

Aeroengine performance seeking control at Maxpower state based on Adaptive archives Management Multi-object PSO Algorithm

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Abstract. Aero-engine may appear over-ride and over-temperature phenomenon in maximum military status while the performance deterioration has occurred. Those phenomenons imperil the structural stability and accelerate the performance deterioration of the aero-engine. In view of these problems, this paper considerate the performance demand of thrust, specific fuel consumption and surge margin synthetically. Research on the method to optimize and select the controlled quantity based on adaptive archives management multi-object PSO algorithm. It has been proved that the method can offer the optimal control quantity set, in addition, ensure the main optimization objective of aero-engine performance index, and give consideration to the another performance index while the aero-engine has be ensured work in the safe and reliable state.

1. Introduction

Reliability and safety are important indicators to Aeroengine. It must ensure that the aeroengine can work safely even in the worst state when the aeroengine is designing. accordingly. In order to keeping safety, every part of aeroengine needs to maintain sufficient safety margin in the premise of consider the influence of various factors^[1]. The reason that this kind of design method was adopt is short of effective approach of on-line monitor safety margin. The resulting disadvantage is part of the performance is wasted and degraded, especially, in undesigned point. With the life-time use, its performance will deteriorate, and safety margin will decrease^[2].

With the development of aero engine online fault prediction and health management, and advanced full authority digital controller, it is possible to sufficient exploit and optimal the performance. Aero-engine performance seeking control is the method to solve the problem. It's according to the engine on-line state, optimize engine control system, and promote some performance index in the base of ensure safety margin^[3].

Aero-engine performance seeking control (PSC) usually has several kinds of modes, such as maximum thrust, minimum specific fuel consumption (SFC), and minimum exhaust gas temperature (EGT) and so on. Those optimal modes usually only emphasize on single optimal index, instead of comprehensive consideration. Because of the competitive relationship among those performance optimal index, some performance index is optimized at the expense of sacrifice others as long as the constraint condition are met. For example, in the maximum thrust optimal mode, the final optimal goal will promote the thrust, at the same time; the exhaust gas temperature will increase inevitable. Although, optimal algorithm ensure the over-temperature phenomenon won't been occurred, it will accelerate aging while work in the over-temperature critical edge at long-term. Therefore, this paper try to optimize several objects at the same time while one if them is the main optimal object, the others are minor objects. If the maximum thrust is the main optimal object, control system will optimize control quantity to make the thrust maximum, keep EGT and SFC

decrease as far as possible. Obviously, this is a multi-object optimal problem^{[4][5]}.

2. Adaptive archives Management Multi-object PSO Algorithm

Many actual project problems need to optimize several objective functions, especially in the design stage. Many multi-objective problem can convert to single-objective problem, however, Compared to the Single objective Particle swarm optimization algorithm has a unique solution, multi-objective Particle swarm optimization (MOPSO) algorithm have several solutions each iteration^[6]. Particle swarm optimization (PSO) algorithm has its own advantages in solving multi-objective problems. Firstly, it can make use of efficient cluster particle to parallel search the no-inferior solution, and several no-inferior solutions will be searched each iteration. Secondly, it can make use of its own memory function to update search space by tracking the group optimum solution and individual optimum solution. Those advantages make the optimal process have good compute efficient and speed. The most important is that PSO algorithm doesn't depend on the form and analytic characterization of optimal function's solution. Therefore, PSO algorithm is applied to solve the multi-objective optimal problems widely^{[7][8][9]}.

Adaptive archives Management Multi-object PSO Algorithm is the improved algorithm in the base of MOPSO, proposed by Coello and Lechuga, so, it is usually abbreviated to CMOPSO^{[10][11]}. The main idea of CMOPSO is to divide the search space into several hypercube, and update the external archives by judging the number of no-inferior solution in each hypercube. In order to ensure the searched no-inferior solution is the optimal which storage in the external archives. The individual extreme value of each particle is chosen by the combination of adaptive mesh and roulette, the updating of the external memory makes the individual extreme of each generation not identical, so that the individual extreme can be involved in the updating process of the group extreme^[12].

