Reduction technology of solid propellant characteristic signal based on MOPSO algorithm

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Abstract. In order to overcome the multiple characteristic signals of solid propellants which are difficult to be solved by traditional methods, such as experimental exploration method, an improved multi-objective particle swarm optimization algorithm was proposed in this paper, including the establishment of external file, global optimal position and individual optimal location selection strategy. Through the simulation of mathematical model, the optimized distribution ratio scheme of formula group was finally obtained. The accuracy of the solution was within 12%. The results showed that the method was effective and reliable, and can provide a variety of choice for the decision-makers of the formula design.

1. Introduction
The rapid development of new military technology has greatly improved the ability to search and track the target of the detection system. For tactical missiles, it should not only pay attention to the improvement of energy characteristics, but also strengthen its precision attack and reliable guidance ability. However, the solid propellant in the missile engine provides continuous thrust for missile weapons, while the plume of its combustion products also produces a variety of characteristic signals, including one smoke, two smoke, infrared radiation and so on. It may expose the launching platform and flight trajectory of the missile, and reduce the survival and penetration ability of the missile and weaken the missile. Weapon kill effectiveness, so all kinds of technologies to reduce plume characteristic signals appear successively [1, 2].

The reduction of multiple characteristic signals generated by solid propellant combustion is a multi-objective minimization problem (MOP). It is difficult to do this by using the experimental method. However, by virtue of the advantages of parallel computing and random search, intelligent algorithms can be applied to the multi-objective optimization of characteristic signals and find a set of component types and their proportions that make the comprehensive effects of multiple feature signals minimal. At present, some scholars have tried to use this method to solve the problem of other performance optimization of solid propellants and obtain some results. But there is no report of applying intelligent algorithm to reducing the characteristic signal of solid propellant. In this paper, we consider the advantages of particle swarm optimization algorithm (PSO) compared with the other intelligent algorithms, using the improved PSO to solve the formula design problem of comprehensive reduction of multiple characteristic signals of solid propellant quickly and efficiently, and provide reference for the decision-makers of formula design.
2. Multi-objective particle swarm optimization algorithm

2.1. Algorithm implementation process
In this paper, according to the practical problems that need to be solved, this paper chooses the rejection method and the penalty function method to solve the boundary constraint and inequality constraint respectively. The algorithm flow is shown in figure 1.

2.2. Constraint condition processing
First, the rejection method is used to strictly limit the decision variables in a given range, such as formula (1).

\[ x_i = \text{rand} \times (u_i^b - l_i^b) + l_i^b \]  

(1)

Among them, the \( x_i \) is decision variables, \( l_i^b \) and \( u_i^b \) is the lower bound and the upper bound constraint of \( x_i \).

Secondly, the penalty function is used as the penalty term to add the objective function, such as formula (2).

\[ f_{new,i}(x) = f_i(x) - \sigma \cdot \sum_{p=1}^{d} \max(g_p(x) - a_p, 0) \]  

(2)

Among them, the penalty function is the first objective function of the penalty item, and the upper bound constraint condition is the penalty factor. \( f_{new,i}(x) \) is the objective function of \( i \), \( \sigma \) is penalty factor, \( a_p \) is the upper bound constraint of \( g_p(x) \).

2.3. Maintenance of external files
In order to solve the multi-objective optimization problem, the global optimal solution of all the targets is not usually obtained, and a group of non dominant solutions is obtained. The traditional particle swarm optimization algorithm can not store and maintain these non dominant solutions.
Therefore, the external files are introduced to manage these non dominant solutions. The concrete methods are as follows:

Each generation of a new particle is compared with the non dominated relation of the particles in the external file. If the new particle is dominated by more than two particles in the external file, then the particle is abandoned and the particle is regenerated to be compared again; if the new particle is a non dominant solution in the current external file or only one of the external files is in the file. When the particle is dominated, it is stored in the external file, which can appropriately improve the diversity of the particles in the external files. If some particles in the external file are dominated by the particle, the particles in the external files are abandoned and the crowding distance between the new particles and the remaining particles in the external file, and the formula is calculated. If a new particle is added, the number of particles in the external file exceeds the upper limit of the number of particles, then the density of the largest particle in the external file is abandoned to maintain the uniform distribution of the non dominated frontier [3].

