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Principal component analysis and cluster analysis based orbit optimization for earth observation satellites *

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Abstract: This paper proposes a design optimization method for the multi-objective orbit design of earth observation satellites, for which the optimality of orbit performance indices with different units, such as: total coverage time, the frequency of coverage, average time per coverage and maximum coverage gap, etc. is required simultaneously. By introducing index normalization method to convert performance indices into dimensionless variables within the range of [0, 1], a design optimization method based on the principal component analysis and cluster analysis is proposed, which consists of index normalization method, principal component analysis, multiple-level cluster analysis and weighted evaluation method. The results of orbit optimization for earth observation satellites show that the optimal orbit can be obtained by using the proposed method. The principal component analysis can reduce the total number of indices with a non-independent relationship to save computing time. Similarly, the multiple-level cluster analysis with parallel computing could save computing time.

Keywords: satellite orbit; multi-objective optimization; index normalization method; principal component analysis; cluster analysis

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1 Introduction

Earth observation satellites play an important role in the national economy. With increased task complexity, higher requirements for orbit performance indices of

coverage capability as well as tracking telemetry and command (TT&C) have been put forward. The key orbit performance indices of an earth observation satellite include the total coverage time, frequency of coverage, average time per coverage, maximum coverage gap, minimum coverage gap, average coverage gap, average time interval of TT&C and average time of each TT&C^[1]. The aim of orbit design is to determine appropriate orbital parameters, which can make sure all the key orbit performance indices of

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an earth observation satellite are optimal. Thus, orbit design optimization is a typical multi-objective optimization problem.

Many researchers have paid attention to the multi-objective optimization. Qasim et al. [2] proposed the hybrid optimization algorithm, which associated the genetic algorithm (GA) as a global optimizer with sequential quadratic programming (SQP) as a local optimizer to carry out the conceptual design of a multi-stage ground-based interceptor. Wang et al. [3] proposed double global-optimum genetic algorithm-particle swarm optimization (GA-PSO) based on the GA and PSO algorithms to solve the welding robot path planning problem, where the shortest collision-free paths were used as the criteria to optimize the welding path. Chen et al. [4] proposed a simulated annealing based artificial bee colony algorithm (SAABC), which had a higher convergence rate than the artificial bee colony (ABC) algorithm, by introducing simulated annealing algorithm. Hu et al. [5] proposed a two-step improved particle swarm optimization (TIPSO) algorithm, in which four kinds of evolutionary multi-objective optimization algorithms, including GA, PSO, multi-objective GA and TIPSO, must be used simultaneously to get global optimization solution. Wei et al. [6] presented DP (dynamic programming) considering dual-state variables based on the Bellman optimality principle, to reduce fuel consumption and emissions of a dual-clutch hybrid electric vehicle during cold start.

However, applying the above methods to orbit design optimization directly without any simplification of the orbit performance indices will unbearably increase the cost of calculation due to the large number of key performance indices. Having the capability [7] of converting a set of possibly correlated variables into a set of values of linearly uncorrelated variables by using an orthogonal transformation, principal component analysis can reduce the number of orbit performance indices with a non-independent relationship and save

computing time. Wang et al. [8] predicted economic loss of vegetables caused by acid rain by using the principal component concept. Deb et al. [9-10] applied the principal component analysis method to the multi-objective optimization problem. Based on a principal component analysis, targets of conflict were extracted, redundant targets were abandoned, and multi-objective problems reached the goal of dimension reduction. The other method to save computing time is parallel computing. Unfortunately the parallel computing is hard to be implemented in the above methods. The cluster analysis can be applied to orbit design optimization due to its capability of dividing objects into a set of classes, and objects in the same class are more similar to each other than to those in other classes [11-12]. Zitzler et al. [13] used the clustering method in the multi-objective optimization problem to maintain diversity and distribution uniformity. The optimization solution based on principal component analysis and cluster analysis can be divided into two steps. The first step is to generate a large number of candidate orbits randomly and calculate the values of key performance indices of each orbit. The second step is to determine the optimal orbit from all candidate orbits. The parallel computing is easy to be implemented in the first step of cluster analysis. Thus, after the performance indices are converted into dimensionless variables with index normalization method, the principal component analysis and cluster analysis can be applied to the orbit optimization design.