2.1. Multi-objective Optimization

For a multi-objective problem, including n-dimension variables and m-dimension sub-objectives can be expressed as follow: X is a n-dimension decision space, $F(X)$ is a function which mapping from n-dimension decision space to m-dimension objective space; $g_i(X) \leq 0$ ($i=1,2,\dots,q$) and $h_j(X)=0$ ($j=1,2,\dots,p$) is q inequality constraint and p equality constraint respectively. $[X_{\min} \ X_{\max}]$ is search space of decision vector.

$$F(X) = \begin{cases} f_1(X) \\ f_2(X) \\ \vdots \\ f_m(X) \end{cases} \quad (1)$$

$$s.t. \begin{cases} g_i(X) \leq 0, & i=1,2,\dots,q \\ h_j(X) = 0 & j=1,2,\dots,p \\ X \in [X_{\min} \ X_{\max}] & X = [x_1 \ x_2 \ \dots \ x_n] \end{cases} \quad (2)$$

2.2. Dominance judgement of particle

X_f is a set of decision vectors for satisfying the condition to formula (2), $X_a \in X_f$, $X_b \in X_f$, if particle X_a on all objective functions $F(X_a)$ are not less than the corresponding value of $F(X_b)$, and there is at least one objective of $F(X_a)$ superior to $F(X_b)$, then it is said that X_b is dominated by X_a . If X_a can't be dominated by any decision vector of X_f , then X_a is

called as Pareto optimal solution, and the set of all Pareto optimal solutions is called as Pareto optimal solution set, and the surface formed by them is called the Pareto front.

2.3. Adaptive external archives management

The selected Pareto optimal solution set are storage in external Archives management. In each iteration, if the size of Pareto optimal solution set does not exceed the given external file size, then there will be a new non inferior solution is added to the external file; if the external file is full, maintenance just be needed for external archives.

Adaptive archives grid partitioning. The fitness values corresponding to the Pareto optimal solution set are divided into grids evenly, each particle is stored in the corresponding grid according to its location information. The Pareto optimal solution set will be updated once each iteration, and the grid division also will adaptive divide in each generation, and particles will also be updated which storage in each archives mesh, then the partition of adaptive archives grid is realised. When a full file is maintaining, a non dominated solution is randomly removed from a high-density grid firstly, and then the new non dominated set is stored in the corresponding file grid, thus ensuring the diversity of the samples.

2.4. Update the individual extreme value

The non dominated particles are chosen as the individual extreme values ($pbest$) among the current particles and the best historical particles, and if they do not dominate each other, one is selected randomly

2.5. Update the group extreme value

For each contain at least one external definition of individual particle grid adaptive value, and then select a grid based on roulette, finally selected from the grid in a random selection of external particles as the global optimal solution ($gbest$).

2.6. Steps of CMOPSO Algorithm

The steps of CMOPSO as follow:

Step 1: Establish and initial a group, and set the external archives is none.

Step 2: Assess all particle and add the non-inferior solution into the external archives.

Step 3: Update the external archives based on adaptive mesh divide method.

Step 4: Choose the $gbest$ and $pbest$ for each particle.

Step 5: Update the location and speed of search particle.

Step 6: Ensure the selected particle is in the search space

Step 7: If the end condition is meet, the algorithm is end and give the result, or else, return to step 2.

Firstly, the target space is divided into several grids by the adaptive mesh method according to the maximum and minimum values of the non dominated particles in the external archives. Each particle is located in the corresponding mesh according to its respective objective function value, if the number of particles in a grid is greater than 1, then the initial fitness of the mesh is divided by the number of particles as the final fitness of the mesh according to the fitness sharing principle. Then, according to the fitness value of all meshes, roulette method is used to select the grid as the non-inferior solution. Finally, the number of non-inferior solutions in the selected grid will be

judged, if it is greater than 1, one of them is chosen as the leading particle, or else as the leading particle.

