Research on Optimization of Organizational Training Efficiency under Multiple Training Objectives Based on AHP-GA Algorithm

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Abstract. This paper proposes a solution that combines Analytic Hierarchy Process (AHP) and Genetic Algorithm (GA) to optimize the training duration of training institutions with multiple training objectives by establishing a mathematical model for optimizing organizational training benefits under multiple constraints. This method not only utilizes expert experience values to avoid the influence of extreme values, but also draws on the advantages of genetic algorithm to solve the optimal solution. Using AHP for quantitative and qualitative analysis to determine the weight of training target allocation, a combination of elite retention strategy and roulette wheel algorithm was used to select genetic operators, and simulation experiments were conducted to calculate the training duration allocation scheme with limited training duration and optimal training efficiency under multiple training objectives.

Keywords: multiple training objectives; Genetic algorithm; Analytic Hierarchy Process

1 Introduction

With the accelerated evolution of the form of war from traditional informatization to intelligence, there have been significant changes in training content, objectives, and modes, posing higher requirements for the training capabilities of military training institutions. Taking intelligent training for future wars as an example, in addition to traditional professional training, it is particularly important to preset intelligent combat capabilities. The cultivation of intelligent training capabilities involves multiple training objectives in the fields of thinking, management, training, and business. How to optimize the effectiveness of organizational training within a limited military training period with multiple training objectives is a basic requirement advocated by current military departments for intensive organizational training.

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In recent years, some scholars have used Genetic Algorithm, Simulated annealing algorithm, Ant colony and other intelligent optimization algorithms to solve some problems in teaching management[1-4]. For example, using intelligent optimization algorithms to solve complex scheduling problems, establishing scheduling models, and providing fast solutions for reducing conflicts under practical constraints; Some scholars have applied genetic algorithm to the intelligent paper generation module of exam systems to ensure the convenience and operability of problem setting. Through mathematical models, the implementation process of genetic algorithm in the paper generation module is analyzed[5-7]. Similarly, for some organizational training problems in military training, intelligent optimization algorithms can also be used to solve them, providing better solutions for training organizations. Compared to general teaching, military training has a slightly different situation. Throughout the year, a training plan for this year is formulated based on the functional tasks and actual situation of each major unit. As a part of cultivating new combat capabilities, intelligent training is designed in advance and relatively fixed in class hours, which can serve as a constraint. The intelligent training objectives have diversity and asymmetry, and the emphasis on the training objectives may vary from unit to unit. The corresponding weight values of the training objectives may vary, and the corresponding target weights can be adjusted according to needs.

2 Objective of Cultivating Intelligent Organizational Training Ability

2.1 Intelligent Organizational Training

With the emergence of intelligent warfare in the Russia-Ukraine conflict and many other practical battles, the research and practice of intelligent organizational training, as a key link in generating intelligent combat capabilities, is also very urgent. Compared to traditional military training, intelligent organizational training involves some new field capabilities, such as how to transform traditional warfare and training thinking, how to respond to the revolutionary introduction of intelligent weapons and equipment into warfare, how to use intelligent means to carry out military training, and so on[8]. How to balance the achievement of these ability goals and achieve optimization of training effects within a limited training time is a key issue that needs to be considered when conducting intelligent organizational training.

2.2 Intelligent Organizational Training Ability Target Model

This paper uses Grounded theory to collect 19 intelligent training objectives. Firstly, preliminarily classify and integrate the collected target items. Based on the principles of hierarchy, systematicity, comparability, and operability, 10 sub goals were selected and ultimately determined. The hierarchical structure between each level and the subordinate relationship of each requirement are shown in Table 1, where the first layer

A is the overall goal of intelligent training capability; The second layer B is the target domain; The third layer C is the specific sub capability objective.