In this paper, an orbit design optimization model for earth observation satellites consisting of optimization objectives, constraints and design variables was built. Then, the index normalization method was used to convert performance indices into dimensionless variables, the principal component analysis and cluster analysis based optimization processing flow was proposed and presented in detail. Finally, an example of orbit design optimization for earth observation satellites was carried out.

2 Orbit optimization model for earth observation satellites

2.1 Orbital dynamics model and orbit parameters

For earth observation satellites, orbit dynamics equations are as follows.

$$\left. \begin{aligned} \ddot{x} &= -\frac{\mu x}{r^3} \\ \ddot{y} &= -\frac{\mu y}{r^3} \\ \ddot{z} &= -\frac{\mu z}{r^3} \end{aligned} \right\}, \quad (1)$$

where x , y , and z are the Cartesian coordinates of a satellite; $r = \sqrt{x^2 + y^2 + z^2}$ denotes the distance between the satellite and the earth's core; μ is the geocentric gravitational constant. Neglecting the disturbances and perturbations without orbit maneuvers, the satellite positions at each moment can be determined by using Eq. (1) and six general orbital elements. A group of classic six general orbital elements are: semi-major axis a , eccentricity e , inclination i , argument of perigee ω , longitude of the ascending node Ω , and mean anomaly at epoch t_p . Then the key performance indices of an earth observation satellite can be calculated by using the satellite positions at each moment^[14-15].

2.2 Coverage and TT&C performance indices

The key performance indices of an earth observation satellite's coverage capability over a specified location or area on the earth's surface include the total coverage time (TCT), frequency of coverage (FC), average time per coverage (ATC), maximum coverage gap (MCG), minimum coverage gap (ICG), and average coverage gap (ACG). The tracking telemetry and command (TT&C) performance indices consist of the average time interval of TT&C (ATI-TT&C), and average time

of each TT&C (AT-TT&C). The total coverage time T_{Cover} in the simulation time T_{total} is as follows.

$$T_{\text{Cover}} = \sum_{i=1}^{N_{\text{Cover}}} \Delta t_i, \quad (2)$$

where N_{Cover} is the total number of coverage times in simulation time T_{total} ; and Δt_i is the time in the i^{th} coverage.

The frequency of coverage F_{Cover} in the simulation time is

$$F_{\text{Cover}} = N_{\text{Cover}} / T_{\text{total}}. \quad (3)$$

The average time per coverage T_{Aver} is

$$T_{\text{Average}} = T_{\text{Cover}} / N_{\text{Cover}}. \quad (4)$$

The maximum coverage gap T_{MaxGap} is

$$T_{\text{MaxGap}} = \text{Max}(\Delta t_{\text{Gap},i}) \quad (i = 1, 2, \dots, N_{\text{Gap}}), \quad (5)$$

where $\Delta t_{\text{Gap},i}$ is the time of the i^{th} coverage gap; N_{Gap} is the total number of coverage gaps in the simulation time.

The minimum coverage gap T_{MinGap} is

$$T_{\text{MinGap}} = \text{Min}(\Delta t_{\text{Gap},i}) \quad (i = 1, 2, \dots, N_{\text{Gap}}), \quad (6)$$

The average coverage gap T_{AveGap} is

$$T_{\text{AveGap}} = \sum_{i=1}^{N_{\text{Gap}}} \Delta t_{\text{Gap},i} / N_{\text{Gap}}. \quad (7)$$

The average time interval of TT&C T_{AveTel} is

$$T_{\text{AveTel}} = \sum_{i=1}^{N_{\text{Tel}}} \Delta t_{\text{Tel},i} / N_{\text{Tel}}, \quad (8)$$

where $\Delta t_{\text{Tel},i}$ is the time interval of the i^{th} TT&C; and N_{Tel} is the total times of time interval of TT&C.

