Journal of Theoretical and Applied Information Technology
20th February 2013. Vol. 48 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

THE AIR DEFENSE MISSILE OPTIMUM TARGET ASSIGNMENT BASED ON THE IMPROVED GENETIC ALGORITHM

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ABSTRACT

The problem of target assignment is crucial in the air defense operations, and the optimum target allocation scheme can greatly enhance the performance of the air defense missile weapon system. Based on the general mathematical model of the target assignment problem and the principle of assignment, this paper analyses cultural genetic algorithm (CGA) combined with the reversal operation, and presents a specific hybrid optimization methodology which can address the problem of target assignment. The simulation results show that the probability of finding the global optimal solution and the convergence rate of the improved genetic algorithm based on cultural algorithm (CA) is obviously superior to that of the basic genetic algorithm (BGA) and cultural algorithm. Finally we get a better target assignment results; thus it provides a beneficial reference for addressing the problem of air defense deployment effectively.

Keywords: *Target Assignment, Air Defense Missile, Genetic Algorithm, Cultural Algorithm*

1. INTRODUCTION

The purpose of the target allocation, with the principle of the target allocation, is to maximize the characteristics of a large variety of air defense weapons, which are distributed reasonably and effectively, and earn the smallest loss and the maximum lethality to defense our positions effectively in the complex air defense war of wide airspace, full time domain, all-round, multiple types of airplane, multi-wave. It is essential to seek the optimal solution of the target allocation, because the rationality of target allocation is closely related to the tactical effect and the play of battle effectiveness. This also has been a concern of many experts.

The reference [1] describes a new hybrid optimal algorithm, named genetic-simulated annealing, that combines features of genetic algorithm and simulated annealing, and it is employed to address the problem of optimal weapon allocation in multilayer defense scenario, in order to achieve a better solution than produced by single algorithm. The reference [2] presents that the improved genetic algorithm based on good gene genetic operator is used to address the problem of target assignment. Simulation results show that the efficiency of the modified algorithm grows and levels off at sixty percent. The advantage of the algorithm is more obvious in multi-aircraft environment, but the efficiency is expected to be boosted more greatly. In the reference [3], on the basis of the analysis to the principle of genetic algorithms and simulated annealing algorithm, GASA mixed optimized strategy is proposed for solving the target assignment problem, which combined the advantages of the two algorithms. It is a effective solution to the target optimal assignment in the air defense combat. The study of greedy genetic algorithm (GGA) that greedy mechanism is applied to GA on target assignment is presented in reference [4]. GGA avoids the existing shortcoming of genetic algorithm (GA) solving the problem, such as the slow convergence, enclosure completion etc. The algorithm is relatively stable, and can lay the foundation for the application of the greedy genetic algorithm on the combinatorial problems of objective optimization. The reference [5] proposes a multi-sensor target assignment algorithm on genetic particle swarm optimization. The algorithm can effectively achieve the target allocation with the constraint of the sensor resource and has a high stability and fast convergence rate. To a great extent, these studies solve the target allocation problem and promote the rapid development of air defense systems, but

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the more in-depth and effective study is continuous on algorithm of the target assignment.

The genetic algorithm is an adaptive global optimization search algorithm, which formed from the process of simulating the heredity and evolution of the organism in the natural environment [6]. The genetic algorithm has strong robustness and global convergence, but it is easy to be premature convergence, besides it has poor local searching capability, however, it is very convenient to combine with other algorithms to speed up the convergence and enhance the ability of local optimization. On the basis of analyzing the merits and demerits of genetic algorithm (GA) and cultural algorithm, this paper focuses on the study of the hybrid algorithm, genetic algorithm based on cultural algorithm, and enhances the hybrid algorithm through introducing truncation selection and inversion operation. Then based on the common mathematical model of the target allocation, the paper analyses the performance of the algorithm, which include the genetic algorithm, the cultural algorithm, the hybrid algorithm and the enhanced hybrid algorithm, through simulation in the target allocation.

2. THE PRINCIPLE OF MISSILE TARGET ALLOCATION AND MATHEMATICAL MODEL [7]

2.1 The Principle of Missile Target Allocation

(1) The least time. That is, select fire units whose shooting range the target is prior to reaching through calculating the firing data of target, and then fire the targets to reduce the threat to us as far as possible.