Table 1. Hierarchical Structure of Intelligent Training Capability Objectives

First layer A	First layer B	First layer C	
The overall goal of intelligent training capability: Cultivate military personnel with artificial intelligence technology thinking, information literacy, joint operation thinking, and innovative thinking, who can impart basic military theoretical knowledge and professional skills, and have strong operational and organizational capabilities for intelligent information warfare equipment.	Thinking Field B1	C1	Establishing a correct military stance and basic viewpoints on military ideology, and understanding the essence of intelligent warfare
		C2	Having basic concepts of intelligent technology such as data view, knowledge view, algorithm view, model view, human-machine collaboration view, etc
	Management Field B2	C3	Familiar with relevant regulations and basic task requirements for equipment training
		C4	Conduct targeted ideological education work
		C5	Capable of managing relevant personnel, equipment, facilities, etc
	Training Field B3	C6	Mastering theoretical knowledge of organizational training
		C7	Capable of organizing planning, teaching and training, and evaluating and summarizing
		C8	Ability to reform and innovate intelligent organizational training subjects and methods
	Business Field B4	C9	Understand the application fields and scenarios of intelligent equipment
		C10	Mastering knowledge of intelligent equipment principles, operational and usage skills, maintenance and repair skills, and tactical application methods

2.3 Organizational Training Benefit Model under Multiple Training Objectives

Assuming the total training duration is constant, it is M; Among the 10 sub abilities, the training duration occupied by each sub ability is x_i, where x_i represents the duration occupied by the i-th sub ability; a_i is the weight of each sub capability, and has

$$A = [a_1, \cdots a_i, \cdots a_{10}]. \quad (1)$$

The larger the value of a_i, the more important the i-th sub ability is; b_{ji} is the support of ability x_j for ability x_i, or the pre capacity. With the mastery of x_j, x_i will receive a gain, which can be understood as the prior basis of x_i. It is similar to learning basic courses and then studying professional courses, which can make learning professional courses more efficient and efficient, and has

$$B = \begin{pmatrix} b_{11} & \cdots & b_{1,10} \\ \vdots & \ddots & \vdots \\ b_{10,1} & \cdots & b_{10,10} \end{pmatrix}. \tag{2}$$

Among them, when i=j, $b_{ji} = 0$.

In summary, the optimization goal of organizational training efficiency under multiple training objectives is to allocate training time reasonably for each sub ability, so as to maximize the organizational training efficiency. The objective function of organizational training benefits can be expressed as:

$$F(x) = \sum_i (a_i + \sum_j b_{ji} x_j) \cdot x_i. \tag{3}$$

The constraint conditions are:

$$\sum_i x_i = M. \tag{4}$$

(1) The total training duration is fixed, i.e.

(2) The certainty of the training plan determines that the implementation order of each training unit is fixed and cannot be changed;

(3) Each training duration is a positive integer, i.e $x_i > 0$， $x_i \in Z$， $\forall x_i \neq 0$.

Under the above constraints, the problem is transformed into solving the value of the duration x_i of each training unit, so that the objective function of equation (3) is maximized, that is, the optimal solution of the training duration allocated to each ability objective under the condition of maximum organizational training benefit.

3 Optimization of Organizational Training Benefits based on AHP-GA algorithm

3.1 Determine Target Weights Based on AHP

Analytic Hierarchy Process (AHP) is a systematic, hierarchical, qualitative and quantitative method. Its basic steps are to construct a positive and negative judgment matrix for each layer, calculate indicator weight vectors, and perform consistency checks based on expert opinions, ultimately quantifying the decision-maker's experience.

Construct a Judgment Matrix.

After the capability objective model is determined, the relative importance of each element in each layer of the hierarchical structure model is judged in numerical form. The indicators are assigned values using the 1-5 scale method, and a pairwise comparison judgment matrix is generated. The weights of each level of indicators are calculated layer by layer, forming the A-B level judgment matrix and B-C level judgment matrix as follows:

$$A_B = \begin{bmatrix} \frac{1}{4} & 1 & \frac{1}{4} & \frac{1}{5} \\ \frac{1}{3} & 4 & 1 & \frac{1}{2} \\ \frac{1}{2} & 5 & 2 & 1 \end{bmatrix}, B_{1C} = \begin{bmatrix} 1 & \frac{1}{3} \\ 3 & 1 \end{bmatrix}, \; B_{2C} = \begin{bmatrix} 1 & \frac{1}{3} & \frac{1}{2} \\ 3 & 1 & 2 \\ 2 & \frac{1}{2} & 1 \end{bmatrix},$$

$$B_{3C} = \begin{bmatrix} 1 & 1/5 & 1/3 \\ 5 & 1 & 2 \\ 3 & 1/2 & 1 \end{bmatrix}, \qquad B_{4C} = \begin{bmatrix} 1 & \frac{1}{5} \\ 5 & 1 \end{bmatrix}.$$

Determine Weights.