The average time of each TT&C $T_{\text{AveTT\&C}}$ is

$$T_{\text{AveTT\&C}} = \sum_{i=1}^{N_{\text{TT\&C}}} \Delta t_{\text{TT\&C},i} / N_{\text{TT\&C}}, \quad (9)$$

where $\Delta t_{\text{TT\&C},i}$ is the time of the i th TT&C; and $N_{\text{TT\&C}}$ is the total times of TT&C.

In all eight performance indices, it is better that the total coverage time, the frequency of coverage, the average time per coverage, and the average time of each TT&C are larger, and the maximum coverage gap, the minimum coverage gap, and the average coverage gap are smaller. It is the best when the average time interval of TT&C is within an expected range.

2.3 Orbit design optimization model

The orbit design optimization model of earth observation satellites is as follows.

$$\begin{cases} \text{Expected: } T_{\text{Cover}}, F_{\text{Cover}}, T_{\text{Average}}, T_{\text{MaxGap}}, T_{\text{MinGap}}, \\ T_{\text{AveGap}}, T_{\text{AveTel}}, T_{\text{AveTT\&C}} \\ \text{s.t.: } a_{\min} < a < a_{\max} \\ \text{By find: } a, e, i, \omega, \Omega, t_p \end{cases} \quad (10)$$

The optimization objective is the eight key performance indices reaching maximum or minimum or within an expected range. The restrictive condition is $a_{\min} < a < a_{\max}$. The design variables are the six general orbital elements. The orbit design optimization model of Eq. (10) is a typical multi-objective optimization problem.

3 Orbit design optimization method based on principal component analysis and cluster analysis

3.1 Processing flow

For orbit design optimization of an observation satellite, the processing flow of the optimization

method based on principal component analysis and cluster analysis is as shown in Fig. 1.

The details are as follows.

Step 1. Use a random number generator to generate various initial (additional) candidates of the six general orbital elements according to the ranges of the elements. Use dynamic simulation technology to calculate the coverage and the TT&C performance indices of each candidate orbit. Parallel computing can be implemented easily in this step to save computing time.

Step 2. Use the index normalization method to normalize the coverage and TT&C performance indices. Use the principal component analysis to compute the principal components of performance indices of each orbit.

Step 3. Use multiple-level cluster analysis to classify the candidate orbits according to the principal components. Clustering the candidate orbits according to the principal components can save more computing time than according to the performance indices, because the number of principal components is smaller than that of the performance indices for an orbit. Use a weighted evaluation method to find out the optimal class.

Step 4. If the total number of candidate orbits in the optimal class is greater than six, then implement Step 1.

In Step 1, drawing lessons from the idea of obtaining the best individual by using the genetic operation on the individuals of low utility in the genetic algorithm, various additional six general orbital elements are generated randomly. The ranges of additional six general orbital elements are the same as the corresponding ranges of all orbits in this optimal class, and their total number is identical with the total number of candidate orbits in this optimal class. If the total number of candidate orbits in this optimal class is smaller than six, then the optimal orbit will be found out by using the weighted evaluation method from this optimal class.

