The Hybrid Intelligent Optimization Algorithm and Multi-objective Optimization Based on Big Data

Xin NIE*, Jian LUO²

*School of Computer Science & Engineering, Wuhan Institute of Technology, Wuhan, China

²School of Computer Science, Wuhan Qingchuan University, Wuhan, China

*nix83@163.com

Abstract. Multi objective optimization problem (MOP) usually has more than two objective functions, and the optimal solution based on Pareto frontier is obtained. The traditional optimization algorithm cannot meet the needs of industrial application when dealing with multi-objective optimization problems. With the good performance of evolutionary algorithm in solving complex problems, its application field is also extended to multi-objective optimization problems. The Pareto optimal solution and evaluation system of multi-objective optimization problem are analysed. Particle swarm optimization (PSO), one of the evolutionary algorithms based on swarm intelligence, is briefly introduced. The combination of particle swarm optimization algorithm and multi-objective optimization is studied.

Keywords: multi-objective optimization problem; traditional optimization algorithms; evolutionary algorithm; particle swarm optimization; ant colony optimization algorithm

1. Introduction

Multi objective optimization is a common problem in all fields of reality. Each objective cannot be optimized at the same time, and each objective must have its own weight. However, how to allocate the weight has become a hot issue. At the same time, the genetic algorithm based on the theory of biological evolution has also attracted people’s attention. The combination of the two can make use of the global search ability of genetic algorithm, avoid the traditional multi-objective optimization method falling into the local optimal solution in the process of optimization, and keep the diversity of solution individuals. Therefore, the multi-objective optimization strategy based on genetic algorithm has been applied in various fields.

In general, multi-objective optimization problems, each sub-objective is usually transformed into a single objective function by setting decision-making coefficients, where the decision-making coefficients are mainly set by decision-makers or obtained by adaptive methods. The common classical multi-objective optimization methods include weighted method, constraint method, minimax method, objective programming method, etc. The traditional multi-objective method has the advantages of simple operation and easy realization, but it also has some disadvantages, such as the subjectivity of weight distribution between different objectives is not easy to grasp, the optimization progress of each objective is not easy to operate, and each decision variable is easy to restrict each
other. Intelligent optimization algorithms by simulation of natural phenomena, abstract mathematical models in order to comply with certain laws. Intelligent optimization algorithm is self-organizing, adaptive and other features, provides an important technical approach to solve complex engineering practice [1].

2. Multi-objective optimization problem

2.1. Mathematical description of multi-objective optimization problem

Mathematical description of multi-objective optimization problem by the decision variables, objective function, constraints composition. Because different areas of application of multi-objective optimization problem, which is different mathematical description, including the general multi-objective optimization, dynamic multi-objective optimization, to determine the multi-objective optimization and multi-objective optimization of several uncertain. General multi-objective optimization mathematical description is as follows:

\[
\min y = f(x) = [f_1(x), f_2(x), ..., f_N(x)](n = 1, 2, ..., N) \\
\text{s.t.} g(x) = [g_1(x), g_2(x), ..., g_M(x)] \\n\quad = 0 \\
\quad h(x) = [h_1(x), h_2(x), ..., h_M(x)] = 0 \\
\quad x = [x_1, x_2, ..., x_d, ..., x_D] \\
\quad x_{d_{\text{min}}} \leq x_d \leq x_{d_{\text{max}}}(d = 1, 2, ..., D)
\]

Among them: \( x \) is the D-dimensional decision variable, \( y \) is the objective function, and \( N \) is the total number of optimization objectives; \( f_n(x) \) is the \( n \)-th sub-objective function; \( g(x) \) is the K-term inequality constraint, and \( h(x) \) is the M-term equality constraint. The constraints constitute feasible Domain; \( x_{d_{\text{min}}} \) and \( x_{d_{\text{max}}} \) are the upper and lower limits of vector search. The multi-objective optimization problems represented by the above equations include the minimization problem (min) and the maximization problem (max) and the determination of multi-objective optimization problems.

