A Local High-Capacity LEO Satellite Constellation Design Based on an Improved NSGA-II Algorithm

Chao Zheng(✉), Bing Zhao, and Daoxing Guo

Army Engineering University of PLA, Nanjing 21007, Jiansu, China
1599974708@qq.com

Abstract. As we all know, satellite communication has the advantages of wide coverage, large communication capacity, etc. compared to terrestrial communication, and is not easily affected by geographical natural disasters. But the coverage of one satellite is limited, so we often need a constellation satellite communication system composed of multiple satellites to communicate. Also, the cost of satellites is relatively high, and the satellite constellation usually needs to consider both cost and communication performance, how to use the least cost to achieve a best communication performance. We construct a design multi-objective optimization model of satellite constellation for a local high capacity, using the improved NSGA-II algorithm to solve model, using STK software to simulate the results of the solution.

Keywords: Constellation satellite communications design · Multi-objective optimization · Improved NSGA-II

1 Introduction

Compared with a single satellite, constellation satellites have the characteristics of orbit diversification, strong system survivability, short communication delay, large communication capacity, and wide coverage [1]. Various constellation design schemes have been proposed in different countries, and some constellation satellite communication systems have also been established. The primary commercial constellation satellite communication systems built and operated are Iridium, Globalstar, OneWeb system, SpaceX Starlink and Hongyan constellation of China.

According to the different satellites in the design scenario, the optimization of satellite constellation is mainly divided into two situations for local high capacity and wide-area supplementary coverage. Scholars have conducted a lot of research on these two design scenarios, and have proposed corresponding constellation design and optimization schemes. Literature [2,3] proposed a global-oriented constellation design scheme, in which literature [2] proposed an improved algorithm

Q. Wu et al. (Eds.): WiSATS 2020, LNICST 357, pp. 391–403, 2021.
https://doi.org/10.1007/978-3-030-69069-4_33

to utilize the minimum number of satellites to achieve a stronger satellite constellation coverage performance; literature [3] based on navigation accuracy and satellite orbit parameters , based on the Walker constellation, proposed an optimized design scheme for the global navigation satellite constellation. References [4,5] and [6] proposed an area-oriented constellation design scheme. Reference [4] divided the target area into three parts according to latitude and longitude, combined with the satellite constellation coverage multiple, minimum coverage requirements and the total number of satellites. The optimization problem is solved by using genetic algorithm, and finally the regional-oriented constellation design scheme is given; In [5], the maximum value is given by combining the satellite orbit and the average communication elevation angle. The constellation design scheme that minimizes the coverage factor and minimizes the semi-major axis of the orbit; [6] gives an optimization algorithm for inter-satellite routing, and a satellite network design scheme based on multi-layer satellites.

We can see that the satellite constellation is the basis of the satellite communication system. The constellation design need to consider how to meet the QoS of different communication services, the coverage of this constellation, the way of satellite access and switching, communication delay and throughput, etc., and the need to minimize construction costs must also be considered because the design needs to achieve the trade-off between multiple goals, so this satellite design problem can be regarded as Multi-objective optimization problem. It was proposed by Italian economist Pareto and was first used to solve the trade-off problem in political economy. The multi-objective optimization problem can be defined as determining the vector composed of decision variables in the feasible domain so that a set of conflicting objective function values reach the maximum value at the same time. There are many methods for solving multi-objective optimization problems, for example, ant colony algorithm, simulated annealing, genetic algorithm, tabu search, combinatorial optimization algorithm, etc. [7].

The design and optimization of the constellation satellite constellation for the local high-capacity LEO satellite communication system are aimed at reducing the deployment cost of the satellite constellation and building a more convenient and economical satellite communication system. The traditional satellite communication design focuses on the optimization of communication performance such as satellite coverage multiple, average communication elevation angle, lack of consideration for the needs of ground users and deployment costs, resulting in excessive waste of satellite-related orbits, frequencies, and other resources. We chose China as the target area, longitude range: 73°E to 135°E, latitude range: 3°N to 53°N. The letter is mainly for the design of high-capacity low-orbit satellites for the target area. In the design and optimization process of this constellation, the constellation design is closely combined with the actual needs of users, under the dual conditions of communication quality and cost efficiency, giving a feasible constellation deployment solution for a local high-capacity satellite communication system. Also, in this optimized design, We chose the walker constellation as the basic configuration, continue to optimize the number of satellites, the number of orbits, satellite orbit period, orbit tilt angle, and other parameters.

