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Application Research on Improved Particle Swarm Computational Intelligence Algorithm for Multiobjective Optimization

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ABSTRACT

In today's world, optimization problems are becoming increasingly prominent, and the progress in optimization technologies can not only bring considerable economic benefits but also highlight their outstanding social value, making significant contributions to the sustainable development of the ecological environment. Due to their educational positioning and disciplinary development needs, local application-oriented universities tend to overlook the optimization and development of ideological and political theory courses in their growth, leading to lagging reforms in ideological and political education and suboptimal teaching outcomes. To enhance the teaching effects in local application-oriented universities, it is essential to scientifically design class contents, actively carry out practical teaching, adapt to the needs of the times, build an "Internet + Courses" online teaching platform, and continuously innovate teaching modes of courses.

Keywords: *Educational Courses, Online Teaching, Particle Swarm Computation, Multiobjective Optimization*

1. Introduction

In constructing higher education institutions, we must emphasize cultivating students' moral character and abilities rather than simply relying on provided vocational skill training. It is imperative to strengthen the study and practice of ideological and political theory courses, making them the core qualities we cultivate [1]. The particle swarm algorithm boasts high efficiency, compact structure, small parameter variations, complete information transmission, easy manipulation, and strong robustness. Hence, it has been successfully applied to the field of multi-objective optimization. Integrating it with the latest algorithms, such as neural networks and neural network communities, effectively solves complex multi-objective problems. With technological *characteristics, has gained attention, not only domestically but also globally in academia, despite its increasing application scope. Nonetheless, some core challenges still need to be overcome. In dealing with complex multi-objective optimization problems [2], we face numerous challenges, including achieving efficient outcomes under the interaction of various factors and preventing the algorithm from falling into local optimum. Furthermore, we must adopt appropriate techniques, like optimal particle selection, storage, and maintenance [3], while ensuring diversity. This paper aims to explore the optimization of the multi-objective particle swarm algorithm, including constrained, unconstrained, and partially constrained cases, and attempts to propose improvements from various angles in hopes of achieving better results in the field of ideological and political education.*

2. Related Work

Many applied universities still employ relatively outdated teaching methods for ideological and political courses [4]. They usually resort to dull lecturing methods, exhausting all theoretical knowledge in the classroom. Even when using multimedia tools, they merely perform superficial drills without a profound exploration. As we are in a dynamic and rapidly changing information era, we must continually update our educational tools to accommodate the needs of post-95 college students for digital tools. We should strive to explore various innovative educational models, like online education, MOOC, and flipped classroom, to better cater to the requirements of post-95s college students for digital tools. Only through continuous reform can we make our ideological and political courses more appealing and successful. Early multi-objective optimization technologies, with their strong computing power, precise models, high-precision computational structures, and high-precision computational processes, provided decision-makers with a more efficient decision model, including weighted summation [5], constraint method, max-min method, and other new computational techniques. Their advantage lies in more precise computational structures, simpler processes, and more accurate results. Because it was impossible to perfectly meet multiple objectives simultaneously, the performance of MOP was severely damaged, thus reducing the overall cost-effectiveness. Moreover, due to the variability of the structure and function of MOP, its usage was somewhat limited, which hindered its sustainability and scalability. Therefore, Sub-I is striving to find a more efficient and reliable MOP better to handle the growing optimization challenges [6]. Haiyan Y and other researchers proposed a new hybrid algorithm, which can effectively optimize complex optimization processes and improve efficiency without affecting overall performance. This algorithm uses the PSO algorithm and distributed search technology, which can effectively improve the reliability and manipulability of optimization results. Furthermore, it can also effectively help researchers optimize fertilization methods for oil crops [7]. Ran and other researchers used the frontier technology of the NSGA-II algorithm to develop a fast, non-dominated sorting strategy to realize an effective Firefly Algorithm. It can carry out an orderly individual search according to different dominance relationships and adjust the search method according to needs to ensure the accuracy and reliability of the search [8]. Chen T's diversification techniques brought significant breakthroughs to developing the MOPSO algorithm. His multi-strategy fusion algorithm [9].

