

# Preference-based Evolutionary Many-objective Optimization for Regional Coverage Satellite Constellation Design

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**Abstract**—For the satellite constellation design problem, the computational complexity of regional coverage performance evaluation has posed great difficulty to classical Pareto dominance-based algorithms discovering the entire Pareto front of the problem, while the decision makers are often interested in a limited part of it. In this paper, a preference-based many-objective evolutionary algorithm, HMOEA-T, is utilized to solve this problem. The optimization includes two steps. The first step describes the preference information of decision maker by target region, while the second step focuses the search process on the preferred region and maintaining well convergence and diversity within the region. A visualization method is applied to intuitively analysis the performance of different methods handling the problem. Experimental results have shown the advantage of integrating preference information into the optimization process, and the comparative study with other state-of-the-art preference-based methods (T-MOEA/D and T-NSGA-III) indicate that the proposed method can achieve competitive and better performance.

**Keywords**—*evolutoinary algorithm; preference articulation; constellation design; many-objective optimization*

## I. INTRODUCTION

The task of designing satellite constellations involves trades between cost, coverage performance, image quality and so on. Generally, the multi-objective optimization problem with more than three objective dimensions is defined as many-objective optimization problem (MaOPs) [1]. Because of the discontinuous, non-differentiable, and noisy characteristics of the objective functions [2], heuristic and meta-heuristic approaches have been widely used to solve the problem, such as genetic algorithm [3], ant colony algorithm [4], neighbor immune algorithm [5], particle swarm optimization [6] and so on.

Most existing methods attempt to approximate the entire Pareto front (PF) with a set of non-dominated solutions. However, attribute to the dominance resistance [7], the Pareto dominance-based algorithms face with the problem of selection pressure loss. In context of regional coverage satellite constellation design problem, the calculation of coverage performance index is rather time-consuming, which reveals that discovering the whole PF is of large computational cost. On the

other hand, the decision makers (DMs) are often interested in a limited part of the entire PF. Seen from the perspective of DM, acquiring the un-preferred solutions is a waste of precious computational resource. In addition, selecting from the large-scaled candidate solutions is not a trivial task for DMs.

In the last decade, incorporating the preference information of DM into the optimization process has been demonstrated an efficient and effective means for handling MaOPs [8] [9]. Recently, Xiong et al. [10] proposed a hybrid evolutionary algorithm with region preference for decision makers (HMOEA-T), which guide the search process to the predefined preference region and merely obtain solutions located within the region. As a result, the difficulty of dominance resistance, computational expensive and selection burden is solved to some extent.

In this paper, we propose a preference-based evolutionary many-objective optimization method for regional coverage satellite constellation design. HMOEA-T is applied to obtain the preferred constellation plans while excluding the unnecessary solutions. The framework is demonstrated on three scenarios reflecting different design requirements. Comparative studies with a powerful but non-preference-based algorithm ( $\Theta$ -DEA [11]) indicates the advantage of incorporating the preference information into the optimization process. And two similar state-of-the-art preference-based methods (T-MOEA/D, T-NSGA-III [12]) are selected to test the performance of HMOEA-T. In addition, we apply a visual clustering method to intuitively present the performance of different algorithms.

## II. REGIONAL COVERAGE CONSTELLATION DESIGN

In this section, the performance metrics for regional coverage constellation are first given, and we formulate the design as a five-objective optimization problem.

### A. Regional Coverage Constellation Objective Functions

#### 1) Coverage Performance Objective Functions

Coverage performance is not an easily characterized statistically distributed parameter, and such it is usually calculated on a grid of points on the surface of regional area. Constrained by the field of view, sensor capability and viewing

geometry, the access time intervals during the simulation time  $T$  are computed, in which the grid points are seen by any of the

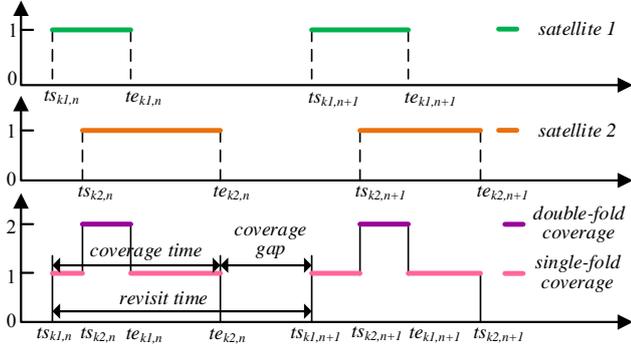


FIGURE I. COVERAGE TIME SETS OF THE CONSTELLATION OF 2 SATELLITES.