NSGA-II is an algorithm for searching the optimal solution derived from simulating biological genetics and evolution theory. We use the improved NSGA-II algorithm to solve the satellite design, which involves multiple optimization parameters, the optimal solution and use STK software to simulate and evaluate the performance of the satellite constellation scheme, and compare with Globalstar to verify the effectiveness of this constellation design.

The rest of the letter is organized as follows. In Sect. 2, the system model is described. Section 3 introduces the improved NSGA-II algorithm, and the model is solved. The results are simulated by STK software and compared with Globalstar. Conclusions are drawn in Sect. 4.

2 System Model

According to the previous discussion, we need to achieve a balance between the performance and cost of the constellation. It can generally be modeled as a multi-objective optimization problem. Assuming that there are q optimization goals, and these q optimization goals may conflict with each other, the mathematical model can usually be expressed by the following formula:

$$\begin{cases} minF = [f_1(x), f_2(x), ..., f_q(x)] \\ s.t. g_i(x) \leq 0, i = 1, 2, ..., m \end{cases} \tag{1}$$

In the formula, $x = (x, x, ..., x,)^T$ is an n-dimensional decision vector, and its space is called the decision space, where each variable x_n, which is the decision variable, affects the performance of the optimization goal: $(f_1(x), f_2(x), ..., f_q(x))$ are q-dimensional target vectors, and their space is called the target space. Each target function $f_q(x)$ corresponds to the sub-goal to be optimized; $g_i(x) \leq 0$ is the inequality constraint condition, which means the constraint condition to be met by the variables in the decision space. In this letter, we divided the entire constellation design optimization target into performance target and cost target. In the performance target, the coverage N of the satellite to the target area and the communication capacity C of the constellation are mainly considered. The coverage of the constellation is an important indicator to measure the performance of the constellation. High coverage rate is an important factors to achieve seamless connection for ground terminals and ground stations. The communication capacity of the constellation mainly refers to the ability of the constellation to serve the target area. In summary, the performance objective function is expressed as increasing communication capacity and coverage as much as possible. In the cost targe, since the total cost of a single satellite is still relatively high, reducing the cost of satellite constellation is also the focus of research.

2.1 Performance Target

Since the Walker constellation coverage performance is stronger than the polar orbit constellation, and the design of the regional constellation is not troubled by the establishment of the ground station, the Walker is selected as the basic configuration of the constellation design. Divide into small grids according to 1 ° of latitude and longitude, and the points on the grid are the feature points. Assuming that the total number of feature points is n, then it is considered to be measured every minute within an orbital period to calculate the constellation coverage at the current time. The rate is m/n, and the average constellation coverage of one orbit period is our optimization goal, which is expressed as follows:

$$C = \frac{1}{[P]} \sum_{k=1}^{[P]} \frac{m_k}{n_k} \tag{2}$$

In the formula, [.] indicates rounding down, C indicates the average coverage rate of the target area at the kth measurement, the number of covered feature points is m_k, the total number of feature points in the target area is n_k, and p is the orbital period.

Analysis of constellation satellite capacity requires comparison with the user needs to form a constraint. The constellation capacity we define here refers to the service capability of the satellite constellation for the target area, that is, the number of satellites that the constellation can serve for the target area. The mathematical model established is as follows:

First, the capacity of a single satellite is as follows:

$$C_{sat} = \frac{P_{sat} G_{sat} G L_f L_M - I}{SNRkTR_{user}} \tag{3}$$

L_M represents the rain attenuation of the signal in free space, R_{user} represents the user rate of a single user, P_{sat} represents the transmission power of the satellite to the user, G_{sat} represents the satellite antenna gain, G represents the user antenna gain, and L_f represents the signal when the signal propagates in free space Path loss. SNR represents the required signal-to-noise ratio of the user, k represents the Boltzmann constant, T represents the noise temperature of the user terminal, and R_{user} represents the data rate of the user terminal. In the process of serving users, the satellite receives interference from other satellites as follows:

$$I = \sum_{j \in N and j \neq i} P_{sat,j} G_{sat,j} G_j \left(\frac{\lambda}{4\pi d_j} \right)^2 \tag{4}$$