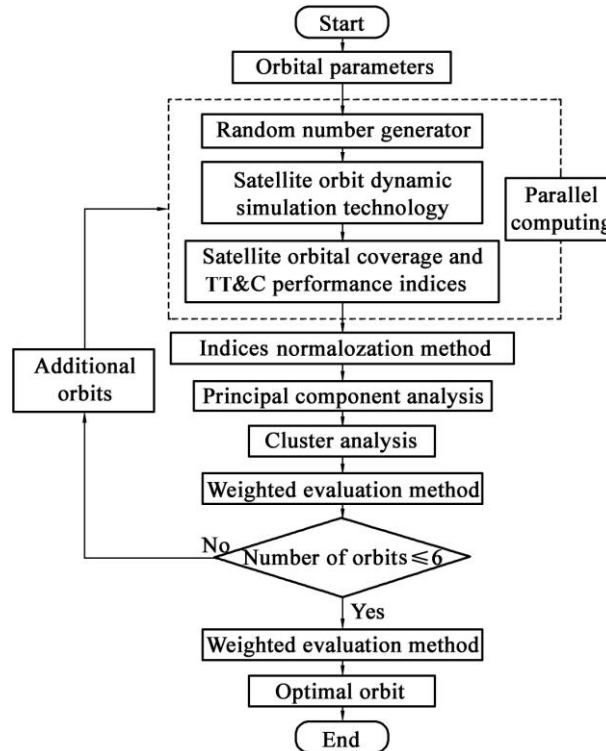


Fig. 1 Analysis flow chart of orbit optimization design

3.2 Details of the orbit design optimization method

3.2.1 Index normalization method

After various candidate six general orbital elements are generated and performance indices of each candidate orbit are calculated, performance indices need to be converted to dimensionless ones within the range of [0, 1]. Considering that it is better that some of the performance indices of an earth observation satellite (such as the total coverage time) are larger and some are smaller (such as the maximum coverage gap), and it is the best for some of the indices to be within the expected range (such as the average time interval of TT&C, for which an excessively large interval would

prevent timely data return and an excessively small interval would create data retransmission), a dimensionless method for the three categories of performance indices is shown in Eq. (11). For the n_{big} performance indices which are better to be larger, the normalization coefficient is equal to the performance index value divided by the maximum value of all the candidate values. For the n_{small} performance indices which are better to be smaller, the normalization coefficient is equal to the reciprocal of the performance index value divided by the minimum value of all the performance indices. For the n_{range} performance indices which are better to be within an expected range, the normalization coefficient is equal to the performance index value divided by the median of the range when

the performance index is smaller than the median of the range, and normalization coefficient is equal to the reciprocal of the performance index value divided by the median of the range when the performance index is greater than the median of the range.

$$(C_i)_j = \begin{cases} \frac{(I_i)_j}{\max(I_i)} & i = 1, \dots, n_{\text{big}} \\ \frac{\min(I_i)}{(I_i)_j} & i = 1, \dots, n_{\text{small}} \\ \frac{(I_i)_j}{\overline{(I_i)_j}} & (I_i)_j < \overline{(I_i)_j} \quad i = 1, \dots, n_{\text{range}} \\ \frac{\overline{(I_i)_j}}{(I_i)_j} & (I_i)_j > \overline{(I_i)_j} \quad i = 1, \dots, n_{\text{range}} \end{cases} \quad (11)$$

where $(C_i)_j$ is the normalization coefficient of the i th performance index of the j th orbit $(I_i)_j$.

3.2.2 Principal component analysis

Because the total number of normalization coefficients of each orbit is large, and there is a non-independent relationship among different normalization coefficients, principal component analysis will be conducted to reduce the number of normalization coefficients to save computing time.

Principal component analysis can transform a large number of normalization coefficients into a small number of principal components, by using a linear transformation^[7], without any loss of information of the performance indices, and with the important influencing factor of performance indices identified. Thus, principal component analysis can simplify multi-objective design optimization problem and improve computing efficiency. When the normalization coefficients of orbit performance indices are C_1, C_2, \dots, C_p , where p is the number of orbit performance indices of each orbit, the normalization coefficients can be expressed with vectors $C = (C_i)$, then $C_1, C_2, \dots, C_{n_{\text{total}}}$ are the normalization coefficients of orbit performance

indices of different candidate orbits, where n_{total} is the total number of candidate orbits. The elements u_{ij} of the covariance matrix $U = (u_{ij})_{p \times p}$ can be calculated by