constellation satellites. As shown in Figure 1, suppose  $ts_{ki,n}$  and  $te_{ki,n}$  is the  $n$ th access start and end time of satellite  $i$  to grid point  $k$ , the  $n$ th coverage time, coverage gap and revisit time can be calculated respectively by

$$tc_{k,n} = te_{k,n} - ts_{k,n} \quad (1)$$

$$tg_{k,n} = ts_{k,n+1} - te_{k,n} \quad (2)$$

$$tr_{k,n} = ts_{k,n+1} - ts_{k,n} \quad (3)$$

All the coverage metrics can be calculated by different aggregate ways of access and gap intervals. Some of the most widely used metrics are given below, and all of them are defined on a single grid point  $k$ :

#### • Descriptive Statistics

The statistical characteristic of the access and gap interval time sets is described, including the minimum, maximum, median, mean, variance and different percentiles.

#### • Percent Coverage

Percent coverage shows the accumulated access time proportion over the total simulation time  $T$ , during which the point  $k$  is seen by at least one satellite of the constellation:

$$PC_k = \frac{\sum_n tc_{k,n}}{T} \quad (4)$$

where  $tc_{k,n}$  is the  $n$ th coverage time for grid point  $k$ .

#### • Mean Response Time

Response time is defined as the time period from a random observation mission is received to the constellation can actually start the observation. The response time is a function of time  $R_k(t)$ . For a given time  $t$ , the response time to point  $k$  is,

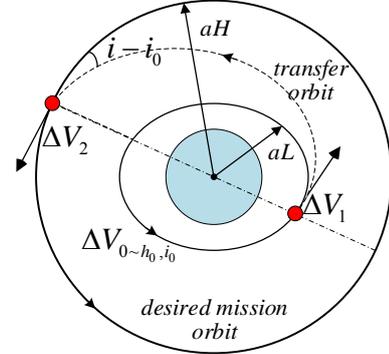


FIGURE II. SCHEMATIC DIAGRAM OF AN OUT-OF-PLANE HOHMANN TRANSFER.

$$R_k(t) = \begin{cases} 0 & ts_{k,n} \leq t \leq te_{k,n} \\ ts_{k,n+1} - t & te_{k,n} \leq t \leq ts_{k,n+1} \end{cases} \quad (5)$$

Thus, the mean response time  $R_k$  is defined as,

$$R_k = \frac{1}{T} \int R_k(t) dt = \frac{\sum_n tg_{k,n}^2}{2T} \quad (6)$$

#### 2) Cost Objective Functions

Naturally, the total cost of the constellation is traded with the coverage performance, which should be considered in design phase. However, the total cost estimating is a challenging task. Hence the proxies are often used instead of the commercial cost itself. In this paper, the cost model is consist of the construction cost  $C_{Const}$  and launch cost  $C_{Launch}$ ,

$$Cost = C_{Const} + C_{Launch} \quad (7)$$

#### • Construction Cost

The cost of a single satellite [13] can be approximated by

$$C_{Sat} = 1064 + 35.5 \cdot m_{Sat}^{1.261} \quad (8)$$

In the process of construction cost estimation, the productivity improvements as the number of satellites increases should be taken into account. Hence a learning curve  $L$  is introduced to modify the construction cost. In this paper, the factor  $S$  is set to be 0.9.

$$C_{Const} = C_{Sat} \cdot L = C_{Sat} \cdot n_{Sat}^{1-\log_2(100\%/S)} \quad (9)$$

• **Launch Cost**

The launch cost  $C_{Launch}$  is calculated under the assumption that constructing each orbit plane requires an additional launch,

$$C_{Launch} = n_{Planes} \cdot C_{Lv} \quad (10)$$

where  $C_{Lv}$  is the cost of a single launch.

