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Control Performance Optimization of Variable Cycle Aero-engine Based on MTLBO

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Abstract. In view of the characteristics of variable cycle aero-engine with many adjustable variables, Modified Teaching-Learning-Based Optimization (MTLBO) algorithm is adopted to construct an optimization program to optimize the steady-state performance of multi-variable. Under the condition of non-afterburner single-duct with constant main fuel flow, the maximum thrust is optimized under the operation points of low altitude & speed and high altitude & speed, respectively based on MTLBO algorithm. The results show that the convergence of the optimization algorithm is stable, and the possibility of falling into local optimum can be avoided, which proves that the MTLBO algorithm can solve the performance optimization problem of variable cycle aero-engine.

1. Introduction

Variable cycle aero-engine takes into account the advantages of sufficient thrust at supersonic speed for turbojet engine and low fuel consumption at subsonic speed for turbofan engine. It is an ideal power plant for the fourth generation multi-purpose fighter [1]. In order to meet the ever-increasing performance requirements of variable cycle aero-engine, the design of aero-engine control system is becoming more sophisticated and complex, and the number of geometry variables is also increasing [2]. Up to now, foreign research on performance optimization of variable cycle engine is not limited to the optimization of model, but the targeted research on gas path characteristics, load characteristics et al. have been carried out [3]. Literature [4] presents a method to improve the real-time performance of aero-engine online optimization on the premise of guaranteeing the optimization effect, the digital simulation and semi-physical simulation verification under the mode of maximum thrust and minimum fuel flow are completed. It is necessary to produce a new method to effectively solve this kind of multi-variable, multi-objective and non-linear optimization problems. In this paper, a new intelligent optimization algorithm, teaching-learning-based optimization (TLBO) algorithm, is studied and applied to the control optimization of variable cycle aero-engine.

Teaching-Learning-Based Optimization (TLBO) [5] is an effective evolutionary computation method proposed by Rao and Kalyankar, Indian scholars. The algorithm constantly updates the population by simulating the teaching process in classroom to find the optimal solution. It is a new meta-heuristic optimization method based on population to solve global optimization problems. Regarding the improvement of TLBO, R. Venkata elaborated comprehensively on the number of teachers and teaching factors, and proved the advantages of the improved algorithm in practical application [6]. Due to the advantages over other optimization algorithms in global convergence and convergence speed, TLBO algorithm can be applied to aero-engine performance optimization control.

2. Mathematical model and geometry characteristic analysis of variable cycle aero-engine

Component level model of variable cycle aero-engine is adopted in this paper. Geometry variables include mode selection (VABI), high-pressure turbine guider area (*HTG*), low-pressure turbine guide area (*LTG*), fan guide angle (*FGA*), CDFS guide angle (*DGA*), compressor guide angle (*CGA*). The performance parameters include relative rotor speed of low-pressure turbine (*PNF*), relative rotor speed of high-pressure turbine (*PNC*), maximum thrust (*F*), specific fuel consumption (*SFC*), turbine front temperature (*T4*), pressure ratio of compressor (*PRC*), pressure ratio of high-pressure turbine (*PRHT*), pressure ratio of low-pressure turbine (*PRLT*), surge margin of fan (*SMF*), surge margin of compressor (*SMC*). The influence on performance by the adjustment of geometric variables separately is analysed.

1) Operational mode (VABI)

The main modes of variable cycle aero-engine are turbofan and turbojet, the variable area bypass injector (VABI) is set to be 0.5&0 when valve is open&closed. Generally, when VABI decreases gradually, that is, when the turbofan mode is converted to the turbojet, the outer culvert starts to shrink and become smaller, which decreases the inlet flow of fan, the inner flow increase and the culvert ratio decrease.

2) The area of high-pressure turbine guider (*HTG*)

The calculated characteristics of high-pressure turbine at H=11km&Ma=0.8 and main fuel flow WFB=0.9kg/s under different operation modes are shown in Table 1. It can be seen that when *HTG* is turned up, the pressure ratio of compressor increases, the rotor speed of compressor also increases, the specific fuel consumption decreases, the thrust F increases, and the surge margin of fan and compressor decreases.