N represents the number of satellites in this constellation, of which m satellites interfere with the target satellite, where $P_{sat,j}$ represents the transmission power of the satellite labeled j, and $G_{sat,j}$ represents the satellite labeled j for the user's antenna gain, G_j represents the user terminal's reception gain for the interfering satellite marked j, and the last part represents the path loss of the satellite marked j in free space.

The total satellite capacity of the constellation is calculated as follows:

$$C_{total} = N_p N_{sat} C_{sat} \frac{S_t}{S_c} \tag{5}$$

N_p represents the number of orbits, N_{sat} represents the number of satellites in each orbit, S_t represents the area when the target area is mapped into space, depends on the periods of the satellite constellation orbit and the area of the target area, S_c represents the size of the constellation coverage area, the value depends on satellite constellation orbit period P and orbit inclination angle i [8].

Demand of users is represented by the number of satellite communication users in the target area. Therefore, the user demand model is mainly to establish the relationship between the population of the target area and the size of the communication market and the number of satellite communication users. First of all, the population of the target area can be calculated by the density of the ground population and the population distribution. In this model, the actual population mainly refers to the statistical results of NASA's International Earth Science Center. Based on the relevant information on the website, the population density of the ground can be calculated. We use population density data for 2020, see the Fig. 1. The scale of the communication demand mainly depends on the economic development of the target area and the user's acceptance of satellite communication. These indicators are reflected in the user demand model.

Fig. 1. Global 2020 population density of NASA's International Earth Science Center

We have previously calculated the coverage rate and divided the target area into several small grids. We directly obtained the population density of each small grid from the data, and then normalized the population density. The normalized formula is as follows:

$$\sum_{grid=1}^{N_g} D(grid) = 1 \tag{6}$$

N_g represents the number of all grids, $grid$ represents the number of the grid, and $D(grid)$ represents the normalized population density distribution. Therefore, the satellite communication users in each grid are as follows:

$$DM(grid) = f_{sat} M_{number} D(grid) \tag{7}$$

2.2 Cost Target

Due to the complexity of satellite cost calculation, there is currently a variety of satellite cost calculation methods. This letter mainly calculates based on the cost model given in Reference [9]. To simplify the calculation, this letter focuses on analyzing the deployment cost of the space segment. The total cost of a satellite communication system includes satellite cost, launch cost, maintenance cost, number of satellites, satellite power, and satellite quality. Therefore, the cost is as follows:

$$COST = N_P * N_{sat} * (1+\beta) * (1+\alpha+0.00049*((((\frac{T}{2\pi})^2 * GM)^{\frac{1}{3}} - r)^{0.43}) * W_{sat} \quad (8)$$

β represents the proportion of insurance costs, α represents the ratio of the weight of the aircraft to the weight of the loader, W_{sat} represents the weight of the satellite.

$$W_{sat} = (1+\alpha)(W_{array} + W_{battery} + W_{tran} + W_{antenna})$$

$W_{arag} \approx 0.1 \times P_{total}$ represents the weight of the solar array, $W_{batten} \approx 0.125 \times P_{total}$ represents the weight of the battery, $W_{ren} \approx 0.075 P_{rotal} + 50$ represents the weight of the on-board transponder, and $W_{antema} \approx \frac{(\frac{GM}{(\frac{2\pi}{P})^2})^{\frac{1}{3}}}{200}$ represents the weight of the on-board antenna. P_{total} represents the total power of the satellite.