The mathematical description of dynamic multi-objective optimization problems adds time variable \( t \) to the general multi-objective optimization problem. The equation is expressed as follows:

\[
\min \& \max y = f(x,t) = [f_1(x,t), f_2(x,t), ..., f_N(x,t)](n = 1, 2, ..., N) \\
\text{s.t.} g(x,t) = [g_1(x,t), g_2(x,t), ..., g_M(x,t)] \\n\quad = 0 \\
\quad h(x,t) = [h_1(x,t), h_2(x,t), ..., h_M(x,t)] = 0 \\
\quad x(t) = [x_1(t), x_2(t), ..., x_d(t), ..., x_D(t)] \\
\quad x_{d_{\text{min}}}(t) \leq x_d(t) \leq x_{d_{\text{max}}}(t)(d = 1, 2, ..., D)
\]

The mathematical description of uncertain multi-objective optimization problems adds q-dimensional uncertainty \( a \) on the basis of general multi-objective optimization problems. The equation is expressed as follows:

\[
\min \& \max y = f(x,a) = [f_1(x,a), f_2(x,a), ..., f_N(x,a)](n = 1, 2, ..., N) \\
\text{s.t.} g(x,a) = [g_1(x,a), g_2(x,a), ..., g_M(x,a)] \leq v_i^l \\
\quad h(x,a) = [h_1(x,a), h_2(x,a), ..., h_M(x,a)] = b_i^l \\
\quad a \in a^l = [a^l, a^u] \\
\quad x = [x_1, x_2, ..., x_d, ..., x_D] \\
\quad x_{d_{\text{min}}} \leq x_d \leq x_{d_{\text{max}}}(d = 1, 2, ..., D)
\]

Among them: \( a^l \) represents the uncertainty \( a \), and the interval of \( a^l \) is from \( a^l \) to \( a^u \); \( v_i^l \) represents the allowable interval of inequality constraints; \( b_i^l \) represents the allowable interval of equality constraints.
2.2. *Pareto optimal solution of multi-objective optimization problem*

The process of solving the multi-objective optimization problem is the process of finding the Pareto optimal solution. The so-called Pareto optimal solution is also called non-inferior optimal solution. Pareto optimal solution is a vector evaluation method for multi-objective solutions proposed on the basis of set theory. Therefore, the so-called optimal solution is just a criterion for evaluating the pros and cons of the solution. The so-called pros and cons mean that the further optimization of one or more sub-objective functions in the solution set of the objective function will not cause the solutions of other sub-objective functions to exceed the specified range, that is, in the multi-objective optimization, some sub-objectives are optimized. The optimization of cannot affect the optimization of other sub-objectives and allow the optimal solution of the entire multi-objective. In the Pareto optimal solution, a dominant vector is introduced. The definition of the dominating vector is as follows:

For any \( d \in [1, D] \), satisfy \( x_d^j \leq x_d \) and exist \( d_0 \in [1, D] \) and \( x_d^j \leq x_{d_0} \), then vector \( x' = [x_1', x_2', \ldots, x_d', \ldots, x_D'] \) dominates vector \( x = [x_1, x_2, \ldots, x_d, \ldots, x_D] \). When \( f(x') \) and \( f(x) \) satisfies the following conditions, \( \forall n, f_n(x') \leq f_n(x) \), \( n = 1, 2, \ldots, N \), \( \exists \eta \in [1, N] \) \( f_\eta(x') < f_\eta(x) \), then \( f(x') \) dominates \( f(x) \). The dominance relationship of \( f(x) \) is consistent with that of \( x \).

Visible, Pareto optimal solution only gives the evaluation standard solution of multi-objective optimization problems, did not provide a practical solution process, therefore, made from a multi-objective optimization problem to propose optimal solutions Pareto, have failed to reach the essence of multi-objective optimization problem. Multi-objective optimization problem needs to put forward a variety of different algorithms to achieve the final solving. Research is focused on the research and optimization algorithms in conjunction with the specific engineering practice of the current multi-objective optimization problem. In order to evaluate the various algorithms, we shall introduce performance evaluation system optimization algorithm [2].

2.3. *Performance evaluation of multi-objective optimization algorithm*

The rating indicators of multi-objective optimization algorithms usually have the following items: approximation GD (Generational Distance), uniformity SP (Spacing), broadness EX, optimal solution number ER (Error Ratio), convergence measure \( \gamma \) and diversity metric \( \Delta \).