(2) Prior to firing the key targets. Prior to intercepting and firing the key targets which is specified by superior or the targets that pose a serious threat to us.

(3) Prior to firing airborne jammer to eliminate electronic jamming in order to enhance the firing efficiency of our anti-aircraft firepower.

(4) Achieve the optimal allocation as a whole, specifically, assign single target to the most favorable fire units for shooting.

(5)Take into account the amount of ammunition of each fire units while assigning targets, and try to keep all fire units with enough ammunition to fight continuously after fighting against an air-raid.

2.2 Mathematical Model

Essentially, the problem of target optimal allocation is a problem of calculating maximum of object function. The problem is described as follow: m ground-to-air missile fire units are assigned to n batches air-raid targets, in which m and n denote the number of ground-to-air missile fire units and air-raid targets, respectively. Satisfying the basic principles of target assignment, the purpose of the target assignment is to pursuit the maximum of the overall effectiveness, which is given by:

$$Benefit = \max \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} x_{ij} \tag{1}$$

$$\begin{cases} \sum_{i=1}^{n} x_{ij} = 1, \; j = 1,2,...m \\ \sum_{j=1}^{m} x_{ij} = 1, i = 1,2,...n \\ x_{ij} = 1 or 0 \end{cases} \tag{2}$$

Where, $c_{ij} = \omega_j \cdot p_{ij}$, in which ω_j is the threat evaluation of the jth target, and p_{ij} shows the effective estimator of the ith fire units firing the jth batch targets. c_{ij} represents the overall effectiveness of each fire units intercepting each targets. x_{ij} denotes whether the ith fire unit fires the jth batch targets.

3. INTRODUCTION OF THE ALGORITHMS

3.1 The Genetic Algorithm

The genetic algorithm which was firstly proposed by John Holland in 1975 is a stochastic parallel search algorithm based on the principle of natural selection and genetics. The algorithm is inspired the mechanism of natural selection, a biological process in which the rule is “the fittest will survive”, that is, the stronger individuals are likely to be the winners in the competing environment. GA uses a direct analogy of such a natural type of evolution to search the optimal solution. At first, generate initial population randomly, then calculate the fitness value by the fitness function and estimate whether it meets the optimal solution or actual demands. If it is true, the calculation will be end. Otherwise, optimize the population through the so-called genetic operators, such as selection operator, crossover operator and mutation operator, so that next generation population can be able to adapt to environment better. Finally, the solution will be closer to the optimal solution through the evolution of each generation.

The role of the selection operator based on certain rules is to select the best individuals as the parent individuals in the next generation, that is, the survival of the fittest. The crossover operator

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

can exchange partial genes with a small predetermined or adaptive probability between the mutual paired chromosomes. It is the main method of generating new individuals. As a matter of fact, it decides the global search ability of genetic algorithm. Flow diagram of the genetic algorithm is given in Figure 1.

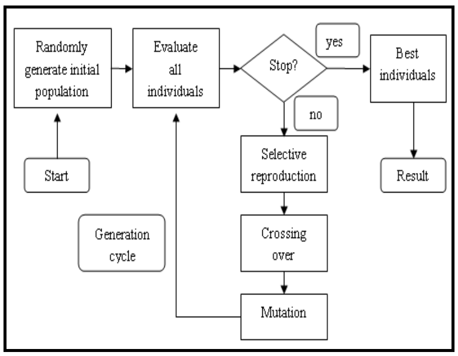

Figure 1: Flow Diagram Of The Genetic Algorithm

3.2 The Cultural Algorithm

The cultural algorithm [8] which was proposed by Robert G. Reynolds in 1994 was an algorithm of simulating the evolution of human society with double evolutionary mechanism. It is mainly composed of two spaces, namely, population space and belief space, as shown in the basic framework of the cultural algorithm (Figure 2). They not only achieve evolution independently, but also extract and manage the evolutionary information effectively through specific agreement including 'accept ()' function and 'influence ()' function, and then use these information to guide the evolution of the population space and to exchange and update the information. The 'accept ()' function can transmit the experience of excellent individuals generated from the process of the evolution to the belief space. The 'update ()' function compares the current individual experience with new individual experience, and then updates them to obtain new experience and knowledge. The 'influence ()' function guides the evolution of the population space using the experience and knowledge of the population in the belief space. The 'objective ()' function is the objective function which evaluates individual fitness value in the population space. According to the population experience, the 'generate ()' function generates the next generation individuals. On the basis of the related rules, the 'select ()'function selects partial individuals form new individuals as the parents of next generation individuals.

