Low Earth Orbit Regional Satellite Constellation Design via Self Organization Feature Maps

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Abstract

Satellite constellation design is one kind of typical Multiobjective Optimization Problem (MOP). In this paper, aim at feature of high-dimensional decision space, an model-based multiobjective Evolutionary Algorithm (EA) via Self Organization Feature Map (SOM) is put forward for reducing decision space dimension of satellite constellation design: internal topology of input training set in the population can be kept by neurons of SOM network, which makes topology similar points between in high-dimensional input data space remains neighboring relationship in low-dimensional data space after mapping, so as to achieve the dual purpose to maintain diversity of population and accelerate convergence of algorithm. Experiment on low earth orbit regional satellite constellation design shows that the optimization results can meet the demand of coverage performance for specific region, but running speed of the algorithm should be improved, the reason is maybe that SOM modeling is time-consuming with increasing of decision space dimension.

Keywords: Satellite Constellation, Self Organization Feature Map, Model-based Multiobjective Evolutionary Algorithm

1. Introduction

1.1. Satellite Constellation

With development of satellite technology and its application, single satellite has become difficult to accomplish complex space missions, for this reason, satellite network so-called satellite constellation[1] consisting of satellites has become an inevitable research trend. Satellite constellation is a specific collection of satellites which are composed in accordance with certain rules[2], satellite constellation has incomparable superiority of single satellite.

Among orbital elements, the orbital altitude is a key indicator which will influence the number of satellite and other feature of satellite constellation, based on orbital altitude, there are four kind of constellation: Geostationary Earth Orbit (GEO), Low Earth Orbit (LEO), Medium Earth Orbit (MEO) and High Elliptical Orbit (HEO). Relative to other, LEO has the following features: short propagation delay, less signal loss and to facilitate the miniaturization of the user terminal network, stabilized network and LEO has outstanding advantages on supporting large number of mobile user’s communication in wide range, for above reasons, LEO is very suitable for the space application of military and government department. At the same time, according to coverage performance, there are three kind of constellation: global coverage constellation, band coverage satellite constellation and regional coverage constellation [3].

1.2. Conception and Method of Satellite Constellation Design

The aim of satellite constellation design is that using satellites as little as possible and designing reasonable satellite orbital configuration parameters for meeting pre-set of constellation performance requirements [3]. Figure 1 shows an example of communication satellite constellation design[4]. First step is satellite constellation demand analysis, find out system design constraint on the pre-condition of meet mission requirements which is foundation of satellite constellation design. Second, according the system design constraint of constellation configuration, the number of satellites is be determined, and calculate percentage of constellation coverage performance, constellation configuration must be re-
designed until requirement of satellite constellation coverage performance is meeting. For the orbit parameters solved by the second step, proceed space segment designs of satellite constellation. Third, in part of satellite communication network design, its optimization objects are bit error rate and communication delay, the main works are topological structure design of satellites, access method and radio frequency link design. After above three steps, ground segment design will be work out.

**Figure 1. System Design of Satellite Constellation from Above to Below[4]**

1.3. Problem Complexity and Method of Satellite Constellation Optimization

Satellite constellation design is a kind of very complex problem, its optimization results are relate to a variety of optimization indicators which functions are computational complexity and even have no analytical expression; At the same time, because relationship between constellation coverage performance and orbit elements is complex, so satellite constellation is a kind of typical multi-objective optimization problem which have characteristics of high-dimensional, modality, fitness hard-calculate, so usually these constellation optimization indicators shows in Figure 1 are to be converted into objective functions or constraints in order to establish correct problem description and mathematical optimization model. Overall, general design method of satellite constellation include geometry analysis, compare method based on simulation and modern optimization method, among above three methods, modern optimization method, especially Evolutionary Algorithm(EA) is more suitable for solving satellite constellation design than the other two, the reason is that searching space can be expanded and then distributed or heterogeneous constellation configuration can be worked out rapidly by Evolutionary Algorithm(EA), however on the precondition of meeting coverage performance, the key point of constellation design based on Evolutionary Algorithm(EA) is constellation configuration and orbit design, the flowing is recently research.