In this paper, each small satellite is assumed to have no propulsion capability for out-of-plane maneuvering. And the total cost of propellant required to put spacecraft to the desired mission orbit is utilized to approximate the total cost [14]. The launch process is described as an out-of-plane Hohmann transfer. As shown in Figure 2, the  $\Delta V_{h,i}$  required from the launch site to the desired orbit altitude  $h$  km and inclination  $i$  is composed of three aspects,

$$\Delta V_{h,i} = \Delta V_{0 \sim h_0, i_0} + \Delta V_1 + \Delta V_2 \quad (11)$$

where  $\Delta V_{0 \sim h_0, i_0}$  is a typical low  $\Delta V$  launch to LEO orbit of  $h_0$  km and  $i_0^\circ$ ;  $\Delta V_1$  put the spacecraft to transfer orbit without changing the orbit plane;  $\Delta V_2$  put the spacecraft to mission orbit and change the orbit inclination, then,

$$\Delta V_1 = \sqrt{\mu} \left( \sqrt{\frac{2}{a_L} - \frac{1}{a_T}} - \sqrt{\frac{1}{a_L}} \right) \quad (12)$$

$$\Delta V_2 = \left\{ \mu \left( \frac{2}{a_H} - \frac{1}{a_T} \right) + \frac{\mu}{a_H} - 2 \cdot \sqrt{\mu \left( \frac{2}{a_H} - \frac{1}{a_T} \right)} \cdot \sqrt{\frac{\mu}{a_H}} \cdot \cos(i - i_0) \right\}^{1/2} \quad (13)$$

where  $a_L$  and  $a_H$  is the semi-major axes of  $h_0$  km and  $h$  km orbits,  $a_T$  is the mean value of  $a_L$  and  $a_H$ ;  $\mu$  is the earth gravitational parameter.

Hence the total propellant mass  $m_{prop}$  is obtained,

$$m_{prop} = (m_s + m_{pload}) \cdot (e^{\left(\frac{\Delta V_{h,i}}{g_0 I_{sp}}\right)} - 1) \quad (14)$$

where  $m_s$  and  $m_{pload}$  the mass of launch vehicle and payload;  $I_{sp}$  is the impulse of the propellant.  $m_s=1200$ kg and  $I_{sp}=200$ s are assumed in this paper.

Finally, the cost of a single launch is obtained,

$$C_{Lv} = C_{Rock} + c_p \cdot m_{prop} \quad (15)$$

where  $C_{Rock}$  is the cost of a single rocket and  $c_p$  is unit price of propellant, assumed to be 4.26M\$ and 17 \$/kg, respectively.

It should be noted that the cost objective modeled in this section is used to describe the variation of cost with the change of constellation scale, orbit inclination and altitude, rather than the absolute commercial cost estimations.

**B. Problem Formulation**

The types and number of metrics selected as the optimization objectives varies from mission to mission. In this work, one cost, three regional coverage and one important target observation objective function are formulated for the regional coverage constellation design problem. The overview of objective functions is shown in Table 1. (R) and (T) stands for the coverage performance for regional and important target, respectively.

TABLE I. SUMMARY OF OBJECTIVE FUNCTIONS

$f(x)$	Description	Optimization Direction
$f_1$	total cost	minimize
$f_2$	percent coverage (R)	maximize
$f_3$	max revisit time (R)	minimize
$f_4$	mean revisit time (T)	minimize
$f_5$	mean response time (R)	minimize

**III. PROPOSED METHOD**

In regional coverage constellation design problem, the desired performance of constellation on each objective varies according to different mission requirements. In addition, during the optimization process, the preference information of DM may change. Recently, a preference region-based evolutionary algorithm, HMOEA-T [10], is proposed, which shows a good performance on benchmark test suits. Hence, we extend the previous work to real-world application and proposed a preference-based optimization method for regional coverage constellation design. The framework of the proposed method is shown in Figure 3, which is composed of three parts: preference region-based search, constellation performance evaluation, selection and determine. The basic process can be described as:

Step 1: Initialization. Generate the randomly distributed initial population  $P_o$ , the population size is  $N$ ;

Step 2: Constellation plan performance evaluation. Each individual of the population denotes to a constellation plan. Decoding the individual and evaluate the overall performance of constellation, which corresponds to the fitness value of the population;

Step 3: Preference region-based search. The preference information of DM is defined by the preferred range on each objective, which corresponds to a hypercube in objective space. Then the uniformly distributed reference points is regulated on the unit hypersphere leading towards the preference region. The preference region and regulated reference points makes up a hybrid model. Then a corresponding tri-level ranking criterion works to guide the search process towards the preferred region while balancing the diversity and convergence within the region. With the application of HMOEA-T, merely the constellation plans satisfying the preference would be eventually obtained. Loop Step 2 and 3 until the predefined max optimization generation is satisfied.