By calculating the weights of each level layer by layer and normalizing the weight vectors, it can be concluded that the weight vectors of the judgment matrix AB are:

$$W_{AB} = (0.4594, 0.0667, 0.1491, 0.3248)^T.$$

The weight vectors of other judgment matrices are:

$$W_{B1C} = (0.25, \; 0.75)^T, W_{B2C} = (0.1634, \; 0.5396, \; 0.2970)^T,$$
$$W_{B3C} = (0.1095, \; 0.5815, \; 0.3090)^T, W_{B4C} = (0.1667, \; 0.8333)^T.$$

Therefore, the weight of Level C to Level A is the result of multiplying the weights of the two levels, as shown in the Table 2.

Table 2. Weights of Layer C to Target Layer A

	C_1	C_2	C_3	C_4	C_5
weight	0.1149	0.3445	0.0109	0.0360	0.0198
	C_6	C_7	C_8	C_9	C_{10}
weight	0.0163	0.0867	0.0461	0.0541	0.2707

Consistency Inspection.

Calculate the consistency ratio CR of each judgment matrix, and when CR=0, A has complete consistency. When CR<0.1, it is considered that the degree of inconsistency of A is within the allowable range and has satisfactory consistency, passing the consistency test. When CR ≥ 0.1, A has unsatisfactory consistency and should be adjusted or discarded. The maximum eigenvalue and consistency ratio test indicators of each judgment matrix are shown in Table 3.

Table 3. Maximum Eigenvalues and Consistency Ratio Test Indicators for Each Judgment Matrix

Judgment Matrix	**A_B**	**B_{1C}**	**B_{2C}**	**B_{3C}**	**B_{4C}**
λ_{max}	4.1497	2	3.0092	3.0037	2
CI	0.0499	0	0.0046	0.0019	0
CR	0.0561	0	0.0088	0.0037	0

3.2 Optimization of Organizational Training Benefits Based on GA

Genetic algorithm (GA) is a heuristic algorithm that simulates Darwin's evolution theory and the survival of the fittest mechanism in nature to search for global optimal solutions. GA transforms the problem-solving process into a process similar to the crossover and mutation of chromosomal genes in biological evolution, typically including basic operations such as selection, crossover, and mutation. Research has shown that genetic algorithms have strong robustness, intelligence, and efficiency in solving optimal solution scheduling optimization combinations. Compared to other heuristic algorithms for searching and solving problems, they do not have a high demand for knowledge background in the algorithm field[2-4]. However, a single heuristic algorithm has certain limitations, such as GA's weak local search ability, susceptibility to premature convergence, and susceptibility to falling into local optima when solving large-scale complex optimization problems. This article improves the original roulette strategy by combining elite retention strategy and roulette wheel strategy to solve the selection operator, effectively solving the defects of genetic algorithms that are prone to falling into local optima and leading to the loss of optimal solutions.

Coding.

This article uses a random method to generate the initial population, in order to ensure that the initial population is evenly distributed throughout the entire solution space as much as possible. The training unit duration corresponding to the training target is used as the gene of the chromosome, represented by a positive integer, and the actual meaning is the number of class hours. Therefore, by encoding the corresponding units of 10 training targets, the coding scheme for genes in the formed chromosomes is as follows:

Training unit coding: 5 2 2 2 1 6 4 1 3 4

The above training unit coding scheme represents a training duration of 5 class hours for training unit 1, 2 class hours for training unit 2, and so on.

Crossover.