2.4. Global optimal position and individual optimal position selection

The global optimal position and the individual optimal position are two important information to guide the particle to search the optimal solution in the feasible solution space. In the standard particle swarm optimization algorithm, the global optimal position is the best particle position in all the particles in the current particle, and the individual optimal position is the objective function value of the particle in its own flight. The best position. The multi-objective particle swarm optimization algorithm is a non dominant solution, that is, there is no feasible solution to achieve the optimal value of all target functions, so the selection of these two positions is not the same as the standard particle swarm optimization algorithm, and it is more critical. In this paper, when selecting the global optimal position, the dominant relation between particles and the space distance of the particle are taken into full consideration. When selecting the optimal position of the individual, the dominant relation between particles and the optimal value of the utility function are considered, which can satisfy the convergence principle and satisfy the convergence principle of the non dominant solution. Diversity requirements [4].

When selecting the global optimal position, we first calculate the space distance of all non dominated particles in the external files, such as the formula (3), then the particles in the external files are sorted from large to small in accordance with the space distance, and the former $W/3$ particles are screened out, and the random numbers $P_w$ are produced, if they are within the space distance probability of some particles in these particles, The position of the particle is the global optimal position.

$$D_i = \min(D(x_{w,1}, x_1), D(x_{w,1}, x_2), \ldots, D(x_{w,1}, x_w), D(x_1, x_{w+1}), \ldots, D(x_w, x_w))$$

$$D_2 = \min\{D(x_{w,1}, x_1), D(x_{w,1}, x_2), \ldots, D(x_{w,1}, x_w), D(x_1, x_{w+1}), \ldots, D(x_w, x_w)\} - \{D_1\}$$

$$D_w = (D_1 + D_2) / 2$$

Among them, $D_1$ is the minimum value of the crowding distance between the first particle and other particles in the external file, $D_2$ is the second minimum of the crowding distance between the first particle and the other particles in the external file, $D_w$ which is the space distance of the first $w$ particle in the external file.

2.5. Population diversity conservation strategy

The characteristics of fast convergence of particle swarm optimization algorithm easily make the algorithm fall into local optimum and appear "precocious". In this paper, the mutation operation of some particles in the later period of operation is carried out to maintain the population diversity [5]. The specific process is as follows:
First, the average convergence degree of the particles in the external files is calculated as the feedback information of the algorithm convergence, for formula (4), if it is less than a given threshold $\delta$, a particle $W/20$ is randomly selected in the external file and then generates a random number $\text{rand}$. If it is less than a given probability $p_m$, then a particle is selected for mutation operation in a particle. In the end, the particle in the population is sorted from large to small, and the former $W/20$ particle is replaced. On the one hand, the particle can be properly maintained by the mutation operating particles. The particles without the mutation operation can provide more information on the non dominant solution frontier and improve the efficiency of the algorithm convergence.

$$C = \sum_{j=1}^{n} \sum_{i=1}^{\text{max}} (f_j(x_i) - f_j^{\text{min}})^2$$

Among them,

$$f_j^{\text{min}} = \text{min}(f_j(x_1), f_j(x_2), \ldots, f_j(x_i))$$

$C$ is average convergence of particles in external files, $f_j^{\text{min}}$ is the minimum value of the first target of all particles in the external file.

$$x^{t+1} = x^t + (-1)^{t'} \cdot (x^t - (U^R - L^R) / 2) \cdot \text{rand} \cdot (1 - 1 / M)^2$$

In the formula (7), it can be seen that the range of particle variation is larger in the early stage of the algorithm, which is conducive to the preservation of the diversity of the population. With the increase of the number of iterations, the variation of the particle is becoming smaller and smaller, which is beneficial to the local precise search of the algorithm in a small range. When the number of iterations of $(-1)^{t'}$ is positive, the odd number is negative, the symbol of $x^t - (U^R - L^R) / 2$ can not be determined, but it can be negative and positive. Further, the direction of the particle variation is random, which is more conducive to the conservation of the population diversity.

3. Engineering application

3.1. Model establishment

The comprehensive reduction of a variety of characteristic signals produced by solid propellant combustion is a multi-objective minimum value optimization problem. There may be a conflict between these characteristic signals. It is impossible to obtain the composition types and their proportions of a variety of characteristic signals at the same time at the same time. However, the multi-objective particle swarm optimization algorithm presented in this paper can be used. In order to find a set of composition types and their proportions which make all kinds of characteristic signals have the least combined influence. In order to simplify the model and combine the distribution ratio of solid propellant formula and the maximum radiant energy data produced by the combustion of solid propellant given by [2], this paper tries to find out a set of multiple characteristic signals produced by the multi-objective particle swarm optimization algorithm on the basis of determining the component type of solid propellant. The minimum distribution ratio of this type of formula group.