$$u_{ij} = \frac{1}{n_{\text{total}} - 1} \sum_{k=1}^{n_{\text{total}}} ((C_i)_k - \overline{(C_i)})((C_j)_k - \overline{(C_j)}), \quad (12)$$

where k is loop variable; and

$$\overline{(C_i)} = \frac{1}{n_{\text{total}}} \sum_{k=1}^{n_{\text{total}}} (C_i)_k, \quad \overline{(C_j)} = \frac{1}{n_{\text{total}}} \sum_{k=1}^{n_{\text{total}}} (C_j)_k. \quad (13)$$

Then the eigenvalues λ_i of covariance matrix U can be calculated. The cumulative contribution ratio of previous m eigenvalues η_m is as follows:

$$\eta_m = \sum_{i=1}^m \lambda_i / \sum_{i=1}^p \lambda_i. \quad (14)$$

When $\eta_m > 88\%$, the minimum m is the number of principal components, and $m \in [1, p]$. Then the principal component Z_j of the j^{th} candidate orbit can be calculated with the orthogonal normalize eigenvector e_i^T of the covariance matrix U :

$$Z_j = [e_1^T X_j, e_2^T X_j, \dots, e_m^T X_j]^T \quad (j = 1, 2, \dots, n_{\text{total}}). \quad (15)$$

Because $m < p$, the total number of principal components to be classified is smaller than the total number of performance indices. The amount of computation is reduced.

3.2.3 Multiple-level cluster analysis

The optimal orbit can be obtained from all candidate orbits by cluster analysis. During cluster analysis, the number of classes within a certain range is arbitrary^[11-12]. When the number of classes is too large in a one-time clustering, the differences among various classes are obscure. It is not conducive to determining the optimal class from all classes. The too small number of classes in a one-time clustering makes the differences among various classes great but the number

of orbits in each class is too large to obtain the optimal orbit. Therefore, considering the large number of candidate orbits, this paper proposes a multiple-level cluster strategy. Firstly, a small number of classes are classified, and then the performance indices of each class center are evaluated by using the weighted evaluation method described hereinafter in Section 3.2.4. The class with the largest evaluation index becomes the first-level optimal class. Then, the second-level optimal class is selected from the first-level optimal class according to the above-mentioned method. By this analogy, the optimal class becomes the end result of clustering optimization when the number of orbits in the optimal class is sufficiently small, as shown in Fig. 1.

In multi-level cluster analysis, this paper draws lessons from the idea of obtaining the best individual by using the genetic operation on the individuals of low utility in genetic algorithm. When the total number of orbits in the optimal class after a one-time clustering is larger than six, various additional six general orbital elements are generated randomly. The ranges of additional six general orbital elements are the same as the corresponding ranges of all orbits in the optimal class, and the performance indices of each additional orbit are calculated. Then original performance indices in the optimal class and additional performance indices are processed simultaneously by cluster analysis. Until the total number of orbits in the optimal class is smaller than six, the cluster analysis is terminated. Finally, the optimal orbit to meet the optimization goal is selected from the optimal class by using the weighted evaluation method. The role of generating additional orbits is similar to the function of genetic operation in a genetic algorithm.

This paper applies a total class distance criterion to determine the optimal number of classes in each clustering. Firstly, the cluster analysis method is used to separate the orbits into 4, 5 and 6 classes. Then, the total class distance δ is calculated with

$$\delta = \sum_{i=1}^q \delta_i, \quad \delta_i = \sqrt{\frac{1}{n_i} \sum_{j=1}^{n_i} d_j^2}, \quad (16)$$

where q is the number of classes per clustering ($q=4, 5$ and 6); n_i is the number of orbits in each class; and d_j is the distance between the class center and each orbit in this class. The number of classes in the three clustering analyses with the smallest δ is taken as the final class number of this clustering.