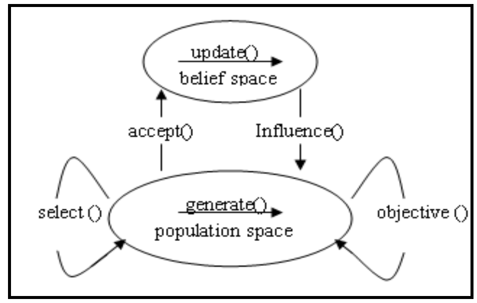

Figure 2：Basic Framework Of The Cultural Algorithm

4. THE HYBRID ALGORITHM

4.1 The Basic Idea of Hybrid Algorithm

The cultural algorithm is characterized by combating hybrid problem which support different algorithms and achieving dual evolution. The population space and belief space inherit their own parental information separately, and the information stored in the belief space guide the evolution of the population space. Furthermore, the cultural algorithm supports two hierarchical structures which can be able to evolve adaptively with different speed.

The genetic algorithm has strong global search capability in a wide range and starts to search from population. In addition to the potential parallelism, it is guided by fitness function. The process of the genetic algorithm is easy to achieve, moreover it is easy to combine with other algorithms since it has good expansibility.

Reversal operation can enhance the local search capability of GA to maintain population diversity. Reversal is unidirectional, i.e., this operation only accepts reversal directed to optimal solution; thus it has strong capability of searching optimal solution.

Truncation selection can take three benefits obviously, firstly, it is not necessary to keep fitness value positive; secondly, It restrains mass replication of the best individuals; thirdly, it also keep superior individuals account for a large proportion.

According to these characteristics, if combing the two algorithms to form a hybrid optimization algorithm which includes merits of both algorithms, the shortcomings of single algorithm will be remedied, and then its performance will be boosted greatly. The framework of the cultural algorithm provides a computational model with mechanism of multi-layer evolution. Any evolution algorithm with the requirement of the cultural algorithm can be embedded into the framework of the cultural algorithm, and then it will be an evolutionary process of population

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

space. This paper attempts to introduce the genetic algorithm into the framework of the cultural algorithm, and combines the global search ability of GA, the local search ability of the reversal operation and the advantage of truncation selection with the evolutionary characteristics of two layer space of the cultural algorithm effectively, thereby improving the optimizing performance of the algorithm, and achieving more effective allocation result in the problem of air defense missile target allocation, and enhancing the operational effectiveness of the air defense missile weapon system.

4.2 Steps of the Hybrid Algorithm

Step 1 Initialize population space, namely, generating initial population space in the domain of definition randomly.

Step 2 Estimate the individuals in the population space through a fitness function.

Step 3 According to the given range and the candidate solutions in the initial population space, generate the belief space based on the structure of belief space.

Step 4 On the basis of the influence function, make each parental generation accept mutation operation to generate sub generation correspondingly.

Step 5 Run truncate operation, that is, copy part existing best individuals with certain proportion, an then delete the worst individuals with the same proportion.

Step 6 Run reversal operation, i.e., locate two points randomly in the coding sequences of the individuals, and then exchange the genes between the two points symmetrically.

Step 7 Crossover and mutation operation of the basic genetic algorithm.

Step 8 Set the accept function, and update the belief space in accordance with rules.

Step 9 If the terminal condition is not satisfied, the process of the program will return to step 4, otherwise, the program will be end.