Since 1996, Eric Frayssinhes[5] found GA is very effective for GPS system, optimization symmetrical or unsymmetrical circular orbit constellation has been designed using real code Genetic Algorithm (GA), and advantage has been pointed out about GA for solving constellation design. In 1997, George[6] designs global discontinuous coverage constellations by Genetic Algorithm(GA). In 1998, Mason et al[7] by multi-objective GA, global continuous coverage of the constellation has been lay out in which results were bring into Satellite Tool Kit (STK) for evaluating coverage performance of constellation. Owing to some constellation does not require to achieve global coverage, just converging for given region. In 2000, Crossley et al[8] compare research have been carry out between using Simulated Annealing Algorithm (SA) and GA for satellite constellation. In 2001, Confessore et al[9] propose a kind of heuristic genetic algorithm for bands coverage or regional coverage elliptical orbit constellation. In 2001 and in [10], the largest coverage gap and the average coverage gap was elected as two optimization objects which Pareto Optimal Solution(PS) can be obtained by Genetic Algorithm(GA). In 2001, based on heuristic tabu search genetic algorithm, Enguerran

In China, widely and deep research has been carried out about constellation configuration design method. As far back as in 1994, Hefeng Bai[14] researched two questions: one is mechanism of global and regional coverage constellation, another is design method via analysis method. In 1999, Kaiheng Xiang[15] has studied basic constellation design theory and simulation of constellation. In 2000, Zang Li[16] has studied mobile communication satellite constellation design and its Inter satellite Links design, at the same time, analyzing and computing method of Inter satellite Link' geometric parameters which can be build by any two satellites. In 2001, Haili Wang[17] has banded simulation method together analysis method to design global coverage constellation. In 2002, Rui wang[18] has designed regional coverage constellation via Genetic Algorithm. In 2004, one kind of evolutionary algorithm which can optimize constellation structure and parameters simultaneous has been proposed for regional coverage satellite constellation design in[19]. In 2005, Sudang Li[20] has devised improved Genetic Algorithm for LEO regional satellite constellation design. In 2007, Wei Zheng[21] and Li xiaomeng[22] adopted OMEA and SPEA respectively for the optimal design of constellation. In 2007, WU Ting-yong[23] processed optimal design of regional coverage common-track satellite constellation via Genetic Algorithm. In 2008, LIU Wen et al[24] used Multi-objective Evolutionary Algorithm for optimization of communication satellite constellation. In 2009, via Particle Swarm Optimize(PSO) , Meng Bo et at optimized navigation satellite constellation. In 2009, Wang Jianwen[26], a regularity model-based multiobjective distribution estimation algorithm was used for satellite constellation optimization. In 2010, respectively by Indicator-Based Evolutionary Algorithm IBEA and algorithm of model-based multiobjective distribution estimation, Zhang Jingcheng[27] and Li Yanzhi[28] has designed regional low orbit satellite constellation successfully. In 2010, Wang Chunming[29] designed infrared LEO constellation design by GDE 3 algorithm and Sang Wengang[30] used a kind of improved Ant Colony Algorithm(ACO) to design regional pseudolite-augmented GPS constellation. In 2011, Baoqiu Xiao[31] purposed a improved NSGA-II for satellite constellation optimization.

1.4. SOM and its Superiority for Solving Satellite Constellation Design

Self Organization Feature Map(SOM)[32][33] is a kind of without supervised learning Neural Network(NN), it was invented by a man named Teuvo Kohonen, a professor of the Academy of Finland, and it provides a way of representing multidimensional data in much lower dimensional spaces – usually one or two dimensions. This process, of reducing the dimensionality of vectors, is essentially a data compression technique known as vector quantization. In addition, the Kohonen technique creates a network that stores information in such a way that any topological relationships within the training set are maintained.

