dominated set of past generations. Firstly, calculate the shortest distance from i to P^* for each individual in the current non dominated set:

$$Pd_i = \min_{j=1}^{|P^*|} \sqrt{\sum_{k=1}^{m} \frac{f_k(i) - f_k(j)}{f_k^{\max} - f_k^{\min}}}, \tag{3}$$

where $f_k^{\max}$ and $f_k^{\min}$ are the maximum and minimum values of the kth target in reference set P^* respectively. Calculate the average of Pd_i:

$$C(P^t) = \sum_{i=1}^{\mathrm{NDSet}^t} \frac{Pd_i}{\mathrm{NDSet}^t}. \tag{4}$$

In order to satisfy $C(P^t) \in [0,1]$, normalization processing is used as:

$$\bar{C}(P^t) = C(P^t)/C(P^0), \tag{5}$$

where $\bar{C}(P^t) \in [0,1]$. The smaller the value of $\bar{C}(P^t)$, the closer the solution set to the Pareto optimal boundary.

2.4. Validity Test

In order to verify the improved performance of the proposed algorithm, two benchmark functions are used for comparison:

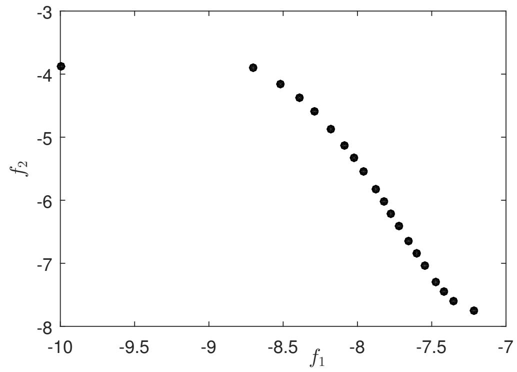
The test function 1:

$$\begin{aligned}
&minF_1 = (f_1(x_1,x_2), f_2(x_1,x_2)),\\
&f_1 = -10e^{-0.2\sqrt{x_1^2+x_2^2}},\\
&f_2 = -\sum_{i=1}^{2}(|x_i|^{0.8} + 5sinx_i^3),\\
&x_1 \geqslant -5; x_2 \leqslant 5,
\end{aligned}$$

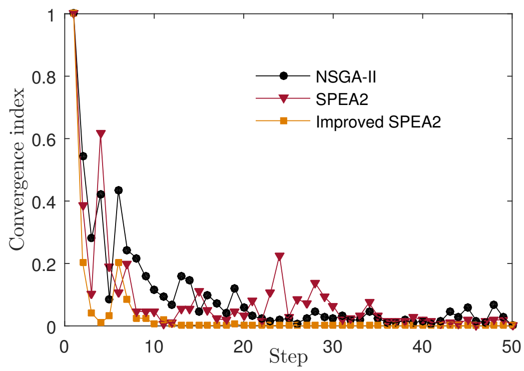
The test function 2:

$$\begin{aligned}
&minF_2 = (f_1(x,y), f_2(x,y)),\\
&f_1 = x,\\
&f_2 = (1+10y) \times [1 - (\frac{x}{1+10y})^a - \frac{x}{1+10y}sin(2qx\pi)],\\
&x \geqslant 0; y \leqslant 1; q = 4; a = 2.
\end{aligned}$$

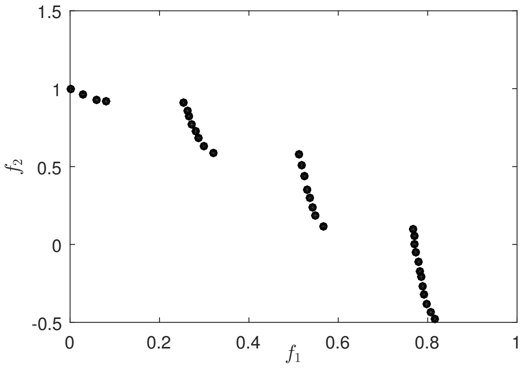
The experimental parameters are as follows: the initial population size is 60, the external archive size is 30, the crossover probability is 0.6, and the mutation probability is 0.3. All the experimental selection strategies are based on the binary tournament selection method. Figure 3a,c are the distribution of the Pareto optimal set obtained by the improved SPEA2 method for two test functions. The results show that the optimal solution is evenly distributed over the entire Pareto boundary, and there is no clustering phenomenon of optimal points. Figure 3b,d are the comparisons of convergence performance between the improved algorithm and the standard algorithm SPEA2 and NSGA-II. The convergence ability of the improved algorithm is improved. The traditional SPEA2 and NSGA-II method are difficult to converge to the final Pareto boundary, and the convergence ability of the improved algorithm is improved. The reason is that the local search improves the probability of searching the global optimal solution. At the same time, the improved crossover operator can reduce meaningless operations, make the crossover operation more targeted, reduce the computational burden and improve the convergence ability. The test shows that the improved algorithm is effective.