The approximation GD is used to describe the distance between the non-inferior optimal solution obtained by the algorithm and the Pareto front end.

\[
GD = \sqrt{\frac{1}{n} \sum_{i=1}^{n} d_i^2},
\]

where \( d_i \) is the distance between the first non-inferior solution and the front end of Pareto.

Uniformity SP is used to describe the distribution range of non-inferior solutions on the Pareto front end. \( SP = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} d_i^2} \). In the formula, \( d_i \) represents the distance between two non-inferior solutions, and \( \overline{d} \) is its average value.

The average value is the convergence measure \( \gamma \). The diversity measure \( \Delta \) is used to measure the distribution of the Pareto front end. The evaluation method of diversity measurement distributes all the non-inferior solutions obtained by the algorithm in the Pareto front end in an orderly manner according to the objective function, and then calculates the distance \( d_i \) and \( \overline{d} \) of the continuous solutions in these non-inferior solutions, and calculates the distance of the extreme point in the Pareto front end. The distance between \( d_i \) and the boundary point \( d_i \), the diversity index is expressed as the following formula:

\[
\Delta = \frac{d_i + d_i + \sum_{i=1}^{n} |d_i - \overline{d}|}{d_i + d_i + (n-1)\overline{d}}.
\]

The diversity measure \( \Delta \) reflects whether the non-inferior solutions are evenly distributed.
The above evaluation criteria represent the distribution of the non-inferior solutions obtained by the algorithm in the Pareto front end from various aspects. Among them, the most commonly used evaluation indicators are the convergence measure $\gamma$ and the diversity measure $\Delta$. There are three main types of evaluation methods: the first is to evaluate the convergence performance of non-inferior solutions; the second is to evaluate the diversity performance of non-inferior solutions; the third evaluation includes the comprehensive performance of convergence and diversity.

3. Intelligent optimization algorithm

For multi-objective optimization problem of intelligent optimization algorithms no longer simply seek to derive from the evolution of Pareto optimal solution of pure mathematics, but to learn from the intersection of the development of life science and information science in the form of derived. Intelligent optimization algorithms by simulation of biological evolution and animal populations and other vital activities, achieved using iterative calculation for solving multi-objective optimization problem [4].

Evolutionary algorithm is a kind of search and optimization algorithm based on Darwinian evolution theory. It can obtain the optimal solution of a specific problem by simulating the survival of the fittest in the process of biological evolution. Evolutionary algorithm starts from a random initial population, and everyone in the population represents a feasible solution of the problem. These individuals correspond to the chromosomes in the organism, and the fitness value of chromosomes can be calculated through the evaluation function, which reflects the merits and demerits of individuals. The coding methods and evaluation functions of chromosomes vary with specific problems. The individuals in the parent population generate the offspring population through genetic operation. Some individuals with high fitness are retained by the selection mechanism, while the individuals with relatively low fitness are gradually eliminated. Thus, the fitness of individuals in the population is getting higher and higher. After several iterations, the evolutionary algorithm converges to the optimal solution of the problem.

Particle swarm optimization PSO is a typical swarm intelligence. How mutual cooperation between the ACO and ACO algorithm similar, PSO is the use of computer simulation of flight behavior of birds and predatory behavior by studying birds in flight and prey on individuals (referred to as particles) and collaboration to implement the entire population optimization. So-called particle swarm algorithm has two versions, namely the global and the local version. Both the focus is not the same: the global version, two extreme fine tracking for its own position and the most optimum position of the population; and local release, the particle tracing two extreme positions and for their own optimum topological optimum position in the field of so-called microparticles. Applied to multi-objective optimization problem by particle swarm algorithm generally dominated the global version.

PSO algorithm to construct a mathematical model based on five key principles cluster of artificial life system. The five key principles are: proximity principle, that group should be able to perform simple arithmetic space and time; the quality of the principle that the group should be able to feel the changes in the quality factor of the surrounding environment and respond; reflect the diversity principle, namely groups the approach should not limit access to resources within a narrow range; the principle of stability, that is, with every group should not change the environment and change their behavior patterns; principle of adaptability, that is, when the return is caused by changes in behavior patterns it is worth the time, groups should change their behavior patterns. We can build a mathematical model of particle swarm algorithm based on the above principles.