One of the most interesting aspects of SOM is that it learns to classify data without supervision. You may already be aware of supervised training techniques such as back-propagation where the training data consists of vector pairs – an input vector and a target vector. With this approach an input vector is presented to the network (typically a multilayer feed-forward network) and the output is compared with the target vector. If they differ, the weights of the network are altered slightly to reduce the error in the output. This is repeated many times and with many sets of vector pairs until the network gives the desired output. Training a SOM however, requires no target vector. A SOM learns to classify the training data without any external supervision whatsoever.

SOM has been widely used in data mining and visualization of high dimensional data, and it has achieved very good results, as we known, if we use Evolutionary Algorithm(EA) to solving satellite constellation optimization, the chromosomes’ dimensionality of EA are exactly one kind of high dimensional data which can be shortened by SOM, just because of this, in this paper an algorithm for low earth orbit regional satellite constellation design Via SOM is proposed for reducing dimension of decision space and accelerating convergence.
1.5. Scope

In this paper, a kind of Model-Based Multiobjective Evolutionary Algorithm via SOM is proposed for solving LEO regional coverage satellite constellation design. In part 2, orbital elements of satellite will be discussed, in part 3, algorithm of satellite constellation design based on SOM will be introduced, and there are experimental results on a regional coverage satellite constellation example. In part 4, analyze algorithm and summary whole paper.

2. Satellite Constellation Orbit Parameters

2.1. Satellite Orbital Elements

A satellite’s orbit parameters called satellite orbital elements[3], expressed as $\text{Sat} = (a, e, i, \omega, \Omega, M)$, as shown in Figure 2(A), where $a$ is Semi major axis, $e$ is Eccentricity, $i$ is Inclination, $\omega$ is Argument of periapsis, $\Omega$ is Longitude of the ascending node, $M$ Mean anomaly at epoch, $a$ and $e$ determines orbit geometry shape, $i$, $\omega$ and $\Omega$ determines position of orbital plane in space, $M$ determines location of satellite in orbit at some time.

![Figure 2. (A) Orbital Elements (B) Coverage Performance Analysis on Satellite Constellation](image)

2.2. Coverage Performance Analysis on Satellite Constellation

Figure 2 (B) demonstrates how to analyze coverage performance of single satellite, where $R_e$ is radius of the Earth, $h$ is altitude of satellite, $R_{sat} = R_e + h$ is geocentric radius of satellite, $\varphi$ is nadir angle, $\gamma$ is minimum elevation angle. As we known, if elevation angle of certain point on the ground is bigger than $\gamma$, this ground point can communicate with satellite, that is to say the point can be covered by the satellite, consequently, corresponding ground points with $\varphi$ is area covered by satellite, so central angle is:

$$\theta = \arccos\left(\frac{R_e}{h + R_e}\cos\gamma\right) - \gamma$$

(1)

And then nagir angle is:

$$\varphi = \arcsin\left(\frac{R_e}{h + R_e}\cos\gamma\right)$$

(2)

Coverage radius of satellite is:
\[ r = R \theta \]  

(3)

At certain moment, we denote the angle between ground feature point and geocentric by \( \phi \), it can be deduced easily that \( \phi \leq \theta \) means the ground feature point is in the coverage range of satellite, otherwise is not, with regard to coverage performance analysis of multiple satellites, and so on.

There are diverse criterions for coverage performance analysis of satellite constellation composed of multiple satellites, such as: total coverage time, coverage percentage, coverage count, average coverage time, maximum coverage time slot and average coverage time slot. Coverage performance of some specific points selected from area need to be covered represent coverage performance of whole area.