Table 1. Characteristic parameters of high-pressure turbine

	Manipulated variable	Aero-engine performance parameters (%)									
	(*HTG*)	*PNF*	*PNC*	*F*	*SFC*	*T4*	*PRC*	*PRHT*	*PRLT*	*SMF*	*SMC*
Double external ducts	15	0.90	1.54	0.43	-0.37	-0.37	1.88	0.25	1.21	-3.75	-2.03
	-15	-0.85	-1.44	-0.42	0.35	0.36	-1.68	-0.25	-1.21	3.13	2.03
Single eternal duct	15	0.36	0.47	0.15	-0.11	-0.10	0.73	0	0.42	-0.77	-1.12
	-15	-1.90	-2.74	-1.17	0.89	0.92	-3.74	-0.74	-2.53	4.98	15.73

3) The area of low-pressure turbine guider (*LTG*)

Similar to the calculation process of *HTG*, the area of low-pressure turbine guide at the same design point is shown in Table 2.

Table 2. Characteristic parameters of low-pressure turbine

	Manipulated variable	Aero-engine performance parameters (%)									
	(*LTG*)	*PNF*	*PNC*	*F*	*SFC*	*T4*	*PRC*	*PRHT*	*PRLT*	*SMF*	*SMC*
Double external ducts	10	0.10	5.53	6.62	2.36	-6.04	1.88	0.25	1.21	-14	82.46
	-10	-4.55	14.13	-1.72	4.15	0.71	-1.68	-0.25	-1.21	-30.4	-66.8
Single eternal duct	15	0.36	0.47	0.15	-0.11	-0.10	0.73	0	0.42	-0.77	-1.12
	-15	-1.90	-2.74	-1.17	0.89	0.92	-3.74	-0.74	-2.53	4.98	15.73

From table 2 it can be seen that with the increase of *LTG*, the pressure ratio compressor increase, the rotational speed increases, the thrust increases, the specific fuel consumption decreases, and the temperature in front of the turbine decreases.

4) Fan guider angle (*FGA*)

The angle affects the flow capacity of fan, and further affects the airflow and duct ratio of aero-engine. The variation of performance parameters with *FGA* can be seen from table 3. When the angle is turned up, the fan pressure ratio increases, the rotational speed of high and low pressure rotors decrease, the surge margin of fan increases, the surge margin of compressor decreases, the specific fuel consumption decreases, the thrust increases, and the temperature in front of the turbine decreases.

Table 3. Characteristic parameters of *FGA*

	Manipulated variable (*FGA*)	Aero-engine performance parameters (%)									
		PNF	*PNC*	*F*	*SFC*	*T4*	*PRC*	*PRHT*	*PRLT*	*SMF*	*SMC*
Double external ducts	10	-0.46	-0.48	1.23	-1.06	-0.89	1.16	-0.40	1.21	2.50	-0.41
	-10	0.48	0.49	-1.24	1.09	0.92	-1.16	0.40	-3.13	-3.13	0.41
Single eternal duct	10	-0.05	-0.04	0.11	-0.08	-0.07	0	0	0.42	0.38	0
	-10	0.95	0.73	-1.91	1.50	1.36	-2.19	-0.74	0.42	-3.07	2.25

5) Guider angle of CDFS (*DGA*)

The effect of adjusting the guider angle of CDFS on engine performance under different duct modes under design point H=11km&Ma=0.8 and WFB=0.9kg/s is shown in table 4.

Table 4. Characteristic parameters of *DGA*

	Manipulated variable (*DGA*)	Aero-engine performance parameters (%)									
		PNF	*PNC*	*F*	*SFC*	*T4*	*PRC*	*PRHT*	*PRLT*	*SMF*	*SMC*
Double external ducts	10	-1.97	-0.7	-0.97	0.84	2.38	-3.17	-2.43	1.21	8.12	-9.76
	-10	1.90	0.74	0.92	-0.79	-2.16	3.27	2.43	-8.12	-8.12	9.35
Single eternal duct	10	-4.71	-1.2	-3.33	2.71	5.32	-6.34	-5.49	0.42	8.43	-17.4
	-10	0.35	0.13	0.20	-0.16	-0.36	0.62	0.42	0.42	-0.77	5.62

With the increase of *DGA*, the pressure ratio of compressor decreases, the rotational speed decreases, the thrust decreases, the specific fuel consumption increases, the surge margin of fan increases, and the surge margin of turbine decreases.