In summary, we unified the performance target and the cost target to make the performance target as large as possible and the cost target as small as possible. We proposed a multi-objective optimization model for the local high-capacity satellite constellation optimization model. This constellation design is to use the minimum satellite deployment cost to achieve a low-orbit satellite constellation that meets the needs of users in the target area. The Walker constellation is used as the basic constellation. The orbit altitude is limited to [500, 2000] kilometers. The minimum communication elevation angle when it is not greater than 60, deploy a low-orbit satellite constellation that serves users in the target area. Therefore, the optimization model is as follows:

$$\min_{N_p, N_{sat}, P, \theta} (COST, -C_{total}, -C)$$

$$s.t. \begin{cases} C_{total} \geq \sum_{grid=1}^{N_p} DM(grid); \\ C \geq 90\%; \\ N_{p\max} \geq N_p \geq N_{p\min}; \\ N_{sat\max} \geq N_{sat} \geq N_{sat\min}; \\ 2\pi\sqrt{\frac{(r+2000)^2}{GM}} \geq P \geq 2\pi\sqrt{\frac{(r+500)^2}{GM}}; \\ \theta_{\max} \geq \theta \geq \theta_{\min} \end{cases} \quad (9)$$

In order to achieve better economic benefits and optimization effects, the number of satellites in the constellation and the orbit period need to be controlled within a certain range. Walker is the basic configuration in the design process of this constellation, so the orbital inclination is limited to between 40 and 60. It can be seen that the design of satellite constellation for local high capacity is an optimization process that includes multiple optimization goals. From the objective function, it can be seen that the satellite deployment cost, satellite constellation coverage, and satellite capacity are mutually restricted. As the number of satellites increases, the coverage of the satellite constellation increases, and the satellite constellation capacity increases first and then tends to be flat. However, the increase in the number of satellites will increase the cost of satellite deployment. The traditional mathematical optimization solution method is not suitable for solving such multi-objective optimization problems, so we will use the improved NSGA-II algorithm [10] to solve the optimization problem in the next section.

3 Improved NSGA-II Algorithm to Solve the Model

Given the shortcomings of NSGA, Deb et al. proposed NSGA's improved algorithm-non-dominated set sorting genetic algorithm with elite strategy (NSGA-II). NSGA-II is a genetic algorithm based on Pareto optimal concept. Compared with NSGA, NSGA-II has made the following improvements [11]:

(1) Using the fast non-dominated sorting method, the computational complexity is reduced from O(kN^3) to O(kN^2). Where k is the target number and the number of individuals in the N-group.
(2) The crowded distance is adopted to maintain the diversity of the population.
(3) Introduce elite strategies to prevent the loss of excellent solutions.

Experiments show that the results of NSGA-II are better than several other representative algorithms, but the performance of the SBX (Simulated Binary Crossover) cross operator is relatively weak, which limits the search performance of the algorithm to a certain extent. Besides, NSGA-II has yet to be improved in terms of convergence rate and maintaining the diversity of the population.

Lei Peng et al. applied the reverse learning mechanism to the population's initialization process and obtained good results [12]. Because it considers both population P and reverses population P*, it is larger than simple random initialization. The probability is close to the optimal goal of the problem. Apply reverse learning mechanism to genetic process. In the genetic process of each generation, the reverse population P* of its population P is calculated, and N optimal individuals are selected from the population P and the reverse population P* as the evolutionary population of the next generation. However, considering the significance of solving the inverse later in the algorithm, it reduces the speed of the algorithm. Therefore, the following method is adopted: In each generation of the evolution process, its population P is calculated with a certain probability O_r (opposite rate) of its reverse population P*, and during the evolution process, it decreases linearly, namely:

$$O_r = \max O_r - \frac{g}{MGG}\left(\max O_r - \min O_r\right) \tag{10}$$

where MGG is the maximum genetic generation, g is the current generation, and $maxO_r$ and $minO_r$ are the maximum and minimum values of O_r, respectively. In the way, the reverse learning mechanism can accelerate the convergence of the algorithm. To maintain the diversity of the population in the evolution process, when the individual $x_{ij}(g)$ and the individual $ox_{ij}(g)$ of the reverse population are not dominated by each other, ox_{ij} (accept rate) is accepted with a certain probability. Similarly, the probability of $accR$ is also linearly decreasing:

$$accR = \max accR - \frac{g}{G}\left(\max accR - \min accR\right) \tag{11}$$

Considering that in the genetic process, it is hoped that individuals with better distribution (low-rank value) and better distribution (large dist value) will occupy a larger proportion of the genes of individual offspring, for this reason, The crossover operator is as follows:

$$\alpha = \begin{cases} \frac{B \cdot rank}{A \cdot rank + B \cdot rank}, A \cdot rank \neq B \cdot rank \\ \frac{A \cdot dist}{A \cdot dist + B \cdot dist}, A \cdot rank = B \cdot rank \end{cases} \tag{12}$$