3. Materials and Method

3.1. Concept and Application Method of Constraint Optimization Problem

A constraint optimization problem is a special kind of optimization method. Its emergence allows many non-inferior solutions to be effectively addressed without rendering the entire optimization process futile. COP is a complex mathematical programming problem, the solution of which is extremely difficult. Therefore, researching effective constraint optimization methods is crucial for improving optimization efficiency and computational precision. The success of constraint optimization problems depends not only on an effective constraint control mechanism but also requires applying the latest search techniques. Depending on the number of objectives, constraint optimization problems can be divided into single-objective optimization and multi-objective optimization. To better meet specific needs, we describe single-objective optimization problems as follows:

$$g_i(\vec{x}) \leq 0, i = 1, 2, ..., q \tag{1}$$

The translation for the text you provided would be:

Where, = (x, r... yxp)EXc in n-dimensional decision space, = (X, x..., x,) represents the decision vector, and f() is the function used to specify the objective. g,() ≤ 0 (i=1,2,…,q) are the inequality constraint functions, totaling q; h(x)=0 (i=q+1,…,m) are the equality constraint functions, totaling m-q. In the decision space, X is a 9-dimensional cuboid, X'≤ xsx", x,' and x" are the upper and lower bounds of the kth dimension respectively, where k=1 to n. The decision space is referred to as m solutions when m constraint conditions are satisfied, and these solutions constitute a complete solution space structure. In the case of constrained optimization, constraint conditions can be regular shape variables or irregular shape variables. For instance, when individual x meets the ith constraint, its constraint compliance situation can be described by the following formula:

$$G_i(x) = \begin{cases} max\{g_i\,(x), 0\},\ 1 \le i \le q \\ max\{|h_i\,(x)| - \delta, 0\},\ q+1 \le i \le m \end{cases} \tag{2}$$

In this formula, there are m types of constraint conditions. When these constraints are transformed into different forms, the possible allowable value a might be 0.001, or it could be 0.0001. Therefore, this method can be used to measure an individual's compliance with certain constraints, which is to say, this situation is referred to as constraint compliance.

$$v(x) = \sum_{j=1}^{m} G_i(x) \tag{3}$$

Due to constraints in multi-day marker optimization problems, the optimal solution set must be established based on the feasibility of the decision vector. Therefore, the optimization process needs to not only satisfy the feasibility of the decision vector but also consider the fittingness of the optimal solution set, distribution characteristics, and other factors. Consequently, compared to single-objective constrained optimization, the solving process for multi-objective constrained optimization is more complex and challenging.

3.2. Core Concepts of Particle Swarm Optimization Algorithm

The PSO algorithm is an effective data mining technique. It can determine the optimal search plan based on bird characteristics such as species, quantity, size, etc. It can convert these bird characteristics into "particles", and these types may mutate due to the characteristics of the species, but the "particles" may also mutate as a result, enabling the PSO algorithm to effectively extract meaningful search plans. Comparative analysis reveals that combining the best state of the population with the best individual state can realize the iteration of particles, just as shown in Figure 1.

