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Research on Computational Intelligence Algorithm Suitable for Complex Optimization Problems

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Abstract

Complex systems widely exist in scientific research and in real term engineering. For most complex systems, people can no longer make reasonable decisions only by empirical judgment and numerical analysis. Instead, it is necessary to use computer technology and find new mechanisms to realize manual intervention and decision support. In multi-objective optimization problems, multiple objectives often conflict with each other. Therefore, it is impossible to use a single solution to make all objectives optimal at the same time, and a set of balanced solutions are usually needed. In this paper, genetic algorithm, particle swarm optimization algorithm and other multi-objective evolutionary algorithms are adopted to study complex optimization problems.

Keywords

Genetic algorithm, particle swarm optimization, multi-objective evolutionary algorithm.

1. Introduction

Traditional mathematical optimization methods, such as gradient descent method and Newton method, usually use the gradient information of the mathematical model of optimization problems to find solutions. These methods can only be used to solve some simple single-objective optimization problems, and the objective function of single-objective optimization problems must be continuous or differentiable. In addition, there are some traditional multi-objective optimization algorithms, such as weighted sum method, E-constraint method and minimum-maximum method. When solving multi-objective optimization problems, most multi-objective evolutionary algorithms tend to choose solutions with better convergence. When the convergence of the solutions is similar, the diversity preservation strategy will be used to select the solutions.

However, as a random search algorithm, evolutionary algorithm does not need gradient information or to consider whether the function is continuous or not. It does not need to pay attention to the concavity and convexity of the function, either. These bring it great advantages in solving highly complex nonlinear optimization problems. The solution of multi-objective optimization problem is a set composed of multiple Pareto optimal solutions. When measuring the performance of multi-objective evolutionary algorithm, the convergence and diversity of approximate solution set are two key factors. Following is a study on complex optimization problems with genetic algorithm and particle swarm optimization algorithm.

2. Genetic Algorithm for Multi-objective Optimization (NSGA2)

The first generation of Non-dominated Sorting Genetic Algorithm (NSGA) is implemented according to the hierarchical relationship between dominant and non-dominant individuals. It has the advantages of accepting optional number of optimization objectives, making uniform distribution of non-dominated optimal solutions and allowing multiple different equivalent solutions. However, it also has shortcomings such as lacking of elite retention mechanism and requiring to preset shared parameters.

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As one of the better genetic algorithms at present, the second generation of NSGA (NSGAII) has the following characteristics: i. a fast non-dominated sorting operator is proposed, which reduces the computational complexity of the algorithm; ii. the congestion degree operator and the comparison rule of congestion degree are put forward. Iii. the strategy of elite selection is put forward, which increases the number of elite individuals. This part of the paper will analyse the processing of NSGA2 algorithm for multi-objective optimization problems from the above characteristics.

Fast non-dominated sorting operator is the most essential feature of NSGA2 algorithm, which is different from other genetic algorithms. Its core idea is to set two parameters Sp and Np for any individual p in the group P. Among them, Sp is a set with an empty initial value, which is used to store all individuals dominated by individual p, and Np is a scalar with an initial value of zero, which is used to record the number of all individuals in the group that can dominate individual p. In this way, for any individual p in the group P, when Np=0, it indicates that no individual in the current group can dominate the individual p. All the individuals in the current group that meet Np=0 are taken out and put into the set F1 as the individuals with the highest non-domination level in the current group, and the non-domination order value of each individual in F1 is given 1. Then, the group Sq dominated by each individual p in F1 is investigated, and the parameter Nq corresponding to each individual q in Sq is subtracted by 1. If Nq-1=0, then the individual q is the individual with the highest non-dominant level in the current group Sq. At this time, the individual q is put into another set Q, and the individuals in Q continue to perform non-dominant ranking. The above operations are repeated until all individuals in the group P have completed the non-dominated ordering.

Crowding degree operator and congestion degree comparison operator are used to ensure good group distribution. The main idea of congestion operator is to judge the density of the environment in which the current individual is located by calculating the Euclidean distance between the current individual and two adjacent individuals. Among them, the greater the distance of crowding degree, the better the distribution of the individual, and vice versa.

Elite retention operator can retain the excellent individuals in the parent group, increase the probability of generating the optimal solutions, reduce the number of iterations and improve the convergence of the algorithm. The elite retention strategy can be described as follows: a parent group Pt with a size of N and an offspring group Qt with a size of N are combined into a group Rt with a size of 2N. Then, non-dominated sorting and congestion distance value calculation are performed for each individual in the group Rt to select the next generation parent group according to the optimization rule.