$A \cdot rank$ represents the non-dominated ranking of individual A of the current generation, and $A \cdot dist$ represents the crowded distance of individual A of the current generation. In the later stage of the algorithm, the genes of the better-distributed individuals are better preserved, and thus improved algorithms [10] is as follows:

Algorithm 1. Improved NSGA-II algorithm

```
Random initialization of population P and calculate opposite population P*
Selecting N fittest individuals from Pand P* as initial population
Evaluate initial population
while the halting criterion is not satisfied do
   Tournament Selections routines
   Arithmetic Crossover routines
   Polynomial Mutation routines
   Evaluate population P
   if (rnd(0,1) < O_r) then
      Compute opposite population P*
      Select PopSize fittest Individuals from P and P*
   end if
end while
```

The flowchart of satellite constellation optimization is as Fig. 2.

Some notes on algorithm solving:

a) In the entire constellation design, the decision variables are the number of satellite constellation orbits, the number of satellites in a single orbit, the satellite orbit tilt angle, the satellite orbit period, and the satellite minimum

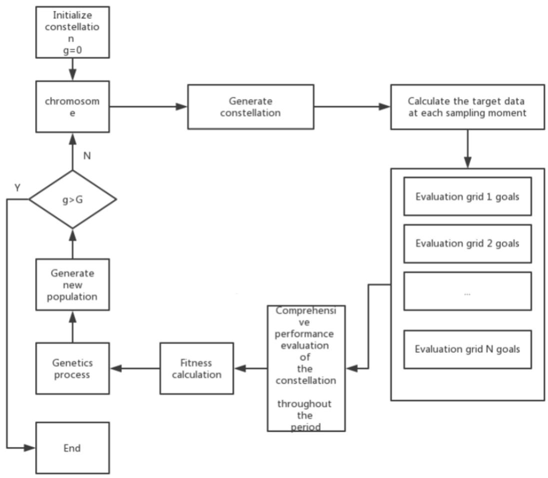

Fig. 2. Satellite constellation optimization flowchart

communication elevation angle. In this scenario, the value range and precision range of each decision variable determine its length in the chromosome. Also, the minimum communication elevation angle is directly taken as 10° according to the Globalstar system. The coding method of each chromosome is as follows:

$$X = [N_P/N_{sat}/i/P]$$

b) For each set, each individual has a multi-dimensional optimization target value, sort the optimization target values separately, adjust the individual's level according to the sorting result, and solve the crowding degree.

c) The characteristics of the elite strategy are that the excellent individuals in the parent directly enter the offspring, avoiding the loss of the optimal solution caused by chromosome crossover and gene mutation. First, eliminate the infeasible solutions in the parent; secondly, according to the results of non-dominated sorting, add individuals to the new population in descending order until the new population size exceeds the initial population size. Sort the population from large to small to fill the new population and build a new parent.

d) Select individuals from each generation according to the roulette wheel selection method. In general, the probability of individual inheritance depends on the size of the individual's crowding degree, and the probability that an individual with a large crowding degree inherits the next generation is greater. As shown in the following formula.

$$P_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \tag{13}$$

e) The selection table of some related parameters is shown in the Table 1.

Table 1. Algorithm related parameter table

Algorithm related parameters	Value
Chromosome length	50
Maximum genetic generation	100
Gene crossover probability	0.8
Gene variation probability	0.3
Chromosome coding method	Binary
Binary code length	48
User terminal rate R_0	1.544 Mbps
Downlink frequency f	40 GHz
User terminal antenna gain G	41 dB
User terminal system noise temperature T	135 K
SNR	4.8 dB
Rain attenuation and other losses L_M	–5 dB

f) To ensure the cost of constellation design, the total number of constellation satellites is limited to 100, the number of orbits does not exceed 10, and the number of satellites in each orbit does not exceed 10. Besides, the inclination angle range of the track is limited to 30 to 60.