5. HYBRID ALGORITHM DESIGN

5.1 Design of Code

This paper uses decimal encoding. The length of individual denotes the number of targets, the each gene value of the individual correspond to the code of the fire units, and the position of the genes is the code of targets, i.e. , the fire units corresponded to gene value attack targets which denoted by the code of the position of the gene. An individual represents a distribution scheme. After evaluation of the fitness value, the individual with the maximum will be the optimal target allocation scheme needed actually. E.g. the number sequence [3 7 7 4 6 8 6 2 8 6 5 5 3 2 4] represents an individual, it mains that the third fire unit attacks the first and the thirteenth target, the seventh fire unit attacks the second and the third target, the fourth fire unit attacks the fourth and the fifteenth target etc.

5.2. Fitness Value

The purpose of target optimal allocation is to seek the best overall effectiveness; therefore, the overall effectiveness is regarded as fitness value which is expressed as:

$$Benefit = \max \sum_{j=1}^{15} c_{ij}, i = 1,2,3...8 \tag{3}$$

Where, c_{ij} represents the effectiveness of the i^{th} fire unit attacking the j^{th} target.

5.3 The Genetic Operators

This paper adopts single-point crossover which determines a point in two individuals paired randomly, and then exchanges the partial chromosome that is located the point to form new individuals.

In this paper, uniform mutation is used as mutation operator, i.e. it can designate each locus of encoded individual as mutation point in sequence, and then replace the original gene by a random number generated in the range of gene with a small probability.

5.4 Improved Measures

5.4.1 Truncation Selection

According to the idea of selection by probability, truncation selection is demonstrated as follow in detail: Firstly, according to fitness value, arrange individuals in descending order; secondly select the forward individual with certain proportion (p), that is 20% in this paper; then copy the individual one time; and then duplicate the middle 1-2p individuals with one copy; lastly, delete the backward p ones. E.g., if we address a maximum problem, a sequence in descending order which is illustrated as the following transposed matrix:

[1 2 3 4 5 6 7 8 9 10]'

After taking the above selection measure, in which the proportion is 30%, it will be shown as:

[1 2 3 1 2 3 4 5 6 7]'

5.4.2 Reversal Operation

Generate two numbers randomly in each individual, which are greater than or equal to one and less than or equal to fifteen, x and y is defined

Journal of Theoretical and Applied Information Technology
20th February 2013. Vol. 48 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

as the maximum and minimum in the two numbers respectively, then exchange the genes between x and y symmetrically. E.g., the two numbers generated randomly are 12 and 6; thus, x and y are 6 and 12 separately. Suppose that an individual is given as follow:

2 8 9 5 4 |7 1 8 3 7 8| 6 7 8 2

After taking the reversal operation above measure, the individual is shown as follow:

2 8 9 5 4 |8 7 3 8 1 7| 6 7 8 2

6. SIMULATION RESULTS AND ANALYSIS

Related parameters in the algorithm are chosen as follow: the running numbers are 30, the population size was 40. The number of variable was 15, and the each variable was greater than or equal to 1 and less than or equal to 8. The crossover rate and the mutation rate was 0.8 and 0.01 separately. 8 fire units intercepted 15 targets. The threaten level of the jth target was given by:

$$w = \omega_j \qquad (4)$$

Assume that the favoring degree evaluation of the ith fire unit attacking the jth target was written as:

$$p = (p_{ij})_{8\times 15} \qquad (5)$$

The program was then executed for 100, 200, 300 and 500 generations respectively. The relevant data are indicated in table 1.

Table 1: Simulation Parameters

p_{ij}	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0.87	0.52	0.11	0.78	0.72	0.69	0.94	0.72	0.36	0.28	0.27	0.74	0.24	0.78	0.45
2	0.87	0.52	0.11	0.78	0.72	0.69	0.94	0.72	0.36	0.28	0.27	0.74	0.24	0.78	0.45
3	0.87	0.52	0.11	0.78	0.72	0.69	0.94	0.72	0.36	0.28	0.27	0.74	0.24	0.78	0.45
4	0.87	0.52	0.11	0.78	0.72	0.69	0.94	0.72	0.36	0.28	0.27	0.74	0.24	0.78	0.45
5	0.87	0.52	0.11	0.78	0.72	0.69	0.94	0.72	0.36	0.28	0.27	0.74	0.24	0.78	0.45
6	0.87	0.52	0.11	0.78	0.72	0.69	0.94	0.72	0.36	0.28	0.27	0.74	0.24	0.78	0.45
7	0.62	0.87	0.70	0.22	0.80	0.42	0.43	0.90	0.13	0.95	0.18	0.19	0.12	0.61	0.35;
8	0.48	0.20	0.42	0.16	0.43	0.58	0.69	0.03	0.34	0.72	0.15	0.24	0.29	0.30	0.75
ω_j	0.47	0.97	0.76	0.62	0.48	0.77	0.33	0.74	0.54	0.65	0.43	0.35	0.63	0.66	0.57