3.2.4 Weighted evaluation method

This paper proposes a weighted evaluation method to determine the optimal class from all classes and to obtain the optimal orbit from the last optimal class. The evaluation index ξ is as follows.

$$\xi = \left(\sum_{i=1}^{n_{\text{big}}} (C_i) W_i + \sum_{i=1}^{n_{\text{small}}} (C_i) W_{n_{\text{big}}+i} \right) \prod_{i=1}^{n_{\text{range}}} f(C_i), \quad (17)$$

where $W_i (i=1, 2, \dots, n_{\text{big}} + n_{\text{small}})$ is the weight coefficient of the i th key performance index, whose range is $[0, 1]$.

The calculation method for the representative coefficient $f(C_i)$ is as follows..

$$f(C_i) = \begin{cases} 1 & S_{\min} \leq C_i \leq S_{\max} \\ 0 & C_i > S_{\max} \text{ or } C_i < S_{\min} \end{cases} \quad (18)$$

where $[S_{\min}, S_{\max}]$ is the expected range of C_i .

4 Orbit design results and analysis

4.1 Orbit optimization problem

For a certain earth observation satellite with an observation target locating at latitude and longitude coordinates of $(120^\circ, 25^\circ)$ and with a vision field angle of 25° , the TT&C station had latitude and longitude coordinates of $(120^\circ, 40^\circ)$, and a minimum elevation angle of 5° . The expected range of average time

interval of TT&C was from 300 s to 1 000 s. The range of the semi-major axis was from 400 km to 600 km. $W_i (i = 1, 2, \dots, n_{\text{big}} + n_{\text{small}})$.

4.2 Optimization results and analysis

A total of 1 000 000 initial candidate orbits were randomly generated. The simulation time for each candidate orbit was 100 d. The coverage as well as the TT&C performance indices of the candidate orbits were calculated. The index normalization method was used to normalize the performance indices of the candidate orbits. Four computers were utilized to carry out parallel computing. About 3/4 time was saved. The principal component analysis method was used to handle the performance indices dimension reduction. The contribution rates of the first three principal components obtained through principal component analysis were 63.95%, 15.01%, and 13.17%, respectively, at the first clustering, as shown in Fig. 2.

Fig. 2 shows that the first three principal components had greater contribution than the others. The cumulative contribution rate of the first three principal components reached 92.13%. Therefore, an eight-dimension data space could be projected into a three-dimensional space. The number of principal components was found to be three in all clustering, although the contribution rates of the first three principal components changed slightly. Multi-level cluster analysis was conducted on three principal components, which reduced the computing time by 62.5%.

The total class distance criterion indicated that the optimal number of classes for the first clustering was 5. The principal components in the 5 class centers were as shown in Table 1, which shows the very obvious differences among the 5 class centers. Class 3 had the greatest principal component 1; Class 2 had the greatest principal component 2; and Class 4 had the greatest principal component 3.

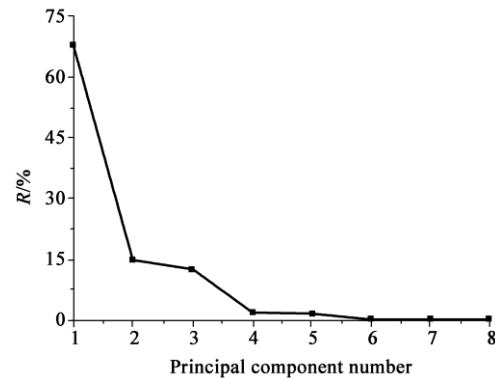


Fig. 2 Contribution rate (R) of different principal component at the first clustering

Fig. 3a demonstrates the distribution characteristics of the principal components in the five class centers. Because the principal components did not have a physical meaning, it was difficult to determine the optimal class according to the principal components; Fig. 3b shows the obvious differences among the performance indices of class centers, and the weighted evaluation method could then be easily used to select the optimal class by evaluating the performance indices of class centers.