Step 4: Interaction and determine. Once the termination criterion is satisfied, a non-dominated solution visualization method [15] is utilized to help the DM intuitively analysis the current population and determine. If satisfied, the adjusted preference region and current population  $P_c$  serve as the new input, back to Step 2 and start the new optimization;

Step 5: Select and determine. Based on the design requirements and with the aid of visualization method, DM select the satisfactory solution in the non-dominated solution set as the final constellation plan.

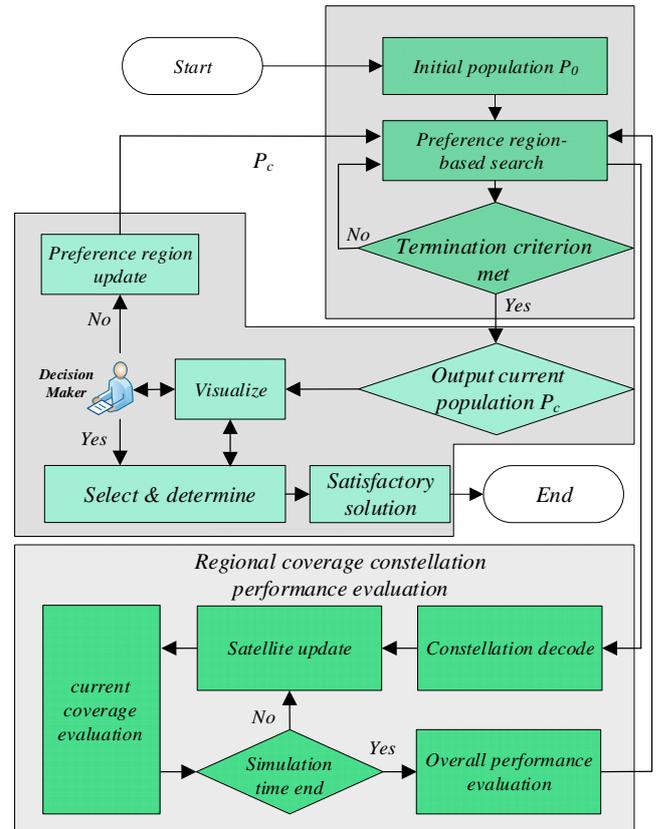


FIGURE III. FRAMEWORK OF THE PROPOSED METHOD FOR REGIONAL COVERAGE CONSTELATION DESIGN.

#### IV. EXPERIMENTAL STUDIES

##### A. Experimental Settings

To validate the efficiency and accuracy of the proposed method, the experimental comparisons on three problem cases reflecting different mission requirements are conducted in this section. Note that all the objective value is normalized to  $[0,1]$  by  $[2*10^8, 25, 1.25*10^4, 2.2*10^3, 1.4*10^3]$  and  $[5.8*10^{10}, 10, 2.9*10^4, 4.9*10^3, 3.2*10^3]$ . Table 2 shows the predefined preference regions in different problem cases.

TABLE II. PROBLEM CASE LIST

Problem Case	Preference Region
1	$\{[0.15 \ 0.15 \ 0.2 \ 0.3 \ 0.2], [0.85 \ 0.5 \ 0.45 \ 0.7 \ 0.5]\}$
2	$\{[0 \ 0.5 \ 0.5 \ 0 \ 0.4], [0.3 \ 1 \ 1 \ 0.4 \ 1]\}$
3	$\{[0.7 \ 0 \ 0 \ 0.5 \ 0], [1 \ 0.5 \ 0.4 \ 1 \ 0.45]\}$

The epoch time of the orbit and the start time of simulation is 1 May 2020 4:00:00.000 UTCG, and the total simulation time is 7 says. The satellite sensors have a cone view field with the maximum half angle of  $10^\circ$ . To reduce the total optimization time, the satellite constellation is assumed to have

a walker constellation. The other parameter settings of the scenario us shown in Table 2.