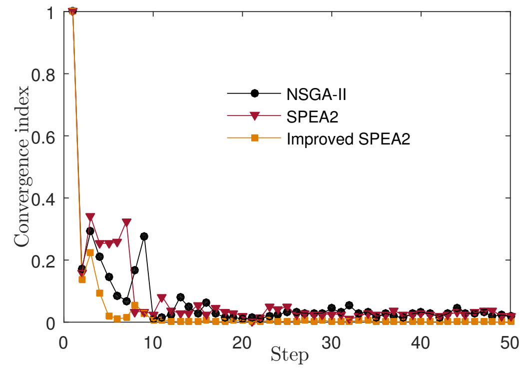
(**a**) Pareto boundary of Function 1



(**b**) Comparison for Function 1



(**c**) Pareto boundary of Function 2



(**d**) Comparison for Function 2

Figure 3. Pareto boundary of two test functions and comparison of convergence results of different methods.

3. Multi-Objective Decision-Making in Enterprise Investment

In the traditional sense, profit oriented investment decisions can be expressed as following. The annual investment budget of one enterprise in one n year plan period is b_i, $(i = 1, 2, ..., n)$, and there are m different projects that can be invested. d_{ij} is known to represent the profit from the jth $(j = 1, 2, ..., m)$ per unit investment project in year i. The goal is to maximize the total profit during the planned period. However, the profit based single objective decision often fails to take account of the complexity of investment. The evaluation of an investment is often carried out from many angles, such as investment profits, investment risks and the environmental cost of the project. In this work, investment profits, investment risks and environmental cost of the project are considered in the investment decision-making. In economics, environmental cost (EC) [44] can be understood as the consumption of energy corresponding to investment.

Table 1 shows the investment plan to be determined, in which the variable I_{ij} represents the capital invested in the jth investment project in year i, R_i is the investment risk of ith project, and E_i is the energy consumption per unit output of ith project. Thus, the optimization objective considering investment risk, investment profit and environmental cost can be expressed as:

$$
\begin{aligned}
\max \quad & \text{Profit} = \sum_i \sum_j d_{ij} I_{ij}, \\
\min \quad & [\text{Risk} = \sum_i \sum_j R_j I_{ij}, \text{EC} = \sum_i \sum_j E_j d_{ij} I_{ij}].
\end{aligned}
$$

Among them, the total amount of investment in the ith year should not exceed the investment budget in the ith year, and the investment amount should not be negative. The above model is a general investment planning model, which can be slightly modified in practical application and extended to other economic activities (such as: selection of construction projects, utilization of foreign capital). In this model, the values of d_{ij}, R_j, and E_j are known as inputs of the investment optimization decision model, which are needed to solve the multi-objective optimization decision problem. I_{ij} is the optimization parameter, which is the optimized output of this paper. Profit, risk and environmental consumption are the optimization objectives. The purpose of investment decision-making is to seek the optimal investment decision (i.e., the optimal value of I_{ij}) to maximize investment profit and minimize investment risk and environmental consumption.

Table 1. Description of investment parameters.