The crossover operator determines the global search ability of the algorithm, specifically by exchanging some genes between the two chromosomes 1 and 2 obtained by the selection operator, thereby forming a new individual. In this paper, the partial matching crossover strategy is selected, and two training units are randomly selected as the crossover points to compare the values of the crossover points i and j. If $[(x_i - x_j) * (x_i' - x_j')] < 0$, then the value of the i-th crossover point of Chromosome 1 decreases by 1, the value of the jth crossover point increases by 1, the value of the ith crossover point of Chromosome 1 increases by 1, and the value of the jth crossover point decreases by 1; Otherwise, reverse the operation. According to the above coding case, two crossover positions are randomly selected for the following Chromosomes 1 and 2, and the operation process is as Fig.1:

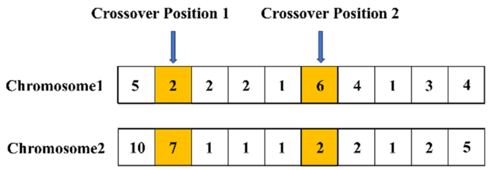


Fig. 1. Before Crossover

Assuming you choose the 2nd and 6th positions, due to (2-6) * (7-2)<0, then the 2nd position of the first chromosome is subtracted by 1, the 6th position is added by 1, the 2nd position of the second chromosome is added by 1, and the 6th position is subtracted by 1. After crossing, it is as Fig.2:

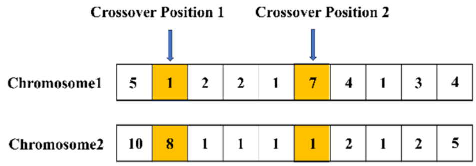


Fig. 2. After Crossover

Mutation.

Mutation operations can help algorithms jump out of local optima. Considering the small number of genes in the project and the comprehensive factors of moderately increasing population diversity, a two point mutation method was selected, which randomly selects two points and randomly increases or decreases the values at the points by 1. The following diagram is abbreviated as follows: assuming the selection of the second and sixth positions, assuming the random number d>0.5, the second position will be increased by 1, and the sixth position will be reduced by 1. After the mutation, it is shown in the following Fig.3:

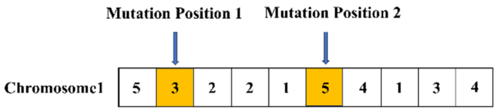


Fig. 3. After Mutation

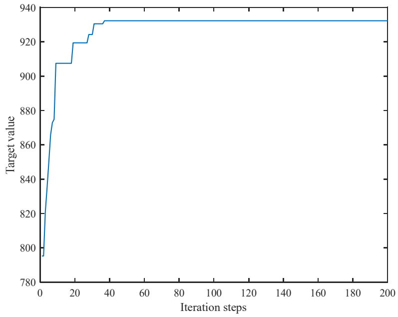
Selection.

Considering the roulette wheel selection strategy, the selection operator uses fitness as a measure to perform survival of the fittest on the population, resulting in a higher probability of individuals with higher fitness being inherited to the next generation of population. However, this method can easily lead to a large number of individuals with high fitness breeding, resulting in the algorithm's search scope being too limited. When using the elite retention strategy for selection operations[9-11], a good portion of individuals in each generation of the population serve as elite individuals and are directly retained until the next generation, ensuring that the optimal individuals so far will not be destroyed by genetic operations such as crossover and mutation.

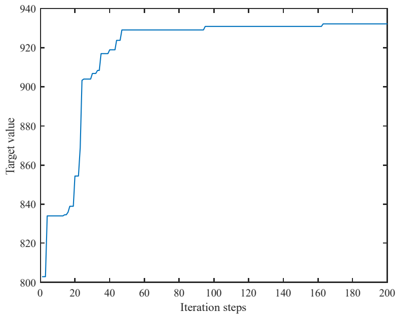
Therefore, to ensure the genetic inheritance of the optimal individuals in each generation, the selection method adopted in this article combines the elite retention strategy and the roulette degree strategy. After each iteration, the individual with the highest target value is directly placed in the next generation, and the remaining N-1 individuals are selected by roulette.