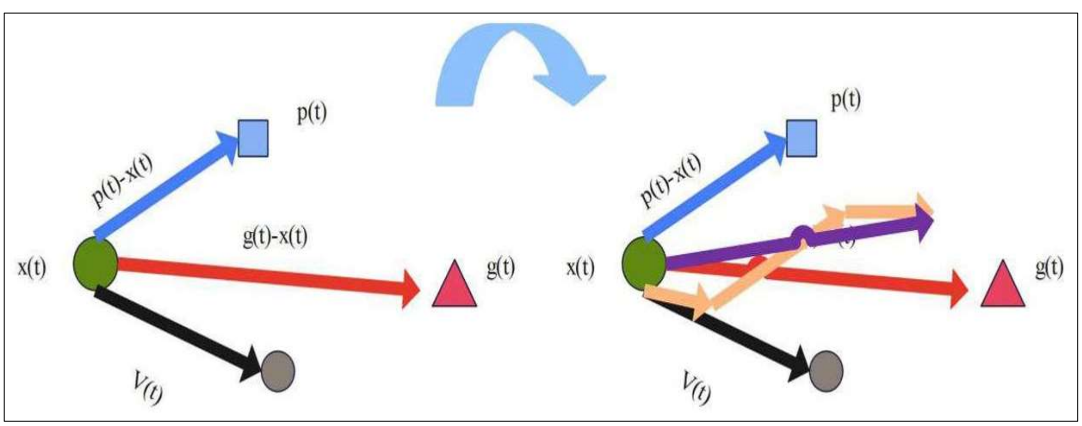

Figure 1. Movement of Particles in Decision Space

In Figure 1, the velocity v of particle i at the next moment (t+1) is determined collectively by its current velocity, its current optimal position, the current maximum and minimum, and the current maximum gb(t). They will move from the current position x, (t), to a new position according to the updated velocity and reach the maximum at t+1. With the continuous advancement of the "leader", the particle swarm continuously explores the best solution in the decision space, achieving more efficient results. The optimization steps of the PSO algorithm include: firstly, determining the position and movement trajectory of each particle according to the expected population size; secondly, analyzing the performance of each particle according to the fitness function, so as to determine the best combination in the population and the best individual combination. We can improve the original numerical model through the PSO algorithm to obtain new orientations and motion characteristics. In addition, we can also evaluate the current numerical model, and if it is found to be closer than the original model, we can consider it as a new model. The collective wisdom and each member's unique ability are integrated through continuous iterations to achieve optimal global effects. The PSO algorithm formula (3) consists of three main components: firstly, it considers the operation in the early stage, i.e., the previous operation speed and its impact on the current operation. Secondly, it considers the stability of the current operation, i.e., the accuracy of the operation and its contribution to the previous operation. The third element is how to affect the operation of the population. They can make use of the different geographic locations of different individuals for effective communication and can achieve mutual learning, communication, and understanding, thus achieving effective resource allocation. These three elements will affect the operation of the population. The first part is the previous rate, which brings vitality to the particle to avoid blank searches. The second part is the individual cognition, the third part is the information transmission between species. Under the premise of continuous development of individual characteristics, accept and digest valuable information, thereby achieving rapid discovery and effective solving of problems.

4. Results

4.1. Experimental Design

This paper will use the five minimization functions of the ZDT benchmark function test set, representing ZDT1, ZDT2, ZDT3, ZDT4, and ZDT6. We found that the PF values of these parameters show convex characteristics, while the PF values of ZDT3 and ZDT6 show discontinuous characteristics, and the PF values of ZDT2, ZDT4, and ZDT6 show concave characteristics. Since the Boolean function ZDT5 must be represented in binary, it did not pass the test. In contrast, the decision variables used by ZDT1, ZDT2, and ZDT3 are all 30-dimensional, while ZDT4 and ZDT6 use 10-dimensional decision variables.

4.2. Experimental Results and Analysis

By comparing the AAD-MOPSO algorithm, IMOPSO algorithm, and PCCSMOPSO algorithm, we can better evaluate the reliability of these algorithms when preserving external archive sets. The IMOPSO algorithm uses a new technique that can effectively automatically divide the target space according to needs, thus achieving efficient management. In contrast, the PCCSMOPSO algorithm uses parallel coordinate systems, can manage the external archive set more effectively, and can adjust the congestion of the archive set as needed. Through in-depth research, we found that the AAD-MOPSO algorithm can effectively replace the traditional D2MOPSO algorithm and the DCMOPSO algorithm with congestion distance, thereby achieving the algorithm's integrity. The D2MOPSO algorithm analyzes data to improve the performance of PF, it can provide richer information and meet different needs. In contrast, the DCMOPSO algorithm relies more on non-domination sorting for more efficient computing. To obtain an accurate comparison, we use the initial particle distribution as a reference so that without changing the original basis, we can accurately compare the results of different algorithms and obtain reliable conclusions. Through the ZDT1-ZDT6 algorithm, we can obtain accurate results of the AAD-MOPSO algorithm and IMOPSO algorithm and display their correspondence so that users can directly view them.