NSGAII algorithm reduces the computational complexity, improves the distribution of the algorithm to a certain extent, and can effectively select suitable individuals in the group. It is effective in solving low-dimensional multi-objective optimization problems.

3. Particle Swarm Optimization for Multi-objective Optimization (PSO)

Firstly, the specific steps of particle swarm optimization are as follows: i. initialization: Aiming at the optimization problem, the dimension of objective function is determined, and the particle group size, maximum evolution times and search accuracy are set. For each dimension of each particle, an initial position and velocity in the search domain are randomly given, and setting the initial position of each particle as the best position of its own individual. ii. update that velocity and position of each particle according to the particle velocity update formula and the position update formula, and adopt an equal proportion mapping method to ensure that the position and velocity of each particle are within the corresponding search domain range in view of the situation that some particles exceed the boundary of the search domain. iii. calculating the fitness value of each particle. iv. comparing the fitness value of each particle calculated in iii

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with the best fitness value of its own historical individual, if the current fitness value of the particle is less than the best fitness value of the historical individual, it will be taken as the best position of its own historical individual, otherwise it will not change. v. for each particle, compare its fitness value with the global optimal fitness value of the group history, if the fitness value of the particle is less than the global optimal fitness value of the group history, it is taken as the global optimal fitness value of the group history, otherwise it is unchanged. vi. cyclic condition judgment: if that search accuracy is satisfied or the set maximum evolution frequency is reached, the search is terminated and the optimal fitness value and its corresponding position are output. Otherwise, return to ii.

Global mode particle swarm optimization algorithm converges fast, but its robustness is relatively poor. On the contrary, local mode particle swarm optimization algorithm has good robustness, but the convergence speed of particles is relatively slow. Therefore, when using particle swarm optimization to solve different optimization problems, different modes of particle swarm optimization should be selected according to specific conditions.

In order to find the global optimum quickly, inertia weight is introduced, which makes particles keep inertia all the time, and makes them have the trend of expanding new search space, thus improving the exploration ability of new areas. If the inertia weight is large, global search ability of the group is stronger; If the inertia weight is small, local search ability of the group is strong. On the whole, compared with the original particle swarm optimization algorithm, the particle swarm optimization algorithm with inertia weight has higher search accuracy and is relatively more stable.

PSO is not very effective when directly applied to multi-objective optimization problems, and much literature has proposed relative algorithms to solve this problem. For example, the optimal solution evaluation and selection algorithm initializes a particle swarm in the decision variable space, and jointly guides the flight of particles in the decision variable space through each objective function in the multi-objective optimization problem, so that they can finally fall into the non-inferior optimal solution set. Reflected in the objective function space, particles will fall into the non-inferior optimal objective domain.

Particle swarm optimization algorithm can solve complex optimization problems effectively through decision spatial clustering,sub group evolution and local optimal solution adjustment.

4. Strong Pareto Multi-objective Evolutionary Algorithm (SPEA)

SPEA algorithm introduces the optimal preservation strategy by explicitly reserving an external group account. The external group preserves a fixed number of non-inferior solutions. In each generation, the newly discovered non-inferior solution is compared with the present external group and the final non-inferior solution is preserved. SPEA algorithm not only preserves the optimal solutions, but also uses these optimal preserved solutions to participate in genetic operations with the current group to make the group develop along the good region in the search space.

The algorithm first establishes a group P of size N and an external group P'of maximum capacity N'. In the k generation, the optimal non-inferior solution of the group Pt belongs to the first non-inferior layer and is copied to the external group Pt '. After that, the inferior solution of the modified external group is deleted from the group. What remains in the external group is the optimal non-inferior solution of the joint group containing the original optimal preservation solution and the new optimal preservation solution. To limit excessive growth of the external group, its size is limited within the size of N'.

When the group size is larger than N', not all the optimal preservation solutions can be accommodated in the external group. Therefore, researchers proposed a beam method to accomplish this task. Once the new optimal preserving solution is preserved as the next generation external group P_{t+1} ', the algorithm then assigns a fitness value to each individual in the group. Fitness values will be assigned not only to individuals in the current group, but also to individuals in the external group. This fitness allocation method considers that individuals with smaller fitness values are better.

It is obvious that in the SPEA algorithm, the use of a small external group will lead to a certain loss of the optimal preservation solution, whereas the use of a large external group will increase the selection pressure of the optimal preservation solution. Thus it can be seen that the size selection of external group size N 'is the key factor to balance the two, and is also the key to the successful operation of the SPEA algorithm.

But other than that, the advantages of SPEA algorithm can not be ignored since once a solution in the Pareto optimal domain is found, it is saved in the external group. Only when a Pareto optimal solution leading to better distribution is found will the original solution be deleted, which ensures the accuracy and robustness of the algorithm. At the same time, the complexity is reduced because the fitness allocation process is easy to calculate.