4 Analysis of Simulation Results

Taking the preparation of monthly training plans as an example, the intelligent training duration M is 30 class hours. In the genetic algorithm, the population size is 100, and the iteration steps are 200. The two point mutation method, elite retention strategy, and roulette wheel strategy are adopted. From the simulation results, it can be seen that the iteration process in Fig.4(a) selects a crossover rate of 0.9 and a mutation rate of 0.2. It can be seen that the target value starts to converge quickly, slows down after 20 steps, and reaches convergence around 40 steps, with a convergence target value of 932.19. The iteration process in Fig.4(b) selects a crossover rate of 0.1 and a mutation rate of 0.2. After 30 steps, it slows down and converges around 160 steps, with a convergence target value of 932.19. From this, it can be seen that the adjustment of crossover rate and mutation rate affects the speed of convergence iteration.



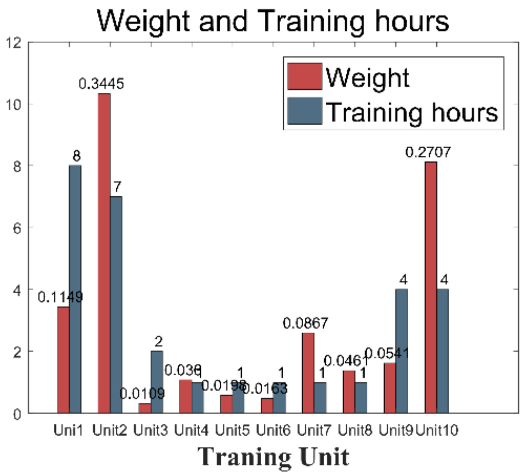
(a)crossover rate 0.9, mutation rate 0.2



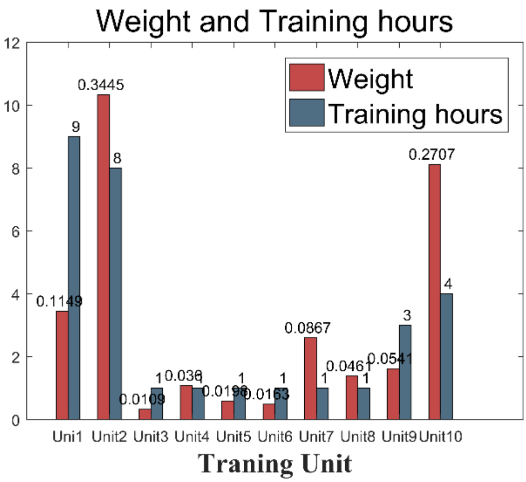
(b)crossover rate 0.1, mutation rate 0.2

Fig. 4. Iterative process

As shown in Fig.5, the training duration is $x_i = [8,7,2,1,1,1,1,1,4,4]$ and $x_i = [9,8,1,1,1,1,1,1,4,3], i = 1,2,\ldots,10$, basically stable with slight fluctuations. It can be seen from the relationship between class hours and weights that the training unit 2 with the highest weight (weight 0.3445) is not assigned the maximum number of courses, but instead the training unit 1 with a weight of only 0.1149 is assigned a larger number of 7 class hours. Therefore, it can be seen that the rationality of training time allocation is not only related to the importance of each training unit, but also to its subsequent continuity and necessity. It is related to the intrinsic connection and degree of correlation between the training objectives and their achievement. It is not a relatively reasonable method to rely solely on the weight values determined by chromatography for simple training planning.



(a)crossover rate 0.9, mutation rate 0.2



(b)crossover rate 0.1, mutation rate 0.9

Fig. 5. Comparison of weight and training duration

5 Conclusion

In general training planning, training duration is often planned based on training experience. Due to the neglect of the inherent correlation between multiple training objectives, the training plan made cannot achieve the best intensive training benefits. The organizational training benefit optimization scheme based on AHP-GA algorithm proposed in this article can combine the training experience of organizational trainers and intelligent optimization algorithms to solve the problem of training duration allocation in training management, and the effectiveness of the solution has been verified through simulation. Subsequent research will be based on this and further research will be conducted on the application of training duration that can be adjusted independently according to the training situation.

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