TABLE III. MAIN PARAMETER STEEINGS OF THE SCENARIO

Parameter	Minimum	Maximum
Number of satellite	15	15
Number of plane	5	5
Orbit altitude/km	500	1500
Orbit inclination/deg	29	70
Latitude/deg	33	43
Longitude/deg	125	130

Four important ground target are selected in the area, which are located in  $[35.92^{\circ}\text{N},128.28^{\circ}\text{E}]$ ,  $[39.92^{\circ}\text{N},125.50^{\circ}\text{E}]$ ,  $[33.49^{\circ}\text{N},126.50^{\circ}\text{E}]$  and  $[41.79^{\circ}\text{N},129.75^{\circ}\text{E}]$ . Population size  $N$  and maximum generation is set to be 210 and 3000, respectively. Two recently proposed PMOEAs, T-MOEA/D, T-NSGA-III [], and a non-preference incorporated algorithm  $\Theta$ -DEA are selected as comparison algorithms.

B. Results and Discussion

The goal of solving the regional coverage constellation design problem with PMOEAs is to obtain the constellation design plan within the preference region, and the population representing the constellation plans should maintain good convergence and diversity within the region. In addition. The time cost of constellation design is also an important factor that should be considered in the design process. Therefore, this section will compare and analyze the experimental results from three aspects: the effectiveness, convergence and diversity, time cost.

Figure 4 presents the distribution of the final population that HMOEA-T, T-MOEA/D, T-NSGA-III and obtained while solving case 1~3. The visualization method proposed in [15] is utilized to intuitively examine and compare the performance of different algorithms. In the plot, the red and blue lines denotes to the solutions located inside and outside the preference region, respectively.