5. Niche Pareto Genetic Algorithm (NPGA)

NPGA uses a dynamically updated niche strategy. By using league selection, two individuals i and j are selected from the parent group P, and compared with the sub group T selected from the parent group at the beginning. Each individual i, j is compared with each individual of the sub group. Based on this step, there will be two situations: first, if all individuals in the sub group are not superior to the individual, and at least one individual in the sub group is superior to another individual, the former individual is selected; In the second case, at least one individual in the sub group is superior to the two individuals, or all individuals are not superior to the two individuals. At this time, the two individuals are put into the sub group respectively and their total number is calculated. The individual with the smaller total number wins the league.

An important feature of NPGA is that it is not necessary to specify any specific fitness value of each individual. League selection prefers non-inferior solutions in a random way, only performs pros and cons comparisons within a sub group, and selects parents located in sparse areas in the offspring group when pros and cons cannot be distinguished. Moreover, it is not necessary to allocate clear fitness values, which can avoid subjectivity in the process of fitness allocation. In addition, if the size of the selected sub group is much smaller than that of the parent group, the computational complexity of NPGA is lower and the amount of computation is smaller.

6. Pareto Archive Evolutionary Strategy Algorithm (PAES)

The main purpose of PAES algorithm is to provide local search operation and deal with all Pareto optimal solutions in the same way. PAES algorithm initially generates an initial solution, which is generated by simple random mutation, and then puts the target value of the initial solution into a set file. The second step is to generate a new solution by mutating the parent solution, compare the dominant relationship to see whether the new solution is dominated by the parent solution and the dominant relationship between the new solution and other solutions, randomly select a solution as the new parent solution after updating the file, and repeatedly execute this process until the set iteration times are completed.

PAES algorithm is simple and fast. It uses an adaptive grid method based on repeated partition, which has low computation and does not require selection operations. It mainly focuses on more reasonable and better solutions.

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On the whole, the core of PAES algorithm is an external file and (1 +1) strategy, which makes a parent unit generate an offspring unit, and uses external archive to compare each mutation individual. It features simple algorithm principle and positive process.

7. Summary

Multi-objective optimization problems, such as production scheduling and intelligent planning, widely exist in life. For such problems, it is often necessary to find a set of undifferentiated equilibrium solutions, rather than the unique solution. Through research and summary of corresponding computational intelligence algorithms, it is possible to find the common Pareto dominance mechanism and compare different fitness allocation strategies and selection mechanisms, which is helpful to adopt different schemes to ensure group diversity when facing specific problems and find the global optimal solution. In the process of sorting and summarizing, the commonness of such computational intelligence algorithms could also be revealed, such as the external groups set by SPEA and the external files of PAES, the comparison of sharing mechanisms between NSGA and NPGA, as well as the individual dominance relationship which is emphasized by most algorithms.

It is clear that the goal of multi-objective evolutionary algorithms is to reach the situation where evolutionary results are evenly distributed and could basically cover the range of each sub objective. It is also clear that the development of this kind of stochastic global optimization algorithm has stronger tendency to achieve an appropriate balance between the search speed of non-inferior solutions, the processing effect of multi-objective optimization problems and the complexity of calculation. Nowadays, computational intelligence algorithms are widely used, and the existence of group diversity, algorithm convergence and other issues also proves that they have extremely high theoretical research value and huge development potential. It is also hoped that the development of such computational intelligence algorithms could further promote the progress in the field of scientific engineering.

References

[1]Wu Lin. Research on Evolutionary Algorithm for Complex Multi-objective Optimization Problems [D].Shenzhen University,2020.

[2]Guoqing Li. Research on Particle Swarm Optimization for Complex Multi-modal and Multi-objective Optimization Problems[D].Zhengzhou University of Light Industry,2019.

[3]Xiaoshen Jiang. Research on Improvement of Particle Swarm Optimization Algorithm in Multidimensional Optimization Problem[D].Zhejiang Sci-Tech University,2016.

[4]Ziru Zhang. Research on PAES Multi-objective Optimization Algorithm and Its Application [D].Lanzhou University of Technology,2012.

[5]Lei Xv. Research and Application of Multi-objective Optimization Problem Based on Genetic Algorithm[D].Central South University,2007.

[6]Qian Feng,Qing Li,Wei Quan,Xuanmo Pei.Overview of Multi-objective Particle Swarm Optimization Algorithm[J/OL].Chinese Journal of Engineering:1-10[2021-04-04].https:// doi.org/10.13374 /j.issn 2095-9389.2020.10.31.001.