According to the proposed optimization scheme, the improved NSGA-II algorithm is used to solve the satellite constellation design of the target area. The results are as follows. The satellite constellation uses the Walker constellation as the basic configuration and consists of 35 low-orbit satellites with a total of 5 orbital inclination angles. It is a 48° orbital plane, and there are 7 evenly distributed satellites in each orbit, with a satellite orbit period of 110 min. The constellation illustration simulated by stk software are shown in Fig. 3 and Fig. 4.

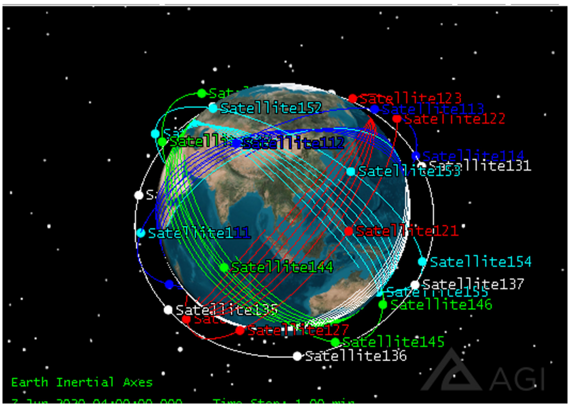

Fig. 3. 3D illustration of satellite constellation

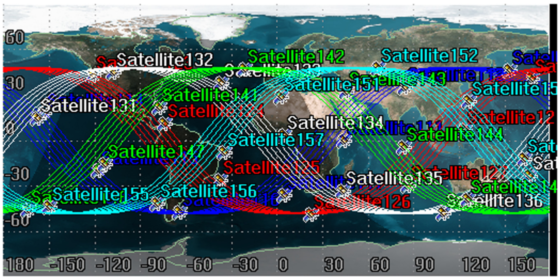

Fig. 4. 2D illustration of satellite constellation

To verify the effectiveness of the LEO satellite constellation scheme given for the target area in this paper, we mainly compare it with the Globalstar system.

First of all, we use the STK coverage analysis module to analyze coverage rate, and use our design and Globalstar to calculate coverage rate for the same small area. The results are shown in Fig. 5 and Fig. 6.

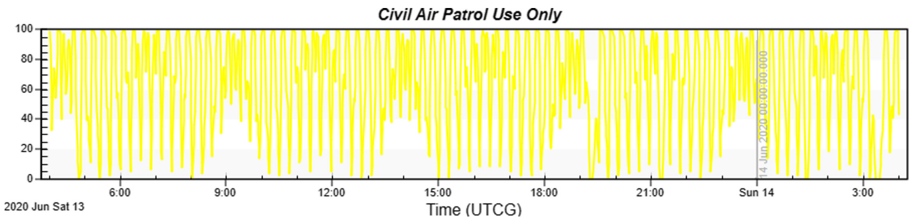

Fig. 5. Coverage rate of our designed scheme

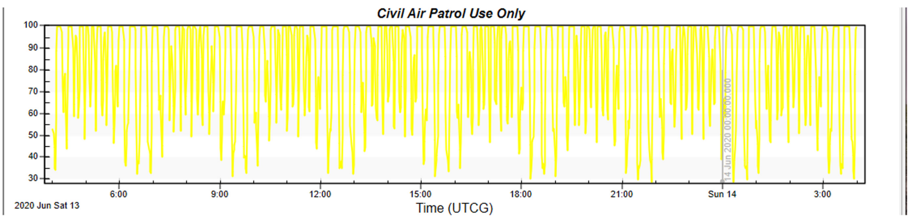

Fig. 6. Coverage rate of Globalstar

The coverage rate of our design is more concentrated in 100%, which shows that the solution is more stable than Globalstar.