As seen in Figure 2, when initializing with ZDT1, ZDT2, and ZDT3, they all adopt the same optimal reference points, resulting in a relatively flat distribution. However, this may potentially reduce their convergence efficiency. Although the complexity of the test functions for ZDT4 and ZDT6 are quite similar, we believe that by adopting this initialization method, a good uniform distribution, broad coverage, and significant reduction in the convergence time of the algorithms can be achieved, leading to satisfactory overall performance. In summary, through its unique initialization mechanism, *the AADMOPSO algorithm greatly improves the particle distribution within the target space and can effectively extend its application range.*

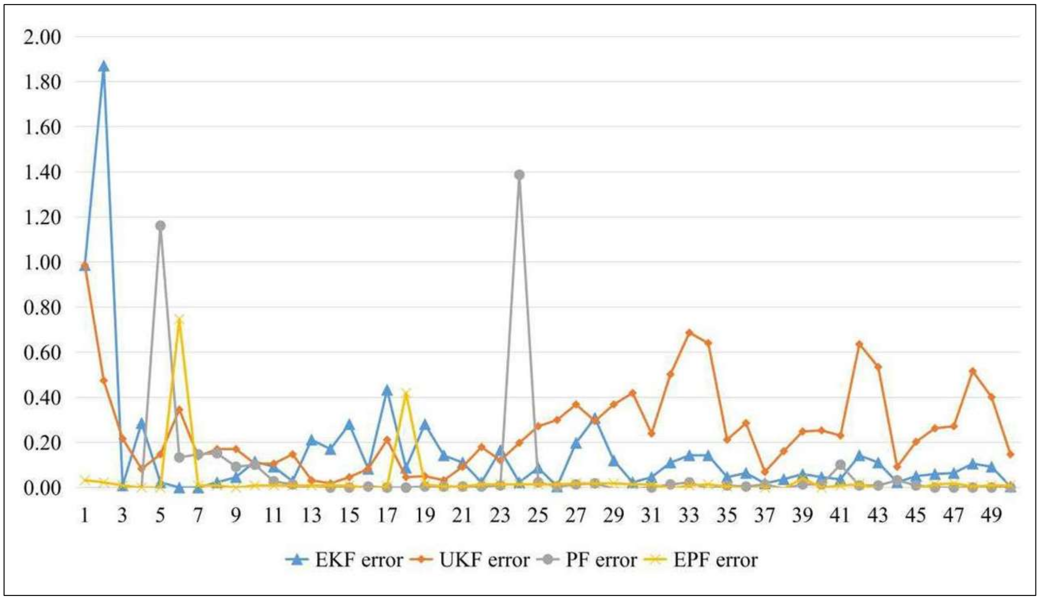

Figure 2. Comparison of Initialization Effects for ZDT1-ZDT6

Figure 3 displays the best performance of the AAD-MOPSO algorithm after 30 runs. To demonstrate the optimization results more clearly, we reduced the AAD-MUPSU boundary to 1 and marked the PF of the five test functions with a red line. The AAD-MOPSO algorithm can effectively map the approximate PF to the actual PF, and this mapping can cover the entire actual PF, thereby enhancing the distributivity of PF. Moreover, the algorithm can introduce boundary particles to change particles in neighbouring areas, thereby improving the optimal solution's global coverage and uniform distribution. To better evaluate the performance of the AAD-MOPSO algorithm, we will compare it