The CMOPSO Algorithm program execution process as follow (fig 1):

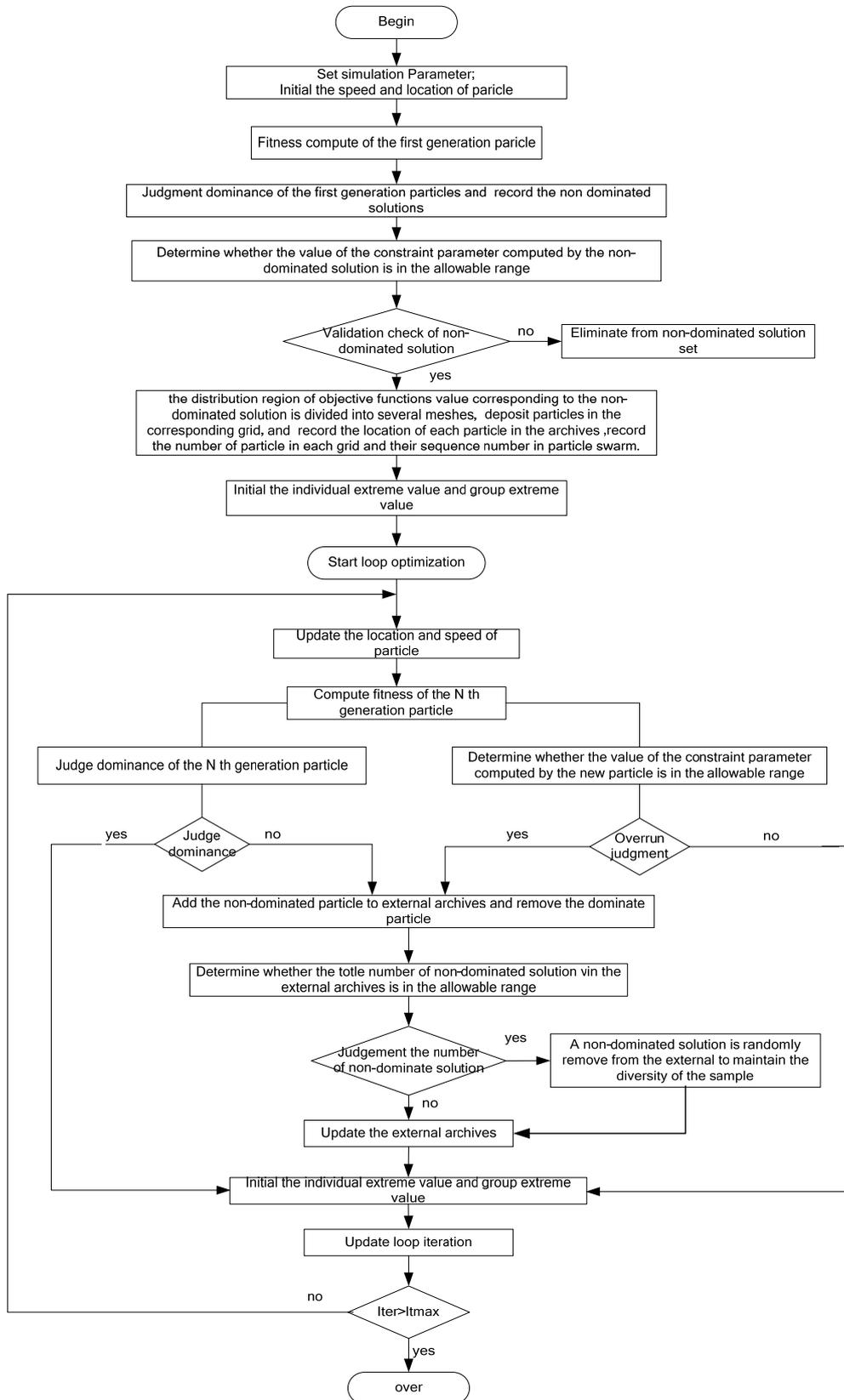


Figure 1 CMOPSO Algorithm program execution process

3. Maximum thrust PSC for aero-engine based on CMOPSO

There are three main models for the performance optimization of a gas turbine engine: maximum thrust control mode, minimum specific fuel consumption (SFC) control mode, and minimum intake gas turbine temperature (IGT) control mode. Among them, the minimum SFC control mode and minimum IGT control mode is in keeping the engine thrust unchanged, It means that if the SFC is reduced, the IGT will be reduced, if reducing the IGT, SFC will be reduced. Therefore, there are not optimal target conflict problem among the three performance indexes in the minimum SFC control and minimum IGT control mode. Therefore, the multi-objective optimization control of the engine is mainly aimed at the maximum thrust control.

In the maximum thrust control mode, the IGT and the speed of the rotor will increase while the increase of engine thrust, although the performance optimization can guarantee the speed and temperature of engine will not appear over-speed and over-temperature, but the service life of the engine will reduce while its climbing and acceleration performance are ensured,. Especially in the condition of thrust degeneration caused by engine performance degeneration, in order to ensure enough thrust, more fuel will be supplied, making the engine speed and turbine inlet temperature more easily in the critical safety edge, threatening the stability of the structure of the engine. If the performance optimization algorithm cans comprehensive consideration optimizes the IGT, SFC and the rotor speed at the expense of a small amount of thrust, and take into account the various performance indicators, it can effectively prolong life usage of the engine.