3. LEO Regional Satellite Constellation Design Via SOM

3.1. Satellite Constellation Code

In theory, satellites in constellation can be lay out in any orbit, however, in practical design, satellite constellation should have a stable configuration and satellite launch mode[24] must be taken into account for laying out satellite easily, for example, in generally, for reducing costs, satellite launch mode of LEO satellite constellation usually adopts multi-satellite, if these satellites are located in the same orbit plane, satellite insertion is more easily, therefore, the constraints of satellite orbital elements is as following:

- Satellites in constellation are in the same orbit, that is the same \( a \) (Semi major axis) and \( e \) (Eccentricity);
- Satellites in the same orbit have the same \( \omega \) (Argument of periapsis);
- If needs multi-orbit plane, the best \( i \) (Inclination) and \( \Omega \) (Longitude of the ascending node) should be selected;
- For multi-satellite in the same orbit plane, the relative position of satellites should be arranged reasonably.

Through above analysis, with respect to LEO regional satellite constellation design, there are six parameters need to be optimized, that is \( a, e, i, \omega, \Omega, M \), but in practical design, \( a \) (Semi major axis) and \( e \) (Eccentricity) is usually be pre-set, so a kind of satellite constellation optimization model so-called \((4N+2)\) Model is to be designed, where \( N \) is the number of satellites in the constellation, 4 represents the four control parameters: \( i, \omega, \Omega \) and \( M \), and 2 represents the other two parameters \( a \) and \( e \). As we known, if design satellite constellation via Evolutionary Algorithm, then an individual in population represents a satellite constellation and the gene code of the individual is as following:

<table>
<thead>
<tr>
<th>( i_1 )</th>
<th>( \omega_1 )</th>
<th>( \Omega_1 )</th>
<th>( M_1 )</th>
<th>( i_2 )</th>
<th>( \omega_2 )</th>
<th>( \Omega_2 )</th>
<th>( M_2 )</th>
<th>( \cdots )</th>
<th>( i_N )</th>
<th>( \omega_N )</th>
<th>( \Omega_N )</th>
<th>( M_N )</th>
</tr>
</thead>
</table>

Suppose population size is \( K \), and then the code of whole constellation population is:

<table>
<thead>
<tr>
<th>Constellation 1</th>
<th>( i_1 )</th>
<th>( \omega_1 )</th>
<th>( \Omega_1 )</th>
<th>( M_1 )</th>
<th>( i_2 )</th>
<th>( \omega_2 )</th>
<th>( \Omega_2 )</th>
<th>( M_2 )</th>
<th>( \cdots )</th>
<th>( i_N )</th>
<th>( \omega_N )</th>
<th>( \Omega_N )</th>
<th>( M_N )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constellation 2</td>
<td>( i_1 )</td>
<td>( \omega_1 )</td>
<td>( \Omega_1 )</td>
<td>( M_1 )</td>
<td>( i_2 )</td>
<td>( \omega_2 )</td>
<td>( \Omega_2 )</td>
<td>( M_2 )</td>
<td>( \cdots )</td>
<td>( i_N )</td>
<td>( \omega_N )</td>
<td>( \Omega_N )</td>
<td>( M_N )</td>
</tr>
<tr>
<td>\vdots</td>
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</tr>
<tr>
<td>Constellation ( K )</td>
<td>( i_1 )</td>
<td>( \omega_1 )</td>
<td>( \Omega_1 )</td>
<td>( M_1 )</td>
<td>( i_2 )</td>
<td>( \omega_2 )</td>
<td>( \Omega_2 )</td>
<td>( M_2 )</td>
<td>( \cdots )</td>
<td>( i_N )</td>
<td>( \omega_N )</td>
<td>( \Omega_N )</td>
<td>( M_N )</td>
</tr>
</tbody>
</table>

3.2. Fitness Computing

Fitness of algorithm is coverage percentage for target area or target points, the fitness computing algorithm of satellite constellation is as following:
Algorithm: Fitness Computing of Satellite Constellation