Year	Projects					
	1	**2**	$\cdots$	j	$\cdots$	m
1	I_{11}	I_{12}	$\cdots$	I_{1j}	$\cdots$	I_{1m}
2	I_{21}	I_{22}	$\cdots$	I_{2j}	$\cdots$	I_{2m}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
i	I_{i1}	I_{i2}	$\cdots$	I_{ij}	$\cdots$	I_{im}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
n	I_{n1}	I_{n2}	$\cdots$	I_{nj}	$\cdots$	I_{nm}
Risk	R_1	R_2	$\cdots$	R_j	$\cdots$	R_m
EC	E_1	E_2	$\cdots$	E_j	$\cdots$	E_m

A specific investment plan is used as a case to discuss the specific application of ant colony algorithm. During the three-year planning period, an enterprise needs to invest four development projects as follows: Project A can be invested at the beginning of the first year to the third year. It is estimated that every 10,000 dollars of investment can make a profit of 2000 dollars from the investment projects, and the annual capital and profits of that year can be reinvested into the investment plan, while project B needs to be invested at the beginning of the first year. After two years of investment, it can make a profit of 5000 dollars per 10,000 dollars, and it can be reinvested into the investment plan. However, the maximum investment for the project should not exceed 200,000 dollars, while project C needs to be invested at the beginning of the second year. After two years, every 10,000 dollars of investment can make a profit of 6000 dollars per year, but the amount of investment for this project should not exceed 100,000 dollars, while project D needs to be invested in the third year, with a profit of 4000 dollars per 10,000 dollars, but the amount of investment for the project is limited to 150,000 dollars. During the entire planning period, the amount of investment that the enterprise can invest is 300,000 dollars. What needs to be solved is which kind of investment plan can make the enterprise obtain the maximum profit in the whole investment plan. However, there will be risks for every investment. Enterprises always expect the least risk when they invest. The risk parameters associated with each investment are $R = [0.1, 0.25, 0.5, 0.75]$. At the same time, enterprises expect the environmental cost of investment as low as possible. Here, the environmental cost coefficients are $E = [0.15, 0.3, 0.2, 0.4]$.

This is a problem of determining the optimal investment plan. There are many feasible plans to satisfy this investment plan. Due to the limitations of various investment conditions, it is difficult to find the optimal investment plan by general methods. The optimization objective can be expressed as:

$$
\begin{aligned}
\max \quad & \text{Profit} = 0.2I_{1A} + 0.2I_{2A} + 0.2I_{3A} \\
& +0.5I_{1B} + 0.6I_{2C} + 0.4I_{2D}, \\
\min \quad & \text{Risk} = 0.1(I_{1A} + I_{2A} + I_{3A}) + 0.25I_{1B} \\
& +0.5I_{2C} + 0.75I_{2D}, \\
\min \quad & \text{EC} = 0.15 \cdot (0.2I_{1A} + 0.2I_{2A} + 0.2I_{3A}) \\
& +0.3 \cdot 0.5I_{1B} + 0.2 \cdot 0.6I_{2C} + 0.9 \cdot 0.4I_{2D}, \\
\text{s.t.} \quad & I_{1A} + I_{1B} \leqslant 30 \\
& I_{2A} + I_{2C} \leqslant 30 - I_{1B} + 0.2I_{1A} \\
& I_{3A} + I_{3D} \leqslant 30 + 0.5I_{1B} + 0.2I_{1A} + 0.2I_{2A} - I_{2C} \\
& I_{2B} \leqslant 20; I_{2C} \leqslant 15; I_{3D} \leqslant 10 \\
& I_{1A} \geqslant 0; I_{2A} \geqslant 0; I_{2A} \geqslant 0 \\
& I_{1B} \geqslant 0; I_{2C} \geqslant 0; I_{3D} \geqslant 0.
\end{aligned}
$$

The proposed method is used to solve this problem. The model parameters are as follows: the initial population size is 300, the external archive size is 50, the crossover probability is 0.6, and the mutation probability is 0.3. Firstly, we only consider investment profit and investment risk as optimization objectives.