Taking a turbofan engine as the analysis object, the fuel flow of the main combustion chamber (W_f) and the nozzle area (A_8) are selected as the control variables. When the engine is not optimized, the steady-state control quantity are $W_{f,0}$ and $A_{8,0}$, and the optimization objective is to maximize thrust, minimize SFC, minimize IGT at the same time, and all performance parameters of the engine are not exceeded.

$$\text{Objective functions} \quad \max F \quad \min SFC \quad \min T_4 \quad (3)$$

$$\text{Constraint} \quad \left\{ \begin{array}{l} T_4 < T_{4,\max} \\ N_H \leq N_{H\max} \\ N_L \leq N_{L\max} \\ SM_{LC} > SM_{LC\min} \\ SM_{HC} > SM_{HC\min} \end{array} \right. \quad (4)$$

$$\text{Decision space} \quad x = [W_f \quad A_8]^T \in \left[\begin{array}{cc} (1-10\%)W_{f,0} & (1+10\%)W_{f,0} \\ (1-10\%)A_{8,0} & (1+10\%)A_{8,0} \end{array} \right] \quad (5)$$

The maximum military state of the aero-engine is set up as the state of multi-objective particle swarm optimization simulation analysis. $H = 0$, $Ma = 0$. Set the size of particle set is 100, the maximum iteration is 50, the size of external archives particle is 100, and intake turbine temperature $T_{4,\max} = 1440$ K ; high rotor speed $N_{H\max} = 102\%N_H$; Low rotor speed $N_{L\max} = 100\%N_L$; low compressor surge margin $SM_{LC\min} = 0.1$; high compressor surge margin $SM_{HC\min} = 0.1$; the simulation result of fitness are shown in the figure (2) to(5).