Basing on the simulation environment of MATLAB, this paper uses CA, BGA, CAG and Improved CGA to simulate the problem of the basic target allocation through computer. The results, on average, of simulation are shown in the following tables and figures.

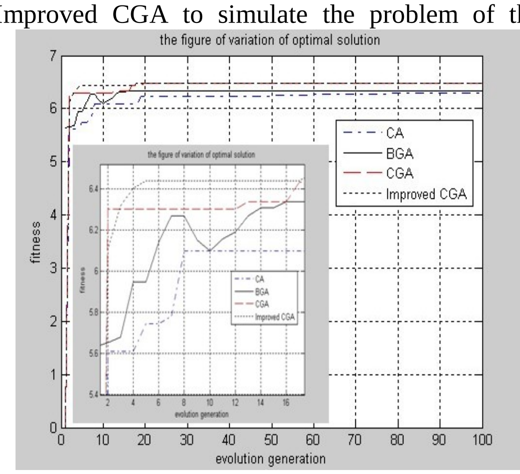

Figure 3: The Variation Of Optimal Solution While Running 100 Generations

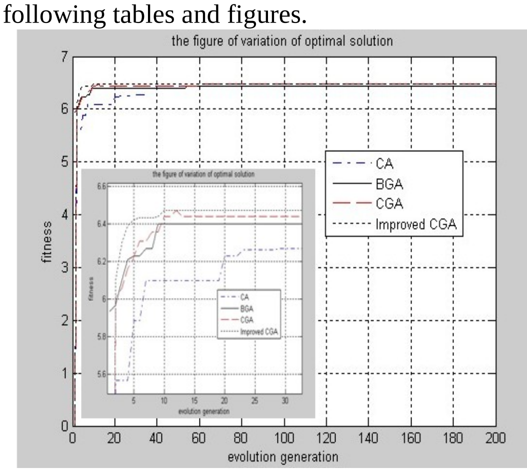

Figure 4：The Variation Of Optimal Solution While Running 200 Generations

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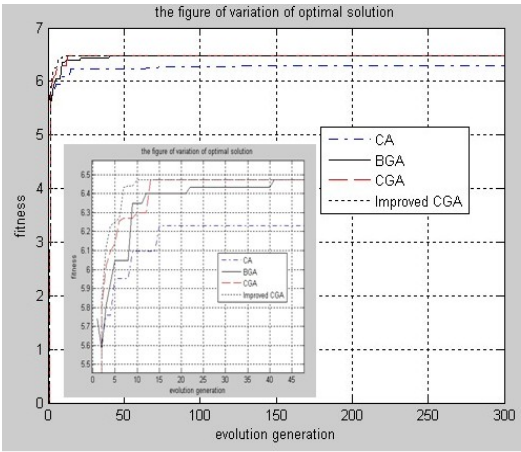