Performance analysis is the basis of control system and the premise of aero-engine design and research. In this paper, the effect of geometry variables on the performance parameters of variable cycle aero-engine is analysed. In addition, the performance optimization of variable cycle aero-engine is to investigate how to adjust multi-variable to promote operation performance under non-overheating, non-overturning and non-surge, the relationships between geometry variables are also involved, which cause the performance optimization more complex and difficult.

3. Multi-variable optimization

MTLBO algorithm is utilized to solve this complex problem of multi-variable, multi-objective, non-linear performance optimization. In the optimization process, MTLBO algorithm will undergo the stage of teachers' teaching and students' mutual learning. The subroutine of dynamic mathematical model will be used many times to obtain the fitness function value, and make the "best" selection to decide whether to update the control variables. In the process of performance optimization, the constraints of non-overheating, non-overturning and not-surge need to be satisfied. The range of some performance parameters on aero-engine mathematical model are expressed as follows:

$$SMF \geq 10\%, SMC \geq 10\%, PNF \leq 104, T4 \leq 1850\text{K} \tag{1}$$

where *SMF* and *SMC* are fan surge margin and compressor surge margin respectively, *PNF* and *PNC* represent the low-pressure relative rotational speed and high-pressure relative rotational speed respectively, *T4* stands for turbine front temperature. In the program, penalty function method is used to restrict each constraint.

4. MTLBO algorithm

4.1. Theory

In the teaching-learning-based optimization (TLBO), the main idea is divided into two stages: the stage of teachers' teaching and the stage of students' mutual learning. Students can improve their performance by learning from teachers and communicating with their classmates. That is, an individual can be optimized twice during one iteration, which speeds up the convergence rate.

4.2. TLBO algorithm procedure

1) Population initialization: Determine the number of students χ , number of variables *D*, total iterations *K*, inertia weight *w*, upper and lower bounds of variables $X_{\max}$ and $X_{\min}$, fitness function *f*(*X*), and class matrix $P=[X_1, X_2, \ldots, X_{NP}]^{\mathrm{T}}$ is randomly generated according to the following formula (2):

$$X_{\mathrm{i}} = X_{\min} + rand(X_{\max} - X_{\min}) \tag{2}$$

where $X_{\mathrm{i}}=[x_{i1}, x_{i2}, \ldots, x_{i\mathrm{D}}]$.

2) Teaching stage

a. The objective function of population is evaluated to take the one with best fitness as the teacher

$$X_{teacher} = X_{f(X)=\min} \tag{3}$$

b. Calculate the average mean of each column of the class matrix for each group according to formula (4). Let *t* be the number of iterations and *Teacher* stands for teacher of each group, update the group according to formula (5) and (6).

$$Mean = [\frac{\sum_{i=1}^{\chi} x_{i,1}^k}{\chi}, \ldots, \frac{\sum_{i=1}^{\chi} x_{i,D}^k}{\chi}] \tag{4}$$

$$\Delta x_{ij}(t+1) = k*[Teacher_j(t) - TF*Mean_{ij}(t)] \tag{5}$$

$$newX_{ij}(t+1) = X_{ij}(t) + \Delta x_{ij}(t+1) \tag{6}$$

where $Teacher_j(t) - TF*Mean_{ij}(t)$ stands for the expression of students learning from teachers.

c. Make preferential selection between $newX_{ij}(t+1)$ and $X_{ij}(t)$ according to formula (7).

$$x_{ij}(t+1) = \begin{cases} newx_{ij}(t+1), f(newx_{ij}(t+1)) > f(x_{ij}(t)) \\ x_{ij}(t), f(x_{ij}(t)) > f(newx_{ij}(t+1)) \end{cases} \tag{7}$$