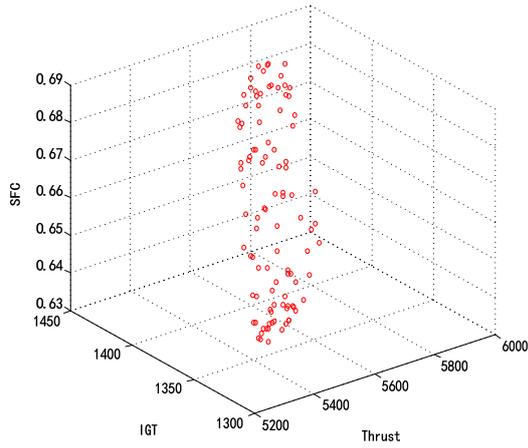


Figure.2 Fitness of 1th CMOPSO

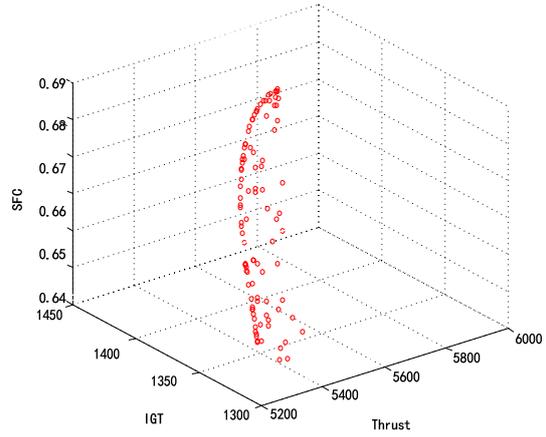


Figure.3 Fitness of 5th CMOPSO

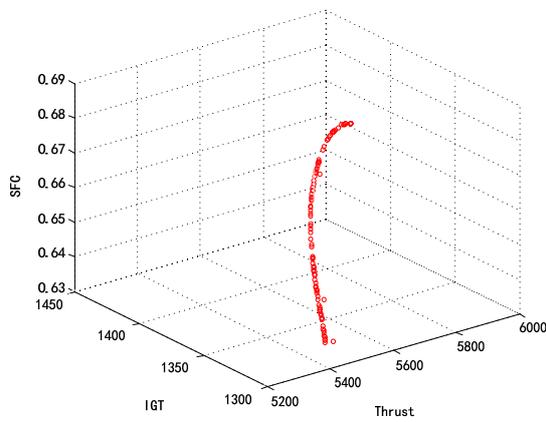


Figure.4 Fitness of 10th CMOPSO

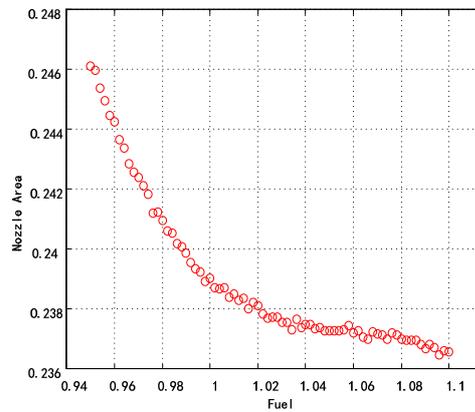


Figure.5 NOP of 10th CMOPSO

According to the graph, the fitness corresponding to the selected particles are chaotic and irregular in the first generation. With the iteration, the fitness corresponding to the selected particles gradually tends to the optimal, and the Pareto optimal solution set is obtained up until the 10th iteration. The figure (5) show that the Pareto optimal solution set is curve. If the particle corresponding to maximum fitness of the thrust is selected as the control quantity, the optimization effect is equivalent to single objective maximum thrust optimization. Similarly, if the particle corresponding to minimum fitness of the SFC or minimum EGT is selected as the control quantity, the multi-objective optimal problem is equivalent to single objective optimization. The advantage of multi-objective optimization is that the Pareto optimal solution set provides more optional control quantity. When the flight mission or optimal objective is changed, the control quantity is chosen conveniently and flexible, especially, under the compromise optimization scheme.

Table 1 Analysis of performance improve Contrast SOPSO with CMOPSO

parameter	unit	Normal state	Single-objective PSO	Multi-objective PSO
HC Rotor	%	98.42	100.2	99
LC Rotor	%	94.25	97.79	95.87
IGT	K	$T_{4.0}$	$T_{4.0} +42$	$T_{4.0} +26$
LC Surge Margin	%	$SMLC_0$	$SMLC_0 -6.36$	$SMLC_0 -4.19$
HC Surge Margin	%	$SMHC_0$	$SMHC_0 -2.37$	$SMHC_0 -1.66$
Fuel	Kg/s	$W_{f,0}$	105.4% $W_{f,0}$	103% $W_{f,0}$
Nozzle Area	Cm ²	$A_{8.0}$	98% $A_{8.0}$	98.5% $A_{8.0}$
Thrust	Kg	F_0	104.7% F_0	103.5% F_0
SFC	Kg/(Kg.h)	SFC_0	$SFC_0 +0.0325$	$SFC_0 +0.025$