Figure 5：The Variation Of Optimal Solution While Running 300 Generations

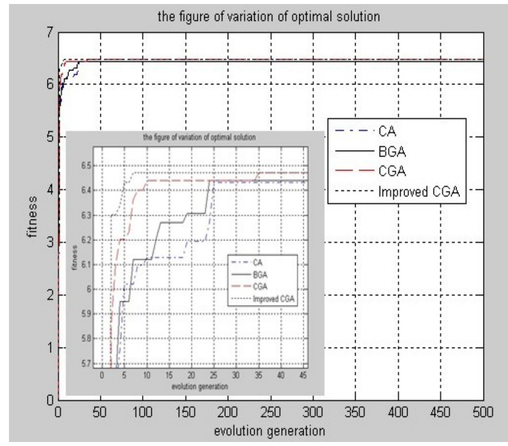

Figure 6：The Variation Of Optimal Solution While Running 500 Generations

Table 2: The Data Of Simulation With 100 Generations

100 Generations	First Convergent generation	Average Convergence Generations	Max	Average	Convergence Rate
CA	49	30.7	6.34536	6.34447	4.33%
BGA	43	60.3	6.39090	6.06563	35.33%
CGA	36	63.7	6.46323	6.44897	87.00%
Improved CGA	30	69.7	6.46619	6.45132	90.00%

Table 3: The Data Of Simulation With 200 Generations

200 Generations	First Convergent generation	Average Convergence Generations	Max	Average	Convergence Rate
CA	94	86	6.37828	6.37781	12.00%
BGA	63	134.9	6.43263	6.09496	49.00%
CGA	47	152.7	6.47051	6.45324	97%
Improved CGA	41	158.9	6.4717	6.45448	99.33%

Table 4:The Data Of Simulation With 300 Generations

300 Generations	First Convergent generation	Average Convergence Generations	Max	Average	Convergence Rate
CA	147	152.1	6.38716	6.38716	22.33%
GA	93	209.6	6.43315	6.09479	53.67%
CGA	48	247.6	6.47180	6.45478	99.67%
Improved CGA	45	255	6.4719	6.45552	100%

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 5:The Result Of Simulation With 500 Generations

500 Generations	First Convergent generation	Average Convergence Generations	Max	Average	Convergence Rate
CA	237	262.2	6.41050	6.41016	34.33%
GA	149	350.3	6.45083	6.10718	66.67%
CGA	46	453.1	6.4719	6.45497	100%
Improved CGA	46	453.7	6.4719	6.45505	100%

The tables and figures describe that no matter how many generations the algorithms evolve, the first convergent generations of the CA, GA, CGA and the improved CGA show a downward trend, i.e., the speed of convergence of these algorithms accelerates in sequence. It is obvious that the improved algorithm in this paper has the fastest speed, the highest optimal solution and the average. Consequently, we will get best effectiveness and the best allocation results. In addition, comparing with other algorithms, the convergence rate of the modified algorithm is the highest, and it has reached 100% in 300 generations. Hybrid optimization algorithm has optimizing performance, optimizing speed and initial robustness; thus, the improved hybrid algorithm will have better performance than simple hybrid algorithm. The optimization quality of the simple hybrid algorithm is superior to the traditional GA and CA, and the improved algorithm is also significantly better than simple hybrid algorithm.

7. CONCLUSION

In allusion to the problem of the target assignment, this paper studies the simple genetic algorithm, the cultural algorithm, the hybrid algorithm which combines the two algorithms above and the modified hybrid algorithm, and then use them to address the problem of the optimal target allocation on the basis of the basic target allocation model. The simulation results describe that the improved cultural and genetic algorithm is reasonable, the probability of this hybrid algorithm search the global optimal solution has rose to just over 99% when the algorithm runs 200 generations, while it runs 300 generations, the probability will peak at 100%, namely, the convergence rate rises greatly. Comparing with other algorithms which are involved in this paper, the improved hybrid algorithm achieves the higher probability of searching optimal solution and the greater efficiency with lesser evolution generations. It is proved that this improved hybrid algorithm is effective and feasible; thus the algorithm can provide an efficient path for addressing the problem about the optimal target allocation of the anti-aircraft missile. However, because of the actual system requirement, how to enhance the instantaneity of the hybrid algorithm will be a problem studied in next step.

ACKNOWLEDGMENTS

This work was supported by the Natural Science Foundation of China (No.61262019), the Natural Science Foundation of Jiangxi Province (No.20114BAB201046), the Science and Technology Research Project of Jiangxi Provincial department of Education (No.GJJ12435), the Open-end Foundation of the Key Laboratory of Nondestructive Testing (Ministry of Education) and the Graduate Technological Innovation Project of Nanchang Hangkong University (No.YC2012025).

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