3) Students' mutual learning stage

a. Two students *A* and *B* their teachers *NTeacher* are randomly selected. If the fitness of student *A* is better, it is updated according to formula (8), otherwise it is updated according to formula (9).

$$newX_{ij}(t+1) = X_{ij}(t) + k_1*[x_{Bj}(t) - x_{Aj}(t)] \tag{8}$$

$$newX_{ij}(t+1) = X_{ij}(t) + k_1*[x_{Aj}(t) - x_{Bj}(t)] \tag{9}$$

where k_1 is the random number between [0,1], *A* and *B* are the random number between [1, χ].

b. Make the preferential selection according to formula (7).

4) Termination Condition

Whether the maximum number of iterations or the specified index requirements are reached is regarded as the termination condition, and if satisfied, the optimal solution is output, otherwise turn to step 2) until the termination condition is satisfied.

4.3. Key points of MTLBO algorithm

The modification of TLBO algorithm in this paper is as follows

1) Inspired by the inertia weight of standard particle swarm optimization (SPSO), this idea is introduced into MTLBO algorithm. In the real society, students will have their own learning experience when they focus in study, which can help them arrange their future learning more accurately. This

process can be achieved by adding inertia weight to the updated formula. The addition of inertia weight guides learning direction and trend of students, and helps to maintain the balance between global and local search ability. Meanwhile, students' self-learning promotion is considerable in actual learning process, so the self-learning part is added. Formula (5) is replaced by (10):

$$\Delta x_{ij}(t+1) = w * k_1 * \Delta x_{ij}(t) + k_2 * [Teacher_{ij}(t) - TF * Mean_{ij}(t)] + k_3 * \left| X_{hh} - X(t) \right| \tag{10}$$

where $k_i (i = 1, 2, 3) \in [0,1]$ is a random constant, X_{hh} stands for the fittest student in the class.

2) At the end of the teaching and learning stage, chaotic mutation is added to avoid the possibility of falling into local optimum. Some individuals with poor fitness are put into chaotic mutation to ensure the diversity of population and enhance the dispersion of search.

5. Optimization results and analysis

The bypass ratio *B*=0 is set in the non-afterburning single-duct mode of variable cycle aero-engine. Two flight conditions are selected. The afterburner fuel flow is still set to 0, and the main fuel flow is limited to 0.9kg/s. The upper and lower limits of variable nozzle area *A8* are (±5%), while the upper and lower limits of other variables are (±5deg). The number of population is set to 100, the number of optimization variables is 6, and the max iterations is 200. The results are compared with the optimization under genetic algorithm (GA). The population size is 100, the maximum genetic algebra is 200, the crossover probability is 0.99, and the mutation probability is 0.001. The optimization results of the two algorithms under two conditions are shown in table 5 and table 6. The curve of the maximum thrust with iterations in the optimization process is shown in figures 1-2.

Table 5. Optimization with *H*=9km, *Ma*=0.8

Variables	*A8*/m^2	*FGA*/(°)	*DGA*/(°)	*CGA*/(°)	*HTG*/(°)	*LTG*/(°)	*F*/N
Initial	0.265	9	-8.5	-7	10	12.5	33664.095
GA	0.251	5.410	-12.56	-3.840	14.770	14.050	36403.827
MTLBO	0.251	14	-3.50	-2	15	17.5	37559.384

Table 6. Optimization with *H*=12km, *Ma*=1.2

Variables	*A8*/m^2	*FGA*/(°)	*DGA*/(°)	*CGA*/(°)	*HTG*/(°)	*LTG*/(°)	*F*/N
Initial	0.265	9	-8.5	-7	10	12.5	32046.153
GA	0.251	12.680	-5.872	-10.420	8.860	8.020	33582.573
MTLBO	0.278	14	-2	-3.5	15	17.5	36057.868