In order to contrast the CMOPSO with SOPSO, choose a compromise optimization solution

from the solution set of CMOPSO ($W_f = 103\% W_{f,0}$, $A_8 = 98.5\% A_{8,0}$). The analysis data is show in table 1. The simulation results show that when the single objective particle swarm optimization with the maximum thrust as the objective function is used, the optimal control quantity can increase the thrust by 4.7%, but the IGT is increased by 42 degrees,. Thrust increase is achieved by increasing fuel flow (W_f) and decreasing the area of nozzle area (A_8). Although the optimization effect is remarkable, the performance increases with the rise of IGT, the surge margin and the speed increase. The IGT reaches 1433K, close to the critical temperature. Therefore, we hope to achieve more satisfied results through multi-objective optimization. After multi-objective optimization, the thrust is increased by 3.5% and the intake turbine temperature decrease by 16 degrees.

4. Conclusion

Through data comparison and analysis, we can see that single-objective performance seeking control (SOPSC) can provides the maximum thrust in the base of ensure the EGT isn't overrun, but the multi-objective performance seeking control (CMOPSC) can provide compromise optimization solution as the control quantity, and the provided solution is a solution set. This advantage is much better than the SOPSC. With the development of aero-engine PHM and the life extension control theory, MOPSC is gradually taken seriously, especially, because of the feature of compromise several objectives.

References

- [1]Wu, D.N, and Jaw, L.C. Intelligent Engine Life Usage Control Demonstration-Final Report[R]. NASA-98112, 2002
- [2]LI Yuebo, LI Qihong. Performance Deterioration Mitigation Control of Aero-engine [J]. Journal of Aerospace Power. 2012, 27(4): 930-936
- [3]LI Qihong, SUN Jianguo, WANG Qianyu, Direct thrust control of aero-engine[J], Journal of Nanjng University of Aeronautics and Astronautics, 2010, 42(5): 557-561.
- [4]LI Yue. Multi-objective optimization control of aero engine based on multi-objective evolutionary Algorithm. [D]. Nanjing. Nanjng University of Aeronautics and Astronautics.2007
- [5]YUAN Chunfei, SUN Jianguo. Multi-objective optimization control of propulsion system based on genetic algorithm [J]. Journal of Propulsion Technolohy, 2010, (5): 208-211.
- [6]ZHAO Bo, CAO Yijia. Multiple objective particle swarm optimization technique for economic load dispatch. [J]. Journal of Zhejiang University SCIENCE, 2005, 6A (5): 420-427.
- [7]K. E. Parsopoulos, M. N. C. Vrahatis. Particle swarm optimization method in multi-objective problems[C]. The 2002 ACM Symposium on Applied Computing, 2002: 603-607.
- [8]Parsopoulos K E, Vrahatis M N. Particle swarm optimization method in multi-objective problems[C]. Proceedings of the 2002 ACM symposium on Applied computing , ACM, 2002: 603-607
- [9]Ho S L, Yang S, Ni g, et al. A Particle swarm optimization-based method for multi-objective design optimizations. [J]. IEEE Transactions on Magnetic, 2005, 41(5): 1756-1759.
- [10]PAN Feng, LI Weixing, GAO Qi. Particle Swarm Optimizer and Multi-object Optimization. [M]. Beijing Institute of Technology Press, 2013.
- [11] Coello C A C, Lamout G B, Van Veldhuisen D A. Evolutionary algorithms for solving multi-objective problems [M]. Springer, 2007.
- [12] Coello C A C, Pulido G T, Lechuga M S. Handling multiple objectives with particle swarm optimization [J]. IEEE Transactions on Evolutionary Computation, 2004, 8(3):256-279.