Table 2 gives the eight performance indices values of the five class centers. It shows that Classes 1 and 2 both lacked coverage and should be eliminated. Class 4 was determined as the optimal class by the weighted evaluation method.

Fig. 3b indicates that Class 4 had relatively large values in the total coverage time, frequency of coverage, average time per coverage, and average time of each TT&C, and relatively small values in the maximum coverage gap, average coverage gap, and minimum coverage gap. Class 4 was the optimal class of the five classes. The optimal class obtained by the weighted method was the same as the conclusion of the orbital characteristics analysis.

Class 4 of the first clustering was selected to

continue with clustering. The principal components and eight performance indices in the class center after clustering fourteen times using the above-mentioned method are shown in Figs.4. The analysis results using the weighted evaluation method indicated that Class 4 was the optimal class.

The eight performance indices for the five orbits of Class 4 are shown in Fig. 5. Fig. 5 indicates that Orbit

2 had relatively large values in the total coverage time, frequency of coverage, average time per coverage, and average time of each TT&C, and relatively small values in the maximum coverage gap, average coverage gap, and minimum coverage gap. Orbit 2 was the optimal class of the five orbits. The optimal orbit obtained by the weighted method was the same as the conclusion of the orbital characteristics analysis.

Table 1 Principal components in the class centers at the first clustering

Principal component number	Value				
	Class 1	Class 2	Class 3	Class 4	Class 5
Principal component 1 (PC1)	-1.28	0.90	0.95	-0.38	-0.66
Principal component 2 (PC2)	0.13	2.05	-0.59	-0.94	-0.24
Principal component 3 (PC3)	-1.43	0.05	-0.23	3.13	1.19

Table 2 Eight performance indices of the five class centers at the first clustering

Performance index	Normalization coefficient				
	Class 1	Class 2	Class 3	Class 4	Class 5
Frequency of coverage (FC)	0.00	0.00	0.26	0.59	0.20
Total coverage time (TCT)	0.00	0.00	0.24	0.56	0.16
Average time per coverage (ATC)	0.00	0.00	0.62	0.66	0.58
Maximum coverage gap (MCG)	0.00	0.00	0.38	0.42	0.79
Average coverage gap (ACG)	1.00	1.00	0.41	0.23	0.47
Minimum coverage gap (ICG)	0.00	0.00	0.14	0.08	0.63
Average time interval of TT&C (ATI-TT&C)	0.30	0.00	0.30	0.36	0.29
Average time of each TT&C(AT-TT&C)	0.56	0.00	0.61	0.56	0.60