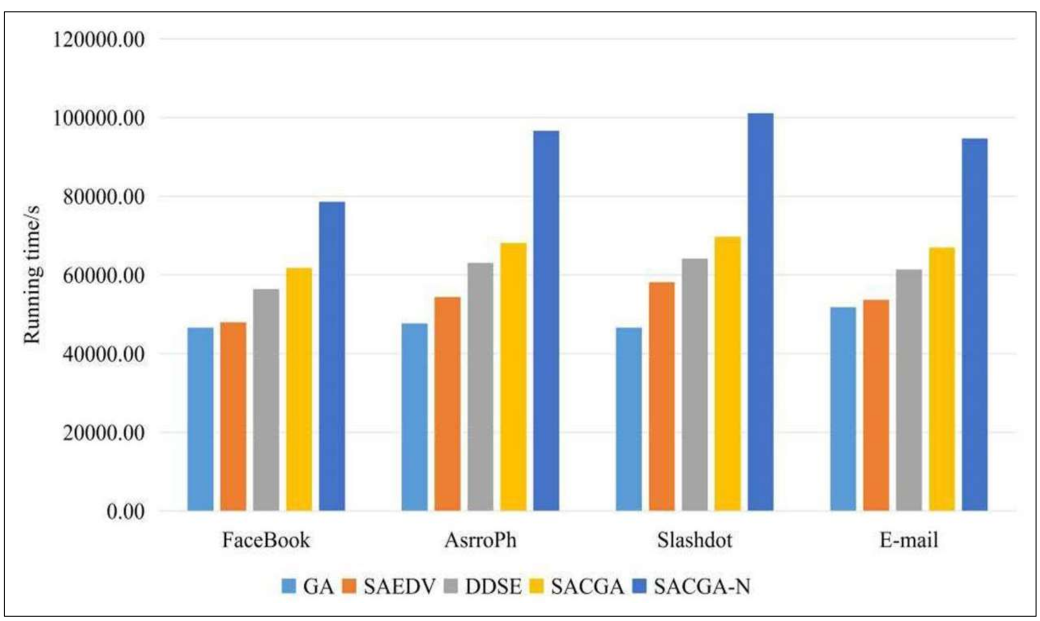

Figure 3. Results of AAD-MOPSO Algorithm

with other algorithms to assess their performance differences. By using the AAD-MOPSO algorithm and six similar algorithms to solve the problem of ZDT measurement functions, we found that, based on these algorithms, we also used the optimization of the SP index and maximized these optimizations in Figure 3. This indicates that the AAD-MOPSO algorithm performs better in dealing with these algorithms. By using ZDT1, ZDT2, and ZDT4, we found that the value of the SP index significantly decreased, demonstrating our solution's clear superiority. This allows our solution to generate smoother PFs and perform well in distribution.

5. Conclusions

In this paper, we conducted in-depth research on three different improved particle swarm algorithms, which can meet various needs without restrictions, thereby providing better results for practical mining development. In addition, we attempted to use these algorithms to better control processes such as mining, processing, and combustion in practice to achieve higher efficiency. By introducing a two-stage constraint particle swarm algorithm of the dual-objective method, we can effectively solve multi-objective optimization problems in ideological and political fields. Based on the dual-objective optimization method, it can achieve two-stage adjustment of constraint optimization to meet various constraint optimization needs. In today's society, all kinds of applied universities need to strengthen the education of students' creativity, criticism, practice, and teamwork. Therefore, in the education process, we must, based on this, reasonably construct ideological and political education in order to cultivate talents with good morals, health, culture, art, and other qualities.

References

[1] Bai, X., Xu, Y., Liu, S. (2021). Research on the regional leading industry selection of "Kashgar urban agglomerations" based on multi-attribute weighted intelligent grey target decision-making evaluation model. *Grey Systems: Theory and Application, 11*(3), 418-433.

[2] Wang, Y. L., Wu, Z. P., Guan, G., et al. (2021). Research on intelligent design method of ship multideck compartment layout based on improved taboo search genetic algorithm. *Ocean Engineering, 225*(2), 108823.

[3] Qing, Y., Zejun, W. (2021). Research on the impact of entrepreneurship policy on employment based on improved machine learning algorithms. *Journal of Intelligent & Fuzzy Systems: Applications in Engineering and Technology, 2021*(4), 40.

[4] Xie, J. (2022). Research on the Dominant and Implicit Integration Mechanism of Mental Health Education in Ideological and Political Education. *Journal of Healthcare Engineering, 2022*(12), 13-19.

[5] Ying, J., Liu, B. (2018). Binocular optical axis parallelism detection precision analysis based on Monte Carlo method. In *Fourth Seminar on Novel Optoelectronic Detection Technology and Application* (pp. 320-327). SPIE, 10697.

[6] Haiyan, Y. (2021). Research on the Coupling Development of Main Melody Songs in the Teaching of Ideological and Political Courses in Colleges and Universities. In *2021 6th International Conference on Modern Management and Education Technology (MMET 2021)* (pp. 295-299). Atlantis Press.

[7] Peng, Z. (2021). Research on the problems and countermeasures of ideological and political education management based on the analysis of big data in the era of convergence media. *Journal of Physics Conference Series, 1744*(4), 042106.

[8] Wucheng, Y., Ling, C., Qingdao, S., et al. (2016). Exploration of new methods of ideological and political education for college students: Integration of new media and construction of micro-environment. In *The Fifth International Conference on E-Learning and E-Technologies in Education (ICEEE2016)* (p. 77).

[9] Chen, T. (2022). Research on the dilemma and breakthrough path of ideological and political education in colleges and universities in the era of big data. *Journal of Higher Education Research, 3*(2), 203-206.