The particle is defined as the point $x_i = (x_{i1}, x_{i2}, ..., x_{id}) (i = 1, 2, ..., N)$ in the $D$-dimensional space, and the initial velocity $v_i = (v_{i1}, v_{i2}, ..., v_{id}) (i = 1, 2, ..., N)$ of the particle is assigned at the same time, so that each particle is given the initial position and initial velocity as the optimized initial state. Then a fitness function similar to evolutionary algorithm should be established according to the objective function and constraint conditions of the multi-objective optimization problem. After given initial conditions and fitness function, the particles start to run in the search space. During each
iteration, the particle tracks its own optimal position (pbest) and group optimal position (gbest) at the same time, and its tracking equation is as follows:

In order to improve the convergence speed and solution quality of the particle swarm algorithm, the basic particle swarm iterative equation is improved to produce the PSO algorithm with inertia weight $W$ to achieve the optimal solution. In addition, some studies have proposed to introduce a compression factor into the particle swarm algorithm to ensure the convergence of the particle swarm algorithm. Its iterative equation:

$$v_{i}^{k+1} = \chi \{v_{i}^{k} + c_{1}r_{1}(p_{best}^{k} - x_{i}^{k}) + c_{2}r_{2}(gbest^{k} - x_{i}^{k})\}$$ (4)

among them, $\chi = \frac{2}{\sqrt{2 - \varphi - \sqrt{\varphi^{2} - 4\varphi}}}$ ($\varphi = c_{1} + c_{2}$). Call it the compression factor. The introduction of compression factor can improve the performance of particle swarm algorithm.

4. Conclusion

In traditional multi-objective optimization problems, each sub-objective is usually transformed into a single objective function by setting decision-making coefficients, where the decision-making coefficients are mainly set by decision-makers or obtained by adaptive methods. The common classical multi-objective optimization methods include weighted method, constraint method, minimax method, objective programming method, etc. The traditional multi-objective method has the advantages of simple operation and easy realization, but it also has some disadvantages, such as the subjectivity of weight distribution between different objectives is not easy to grasp, the optimization progress of each objective is not easy to operate, and each decision variable is easy to restrict each other. Evolutionary algorithm is to search multiple non inferior solutions in a wide space in a parallel way. It is a population-based approach, and multiple non inferior solutions can be obtained at one time, so it is very suitable for multi-objective optimization problems. Therefore, multi-objective evolutionary algorithm has been widely used in engineering and science and technology research.

References

[1] Li J Q, Sang H Y, Han, Y Y, Wang C G and Gao K Z, April 2018 Efficient multi-objective optimization algorithm for hybrid flow shop scheduling problems with setup energy consumptions. Journal of Cleaner Production 1\textit{81} 584-598

[2] Qi Y, Hou Z, Yin M, Sun H and Huang J September 2015 An immune multi-objective optimization algorithm with differential evolution inspired recombination. Applied Soft Computing 2 395-410

[3] Xiao J K, Li W M, Xiao X R and C Z L V March 2016 A novel immune dominance selection multi-objective optimization algorithm for solving multi-objective optimization problems. Applied Intelligence 46 1-17

[4] Singh, K., Singh, K., Son, L. H., & Aziz, June 2018 A. Congestion control in wireless sensor networks by hybrid multi-objective optimization algorithm. Computer Networks 138 90-107

[5] Meza Joaquin Espitia H, Montenegro C and González Crespo R September 2016 Statistical analysis of a multi-objective optimization algorithm based on a model of particles with vorticity behavior. Soft Computing 20 3521-3536

[6] Xia B, Baatar N, Ren Z and Koh C S March 2015 A numerically efficient multi-objective optimization algorithm: combination of dynamic taylor kriging and differential evolution. IEEE Transactions on Magnetics 51 1-4

[7] Altinöz O T and Deb K, May 2016 Late parallelization and feedback approaches for distributed computation of evolutionary multi-objective optimization algorithms. Neural Computing and
Applications 30 1-11