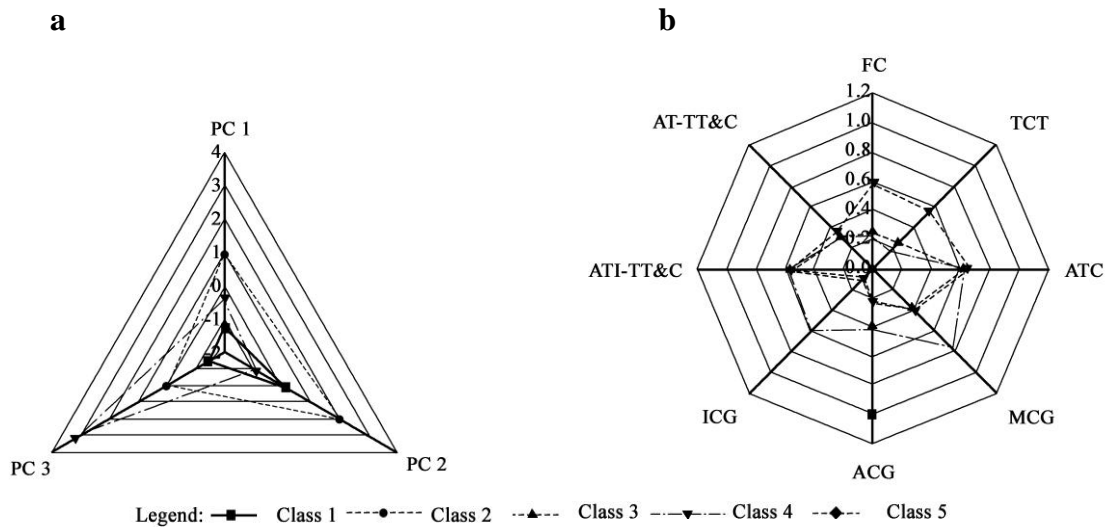


Fig. 3 Results of the first clustering: a) principal components in the five class centers; and b) performance indices of the five class centers

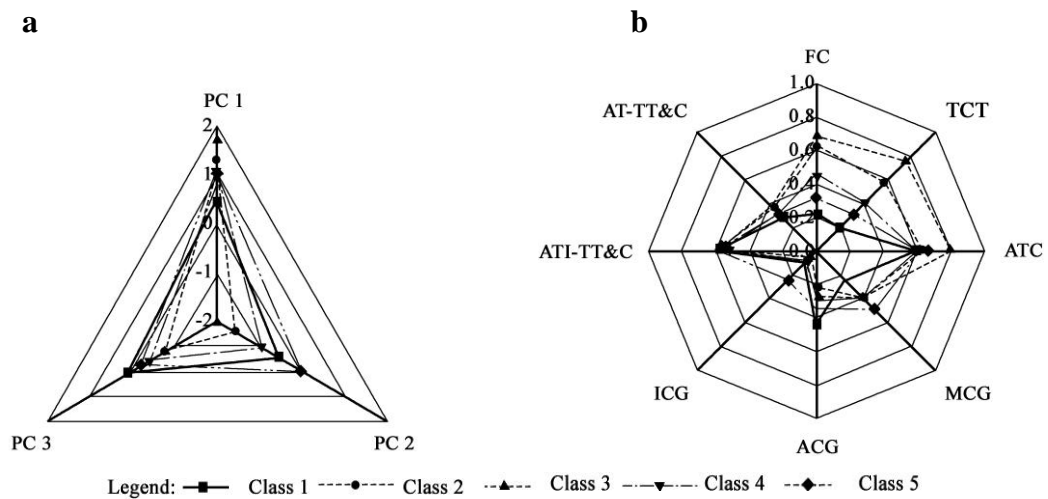


Fig. 4 Results of the fourteenth classifying: a) principal components in the five class centers; and b) performance indices of the five class centers

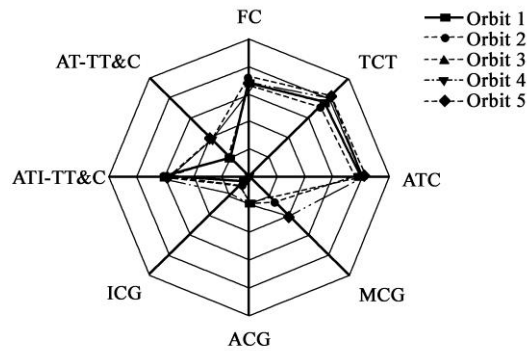


Fig. 5 Performance index for the five orbits in Class 4 after the 14th classifying

5 Conclusions

This paper establishes an orbit design optimization model for earth observation satellites, and proposes a design optimization method consisting of index normalization method, principal component analysis, multi-level cluster analysis, and weighted evaluation method. An example of orbit design optimization for earth observation satellites showed that when 1 000 000 initial candidate orbits and additional orbits after a one-time clustering were randomly generated, the optimal orbit was obtained by using proposed orbit design optimization method based on principal component analysis and cluster analysis. The principal component analysis reduced the computing time by linearly transferring eight orbit performance indices into three principal components. It saved 5/8 of the computing time in multiple-level cluster analysis. Simultaneously, the parallel computing with four computers was implemented easily in generating candidate orbits. It used only 1/4 of the time the method without parallel computing used.

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