Then the cost analysis. In our design, there is only 35 satellites and Globalstar has 48 satellites. In terms of space segment deployment cost, the overall cost of the constellation we design is lower than Globalstar, which just meets the design goals of this article and greatly saves Constellation deployment costs.

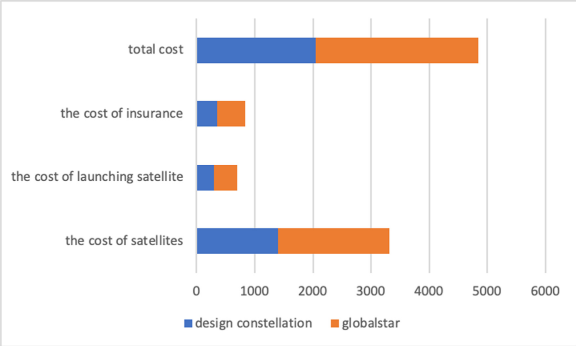

Fig. 7. Cost comparison analysis

4 Conclusion

In this letter, the constellation design problem for the target area is proposed. In order to achieve a compromise between cost and performance of satellites, this paper construct a design multi-objective optimization model of satellite constellation and use the improved NSGA-II algorithm to solve model, using STK software to simulate the results of the solution. But, the letter should be more innovative, our solution just compare the design with Globalstar. Comparing the design with Globalstar, we can see that our solution is better than Globalstar in terms of coverage performance and cost. In addition, due to some shortcomings in our design scheme, such as not considering the impact of inter-satellite links, not considering the ground cost, etc., we will improve it in future work.

References

1. Re, E., Ruggieri, M. (eds.): Satellite Communications and Navigation Systems. Springer, New York (2007)
2. Fernandez-Prades, C., Presti, L.L., Falletti, E.: Satellite radiolocalization from GPS to GNSS and beyond: novel technologies and applications for civil mass market. Proc. IEEE **99**(11), 1882–1904 (2011)
3. Ioannides, R.T., Pany, T., Gibbons, G.: Known vulnerabilities of global navigation satellite systems, status, and potential mitigation techniques. Proc. IEEE **104**(6), 1174–1194 (2016)
4. Meziane-Tani, I., Métris, G., Lion, G., Deschamps, A., Bendimerad, F.T., Bekhti, M.: Optimization of small satellite constellation design for continuous mutual regional coverage with multi-objective genetic algorithm. Int. J. Comput. Intell. Syst. **9**(4), 627–637 (2016)
5. Mo, Y., Yan, D., You, P., Yong, S.: Comparative study of basic constellation models for regional satellite constellation design. In: 2016 Sixth International Conference on Instrumentation & Measurement, Computer, Communication and Control (IMCCC), pp. 171–176. IEEE (2016)

6. Soterroni, A.C., Galski, R.L., Ramos, F.M.: Satellite constellation design using the qG global optimization method. In: 2015 Third World Conference on Complex Systems (WCCS), pp. 1–6. IEEE (2015)
7. Deb, K.: Multi-objective optimization. In: Burke, E., Kendall, G. (eds.) Search Methodologies, pp. 403–449. Springer, Boston (2014) https://doi.org/10.1007/978-1-4614-6940-7_15
8. Asvial, M., Tafazolli, R., Evans, B.G.: Satellite constellation design and radio resource management using genetic algorithm. IEE Proc. Commun. **151**(3), 204–209 (2004)
9. Lei, L., Qiongqing, Y., Dongtang, M.: Cost analysis and comparison of constellation satellite mobile communication systems. Ph.D. dissertation (2007) (in chinese)
10. Xiao, B., Liu, Y., Dai, G.: Improved nsga-ii algorithm and its application in optimization of satellite constellation. Comput. Eng. Appl. **48**(10), 47 (2012)
11. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.A.M.T.: A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. **6**(2), 182–197 (2002)
12. Peng, L., Wang, Y., Dai, G.: A novel opposition-based multi-objective differential evolution algorithm for multi-objective optimization. In: Kang, L., Cai, Z., Yan, X., Liu, Y. (eds.) ISICA 2008. LNCS, vol. 5370, pp. 162–170. Springer, Heidelberg (2008). https://doi.org/10.1007/978-3-540-92137-0_18