Parameters: $S$ represents a satellite, $A$ is a point on the earth, $K$ is population size, $m$ is number of target points need to be covered, $T$ is the simulation duration, $t$ is sampling period, so $n=\frac{T}{t}$ is sampling count, $t_j$ is sampling instant at time $j$ ($1 \leq j \leq n$), $COV_i(1 \leq i \leq K)$ is coverage percentage of the $i$ constellation in population during $T$; $N$ is the number of satellites in every constellation; $C_{ij}$ is coverage percentage of the $i$ constellation in population at time $t_j$.

\[
\text{for}(i=1 ; i?K ; i++)
\{
\text{for}(t_j=t ; t_j?T ; t_j=t_j+t)
C_{ij}++ ; \quad \text{// Inside loop: Compute $C_{ij}$ during $T$}
\text{Average}(C_{ij})=\frac{C_{i1}+C_{i2}+C_{i3}+\ldots+C_{in}}{n} ; \quad \text{// Compute average value of $C_{ij}$}
COV_i = \text{Average}(C_{ij}) \quad \text{//Outside loop: Compute $COV_i$ successively during $T$}
\}

3.3. Self Organization Feature Map

The SOM (Self Organizing Feature Maps) [32] [33] [34] is a feed-forward network, and it consists of an input and an output layer. Output layer consists of $M$ units or neurons arranged on a regular grid, and each output neuron is connected to input vector. Figure 3(A) illustrates a typically two-dimension SOM grid.

As shown as in Figure 3, each neuron in SOM grid has a specific topological position (an $x$, $y$ coordinate in the lattice) and contains a vector of weights of the same dimension as the input vectors. That is to say, if the training data consists of vectors $\mathbf{v}^i = (v_1^i, v_2^i, \ldots, v_n^i)^T$, $i = 1, 2, \ldots, T$, $n$ is the SOM dimension and $T$ is the number of vectors, each neuron contains a corresponding weight vector $\mathbf{w}^j = (w_1^j, w_2^j, \ldots, w_n^j)^T$, $j = 1, 2, \ldots, M$.

Figure 3. (A) With two-dimension quadrilateral distribution of SOM network (B) Mapping of input layer vector and the neuron

The SOM training procedure can be summarized into the following framework and more detailed algorithm can be found in [32] [33] [34].
3.4. Algorithm of LEO Regional Satellite Constellation Design Via SOM

In order to capture and utilize the regularity of the Pareto set explicitly, Qingfu Zhang and Aimin Zhou proposed a regularity model-based multiobjective estimation of distribution algorithm (RM-MEDA) [35]. RM-MEDA uses local Principal Component Analysis (PCA) to build the probability model of decision space. Compared with other model-based multiobjective algorithms[36]-[39] on a set of bi-objective or tri-objective test instances with linear or nonlinear variable linkages, RM-MEDA performs well.

But the disadvantage of RM-MEDA is that local PCA for cluster in RM-MEDA makes computation particularly complexity and time-consuming, so in this paper, local PCA in RM-MEDA replace by SOM, and propose a hybrid multi-objective evolutionary algorithm via SOM for LEO regional satellite constellation design, in order to mining high-dimension data manifold and reduce dimension of decision space to and accelerate convergence of algorithm[34], it works as follows:

Algorithm 2: Satellite Constellation Design Via SOM

**Parameters**: The population is $Pop(t) = \{X^1, X^2, \ldots, X^K\}$, where $K$ is population size, $t$ is current running population of algorithm; The individual fitness is $\bar{F}(X) = (COV_1(X), COV_2(X), \ldots, COV_m(X))^T$, where $m$ is the number of targets, $COV_m(X)$ is coverage percentage of every constellation and it can be computed out by Alg 1.

1: Initialization: Set $t = 0$, generate an initial constellation population $Pop(0)$ randomly and compute its corresponding fitness values $\bar{F}$ of each solution in $Pop(0)$ via Algorithm 1, and randomly initialize the neuron’s weights in SOM grid.

2: Modeling: Set the current population $Pop(t)$ as input training data of the SOM, and train the SOM to learn constellation manifold distribution of the solutions in $Pop(t)$ through Algorithm 2.