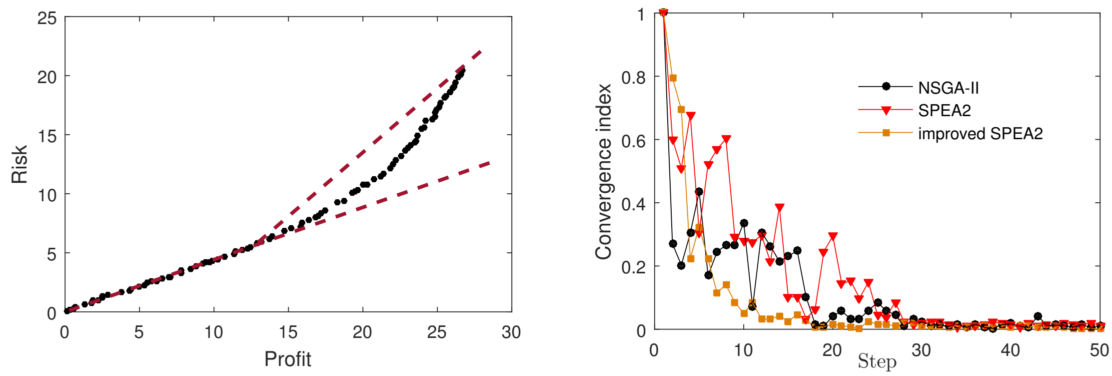
Figure 4a gives the Pareto optimal boundary considering profit and risk. It can be seen from Figure 4a that profits and risks are positively correlated. When the risk is less than 8, the profit and risk are almost linear, but when the profit is greater than 16 (within the dashed line of Figure 4a), the risk will accelerate. This conclusion can provide data support for decision-makers, who can maximize profits according to the risk range they can bear. Table 2 gives a strategy for investment only considering profit. Table 3 gives an investment strategy considering both profit and risk. The total profit of the investment strategy given in Table 2 is 275,000 dollars, but if the risk is taken into account, the risk of the investment strategy is 22.24. Table 3 gives an investment strategy considering both profit and risk. The total profit of the investment strategy is 23.88, but the risk is reduced to 15.64. Under Table 3 investment strategy, the profit is only 13.16% less than the investment strategy of Table 2, but the risk is reduced by 29.68%. From the above results, it can be seen that, while maximizing profits, minimizing investment risks is particularly important for enterprises. Figure 4b gives a convergence comparison between the improved SPEA2 method and the methods of NSGA-II and SPEA2. As can be seen from Figure 4b, for the complex solution space of investment decision, the method in this paper can converge to the Pareto optimal boundary faster than the other two methods, and the final convergence result is more stable, which indicates that the results obtained by improved SPEA2 method are more close to the Pareto optimal boundary than the other two methods.

Table 2. Investment strategy (only profit is considered).

Year	A	B	C	D
1	12.5	17.5		
2	0		15	
3	16.25			10

Table 3. Investment strategy (profit and risk are considered).

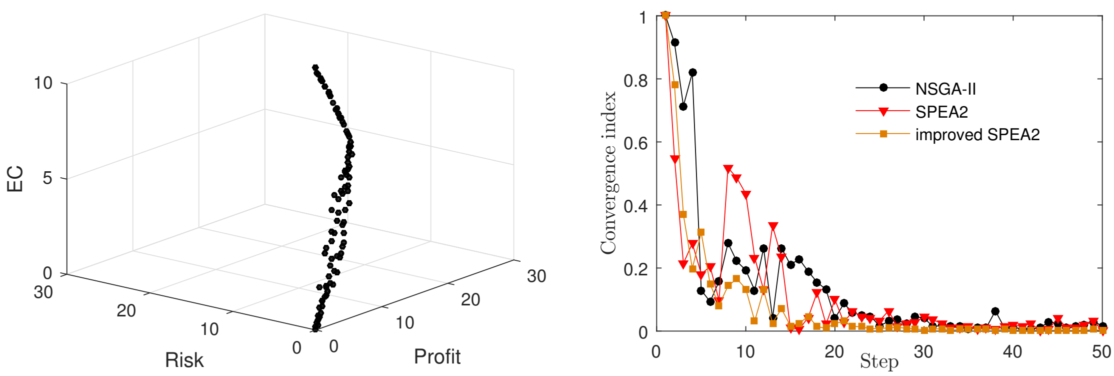
Year	A	B	C	D
1	16.52	13.47		
2	7.27		11.89	
3	19.66			3.33



(**a**) Pareto boundary for profit and risk (**b**) Pareto boundary for three targets

Figure 4. Pareto boundary for investment decision-making.