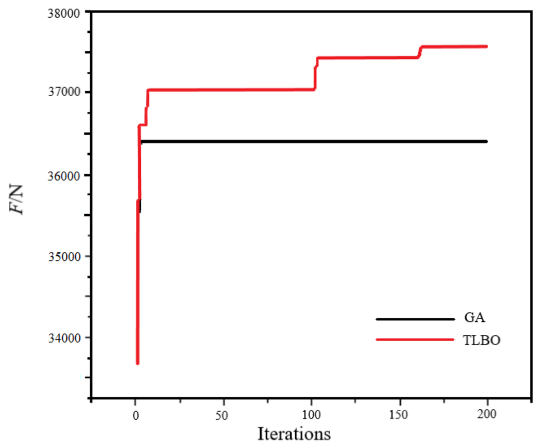

Figure 1. Optimization Curves of Maximum Thrust with Iteration under *H*=9km, *Ma*=0.8

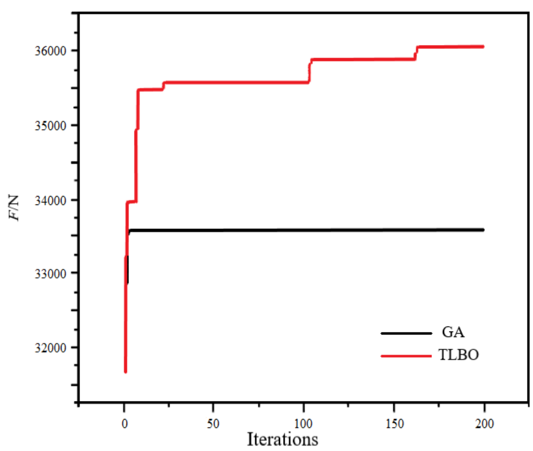

Figure 2. Optimization Curves of Maximum Thrust with Iteration under *H*=12km, *Ma*=1.2

From Table 5, it can be seen that the maximum thrust F=36403.827N optimized by genetic algorithm is 8.14% higher than the initial F=33664.095N. The maximum thrust F based on MTLBO algorithm is 37559.384N, which is 11.57% higher than the initial F and 3.17% higher than the one based on genetic algorithm. Obviously, the performance of variable cycle aero-engine based on MTLBO algorithm is better. It can also be seen that the improved MTLBO algorithm is less likely to fall into local optimum. Combined with the geometry characteristics of the variable cycle aero-engine mentioned above, it is obvious that not all variables in the two groups have reached the optimal state. This phenomenon is not difficult to explain, the aero-engine optimization process needs to satisfy the conditions of non-overheating, non-overturning, non-surge et. al, due to the penalty function, some variables are eliminated. It can be seen that the result of optimization is a trade-off between all variables.

Similarly, under operation point H=12km&Ma=1.2, the maximum thrust F based on genetic algorithm is 33582.573N, which is 4.79% higher than the initial F=32046.153N, and the maximum thrust F based on MTLBO algorithm is 36057.868N, which is 12.52% higher than the initial F and 7.37% higher than the one based on genetic algorithm. From figure 2, it can be seen that the MTLBO algorithm has a distinct trend in the process of optimization, and eventually converges to a stable value. Compared with genetic algorithm, it has better global performance and avoids the possibility of falling into local optimum.

6. Conclusions

In the non-afterburning single-duct mode of variable cycle aero-engine, the main fuel flow is limited to WFB=0.9kg/s, the two operation points (H=12km, Ma=1.2) and (H=9km, Ma=0.8) are selected, the optimization results of maximum thrust based on MTLBO algorithm are analysed and compared with the results based on genetic algorithm. The results show that MTLBO algorithm can significantly reduce the possibility of falling into local optimum, it is feasible to optimize the performance of variable cycle aero-engine with more geometry variables based on MTLBO algorithm, which can solve the performance optimization problems with multi-variable, strong-nonlinearity and serious coupling, and the improvement is more visible than that of genetic algorithm.

The method above remains an off-line performance optimization method and the results are obtained by simulation. So the potential of real-time optimization of the algorithm should be further investigated by the combination with actual application. The method and conclusions in this paper provide a new idea for intensive research of aero-engine performance and its control system.

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