Design of New Test Function Model Based on Multi-objective Optimization Method

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Abstract. Space partitioning method, as a new algorithm, has been applied to planning and decision-making of investment portfolio more and more often. But currently there are so few testing function for this algorithm, which has greatly restrained its further development and application. An innovative test function model is designed in this paper and is used to test the algorithm. It is proved that for evaluation of space partitioning method in certain applications, this test function has fairly obvious advantage.

Keywords: Multiple-objective optimization, test function, investment portfolio, model design, space partitioning method

1. Introduction

Test function is an important tool for algorithm evaluation. Generally it evaluates an algorithm's performance from 3 aspects – time complexity, distribution and convergence. Whitley^[1] proposed a guideline for test function design in 1996. Deb^[2] divided the design method of test function into three types. In addition, the test function proposed by literature^[3] in 1999 is widely accepted. A test function of alterable decision variables dimension was proposed in the literature^[4]. An index for distribution

assessment proposed by Schott, et al^[5] is the most popular parameter now. In 2010, Ishibuchi et al^[6] proposed to evaluate the fitness of the individual using different Scalarizing Functions in MOEA/D at the same time. In recent years, new test functions are proposed one after another. Some of them are already well-known such as the test method based on non-dominated sorting proposed by Srinivas^[7], the test method based on genetic algorithm proposed by Deb^[8], and the scalable multi-objective test toolkit proposed by Huband^[9].

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The test function must be closely related to the problem solved by the algorithm, in other words, individualized test function shall be adopted according to characteristics of the problem to make it worthy. A large portion of current functions are universal functions based on historical data and complex solution; there are quite few specific test functions facing certain type of problems. In view of the above limitation, a new test function for space partitioning application in investment portfolio as well as the performance measurement index is designed in this paper. Considering the requirement of portfolio on risk scattering, the design makes a point of test stability and distribution uniformity; considering the investor may want to control and intervene in the decision-making process, this test function is designed to be visualized and controllable.

Since the test function is designed for space partitioning method, distribution uniformity has to be the most important evaluation index. The solution set which distributes evenly can not only provide better options to the decision-maker, but also affect search capability of the algorithm to a large degree^[10]. There are multiple possible reasons for nonuniform distribution of population. For example, the target function is nonlinear or has multiple variables; parameters of different target functions are interrelated; nonlinear mapping exists between decision variables and

parameters; the Pareto frontier is inconsecutive^[11], etc. Therefore the test function proposed in this paper is designed not only to avoid that the population fall in the optimal zone of a single target function, but also to reflect restrictive relation between target function and solution through assessing the distribution uniformity. Most algorithm just considers the impacts of the entirety on the individuals and does not consider the impacts between individuals. But in some practical cases, the affect is although small, but can't be ignored. Therefore, this article fully considers the influence between individuals, and also screens the running solution and performs maintenance on the external population by using test function.

The algorithm proposed in this paper showed great superiority in the application field which have high request for dispensability. For example, in specific application of portfolio decision-making and planning, the investor values risk diversification of portfolio, avoid the combination plan is too single and close, and also avoid deviating from the actual. It is the major need for avoiding the interest rate risk. Correspondingly, the stability and distribution evenness were highly stressed during the designing of the test algorithm.

2. Experimental

Firstly define the test function as:

$$TES_i = \alpha^2 + \beta \frac{K}{k} \quad (1)$$

i is the individual code; α is the number of individuals which fall in the grid where i stays; β is the number of individuals which fall in adjacent grids; K is the number of all possible grids in adjacent region; k is the number of grids in valid adjacent regions. Higher TES_i represents smaller fitness of individuals. Reason is that in a certain region, more densely the individuals are distributed, less contributions they make to the population. Accordingly these individuals have lower chance to be chosen. The evaluation of an algorithm's performance shall also include deviation of its result to the actual result. Therefore the fuzzy expert evaluation system shall be set. First step is to integrate opinions of the experts and regulate them as Pro_i value, which is called as expert evaluation index. Then the index can be screened and tested as a decision factor after TES_i . The secondary fuzzy expression of the test function is:

$$TES^*_i = \alpha^2 + \beta \frac{K}{k} + Pro_i \quad (2)$$

Then grant weight to two evaluation aspects; the secondary fuzzy expression changes to:

$$TES^*_i = W_T(\alpha^2 + \beta \frac{K}{k}) + W_P Pro_i \quad (3)$$

It shall satisfy:

$$W_T + W_P = 1 \quad (4)$$

W_T is objective weight; W_P is subjective weight. The calculation procedure without expert evaluation index shows as following:

- Step 1. Define scale of the population.
- Step 2. Get TES_i value of the solutions sets.
- Step 3. Re-rank --- according to TES_i .
- Step 4. Compare the results of two ranking and evaluate the algorithm.
- Step 5. Move out or move in individuals from external population according to the result of step 4.
- Step 6. Maintain the population according to Pro_i .

3. Simulation

The original test results generated by using method of literature^[12] are shown in table 1. Then re-rank these results by TES_i value using the method proposed in this paper. The new results are shown in table 2.

Table 1 Original Test Results

No.	1	2	3	4
Indivi dual	18,(4,2-1, 2.000000)	5,(4,2, 2.000000)	4,(5,2-1, 2.400000)	1,(5,2-2, 2.400000)
TES_i	7	7	7	7
No.	5	6	7	8
Indivi dual	6,(3,1, 2.800000)	15,(6,2, 2.800000)	22,(3,4, 2.800000)	25,(8,1, 3.000000)
TES_i	6.3	6	6.3	6.3

No.	9	10	11	12
Indivi	14,(4,4-1,	21,(4,4-2,	24,(7,2,	8,(5,4,
dual	3.200000)	3.200000)	3.200000)	3.600000)
TES _i	7.2	7.2	7	5.8
No.	13	14	15	16
Indivi	23,(8,2,	3,(7,3-1,	13,(7,3-2,	19,(6,4-1,
dual	3.600000)	3.800000)	3.800000)	4.000000)
TES _i	10.8	11	11	7.4
No.	17	18	19	
Indivi	11,(8,3,	20,(8,3,	17,(7,4,	
dual	4.200000)	4.300000)	4.400000)	
TES _i	12	12	9	

Table 2 New Test Results ranked by TES_i value

No.	1	2	3	4
Indivi	8,(5,4,	15,(6,2,	6,(3,1,2.8	22,(3,4,
dual	3.600000)	2.800000)	00000)	2.800000)
TES _i	5.8	6	6.3	6.3
No.	5	6	7	8
Indivi	25,(8,1,	18,(4,2-1,	5,(4,2,	4,(5,2-1,
dual	3.000000)	2.000000)	2.000000)	2.400000)
TES _i	6.3	7	7	7
No.	9	10	11	12
Indivi	1,(5,2-2,	24,(7,2,	14,(4,4-1,	21,(4,4-2,
dual	2.400000)	3.200000)	3.200000)	3.200000)
TES _i	7	7	7.2	7.2
No.	13	14	15	16
Indivi	19,(6,4-1,	17,(7,4,	23,(8,2,	3,(7,3-1,
dual	4.000000)	4.400000)	3.600000)	3.800000)
TES _i	7.4	9	10.8	11
No.	17	18	19	
Indivi	13,(7,3-2,	11,(8,3,	20,(8,3,	
dual	3.800000)	4.200000)	4.300000)	
TES _i	11	12	12	

Through comparison and analysis of the above two ranking results, the algorithm can be evaluated. It shows that the algorithm has comparatively low congestion and good distribution.

4. Conclusions

Through the above experimentation, it shows that the test function considered not only the whole's impact on the individuals, but also the individuals' impacts to each other. In the experimentation, the test function was used to screen data and maintain the external population; it showed the interactions among target functions and interactions among solutions. It not only tested the algorithm, but also optimized distribution of the algorithm.

Since the algorithm tested is mainly applied in the investment portfolio area, higher stability is required. Therefore the algorithm has adopted a selection mechanism integrating elite selection, random selection and test selection. Concerns over random issues, sensitivity analysis and uncertainty analysis of intervals are still to be studied in future practice; moreover how to apply the test function in more complex dynamic situation is also the target for future development.

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