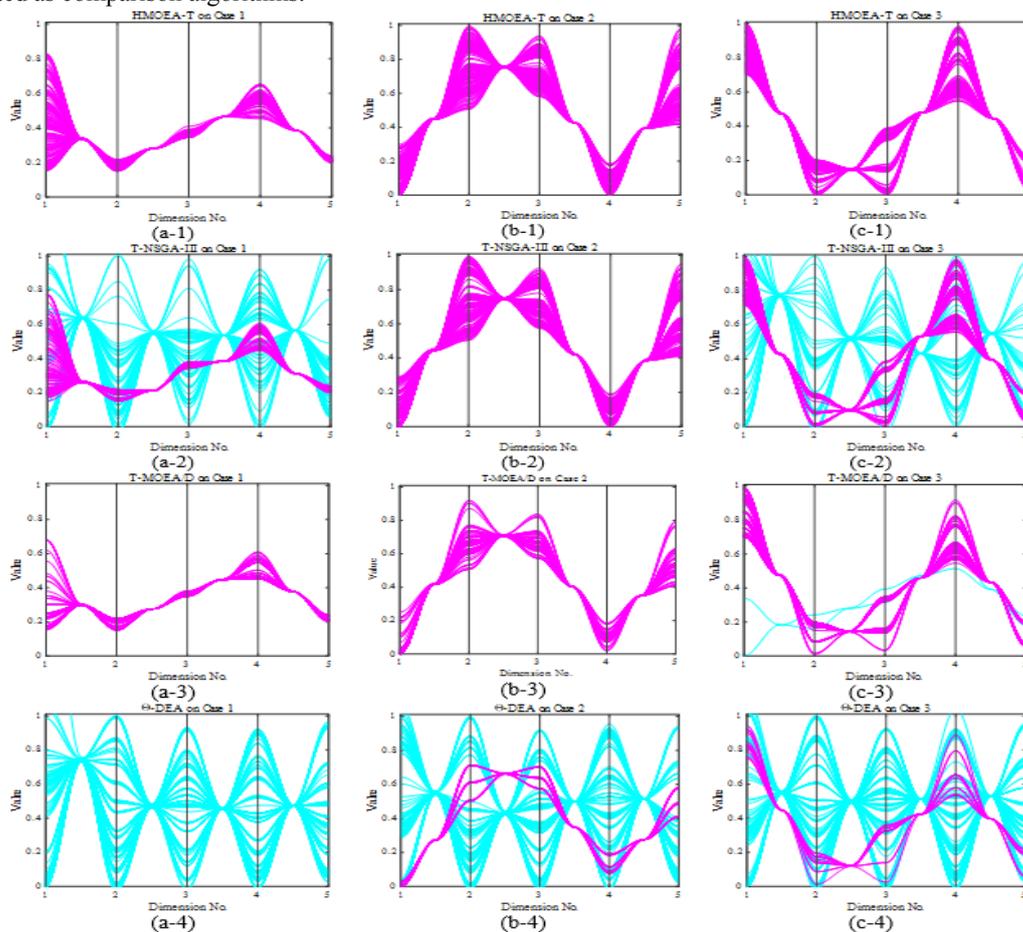


FIGURE IV. THE DISTRIBUTION OF FINAL SOLUTIONS THAT DIFFERENT ALGORITHMS OBTAINED SOLVING CASE 1,2,3

Firstly, in terms of effectiveness, compared with the non-preference information incorporated algorithms (Figure 4(a, b, c-4)), HMOEA-T, T-MOEA/D and T-NSGA-III can effectively increase the proportion of the solutions located within the preference region; Secondly, it can be observed that the lines of are more uniformly

distributed, which indicates that HMOEA-T can maintain a better convergence and diversity. In addition, we notice that when T-NSGA-III is solving case 1 and 3, the proportion of un-preferred solutions in the final solution set comes to 76.7% and 75.7%. The reason of this result will be analyzed in next experiment.

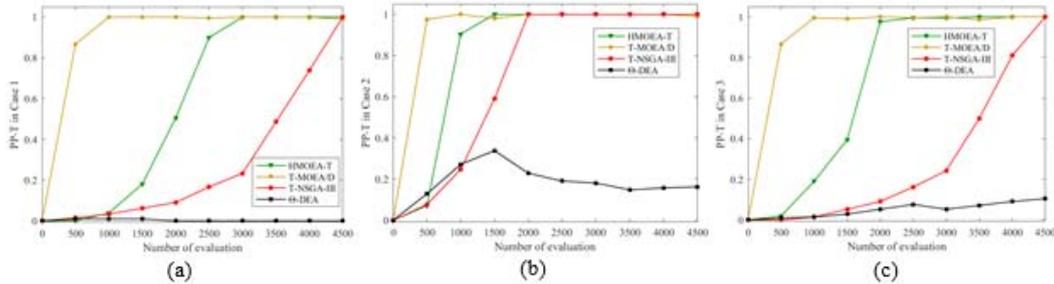


FIGURE 5. THE CONVERGENCE SPEED OF DIFFERENT ALGORITHMS SOLVING CASE 1,2,3

Figure 5 shows the convergence speed of different algorithms solving case 1, 2, 3, which is indicated by the variation of the proportion of solutions within the preference region. The black polyline in the figure indicates convergence speed of  $\theta$ -DEA. It can be seen that the algorithm with no preference information incorporated shows greater randomness and uncertainty to obtain the decision maker's satisfactory solution. And in some cases, even no preferred solution would be obtained (Figure. 5(a)); For the result that T-NSGA-III failed to lead all the population into the preference region, we run for another 1500 generations. It can be seen that the red polyline representing T-NSGA-III eventually converges to the target region in all three problems, indicating that T-NSGA-III can solve the problem, but its convergence speed is significantly lower than HMOEA-T and T-MOEA/D. T-MOEA/D and HMOEA-T have achieved optimal and sub-optimal performance in the convergence speed comparison respectively, but in terms of time cost, HMOEA-T achieved the best performance. Taking case 1 as an example, in the same experimental setup and hardware environment, each algorithm runs 21892.5s, 23523.8s, 22199.9s and 22439.3s. T-MOEA/D has the longest calculation time.

V. CONCLUSION

In this paper, we have presented a preference-based evolutionary many-objective optimization method for regional coverage constellation design, whose search process is guided by the preference information. Given a preference region predefined by the DM, the method is supposed to focus the search on the target region and maintain well convergence and diversity within the region, and merely the preferred solutions would be eventually obtained.

Experimental results shows that the application of HMOEA-T can effectively focus the search process on the interested part of PF. Compared with non-preference incorporated approach, the proposed method is more efficient in finding the solution satisfy different design requirements.

In future studies, we will conduce more numerical analysis on the performance of proposed method.

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