3: Reproducing Constellation: Generate $N_1$ constellations from the SOM grid; perform crossover and mutation on $Pop(t)$ to generate $N_2$ constellations, merge $N_1$ and $N_2$, and get offspring population $Q = Q_1 + Q_2$, then evaluate fitness value $\bar{F}$ of each solution in $Q$.

4: Elitist Selection: Select $N$ excellent constellation solutions from $Q \cup Pop(t)$ to create $Pop(t+1)$ via elitist selection algorithm in [40].

5: Stopping Condition: If the stopping condition is meeting and return the non-dominated solutions in $Pop(t)$, otherwise, let $t = t + 1$ and go to Step 1.

4. Simulation Results

4.1. Experiment Parameters

In this paper, select LEO regional satellite constellation design to test performance of Algorithm 2, set the number of satellites in constellation is 10; orbit altitude $a$ is 1000km; Eccentricity $e$ is 0, that is to say the orbit is round; the range of $t, \omega, \Omega, M$ are all $[0^0, 360^0]$; Population size is 20 and there are 10 satellites in every constellation, so in every individual there are $4\times10 = 40$ parameters need to be optimized, accordingly there are $4\times40 = 800$ parameters need to be optimized in whole population. Suppose simulation duration is 24 hours and sampling period is 1 second.
Set coverage width is 200km and there are 3 ground regions need to be covered which latitude and longitude range is \( F1(0^\circ E \sim 20^\circ E, 10^\circ N \sim 30^\circ N) \), \( F2(30^\circ E \sim 50^\circ E, 40^\circ N \sim 60^\circ N) \) and \( F3(60^\circ E \sim 80^\circ E, 65^\circ N \sim 80^\circ N) \) respective, so if \( F1, F2, F3 \) are divided into target points by one degree on longitude and latitude, then the target points’ count of \( F1, F2, F3 \) is \( 21 \times 21 \), \( 21 \times 21 \) and \( 21 \times 16 \) respective.

Algorithm parameters setting is as following: SOM network is bi-dimensional by 5’, iteration times of SOM is 500, learning rate is 0.1, algorithm run 200 generations and get the following results in Table 1.

4.2. Optimization Results and Analysis

Via Satellite Tool Kit (STK) of American Analytical Graphics Company simulate the above optimization results in Table 1 and get satellite constellation tri-dimensional pictures as shown in Figure 4:

### Table 1. Optimization Results by Algorithm 3

<table>
<thead>
<tr>
<th>Orbit Parameters</th>
<th>Coverage Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a(km) )</td>
<td>e</td>
</tr>
<tr>
<td>------------------</td>
<td>---</td>
</tr>
<tr>
<td>7378.10</td>
<td>0</td>
</tr>
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<td>7378.10</td>
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<td>7378.10</td>
<td>0</td>
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</tbody>
</table>

Due to number of orbit plane and orbit inclination has not be restrained, so the ten satellites in constellation solved out by algorithm lie in ten different orbit planes, which is not reasonable and difficult to be launch in engineering application.

![Figure 4](image-url)
5. Conclusion

Satellite constellation design is a typical high-dimension optimization which relates with multi-objective and optimization retrain, for this reason traditional optimization design method does not take into account a variety of conflicting objectives within a certain range. Regarding above shortcoming of traditional method, so in this paper, for reducing the dimension of optimization for designing satellite constellation a kind of evolutionary algorithm based on SOM (Self Organizing Feature Maps) is proposed.

Experiment shows that SOM can be used in satellite constellation and the results can meet coverage demand of specified regions, but its shortcoming of this algorithm is that calculated amount increases exponentially by increasing of parameters’ dimension, so in the future work, first, orbit parameters more in line with engineering application will be given; secondly, efforts to research how to reduce problem dimension of satellite constellation design by designing more efficient algorithm; on the other hand, try to develop parallel program to reduce running time of the algorithm.

6. Acknowledgment

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7. References