At present, environmental protection has become the consensus of the whole society. How to reduce carbon emissions per unit output while gaining profits is a problem that enterprises need to consider at present. Figure 5a gives Pareto boundaries for investment strategy optimization considering investment profits, investment risks and environmental costs. In order to more intuitively respond to the conclusions given in Figure 5a, Figure 6 shows the plane analysis of Figure 5a. As can be seen from Figure 6, from a trend perspective, profit is positively related to risk and EC. After the profit reaches 230,000, the risk will accelerate. After the profit reached 220,000, EC rose rapidly. In addition, we can get an interesting phenomenon from Figure 5. Under different investment strategies, sometimes the risk increases slightly, while the EC may reduce a lot, while the profit does not change much. This result is consistent with many industrial investment phenomena in reality.



(**a**) Comparison for profit and risk (**b**) Comparison for three targets

Figure 5. Comparison of convergence results of different methods.

Tables 4 and 5 give two different investment strategies. These two investment strategies are all Pareto optimal solutions. The profit, risk and environmental costs under Table 4 are 13.256, 7.529 and 3.252, while those under Table 5 are 13.304, 8.31 and 2.245. It can be seen that the total profit under the two investment strategies is similar, but the investment risk in Table 5 is 10.36% higher than that in Table 4, but the EC in Table 4 is 44.9% higher than that in Table 5. This shows that the choice of investment strategy has a great impact on the final results, which also shows the necessity of optimization model in this paper.

Table 4. Investment strategy I.

Year	A	B	C	D
1	9.34	9.57		
2	2.98		5.22	
3	13.26			0.559

Table 5. Investment strategy II.

Year	A	B	C	D
1	13.60	2.41		
2	3.17		8.45	
3	18.10			0.148

Figure 7 shows the average convergence results of the optimization model 300 times. From Figure 7a, it can be seen that the improved SPEA2 algorithm can approach the optimal Pareto boundary in only 15 steps for bi-objective optimization, and the final $\bar{C}(P)$ value is less than 0.008. However, SPEA2 and NSGA-II methods need more than 20 steps to approach the Pareto boundary, and the final $\bar{C}(P)$ value is always greater than 0.025. The result shows that the traditional SPEA2 and NSGA-II methods are difficult to reach the Pareto boundary, which is due to the insufficient local search ability of the algorithm. Figure 7b shows that the improved SPEA2 algorithm can reach the nearby Pareto boundary in about 20 steps. Because the three-dimensional search space is larger than the two-dimensional search space, the convergence rate is lower than that in Figure 7a. However, this method can effectively stay in the area near the Pareto boundary, and the final $\bar{C}(P)$ value is less than 0.008. The convergence speed of the other two methods is slower than that of the proposed method, and the final solution set is far from the real Pareto boundary. The above experiments indicate that the improved method can effectively solve the multi-objective optimization problem of enterprise investment decision-making.