Literature [2] gives seven formulations of the main components of aluminum powder, oxidant, burning rate catalyst and explosive as the main component and the maximum radiant energy of the four infrared bands produced by its combustion. In this paper, the least square method is used to obtain the proximity between the four kinds of coordination groups and the infrared radiation characteristics by using the least square method. A quantitative relation, such as formula (8).

$$E_{IR} = -0.002143 \times x_A^2 + 0.002143 \times x_O^2 + 7.408993 \times x_{Brc}^2 + 0.059669 \times x_{Es}^2 - 6.282421 \times x_{Inc}$$

Among them, $E_{IR}$ is the maximum infrared radiation energy value, $x_A$ is the quantity of aluminum powder, $x_O$ is the mass fraction of oxidizer, $x_{Inc}$ is the mass fraction of burning rate catalyst, $x_{Es}$ is the mass fraction of explosives.
According to the partial thermal chemical equation of the solid propellant combustion and the law of mass conservation in the combustion process, four formula components and the quantitative relationship of the first smoke which are characterized by the mass fraction in the combustion products \( \text{Al}_2\text{O}_3 \) are established, such as formula (9), and the establishment of four formula components and two times of smoke characterized by the mass fraction in the combustion products \( \text{HCl} \). A quantitative relation, such as formula (10).

\[
M_{P_s} = \frac{102}{54} \cdot x_{Al} \approx 1.89 \cdot x_{Al} \quad (9)
\]

\[
M_{T_s} = \frac{36.5}{117.5} \cdot x_{Oa} \approx 0.31 \cdot x_{Oa} \quad (10)
\]

Among them, \( M_{P_s} \) is the mass fraction of \( \text{Al}_2\text{O}_3 \) in solid propellant combustion products, \( M_{T_s} \) is the mass fraction of \( \text{HCl} \) in solid propellant combustion products.

The mass fraction in the combustion products of solid propellants is the mass fraction in the combustion products of solid propellants.

In order to verify the effect of this algorithm in reducing the multiple characteristic signals of solid propellants, a dual objective function optimization model is set up with infrared radiation and primary smoke as the target, such as formula (11).

A dual objective function optimization model for infrared radiation and smoke is presented.

\[
\begin{align*}
\text{min } E_{IR} & = -0.002143 \times x_{Al}^2 + 0.002143 \times x_{Oa}^2 + 7.408993 \times x_{Brc}^2 + 0.059669 \times x_{Es}^2 - 6.282421 \times x_{Brc} \\
\text{min } M_{P_s} & = \frac{102}{54} \cdot x_{Al} \approx 1.89 \cdot x_{Al} \\
\text{s.t. } & \quad x_{Al} + x_{Oa} + x_{Brc} + x_{Es} < 100 \\
& \quad E_{IR} \leq E_{max} \\
& \quad M_{P_s} \leq M_{max} \\
& \quad 1 \leq x_{Al} \leq 18 \\
& \quad 70 \leq x_{Oa} \leq 87 \\
& \quad 0 \leq x_{Brc} \leq 1.7 \\
& \quad 0 \leq x_{Es} \leq 10 \\
\end{align*}
\]

(11)

3.2. Simulation analysis
The algorithm is used to simulate the model, and the results are shown in figure 2.

**Figure 2.** The Pareto frontier of model one.

As shown in figure 2, the algorithm model 1 obtains a more smooth non dominating solution frontier, which shows that infrared radiation and one smoke are two conflicting optimization targets, one kind of reduction inevitably leads to the other, and it is impossible to get the ratio of both the four components of the hourly formula, but a group of two kinds. Feature signal synthesis is the smallest formulation of the ratio of four components. When the formula is specified, the decision-maker can choose the formula that makes the infrared radiation smaller if the missile weapon requires a higher
infrared radiation. If the missile weapon requires higher energy characteristics, a formula with high content of aluminum powder but a high degree of smoke can be selected. When missile weapons require similar requirements for both, they can choose the least comprehensive formula.

4. Conclusions
The engineering application problem of reducing the multiple characteristic signal of solid propellant can be solved reasonably by the multi-objective particle swarm optimization algorithm proposed in this paper. Compared with the traditional method such as experimental exploration method, it is easier to overcome the conflict between the optimized targets and get a set of closer experimental values and theoretical budget values. The non dominating solution and a smooth non dominating solution edge are within 12%, which provides more formula combination scheme for formula design decision-makers.

The algorithm in this paper is a little worse in solving the multi-objective optimization problem, and the leading edge of the non dominant solution is rough. The next step is to improve the algorithm more systematically and pertinent. In addition, the model in this paper does not incorporate the influence of objective environment, and has little regard for the comprehensive performance requirements of solid propellant energy characteristics.

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