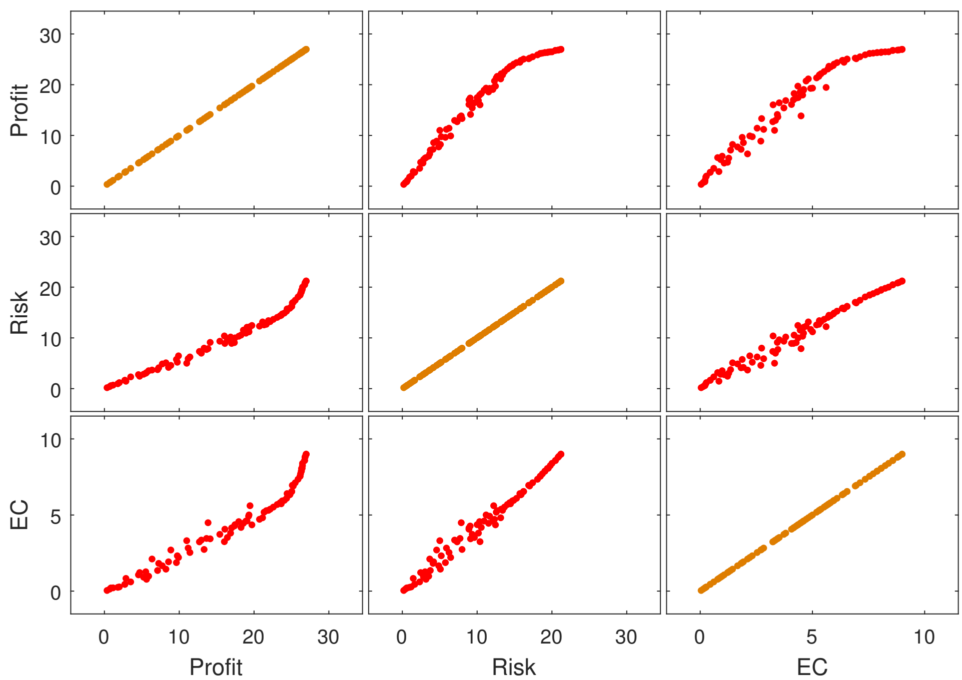
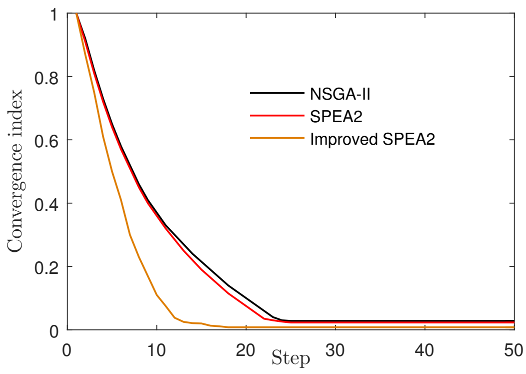
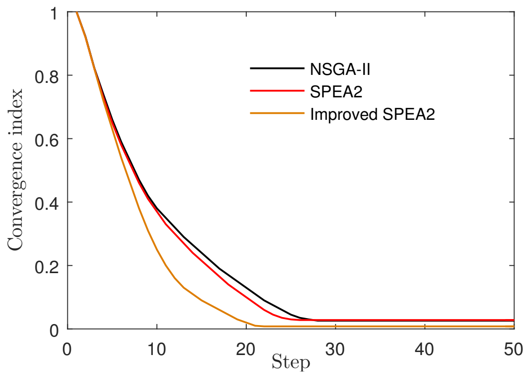


Figure 6. The description of the SPEA2 algorithm.



(**a**) Comparison for profit and risk



(**b**) Comparison for three targets

Figure 7. Mean convergence comparison of 300 experiments.

4. Conclusions

How to determine the investment plan scientifically and create the greatest value with limited funds has attracted more and more attention. The traditional way of investing is based on single objective decision-making, that is, profit maximization. However, due to the influence of many factors, profit-based optimization often fails to measure the whole scheme comprehensively. This paper establishes a multi-objective evaluation index system based on profit, project risk and environmental cost, and makes multi-objective optimization decision for enterprise investment projects. Facing the high complexity of investment decision-making space, traditional multi-objective optimization methods pay too much attention to global search ability because of pursuing convergence speed and avoiding falling into local optimum, while local search ability is insufficient, which makes it difficult to converge to Pareto optimal boundary. To solve this problem, this paper uses an improved SPEA2 algorithm to optimize the multi-objective decision-making of enterprise investment. In this method, an external archive set is set up separately for local search after genetic operation, which guarantees the global search ability and also has strong local search ability. At the same time, the crossover operator and individual update strategy are improved to further improve the convergence ability of the algorithm while maintaining a strong diversity of the population. For the investment optimization problem discussed in this work, we need to know the unit profit, investment risk and investment environment consumption under different investment conditions. The optimal result obtained in this paper is the annual investment amount for different investment products. Of course, there may be other constraints on investment optimization. This work presents a general methodology to solve these investment problems. The experimental results show that the improved method has faster convergence speed than the traditional NSGA2 and SPEA2 algorithms, and the optimization results are closer to the Pareto optimal boundary. Through the optimization of investment by this method, a series of alternative Preto optimal investment schemes can be provided for decision makers, which can optimize environmental costs and profits within a certain risk tolerance range. However, the algorithm can continue to optimize in the following aspect: the speed of this algorithm for a large-scale investment portfolio optimization problem is not ideal, how to further optimize the genetic and mutation operations to improve the search speed and search efficiency is worth further study in the future.

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